JULY 2019 M.Sc. in Electronics and Computer Engineering KURBAN KOTAN

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HASAN KALYONCU UNIVERSITY

GRADUATE SCHOOL OF

NATURAL & APPLIED SCIENCES

COMPARATIVE ANALYSIS OF CLASSIFICATION TECHNIQUES FOR NETWORK ANOMALIES MANAGEMENT

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR MASTER DEGREE OF

M. Sc. THESIS

IN

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Supervisor

Assist. Prof. Dr. Mohammed K. M. MADI

Kurban KOTAN

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GRADUATE SCHOOL OF NATURAL & APPLIED SCIENCES INSTITUTE
M.Sc. ACCEPTANCE AND APPROVAL FORM

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ABSTRACT

COMPARATIVE ANALYSIS OF CLASSIFICATION TECHNIQUES FOR NETWORK ANOMALIES MANAGEMENT A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR MASTER DEGREE OF

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Today, the rapid development in technology is enabling billions of devices to communicate with each other. This development requires new network technologies to allow all these devices to connect to network easily. In recent years, cyber-attacks have been a serious threat to governments, businesses and individuals. Many Intrusion Detection Systems, which were designed to prevent these cyber-attacks failed. Intrusion Detections Systems (IDS) could not sufficiently recognize the attacks and the cunning ways the attackers used, resulting in inefficient IDS solution and vulnerable networks. It would be a much smarter solution to counteract attacks by using machine learning based systems that is the result of data mining and statistics. This approach will provide a more efficient IDS solution than a conventional IDS solution based on attack recognition techniques. The purpose of this thesis is to propose a method for Network Anomaly Detection System (NADS) using machine learning algorithms with the aim of enhancing the processes of the network troubleshooting, and raising the efficiency of the maintenance processes. This study compares the performance of four selected machine learning classifiers with each other. The selected algorithms are: K-Nearest Neighbors (KNN), K-means, Naïve Bayes and Random Forest. This comparison is conducted to detect the network anomaly and analyze the performance of the classification framework. This comparison is conducted to provide recommendations related to the framework selection. The above mentioned algorithms are implemented and tested on KDD CUP99 intrusion detection dataset that is widely used to evaluate intrusion detection prototypes. The experimental outcomes demonstrate that KNN algorithm perform well in terms of accuracy and computation time. Furthermore the results show that KNN has a successful detection of potential threat of 98.0379 % of all known attacks.

Keywords: Network Security, Machine Learning, Artificial Intelligence, Anomaly Detection, K-Nearest Neighbors Algorithm, Principal Component Analysis Algorithm, KDD CUP99 dataset.

ÖZET

COMPARATIVE ANALYSIS OF CLASSIFICATION TECHNIQUES FOR NETWORK ANOMALIES MANAGEMENT A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENT FOR MASTER DEGREE OF

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Bugün, teknolojideki hızlı gelişme milyarlarca cihazın birbiriyle iletişim kurmasını sağlıyor. Bu gelişme, tüm bu cihazların ağa kolayca bağlanabilmesi için yeni ağ teknolojilerini gerektirir. Son yıllarda, siber saldırılar hükümetler, işletmeler ve bireyler için ciddi bir tehdit oluşturuyor. Bu siber saldırıları önlemek için tasarlanan birçok saldırı tespit sistemi başarısız oldu. Saldırı Tespit Sistemleri (IDS) saldırıları ve saldırganların kullandığı kurnazca yollarını yeterince tanıyamadığından yetersiz IDS çözümü ve savunmasız ağlarla sonuçlandı. Veri madenciliği ve istatistiğin bir sonucu olan makine öğrenmesi tabanlı sistemler kullanmak saldırıları önlemek için çok daha akıllıca bir çözüm olacaktır. Bu yaklaşım, saldırı tanıma tekniklerine dayanan klasik IDS çözümüne kıyasla daha verimli bir IDS çözümü getirecektir. Bu tezin amacı, ağ sorun giderme işlemlerini geliştirmek ve bakım işlemlerinin verimliliğini artırmak amacıyla makine öğrenmesini kullanarak Ağ Tabanlı Anomali Tespit Sistemi (NADS) için bir yöntem önermektir. Bu çalışma, seçilen dört makine öğrenme sınıflandırma algoritmasının performansını birbiriyle karşılaştırmaktadır. Seçilen algoritmalar şunlardır: K-En Yakın Komşular (KNN), K-Means, Naïve Bayes ve Random Forest. Bu karşılaştırma ağ anomalisini tespit etmek ve sınıflandırma çerçevesinin performansını analiz etmek içindir. Bu karşılaştırma, çerçeve seçimi ile ilgili öneriler sunmak için yapılmıştır. Yukarıda belirtilen algoritmalar, izinsiz giriş tespit prototiplerini değerlendirmek için yaygın olarak kullanılan KDD CUP99 izinsiz giriş tespit veri setinde uygulanır ve test edilir. Deneysel sonuçlar KNN algoritmasının doğruluk ve hesaplama süresi açısından iyi çalıştığını göstermektedir. Ayrıca, KNN'nin bilinen tüm saldırıların % 98.0379’luk potansiyel tehdidin başarılı bir şekilde tespit ettiğini göstermiştir.

Anahtar Kelimeler: Ağ Güvenliği, Makine Öğrenimi, Yapay Zeka, Anomali Tespiti, K-En Yakın Komşular Algoritması, Temel Bileşen Analizi Algoritması, KDD CUP99 veri seti.

This research work is dedicated to my family, my parents and teachers for strengthening me, and giving me resources and wisdom to finish this project.

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LIST OF ABBREVIATIONS

ACC	: Accuracy Rate
ADS	: Anomaly Detection System
AI	: Artificial Intelligence
CM	: Confusion Matrix
CRISP-DM	: Cross-Industry Standard Process for Data Mining
DARPA	: Defense Advanced Research Project Agency
DoS	: Denial of Service
DR	: Detection Rate
FN	: False Negative
FP	: False Positive
ICMP	: Internet Control Message Protocol
ID	: Intrusion Detection
IDS	: Intrusion Detection System
IP	: Internet Protocol
KDD	: Knowledge Discovery and Data
KDD CUP99	: Knowledge Discovery and Data Mining CUP1999
KM	: K-Means
KNN	: K-Nearest Neighbors
LAN	: Local Area Network
NADS	: Network-based Anomaly Detection System
NAD	: Network-based Anomaly Detection
NB	: Naïve Bayes
PCA	: Principal Component Analysis
PSP	: Percentage of Successful Prediction

RF	: Random Forests
R2L	: Remote to Local
SVM	: Support Vector Machine
TCP	: Transmission Control Protocol
WAN	: Wide Area Network
WinPcap	: Windows Packet Capturing
TN	: True Negative
TP	: True Positive
TPR	: True Positive Rate
U2R	: User to Root
UDP	: User Datagram Protocol
TCP	: Transmission Control Protocol
TCP/IP	: Transmission Control Protocol/Internet Protocol

CHAPTER 1

INTRODUCTION

Network anomalies (network intrusions, network overload conditions, denial of service attacks and malicious/hostile activities) can cause network failures for both private and public entities. Malicious individuals and groups routinely employ cyber-attacks that target businesses and governments in what is now known as cyber-terrorism (Gable 2010). The goal is to cause fear and changes in behavior to affect political or ideological ends. Internet and computer networks are increasing day by day and the number of computers connected to the internet and computer networks are increasing and diversifying. On the other hand, cybersecurity (Cybersecurity is the protection of internet connected systems, hardware, software and data from cyber-attacks) threats are growing every day. Because of these factors, cybersecurity is becoming more complex and costly. Developing flexible and adaptable security-oriented approaches along with new types of attacks that are constantly emerging is a very difficult task. Therefore, anomaly intrusion detection techniques and systems for networks are very innovative to achieve the necessary protection.

The Network Anomaly Detection System (NADS) monitors computer networks and identifies any deviations from the normal profile to detect new attacks. Thus, it takes appropriate action. In this context, it is indispensable and very important for the network. Network anomaly detection (NAD) can be achieved through Statistical-based, Clustering and outlier-based, Classification-based, Knowledge-based, Soft computing and Combination learner based (Baliga, Kamat et al. 2007). These are shown in Figure 1.1.

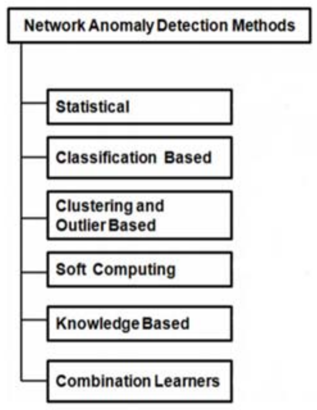


Figure 1.1: Network Anomaly Detection Methods (Baliga, Kamat et al. 2007)

For statistical based NAD an anomaly is an observation. Observation is suspected of being partially or completely unrelated because observation is not generated by the assumed model (Bhuyan, Bhattacharyya et al. 2013). Therefore, any generated traffic with a low probability of occurrence are considered as anomalies. Based on training datasets, classification based NAD tries to assign new data samples to categories (Bhuyan, Bhattacharyya et al. 2013). Any object can be defined by its properties (or features). Clustering is to categorize new sets of objects into clusters (groups) by using a measurement distance or a specific correlation for it. The objects which are in the same set are more related to each when compare to object in the other sets (Garcia-Teodoro, Diaz-Verdejo et al. 2009). Soft computing is sufficient for NADS because it is impossible to find certain solutions sometimes. Soft computing is usually thought of as encompassing methods (Patcha and Park 2007). Knowledge based methods use host or network events first, then check these against predefined rule sets and known attack patterns (Baliga, Kamat et al. 2007). Combination learners combine multiple methods then partition them into three different categories: Fusion-based methods, Hybrid methods and Ensemble-based methods (Garcia-Teodoro, Diaz-Verdejo et al. 2009). The machine learning approach as developed in this thesis will be Statistical-based.

1.1 Problem Statement

After firewall, ADS is protecting the network. Nowadays researchers focus on ADSs but however ADSs have low detection rate, low accuracy rate and high false alarm rate (Kathareios, Anghel et al. 2017).

Many studies have been carried out on the topic of network traffic modeling using machine learning (Mahoney and Chan 2002, Williams, Zander et al. 2006, Lippi, Bertini et al. 2013). K-Nearest Neighbors (KNN) classifier can achieve superior performance similar to Support Vector Machine (SVM) and Neural Networks, which are parametric classifiers. KNN, SVM and Neural Networks are in top of evaluated machine learning algorithms. In contrast to the parametric classifiers, KNN classifier has several important advantages (Duda, Hart et al. 2001). For KNN Classifier, memory requirements are high and KNN Classifier is susceptible to cure of dimensionality (Liao, Vemuri et al. 2007). We will focus on the KNN classifier, which can reduce the memory requirements and sensitivity to cure of dimensionality by using less number of the input features instead of using hundreds or thousands of features. However, we will compare it other algorithms, like K-Means Classifier, Naïve Bayes Classifier and Random Forest Classifier, to compare its performance.

Using machine learning for anomaly detection enhances the speed of detection of structural errors, defects or frauds. Detecting anomalies across an entire network system is a very broad proposition. Here we focus on local area network (LAN) anomalies detection using machine learning.

1.2 Research Objectives

The aim of this research is to use the machine learning techniques for network anomalies detection in LAN. In order to do this, the following objectives are identified:

a) To research the available methods for the network anomalies detection using machine learning.

b) To outline the identified methods taxonomy and identify the advantages, disadvantages and weaknesses of the identified method.

c) To evaluate the performance of the identified method.

1.3 Significance of the Study

This thesis's aim is establishing a network based anomaly detection system with machine learning to detect abnormal behavior of network traffic. This can be achieved by using fast machine learning algorithms that can process and analyze network traffic.

In a brief summary, Detection Rate (DR) will be increased to maximum and NADS will uncover and precisely identify new attacks. The system will use the known attack pattern in phase of training in order to increase detection rate which is actually machine learning.

1.4 Background of the Study

There are five chapters in this thesis. Theoretical background of generic NADS, a brief explanation of methods of NADS, Knowledge Discovery Data mining (KDD CUP99 data set) description, K Nearest Neighbor algorithms, K-Means algorithm (KM), Naïve Bayes algorithm (NB), Random Forest algorithm (RF) and Principal Component Analysis algorithm (PCA) are presented in chapter two. Chapter three presents the methodology and system structure. Implementation and experimental results from the proposed system and comparison of the system with other classification algorithms were presented in chapter four. Conclusions, limitations and suggestions for future work are presented at chapter five.

CHAPTER 2

BACKGROUND AND RELATED WORKS

2.1 Introduction

Network security is getting more and more importance than ever because computer networks are growing enormous with sensitive information and network based services on them. And internet and networks are exposed to increasing number of security threats. There is a big problem on detection of the growing new intrusion types: Labeling of the network data instances by human is usually troublesome, take too much time and expensive. Developing adaptive security oriented and flexible methods are very hard by new types of attacks appearing incessantly. Because of this, against malicious activities protecting target networks and systems, NADS are important technology.

The different methods of NAD are represented under this chapter and it is divided into six main categories (Bhuyan, Bhattacharyya et al. 2013):

- Soft computing
- Clustering and outlier-based
- Classification-based
- Statistical-based
- Combination learner
- Knowledge-based

In consideration of their advantages and drawbacks under this chapter, these six categories will be briefly explained.

2.2 Misuse Detection

In a misuse detection, which is an approach of detecting network attacks, first abnormal system behaviors are defined then all other behaviors are defined as normal. Anomaly detection approach defines normal behaviors first and then defines all other behaviors as abnormal. Therefore, it stands against this approach. In misuse detection everything unknown is normal. Using attack signatures in an intrusion detection system is an example for misuse detection. Generally, term of misuse detection is used to all kinds of computer misuse (Helman, Liepins et al. 1992).

2.3 Anomaly Detection

In anomaly detection, it supposes that intrusions are anomalies that differ from normal behaviors. Generally, anomaly detection creates a profile for normal behaviors and marks them, which deviate largely from the profile, as attacks. Main advantage of anomaly detection is that it can detect unknown attacks. Disadvantage of anomaly detection is that it has high false positive rate because anomalies are not necessarily intrusive in practice. In addition, attacks that do not clearly deviate from normal activities cannot be detected by anomaly detection (Gaber and Discovery 2012).

2.4 KDD CUP 99 Data Set

In KDD-99 the Fifth International Conference on Knowledge Discovery and Data Mining, The Third International Knowledge Discovery and Data Mining Tools Competition was held and a data set was used for network intrusion detector. That data set is KDD Cup 99. Network intrusion detector was built as which predicts intrusions (or attacks) and label them bad connections and predicts normal connections and label them as normal.

There are standard set of data to be audited in this dataset, which simulated in a military network environment and contains a wide range of intrusions. Since 1999, it has been used wildly for the anomaly detection methods. This data set was built based on the data captured in DARPA'98 evaluation program. DARPA'98 had been obtained from 7 weeks of network traffic. And it contains about 5 million connection records. Each connections is about 100 bytes. Dataset is raw binary tcp dump data and it is about 4GB.

KDD training data set includes about 5 million connection vectors. Every vector includes 41 features, which is labeled normal or an attack (Tavallaee, Bagheri et al. 2009). 41 features of vectors are shown in Appendix B.

Attacks fall into one of the following four categories:

***Denial of Service Attack (DoS)*:** DoS is any type of attack that attackers prevent users from accessing the service. In this attack type, attacker usually sends excessive messages and asks the network (or server) to authenticate requests, which have void return addresses. When network (or server) sends the authentication approval, network (or server) will not be able to find attacker's return address and before closing the connection, it will cause the server to wait. When the server ends the connection, attacker sends same type of messages. Therefore, the process of authentication and server waiting process will begin again and it will keep the network (or server) busy.

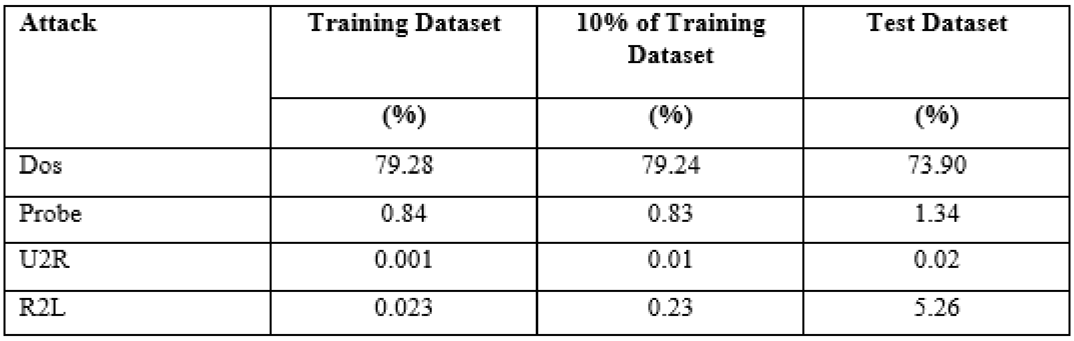
***User to Root Attack (U2R)*:** In this type of attacks, attacker gets on the system with normal user account and then attacker abuses security vulnerabilities to obtain super user privileges.

***Remote to Local Attack (R2L)*:** This is type of attacks that attacker gets access to a local user's computer on system over the internet by sending packets, in order to expose the machines security vulnerabilities and exploit privileges.

***Probing Attack (probe)*:** This is type of attacks that attacker scans a computer or a networking device, in order to expose the machines vulnerabilities and exploit privileges for later use.

Percentages of these attacks in KDD dataset are shown in Table 2.1.

Table 2.1: Distributions of attack classes in 1999 KDD cup dataset (Ahmed and Mahmood 2015, Aljawarneh, Aldwairi et al. 2018)



Attack	Training Dataset	10% of Training Dataset	Test Dataset
	(%)	(%)	(%)
Dos	79.28	79.24	73.90
Probe	0.84	0.83	1.34
U2R	0.001	0.01	0.02
R2L	0.023	0.23	5.26

2.5 Literature Review

In networking, the ADSs are distinctively used to help in detecting anomalies in data of a network. This detection is made possible because the anomalous always occurs in the form of patterns. Nevertheless, other studies have depicted modeling of data in a sequential fashion in the process of detecting subsequences which are anomalous (Parmar and Patel 2017).

A review as well as a survey which has been conducted by (Lazarevic, Ertoz et al. 2003), on anomaly detection. In his review, it is established that the emergence of anomaly-based systems for detecting intrusion have been possible to develop numerous systems which can be utilized to effectively track novel attacks which have been waged on a given system. This has been possible through utilization of techniques such as maintaining a high DR of about 98% as well as a low rate of alarm of 1%. In his analysis, it is clear that he postulates that despite the fact that despite the efficiency level of the anomaly-based approaches in attack detections, the signature-based detections seem to be preferable in the event that there is a need for mainstream implementation of intrusion in a detection system.

In the same perspective, (Dasgupta, Ji et al. 2003) , projects that in enhancing the effectiveness of the anomaly detection systems, it is important to pay distinctive focus on the immunity-based techniques. The reason is that the technique does not focus on offering a remedy to anomalies in the system but it helps the network to be able to remain immune to any form of intrusion. Their analysis is relevant to this study because it offers an alternative to ensuring that the anomaly detection system is developed in a way that the focus is not only on detection of breach but also in enhancing protection of the system from any potential breach. In this way, the application of the immunity-based techniques is an emerging branch of the Artificial Intelligence (AI) and this is very important in the application of security.

The problem of anomaly detection system has been a concern of many intellectuals and this has led to the development of further mechanisms that can be effectively diploid to enhance not only detection of an anomaly but also protection of the system from any form of intrusion. Dorothy E. Denning (Denning 1987) in her analysis presents the detection of anomaly intrusion in a system should be detected in real time. In her opinion, this is very important because it helps in instituting measures that can help reverse the intrusion and block any further intrusion that can be incurred in the system. In this perspective in her analysis, she developed a system that enhanced real-time detection of system anomaly intrusions. The system developed by Dorothy E. Denning (Denning 1987) has the capacity of detecting a form of intrusion whether it is a break-in, a penetration as well as other forms of intrusion. This helps in ensuring that the system is under constant surveillance and protection. In her system, the foundation of the detection is on the hypothesis that through monitoring a system`s audit records for any abnormal patterns of use in the system, it is possible to detect a security violation in the system. In her system, she mentions that to make this possible there is every need to ensure that a profile that is utilized to represents the subject`s behavior has to be maintained. This should be done with respect to the object in terms of metrics as well as statistical models. In the same way, in order to be able to enhance the real-time detection of the anomalies, a rule that enables the system to acquire knowledge about the behavior of the intruder from the audit records will enhance effectiveness in anomalous behavior detection. The important of this model presented by Dorothy E. Denning (Denning 1987) is that it operates independently of any other system. It also does not depend on the application environment of the system in question or under threat of attack, it has to be independent of the system vulnerability as well as the type of intrusion. In this way, it is possible to have a framework for the general-purpose intrusion-detection expert system.

2.5.1 Statistical-based NAD

For statistical-based NAD, because of not generating from the stochastic model assumed an anomaly is an observation, which is suspected of being partially or completely irrelevant (Bhuyan, Bhattacharyya et al. 2013). Therefore, samples are anomalies because they have low probability of being generated. This method has two types: (a) parametric and (b) non-parametric. Parametric methods learn knowledge of distribution and they predict the parameters from data that is given, while nonparametric methods do not (Bhuyan, Bhattacharyya et al. 2013). Namely, parametric methods suppose that network data has certain distribution while non-parametric methods do not. Parametric methods make assumptions about statistical characteristics of the given data. There is no need prior knowledge about normal activity for this method and this is advantage of this it and these methods give accurate alert of malicious activities (Garcia-Teodoro, Diaz-Verdejo et al. 2009, Bhuyan, Bhattacharyya et al. 2013). However, until the network traffic composed during the attack is considered normal, they are vulnerable to be used to by attackers. Setting values for different parameters and metrics is hard, especially balancing between false positives and negatives (Bhuyan, Bhattacharyya et al. 2013). Those are disadvantages of statistical based NAD.

2.5.2 Classification-based NAD

In classification-based NAD, any object can be defined using properties or features. Based on training datasets, classification-based NAD tries to appoint new data samples to categories (Bhuyan, Bhattacharyya et al. 2013). In linear classification, it tries to draw a line between classes but the boundary might be nonlinear (Bhuyan, Bhattacharyya et al. 2013) as in Figure 2.1. By integrating new data, they are able to improve their execution that is why these classification methods are proper for training and testing (Bhuyan, Bhattacharyya et al. 2013). These are advantages of classification-based NAD. In addition, for known anomalies subject to appropriate thresholds these methods have very high detection rate (Bhuyan, Bhattacharyya et al. 2013). They are very sensitive to classifying hypotheses, which is the main disadvantage of classification based NAD. In addition, they are unable to detect unidentified anomalies until appropriate training datasets are given (Bhuyan, Bhattacharyya et al. 2013).

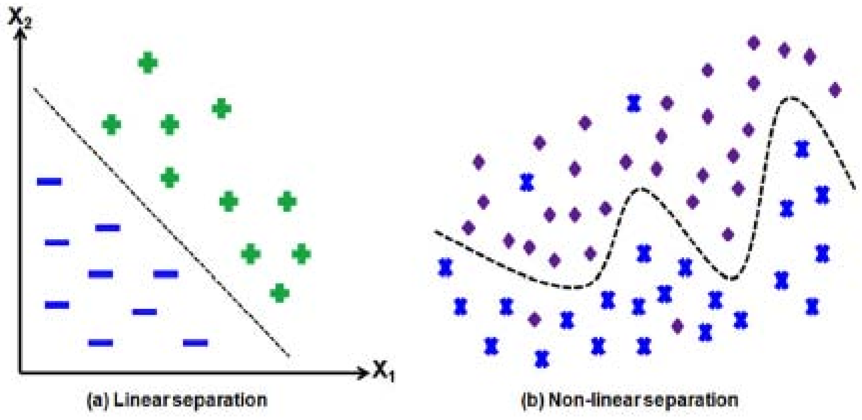


Figure 2.1: Classification-based NAD (Bhuyan, Bhattacharyya et al. 2013)

2.5.3 Clustering and outlier-based NAD

In clustering, it categorizes new sets of objects into groups and these groups are called clusters. It use a specific correlation or measurement distance during clustering. Observations are more related in same set to each other (Garcia-Teodoro, Diaz-Verdejo et al. 2009). As it is shown in Figure 2.2(a), in the most common application of clustering it consists of choosing representative points for each cluster. This is shown in Figure 2.2(a) as two dimensions. There are series of unidentified observations and by drawing ellipses around them; they are grouped into five clusters

(Bhuyan, Bhattacharyya et al. 2013). In Figure 2.2(b), we see that the outliers (abnormal data points) are separated from the normal clusters, which are non-existent clusters (Bhuyan, Bhattacharyya et al. 2013). In small-scale datasets, one of the main advantage for these methods it is able to find outliers easily. On the other hand, its computational complexity might be higher as compared to other NAD methods.

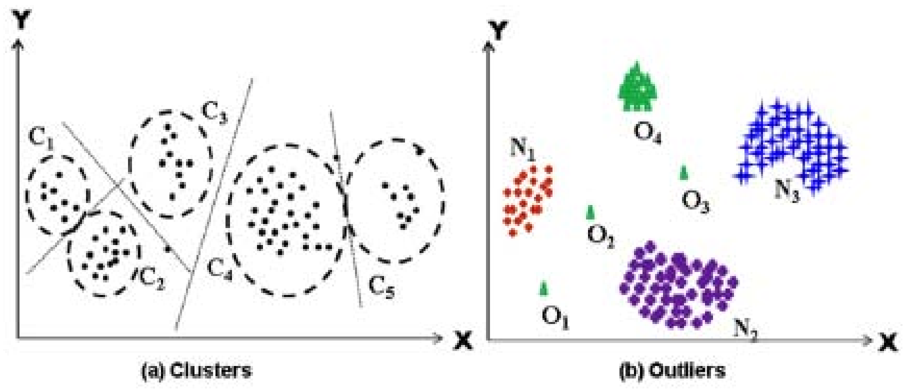


Figure 2.2: Clustering and outlier-based NAD (Bhuyan, Bhattacharyya et al. 2013)

2.5.4 Soft Computing

For NAD, this method is sufficient because finding precise solutions is impossible sometimes (Patcha and Park 2007, Hamamoto, Carvalho et al. 2018). Methods of soft computing are shown below:

- *Artificial Neural Networks*: Artificial Neural Networks has been motivated from its inception by the recognition that the human brain computes in an entirely different way from the conventional digital computer. Artificial Neural Networks are established tools for various applications such as data clustering, feature extraction and anomalous pattern identification in a network.
- *Genetic algorithm (GA)*: Genetic algorithms (GAs) represent a computational model-based on principles of evolution and natural selection.
- *Artificial immune systems*: Artificial Immune Systems represent a computational method inspired by the principles of the human immune

system. The human immune system is adept at performing anomaly detection. The anomaly detection in the human immune system classifies certain external objects that enter the body as undesirable antigens, i.e., objects that may cause illness.

- *Colony algorithms*: Colony algorithms are probabilistic techniques for solving computational problems that can be reformulated to find optimal paths through graphs.
- *Rough Sets*: Rough sets have been effectively used in classification systems, where complete knowledge of the system is not available. A classifier aims to form various classes where members of a class are not noticeably different. These indiscernible or indistinguishable objects are viewed as basic building blocks (concepts) used to build a knowledge base about the real world. This kind of uncertainty is referred to as rough uncertainty.
- *Fuzzy Sets*: The concept of fuzzy logic provides a language with syntax and local semantics for translating qualitative knowledge about a problem to be solved.

These methods have high flexibility and adaptability. This is advantages of soft computing-based anomaly detection methods. Consuming high resource are their disadvantages. So in lack of normal traffic data, the training of the systems becomes very hard.

2.5.5 Knowledge-based NAD

These methods check network or host events against known attack patterns and predefined rule sets. Knowledge based contains methods as shown down:

- Rule-based and expert system approaches
- Ontology and logic-based approaches

Advantages of these methods are scalability flexibility and robustness. If there are available training datasets for normal and anomalies both, these methods have high detection rate. Drawbacks of those methods are the costs and time consumption. Detecting unknown anomalies is very hard for knowledge based NAD (Garcia-Teodoro, Diaz-Verdejo et al. 2009).

2.5.6 Combination learners

This method combines multiple methods first. Then it divides these combined methods into three different categories, which are shown below:

- *Fusion-based methods*: Some methods of Fusion-based methods work in high dimensional feature spaces to extract and concatenate different semantic meanings. Others of Fusion-based methods attempt to combine classifiers trained on different features divided on the basis of hierarchical abstraction levels or the types of information contained.
- *Hybrid methods*: To overcome the limitations of the high false positive rate of anomaly detection and unknown intrusions of misuse detection, hybrid methods make use of features from approaches and get high accuracy.
- *Ensemble-based methods*: Ensemble-based methods are to weigh individual classifiers first and then combine them to get an overall classifier that outperforms all of them.

These methods cost a lot (Garcia-Teodoro, Diaz-Verdejo et al. 2009).

2.6 K-Nearest Neighbor (KNN) Algorithm

K-Nearest Neighbors algorithm is a very simple technique that is used in data mining. All available points are stored first and then KNN classifies new points according to similarity criteria using distance functions as follow:

- *Euclidean* : $\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$
- *Manhattan* : $\sum_{i=1}^{k} |x_i - y_i|$
- *Minkowski* : $\left(\sum_{i=1}^{k}(|x_i - y_i|)^q\right)^{\frac{1}{q}}$

Pseudo Code of K-Nearest Neighbors algorithm is

```
1-Load the data
2-Assign k value (In our example k value will be 1)
3-Iterate steps for all training data points to get predicted class
    i-  Calculate the distance between each points by using any distance function.
    ii- Sort distances values in ascending order.
    iii- From the sorted array, get the first top k points.
    iv- Specify the class that contains most of these points.
    v-  Assign the point as specified class member.
```

An example of the KNN algorithm is shown in Figure 2.3.

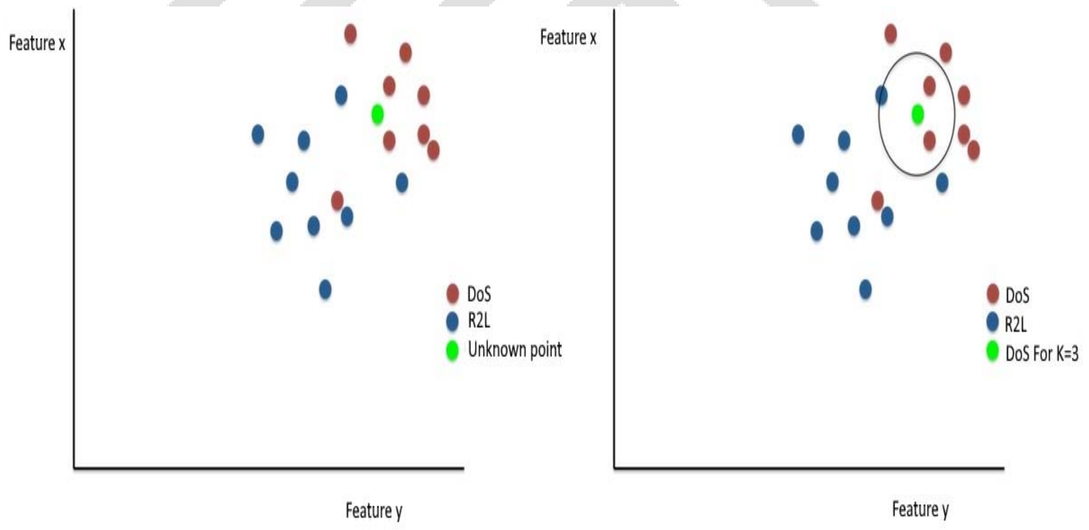


Figure 2.3: An Example of KNN Algorithm

Boundaries that separates two classes according to different k values are shown at Figure 2.4.

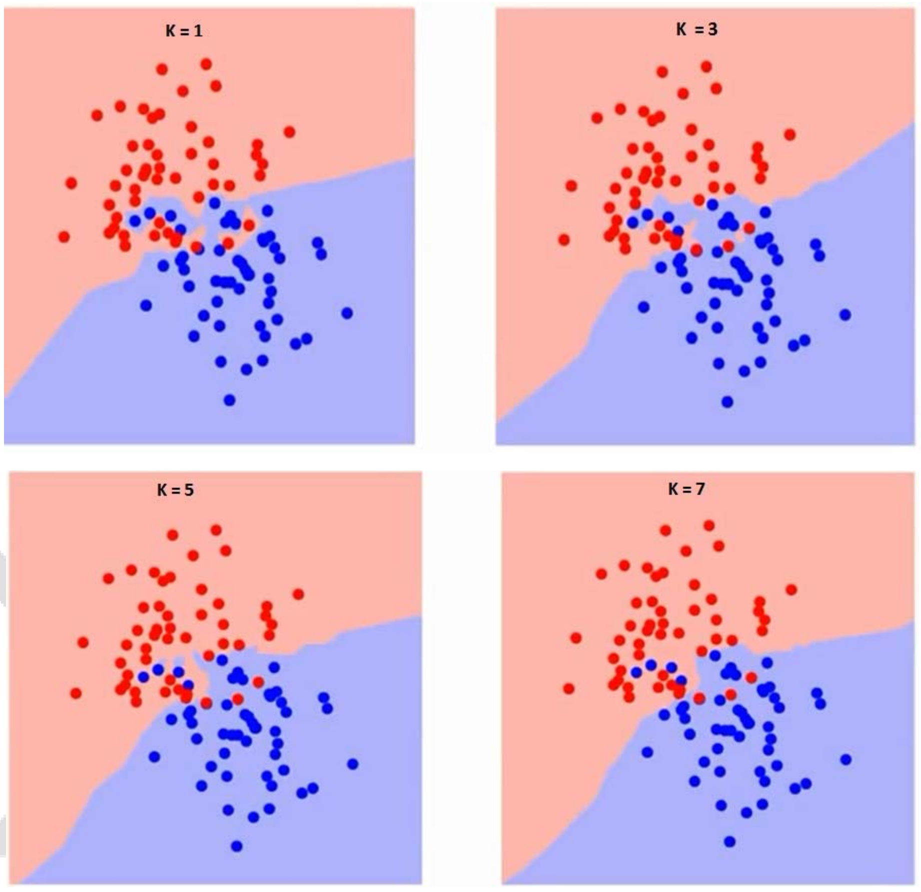


Figure 2.4: Different boundaries separating the two classes with different values of k

KNN is easy to be understood when there are few predictors .It is useful and easy to build models which are non-standard types. For example, text is non-standard type and if model contains text it is useful to use KNN (Omar, Ngadi et al. 2013).

Some other data classification algorithms that briefly described after this section will be compared with the KNN algorithm.

2.7 K-Means Classification Algorithm

K-Means Classification Algorithm is unsupervised. At beginning, it calculates initial class means by equally distributing them in the data space. Then by using a minimum distance measurement method, iteratively it groups data points into the nearest class. In every iteration, it recalculates every class means and according to these new means, it regroups observations. Until the maximum number of iterations is reached or the number of observations in each class changes by less than the selected observations change threshold this iteration continues.

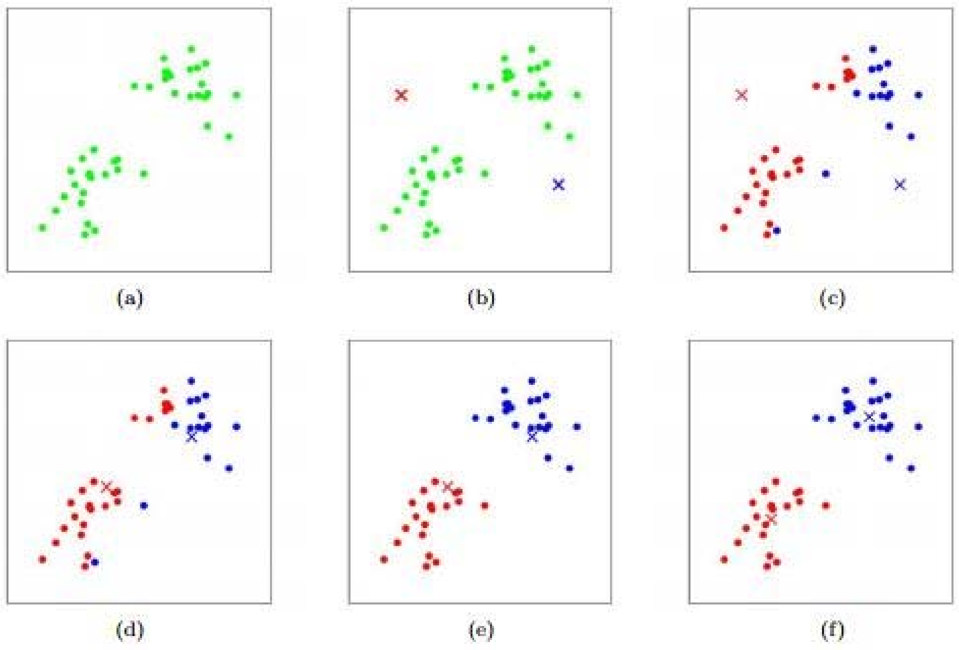
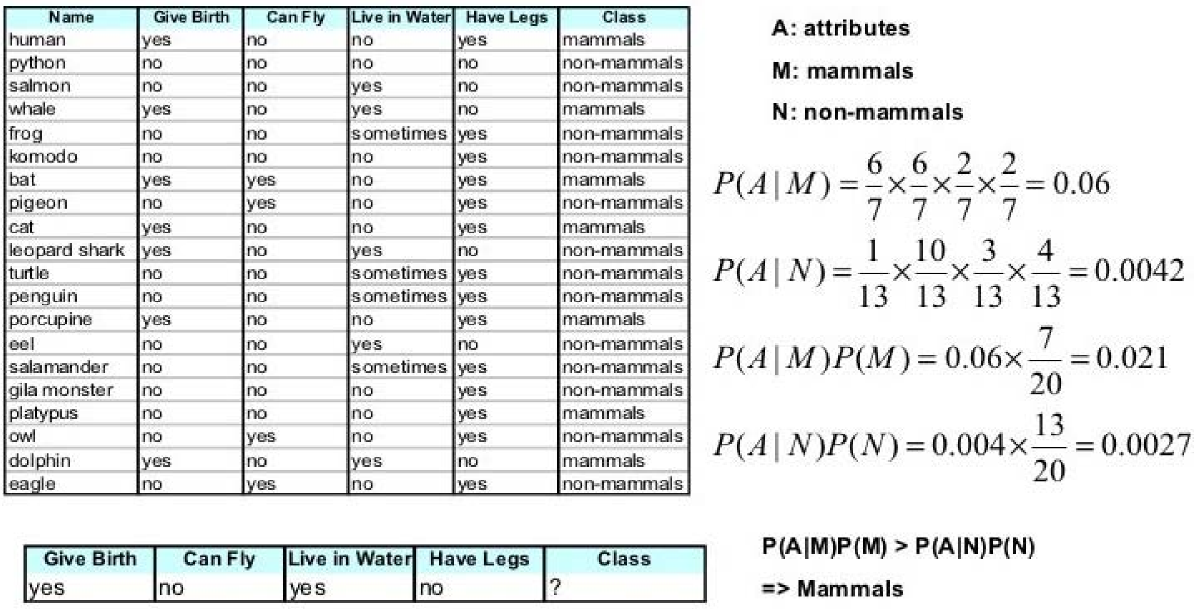


Figure 2.5: An Example of K-Means Classification Algorithm

KM has low complexity but it is obligation to specify k value because it is unsupervised. Disadvantages of KM are that it is sensitive to outlier data points and noise and initial assignment of centroids may change the result too much.

2.8 Naïve Bayes Classification Algorithm

This Classifier is based on the Bayesian Theorem, $(A\backslash B) = \frac{P(B\backslash A)P(A)}{P(B)}$, and it is especially suited to use if features dimensions are high. It can often perform better than complex classification methods despite its simplicity.



Name	Give Birth	Can Fly	Live in Water	Have Legs	Class
human	yes	no	no	yes	mammals
python	no	no	no	no	non-mammals
salmon	no	no	yes	no	non-mammals
whale	yes	no	yes	no	mammals
frog	no	no	sometimes	yes	non-mammals
komodo	no	no	no	yes	non-mammals
bat	yes	yes	no	yes	mammals
pigeon	no	yes	no	yes	non-mammals
cat	yes	no	no	yes	mammals
leopard shark	yes	no	yes	no	non-mammals
turtle	no	no	sometimes	yes	non-mammals
penguin	no	no	sometimes	yes	non-mammals
porcupine	yes	no	no	yes	mammals
eel	no	no	yes	no	non-mammals
salamander	no	no	sometimes	yes	non-mammals
gila monster	no	no	no	yes	non-mammals
platypus	no	no	no	yes	mammals
owl	no	yes	no	yes	non-mammals
dolphin	yes	no	yes	no	mammals
eagle	no	yes	no	yes	non-mammals

A: attributes

M: mammals

N: non-mammals

$$P(A \mid M) = \frac{6}{7} \times \frac{6}{7} \times \frac{2}{7} \times \frac{2}{7} = 0.06$$

$$P(A \mid N) = \frac{1}{13} \times \frac{10}{13} \times \frac{3}{13} \times \frac{4}{13} = 0.0042$$

$$P(A \mid M)P(M) = 0.06 \times \frac{7}{20} = 0.021$$

$$P(A \mid N)P(N) = 0.004 \times \frac{13}{20} = 0.0027$$

Give Birth	Can Fly	Live in Water	Have Legs	Class
yes	no	yes	no	?

P(A|M)P(M) > P(A|N)P(N)

=> Mammals

Figure 2.6: An Example Question of Naïve Bayes Classification Algorithm and Its Answer (Han, Pei et al. 2011)

2.9 Random Forest Classification Algorithm

Random Forest is a supervised, most flexible and easy to use algorithm. A forest that it has more trees is more robust. RF create decision trees on randomly selected data first. Then it gets prediction from each tree. At last, by means of voting, it selects the best solution.

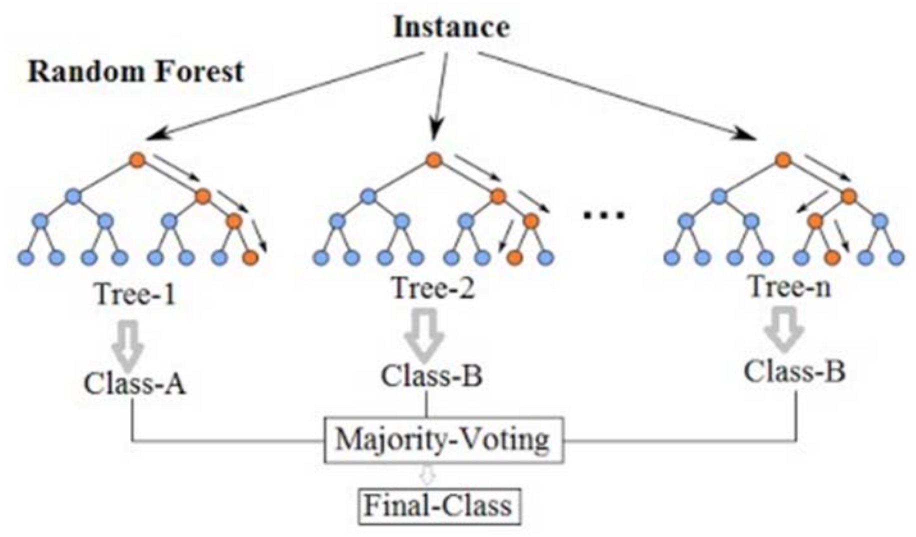


Figure 2.7: Illustration of Random Forest Classification Algorithm

2.10 Principal Component Analysis (PCA) Algorithm

PCA (Jolliffe 1986) is a most used method in data processing and dimension (size) reduction with many applications in social sciences, engineering and biology. Some examples include the handwritten, zip code classification and human face recognition. Nowadays it is used widely in data mining and machine learning.

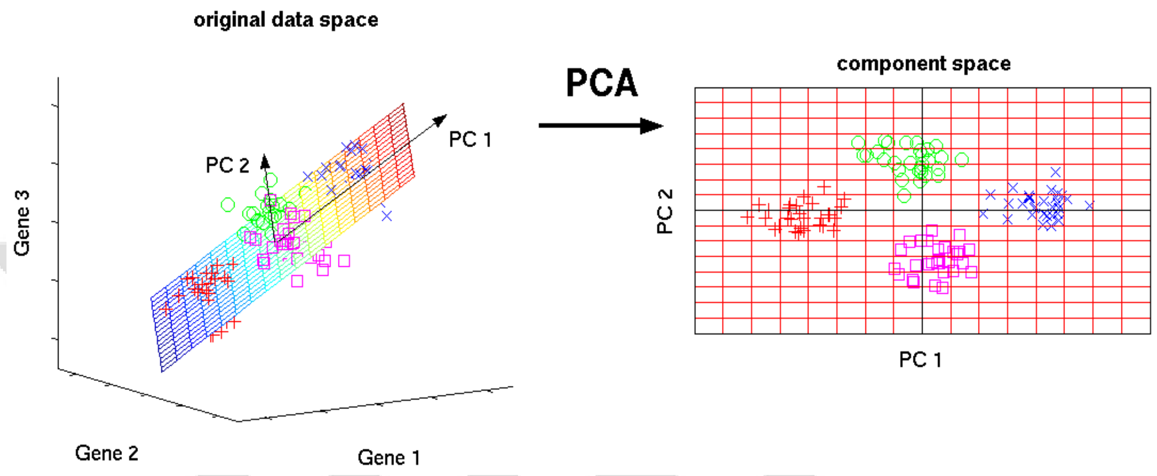


Figure 2.8: An Example of PCA Algorithm

PCA Algorithm will be used for reduction features before using K-Nearest Neighbors classifier in proposed system, which is in Chapter 3 and Chapter 4.

2.11 NADS Algorithm

The pseudo code of the NADS is shown below. It shows the general functions and working steps of the NADS system.

Table 2.2: The NADS Algorithm

```
1.    Start
2.    Read training file.
3.    Train the System
4.    Capture network packets by Wireshark application and extract features vectors.
5.    If vector is normal Than
6.    Mark the vector is normal.
7.    Else
8.    Mark the vector as abnormal.
9.    End
```

In this thesis, one of the efficient and easiest data-mining algorithm called KNN Algorithm is applied. Experimental results on the KDDCUP99 data set show that our approach is very effective in detecting network intrusion. Especially detection rate is 98.0379 %. It is observed that the proposed NADS works much better in terms of detection rate and accuracy rate when it is applied to KDD99 dataset compared with other algorithms (Farid, Harbi et al. 2010, Rao, Srinivas et al. 2011, Shanmugavadivu, Nagarajan et al. 2011).

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Methodology

This chapter presents the NADS, which is machine-learning system for anomalies detection system by using K-Nearest Neighbors Algorithm for classification and Principal Component Analysis Algorithm for dimension reduction in frame of CRISP-DM (Cross-Industry Standard Process for Data Mining) Methodology. It describes typical phases of a project, tasks in every phase and relationships between these tasks as a methodology. It provides a conspectus of the data-mining life cycle as a process model. It contains six steps as follow:

1. ***Business Understanding***: What is the problem we are dealing with?
2. ***Data Understanding***: What is the data we are working with?
3. ***Data Preparation***: What are the transformations and extractions to be done on the data?
4. ***Modeling***: What is the data model we should use?
5. ***Evaluation***: Does the model meet the project goals?
6. ***Deployment***: How should we use the model we developed

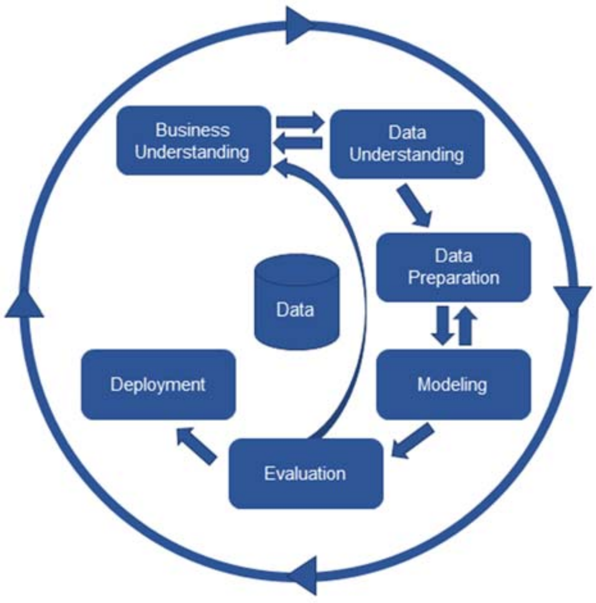


Figure 3.1: CRISP-DM

We will follow the steps of the CRISP-DM methodology in our machine learning system.

3.1.1 Business Understanding

This is first step of the Methodology (Process) is about description of the problem, defining situation, determining goals and success criteria and determining project plan. Chapter one of this thesis is “business understanding” step of methodology. Business understanding of this thesis briefly is:

Network anomalies can cause network failures for both private and public entities. Internet and computer networks are getting larger day by day and by the number of devices connected to it is increasing and getting various. Because of these factors, cybersecurity is becoming more complex and costly. Developing flexible and adaptable security-oriented approaches along with new types of attacks that are constantly emerging is a very difficult task. Therefore, anomaly intrusion detection techniques and systems for networks are very innovative to achieve the necessary protection.

3.1.2 Data Understanding

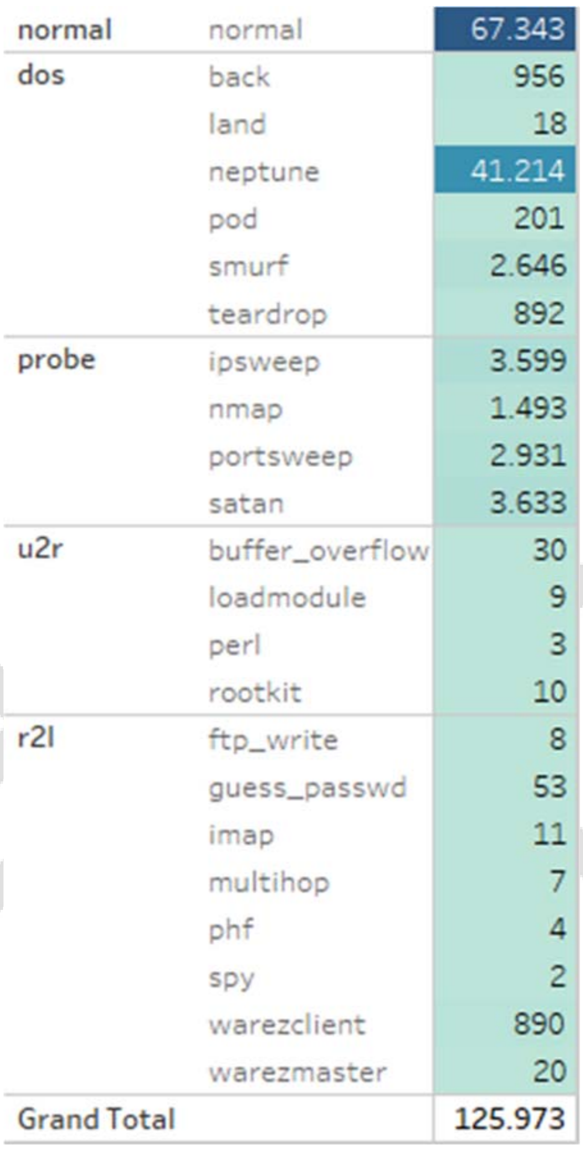
This step of the Methodology (Process) is about understanding of data. Those are gathering data, identify data, investigating data and verifying data quality. Subchapter 2.4 is “data understanding” step of methodology. The following table shows the part of the KDD Cup dataset which is used in proposed system NADS. Data understanding of this thesis briefly is:

KDD Cup 99 data set was used for network intrusion detector. Network intrusion detector was built as which predicts intrusions (or attacks) and label them bad connections and predicts normal connections and label them as normal. KDD training data set includes about 5 million connection vectors. Every vector includes 41 features, which is labeled normal or an attack. Attacks are generally as follow:

DoS, U2R, R2L and Probe.

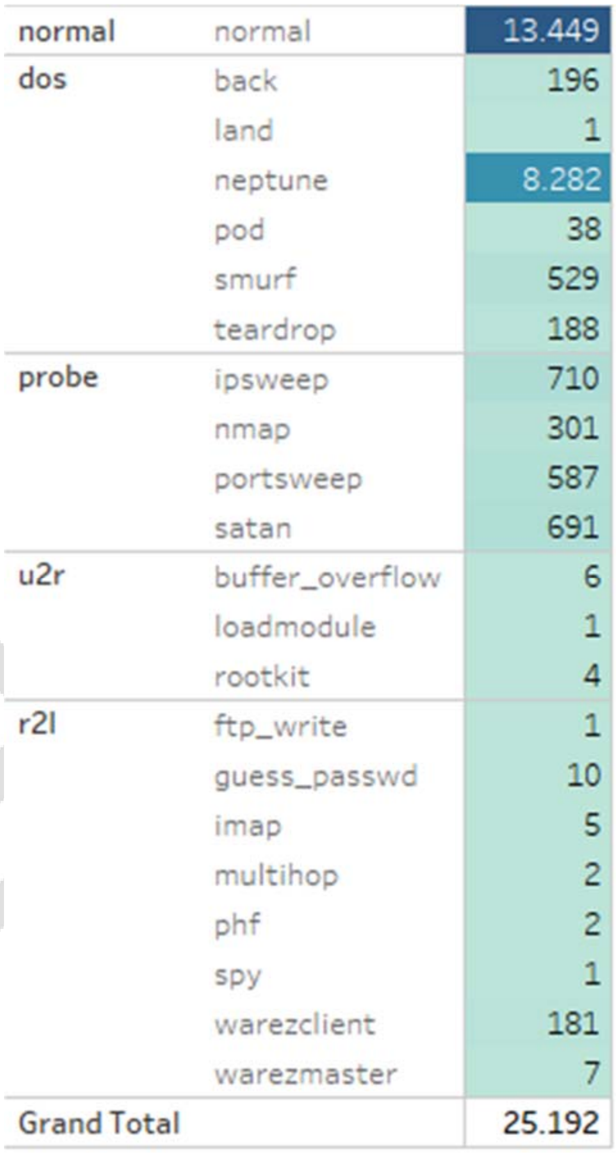
Percentages of these attacks in KDD dataset which are used for training and testing phases are shown in Table 3.1 and Table 3.2.

Table 3.1: Training Dataset of NADS



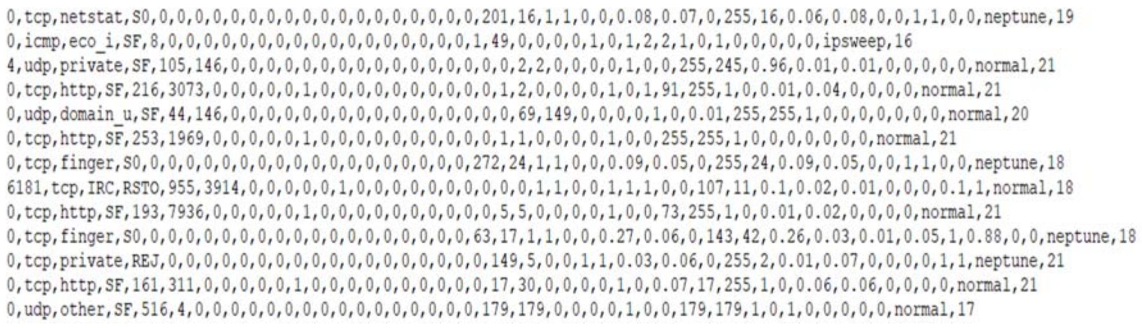
normal	normal	67.343
dos	back	956
	land	18
	neptune	41.214
	pod	201
	smurf	2.646
	teardrop	892
probe	ipsweep	3.599
	nmap	1.493
	portsweep	2.931
	satan	3.633
u2r	buffer_overflow	30
	loadmodule	9
	perl	3
	rootkit	10
r2l	ftp_write	8
	guess_passwd	53
	imap	11
	multihop	7
	phf	4
	spy	2
	warezclient	890
	warezmaster	20
Grand Total		125.973

Table 3.2: Test Dataset of NADS



normal	normal	13.449
dos	back	196
	land	1
	neptune	8.282
	pod	38
	smurf	529
	teardrop	188
probe	ipsweep	710
	nmap	301
	portsweep	587
	satan	691
u2r	buffer_overflow	6
	loadmodule	1
	rootkit	4
r2l	ftp_write	1
	guess_passwd	10
	imap	5
	multihop	2
	phf	2
	spy	1
	warezclient	181
	warezmaster	7
Grand Total		25.192

Figure 3.2 represents some sample vectors of NADS; these vectors were collected from the KDD CUP99 data set, which consists of normal and abnormal behavior for network traffic.



```
0,tcp,netstat,S0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,201,16,1,1,0,0,0.08,0.07,0,255,16,0.06,0.08,0,0,1,1,0,0,neptune,19
0,icmp,eco_i,SF,8,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,49,0,0,0,0,1,0,1,2,2,1,0,1,0,0,0,0,0,ipsweep,16
4,udp,private,SF,105,146,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,2,2,0,0,0,0,1,0,0,255,245,0.96,0.01,0.01,0,0,0,0,0,normal,21
0,tcp,http,SF,216,3073,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,1,2,0,0,0,0,1,0,1,91,255,1,0,0.01,0.04,0,0,0,0,normal,21
0,udp,domain_u,SF,44,146,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,69,149,0,0,0,0,1,0,0.01,255,255,1,0,0,0,0,0,0,0,normal,20
0,tcp,http,SF,253,1969,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,1,0,0,255,255,1,0,0,0,0,0,0,0,normal,21
0,tcp,finger,S0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,272,24,1,1,0,0,0.09,0.05,0,255,24,0.09,0.05,0,0,1,1,0,0,neptune,18
6181,tcp,IRC,RSTO,955,3914,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,1,1,0,0,1,1,1,0,0,107,11,0.1,0.02,0.01,0,0,0,0.1,1,normal,18
0,tcp,http,SF,193,7936,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,5,5,0,0,0,0,1,0,0,73,255,1,0,0.01,0.02,0,0,0,0,normal,21
0,tcp,finger,S0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,63,17,1,1,0,0,0.27,0.06,0,143,42,0.26,0.03,0.01,0.05,1,0.88,0,0,neptune,18
0,tcp,private,REJ,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,149,5,0,0,1,1,0.03,0.06,0,255,2,0.01,0.07,0,0,0,0,1,1,neptune,21
0,tcp,http,SF,161,311,0,0,0,0,0,1,0,0,0,0,0,0,0,0,0,0,17,30,0,0,0,0,1,0,0.07,17,255,1,0,0.06,0.06,0,0,0,0,normal,21
0,udp,other,SF,516,4,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,179,179,0,0,0,0,1,0,0,179,179,1,0,1,0,0,0,0,0,normal,17
```

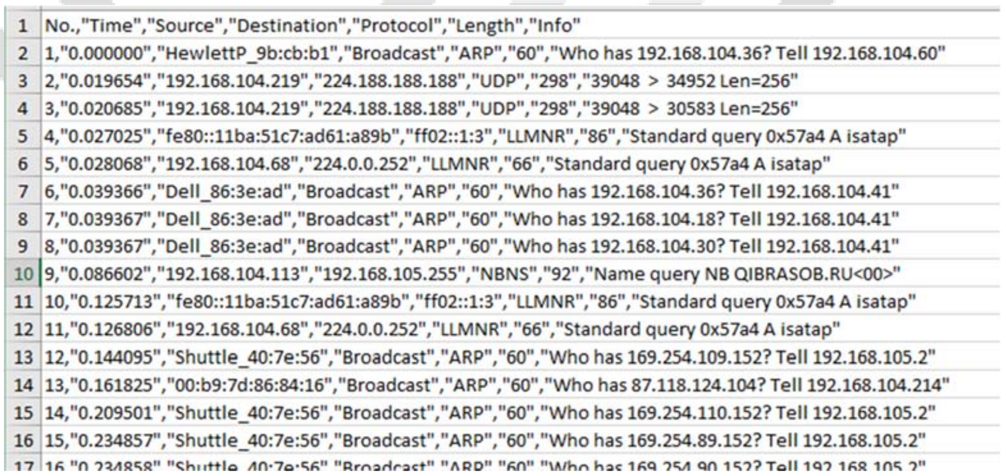
Figure 3.2: Sample vectors of NADS's KDD dataset

3.1.3 Data Preparation

This step of the Methodology (Process) is about integrating data from multi sources, formatting data, feature extraction, cleaning data, constructing data (derive attributes-transformation, filling in missing values) and feature selection.

3.1.3.1 Integrating data

In this part, NADS catches all packets in network (or it will input training file or testing file). All packets in the network is captured. In captured packets, data and time fields are displayed which are data and packet captured time. Typical packets showed in Figure 3.3. All captured packets will be monitored and can be saved for analyzing.

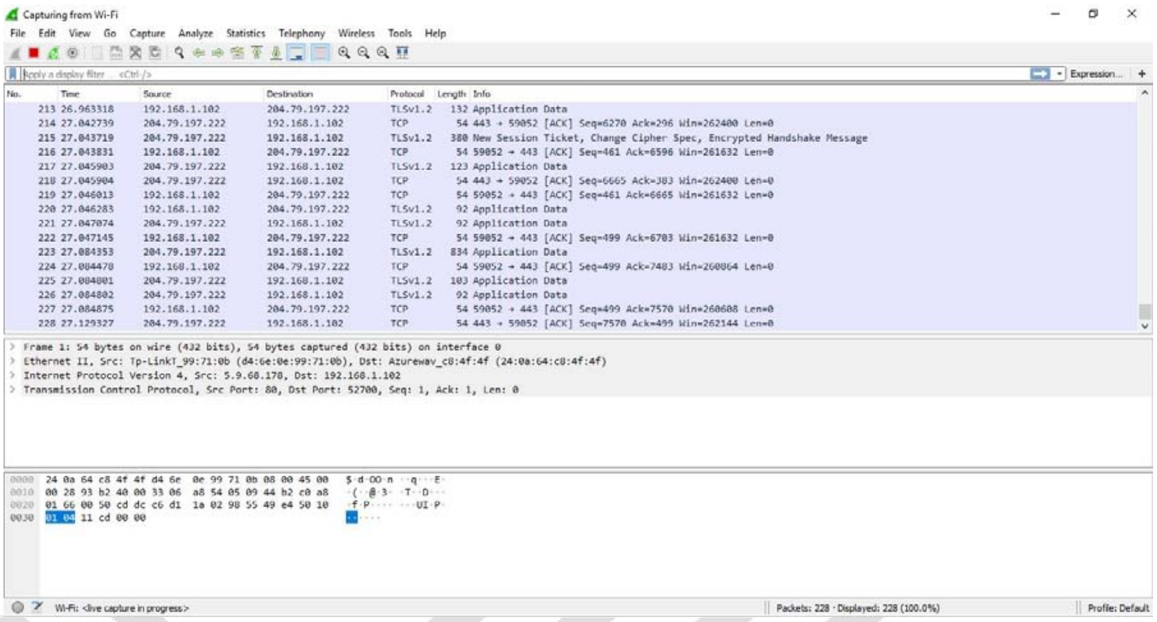


```
No.,"Time","Source","Destination","Protocol","Length","Info"
1,"0.000000","HewlettP_9b:cb:b1","Broadcast","ARP","60","Who has 192.168.104.36? Tell 192.168.104.60"
2,"0.019654","192.168.104.219","224.188.188.188","UDP","298","39048 > 34952 Len=256"
3,"0.020685","192.168.104.219","224.188.188.188","UDP","298","39048 > 30583 Len=256"
4,"0.027025","fe80::11ba:51c7:ad61:a89b","ff02::1:3","LLMNR","86","Standard query 0x57a4 A isatap"
5,"0.028068","192.168.104.68","224.0.0.252","LLMNR","66","Standard query 0x57a4 A isatap"
6,"0.039366","Dell_86:3e:ad","Broadcast","ARP","60","Who has 192.168.104.36? Tell 192.168.104.41"
7,"0.039367","Dell_86:3e:ad","Broadcast","ARP","60","Who has 192.168.104.18? Tell 192.168.104.41"
8,"0.039367","Dell_86:3e:ad","Broadcast","ARP","60","Who has 192.168.104.30? Tell 192.168.104.41"
9,"0.086602","192.168.104.113","192.168.105.255","NBNS","92","Name query NB QIBRASOB.RU<00>"
10,"0.125713","fe80::11ba:51c7:ad61:a89b","ff02::1:3","LLMNR","86","Standard query 0x57a4 A isatap"
11,"0.126806","192.168.104.68","224.0.0.252","LLMNR","66","Standard query 0x57a4 A isatap"
12,"0.144095","Shuttle_40:7e:56","Broadcast","ARP","60","Who has 169.254.109.152? Tell 192.168.105.2"
13,"0.161825","00:b9:7d:86:84:16","Broadcast","ARP","60","Who has 87.118.124.104? Tell 192.168.104.214"
14,"0.209501","Shuttle_40:7e:56","Broadcast","ARP","60","Who has 169.254.110.152? Tell 192.168.105.2"
15,"0.234857","Shuttle_40:7e:56","Broadcast","ARP","60","Who has 169.254.89.152? Tell 192.168.105.2"
16,"0.234858","Shuttle_40:7e:56","Broadcast","ARP","60","Who has 169.254.90.152? Tell 192.168.105.2"
```

Figure 3.3: Captured and converted network packets by Wireshark

First step of proposed system is packet capture. All packets of the real network traffic is captured in this step. This process runs in promiscuous mode. It captures all packets and then stores them as a set of traffic flows in data storage file.

In Figure 3.4 the user can capture packets by Wireshark and convert them csv file which contains features vectors in every line of the file showed in Figure 3.2.


Capturing from Wi-Fi
File Edit View Go Capture Analyze Statistics Telephony Wireless Tools Help
Apply a display filter ... <Ctrl-/>
Expression...
Wi-Fi: <live capture in progress>
Packets: 228 · Displayed: 228 (100.0%)
Profile: Default

```
No.  Time        Source          Destination     Protocol Length Info
 213 26.963318   192.168.1.102   204.79.197.222  TLSv1.2  132 Application Data
 214 27.042739   204.79.197.222  192.168.1.102   TCP       54 443 → 59052 [ACK] Seq=6270 Ack=296 Win=262400 Len=0
 215 27.043719   204.79.197.222  192.168.1.102   TLSv1.2  380 New Session Ticket, Change Cipher Spec, Encrypted Handshake Message
 216 27.043831   192.168.1.102   204.79.197.222  TCP       54 59052 → 443 [ACK] Seq=461 Ack=6596 Win=261632 Len=0
 217 27.045903   204.79.197.222  192.168.1.102   TLSv1.2  123 Application Data
 218 27.045904   204.79.197.222  192.168.1.102   TCP       54 443 → 59052 [ACK] Seq=6665 Ack=383 Win=262400 Len=0
 219 27.046013   192.168.1.102   204.79.197.222  TCP       54 59052 → 443 [ACK] Seq=461 Ack=6665 Win=261632 Len=0
 220 27.046283   192.168.1.102   204.79.197.222  TLSv1.2   92 Application Data
 221 27.047074   204.79.197.222  192.168.1.102   TLSv1.2   92 Application Data
 222 27.047145   192.168.1.102   204.79.197.222  TCP       54 59052 → 443 [ACK] Seq=499 Ack=6703 Win=261632 Len=0
 223 27.084353   204.79.197.222  192.168.1.102   TLSv1.2  834 Application Data
 224 27.084478   192.168.1.102   204.79.197.222  TCP       54 59052 → 443 [ACK] Seq=499 Ack=7483 Win=260864 Len=0
 225 27.084801   204.79.197.222  192.168.1.102   TLSv1.2  103 Application Data
 226 27.084802   204.79.197.222  192.168.1.102   TLSv1.2   92 Application Data
 227 27.084875   192.168.1.102   204.79.197.222  TCP       54 59052 → 443 [ACK] Seq=499 Ack=7570 Win=260608 Len=0
 228 27.129327   204.79.197.222  192.168.1.102   TCP       54 443 → 59052 [ACK] Seq=7570 Ack=499 Win=262144 Len=0

> Frame 1: 54 bytes on wire (432 bits), 54 bytes captured (432 bits) on interface 0
> Ethernet II, Src: Tp-LinkT_99:71:0b (d4:6e:0e:99:71:0b), Dst: Azurewav_c8:4f:4f (24:0a:64:c8:4f:4f)
> Internet Protocol Version 4, Src: 5.9.68.178, Dst: 192.168.1.102
> Transmission Control Protocol, Src Port: 80, Dst Port: 52700, Seq: 1, Ack: 1, Len: 0

0000  24 0a 64 c8 4f 4f d4 6e  0e 99 71 0b 08 00 45 00   $·d·OO·n ··q···E·
0010  00 28 93 b2 40 00 33 06  a8 54 05 09 44 b2 c0 a8   ·(··@·3· ·T··D···
0020  01 66 00 50 cd dc c6 d1  1a 02 98 55 49 e4 50 10   ·f·P···· ···UI·P·
0030  01 04 11 cd 00 00                                  ······
```

Figure 3.4: The application that deal with real packet capturing

Packet decoder are shown in Figure 3.5. The packet decoder grabs packets from Data Link layer via WinPcap library, and defines which protocol is in use for any packet captured. WinPcap is a packet capture library that runs under the Windows operating system and captures packets from the network via the data link layer, the second layer of the OSI.

Wireshark is a multiplatform. It is open source application interface. It is used for monitoring network packets and convert them into other file types. In our thesis, we will use Wireshark which use WinPcap library to capture packets and convert their format for data pre-processing step.

Then, the packet stored in data structure is sent for data pre-processing stage (Rao, Srinivas et al. 2011).

Table 3.3: OSI Layers

Layer	Function	Example
Application – Layer 7	Services that are used with end user applications.	SMTP
Presentation – Layer 6	Formats the data so that it can be viewed by the user. Encrypt and decrypt.	JPG, GIF, HTTPS, SSL, TLS
Session –Layer 5	Establishes/ends connections between two hosts.	NetBIOS, PPTP
Transport – Layer 4	Responsible for the transport protocol end error handling	TCP, UNDP
Network – Layer 3	Reads the IP address from the packet.	Router, Layer 3 Switches
Data Link – Layer 2	Reads the MAC address from the data packet.	Switches
Physical – Layer 1	Send data on the physical wire.	Hubs, NICS, Cable

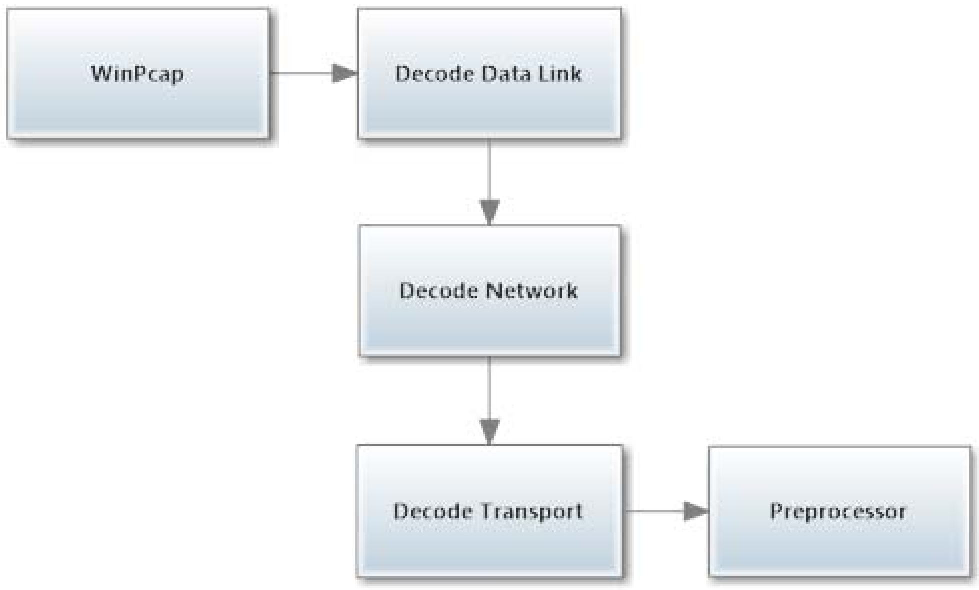


Figure 3.5: Stages of packet decoder (Rao, Srinivas et al. 2011)

3.1.3.2 Data Pre-processing

Data pre-processing steps are shown in Figure 3.6. Data pre-processing means extracting information about the packet connection from its header and create new statistical features from data.

Standard data pre-processing steps contain dataset creation, data cleaning, integration, feature construction to derive new higher-level features, feature selection to choose the optimal subset of relevant features, reduction, optimization and normalization.

Most appropriate steps for NADS are now described below (Shanmugavadivu, Nagarajan et al. 2011):

***Dataset Creation*:** This step contains identifying representative network traffic, which are packets information and some statistical information gathered from network, for the training and the testing phases. These dataset features of proposed system were created from several normal network sessions through weeks of normal work on the network, like dataset KDD CUP99 that we use for NADS. The features have been processed to get the values of the basic and statistical features that are considered normal and abnormal values for the network traffic.

***Features Extraction*:** Detecting anomalies depend on the values of features gathered packets from network. In this step system extracts basic features from packets header (such as protocol type, service, flag etc.) or extracts content features from payload of packets (such as logged in, etc.) or computes statistical values in order to create new features (like count, srv_count, etc.).

***Feature Scaling*:** This step is a technique for standardizing range of features of data or independent variables. Feature scaling is also known as data normalization. In data processing, it is generally performed during the data preprocessing step. In some machine learning algorithms, if the range of values of raw data varies widely without normalization objective functions will not work properly. For instance, most of classifiers calculate the distance between two points by using Euclidean distance. If one of the features has a broad range of values, the distance will be governed by this particular feature. Because of this, the range of all features should be normalized first so that each feature contributes approximately proportionately to the final distance (Ioffe and Szegedy 2015):

- Standardization
- Normalization

***Reduction*:** Reduction is used to determine whether multiple dimensions are related to each other and it is used to decrease the dimensions of the dataset by discarding any unnecessary or unrelated features.

After data pre-processing these feature vectors are suitable as input to machine learning algorithms.

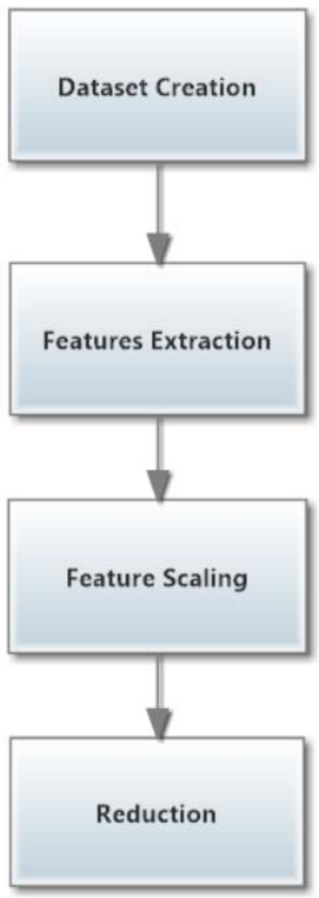


Figure 3.6: The stages of data pre-processing data (Shanmugavadivu, Nagarajan et al. 2011)

3.1.4 Modeling

This step of the Methodology (Process) is about selecting machine learning model (consider computer resources, computation time, number of features, business needs), generating test design (train/test split, cross validation, simulation [chronological order]), building model and assessing model. The most relevant steps of Modeling of Methodology for NADS are described below.

3.1.4.1 Classification

Classification is a method of determining what group a certain observation belongs to by classifier algorithm. For example, categorizing plants, animals, and other life forms into different taxonomies by biologists are classification. Classification is one of the primary uses of machine learning and data mining. In order to determine the correct category for a given observation, following are done by machine learning:

- Applies a classification algorithm to identify shared characteristics of certain classes.
- Compares those characteristics to the data it is trying to classify.
- Uses that information to estimate how likely it is that observation belongs to a particular class.

Then the train data is being classified by algorithms and the system is trained with the train data. In the prediction step, the trained system estimates vectors to determine whether the data is normal or not.

3.1.4.2 Prediction

In this stage, value of machine-learning is realized. Finally, trained system is used to predict the outcome and it labels packets as normal or as attack types. This stage is responsible with deciding whether an event or set of events are intrusion or not.

3.1.5 Evaluation

This step of the Methodology (Process) is about evaluating results in terms of business needs, reviewing process and determining next step. “Evaluation” step will be discussed in chapter four of this thesis.

3.1.6 Deployment

This step of the Methodology (Process) is about planning and deploying the model and planning monitoring and maintenance process. “Deployment” step will be discussed in chapter five of this thesis.

3.2 System Structure

NADS classifies and identifies each connection vector to normal or intrusion types. Then results are displayed as alert. The NADS contains data aggregation, data pre-processing, classification, prediction and response stages. In “Data aggregation” stage, data is captured from network traffic by Wireshark network monitoring application and then data is used to train and to test the NADS in “Classification” and “Prediction” stages. In NADS, data for train is provided by KDD CUP99 dataset and “Pre-processing” stage regulates the data to ensure an efficient configuration of the classification system. KNN classification algorithm is used to build the proposed

NADS and classify the intrusion attacks in offline mode and online mode by cooperation of PCA and Wireshark network monitoring application. The last stage of NADS, "Response" displays the important information and informs the security analyst. Security analyst analyzes the risks, and then takes proper actions.

The system structure is shown in Figure 3.7. It presents a generic structure of NADS.

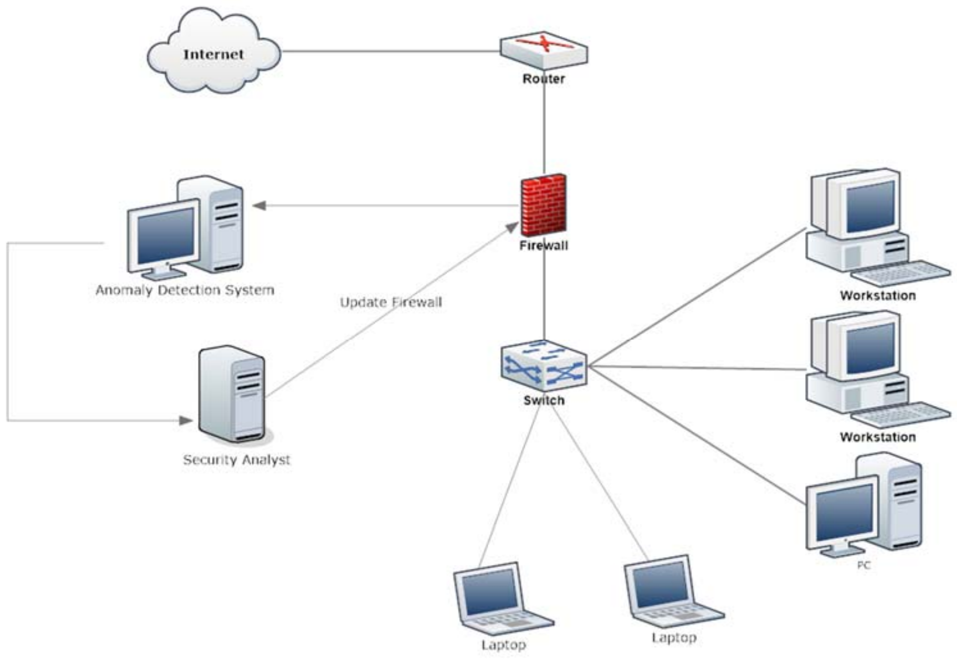


Figure 3.7: A Generic structure of NADS

The most important part of the NADS is to detect abnormal behavior and classify them, and then inform the Security Analyst. Whereupon, Security Analyst takes proper actions, through updating the database of the protection systems (Firewall, Antivirus Servers etc.) on the network.

3.3 The Proposed System

NADS consists of two phases:

- Training phase
- Testing phase.

In Figure 3.8 training phase is shown and there are three steps in training phase, which are summarized as follows:

i. *Input*: Input KDD CUP99 dataset.

ii. *Process*: Train the system.

iii. *Output*: NADS uses the KNN algorithm for classification, PCA algorithm for reduction and as a result, it classifies connections as normal or as attack and it gives attack type. Output of this phase is Trained System.

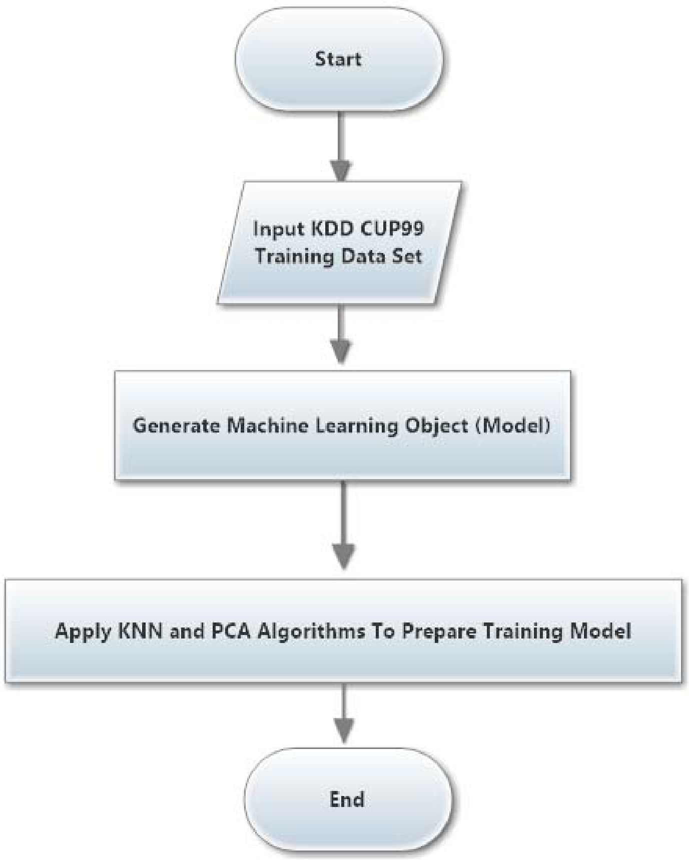

Start
Input KDD CUP99 Training Data Set
Generate Machine Learning Object (Model)
Apply KNN and PCA Algorithms To Prepare Training Model
End

Figure 3.8: Block Diagram of Training Phase.

Testing phase is shown in Figure 3.9 and there are three steps in testing phase, which are summarized as follows:

i. *Input*: Input Trained System is the first step in the testing phase.

ii. *Process*: Trained System (Machine Learning Object) classifies connections as normal or attack types instantly (or testing file in offline mode).

iii. *Output*: System generates monitoring.

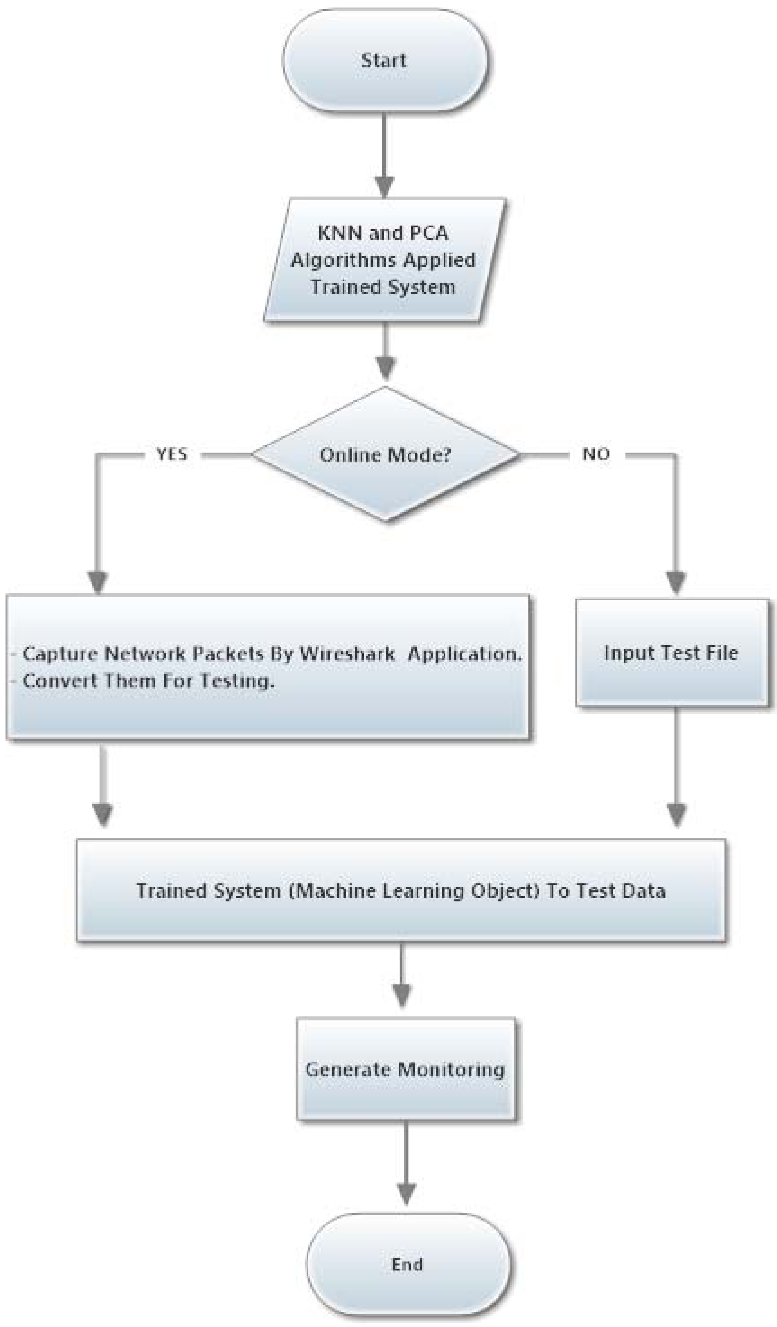

Start
KNN and PCA Algorithms Applied Trained System
Online Mode?
YES
NO
- Capture Network Packets By Wireshark Application.
- Convert Them For Testing.
Input Test File
Trained System (Machine Learning Object) To Test Data
Generate Monitoring
End

Figure 3.9: Block Diagram of Testing Phase.

CHAPTER 4

NADS SYSTEM IMPLEMENTATION AND RESULTS

4.1 Introduction

Chapter four presents implementation of the proposed system by using KNN and PCA algorithms that are described in chapters two with their main points. This chapter also compares KNN algorithm with K-Means, Naïve Bayes and Random Forest algorithms which were explained in chapter two. All algorithms were compared with each other using them in NADS. The system is implemented on a computer which is connected to the LAN and this LAN has WAN connection. NADS were built by using machine-learning which was coded in Python programming language and it can be applied on most networks.

4.2 System Structure

NADS main components are listed below and it is shown in Figure 4.1.

1. Router, it is used for packets routing in network.

2. Switch which is configured in promiscuous mode. It is used for network packets switching and sniffing network packets.

3. NADS, captures packets, pre-processing, classifying attacks or normal connections and warning.

4. Security analyst, takes an appropriate prevention according to warnings.

5. LAN, it contains seven clients, one switch, one router, one firewall.

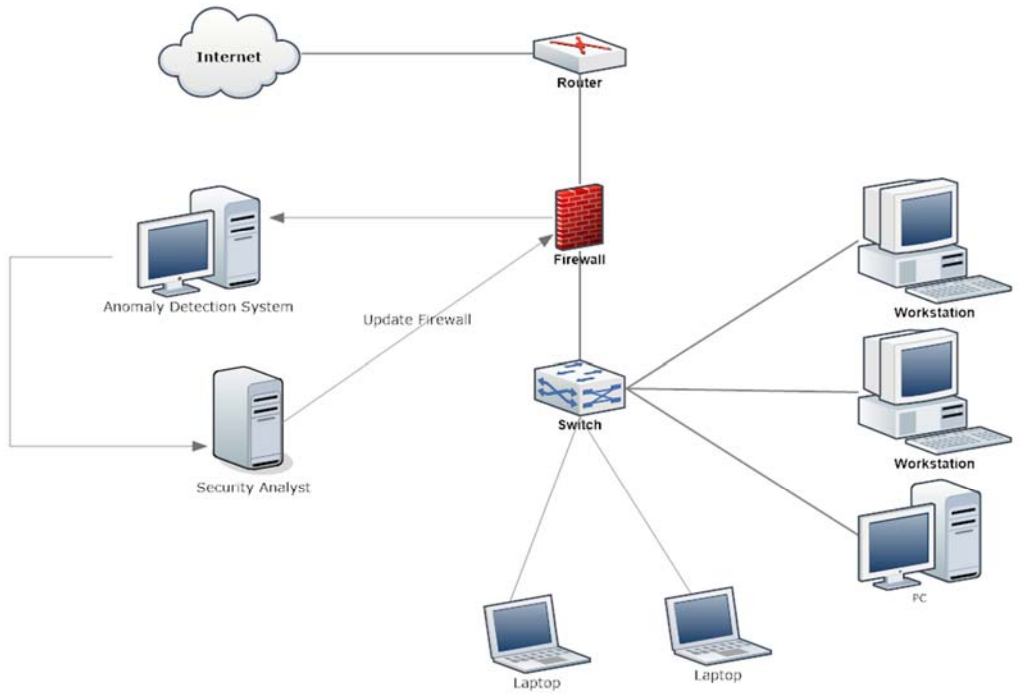


Figure 4.1: System Architecture of NADS

4.3 Performance Metrics

4.3.1 Confusion Matrix

Confusion matrix (CM) is a performance measurement. It is used for machine learning classification problems which has two or more classes as output. It is a table, which contains four different combinations. Those are predicted values and actual values and these values are explained below. Confusion matrix is used to measure the performances of NADS in this thesis. If this measurement is adapted to NADS, following result will be gotten.

Table 4.1: Confusion Matrix for Binary Case (Stallings 2003)

		PREDICTED VALUES	
		Anomaly	**Normal**
ACTUAL VALUES	**Anomaly**	TP	FP
	Normal	FN	TN

1. True Positive (TP): Number of correctly predicted packets as attacks by system (Stallings 2003).

2. True Negative (TN): Number of correctly predicted packets as normal by system (Stallings 2003).

3. False Positive (FP): Number of normal packets, which are predicted as attacks (Stallings 2003).

4. False Negative (FN): Number of attack packets which are predicted as normal (Stallings 2003).

There are standard metrics for evaluating network anomalies detections which are shown below. Percentage of Successful Prediction (PSP), namely Detection Rate (DR) and Accuracy Rate (ACC) are most satisfactory metrics ratios. DR is the ratio between the number of correctly detected attacks and the total number of attacks as in Equation (4.1). Accuracy is a ratio of the total number of correctly classified attacks and normal connections divide to the total number of connections as in Equation (4.2) (Stallings 2003).

4.3.1 Sensitivity-Detection Rate (DR) or True Positive Rate (TPR):

Sensitivity is a ratio of the total number of correctly classified positive examples divide to the total number of positive examples. High DR indicates the class is correctly recognized (Stallings 2003).

$$DR = TPR = \frac{TP}{P} = \frac{TP}{TP + FN} \qquad (4.1)$$

4.3.2 Accuracy:

Accuracy is a ratio of the total number of correctly classified positive and negative examples divide to the total number of examples (Stallings 2003).

$$Accuracy = \frac{TP + TN}{Total} \qquad (4.2)$$

Example Confusion Matrix of NADS which is for multiclass is shown in Table 4.2.

Table 4.2: Example Confusion Matrix of NADS Which Is Multiclass

		PREDICTED VALUES				
		Normal	**Probe**	**DoS**	**R2L**	**U2R**
ACTUAL VALUES	**Normal**	9223	10	0	1	0
	Probe	0	13432	9	8	0
	DoS	2	12	2275	0	0
	R2L	1	9	0	199	0
	U2R	0	1	0	3	7

4.4 Experiments

In this section, we apply four scenarios, where each scenario consists of several experiments, and we summarize experimental results to detect the network anomaly over KDDCUP99 data set. These scenarios are explained as below:

Scenario 1: In order to see effect of the PCA algorithm five experiments were carried out on KDD CUP99 dataset by using KNN Algorithm. The conditions of these experiments are as follow:

Experiment 1: 125,973 lines of KDD CUP99 dataset were used for training and 25,192 lines for testing, but 41 features were selected.

Experiment 2: 125,973 lines of KDD CUP99 dataset were used for training and 25,192 lines for testing, but 30 features were selected.

Experiment 3: 125,973 lines of KDD CUP99 dataset were used for training and 25,192 lines for testing, but 20 features were selected.

Experiment 4: 125,973 lines of KDD CUP99 dataset were used for training and 25,192 lines for testing, but 10 features were selected.

Experiment 5: 125,973 lines of KDD CUP99 dataset were used for training and 25,192 lines for testing, but 5 features were selected.

Scenario 1 Implementation:

The results of first experiment can be seen in Table 4.3. The first experimental result indicated that KNN algorithm achieved a DR percent of 98.0379 % as highest compared with other algorithms. Highest ACC Rate is 99.9603 % that achieved by KNN algorithm. Highest DR percent for Normal achieved by RF algorithm, highest DR percent for Probe achieved by RF algorithm, highest DR percent for DoS achieved by KNN and RF algorithms, highest DR percent for R2L achieved by KNN algorithm, and highest DR percent for U2R achieved by KNN algorithms. Lowest time taken to train is 0.128126 second that achieved by NB algorithm and lowest time taken to test is 0.08962 second achieved by NB algorithm. In addition, lowest memory usage is 0.307209 GB that achieved by KM algorithm.

Table 4.3: Experiment 1

	KNN	**KM**	**NB**	**RF**
DR (%)	98.0379	47.1663	52.2071	96.2549
ACC (%)	99.9603	68.756	88.3773	99.9563
DR For Normal (%)	99.9776	69.797	90.4825	99.9926
DR For Probe (%)	99.7815	44.9104	80.166	99.9563
DR For DoS (%)	100	74.713	89.4303	100
DR For R2L (%)	99.5215	0.9569	0.9569	99.5074
DR For U2R (%)	90.909	45.4545	0	81.8182
Mean Of Cross V. (%)	99.6539	1.6965	88.4578	99.8396
Time For Train (second)	0.66159	3.872822	0.128126	7.694642
Time For Test (second)	1.139292	0.009377	0.006212	0.026766
Memory (GB)	0.304344	0.300694	0.505257	0.308975

The comparison of DR and ACC ratios of all algorithms with each other is shown in Figure 4.2. The comparison of training and testing times of all algorithms with each other is shown in Figure 4.3. The comparison of memory consume of all algorithms with each other is shown in Figure 4.4.

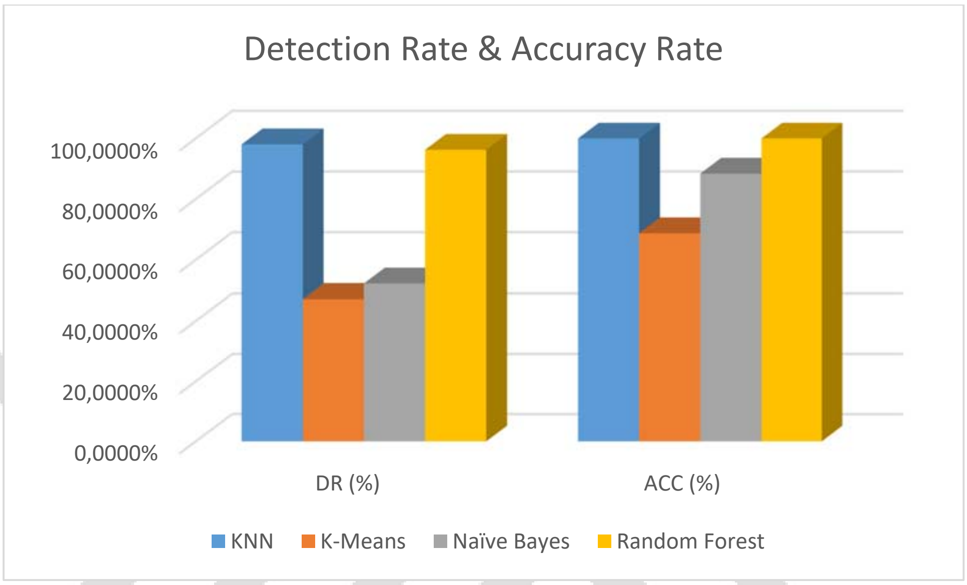


Figure 4.2: Comparison of DR & ACC of First Experiment

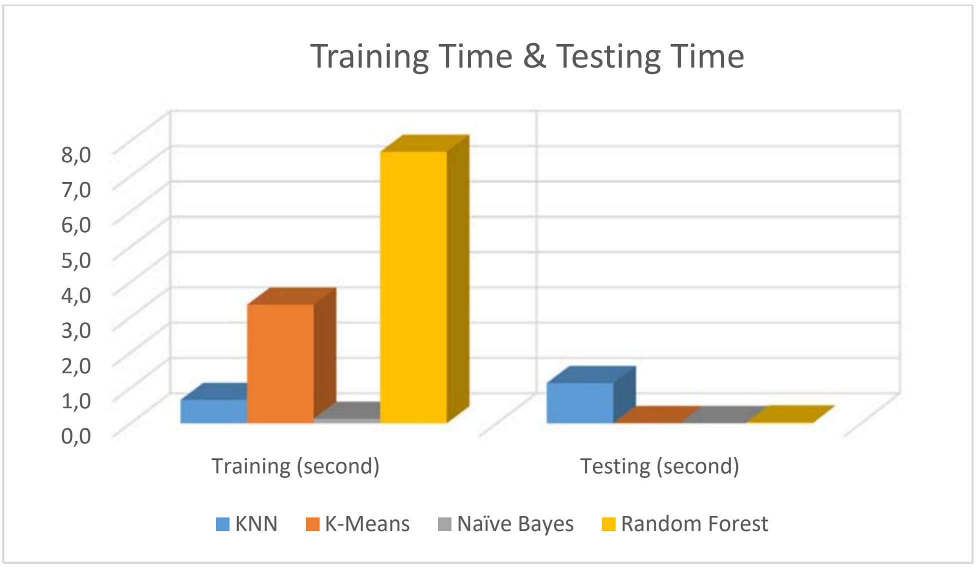


Figure 4.3: Comparison of Training and Testing Time of First Experiment

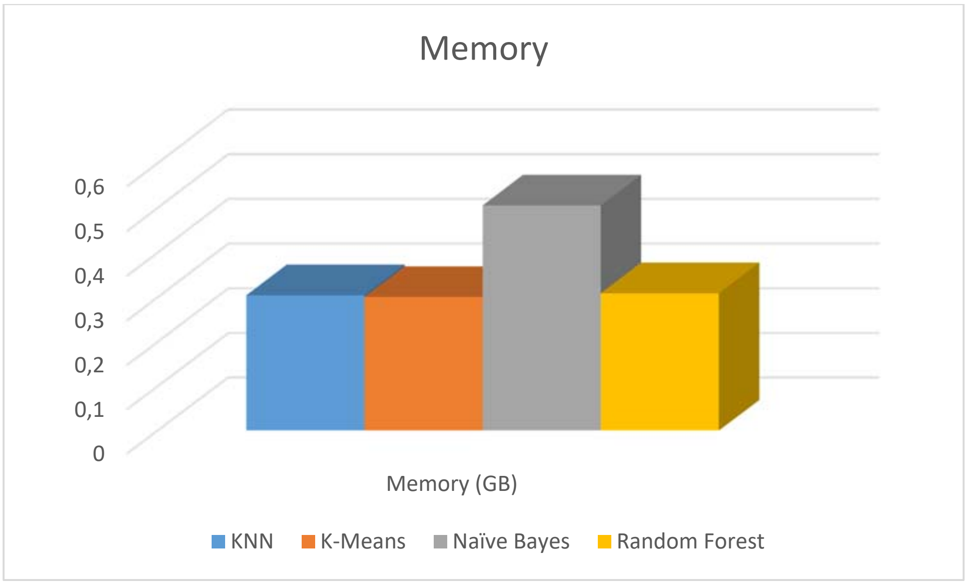
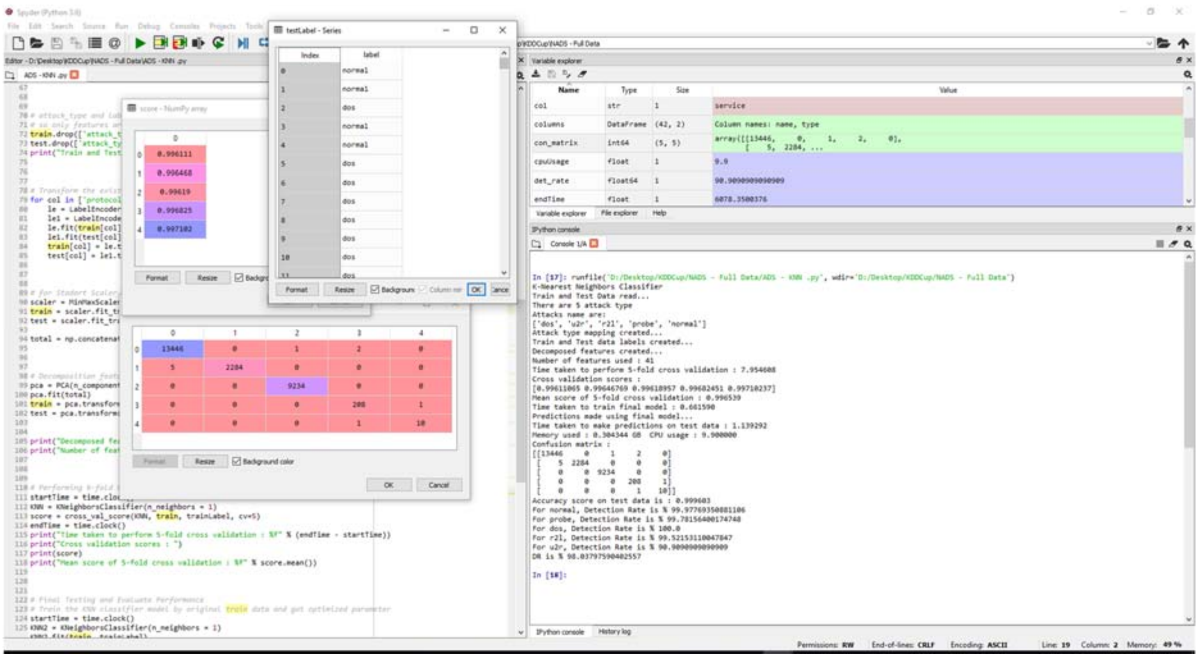


Figure 4.4: Comparison of Memory Consume of First Experiment

Screen shot of first experiment is shown in Figure 4.5 and screen shot of the program code for first experiment is shown in Figure 4.6.

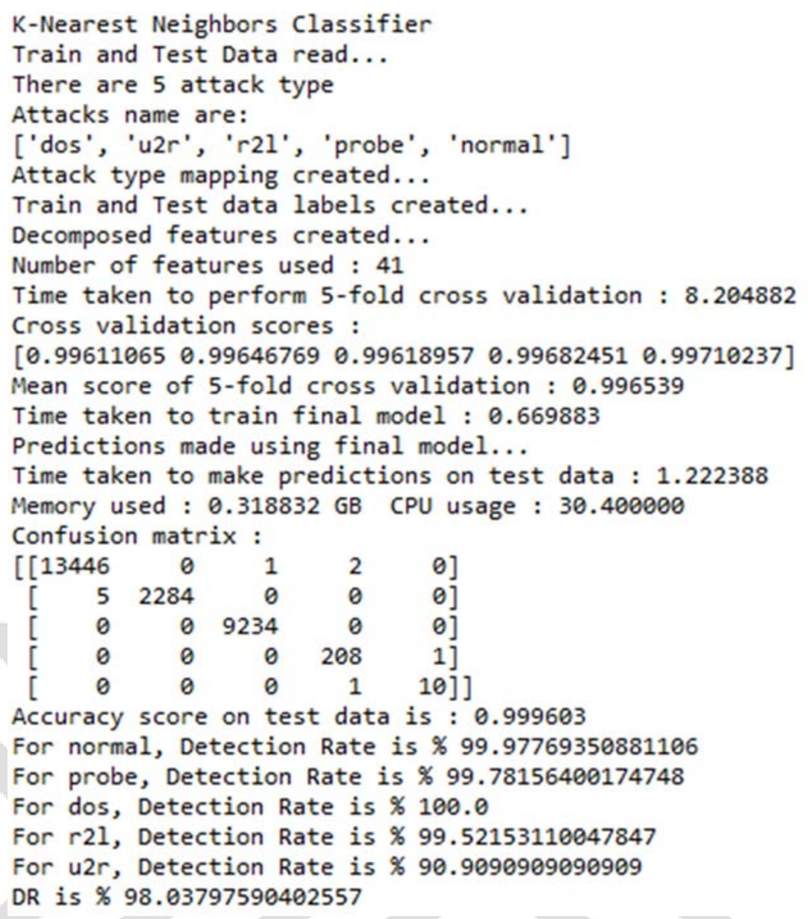


```
startTime = time.clock()
KNN = KNeighborsClassifier(n_neighbors = 1)
score = cross_val_score(KNN, train, trainLabel, cv=5)
endTime = time.clock()
print("Time taken to perform 5-fold cross validation : %f" % (endTime - startTime))
print("Cross validation scores : ")
print(score)
print("Mean score of 5-fold cross validation : %f" % score.mean())
```

```
In [17]: runfile('D:/Desktop/KDDCup/NADS - Full Data/ADS - KNN .py', wdir='D:/Desktop/KDDCup/NADS - Full Data')
K-Nearest Neighbors Classifier
Train and Test Data read...
There are 5 attack type
Attacks name are:
['dos', 'u2r', 'r2l', 'probe', 'normal']
Attack type mapping created...
Train and Test data labels created...
Decomposed features created...
Number of features used : 41
Time taken to perform 5-fold cross validation : 7.954608
Cross validation scores :
[0.99611065 0.99646769 0.99618957 0.99682451 0.99710237]
Mean score of 5-fold cross validation : 0.996539
Time taken to train final model : 0.661590
Predictions made using final model...
Time taken to make predictions on test data : 1.139292
Memory used : 0.304344 GB  CPU usage : 9.900000
Confusion matrix :
[[13446     0     1     2     0]
 [    5  2284     0     0     0]
 [    0     0  9234     0     0]
 [    0     0     0   208     1]
 [    0     0     0     1    10]]
Accuracy score on test data is : 0.999603
For normal, Detection Rate is % 99.97769350881106
For probe, Detection Rate is % 99.78156400174748
For dos, Detection Rate is % 100.0
For r2l, Detection Rate is % 99.52153110047847
For u2r, Detection Rate is % 90.9090909090909
DR is % 98.03797590402557

In [18]:
```

Figure 4.5: Experiment 1 of KNN



```
K-Nearest Neighbors Classifier
Train and Test Data read...
There are 5 attack type
Attacks name are:
['dos', 'u2r', 'r2l', 'probe', 'normal']
Attack type mapping created...
Train and Test data labels created...
Decomposed features created...
Number of features used : 41
Time taken to perform 5-fold cross validation : 8.204882
Cross validation scores :
[0.99611065 0.99646769 0.99618957 0.99682451 0.99710237]
Mean score of 5-fold cross validation : 0.996539
Time taken to train final model : 0.669883
Predictions made using final model...
Time taken to make predictions on test data : 1.222388
Memory used : 0.318832 GB  CPU usage : 30.400000
Confusion matrix :
[[13446     0     1     2     0]
 [    5  2284     0     0     0]
 [    0     0  9234     0     0]
 [    0     0     0   208     1]
 [    0     0     0     1    10]]
Accuracy score on test data is : 0.999603
For normal, Detection Rate is % 99.97769350881106
For probe, Detection Rate is % 99.78156400174748
For dos, Detection Rate is % 100.0
For r2l, Detection Rate is % 99.52153110047847
For u2r, Detection Rate is % 90.9090909090909
DR is % 98.03797590402557
```

Figure 4.6: Experiment 1 of KNN

The results of second experiment can be seen in Table 4.4. The second experimental result indicated that KNN algorithm achieved a DR percent of 98.1387 % as highest compared with other algorithms. Highest ACC Rate is 99.9603 % that achieved by KNN algorithm. Highest DR percent for Normal achieved by KNN algorithm, highest DR percent for Probe achieved by KNN algorithm, highest DR percent for DoS achieved by KNN algorithm, highest DR percent for R2L achieved by KNN algorithm, and highest DR percent for U2R achieved by KM algorithm. Lowest time taken to train is 0.179758 second that achieved by NB algorithm and lowest time taken to test is 0.007657 second achieved by KM algorithm. In addition, lowest memory usage is 0.300423 GB that achieved by NB algorithm.

Table 4.4: Experiment 2

	KNN	KM	NB	RF
DR (%)	98.1387	22.0586	61.1676	92.2005
ACC (%)	99.9603	2.0999	58.6377	99.9166
DR For Normal (%)	99.9702	0.2007	30.374	99.9553
DR For Probe (%)	99.8252	0.131	95.8934	99.8252
DR For DoS (%)	99.9891	5.1765	90.0152	99.9783
DR For R2L (%)	100	4.7846	35.0101	97.6076
DR For U2R (%)	90.909	100	54.5455	63.6363
Mean Of Cross V. (%)	99.6348	1.6953	58.6594	99.6483
Time For Train (second)	0.566747	3.098525	0.179758	8.095981
Time For Test (second)	0.923757	0.007657	0.047077	0.028039
Memory (GB)	0.307774	0.395073	0.300423	0.538746

The comparison of DR and ACC ratios of all algorithms with each other is shown in Figure 4.7. The comparison of training and testing times of all algorithms with each other is shown in Figure 4.8. The comparison of memory consume of all algorithms with each other is shown in Figure 4.9.

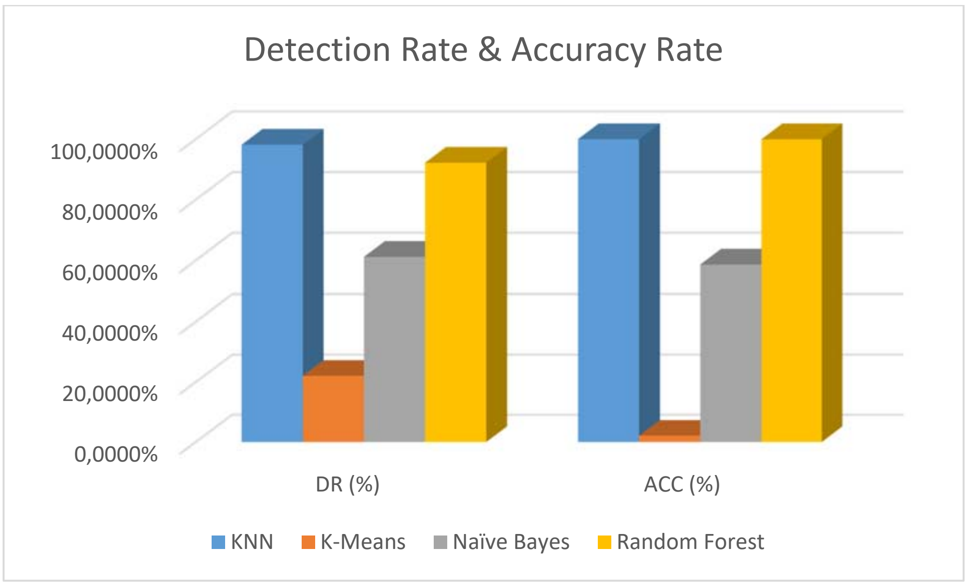


Figure 4.7: Comparison of DR & ACC of Second Experiment

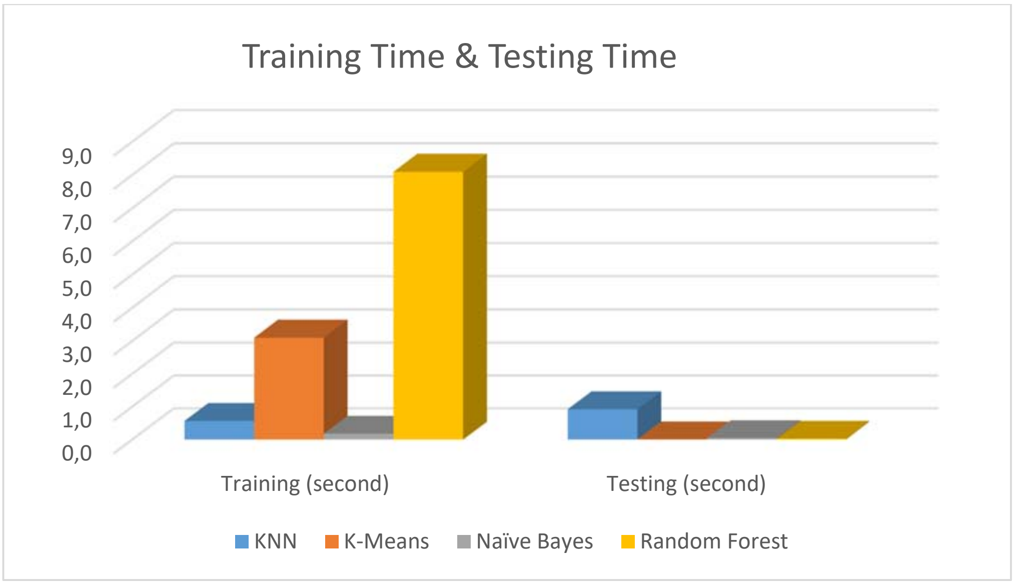


Figure 4.8: Comparison of Training and Testing Time of Second Experiment

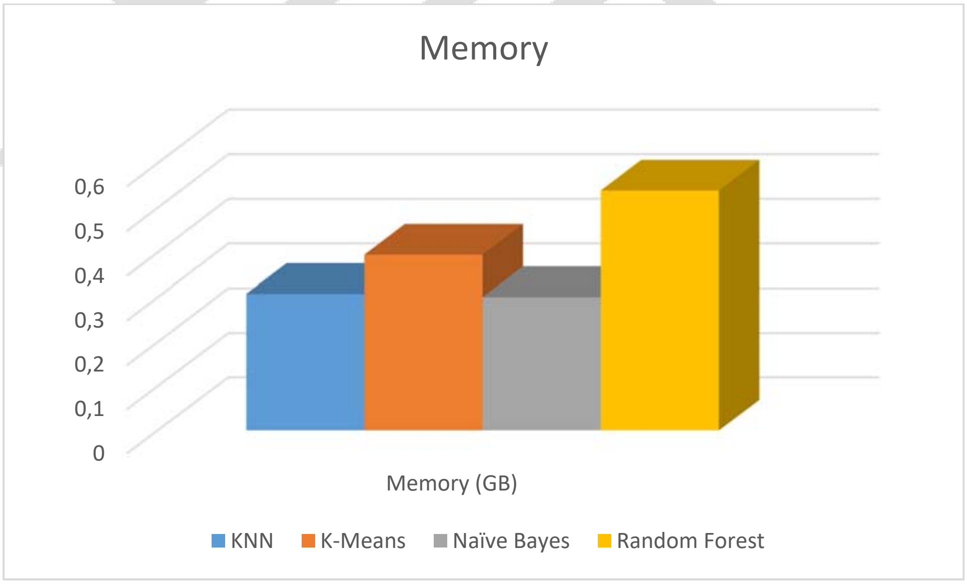


Figure 4.9: Comparison of Memory Consume of Second Experiment

Screen shot of the program code for second experiment is shown in Figure 4.10.

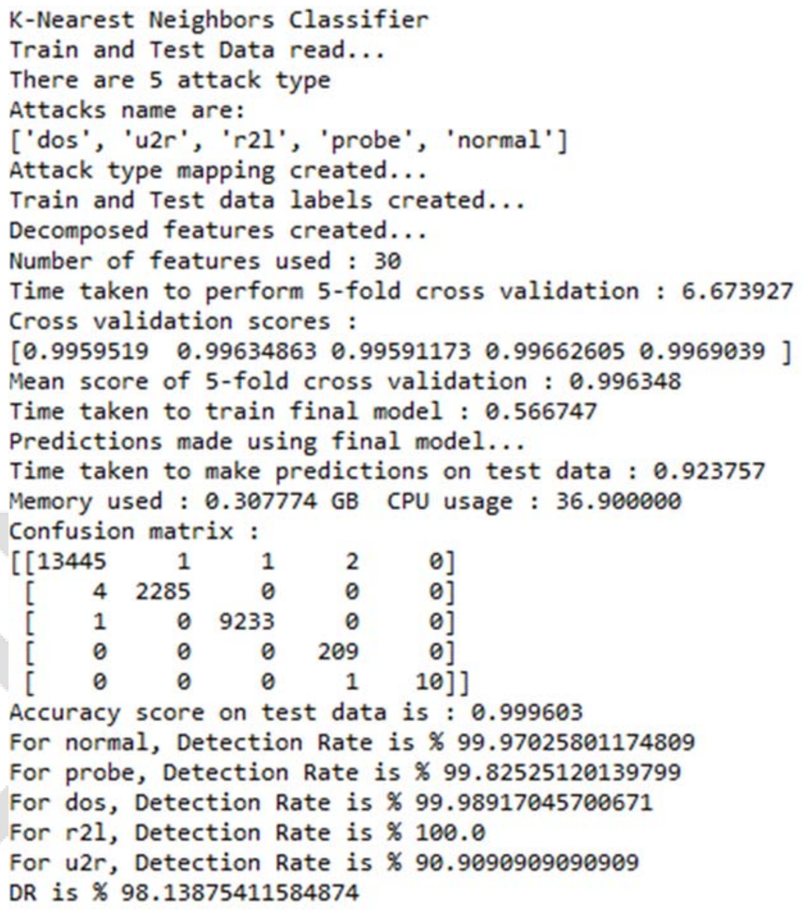

```
K-Nearest Neighbors Classifier
Train and Test Data read...
There are 5 attack type
Attacks name are:
['dos', 'u2r', 'r2l', 'probe', 'normal']
Attack type mapping created...
Train and Test data labels created...
Decomposed features created...
Number of features used : 30
Time taken to perform 5-fold cross validation : 6.673927
Cross validation scores :
[0.9959519  0.99634863 0.99591173 0.99662605 0.9969039 ]
Mean score of 5-fold cross validation : 0.996348
Time taken to train final model : 0.566747
Predictions made using final model...
Time taken to make predictions on test data : 0.923757
Memory used : 0.307774 GB  CPU usage : 36.900000
Confusion matrix :
[[13445     1     1     2     0]
 [    4  2285     0     0     0]
 [    1     0  9233     0     0]
 [    0     0     0   209     0]
 [    0     0     0     1    10]]
Accuracy score on test data is : 0.999603
For normal, Detection Rate is % 99.97025801174809
For probe, Detection Rate is % 99.82525120139799
For dos, Detection Rate is % 99.98917045700671
For r2l, Detection Rate is % 100.0
For u2r, Detection Rate is % 90.9090909090909
DR is % 98.13875411584874
```

Figure 4.10: Experiment 2 of KNN

The results of third experiment can be seen in Table 4.5. The third experimental result indicated that KNN algorithm achieved a DR percent of 98.1249 % as highest compared with other algorithms. Highest ACC Rate is 99.9603 % that achieved by KNN algorithm. Highest DR percent for Normal achieved by KNN algorithm, highest DR percent for Probe achieved by RF algorithm, highest DR percent for DoS achieved by KNN algorithm, highest DR percent for R2L achieved by KNN algorithm, and highest DR percent for U2R achieved by KNN algorithm. Lowest time taken to train is 0.159209 second that achieved by NB algorithm and lowest time taken to test is 0.006390 second achieved by KM algorithm. In addition, lowest memory usage is 0.289413 GB that achieved by RF algorithm.

Table 4.5: Experiment 3

	KNN	**KM**	**NB**	**RF**
DR (%)	98.1249	47.1649	71.1073	88.0633
ACC (%)	99.9603	68.752	87.5318	99.8492
DR For Normal (%)	99.9776	69.7895	86.6979	99.9108
DR For Probe (%)	99.7378	44.9104	89.2093	99.8253
DR For DoS (%)	100	74.713	88.4882	99.9567
DR For R2L (%)	100	0.9569	36.5957	95.1691
DR For U2R (%)	90.909	45.4545	54.5455	45.4545
Mean Of Cross V. (%)	99.5793	1.6572	87.5497	99.5428
Time For Train (second)	0.438048	2.465096	0.159209	5.836239
Time For Test (second)	0.568895	0.00639	0.033312	0.026006
Memory (GB)	0.295273	0.383064	0.289391	0.289413

The comparison of DR and ACC ratios of all algorithms with each other is shown in Figure 4.11. The comparison of training and testing times of all algorithms with each other is shown in Figure 4.12. The comparison of memory consume of all algorithms with each other is shown in Figure 4.13.

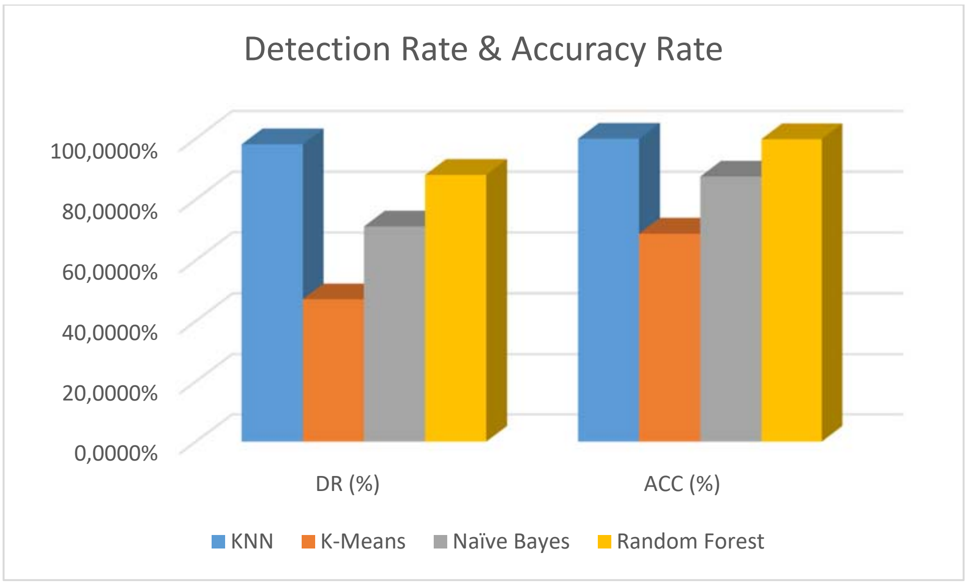


Figure 4.11: Comparison of DR & ACC of Third Experiment

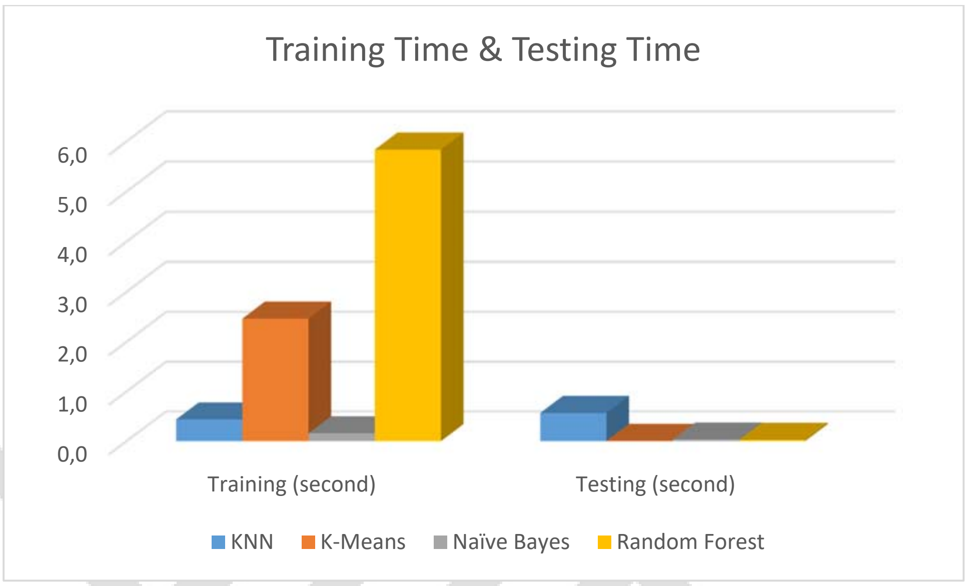


Figure 4.12: Comparison of Training and Testing Time of Third Experiment

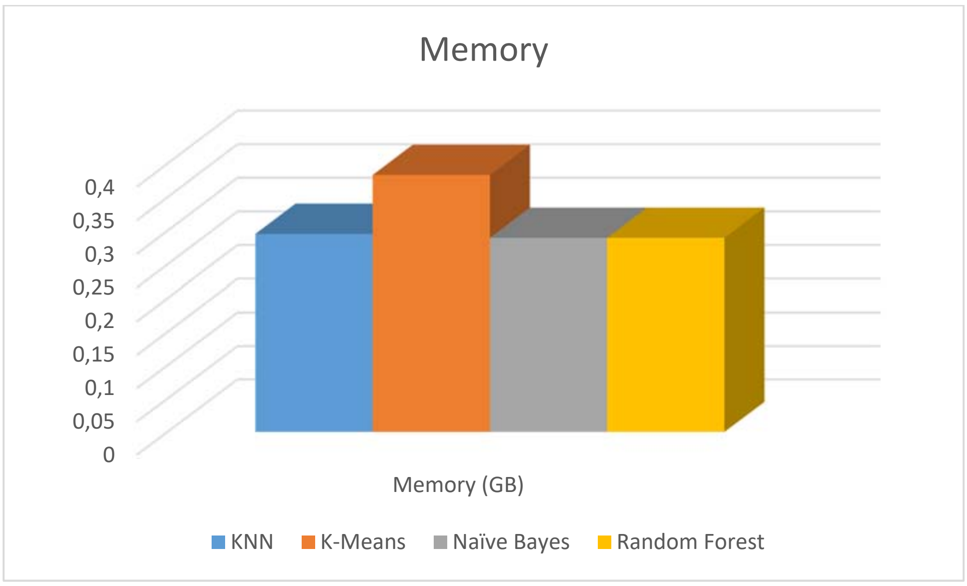
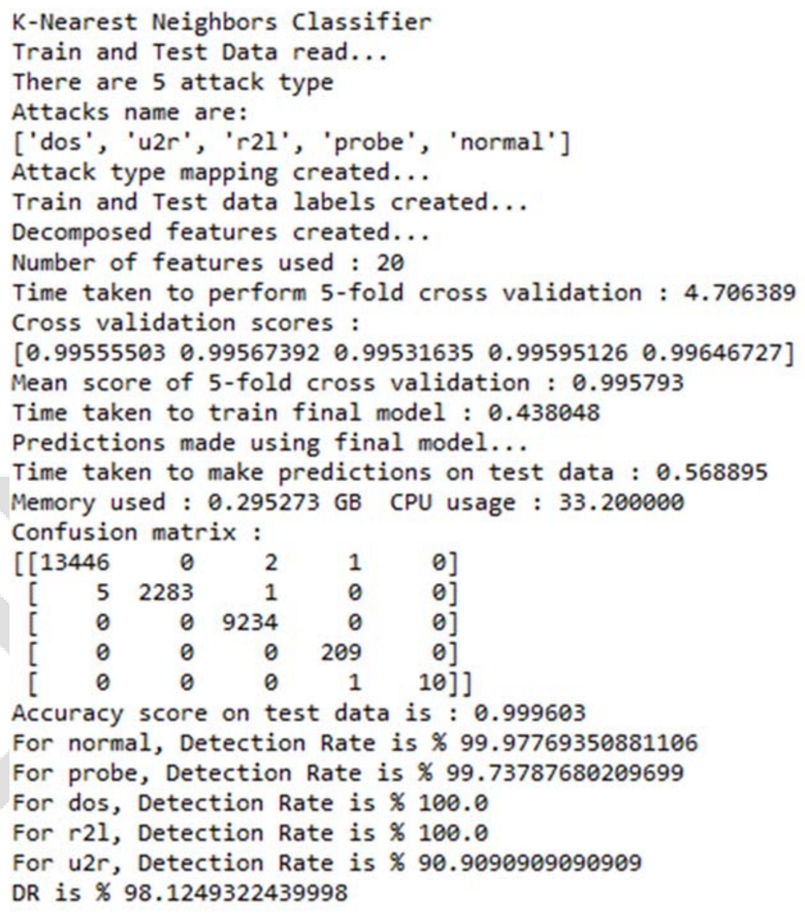


Figure 4.13: Comparison of Memory Consume of Third Experiment

Screen shot of the program code for third experiment is shown in Figure 4.14.



```
K-Nearest Neighbors Classifier
Train and Test Data read...
There are 5 attack type
Attacks name are:
['dos', 'u2r', 'r2l', 'probe', 'normal']
Attack type mapping created...
Train and Test data labels created...
Decomposed features created...
Number of features used : 20
Time taken to perform 5-fold cross validation : 4.706389
Cross validation scores :
[0.99555503 0.99567392 0.99531635 0.99595126 0.99646727]
Mean score of 5-fold cross validation : 0.995793
Time taken to train final model : 0.438048
Predictions made using final model...
Time taken to make predictions on test data : 0.568895
Memory used : 0.295273 GB  CPU usage : 33.200000
Confusion matrix :
[[13446     0     2     1     0]
 [    5  2283     1     0     0]
 [    0     0  9234     0     0]
 [    0     0     0   209     0]
 [    0     0     0     1    10]]
Accuracy score on test data is : 0.999603
For normal, Detection Rate is % 99.97769350881106
For probe, Detection Rate is % 99.73787680209699
For dos, Detection Rate is % 100.0
For r2l, Detection Rate is % 100.0
For u2r, Detection Rate is % 90.9090909090909
DR is % 98.1249322439998
```

Figure 4.14: Experiment 3 of KNN

The results of fourth experiment can be seen in Table 4.6. The fourth experimental result indicated that KNN achieved a DR percent of 94.1806 % as highest compared with other algorithms. Highest ACC Rate is 99.8849 % that achieved by KNN algorithm. Highest DR percent for Normal achieved by KNN algorithm, highest DR percent for Probe achieved by RF algorithm, highest DR percent for DoS achieved by KNN algorithm, highest DR percent for R2L achieved by KNN algorithm, and highest DR percent for U2R achieved by KNN algorithm. Lowest time taken to train is 0.132482 second that achieved by NB algorithm and lowest time taken to test is 0.005167 second achieved by KM algorithm. In addition, lowest memory usage is 0.277580 GB that achieved by NB algorithm.

Table 4.6: Experiment 4

	KNN	KM	NB	RF
DR (%)	94.1806	51.9481	66.115	91.9289
ACC (%)	99.8849	69.2323	88.7028	99.5475
DR For Normal (%)	99.8735	69.7821	89.3895	99.487
DR For Probe (%)	99.7378	44.9104	84.7532	99.7816
DR For DoS (%)	100	74.713	89.3546	99.8484
DR For R2L (%)	98.5645	61.244	30.7143	96.8912
DR For U2R (%)	72.7272	9.0909	36.3636	63.6364
Mean Of Cross V. (%)	99.4721	1.3816	88.9175	99.3816
Time For Train (second)	0.300025	1.947047	0.132482	4.24552
Time For Test (second)	0.306337	0.005167	0.016904	0.024888
Memory (GB)	0.282036	0.372643	0.27758	0.279289

The comparison of DR and ACC ratios of all algorithms with each other is shown in Figure 4.15. The comparison of training and testing times of all algorithms with each other is shown in Figure 4.16. The comparison of memory consume of all algorithms with each other is shown in Figure 4.17.

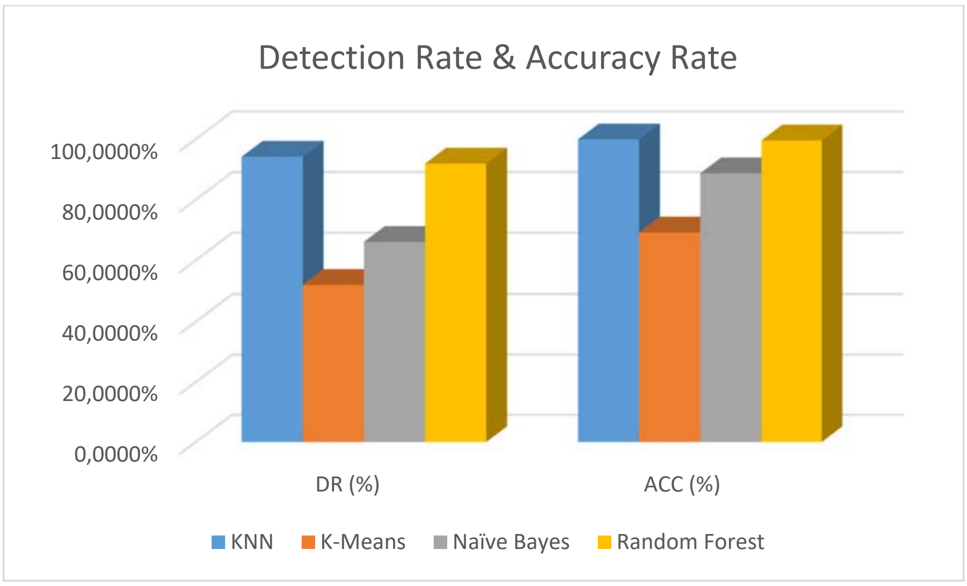


Figure 4.15: Comparison of DR & ACC of Fourth Experiment

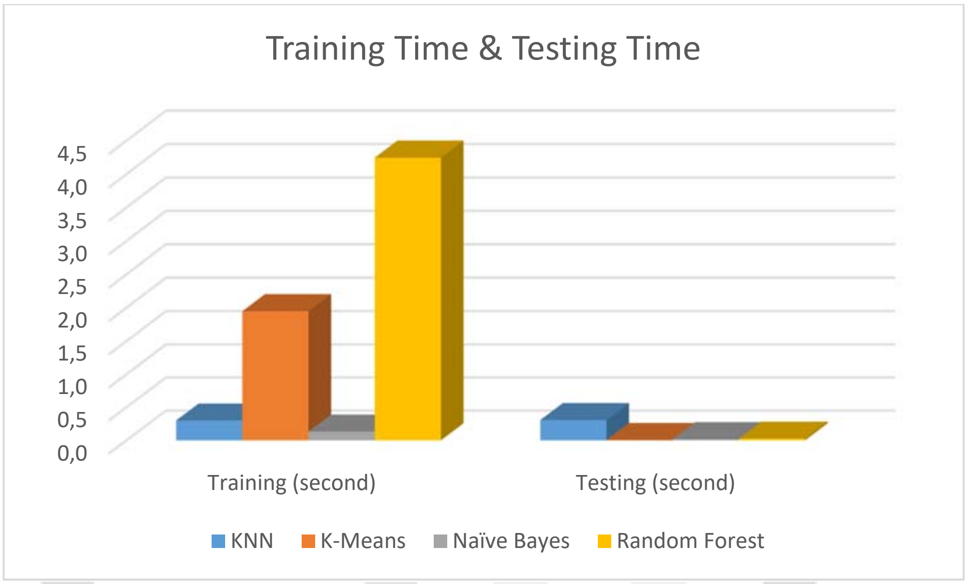


Figure 4.16: Comparison of Training and Testing Time of Fourth Experiment

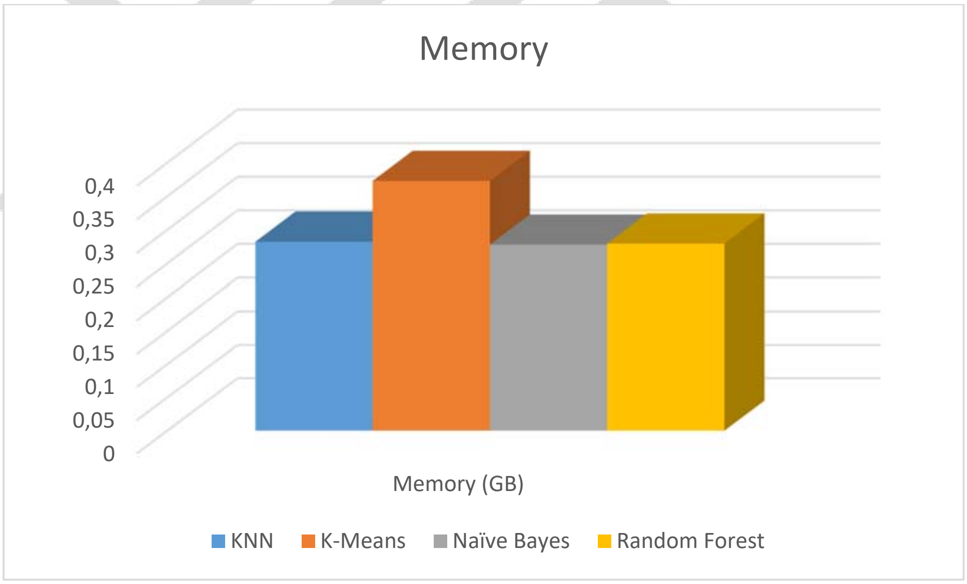
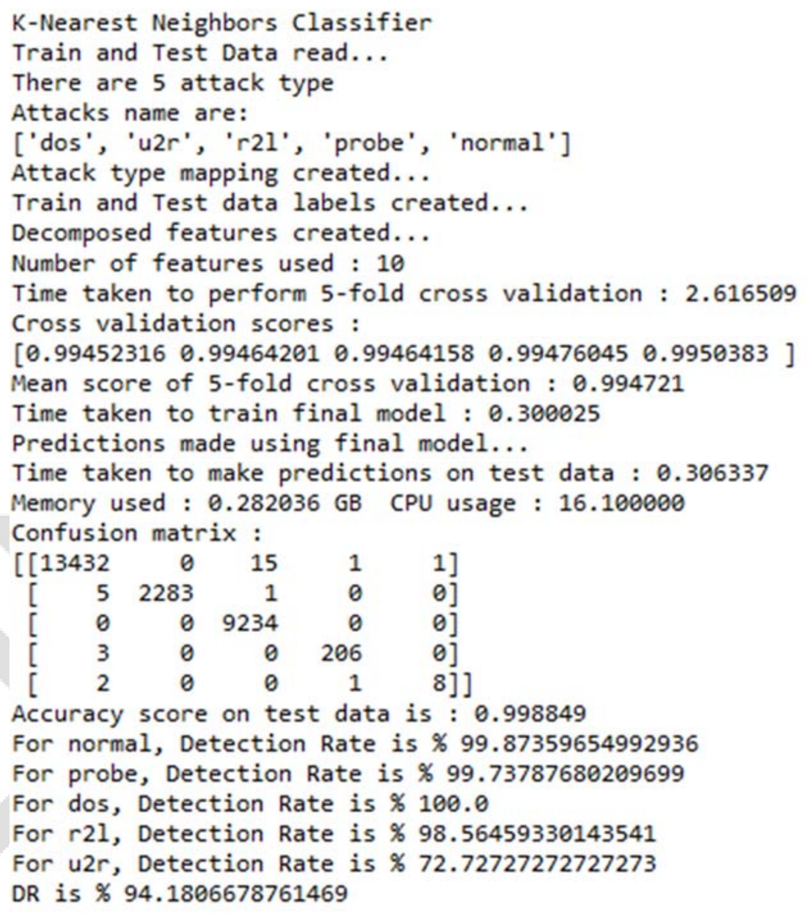


Figure 4.17: Comparison of Memory Consume of Fourth Experiment

Screen shot of the program code for fourth experiment is shown in Figure 4.18.



```
K-Nearest Neighbors Classifier
Train and Test Data read...
There are 5 attack type
Attacks name are:
['dos', 'u2r', 'r2l', 'probe', 'normal']
Attack type mapping created...
Train and Test data labels created...
Decomposed features created...
Number of features used : 10
Time taken to perform 5-fold cross validation : 2.616509
Cross validation scores :
[0.99452316 0.99464201 0.99464158 0.99476045 0.9950383 ]
Mean score of 5-fold cross validation : 0.994721
Time taken to train final model : 0.300025
Predictions made using final model...
Time taken to make predictions on test data : 0.306337
Memory used : 0.282036 GB  CPU usage : 16.100000
Confusion matrix :
[[13432     0    15     1     1]
 [    5  2283     1     0     0]
 [    0     0  9234     0     0]
 [    3     0     0   206     0]
 [    2     0     0     1     8]]
Accuracy score on test data is : 0.998849
For normal, Detection Rate is % 99.87359654992936
For probe, Detection Rate is % 99.73787680209699
For dos, Detection Rate is % 100.0
For r2l, Detection Rate is % 98.56459330143541
For u2r, Detection Rate is % 72.72727272727273
DR is % 94.1806678761469
```

Figure 4.18: Experiment 4 of KNN

The results of fifth experiment can be seen in Table 4.7. The fifth experimental result indicated that KNN achieved a DR percent of 92.5403 % as highest compared with other algorithms. Highest ACC Rate is 99.8690 % that achieved by KNN algorithm. Highest DR percent for Normal achieved by KNN algorithm, highest DR percent for Probe achieved by KNN algorithm, highest DR percent for DoS achieved by KNN algorithm, highest DR percent for R2L achieved by KNN algorithm, and highest DR percent for U2R achieved by KNN algorithm. Lowest time taken to train is 0.124872 second that achieved by NB algorithm and lowest time taken to test is 0.004403 second achieved by KM algorithm. In addition, lowest memory usage is 0.272610 GB that achieved by NB algorithm.

Table 4.7: Experiment 5

	KNN	KM	NB	RF
DR (%)	92.5403	11.3342	65.3491	88.644
ACC (%)	99.869	5.4224	88.3773	99.742
DR For Normal (%)	99.9033	0.2007	90.4826	99.8736
DR For Probe (%)	99.7378	49.5849	80.166	99.6068
DR For DoS (%)	99.9025	2.1009	89.4304	99.8159
DR For R2L (%)	99.5215	4.7846	66.6667	98.4694
DR For U2R (%)	63.6363	0	0	45.4545
Mean Of Cross V. (%)	99.3499	0.8269	88.4578	99.2133
Time For Train (second)	0.231077	1.207119	0.124872	2.755741
Time For Test (second)	0.127503	0.004403	0.005636	0.024517
Memory (GB)	0.27552	0.366207	0.27261	0.274162

The comparison of DR and ACC ratios of all algorithms with each other is shown in Figure 4.19. The comparison of training and testing times of all algorithms with each other is shown in Figure 4.20. The comparison of memory consume of all algorithms with each other is shown in Figure 4.21.

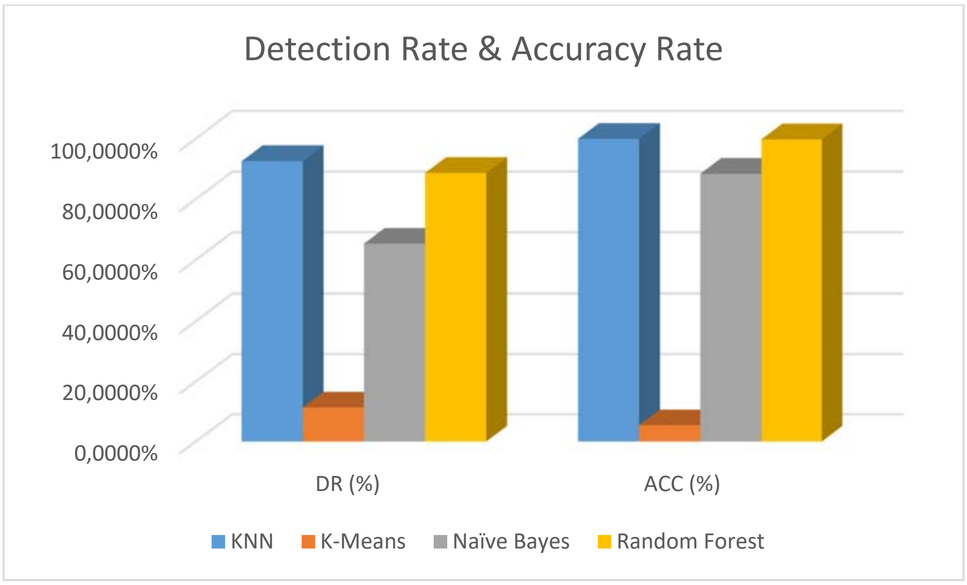


Figure 4.19: Comparison of DR & ACC of Fifth Experiment

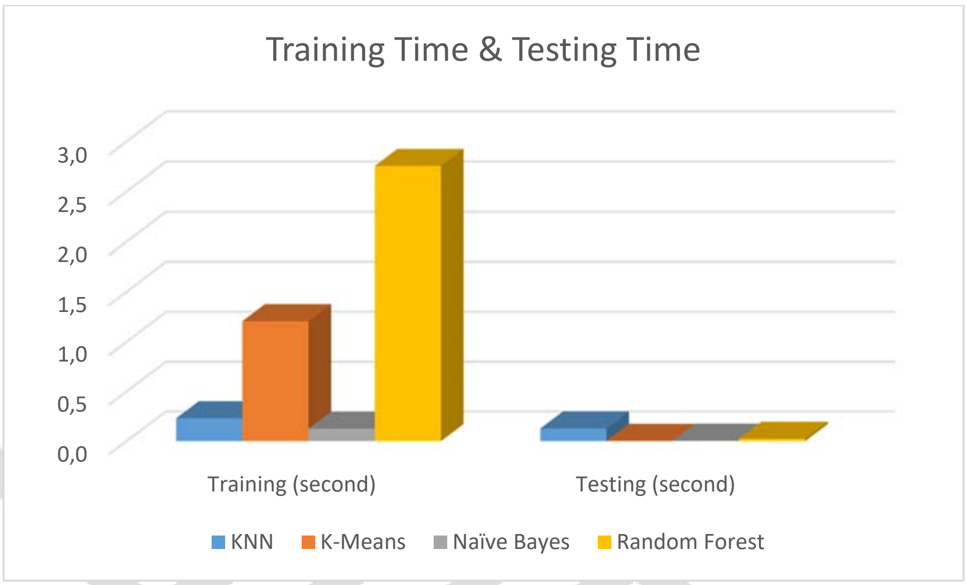


Figure 4.20: Comparison of Training and Testing Time of Fifth Experiment

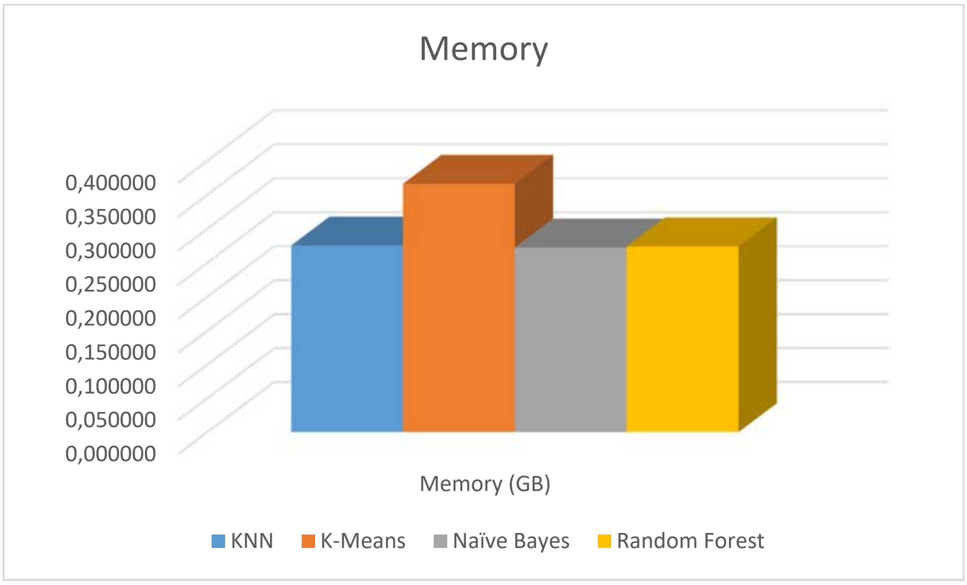
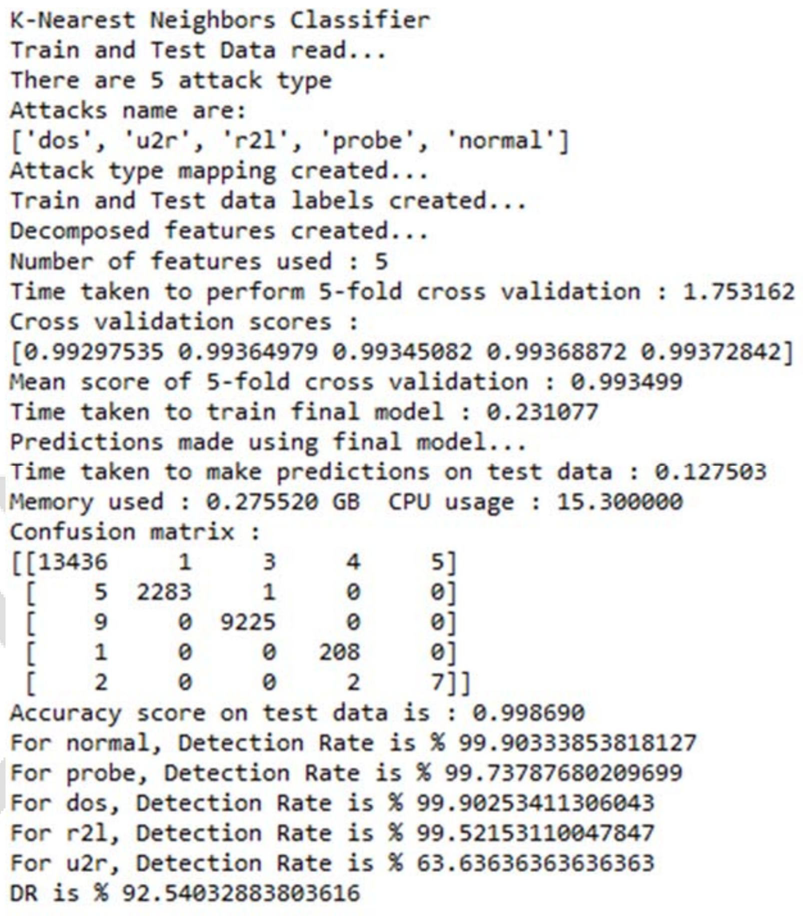


Figure 4.21: Comparison of Memory Consume of Fifth Experiment

Screen shot of the program code for fifth experiment is shown in Figure 4.22.



```
K-Nearest Neighbors Classifier
Train and Test Data read...
There are 5 attack type
Attacks name are:
['dos', 'u2r', 'r2l', 'probe', 'normal']
Attack type mapping created...
Train and Test data labels created...
Decomposed features created...
Number of features used : 5
Time taken to perform 5-fold cross validation : 1.753162
Cross validation scores :
[0.99297535 0.99364979 0.99345082 0.99368872 0.99372842]
Mean score of 5-fold cross validation : 0.993499
Time taken to train final model : 0.231077
Predictions made using final model...
Time taken to make predictions on test data : 0.127503
Memory used : 0.275520 GB  CPU usage : 15.300000
Confusion matrix :
[[13436     1     3     4     5]
 [    5  2283     1     0     0]
 [    9     0  9225     0     0]
 [    1     0     0   208     0]
 [    2     0     0     2     7]]
Accuracy score on test data is : 0.998690
For normal, Detection Rate is % 99.90333853818127
For probe, Detection Rate is % 99.73787680209699
For dos, Detection Rate is % 99.90253411306043
For r2l, Detection Rate is % 99.52153110047847
For u2r, Detection Rate is % 63.63636363636363
DR is % 92.54032883803616
```

Figure 4.22: Experiment 5 of KNN

Scenario 2: Testing the scalability of NADS by using different size of KDD CUP data set.

Scenario 2 Implementation: In order to see the scalability of NADS 3 different size of KDD CUP data set were used as fallow:

1- 125,793 vector of KDD dataset were used to train NADS and 25,192 lines for testing.

2- 494,021 vector of KDD dataset were used to train NADS and 25,192 lines for testing.

3- 1,000,000 vector of KDD dataset were used to train NADS and 25,192 lines for testing.

As a result, the first experimental indicated that KNN achieved a DR percent of 98.0379 % as highest compared with other algorithms. Highest ACC Rate is 99.9603 % that achieved by KNN algorithm. Highest DR percent for Normal achieved by RF algorithm, highest DR percent for Probe achieved by RF algorithm, highest DR percent for DoS achieved by KNN and RF algorithms, highest DR percent for R2L achieved by KNN algorithm, and highest DR percent for U2R achieved by KNN algorithm. Lowest time taken to train is 0.128126 second that achieved by NB algorithm and lowest time taken to test is 0.08962 second achieved by NB algorithm. In addition, lowest memory usage is 0.307209 GB that achieved by KM algorithm.

The second experimental result indicated that RF algorithm achieved a DR percent of 94,8460 % as highest compared with other algorithms. Highest ACC Rate is 99.903 % that achieved by KNN algorithm. Highest DR percent for Normal achieved by RF algorithm, Highest DR percent for Probe achieved by KNN algorithm, highest DR percent for DoS achieved by KNN algorithm, highest DR percent for R2L achieved RF algorithm, and highest DR percent for U2R achieved by KNN and KM algorithms. Lowest time taken to train is 0.517239 second that achieved by NB algorithm and lowest time taken to test is 0.006631 second achieved by NB algorithm. In addition, lowest memory usage is 0.246151 GB that achieved by KNN algorithm.

The third experimental result indicated that RF algorithm achieved a DR percent of 77.4958 % as highest compared with other algorithms. Highest ACC Rate is 91.5092 % that achieved by KNN algorithm. Highest DR percent for Normal achieved by RF algorithm, highest DR percent for Probe achieved by KNN algorithm, highest DR percent for DoS achieved by KNN algorithm, highest DR percent for R2L achieved by RF algorithm, and highest DR percent for U2R achieved by KM algorithm. Lowest time taken to train is 1.079136 second that achieved by NB algorithm and lowest time taken to test is 0.006515 second achieved by NB algorithm. In addition, lowest memory usage is 0.456940 GB that achieved by KNN algorithm.

The results of experiments for KNN can be seen in Table 4.8.

Table 4.8: Scalability Experiments for KNN Algorithm

	1. Exp.	**2. Exp.**	**3. Exp.**
DR (%)	98.0379	94.1442	65.4249
ACC (%)	99.9603	99.1862	91.5092
DR For Normal (%)	99.9776	99.5538	96.9737
DR For Probe (%)	99.7815	98.2088	96.8108
DR For DoS (%)	100	99.2744	84.0805
DR For R2L (%)	99.5215	82.7751	12.9186
DR For U2R (%)	90.909	90.909	36.3636
Mean Of Cross V. (%)	99.6539	95.2493	99.2649
Time For Train (second)	0.66159	190.729492	184.077617
Time For Test (second)	1.139292	1.826953	7.139832
Memory (GB)	0.304344	0.246151	0.45694

For KNN, the comparison of DR and ACC ratios of all experiments with each other is shown in Figure 4.23. The comparison of training and testing times of all experiments with each other is shown in Figure 4.24. The comparison of memory consume of all experiments with each other is shown in Figure 4.25.

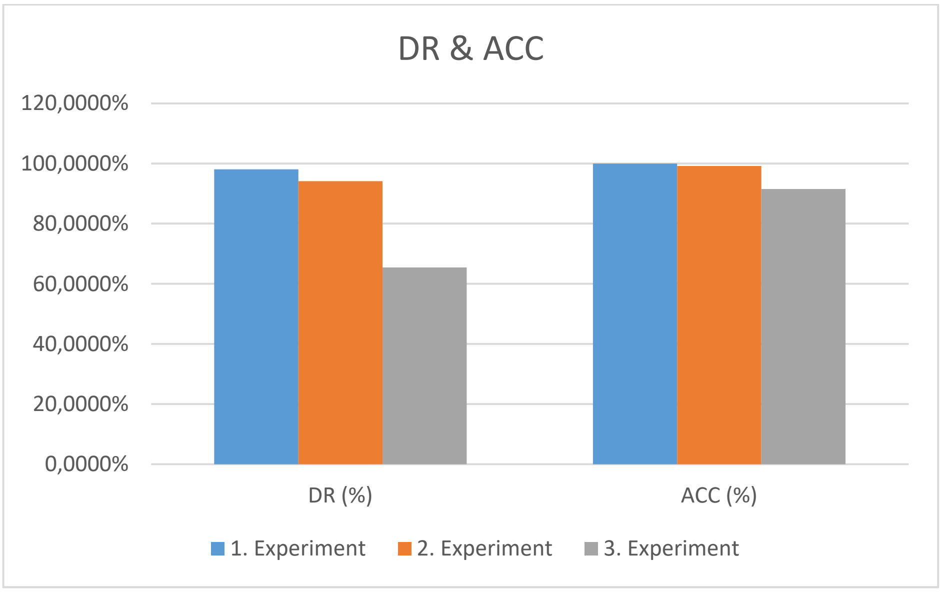


Figure 4.23: Comparison of DR & ACC for KNN Algorithm

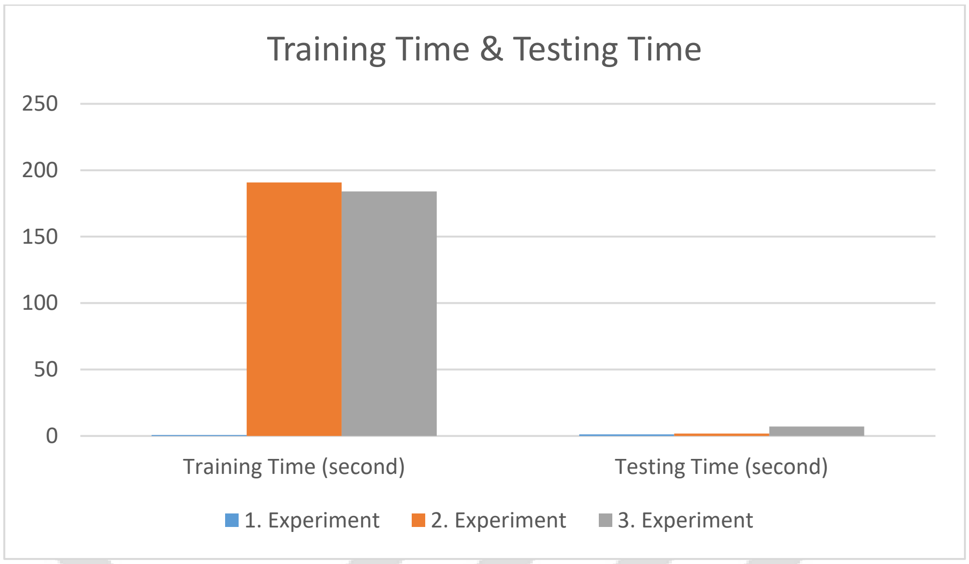


Figure 4.24: Comparison of Training and Testing Time for KNN Algorithm

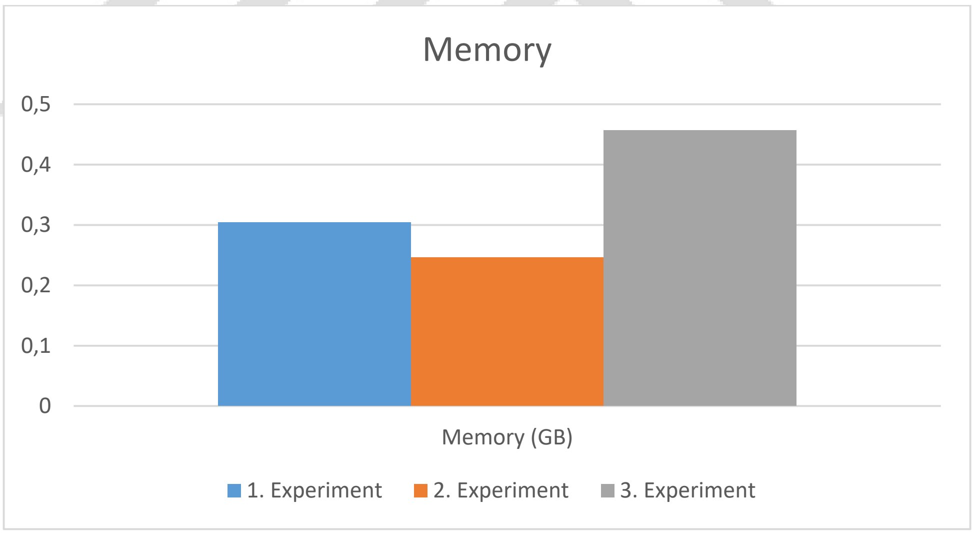


Figure 4.25: Comparison of Memory Consume KNN Algorithm

The results of experiments for KM can be seen in Table 4.9.

Table 4.9: Scalability Experiments for KM Algorithm

	1. Exp.	2. Exp.	3. Exp.
DR (%)	47.1663	29.6809	16.1885
ACC (%)	68.756	6.375	1.3774
DR For Normal (%)	69.797	0.258	0.2899
DR For Probe (%)	44.9104	47.4006	0
DR For DoS (%)	74.713	5.0573	3.1405
DR For R2L (%)	0.9569	4.7846	4.7846
DR For U2R (%)	45.4545	90.909	72.7272
Mean Of Cross V. (%)	1.6965	2.8465	6.2429
Time For Train (second)	3.872822	9.982122	23.515026
Time For Test (second)	0.009377	0.009005	0.008977
Memory (GB)	0.300694	0.82386	1.203556

For KM, the comparison of DR and ACC ratios of all experiments with each other is shown in Figure 4.26. The comparison of training and testing times of all experiments with each other is shown in Figure 4.27. The comparison of memory consume of all experiments with each other is shown in Figure 4.28.

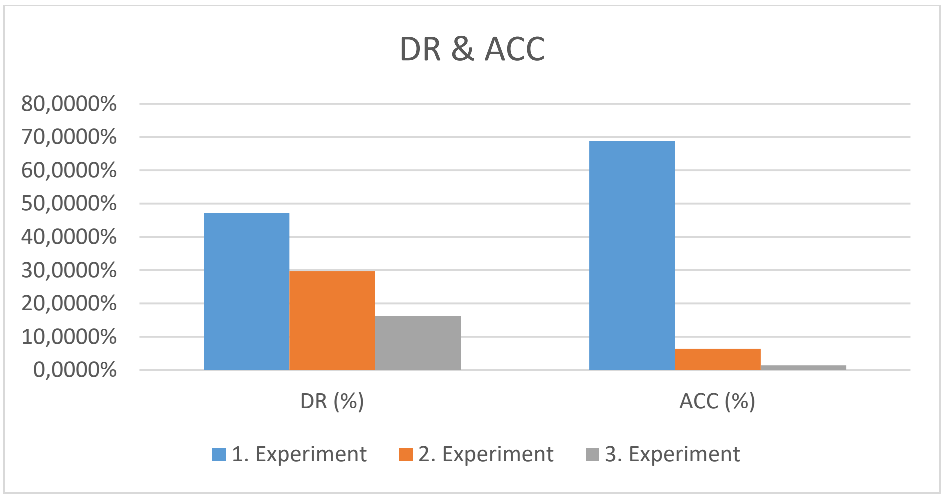


Figure 4.26: Comparison of DR & ACC for KM Algorithm

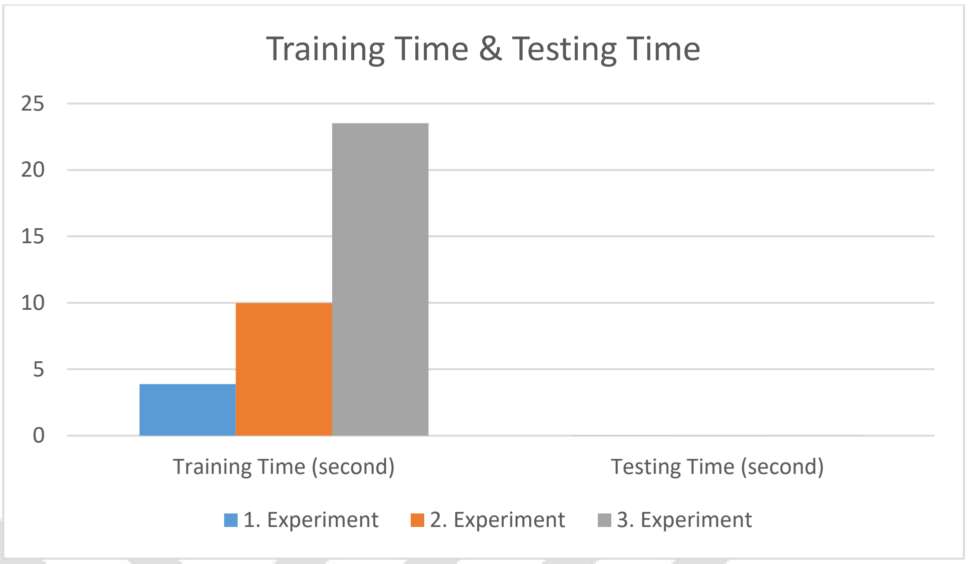


Figure 4.27: Comparison of Training and Testing Time for KM Algorithm

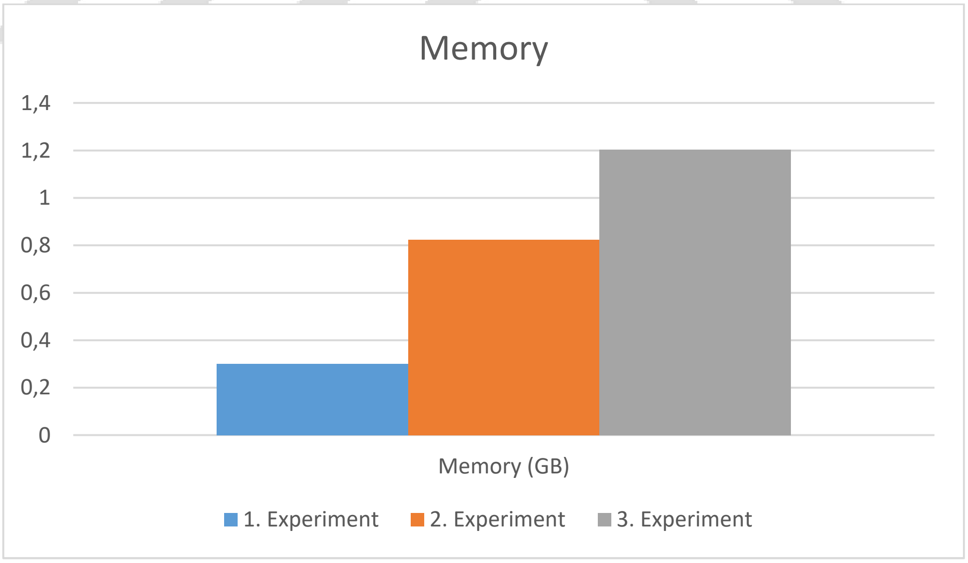


Figure 4.28: Comparison of Memory Consume KM Algorithm

The results of experiments for NB can be seen in Table 4.10.

Table 4.10: Scalability Experiments for NB Algorithm

	1. Exp.	**2. Exp.**	**3. Exp.**
DR (%)	52.2071	51.6936	50.8574
ACC (%)	88.3773	86.0432	79.9817
DR For Normal (%)	90.4825	94.5052	82.9727
DR For Probe (%)	80.166	88.9035	96.1992
DR For DoS (%)	89.4303	75.0596	73.381
DR For R2L (%)	0.9569	0	1.7341
DR For U2R (%)	0	0	0
Mean Of Cross V. (%)	88.4578	93.2765	95.5095
Time For Train (second)	0.128126	0.517239	1.079136
Time For Test (second)	0.006212	0.006631	0.006515
Memory (GB)	0.505257	0.975502	1.12112

For NB, the comparison of DR and ACC ratios of all experiments with each other is shown in Figure 4.29. The comparison of training and testing times of all experiments with each other is shown in Figure 4.30. The comparison of memory consume of all experiments with each other is shown in Figure 4.31.

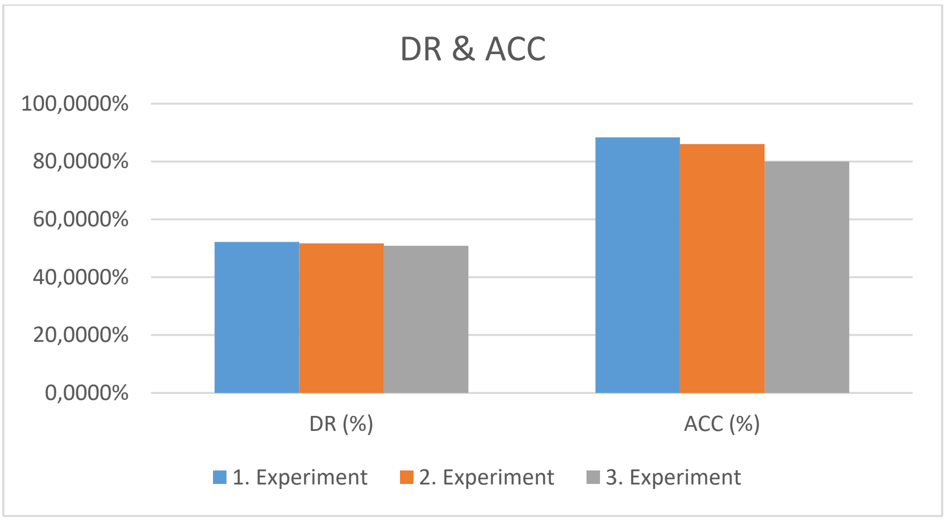


Figure 4.29: Comparison of DR & ACC for NB Algorithm

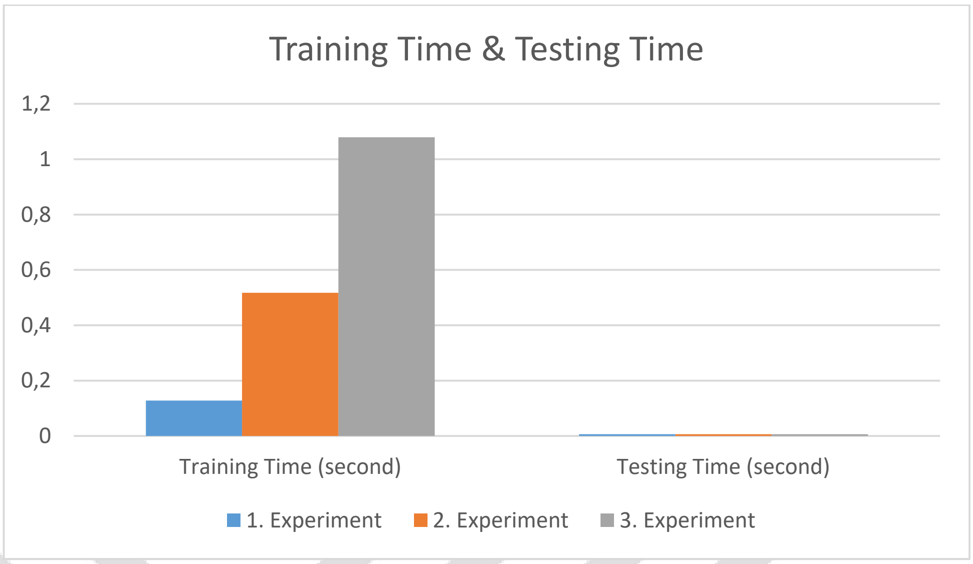


Figure 4.30: Comparison of Training and Testing Time for NB Algorithm

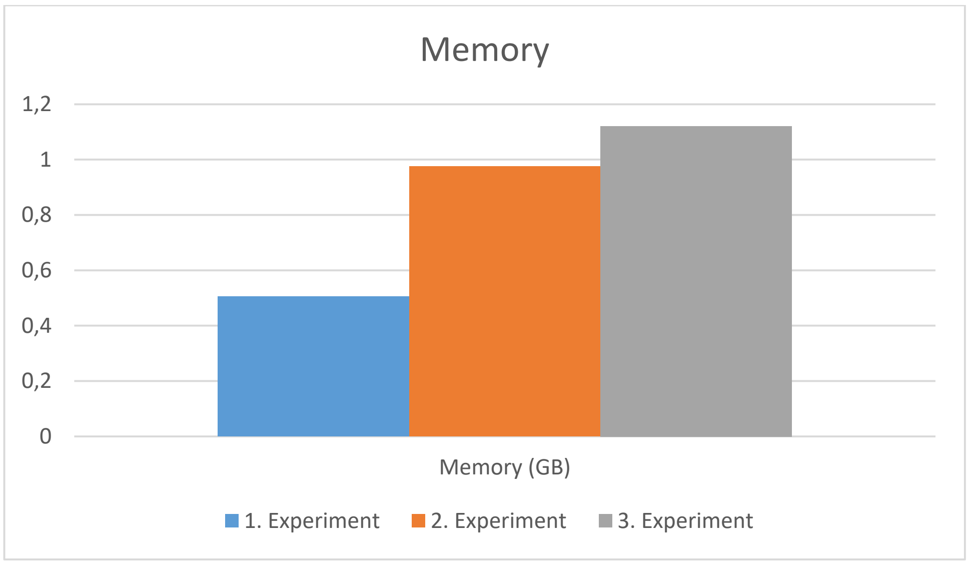


Figure 4.31: Comparison of Memory Consume NB Algorithm

The results of experiments for RF can be seen in Table 4.11.

Table 4.11: Scalability Experiments for RF Algorithm

	1. Exp.	**2. Exp.**	**3. Exp.**
DR (%)	92.2005	94.846	77.4958
ACC (%)	99.9166	99.087	90.3541
DR For Normal (%)	99.9553	99.7769	97.6801
DR For Probe (%)	99.8252	97.204	91.5684
DR For DoS (%)	99.9783	99.112	81.2216
DR For R2L (%)	97.6076	96.319	80.6452
DR For U2R (%)	63.6363	81.8182	36.3636
Mean Of Cross V. (%)	99.6483	95.606	99.4851
Time For Train (second)	8.095981	13.321269	34.635815
Time For Test (second)	0.028039	0.029124	0.029161
Memory (GB)	0.538746	0.969166	1.249306

For RF, the comparison of DR and ACC ratios of all experiments with each other is shown in Figure 4.32. The comparison of training and testing times of all experiments with each other is shown in Figure 4.33. The comparison of memory consume of all experiments with each other is shown in Figure 4.34.

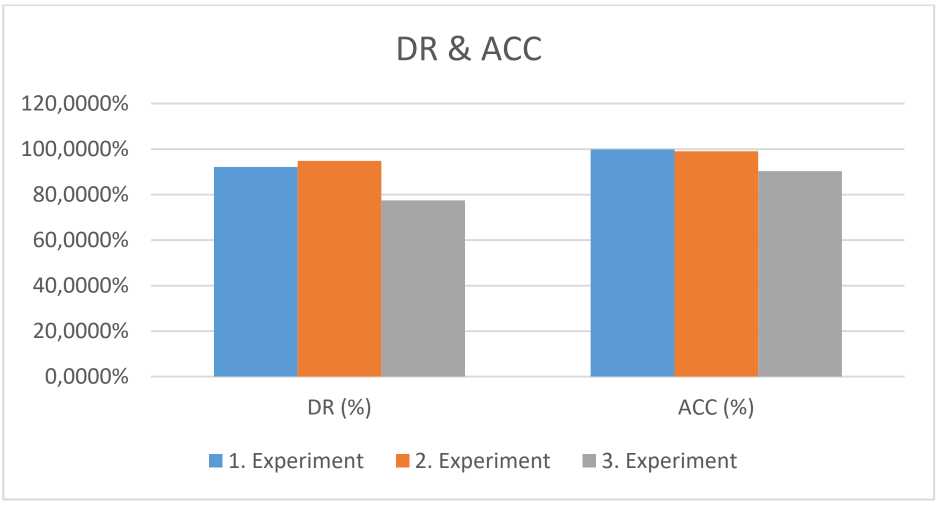


Figure 4.32: Comparison of DR & ACC for RF Algorithm

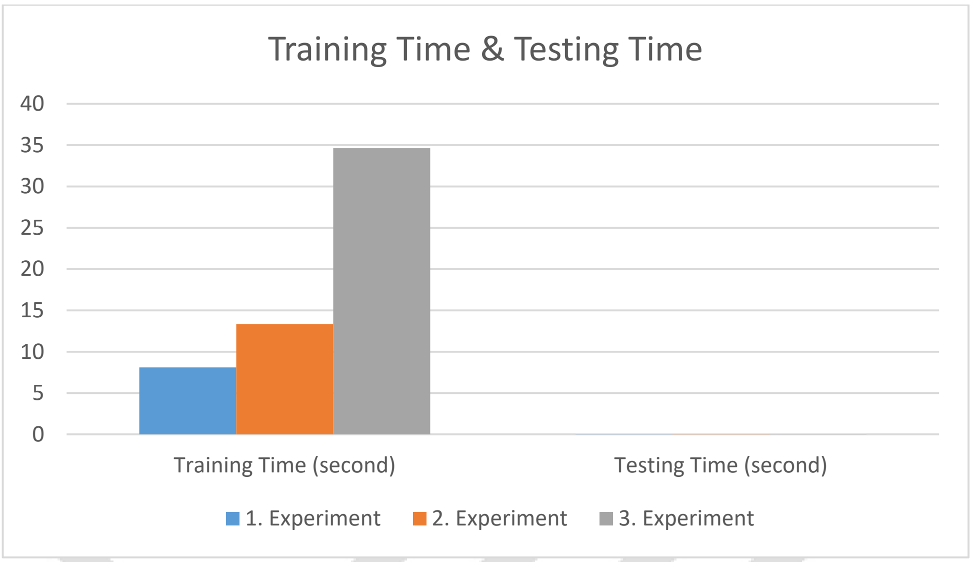


Figure 4.33: Comparison of Training and Testing Time for RF Algorithm

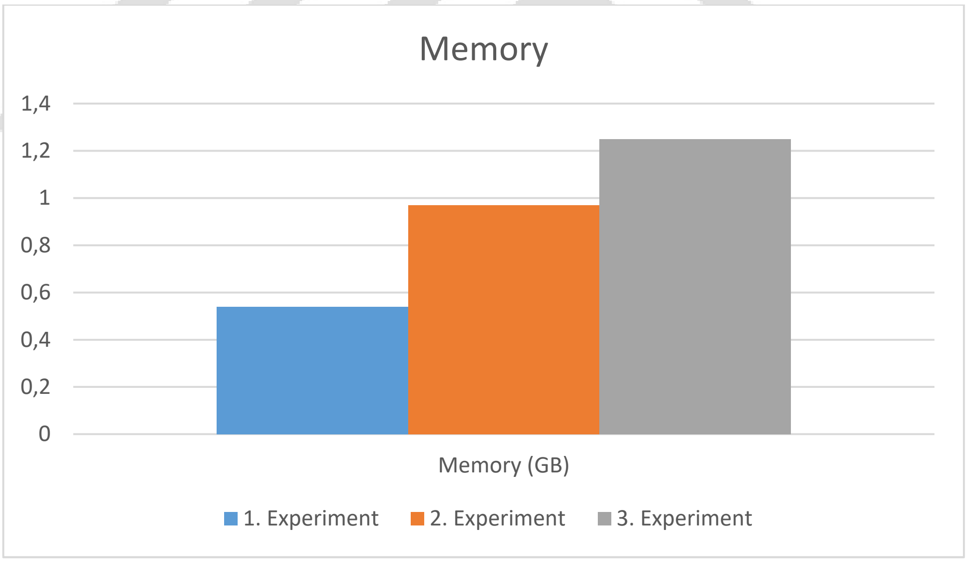


Figure 4.34: Comparison of Memory Consume RF Algorithm

As the size of the dataset used increases, the memory usage size of the algorithm will increase.

Scenario 3: Testing the effect of feature scaling on classification.

Scenario 3 Implementation:

In order to see the effect of feature scaling on classification, codes without feature scaling (Standard Scaler) are compared with the codes with feature scaling. The results of experiments for KNN can be seen in Table 4.12.

Table 4.12: Feature Scaling Experiments for KNN

	With Standard Scale	**Without Standard Scale**
DR (%)	98.0379	99.8544
ACC (%)	99.9603	99.8968
DR For Normal (%)	99.9776	99.9703
DR For Probe (%)	99.7815	99.3884
DR For DoS (%)	100	99.9134
DR For R2L (%)	99.5215	100
DR For U2R (%)	90.909	100
Mean Of Cross V. (%)	99.6539	99.5467
Time For Train (second)	0.66159	0.687662
Time For Test (second)	1.139292	1.195943
Memory (GB)	0.304344	0.29446

For KNN, the comparison of DR and ACC ratios of experiments with each other is shown in Figure 4.35. The comparison of training and testing times of experiments with each other is shown in Figure 4.36. The comparison of memory consume of experiments with each other is shown in Figure 4.37.

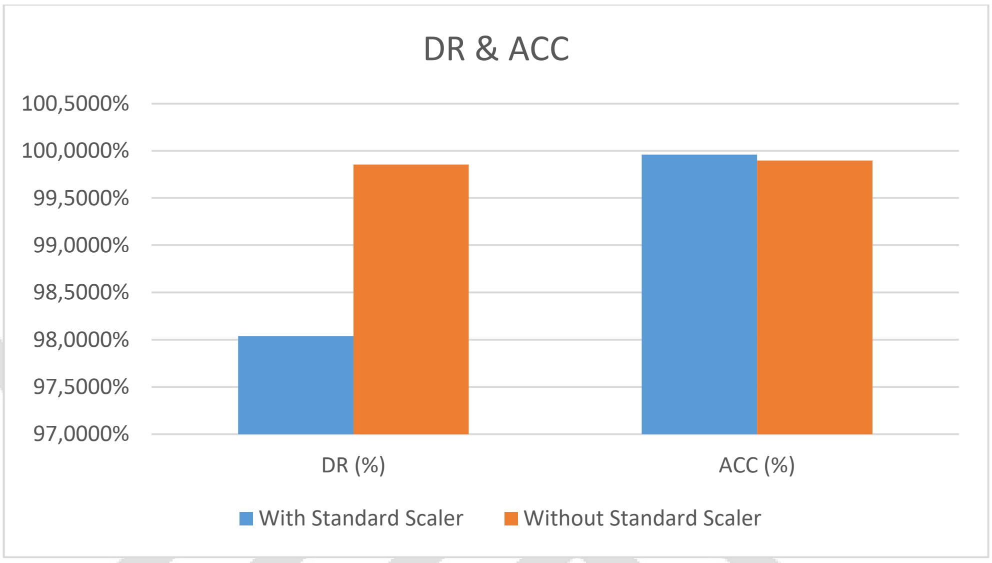


Figure 4.35: Comparison of DR & ACC for KNN Algorithm

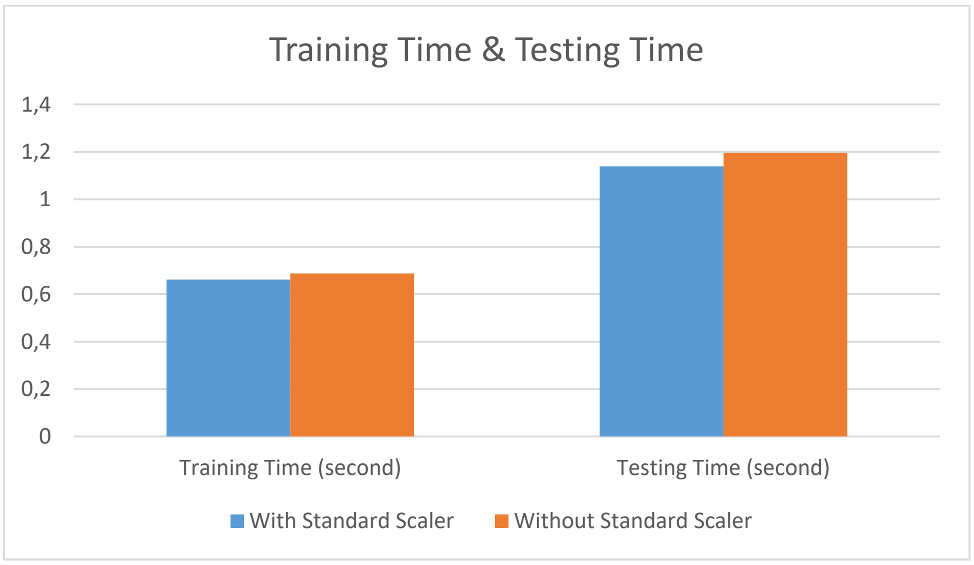


Figure 4.36: Comparison of Training and Testing Time for KNN Algorithm

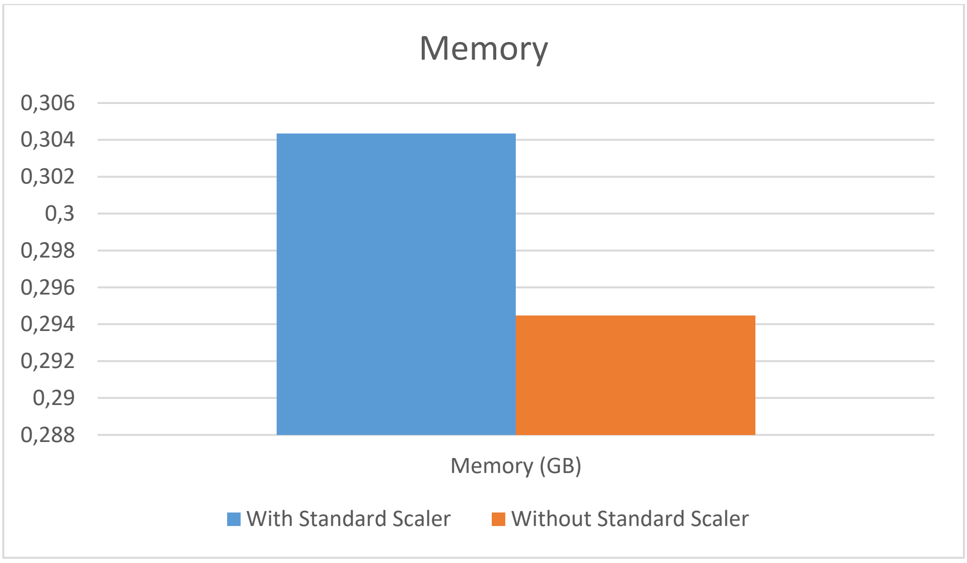


Figure 4.37: Comparison of Memory Consume KNN Algorithm

Without a standard scaler for KNN, the experiment gives a better result because numerical data is not being used in any mathematical process in KNN algorithm. The results of experiments for KM can be seen in Table 4.13.

Table 4.13: Feature Scaling Experiments for KM Algorithm

	With Standard Scale	**Without Standard Scale**
DR (%)	47.1663	20
ACC (%)	68.756	36.6545
DR For Normal (%)	69.797	0
DR For Probe (%)	44.9104	0
DR For DoS (%)	74.713	100
DR For R2L (%)	0.9569	0
DR For U2R (%)	45.4545	0
Mean Of Cross V. (%)	1.6965	0.00000000000003
Time For Train (second)	3.872822	1.659936
Time For Test (second)	0.009377	0.008598
Memory(GB)	0.300694	0.413994

For KM, the comparison of DR and ACC ratios of experiments with each other is shown in Figure 4.38. The comparison of training and testing times of experiments with each other is shown in Figure 4.39. The comparison of memory consume of experiments with each other is shown in Figure 4.40.

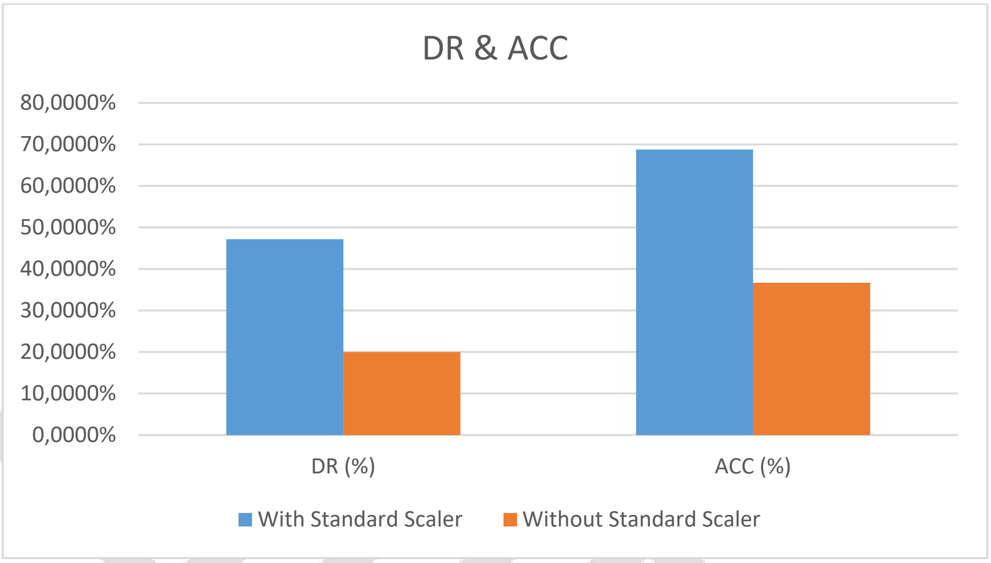


Figure 4.38: Comparison of DR & ACC for KM Algorithm

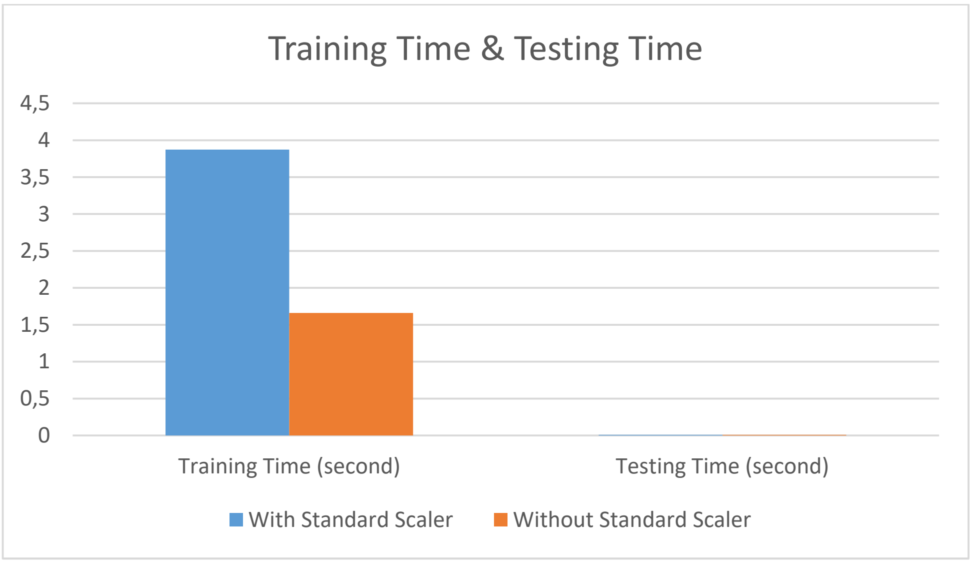


Figure 4.39: Comparison of Training and Testing Time for KM Algorithm

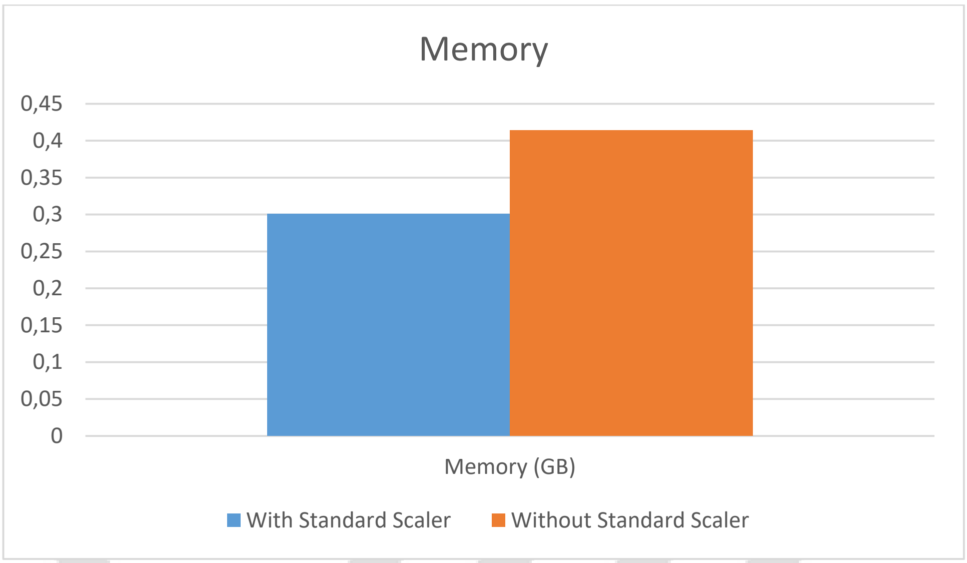


Figure 4.40: Comparison of Training and Testing Time for KM Algorithm

The results of experiments for NB can be seen in Table 4.14.

Table 4.14: Feature Scaling Experiments for NB

	With Standard Scale	**Without Standard Scale**
DR (%)	52.2071	27.9698
ACC (%)	88.3773	38.7861
DR For Normal (%)	90.4825	3.9854
DR For Probe (%)	80.166	8.3879
DR For DoS (%)	89.4303	97.8774
DR For R2L (%)	0.9569	2.3256
DR For U2R (%)	0	27.2727
Mean Of Cross V. (%)	88.4578	38.8377
Time For Train (second)	0.128126	0.206092
Time For Test (second)	0.006212	0.063926
Memory (GB)	0.505257	0.312431

For NB, the comparison of DR and ACC ratios of experiments with each other is shown in Figure 4.41. The comparison of training and testing times of experiments with each other is shown in Figure 4.42. The comparison of memory consume of experiments with each other is shown in Figure 4.43.

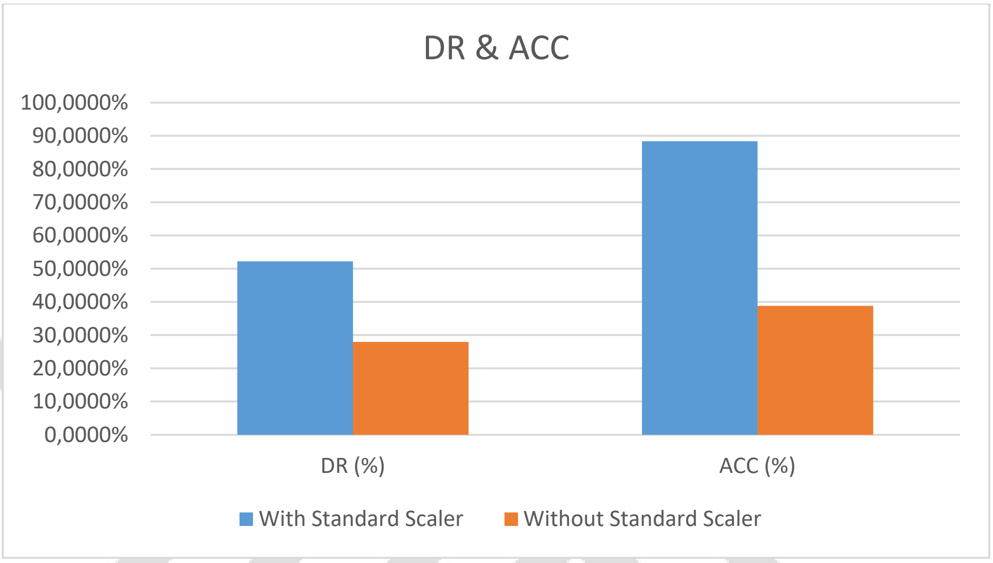


Figure 4.41: Comparison of DR & ACC for NB Algorithm

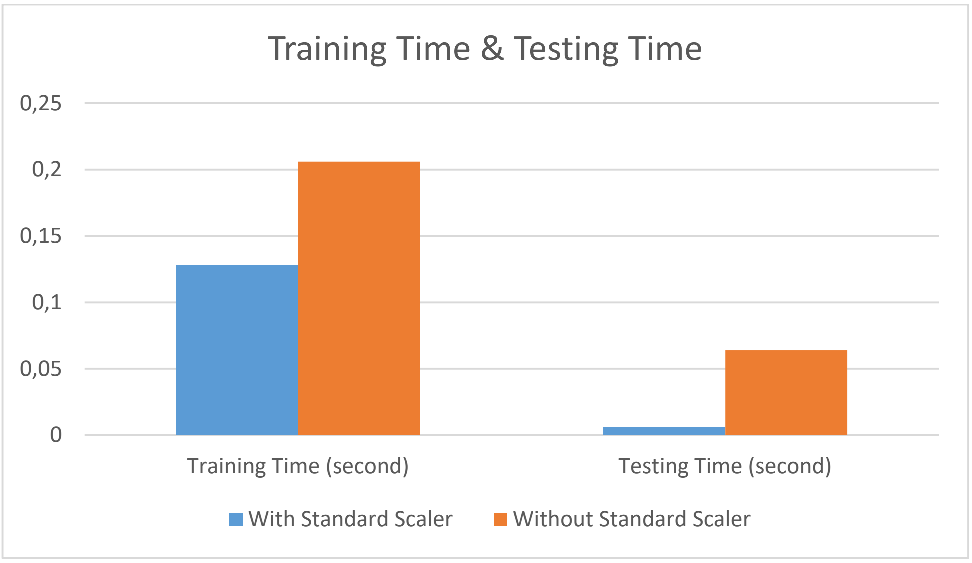


Figure 4.42: Comparison of Training and Testing Time for NB Algorithm

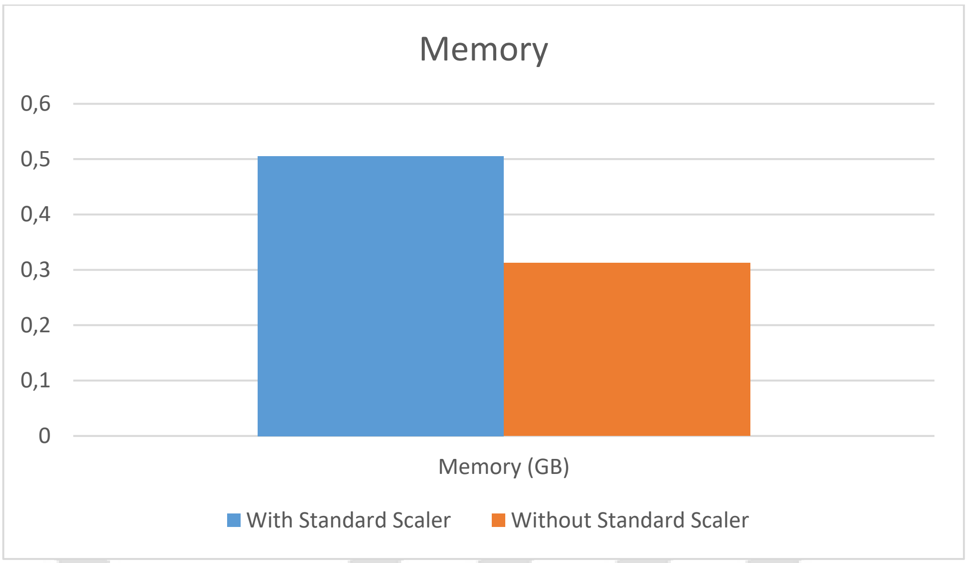


Figure 4.43: Comparison of Memory Consume NB Algorithm

The results of experiments for RF can be seen in Table 4.15.

Table 4.15: Feature Scaling Experiments for RF Algorithm

	With Standard Scale	**Without Standard Scale**
DR (%)	92.2005	96.2967
ACC (%)	99.9166	99.9365
DR For Normal (%)	99.9553	99.9926
DR For Probe (%)	99.8252	99.6942
DR For DoS (%)	99.9783	99.9783
DR For R2L (%)	97.6076	100
DR For U2R (%)	63.6363	81.8182
Mean Of Cross V. (%)	99.6483	99.7904
Time For Train (second)	8.095981	9.033393
Time For Test (second)	0.028039	0.025188
Memory (GB)	0.538746	0.312523

For RF, the comparison of DR and ACC ratios of experiments with each other is shown in Figure 4.44. The comparison of training and testing times of experiments with each other is shown in Figure 4.45. The comparison of memory consume of experiments with each other is shown in Figure 4.46.

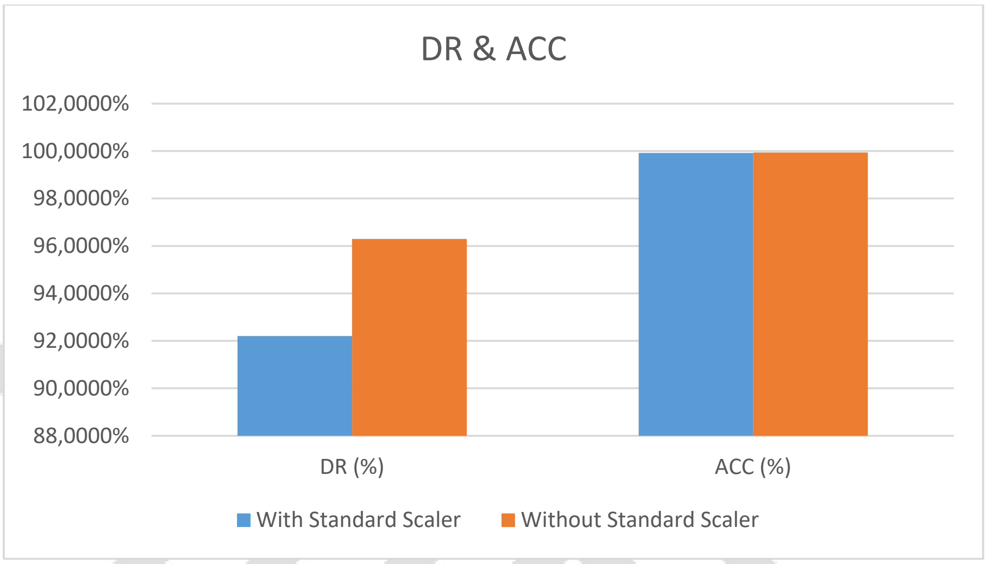


Figure 4.44: Comparison of DR & ACC for RF Algorithm

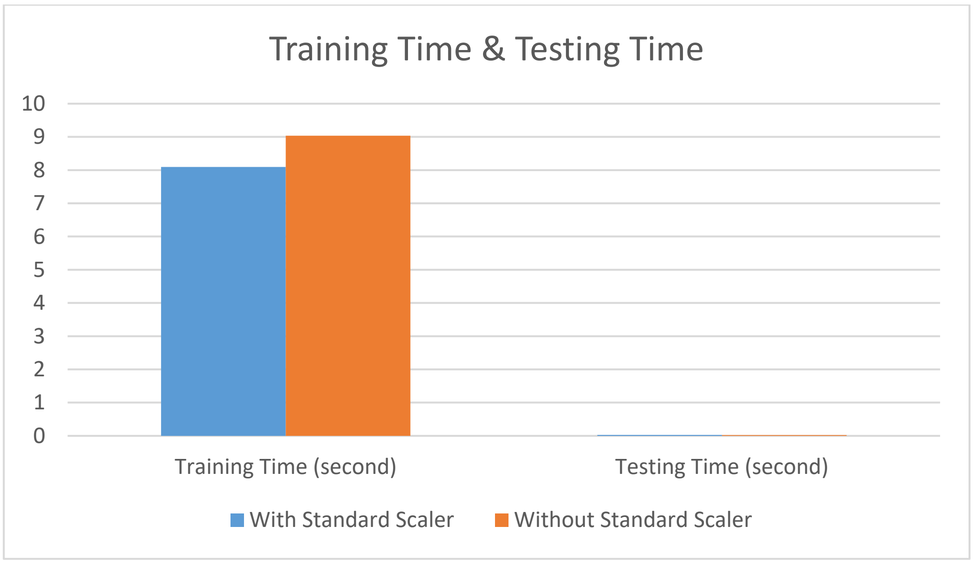


Figure 4.45: Comparison of Training and Testing Time for RF Algorithm

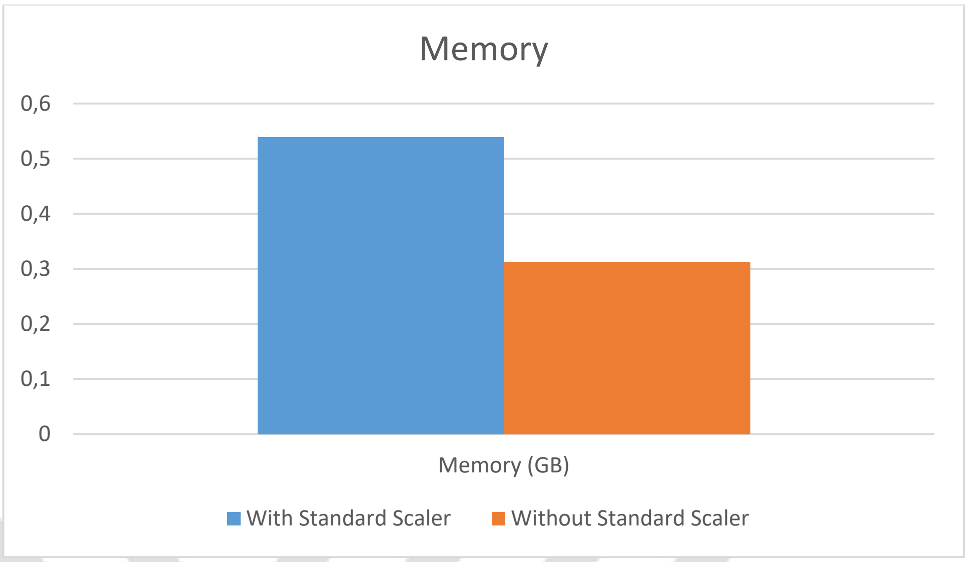


Figure 4.46: Comparison of Memory Consume RF Algorithm

Scenario 4: Testing the effect of imbalanced data on classification.

Scenario 4 Implementation: In order to see the effect of data imbalance, K-fold cross validation is applied to algorithm and every class accuracy are calculated in every experiment.

K-fold cross validation is a statistical method, in order to reduce variability and to avoid bias that involves partitioning the dataset into subsets, training the dataset on a subset and use the other subset to evaluate the model's performance (Kohavi 1995). Steps of K-fold cross validation is:

1. Divide the dataset into k equal parts.
2. Use 1 part for testing and k-1 parts for training.
3. Repeat the procedure k times, rotating the test dataset.
4. Determine an expected performance metric based on the results across the iterations.

Representation of K-fold cross validation is shown in Figure 4.47.

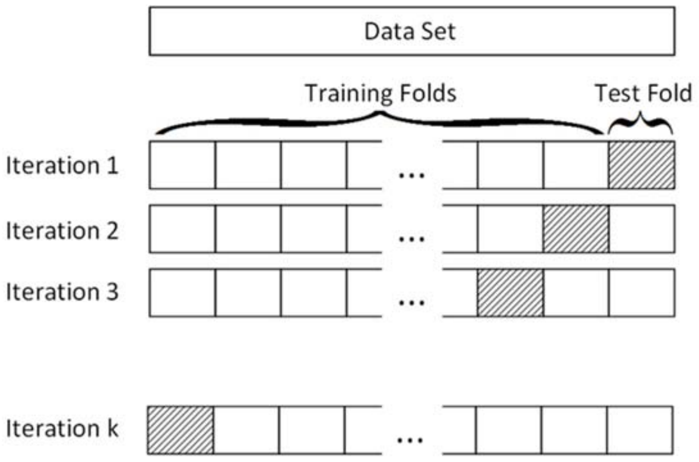


Figure 4.47: K-Fold Cross Validation

4.5 Results

Detection rate and accuracy rate, classification speed and memory allocation are discussed to clarify results.

4.5.1 Detection Rate and Accuracy Rate Results

The KNN algorithm has accuracy performance of 99.9603 %. This also shows that KNN has better accuracy performance compared to other classification algorithms. The aim of our research is to detect many attacks and classify them while maximizing the generation of DR and minimizing test time. Experiments show that NADS which use KNN algorithm is able to detect most of the attacks for the KDD CUP99 data set at a high DR rate of 98.0379 %

4.5.2 Classification Speed Results

KNN uses 0.661590s for training and 1.139292s for testing phases. In terms of training time, KNN has better speed performance compared to other classification algorithms. In terms of testing time, KNN has not much difference than others algorithm because testing time takes very small value for each algorithms.

4.5.3 Memory Allocation Results

Results shows that memory allocation for KNN is very small. The KNN algorithm uses 0.304344 GB. Using less memory will cause the system to perform more efficiently because it is dealing with less data.

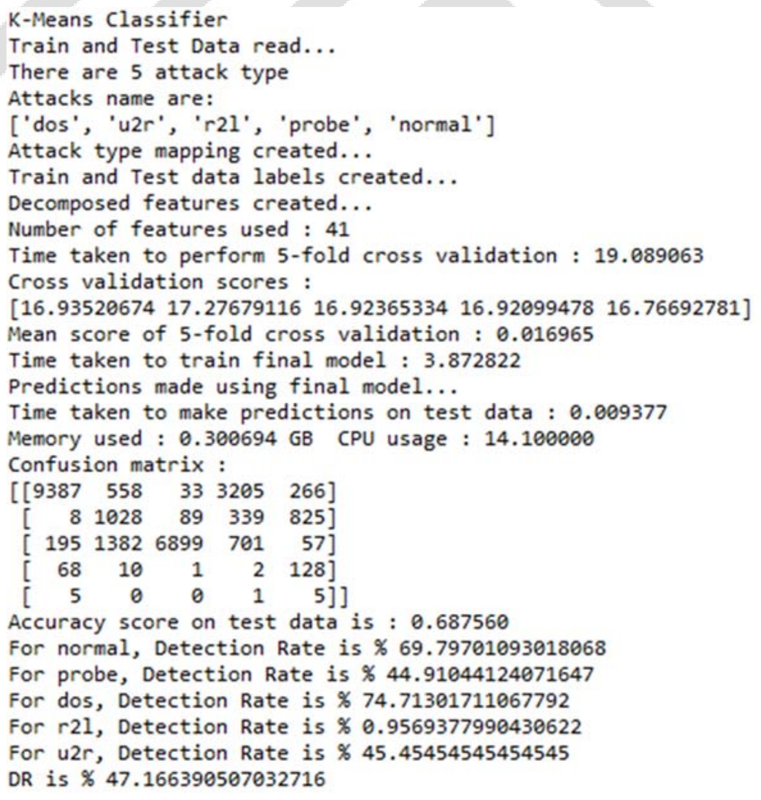
4.5.4 Overall Discussion

The number of examples is an influential factor on the percentage of the classification accuracy and the training and testing time. The proposed NADS using the NB algorithm outperforms all algorithms in terms of training time since it has the lowest time. NADS using KM algorithm has lowest testing according to experiments.

With respect to DR 98.0379% performance, the proposed NADS using the KNN algorithm outperforms all other algorithms. But it has the second lowest speed in the comparison list.

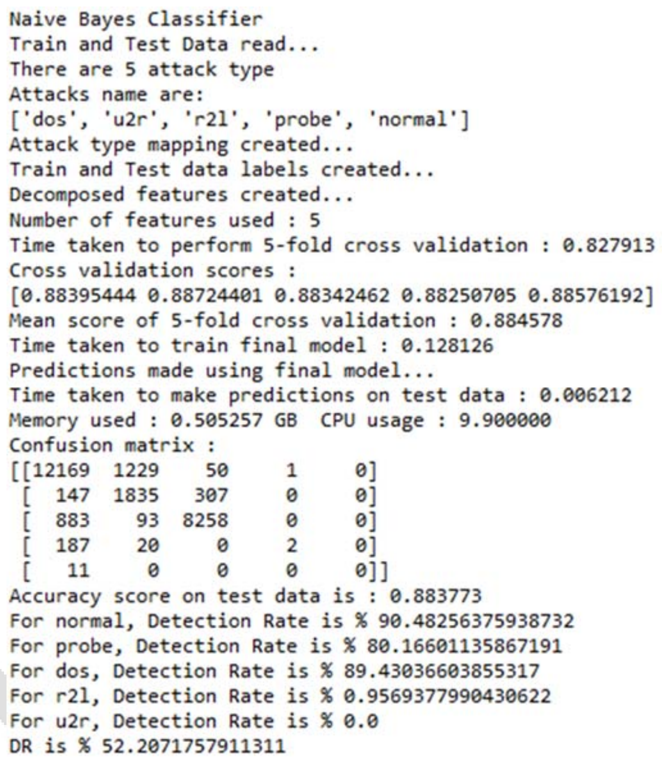
With respect to Accuracy 99.9603% performance, KNN Algorithm outperforms all other algorithms. KNN achieves better performance for the anomaly detection at second highest speed.

In Figure 4.48, Figure 4.49 and Figure 4.50 first experiment of first scenario for KM, NB and RF are shown. Confusion matrix of RF algorithm is the one which is most similar with confusion matrix of KNN algorithm.



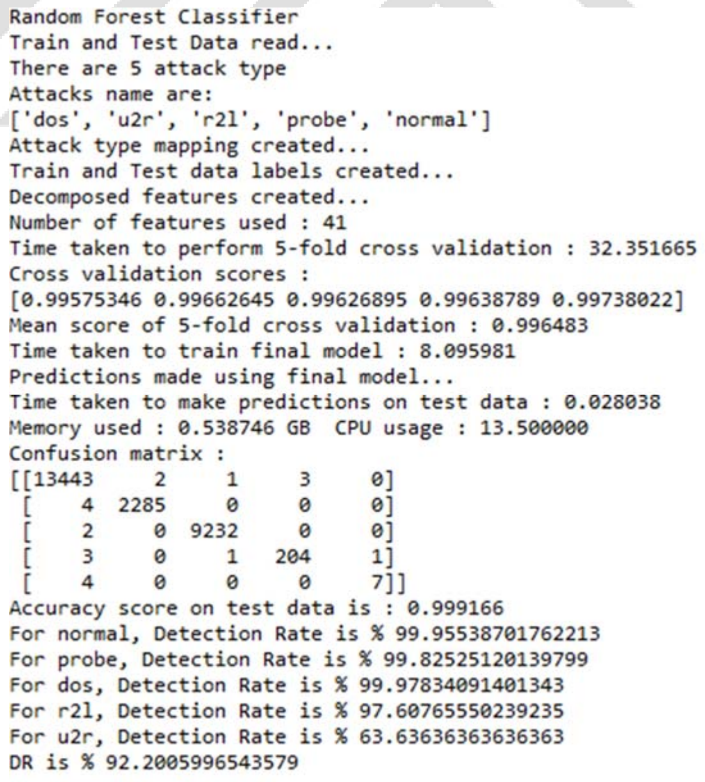
```
K-Means Classifier
Train and Test Data read...
There are 5 attack type
Attacks name are:
['dos', 'u2r', 'r2l', 'probe', 'normal']
Attack type mapping created...
Train and Test data labels created...
Decomposed features created...
Number of features used : 41
Time taken to perform 5-fold cross validation : 19.089063
Cross validation scores :
[16.93520674 17.27679116 16.92365334 16.92099478 16.76692781]
Mean score of 5-fold cross validation : 0.016965
Time taken to train final model : 3.872822
Predictions made using final model...
Time taken to make predictions on test data : 0.009377
Memory used : 0.300694 GB  CPU usage : 14.100000
Confusion matrix :
[[9387  558   33 3205  266]
 [   8 1028   89  339  825]
 [ 195 1382 6899  701   57]
 [  68   10    1    2  128]
 [   5    0    0    1    5]]
Accuracy score on test data is : 0.687560
For normal, Detection Rate is % 69.79701093018068
For probe, Detection Rate is % 44.91044124071647
For dos, Detection Rate is % 74.71301711067792
For r2l, Detection Rate is % 0.9569377990430622
For u2r, Detection Rate is % 45.45454545454545
DR is % 47.166390507032716
```

Figure 4.48: Experiment of KM Algorithm



```
Naive Bayes Classifier
Train and Test Data read...
There are 5 attack type
Attacks name are:
['dos', 'u2r', 'r2l', 'probe', 'normal']
Attack type mapping created...
Train and Test data labels created...
Decomposed features created...
Number of features used : 5
Time taken to perform 5-fold cross validation : 0.827913
Cross validation scores :
[0.88395444 0.88724401 0.88342462 0.88250705 0.88576192]
Mean score of 5-fold cross validation : 0.884578
Time taken to train final model : 0.128126
Predictions made using final model...
Time taken to make predictions on test data : 0.006212
Memory used : 0.505257 GB  CPU usage : 9.900000
Confusion matrix :
[[12169  1229    50     1     0]
 [  147  1835   307     0     0]
 [  883    93  8258     0     0]
 [  187    20     0     2     0]
 [   11     0     0     0     0]]
Accuracy score on test data is : 0.883773
For normal, Detection Rate is % 90.48256375938732
For probe, Detection Rate is % 80.16601135867191
For dos, Detection Rate is % 89.43036603855317
For r2l, Detection Rate is % 0.9569377990430622
For u2r, Detection Rate is % 0.0
DR is % 52.2071757911311
```

Figure 4.49: Experiment of NB Algorithm



```
Random Forest Classifier
Train and Test Data read...
There are 5 attack type
Attacks name are:
['dos', 'u2r', 'r2l', 'probe', 'normal']
Attack type mapping created...
Train and Test data labels created...
Decomposed features created...
Number of features used : 41
Time taken to perform 5-fold cross validation : 32.351665
Cross validation scores :
[0.99575346 0.99662645 0.99626895 0.99638789 0.99738022]
Mean score of 5-fold cross validation : 0.996483
Time taken to train final model : 8.095981
Predictions made using final model...
Time taken to make predictions on test data : 0.028038
Memory used : 0.538746 GB  CPU usage : 13.500000
Confusion matrix :
[[13443     2     1     3     0]
 [    4  2285     0     0     0]
 [    2     0  9232     0     0]
 [    3     0     1   204     1]
 [    4     0     0     0     7]]
Accuracy score on test data is : 0.999166
For normal, Detection Rate is % 99.95538701762213
For probe, Detection Rate is % 99.82525120139799
For dos, Detection Rate is % 99.97834091401343
For r2l, Detection Rate is % 97.60765550239235
For u2r, Detection Rate is % 63.63636363636363
DR is % 92.2005996543579
```

Figure 4.50: Experiment of RF Algorithm

CHAPTER 5

CONCLUSION

The main aim of this thesis is to propose a Network Anomaly Detection System using machine learning, which helps to detect anomalies and respond with appropriate actions. The purpose of the anomaly detection system is to reveal detectable and undetected anomalies. The proposed NADS system uses the KNN Algorithm for classification, PCA Algorithm for reduction and it classifies connections as normal or abnormal.

Results show that the proposed NADS achieved highest classification ACC of 99.9603 % by using the KNN and PCA algorithms and second highest speed after NB which has the highest speed. KNN performance is very high in terms of training time since it has the second lowest time. But it was not possible to verify how the system will behave on larger networks and using bigger dataset and it was not possible to simulate and recreate all possible intrusions and attacks.

Many studies on NADS using machine learning have been recently carried out and new technologies introduced. As a future study, this study can be expanded in different ways such as using other packet sniffing technologies in NADS. In addition, different data sets can be used to test the proposed NADS system.

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APPENDICES

Appendix: A

Machine Learning and Machine Learning Python Libraries

Machine learning is the data analytical method, basically based on algorithms, math and statistics, that applies the ability of learning to machines through data which gathered from the natural experience of humans and animals. We have used some Python Libraries in building our NADS.

1. Numpy (Numerical Python)

Numpy that stands for Numerical Python contains some arrays that operates rapid mathematical operations. Random numbers can be generated with the Numpy Library. Many of mathematical operations can be performed from matrix multiplication to linear algebra operations and Fourier transforms.

2. Pandas

Pandas is an easy-to-use, high-performance data configuration and data analysis library. With this library data can be read and written from many different sources such as excel, json, text (csv) and database. It contains table structures which are one-dimensional as named Serie, 2-dimensional named as DataFrame. Pandas tables can keep many different type of variables (digital, categorical, date etc.). Important data processing steps, such as data conversion, filtering, can be easily performed with this library.

3. Scikit-Learn

This widely used library has many machine learning algorithms. In addition to these algorithms, this library also includes dimensional reduction, data processing and model selection methods.

Appendix: B

Attributes description of KDD CUP 99 dataset.

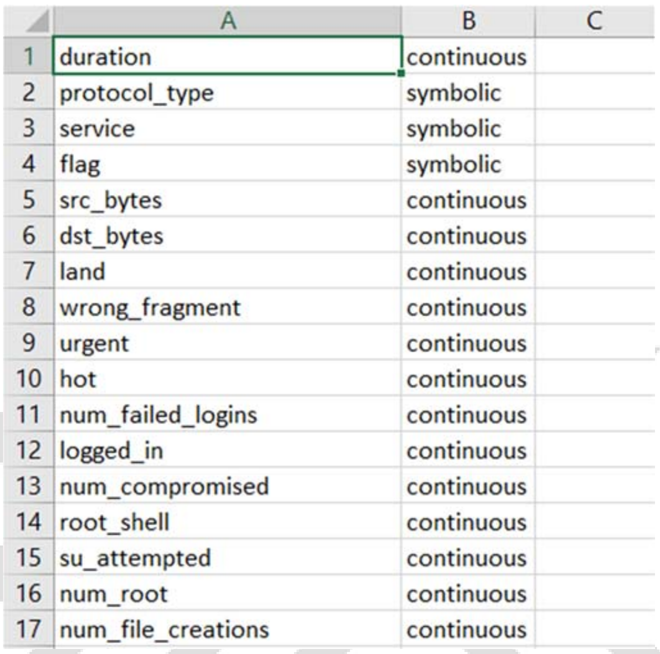
No.	Network attributes	Description	Type
1	Duration	Duration of the connection in second.	Continuous
2	Protocol_type	Connection protocol (e.g. TCP, UDP, ICMP).	Discrete
3	Service	Destination service (e.g. telnet, ftp, http, pop3…)	Discrete
4	Flag	Status flag of the connection (e.g. REJ, SF, S0…)	Discrete
5	Src_bytes	Bytes sent from source to destination	Continuous
6	dst_bytes	Bytes sent from destination to source	Continuous
7	Land	1 if connection is from /to the same host/port; 0 otherwise	Discrete
8	Wrong_fragment	Number of wrong fragments	Continuous
9	Urgent	Number of urgent packets	Continuous
10	Hot	Number of "hot" indicators	Continuous
11	Num_failed_logins	Number of failed logins	Continuous
12	Logged_in	1 if successfully logged in; 0 otherwise	Discrete
13	Num_compromised	Number of "compromised" conditions	Continuous
14	Root_shell	1 if root shell is obtained; 0 otherwise	Continuous
15	Su_attempted	1 if "as root" command attempted; 0 otherwise	Continuous
16	Num_root	Number of root accesses	Continuous
17	Num_file_creations	Number of file creation operations	Continuous
18	Num_shells	Number of shell prompts	Continuous
19	Num_access_files	Number of operations on access control files	Continuous
20	Num_outbound_cmds	Number of outbound commands in an ftp session	Continuous
21	Is_host_login	1 if the login belongs to the "hot" list; 0 otherwise	Discrete

22	Is_guest_login	1 if the login is a " guest" login; 0 otherwise	Discrete
23	count	Number of connections to the same host as the current connection in the past two seconds	Continuous
24	Srv_ count	Number of connections to the same service as current connection in the past two seconds	Continuous
25	Serror_rate	No. of connections that have " SYN" errors	Continuous
26	Srv_ Serror_rate	No. of connections that have " SYN" errors	Continuous
27	Rerror_rate	No. of connections that have " REJ" errors	Continuous
28	Srv_ rerror_rate	No. of connections that have " REJ" errors	Continuous
29	Same_ rerror_rate	No. of connections to the same service	Continuous
30	Diff_ Srv_ rate	No. of connections to different services	Continuous
31	Srv_ Diff_host_ rate	No. of connections to different hosts	Continuous
32	Dst_ host_count	Count of connections having the same destination host	Continuous
33	Dst_ host_ Srv_count	Count of connections having the same destination host and using the same service	Continuous
34	Dst_ host_ Same_ rate	Count of connections having the same destination host and using the same service	Continuous
35	Dst_ host_Diff_ Srv _ rate	No. of different services on the current host	Continuous
36	Dst_ host_ Same_src_port_ rate	No. of connections to current host having the same src port	Continuous
37	Dst_ host_ Srv _ Diff_ host_ rate	No. of connections to same service coming from different hosts	Continuous
38	Dst_ host_ serror_ rate	No. of connections to the current host that have an S0 error	Continuous
39	Dst_ host_ Srv _serror_ rate	No. of connections to the current host and specified service that have an S0 error	Continuous
40	Dst_ host_rerror_ rate	No. of connections to the current host that have an RST error	Continuous
41	Dst_ host_ rerror_ rate	No. of connections to the current host and specified service that have an RST error	Continuous

Appendix: C

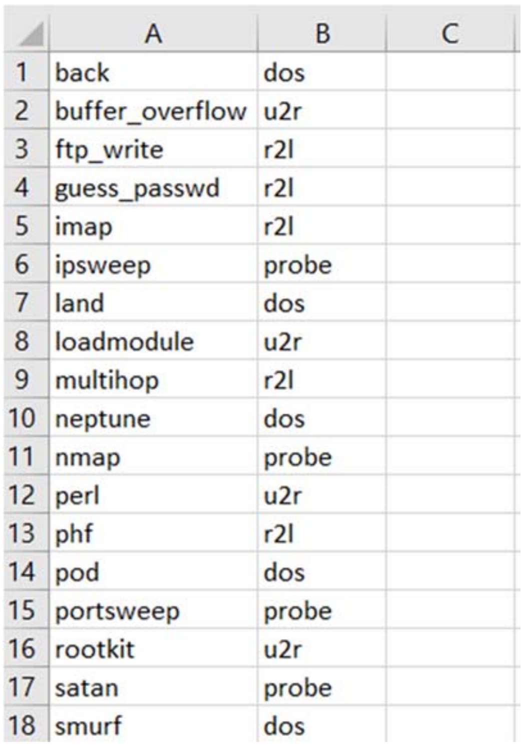
'Fields Name File' shows types of attacks. 'Attack Types File' maps its columns to the attack column of main file.

Fields Name File



	A	B	C
1	duration	continuous	
2	protocol_type	symbolic	
3	service	symbolic	
4	flag	symbolic	
5	src_bytes	continuous	
6	dst_bytes	continuous	
7	land	continuous	
8	wrong_fragment	continuous	
9	urgent	continuous	
10	hot	continuous	
11	num_failed_logins	continuous	
12	logged_in	continuous	
13	num_compromised	continuous	
14	root_shell	continuous	
15	su_attempted	continuous	
16	num_root	continuous	
17	num_file_creations	continuous	

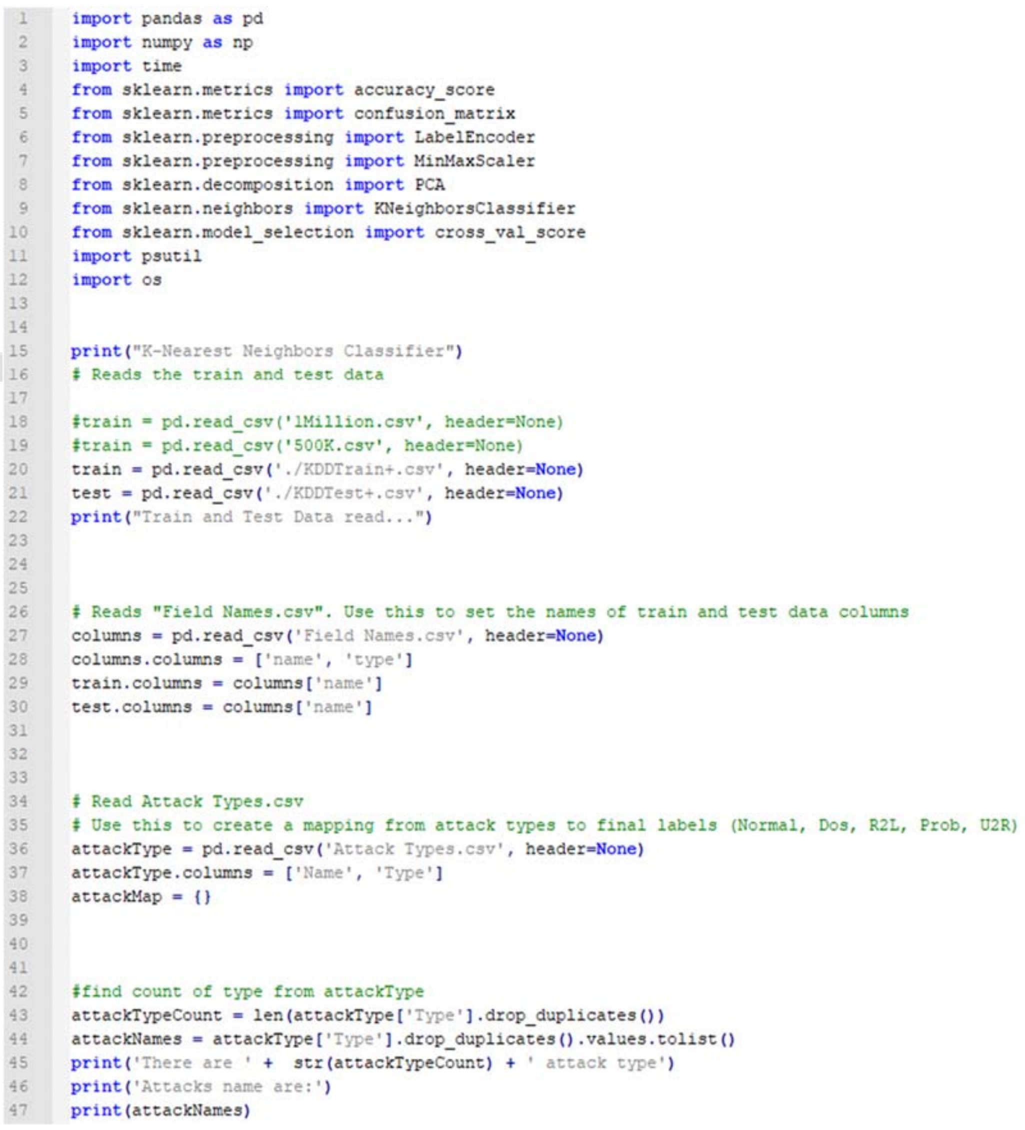
Attack Types File



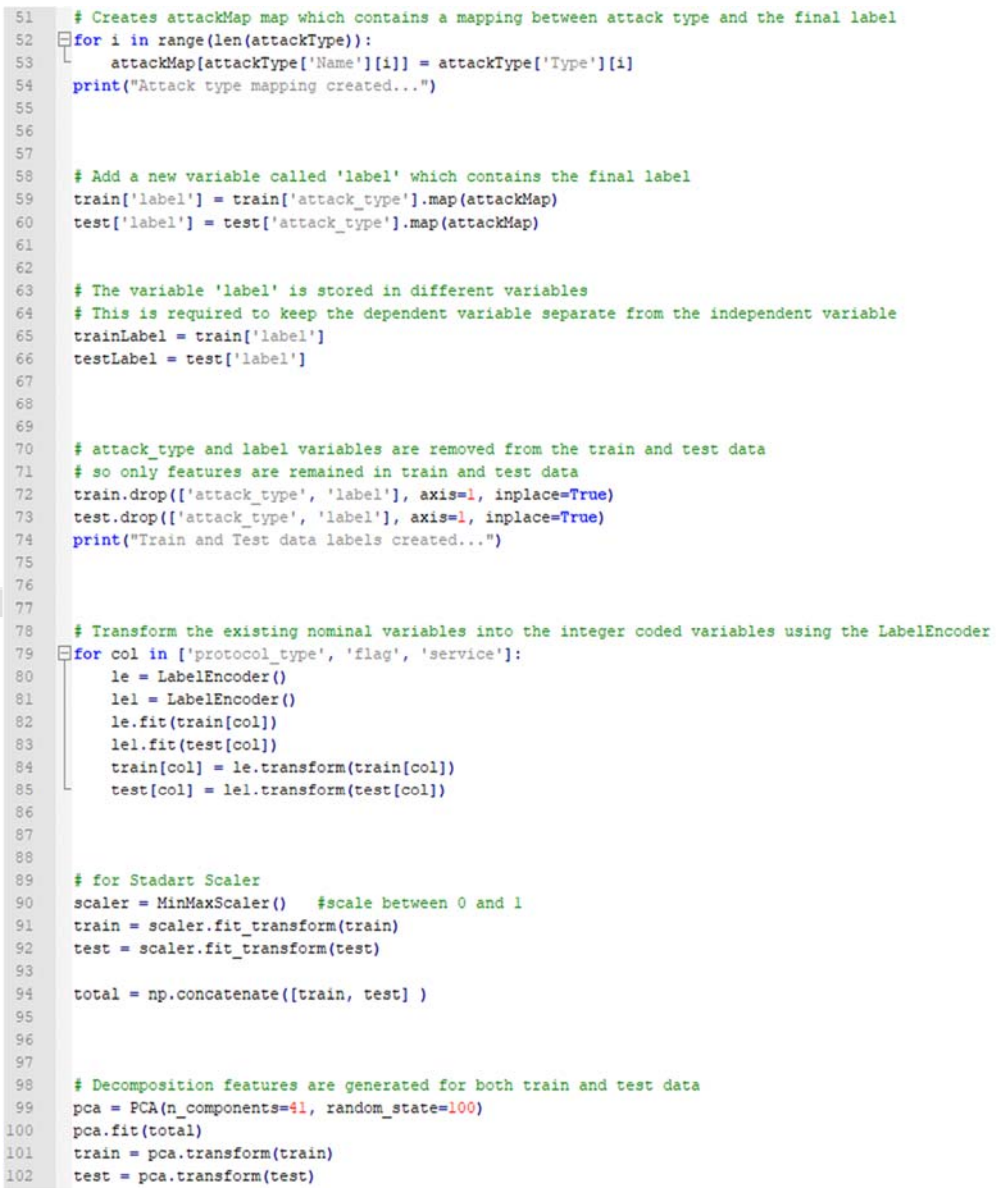
	A	B	C
1	back	dos	
2	buffer_overflow	u2r	
3	ftp_write	r2l	
4	guess_passwd	r2l	
5	imap	r2l	
6	ipsweep	probe	
7	land	dos	
8	loadmodule	u2r	
9	multihop	r2l	
10	neptune	dos	
11	nmap	probe	
12	perl	u2r	
13	phf	r2l	
14	pod	dos	
15	portsweep	probe	
16	rootkit	u2r	
17	satan	probe	
18	smurf	dos	

Appendix: D

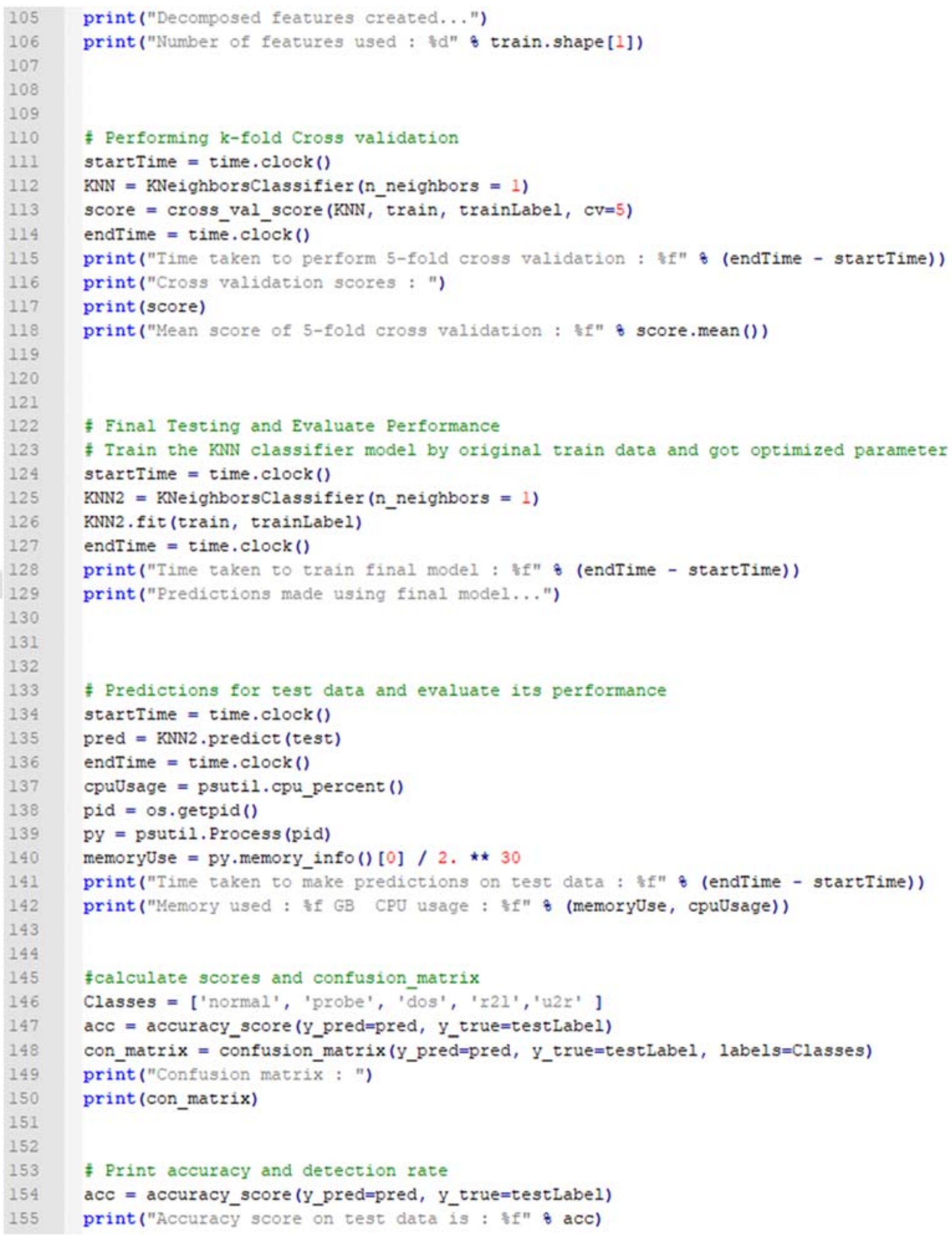
Python Code for K-Nearest Neighbor Classification Algorithm



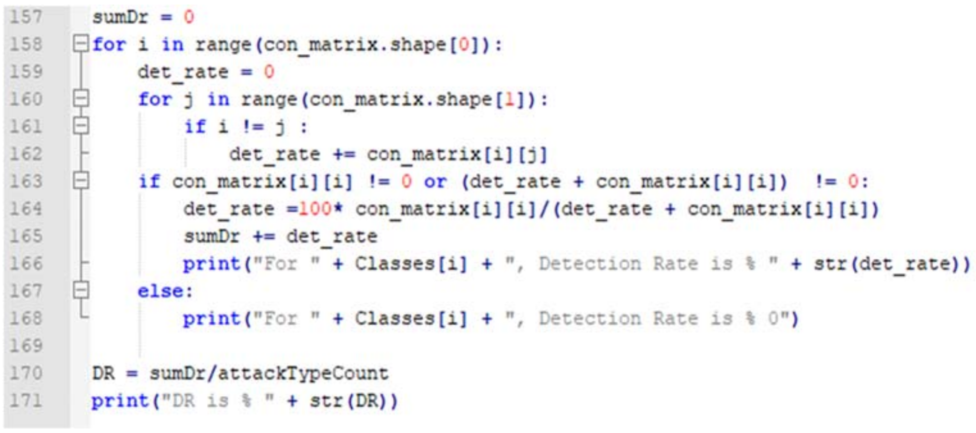
```python
import pandas as pd
import numpy as np
import time
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
import psutil
import os


print("K-Nearest Neighbors Classifier")
# Reads the train and test data

#train = pd.read_csv('1Million.csv', header=None)
#train = pd.read_csv('500K.csv', header=None)
train = pd.read_csv('./KDDTrain+.csv', header=None)
test = pd.read_csv('./KDDTest+.csv', header=None)
print("Train and Test Data read...")



# Reads "Field Names.csv". Use this to set the names of train and test data columns
columns = pd.read_csv('Field Names.csv', header=None)
columns.columns = ['name', 'type']
train.columns = columns['name']
test.columns = columns['name']



# Read Attack Types.csv
# Use this to create a mapping from attack types to final labels (Normal, Dos, R2L, Prob, U2R)
attackType = pd.read_csv('Attack Types.csv', header=None)
attackType.columns = ['Name', 'Type']
attackMap = {}



#find count of type from attackType
attackTypeCount = len(attackType['Type'].drop_duplicates())
attackNames = attackType['Type'].drop_duplicates().values.tolist()
print('There are ' +  str(attackTypeCount) + ' attack type')
print('Attacks name are:')
print(attackNames)
```



```python
# Creates attackMap map which contains a mapping between attack type and the final label
for i in range(len(attackType)):
    attackMap[attackType['Name'][i]] = attackType['Type'][i]
print("Attack type mapping created...")



# Add a new variable called 'label' which contains the final label
train['label'] = train['attack_type'].map(attackMap)
test['label'] = test['attack_type'].map(attackMap)


# The variable 'label' is stored in different variables
# This is required to keep the dependent variable separate from the independent variable
trainLabel = train['label']
testLabel = test['label']



# attack_type and label variables are removed from the train and test data
# so only features are remained in train and test data
train.drop(['attack_type', 'label'], axis=1, inplace=True)
test.drop(['attack_type', 'label'], axis=1, inplace=True)
print("Train and Test data labels created...")



# Transform the existing nominal variables into the integer coded variables using the LabelEncoder
for col in ['protocol_type', 'flag', 'service']:
    le = LabelEncoder()
    le1 = LabelEncoder()
    le.fit(train[col])
    le1.fit(test[col])
    train[col] = le.transform(train[col])
    test[col] = le1.transform(test[col])



# for Stadart Scaler
scaler = MinMaxScaler()    #scale between 0 and 1
train = scaler.fit_transform(train)
test = scaler.fit_transform(test)

total = np.concatenate([train, test] )



# Decomposition features are generated for both train and test data
pca = PCA(n_components=41, random_state=100)
pca.fit(total)
train = pca.transform(train)
test = pca.transform(test)
```



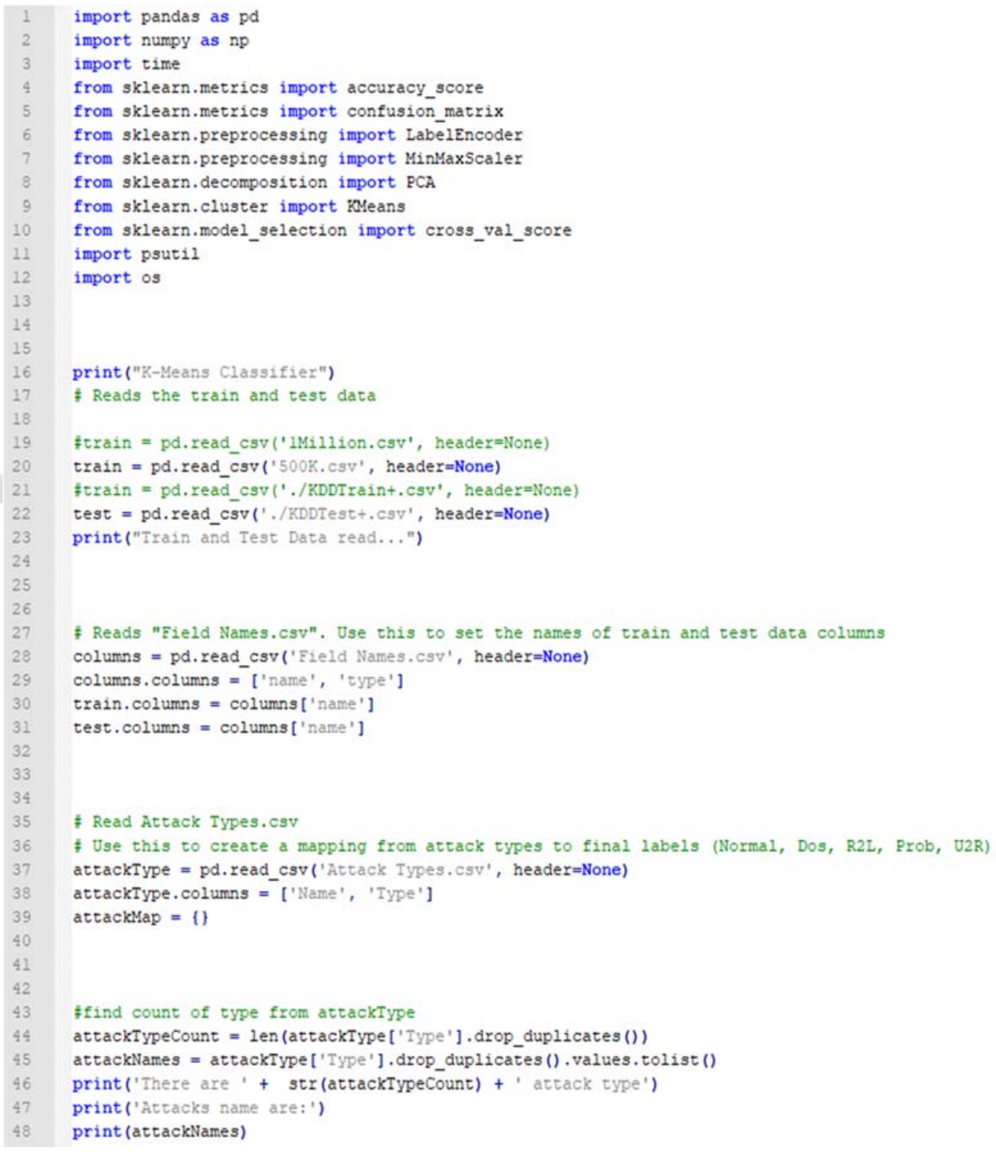
```python
print("Decomposed features created...")
print("Number of features used : %d" % train.shape[1])



# Performing k-fold Cross validation
startTime = time.clock()
KNN = KNeighborsClassifier(n_neighbors = 1)
score = cross_val_score(KNN, train, trainLabel, cv=5)
endTime = time.clock()
print("Time taken to perform 5-fold cross validation : %f" % (endTime - startTime))
print("Cross validation scores : ")
print(score)
print("Mean score of 5-fold cross validation : %f" % score.mean())



# Final Testing and Evaluate Performance
# Train the KNN classifier model by original train data and got optimized parameter
startTime = time.clock()
KNN2 = KNeighborsClassifier(n_neighbors = 1)
KNN2.fit(train, trainLabel)
endTime = time.clock()
print("Time taken to train final model : %f" % (endTime - startTime))
print("Predictions made using final model...")



# Predictions for test data and evaluate its performance
startTime = time.clock()
pred = KNN2.predict(test)
endTime = time.clock()
cpuUsage = psutil.cpu_percent()
pid = os.getpid()
py = psutil.Process(pid)
memoryUse = py.memory_info()[0] / 2. ** 30
print("Time taken to make predictions on test data : %f" % (endTime - startTime))
print("Memory used : %f GB  CPU usage : %f" % (memoryUse, cpuUsage))


#calculate scores and confusion_matrix
Classes = ['normal', 'probe', 'dos', 'r2l','u2r' ]
acc = accuracy_score(y_pred=pred, y_true=testLabel)
con_matrix = confusion_matrix(y_pred=pred, y_true=testLabel, labels=Classes)
print("Confusion matrix : ")
print(con_matrix)


# Print accuracy and detection rate
acc = accuracy_score(y_pred=pred, y_true=testLabel)
print("Accuracy score on test data is : %f" % acc)
```



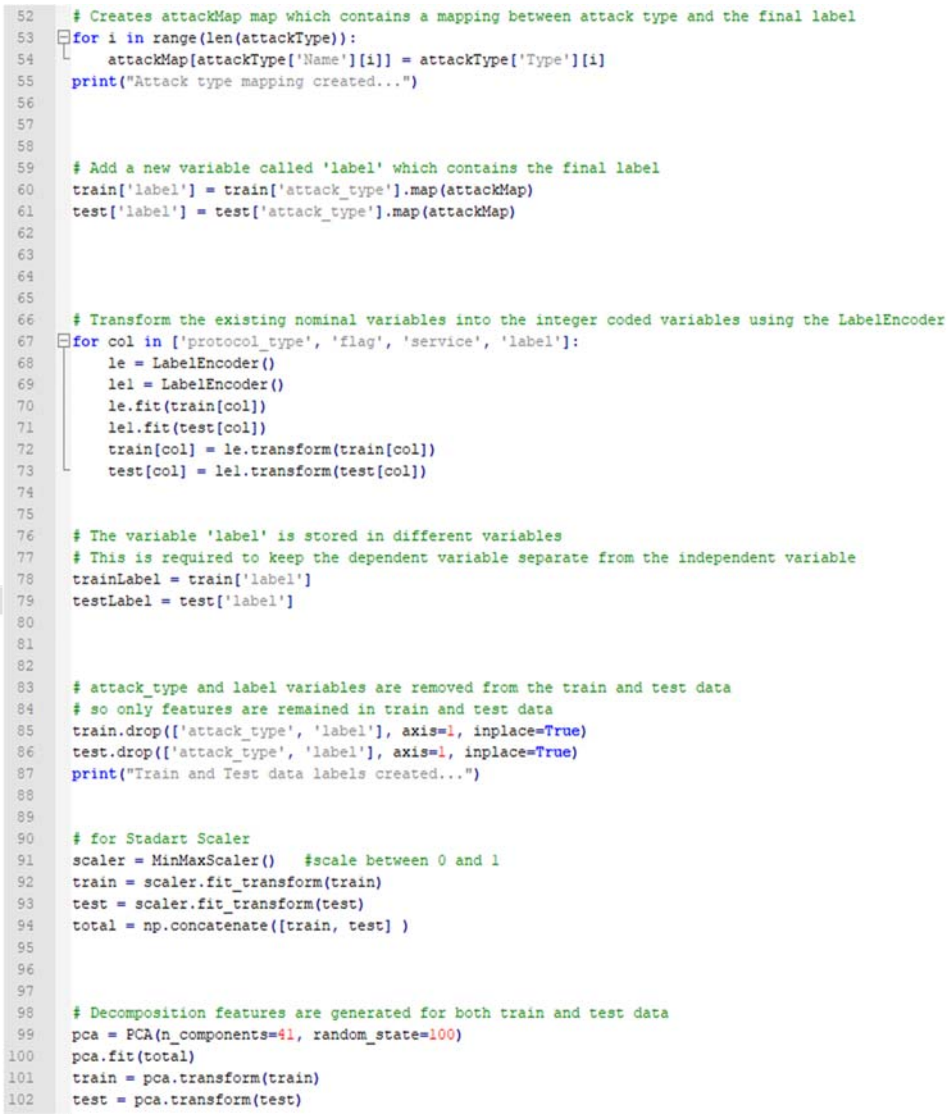
```python
sumDr = 0
for i in range(con_matrix.shape[0]):
    det_rate = 0
    for j in range(con_matrix.shape[1]):
        if i != j :
            det_rate += con_matrix[i][j]
    if con_matrix[i][i] != 0 or (det_rate + con_matrix[i][i])  != 0:
        det_rate =100* con_matrix[i][i]/(det_rate + con_matrix[i][i])
        sumDr += det_rate
        print("For " + Classes[i] + ", Detection Rate is % " + str(det_rate))
    else:
        print("For " + Classes[i] + ", Detection Rate is % 0")

DR = sumDr/attackTypeCount
print("DR is % " + str(DR))
```

Appendix: E

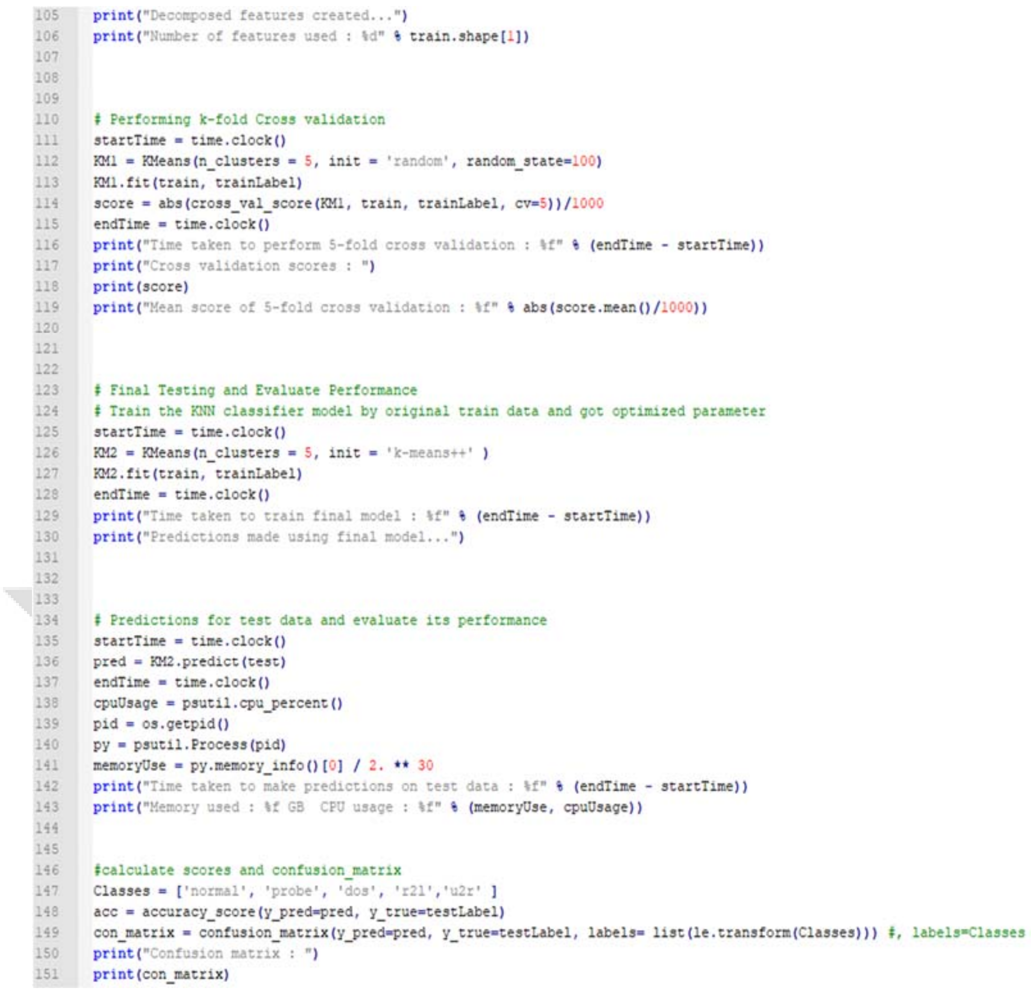
Python Code for K-Means Classification Algorithm



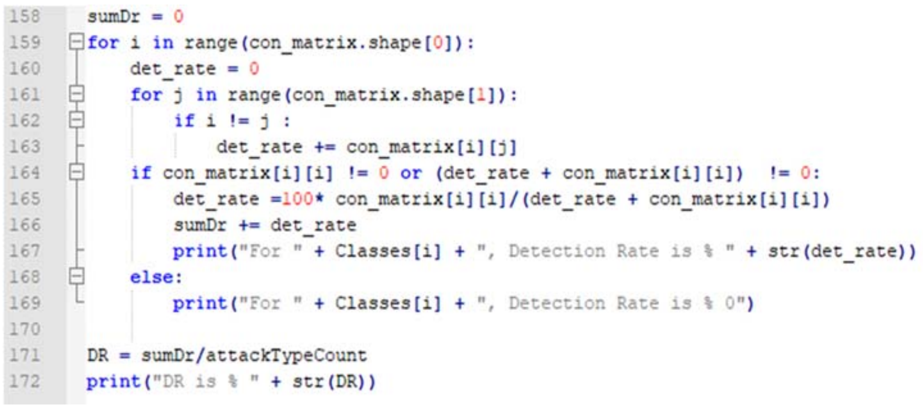
```python
import pandas as pd
import numpy as np
import time
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.model_selection import cross_val_score
import psutil
import os



print("K-Means Classifier")
# Reads the train and test data

#train = pd.read_csv('1Million.csv', header=None)
train = pd.read_csv('500K.csv', header=None)
#train = pd.read_csv('./KDDTrain+.csv', header=None)
test = pd.read_csv('./KDDTest+.csv', header=None)
print("Train and Test Data read...")



# Reads "Field Names.csv". Use this to set the names of train and test data columns
columns = pd.read_csv('Field Names.csv', header=None)
columns.columns = ['name', 'type']
train.columns = columns['name']
test.columns = columns['name']



# Read Attack Types.csv
# Use this to create a mapping from attack types to final labels (Normal, Dos, R2L, Prob, U2R)
attackType = pd.read_csv('Attack Types.csv', header=None)
attackType.columns = ['Name', 'Type']
attackMap = {}



#find count of type from attackType
attackTypeCount = len(attackType['Type'].drop_duplicates())
attackNames = attackType['Type'].drop_duplicates().values.tolist()
print('There are ' +  str(attackTypeCount) + ' attack type')
print('Attacks name are:')
print(attackNames)
```



```
# Creates attackMap map which contains a mapping between attack type and the final label
for i in range(len(attackType)):
    attackMap[attackType['Name'][i]] = attackType['Type'][i]
print("Attack type mapping created...")



# Add a new variable called 'label' which contains the final label
train['label'] = train['attack_type'].map(attackMap)
test['label'] = test['attack_type'].map(attackMap)




# Transform the existing nominal variables into the integer coded variables using the LabelEncoder
for col in ['protocol_type', 'flag', 'service', 'label']:
    le = LabelEncoder()
    le1 = LabelEncoder()
    le.fit(train[col])
    le1.fit(test[col])
    train[col] = le.transform(train[col])
    test[col] = le1.transform(test[col])


# The variable 'label' is stored in different variables
# This is required to keep the dependent variable separate from the independent variable
trainLabel = train['label']
testLabel = test['label']



# attack_type and label variables are removed from the train and test data
# so only features are remained in train and test data
train.drop(['attack_type', 'label'], axis=1, inplace=True)
test.drop(['attack_type', 'label'], axis=1, inplace=True)
print("Train and Test data labels created...")


# for Stadart Scaler
scaler = MinMaxScaler()   #scale between 0 and 1
train = scaler.fit_transform(train)
test = scaler.fit_transform(test)
total = np.concatenate([train, test] )



# Decomposition features are generated for both train and test data
pca = PCA(n_components=41, random_state=100)
pca.fit(total)
train = pca.transform(train)
test = pca.transform(test)
```



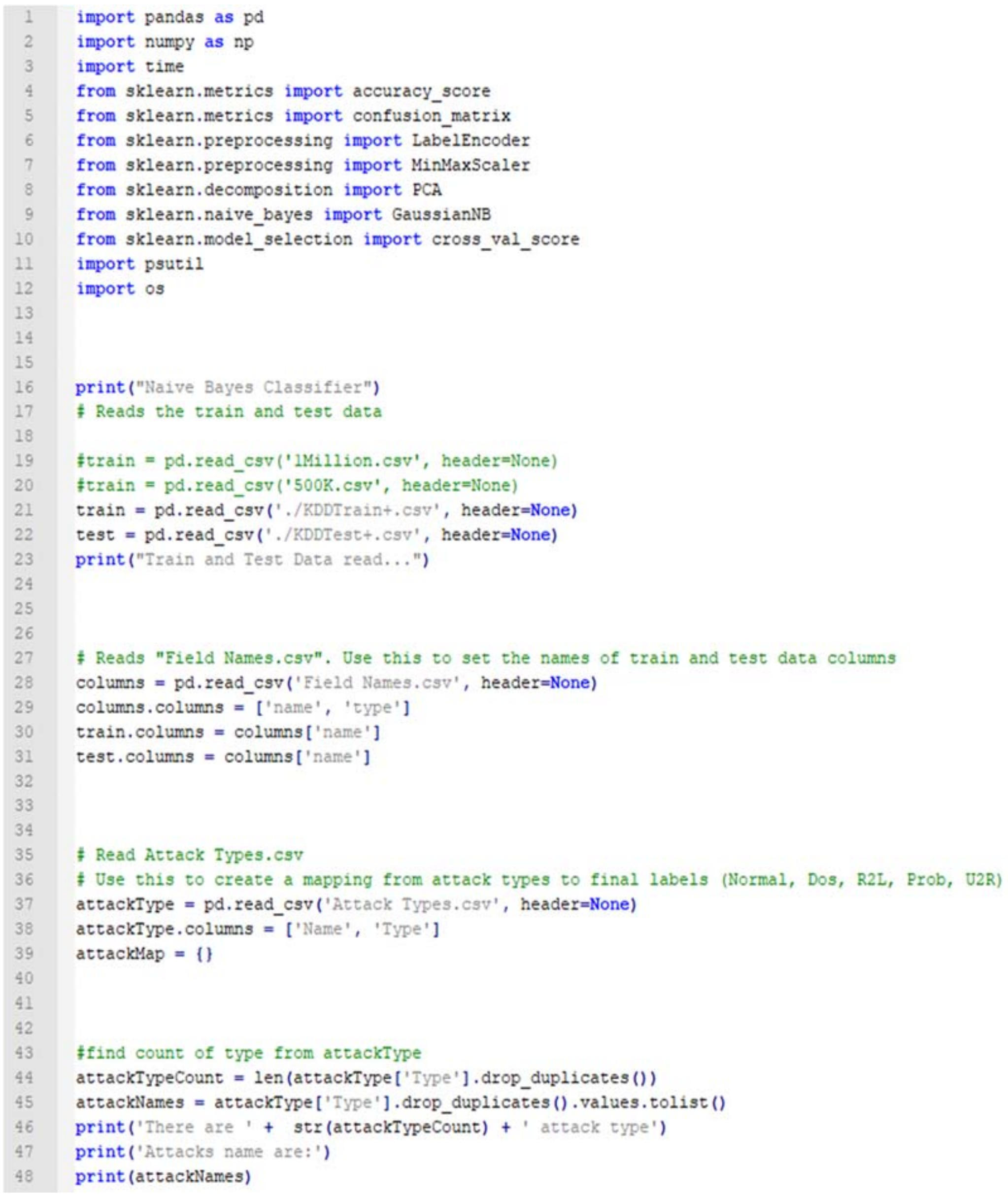
```python
print("Decomposed features created...")
print("Number of features used : %d" % train.shape[1])



# Performing k-fold Cross validation
startTime = time.clock()
KM1 = KMeans(n_clusters = 5, init = 'random', random_state=100)
KM1.fit(train, trainLabel)
score = abs(cross_val_score(KM1, train, trainLabel, cv=5))/1000
endTime = time.clock()
print("Time taken to perform 5-fold cross validation : %f" % (endTime - startTime))
print("Cross validation scores : ")
print(score)
print("Mean score of 5-fold cross validation : %f" % abs(score.mean()/1000))



# Final Testing and Evaluate Performance
# Train the KNN classifier model by original train data and got optimized parameter
startTime = time.clock()
KM2 = KMeans(n_clusters = 5, init = 'k-means++' )
KM2.fit(train, trainLabel)
endTime = time.clock()
print("Time taken to train final model : %f" % (endTime - startTime))
print("Predictions made using final model...")



# Predictions for test data and evaluate its performance
startTime = time.clock()
pred = KM2.predict(test)
endTime = time.clock()
cpuUsage = psutil.cpu_percent()
pid = os.getpid()
py = psutil.Process(pid)
memoryUse = py.memory_info()[0] / 2. ** 30
print("Time taken to make predictions on test data : %f" % (endTime - startTime))
print("Memory used : %f GB  CPU usage : %f" % (memoryUse, cpuUsage))


#calculate scores and confusion_matrix
Classes = ['normal', 'probe', 'dos', 'r2l','u2r' ]
acc = accuracy_score(y_pred=pred, y_true=testLabel)
con_matrix = confusion_matrix(y_pred=pred, y_true=testLabel, labels= list(le.transform(Classes))) #, labels=Classes
print("Confusion matrix : ")
print(con_matrix)
```



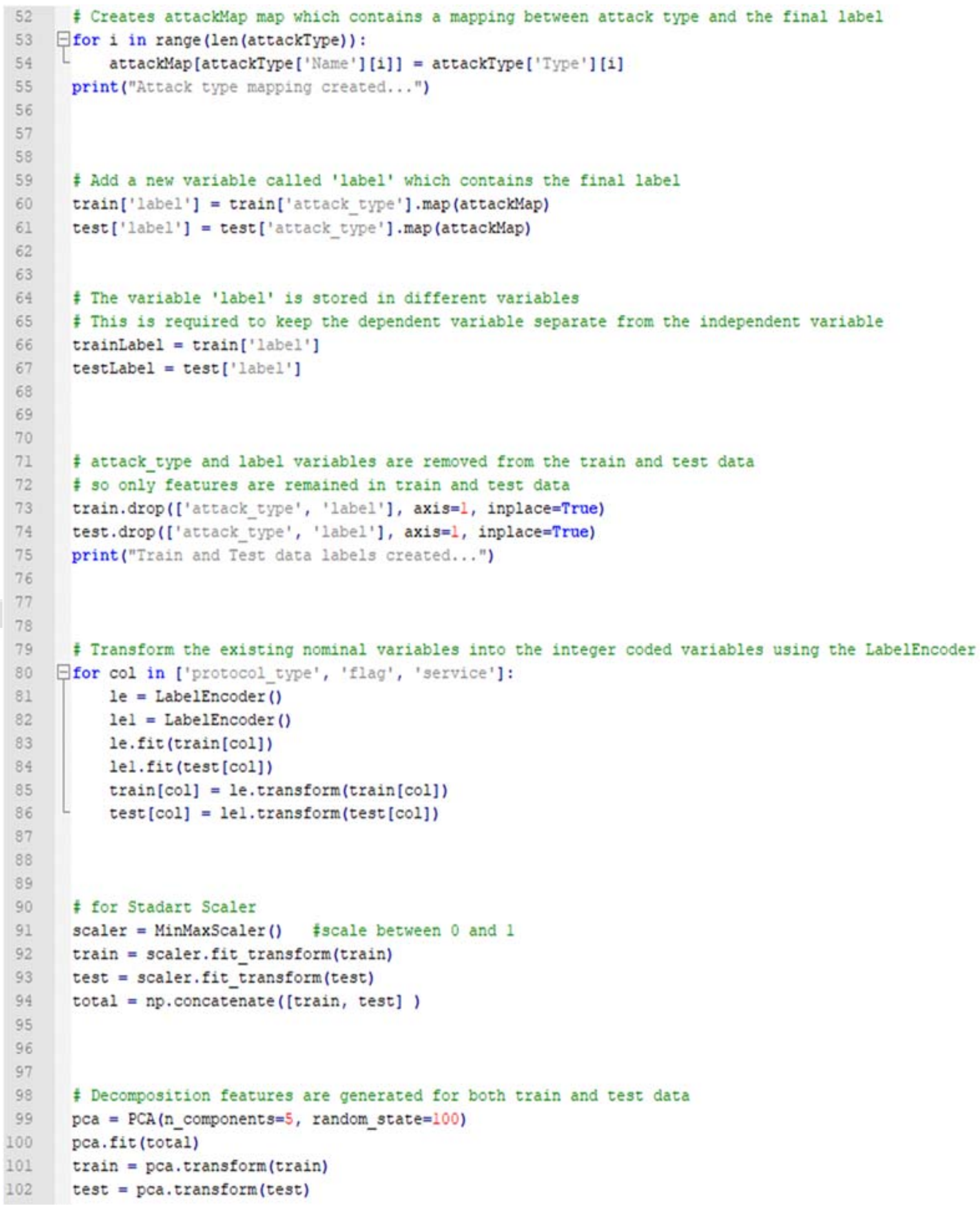
```
sumDr = 0
for i in range(con_matrix.shape[0]):
    det_rate = 0
    for j in range(con_matrix.shape[1]):
        if i != j :
            det_rate += con_matrix[i][j]
    if con_matrix[i][i] != 0 or (det_rate + con_matrix[i][i])  != 0:
        det_rate =100* con_matrix[i][i]/(det_rate + con_matrix[i][i])
        sumDr += det_rate
        print("For " + Classes[i] + ", Detection Rate is % " + str(det_rate))
    else:
        print("For " + Classes[i] + ", Detection Rate is % 0")

DR = sumDr/attackTypeCount
print("DR is % " + str(DR))
```

Appendix: F

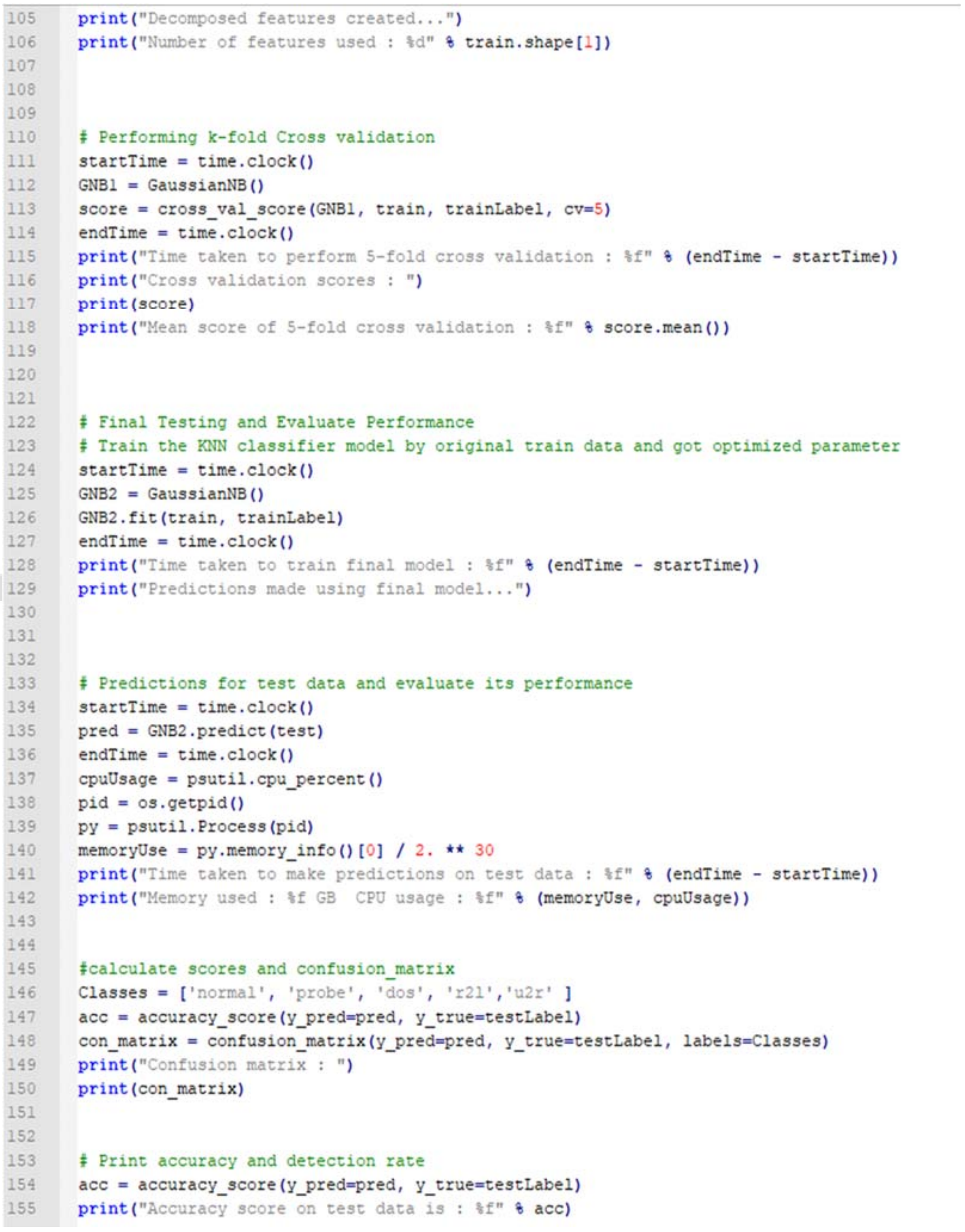
Python Code for Naïve Bayes Classification Algorithm



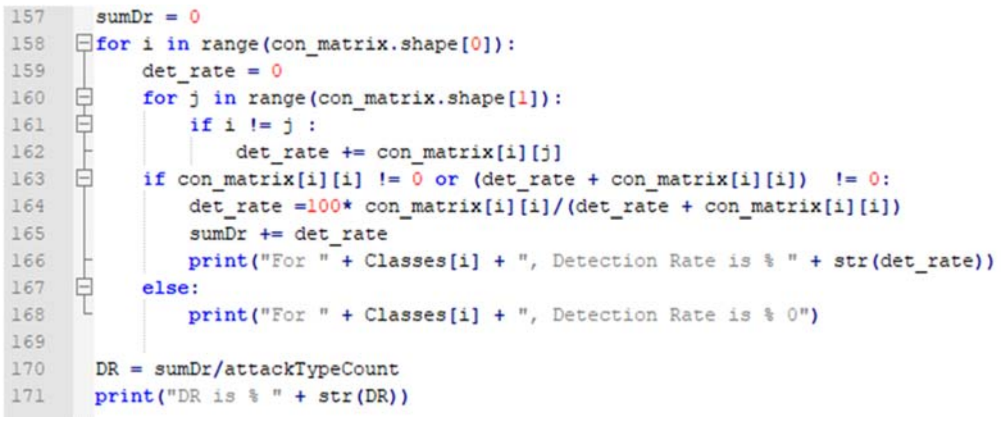
```python
import pandas as pd
import numpy as np
import time
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import cross_val_score
import psutil
import os



print("Naive Bayes Classifier")
# Reads the train and test data

#train = pd.read_csv('1Million.csv', header=None)
#train = pd.read_csv('500K.csv', header=None)
train = pd.read_csv('./KDDTrain+.csv', header=None)
test = pd.read_csv('./KDDTest+.csv', header=None)
print("Train and Test Data read...")



# Reads "Field Names.csv". Use this to set the names of train and test data columns
columns = pd.read_csv('Field Names.csv', header=None)
columns.columns = ['name', 'type']
train.columns = columns['name']
test.columns = columns['name']



# Read Attack Types.csv
# Use this to create a mapping from attack types to final labels (Normal, Dos, R2L, Prob, U2R)
attackType = pd.read_csv('Attack Types.csv', header=None)
attackType.columns = ['Name', 'Type']
attackMap = {}



#find count of type from attackType
attackTypeCount = len(attackType['Type'].drop_duplicates())
attackNames = attackType['Type'].drop_duplicates().values.tolist()
print('There are ' +  str(attackTypeCount) + ' attack type')
print('Attacks name are:')
print(attackNames)
```



```python
# Creates attackMap map which contains a mapping between attack type and the final label
for i in range(len(attackType)):
    attackMap[attackType['Name'][i]] = attackType['Type'][i]
print("Attack type mapping created...")



# Add a new variable called 'label' which contains the final label
train['label'] = train['attack_type'].map(attackMap)
test['label'] = test['attack_type'].map(attackMap)


# The variable 'label' is stored in different variables
# This is required to keep the dependent variable separate from the independent variable
trainLabel = train['label']
testLabel = test['label']



# attack_type and label variables are removed from the train and test data
# so only features are remained in train and test data
train.drop(['attack_type', 'label'], axis=1, inplace=True)
test.drop(['attack_type', 'label'], axis=1, inplace=True)
print("Train and Test data labels created...")



# Transform the existing nominal variables into the integer coded variables using the LabelEncoder
for col in ['protocol_type', 'flag', 'service']:
    le = LabelEncoder()
    lel = LabelEncoder()
    le.fit(train[col])
    lel.fit(test[col])
    train[col] = le.transform(train[col])
    test[col] = lel.transform(test[col])



# for Stadart Scaler
scaler = MinMaxScaler()   #scale between 0 and 1
train = scaler.fit_transform(train)
test = scaler.fit_transform(test)
total = np.concatenate([train, test] )



# Decomposition features are generated for both train and test data
pca = PCA(n_components=5, random_state=100)
pca.fit(total)
train = pca.transform(train)
test = pca.transform(test)
```



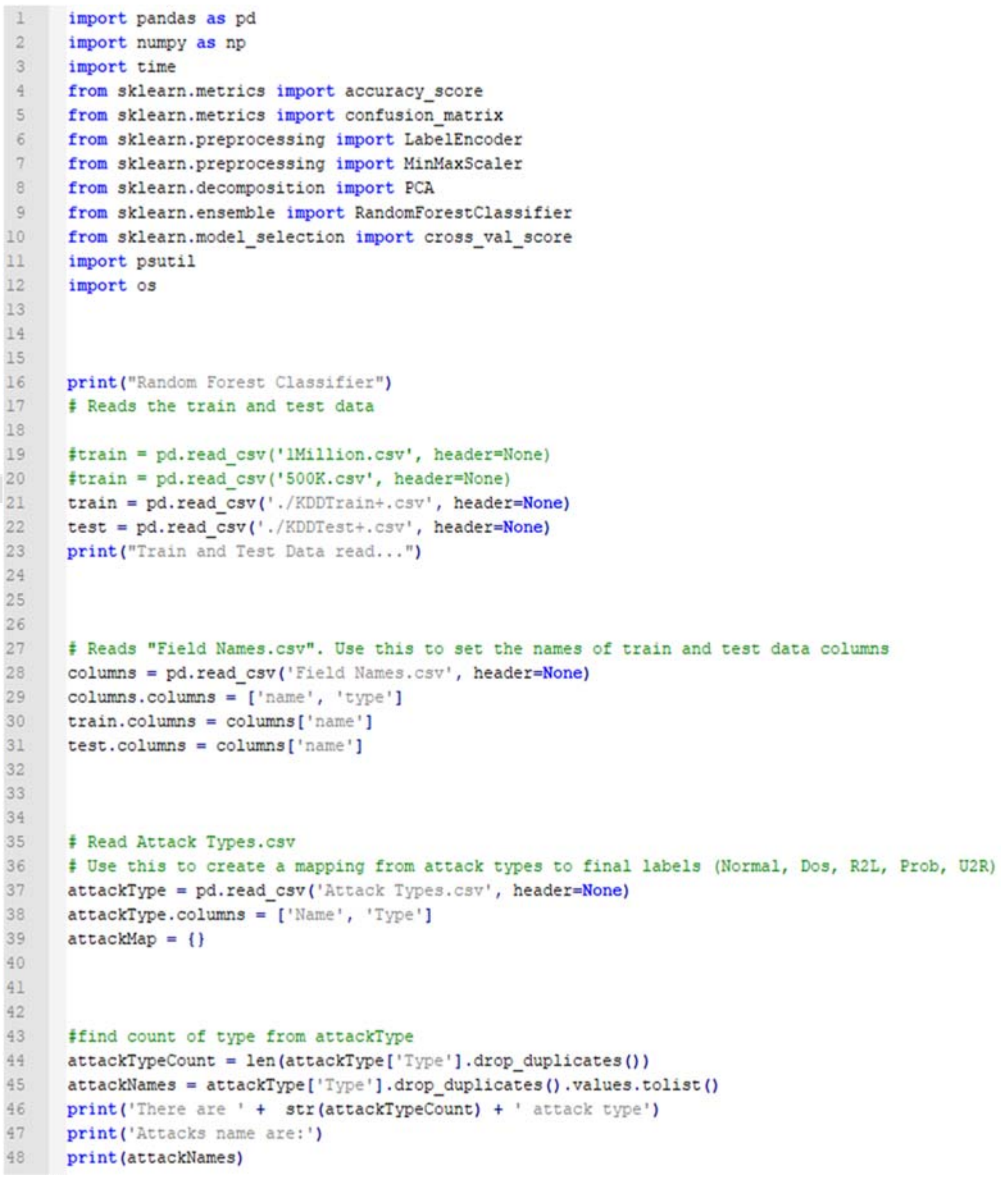
```
print("Decomposed features created...")
print("Number of features used : %d" % train.shape[1])



# Performing k-fold Cross validation
startTime = time.clock()
GNB1 = GaussianNB()
score = cross_val_score(GNB1, train, trainLabel, cv=5)
endTime = time.clock()
print("Time taken to perform 5-fold cross validation : %f" % (endTime - startTime))
print("Cross validation scores : ")
print(score)
print("Mean score of 5-fold cross validation : %f" % score.mean())



# Final Testing and Evaluate Performance
# Train the KNN classifier model by original train data and got optimized parameter
startTime = time.clock()
GNB2 = GaussianNB()
GNB2.fit(train, trainLabel)
endTime = time.clock()
print("Time taken to train final model : %f" % (endTime - startTime))
print("Predictions made using final model...")



# Predictions for test data and evaluate its performance
startTime = time.clock()
pred = GNB2.predict(test)
endTime = time.clock()
cpuUsage = psutil.cpu_percent()
pid = os.getpid()
py = psutil.Process(pid)
memoryUse = py.memory_info()[0] / 2. ** 30
print("Time taken to make predictions on test data : %f" % (endTime - startTime))
print("Memory used : %f GB  CPU usage : %f" % (memoryUse, cpuUsage))


#calculate scores and confusion_matrix
Classes = ['normal', 'probe', 'dos', 'r2l','u2r' ]
acc = accuracy_score(y_pred=pred, y_true=testLabel)
con_matrix = confusion_matrix(y_pred=pred, y_true=testLabel, labels=Classes)
print("Confusion matrix : ")
print(con_matrix)


# Print accuracy and detection rate
acc = accuracy_score(y_pred=pred, y_true=testLabel)
print("Accuracy score on test data is : %f" % acc)
```



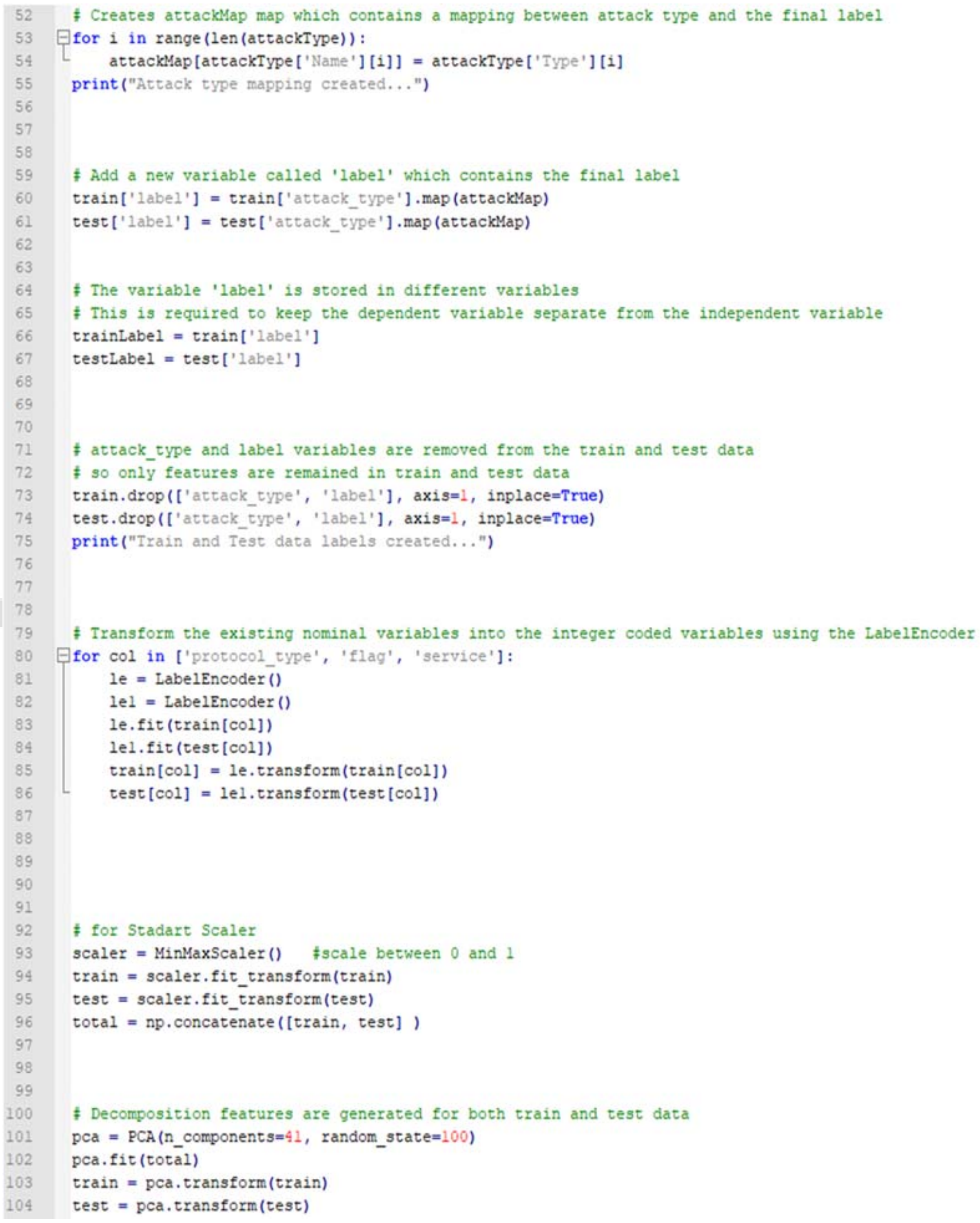
```
sumDr = 0
for i in range(con_matrix.shape[0]):
    det_rate = 0
    for j in range(con_matrix.shape[1]):
        if i != j :
            det_rate += con_matrix[i][j]
    if con_matrix[i][i] != 0 or (det_rate + con_matrix[i][i])  != 0:
        det_rate =100* con_matrix[i][i]/(det_rate + con_matrix[i][i])
        sumDr += det_rate
        print("For " + Classes[i] + ", Detection Rate is % " + str(det_rate))
    else:
        print("For " + Classes[i] + ", Detection Rate is % 0")

DR = sumDr/attackTypeCount
print("DR is % " + str(DR))
```

Appendix: G

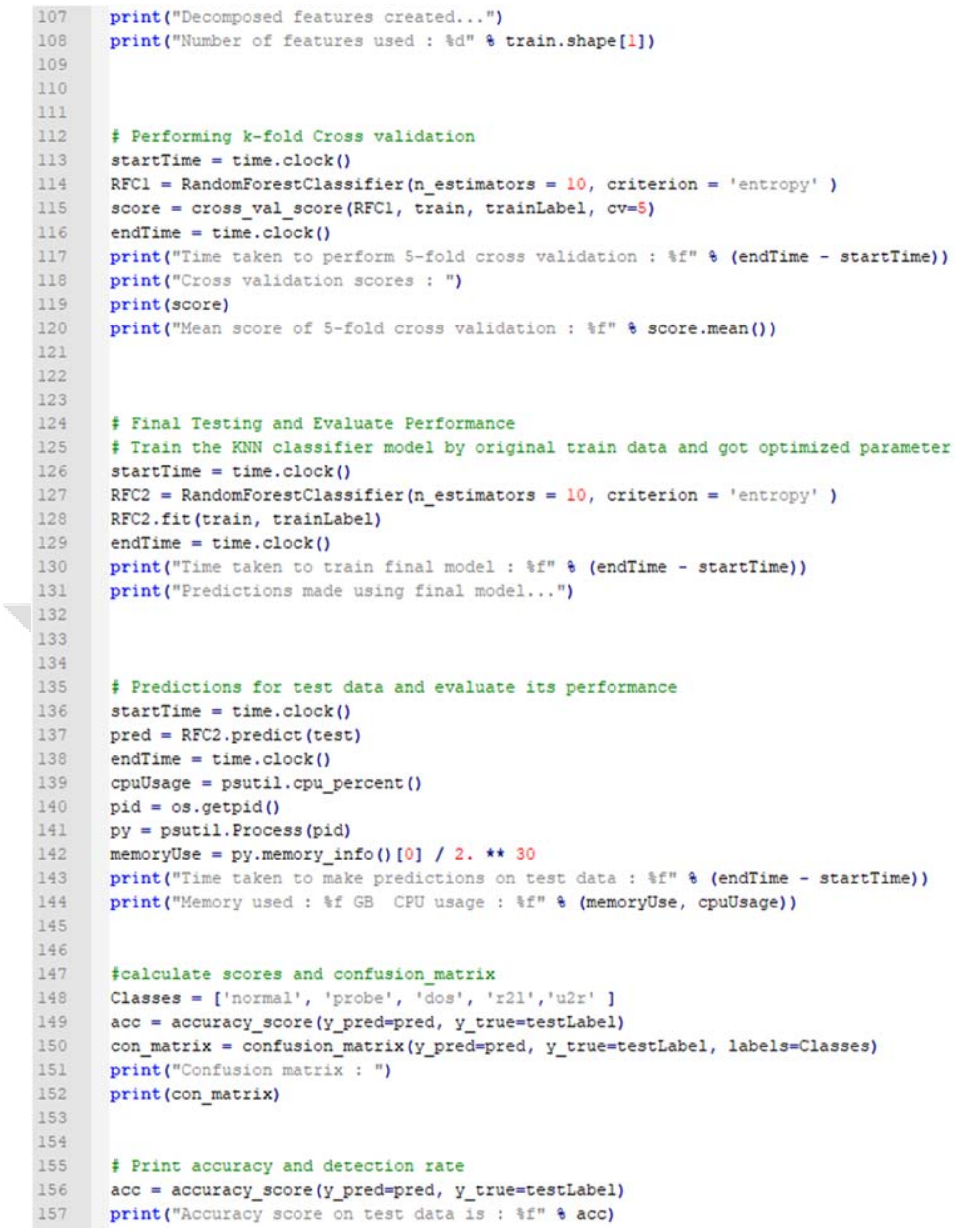
Python Code for Random Forest Classification Algorithm



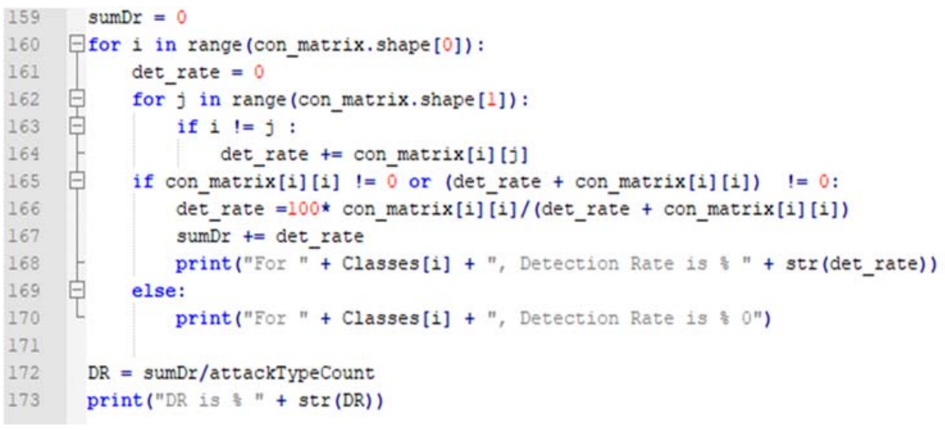
```python
import pandas as pd
import numpy as np
import time
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import MinMaxScaler
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import cross_val_score
import psutil
import os



print("Random Forest Classifier")
# Reads the train and test data

#train = pd.read_csv('1Million.csv', header=None)
#train = pd.read_csv('500K.csv', header=None)
train = pd.read_csv('./KDDTrain+.csv', header=None)
test = pd.read_csv('./KDDTest+.csv', header=None)
print("Train and Test Data read...")



# Reads "Field Names.csv". Use this to set the names of train and test data columns
columns = pd.read_csv('Field Names.csv', header=None)
columns.columns = ['name', 'type']
train.columns = columns['name']
test.columns = columns['name']



# Read Attack Types.csv
# Use this to create a mapping from attack types to final labels (Normal, Dos, R2L, Prob, U2R)
attackType = pd.read_csv('Attack Types.csv', header=None)
attackType.columns = ['Name', 'Type']
attackMap = {}



#find count of type from attackType
attackTypeCount = len(attackType['Type'].drop_duplicates())
attackNames = attackType['Type'].drop_duplicates().values.tolist()
print('There are ' +  str(attackTypeCount) + ' attack type')
print('Attacks name are:')
print(attackNames)
```



```python
# Creates attackMap map which contains a mapping between attack type and the final label
for i in range(len(attackType)):
    attackMap[attackType['Name'][i]] = attackType['Type'][i]
print("Attack type mapping created...")



# Add a new variable called 'label' which contains the final label
train['label'] = train['attack_type'].map(attackMap)
test['label'] = test['attack_type'].map(attackMap)


# The variable 'label' is stored in different variables
# This is required to keep the dependent variable separate from the independent variable
trainLabel = train['label']
testLabel = test['label']



# attack_type and label variables are removed from the train and test data
# so only features are remained in train and test data
train.drop(['attack_type', 'label'], axis=1, inplace=True)
test.drop(['attack_type', 'label'], axis=1, inplace=True)
print("Train and Test data labels created...")



# Transform the existing nominal variables into the integer coded variables using the LabelEncoder
for col in ['protocol_type', 'flag', 'service']:
    le = LabelEncoder()
    le1 = LabelEncoder()
    le.fit(train[col])
    le1.fit(test[col])
    train[col] = le.transform(train[col])
    test[col] = le1.transform(test[col])





# for Stadart Scaler
scaler = MinMaxScaler()    #scale between 0 and 1
train = scaler.fit_transform(train)
test = scaler.fit_transform(test)
total = np.concatenate([train, test] )



# Decomposition features are generated for both train and test data
pca = PCA(n_components=41, random_state=100)
pca.fit(total)
train = pca.transform(train)
test = pca.transform(test)
```



```python
print("Decomposed features created...")
print("Number of features used : %d" % train.shape[1])



# Performing k-fold Cross validation
startTime = time.clock()
RFC1 = RandomForestClassifier(n_estimators = 10, criterion = 'entropy' )
score = cross_val_score(RFC1, train, trainLabel, cv=5)
endTime = time.clock()
print("Time taken to perform 5-fold cross validation : %f" % (endTime - startTime))
print("Cross validation scores : ")
print(score)
print("Mean score of 5-fold cross validation : %f" % score.mean())



# Final Testing and Evaluate Performance
# Train the KNN classifier model by original train data and got optimized parameter
startTime = time.clock()
RFC2 = RandomForestClassifier(n_estimators = 10, criterion = 'entropy' )
RFC2.fit(train, trainLabel)
endTime = time.clock()
print("Time taken to train final model : %f" % (endTime - startTime))
print("Predictions made using final model...")



# Predictions for test data and evaluate its performance
startTime = time.clock()
pred = RFC2.predict(test)
endTime = time.clock()
cpuUsage = psutil.cpu_percent()
pid = os.getpid()
py = psutil.Process(pid)
memoryUse = py.memory_info()[0] / 2. ** 30
print("Time taken to make predictions on test data : %f" % (endTime - startTime))
print("Memory used : %f GB  CPU usage : %f" % (memoryUse, cpuUsage))


#calculate scores and confusion_matrix
Classes = ['normal', 'probe', 'dos', 'r2l','u2r' ]
acc = accuracy_score(y_pred=pred, y_true=testLabel)
con_matrix = confusion_matrix(y_pred=pred, y_true=testLabel, labels=Classes)
print("Confusion matrix : ")
print(con_matrix)


# Print accuracy and detection rate
acc = accuracy_score(y_pred=pred, y_true=testLabel)
print("Accuracy score on test data is : %f" % acc)
```



```
sumDr = 0
for i in range(con_matrix.shape[0]):
    det_rate = 0
    for j in range(con_matrix.shape[1]):
        if i != j :
            det_rate += con_matrix[i][j]
    if con_matrix[i][i] != 0 or (det_rate + con_matrix[i][i])  != 0:
        det_rate =100* con_matrix[i][i]/(det_rate + con_matrix[i][i])
        sumDr += det_rate
        print("For " + Classes[i] + ", Detection Rate is % " + str(det_rate))
    else:
        print("For " + Classes[i] + ", Detection Rate is % 0")

DR = sumDr/attackTypeCount
print("DR is % " + str(DR))
```