EFFECTIVE INTRUSION DETECTION SYSTEM USING HYBRID ENSEMBLE METHOD FOR CLOUD COMPUTING

PROJECT REPORT

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CHAPTER 1
PROBLEM STATEMENT

Cloud computing is often used by organizations to store data and applications, so it is important to ensure that the platform is secure. While the cloud environment offers many benefits, there are also several security challenges that organizations face when using cloud services. Data breaches are a significant concern for cloud service providers, as sensitive data stored in the cloud can be vulnerable to theft or unauthorized access. **DoSS attacks can cause significant disruptions** to cloud services by overloading the system with traffic. This can prevent legitimate users from accessing cloud resources, causing significant financial and reputational damage to the cloud service provider. Organizations may face compliance and regulatory issues when using cloud services, as sensitive data stored in the cloud may be subject to specific regulatory requirements. Cloud service providers may not provide complete transparency about their security measures, making it difficult for organizations to assess the risks associated with using cloud services.

Intrusion Detection System (IDS) is an important security tool in cloud environments that can detect and alert users to potential security breaches or threats. IDS can monitor network traffic, system logs, and user activity to detect and identify potential security incidents or attacks. There is a **constant need for optimization of algorithms and enhancement in IDS due to the increasing threats of attacks on cloud.**

CHAPTER 2
INTRODUCTION

Cloud computing seems to be one of the most emerging technologies in recent years. Although the number of cloud projects has dramatically increased over the last few years, ensuring the availability and security of project data, services, and resources is still a crucial and challenging research issue. Attacks can exhaust the cloud's resources, consume most of its bandwidth, and damage an entire cloud project within a short period of time. Cloud computing is the preferred choice of every organization since it provides flexible and pay per use-based services to its users. However, the security and privacy is a major hurdle in its success because of its open and distributed architecture that is vulnerable to intruders. Cloud computing is made up of three abstract layers: the system layer, the platform layer, and the application layer. Whereas the **first two layers are concerned with Virtual Machines (VM) and operating systems, the last layer covers cloud-based applications** such as web-based apps. The cloud architecture is made up of two distinct components.

One of these is cloud security, which is regarded as a key barrier to cloud adoption by the majority of organizations. This is due to the open and fully dispersed nature of the cloud environment, which makes it more vulnerable to security threats and vulnerabilities. As a result, intruders are encouraged to conduct possible attacks against the cloud or against devices within the cloud. So, an intrusion detection system is needed in order to protect the data.

An Intrusion Detection System (IDS) is a type of technology used to detect malicious activity on a computer or network. It can be used to monitor the network/cloud for suspicious activities and can alert administrators when such activities are detected. The system may also take preventive measures to protect the network from further damage. There are three widely used methods**: hybrid detection, anomaly-based detection**, and signature-based detection. By comparing the acquired data with a database of patterns of well-known assaults or a pre-set set of criteria, signature-based detection, also known as misuse detection, locates intrusions. The latter method's primary flaw is that it can only identify known attacks. Anomaly-based detection, on the other hand, finds intrusions by comparing the gathered data to a pre-determined baseline. When behavior deviates from the norm; it raises the warning that a hostile assault may be imminent. The ability to identify both known and unidentified assaults is the main benefit of anomaly-based detection. Signature-based and anomaly-based detection are combined in a hybrid detection approach. According to reports, CIDS that employ hybrid detection produce superior results than those produced by conventional approaches. There are three different types of cloud computing based on the IDS. **Host-based IDS (HIDS)** is the first intrusion detection software was designed using an original target system as the mainframe computer in which there is some outside interaction was not frequent. The HIDS will operate based on the information is collected using an individual computer system. This monitors all the inbound and the outbound packets from its computer system and will also alert users or the administrator in case there are found to be any suspicious activities like a system call, the thread or processes, the asset or configuration access by means of observance of the host along with its situation. This may be used normally for the purpose of protection of the private information is very valuable for the various server-based systems.

Networks based IDSs (NIDS) will also be capturing the traffic for the whole of the network and will further analyses it for the purpose of detecting all of the possible intrusions like its port scanning or sometimes the DoSS attacks. The NIDS normally performs such detection of intrusion by means of efficiently processing the IP and also the headers of the transport layers for all of the captured network packets. This will make use of this anomaly and then the network packets are collected and a correlation will be arrived at along with all the signatures for the many known attacks and this is used for making a comparison of user behavior along with their known profiles. There are multiple hosts operating within the network that are secured from all the attackers by using the NIDS that are deployed properly and if this has to be run in a stealth mode we also need to know the location of its NIDS which is normally hidden from its attacker. Here the NIDS cannot perform any analysis in cases where the traffic is encrypted. Hypervisor based IDS, the hypervisor will provide levels of interaction in the VMs and the hypervisor that is based on the IDS has been placed on a hypervisor layer. This also helps in the analysis of the available information for detecting anomalous actions of the users. Such information has been based on the multiple level communication inside of the hypervisor based virtual network**. Distributed IDS (DIDS)** consist of the number of IDSs like the NIDS or the HIDS deployed in a network for analyzing traffic for the behavior of intrusive detection. The detection component will examine the behavior of the system and will transmit the collected data using a 5-standard format for the correlation manager. The Correlation manager will combine data from many multiple IDS and will generate a high-level alert keeping up the correspondence for an attack.

The **CICIDS2017 dataset** provides a realistic simulation of a real-world network environment with a diverse set of attacks and benign traffic. It is widely used by researchers and practitioners to develop and evaluate intrusion detection systems and to advance the field of network security. The dataset contains both benign traffic and various types of attacks, including **DoS (Denial of Service), DDoS (Distributed Denial of Service), Port Scan, Botnet, Brute Force, Infiltration, and Web Attack**. The attacks were generated using various tools and techniques commonly used by attackers to compromise or disrupt network systems.

CHAPTER 3
SUMMARY OF RELATED WORK

W. Wang, X. Du, D. Shan, R. Qin and N. Wang, "Cloud Intrusion Detection Method Based on Stacked Contractive Auto-Encoder and Support Vector Machine," in *IEEE Transactions on Cloud Computing*, vol. 10, no. 3, pp. 1634-1646

In this paper, they created a hybrid system that employs a stacked contractive auto-encoder (SCAE) for feature reduction and the SVM classification method for the identification of harmful attacks. They demonstrated experimentally, using the NSL-KDD and KDD Cup 99 intrusion detection datasets, that the proposed SCAE+SVM-IDS model delivers promising classification performance in six metrics when compared to three state-of-the-art approaches.

A. M. Vartouni, S. S. Kashi and M. Teshnehlab, "An anomaly detection method to detect web attacks using Stacked Auto-Encoder," 2018 6th Iranian Joint Congress on Fuzzy and Intelligent Systems (CFIS), 2018, pp. 131-134

This paper employs the SAE technique in order to extract meaningful characteristics from HTTP request logs for anomaly detection in web application firewalls. As a one-class learner, Isolation Forest was used to distinguish between abnormal and normal data. The findings show that deep learning in general and deep models perform differently with various SAE structures.

A. Javadpour, S. Kazemi Abharian and G. Wang, "Feature Selection and Intrusion Detection in Cloud Environment Based on Machine Learning Algorithms," ***2017 IEEE International Symposium on Parallel and Distributed Processing with Applications and 2017 IEEE International Conference on Ubiquitous Computing and Communications (ISPA/IUCC)*****, Guangzhou, China, 2017, pp. 1417-1421F**

This paper introduces a novel approach based on intrusion detection systems and their varied architectures in order to improve the efficacy of intrusion detection in cloud computing. Two techniques—Pearson Linear Correlation and Mutual Information, plugin and irrelevant features are excluded—were used in this paper. In this study, the feature selection techniques for linear correlation and mutual information were integrated to assess the suggested method using the KDD99 database. Different classification techniques were used to the data, including decision tree, random forest, CART algorithm, and neural network.

G. Kene and D. P. Theng, "A review on intrusion detection techniques for cloud computing and security challenges," ***2015 2nd International Conference on Electronics and Communication Systems (ICECS)*****, Coimbatore, India, 2015, pp. 227-232**

This paper lists the various intrusions that compromise the cloud's availability, secrecy, and integrity. They have provided a thorough description of the various IDS types utilized in cloud environments. They have supplied an overview of intrusion detection methods in the form of charts and tables, which make it simple to comprehend the entire cloud computing environment. They came to the conclusion that while several IDS techniques have been suggested and have helped in the detection of intrusions in the cloud, they do not offer total protection.

M. Ficco, L. Tasquier and R. Aversa, "Intrusion Detection in Cloud Computing," 2013 Eighth International Conference on P2P, Parallel, Grid, Cloud and Internet Computing, Compiegne, France, 2013, pp. 276-283

In this paper, a methodology for creating distributed intrusion detection systems in cloud computing is proposed. It is an open-source solution that enables the creation and deployment of security probes on the virtual assets and cloud infrastructure of the customer. The implemented architecture serves as the initial iteration of a cloud-based IDS management system.

U. Oktay and O. K. Sahingoz, "Proxy Network Intrusion Detection System for cloud computing," 2013 The International Conference on Technological Advances in Electrical, Electronics and Computer Engineering (TAEECE), Konya, Turkey, 2013, pp. 98-104

This paper suggests a proxy NIDS design that performs network intrusion detection operations through the gateway. It aims to make it simple for customers and service providers to choose where to locate their protection mechanism in this way. The Proxy Network Intrusion Detection System solution allows providers to place NIDS on mesh topology gateways. As a result, providers will seek to secure their infrastructure with less resource consumption, in addition to users choosing this strategy to utilize and pay a lower value of resources.

H. A. Kholidy and F. Baiardi, "CIDS: A Framework for Intrusion Detection in Cloud Systems," ***2012 Ninth International Conference on Information Technology - New Generations*****, Las Vegas, NV, USA, 2012, pp. 379-385**

This paper develops a framework for "CIDS," a cloud-based intrusion detection system in order to address the shortcomings of existing IDSs. To summarize the alarms and tell the cloud administrator, CIDS additionally offers a component. The CIDS architecture lacks a central coordinator and is elastic and scalable. The advantages of CIDS are discussed in this study, along with its components, architecture, and detection models.

A. Kannan, G. Q. Maguire Jr., A. Sharma and P. Schoo, "Genetic Algorithm Based Feature Selection Algorithm for Effective Intrusion Detection in Cloud Networks," 2012 IEEE 12th International Conference on Data Mining Workshops, 2012, pp. 416-423

This paper presents a new genetic-based feature selection approach for cloud networks. This approach is used to identify the best number of characteristics for intrusion detection from the KDD cup data set. Furthermore, a system for intrusion detection has been suggested that employs this feature selection technique and then applies the existing Fuzzy SVM for successful classification of intrusions using the KDD Cup dataset for safeguarding cloud networks.

I. Shiri, B. Shanmugam and N. B. Idris, "A parallel technique for improving the performance of signature-based network intrusion detection system," 2011 IEEE 3rd International Conference on Communication Software and Networks, pp. 692-696

The parallel approach presented in this paper was recommended to improve the performance of signature-based network intrusion detection systems. The use of an effective string-matching algorithm, hardware acceleration, and finally parallelism have all been suggested in the past because a subpar passive system misses many attacks and drops many packets on a high-speed network.

C. -C. Lo, C. -C. Huang and J. Ku, "A Cooperative Intrusion Detection System Framework for Cloud Computing Networks," 2010 39th International Conference on Parallel Processing Workshops, San Diego, CA, USA, 2010, pp. 280-284

This paper provides a cooperative intrusion detection system for cloud computing networks in order to lessen the effects of DoS attacks. By doing this, cooperative IDS alerts other IDS systems if a DoS attack occurs in one of the cloud computing zones. The same assault sent by one IDS could be gathered by another IDS. The reliability of this alarm message is then assessed using the majority vote approach. The suggested system prevents a single point of failure in the IDS system. Early detection and preventive methods are implemented by these agents working together. IDSs placed in cloud computing zones, apart from the victim one, could therefore stop this kind of attack from happening.

CHAPTER 4
ARCHITECTURE DIAGRAM

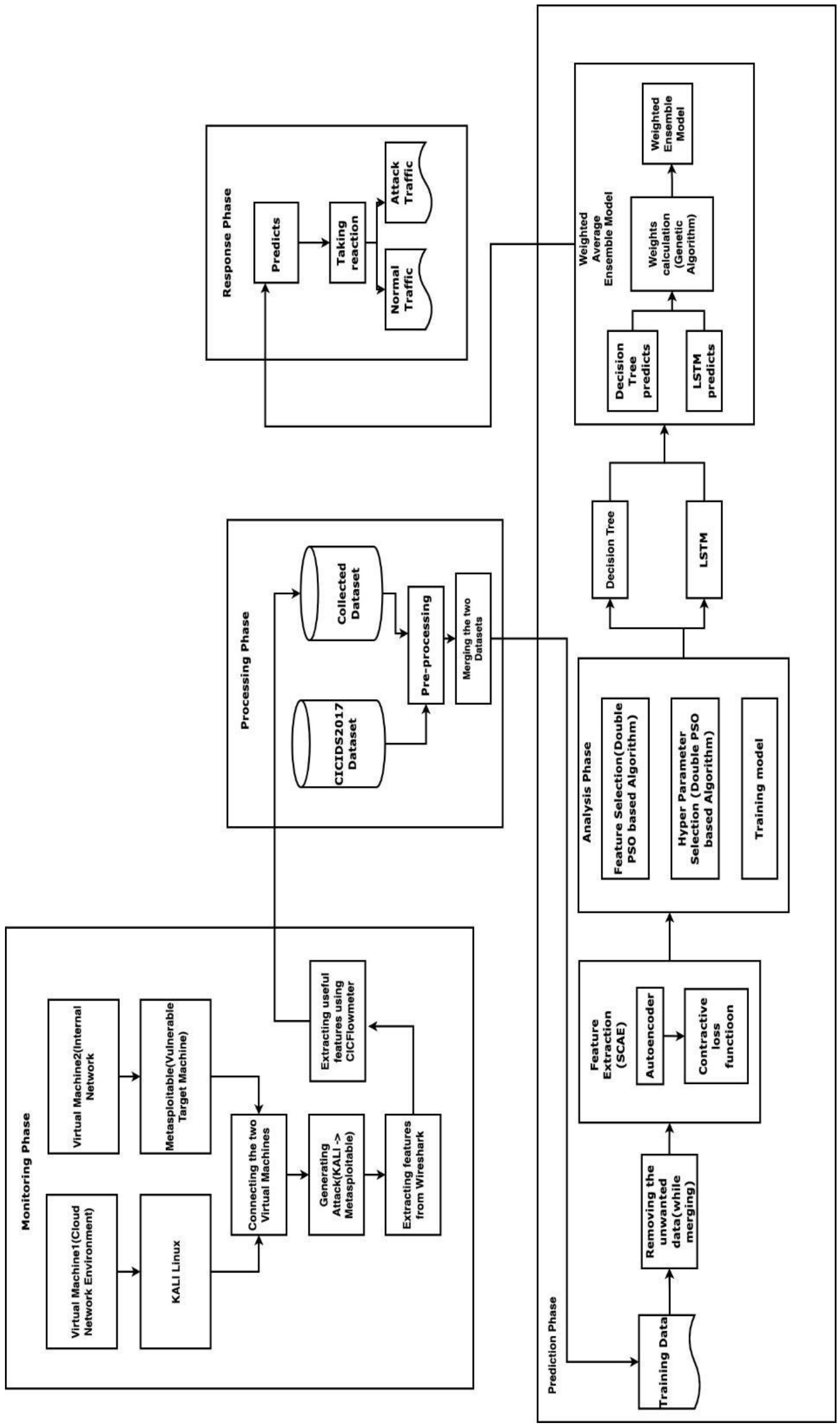


Fig 4.1 ARCHITECTURE DIAGRAM

The Fig 4.1 is a hybrid IDS that uses both real time data and the CICIDS2017 dataset for training the Models. The Models employed here is an ensemble model combining ML and DL algorithms. As the **Monitoring phase** captures the network traffic in the host machine using CIC Flowmeter, the features are captured and preprocessed in **Processing phase** such a way that we are able to detect any known attacks and the rest are labeled as unknown. These known traffics are analyzed in **Analysis phase** using double PSO algorithms and the type of attacks are detected. While the unknown traffic are sent to the **Prediction phase** where an ensemble model is employed to predict the type of traffic or attack. The result of the ensemble model is sent to **Response phase** where the new unknown traffic is stored in the main database after prediction.

CHAPTER 5
DETAILS OF MODULE DESIGN

List of Modules:

1. Monitoring Phase
2. Processing Phase
3. Analysis Phase
4. Prediction Phase
5. Response Phase

MONITORING PHASE:

The monitoring module's initial job is to capture all in-bound and out-bound data packets transiting the cloud network. The monitoring module employs sensors to sensitive network traffic to help in this operation. Furthermore, the monitoring module **may collect data packets** from various application, transport, and network protocols such as TCP, UDP, ICMP, IP, HTTP, SMTP, and so on. Here, this is done by generating the normal and attack traffic using kali linux tools from Kali Linux to Metasploitable (Vulnerable Target Machine) and these packets are captured by using wireshark and collected the useful features by placing CICFlowmeter in Host Virtual Machine.

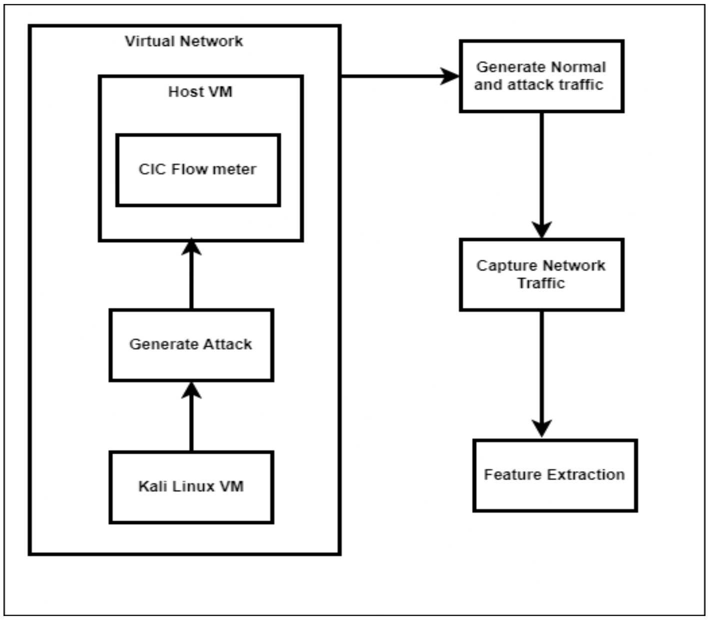


Fig 5.1 MONITORING PHASE

Fig 5.1 describes the capturing of real-time traffic in the virtual machine set in azure environment, in which attack is stimulated from a Kali-Linux on the host machine and captured using CIC Flowmeter where 32 features are captured.

Output: Data packets of real-time traffic

Setup of Monitoring Phase:

1. *Private Cloud is set with multiple Virtual Machine.*
2. *One Virtual Machine, say Kali Linux is used to generate different attack on the host machine.*
3. *CIC Flow meter is used in Host VM to capture the network traffic and export the data as CSV.*
4. *Feature Extraction is to be performed in the exported data.*

PROCESSING PHASE:

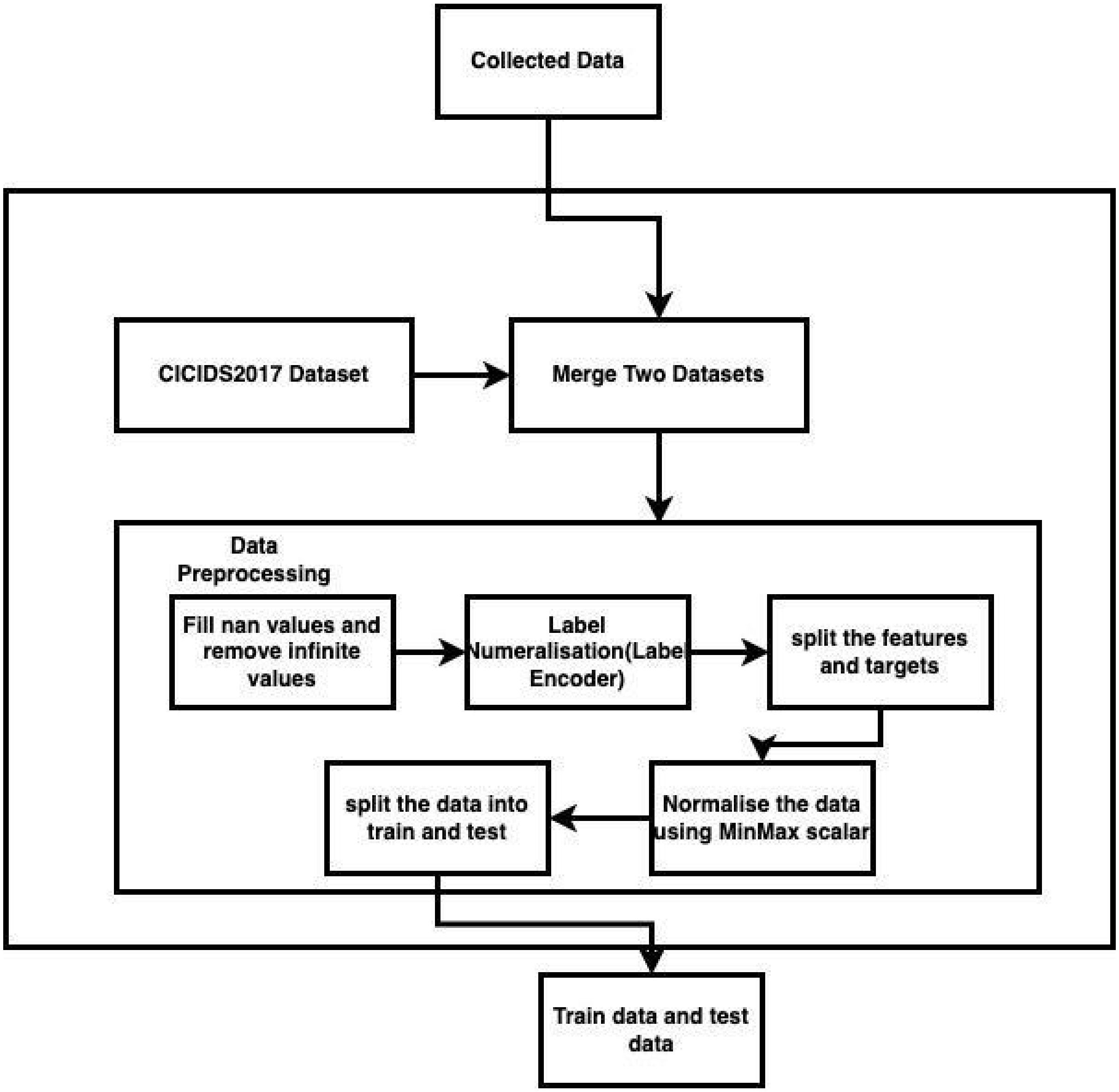


Fig 5.2 PROCESSING PHASE

In Fig 5.2 the processing module completes all necessary missions, prior to the forecast procedure. It initially gets data records from the Monitoring phase and attempts to merge with already existing data that is **CICIDS2017**. After this **the both collected data and the existing data** will go into the pre-processing where the Nan and infinite values are removed, Numeralization and Normalization will take place. These collected data is preprocessed in such a way that it can be fed to the SCAE model for feature extraction.

Input: Collected Data Packets

Output: Preprocessed data

Algorithm:

1. Remove Nan values and infinite values
2. Using label encoder fit the labels and transform it into numbers
3. Split the features and targets
4. Use normalizer as Min Max scaler

$$x_i = (x_i - min) / (max - min).$$

5. Split the data into train and test.

ANALYSIS PHASE:

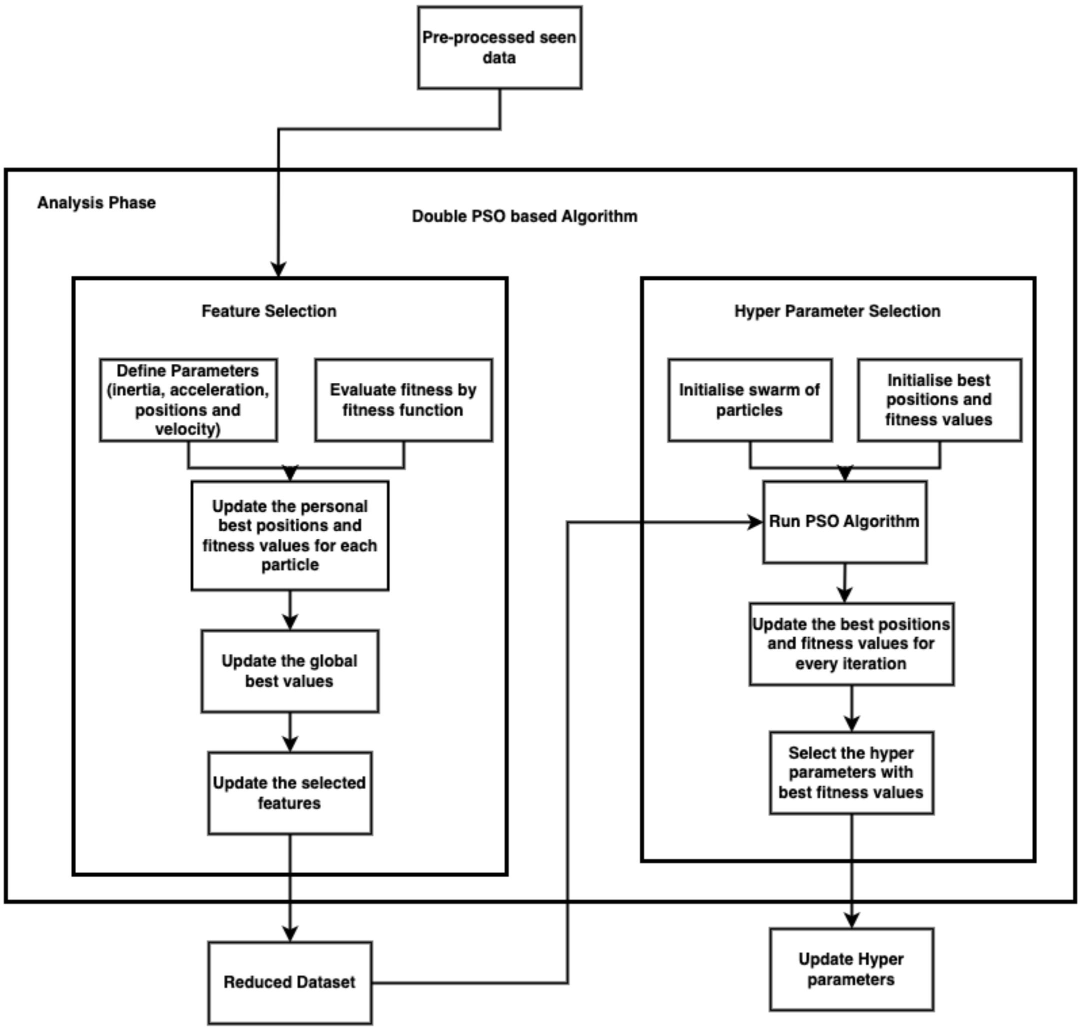


Fig 5.3 ANALYSIS PHASE

In Fig 5.3 the analysis module handles the deep learning models' pre-training and training stages. The analysis module runs the **double PSO-based** method for feature and hyper parameter selection during the pre-training phase. After data preparation, the analysis module obtains a copy of the main database. The upper level of the double PSO-based method is then executed on the main database to determine the best feature subset. The main database is then reduced using only the best characteristics. Then, using the decreased master database, it conducts the bottom level of the double PSO-based method to generate the **ideal hyper parameter vector**.

Input: Dataset of 32 features (from SCAE)

Output: Reduced dataset (Features)

Algorithm - Particle Swarm Optimization Upper Level:

1. *Initialize PSO parameters*
2. *Evaluate the fitness of each particle based on the corresponding feature subset*
3. *Update personnel best positions and fitness values for each iteration*
4. *Update global best positions and fitness values for the swarm.*
5. *Update the velocities and positions of the particle.*

   $$V_i = w * v_i + c1 * rand() * (pbest_{xi} - x_i) + c2 * rand() * (gbest_x - x_i)$$

   $$x_i = x_i + v_i$$

6. *Repeat 2 to 5 until maximum iterations reached*
7. *Select the feature subset corresponding to the global best position.*

Input: Reduced data

Output: Best hyper parameters for executing the model.

Algorithm - Particle Swarm Optimization Lower Level:

1. *Define parameters for PSO*
2. *Initialize swarm particles with randomly using search space*
3. *Evaluate Fitness of each particle*
4. *Update personnel best positions and fitness values for each iteration*
5. *Update global best positions and fitness values for the swarm*
6. *Update Velocity and position of each particle*
    a. *Calculate Inertia weight*

    $$w_i = w_{start} - (w_{end} - w_{start}) * (iter / max\_iter)$$

    b. *Compute Cognitive coefficient*

    $$v_i = w_i * v_i + c1 * rand() * (pbest_i - x_i)$$

    c. *Calculate social coefficient*

    $$v_i = w_i * v_i + c2 * rand() * (gbest - x_i)$$

    d. *Calculate Cognitive component and Social component*

    *Cognitive_component = cognitive_coeff * (part [‘personel_best_position’] - part [‘position’]*

    *Social_component = social_coeff * (part [‘personel_best_position’] - part [‘position’]*

    e. *Update the velocity and position of each particle*

    *Part[‘velocity’] = Part[‘velocity’] * inertia_weight + Cognitive_component + Social_component* *f. Update position of the particle by adding its velocity to its current position.*

7. Repeat 3 to 6 until maximum iterations are done.

8. Select the hyper parameters with the best fitness as the optimal hyper parameter subset.

PREDICTION PHASE:

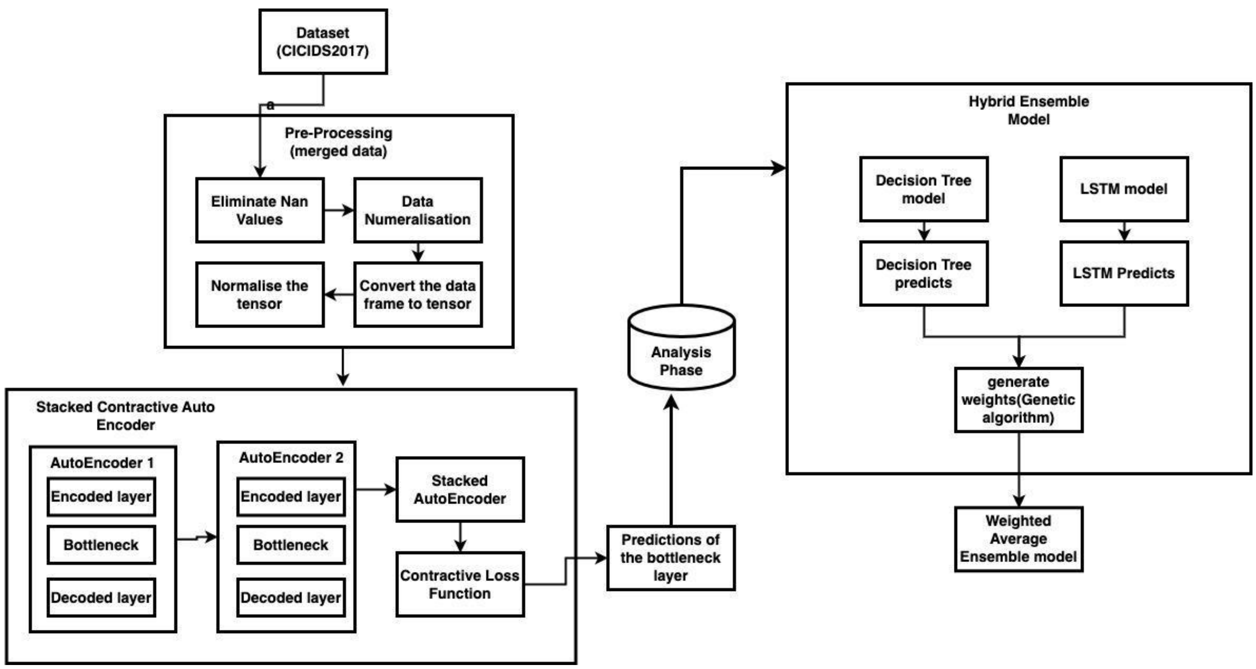


Fig 5.4 PREDICTION PHASE

In Fig 5.4 the prediction module collects the data from the processing module and checks whether there are any vulnerabilities while merging and resolve them. These data will go through **the feature extraction algorithm (SCAE)** and produce an output dataset, which will be used as the input dataset to Feature Selection and Hyper parameter selection in Analysis phase and this phase will receive the data form analysis phase and that data, collected hyper parameters are used to train the model. The created model performs two sequential tasks, which is the core of the proposed CIDS. The first step is to build the **weighted average ensemble system** utilizing the previously trained decision tree and

LSTM models, where the weights for that ensemble model will be generated by the fitness function of the genetic algorithm. The prediction module's second purpose is to successively choose a data record from the preprocessed, unseen database. Following that, the selected data record is tested using the ensemble system, and the weighted ensemble engine's final judgment is sent to the response module.

First of all, convert the dataset from unbalanced to balanced label encoding, and then normalization is needed. The mini-max transformation is used for normalization,

$$\mathbf{x_i = (x_i - min) / (max - min).}$$

Input: Dataset from Processing phase

Output: Feature Extracted data (32 features)

Algorithm-SCAE:

1. *Define hyper parameters like learning rate, coefficient of contractive penalty term (beta)*
2. *Define layers of the autoencoder and stack them on each other*
3. *Define a contractive loss function where,*
    a. *Calculate jacobian matrix and compute each partial derivative and form a matrix*

    $$z_{ij} = \delta f_i / \delta x_j$$

    b. *Calculate Forbenius norm where it is the root of sum of squares of each element in jacobian matrix.*

    $$y = \sqrt{\sum_{i=0}^{n} \sum_{j=0}^{n} x_{ij}}$$

    c. *Calculate the contractive penalty*

    reduce_mean(forbenius_norm)

d. *Return loss output as*

$$\beta * contractivepenalty$$

4. *Compile the model with loss as mean squared error as primary loss and contractive loss as the secondary loss*

5. *Get the predictions by testing the test data and train data with the model.*

Input: Feature Selected data from Analysis phase(24 features) and hyper parameters

Output: Trained Ensemble Model

Algorithm - Weighted Average Ensemble method:

1. *Create Genetic algorithm with 100 iterations to find weights in order to get good accuracy*
   a. *Define weight bounds*

   $$bounds = [(0, 1), (0, 1)]$$

   b. *Define fitness function*

   $$Weight_{predicts} = weight[0] * dt_{predicts} + weight[1] * lstm_{predicts}$$

   c. *Find accuracy for weight_pred*

   Accuracy = (TP + TN) / (TP + FP + TN + FN)

   d. *Repeat b and c until 100 iterations.*
2. *By considering weights from step 1, find the accuracy with the test labels and weight preds.*

RESPONSE PHASE:

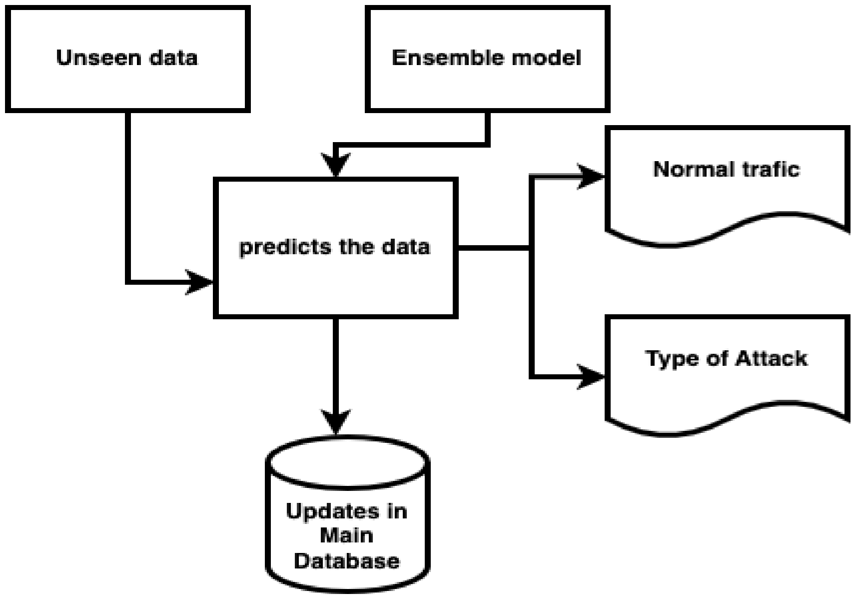


Fig 5.5 RESPONSE PHASE

In Fig 5.5, the response module receives both the final model and the tested data record, and then labels the tested data record with the final model. This function is in charge of reacting to the final decision of **"Normal" or "Attack".** In the instance of "Normal," the response module instructs the prediction module to go to the next data record in the unseen database in order to forecast its label. If, on the other hand, the final choice obtained is "Attack," the response module issues an alert that the cloud network is being subjected to potentially harmful activities.

Input: Unlabeled data

Output: Type of Traffic

CHAPTER 6

IMPLEMENTATION DETAILS (100%)

Data Collection:

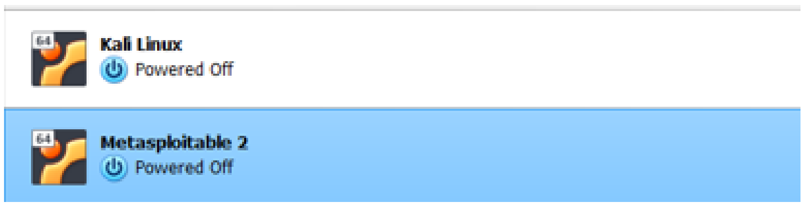


Fig 6.1 shows the 2 VMs namely Kali Linux (an attacker machine) and Metasploitable 2 (a vulnerable linux machine for security and penetration testing purposes)

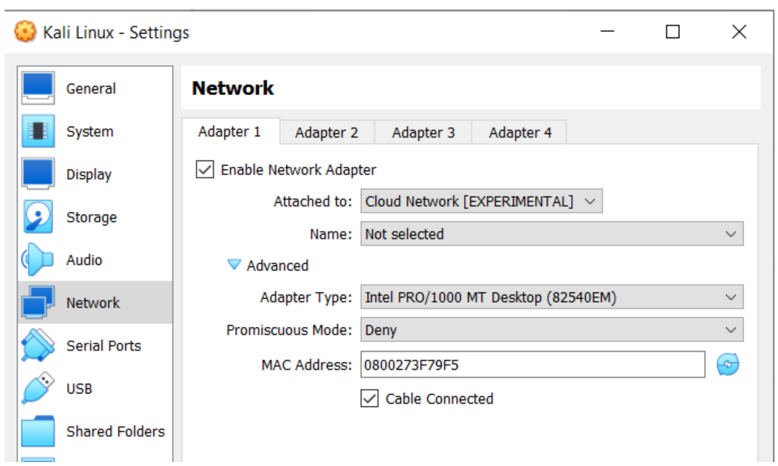


Fig shows the network adapter 1 configuration Kali Linux

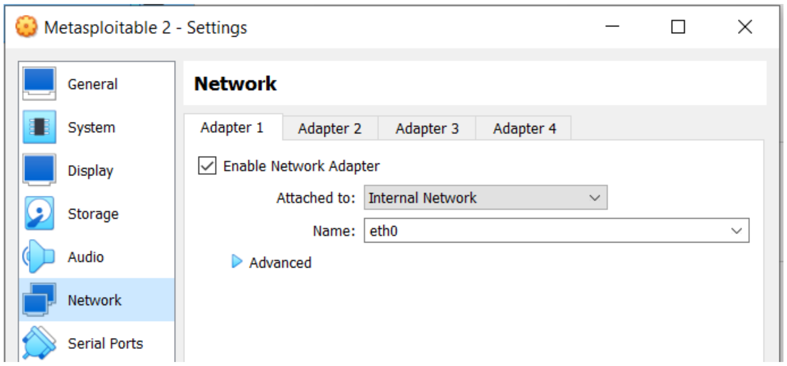


Fig 6.2 shows the network adapter 1 configuration Kali Linux

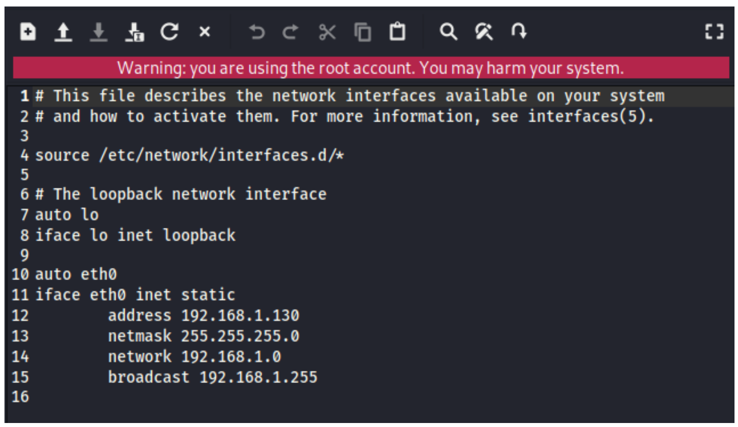


Fig 6.3 shows the network interface file code for sending and receiving packets in Kali Linux

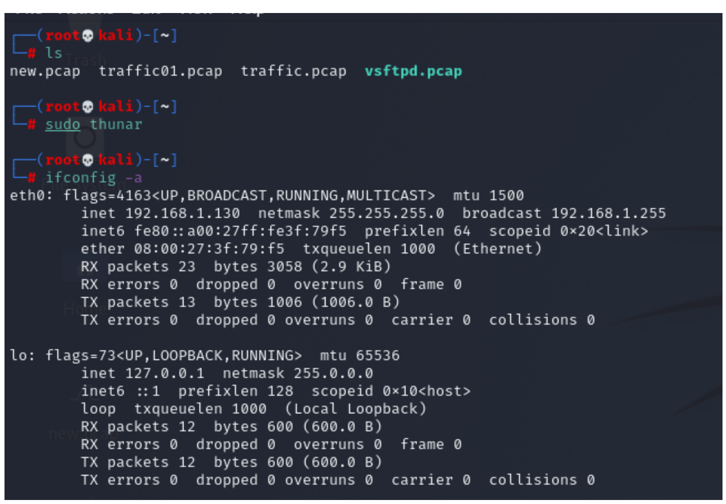
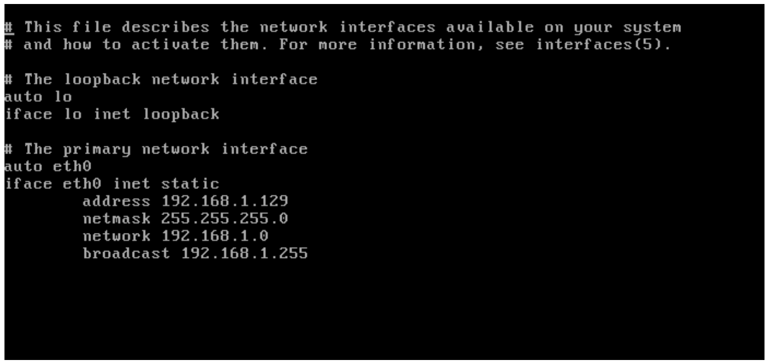
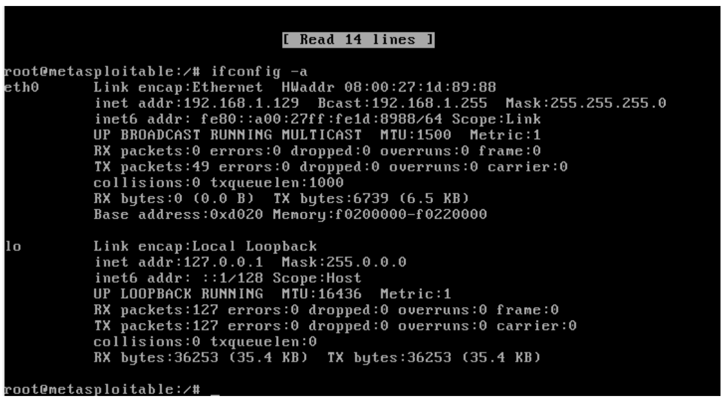


Fig 6.4 shows the network interface configuration in metasploitable-2 server



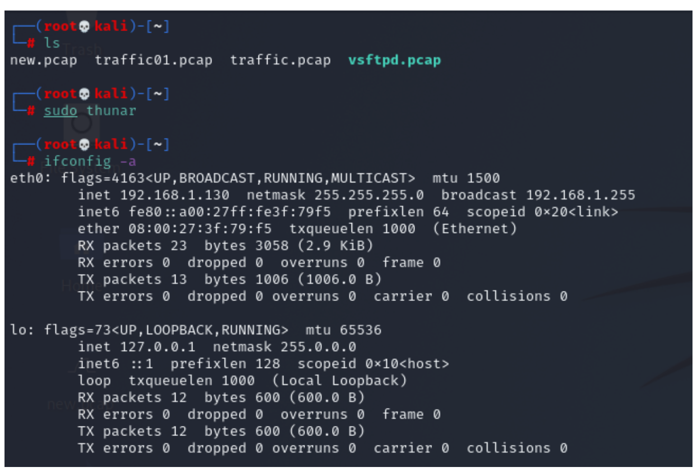
```
# This file describes the network interfaces available on your system
# and how to activate them. For more information, see interfaces(5).

# The loopback network interface
auto lo
iface lo inet loopback

# The primary network interface
auto eth0
iface eth0 inet static
        address 192.168.1.129
        netmask 255.255.255.0
        network 192.168.1.0
        broadcast 192.168.1.255
```

Fig 6.5 Shows the network interface file code for sending and receiving packets in metasploitable



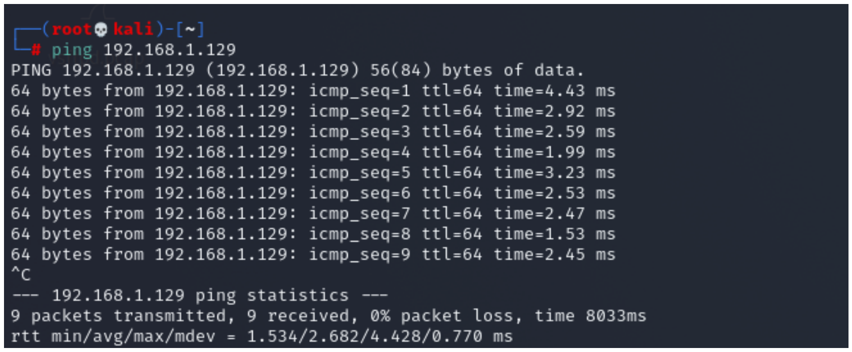
```
                              [ Read 14 lines ]

root@metasploitable:/# ifconfig -a
eth0      Link encap:Ethernet  HWaddr 08:00:27:1d:89:88
          inet addr:192.168.1.129  Bcast:192.168.1.255  Mask:255.255.255.0
          inet6 addr: fe80::a00:27ff:fe1d:8988/64 Scope:Link
          UP BROADCAST RUNNING MULTICAST  MTU:1500  Metric:1
          RX packets:0 errors:0 dropped:0 overruns:0 frame:0
          TX packets:49 errors:0 dropped:0 overruns:0 carrier:0
          collisions:0 txqueuelen:1000
          RX bytes:0 (0.0 B)  TX bytes:6739 (6.5 KB)
          Base address:0xd020 Memory:f0200000-f0220000

lo        Link encap:Local Loopback
          inet addr:127.0.0.1  Mask:255.0.0.0
          inet6 addr: ::1/128 Scope:Host
          UP LOOPBACK RUNNING  MTU:16436  Metric:1
          RX packets:127 errors:0 dropped:0 overruns:0 frame:0
          TX packets:127 errors:0 dropped:0 overruns:0 carrier:0
          collisions:0 txqueuelen:0
          RX bytes:36253 (35.4 KB)  TX bytes:36253 (35.4 KB)

root@metasploitable:/# _
```

Fig 6.6 Shows the network interface configuration in metasploitable-2



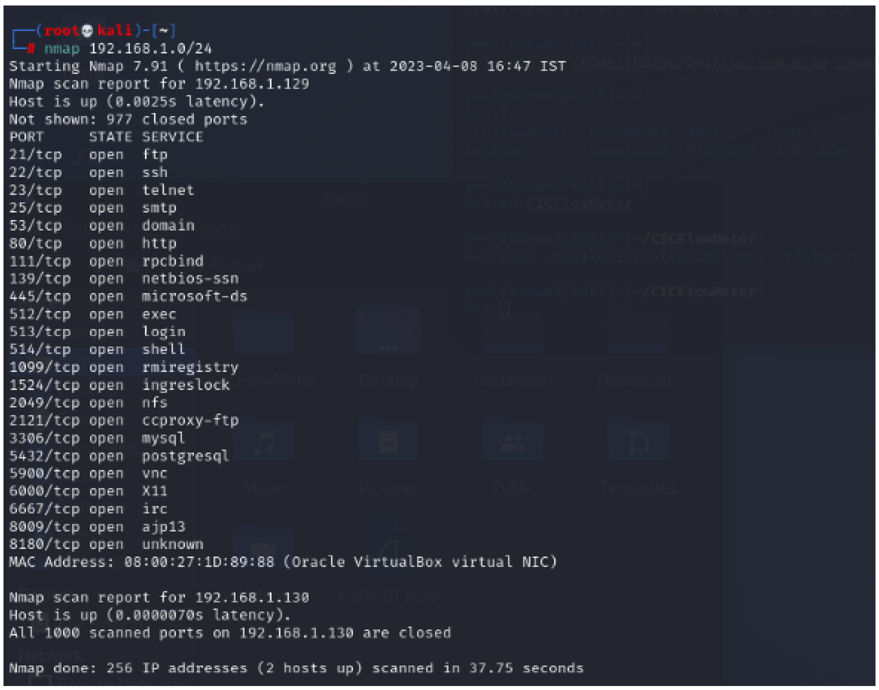
```
┌──(root💀kali)-[~]
└─# ls
new.pcap  traffic01.pcap  traffic.pcap  vsftpd.pcap

┌──(root💀kali)-[~]
└─# sudo thunar

┌──(root💀kali)-[~]
└─# ifconfig -a
eth0: flags=4163<UP,BROADCAST,RUNNING,MULTICAST>  mtu 1500
        inet 192.168.1.130  netmask 255.255.255.0  broadcast 192.168.1.255
        inet6 fe80::a00:27ff:fe3f:79f5  prefixlen 64  scopeid 0x20<link>
        ether 08:00:27:3f:79:f5  txqueuelen 1000  (Ethernet)
        RX packets 23  bytes 3058 (2.9 KiB)
        RX errors 0  dropped 0  overruns 0  frame 0
        TX packets 13  bytes 1006 (1006.0 B)
        TX errors 0  dropped 0 overruns 0  carrier 0  collisions 0

lo: flags=73<UP,LOOPBACK,RUNNING>  mtu 65536
        inet 127.0.0.1  netmask 255.0.0.0
        inet6 ::1  prefixlen 128  scopeid 0x10<host>
        loop  txqueuelen 1000  (Local Loopback)
        RX packets 12  bytes 600 (600.0 B)
        RX errors 0  dropped 0  overruns 0  frame 0
        TX packets 12  bytes 600 (600.0 B)
        TX errors 0  dropped 0 overruns 0  carrier 0  collisions 0
```

Fig 6.7 shows the network interface configuration in Kali Linux VM



```
┌──(root💀kali)-[~]
└─# ping 192.168.1.129
PING 192.168.1.129 (192.168.1.129) 56(84) bytes of data.
64 bytes from 192.168.1.129: icmp_seq=1 ttl=64 time=4.43 ms
64 bytes from 192.168.1.129: icmp_seq=2 ttl=64 time=2.92 ms
64 bytes from 192.168.1.129: icmp_seq=3 ttl=64 time=2.59 ms
64 bytes from 192.168.1.129: icmp_seq=4 ttl=64 time=1.99 ms
64 bytes from 192.168.1.129: icmp_seq=5 ttl=64 time=3.23 ms
64 bytes from 192.168.1.129: icmp_seq=6 ttl=64 time=2.53 ms
64 bytes from 192.168.1.129: icmp_seq=7 ttl=64 time=2.47 ms
64 bytes from 192.168.1.129: icmp_seq=8 ttl=64 time=1.53 ms
64 bytes from 192.168.1.129: icmp_seq=9 ttl=64 time=2.45 ms
^C
--- 192.168.1.129 ping statistics ---
9 packets transmitted, 9 received, 0% packet loss, time 8033ms
rtt min/avg/max/mdev = 1.534/2.682/4.428/0.770 ms
```

Fig 6.8 shows the ping from Kali Linux VM to Metasploitable-2 VM



```
┌──(root💀kali)-[~]
└─# nmap 192.168.1.0/24
Starting Nmap 7.91 ( https://nmap.org ) at 2023-04-08 16:47 IST
Nmap scan report for 192.168.1.129
Host is up (0.0025s latency).
Not shown: 977 closed ports
PORT     STATE SERVICE
21/tcp   open  ftp
22/tcp   open  ssh
23/tcp   open  telnet
25/tcp   open  smtp
53/tcp   open  domain
80/tcp   open  http
111/tcp  open  rpcbind
139/tcp  open  netbios-ssn
445/tcp  open  microsoft-ds
512/tcp  open  exec
513/tcp  open  login
514/tcp  open  shell
1099/tcp open  rmiregistry
1524/tcp open  ingreslock
2049/tcp open  nfs
2121/tcp open  ccproxy-ftp
3306/tcp open  mysql
5432/tcp open  postgresql
5900/tcp open  vnc
6000/tcp open  X11
6667/tcp open  irc
8009/tcp open  ajp13
8180/tcp open  unknown
MAC Address: 08:00:27:1D:89:88 (Oracle VirtualBox virtual NIC)

Nmap scan report for 192.168.1.130
Host is up (0.0000070s latency).
All 1000 scanned ports on 192.168.1.130 are closed

Nmap done: 256 IP addresses (2 hosts up) scanned in 37.75 seconds
```

Fig 6.9 shows the nmap scanned report of the kali linux

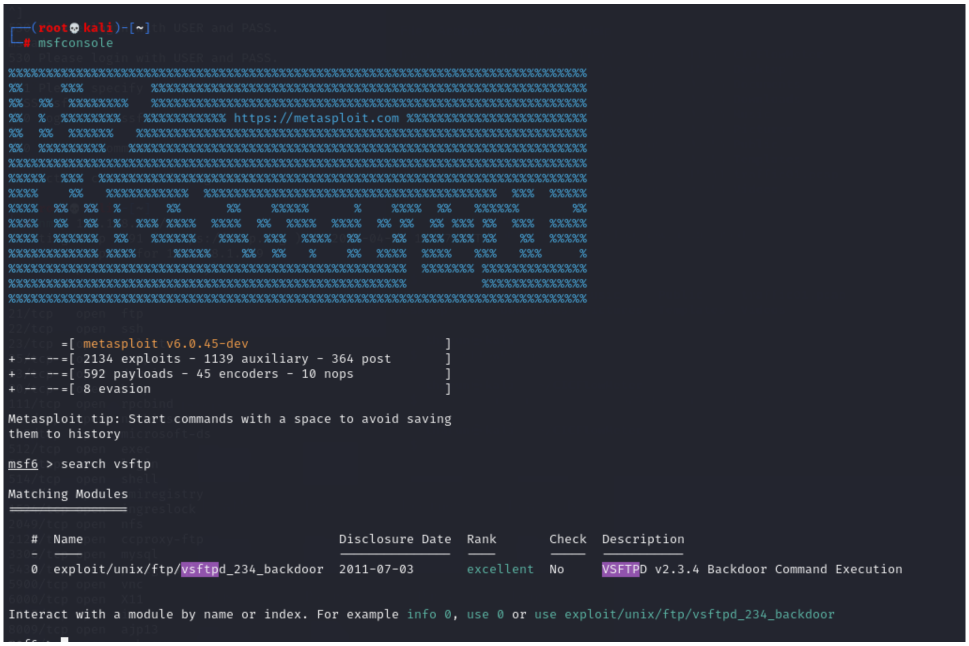


Fig 6.10

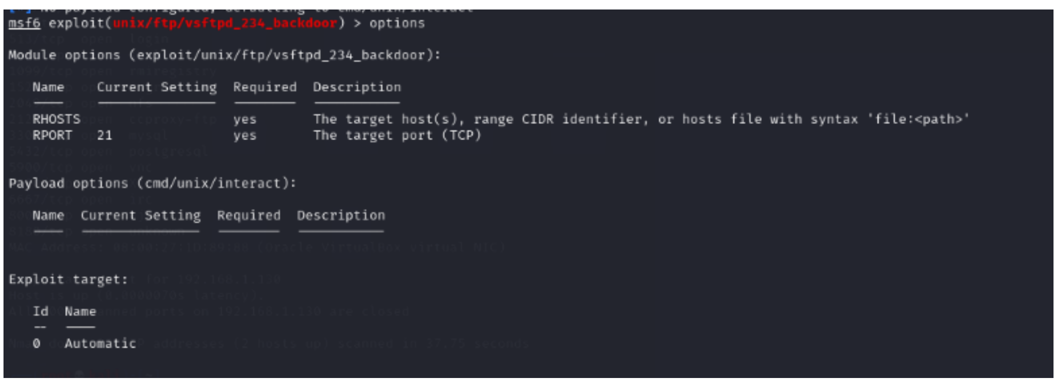


Fig 6.11

```
msf6 exploit(unix/ftp/vsftpd_234_backdoor) > set RHOSTS 192.168.1.129
RHOSTS ⇒ 192.168.1.129
msf6 exploit(unix/ftp/vsftpd_234_backdoor) > options

Module options (exploit/unix/ftp/vsftpd_234_backdoor):

   Name    Current Setting  Required  Description
   ----    ---------------  --------  -----------
   RHOSTS  192.168.1.129    yes       The target host(s), range CIDR identifier, or hosts file with syntax 'file:<path>'
   RPORT   21               yes       The target port (TCP)


Payload options (cmd/unix/interact):

   Name  Current Setting  Required  Description
   ----  ---------------  --------  -----------


Exploit target:

   Id  Name
   --  ----
   0   Automatic
```

Fig 6.12 shows the options of IP addresses to attack

```
msf6 exploit(unix/ftp/vsftpd_234_backdoor) > exploit

[*] 192.168.1.129:21 - Banner: 220 (vsFTPd 2.3.4)
[*] 192.168.1.129:21 - USER: 331 Please specify the password.
[+] 192.168.1.129:21 - Backdoor service has been spawned, handling ...
[+] 192.168.1.129:21 - UID: uid=0(root) gid=0(root)
[*] Found shell.
[*] Command shell session 1 opened (0.0.0.0:0 → 192.168.1.129:6200) at 2023-04-08 16:56:49 +0530

dir
bin    dev   initrd      lost+found  nohup.out  root  sys  var
boot   etc   initrd.img  media       opt        sbin  tmp  vmlinuz
cdrom  home  lib         mnt         proc       srv   usr
```

Fig 6.13 shows the exploitation of U2R attack as kali Linux user can use the Shell of Metasploitable

```
┌──(root💀kali)-[~]
└─# hping3 -S --flood -V -p 80 192.168.1.129
using eth0, addr: 192.168.1.130, MTU: 1500
HPING 192.168.1.129 (eth0 192.168.1.129): S set, 40 headers + 0 data bytes
hping in flood mode, no replies will be shown
^C
--- 192.168.1.129 hping statistic ---
30576538 packets transmitted, 0 packets received, 100% packet loss
round-trip min/avg/max = 0.0/0.0/0.0 ms
```

Fig 6.14 Shows the DOS attack generation using hping3 tool in Kali linux

Pre-processing techniques:

LABEL ENCODING & REMOVING NAN AND INFINITE VALUES:

```
[6] dff = pd.read_csv('/content/drive/MyDrive/FYP/final_dataset.csv')
```

```
[7] dff = dff.fillna(0)
    dff = dff.replace([np.inf, -np.inf], 1e9)
```

```
[8] col_to_encode = ' Label'
    encoder = LabelEncoder()
    dff[col_to_encode] = encoder.fit_transform(dff[col_to_encode])
```

```
[9] dff[col_to_encode].unique()

    array([ 0,  7, 11,  6,  5,  4,  3,  8, 12, 14, 13,  9,  1, 10,  2])
```

```
[14] dff
```

Total Fwd Packets	Total Backward Packets	Total Length of Fwd Packets	Total Length of Bwd Packets	Fwd Packet Length Max	Fwd Packet Length Min	Fwd Packet Length Mean	Fwd Packet Length Std	...	min_seg_size_forward	Active Mean	Active Std	Active Max	Active Min	Idle Mean	Idle Std	Idle Max	Idle Min	Label
2	0	12	0	6	6	6.000000	0.000000	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
2	0	12	0	6	6	6.000000	0.000000	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
7	4	484	414	233	0	69.142857	111.967895	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
9	4	656	3064	313	0	72.888889	136.153814	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
9	6	3134	3048	1552	0	348.222222	682.482560	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
2	0	12	0	6	6	6.000000	0.000000	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
2	0	0	0	0	0	0.000000	0.000000	...	32	0.0	0.0	0	0	0.0	0.0	0	0	0
1	1	6	6	6	6	6.000000	0.000000	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
2	0	248	0	242	6	124.000000	166.877200	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0
1	1	6	6	6	6	6.000000	0.000000	...	20	0.0	0.0	0	0	0.0	0.0	0	0	0

Fig 6.15 LABEL ENCODING - of CICIDS2017 Dataset

NORMALISATION (MIN MAX SCALAR)

```
[11] # Normalize the data in each column
     features = pd.DataFrame(scaler.fit_transform(features), columns=features.columns)
```

```
[12] # Split the data into training and testing sets
     X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.2, random_state=42)
```

```
features
```

	Destination Port	Flow Duration	Total Fwd Packets	Total Backward Packets	Total Length of Fwd Packets	Total Length of Bwd Packets	Fwd Packet Length Max	Fwd Packet Length Min	Fwd Packet Length Mean	Fwd Packet Length Std	...	act_data_pkt_fwd	min_seg_size_forward	Acti Me
0	0.755119	1.333333e-07	0.000005	0.000000	9.302326e-07	0.000000e+00	0.000257	0.002581	0.001010	0.000000	...	0.000005	1.0	
1	0.755119	1.166667e-07	0.000005	0.000000	9.302326e-07	0.000000e+00	0.000257	0.002581	0.001010	0.000000	...	0.000005	1.0	
2	0.001343	5.183333e-06	0.000027	0.000014	3.751938e-05	6.316242e-07	0.009974	0.000000	0.011639	0.015713	...	0.000023	1.0	
3	0.001343	7.433333e-06	0.000036	0.000014	5.085271e-05	4.674629e-06	0.013399	0.000000	0.012269	0.019108	...	0.000033	1.0	
4	0.001343	9.774999e-06	0.000036	0.000021	2.429457e-04	4.650219e-06	0.066438	0.000000	0.058615	0.095779	...	0.000033	1.0	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
1530738	0.936033	2.900000e-06	0.000005	0.000000	9.302326e-07	0.000000e+00	0.000257	0.002581	0.001010	0.000000	...	0.000005	1.0	
1530739	0.609577	1.925000e-06	0.000005	0.000000	0.000000e+00	0.000000e+00	0.000000	0.000000	0.000000	0.000000	...	0.000000	1.0	
1530740	0.935408	3.416666e-07	0.000000	0.000003	4.651163e-07	9.153974e-09	0.000257	0.002581	0.001010	0.000000	...	0.000000	1.0	

✓ 0s completed at 3:03 PM

Fig 6.16 MIN MAX SCALAR – depicts normalizing of dataset

FEATURE EXTRACTION (SCAE):

```
[ ] # Define the hyperparameters
    input_dim = 78
    hidden_dim_1 = 64
    hidden_dim_2 = 32
    learning_rate = 0.001
    batch_size = 32
    num_epochs = 20
    beta = 1.0  # the coefficient for the contractive penalty term

    # Define the layers of the autoencoder
    input_layer = tf.keras.layers.Input(shape=(input_dim,))
    encoder_1 = tf.keras.layers.Dense(hidden_dim_1, activation="relu")(input_layer)
    encoder_2 = tf.keras.layers.Dense(hidden_dim_2, activation="relu")(encoder_1)
    decoder_1 = tf.keras.layers.Dense(hidden_dim_1, activation="relu")(encoder_2)
    decoder_2 = tf.keras.layers.Dense(input_dim, activation="sigmoid")(decoder_1)

    # Define the model and compile it
    autoencoder = tf.keras.models.Model(inputs=input_layer, outputs=decoder_2)
```

Fig 6.17 AUTO ENCODER – creating the auto encoder layers

```python
def contractive_loss(y_true, y_pred):
    """Calculates the contractive loss for a given batch of input data."""
    mse = K.mean(K.square(y_true - y_pred), axis=1)
    W = K.variable(value=autoencoder.get_layer('dense_56').get_weights()[0]) # Get the weight matrix of the first hidden layer
    # Compute the jacobian matrix of the hidden layer outputs with respect to the input layer inputs
    h = autoencoder.get_layer('dense_56').output
    dh = h * (1 - h) # Derivative of the sigmoid activation function
    jacobian = dh[:, None] * W.T[None, :, :] # Compute the jacobian matrix
    jacobian = K.sum(jacobian ** 2, axis=(1, 2))
    return mse + 1e-4 * jacobian


autoencoder.compile(optimizer=tf.keras.optimizers.Adam(learning_rate=learning_rate),
                    loss=contractive_loss,
                    metrics=["accuracy"])
es = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=15)
mc = ModelCheckpoint('/Users/tharun/Desktop/FYP/DATASET/best_model_CNN.h5', monitor='val_accuracy', mode='max', verbose=1, save_best_only=True)
# Train the model
history = autoencoder.fit(X_train, X_train,
                          epochs=num_epochs,
                          batch_size=batch_size,
                          validation_data=(X_test, X_test),callbacks=[es,mc])
```

Fig 6.18 CONTRACTIVE LOSS FUNCTION – specifying the loss function

```
Epoch 1/20
38268/38269 [============================>.] - ETA: 0s - loss: 5.2701e-04 - accuracy: 0.3957
Epoch 1: val_accuracy improved from -inf to 0.54809, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_C
NN.h5
38269/38269 [==============================] - 93s 2ms/step - loss: 5.2701e-04 - accuracy: 0.3957 - val_loss: 1.637
5e-04 - val_accuracy: 0.5481
Epoch 2/20
38262/38269 [============================>.] - ETA: 0s - loss: 1.0424e-04 - accuracy: 0.6519
Epoch 2: val_accuracy improved from 0.54809 to 0.59265, saving model to /Users/tharun/Desktop/FYP/DATASET/best_mode
l_CNN.h5
38269/38269 [==============================] - 112s 3ms/step - loss: 1.0423e-04 - accuracy: 0.6519 - val_loss: 2.32
85e-05 - val_accuracy: 0.5926
Epoch 3/20
38265/38269 [============================>.] - ETA: 0s - loss: 2.3105e-05 - accuracy: 0.6408
Epoch 3: val_accuracy improved from 0.59265 to 0.71753, saving model to /Users/tharun/Desktop/FYP/DATASET/best_mode
l_CNN.h5
38269/38269 [==============================] - 112s 3ms/step - loss: 2.3104e-05 - accuracy: 0.6408 - val_loss: 1.70
70e-05 - val_accuracy: 0.7175
Epoch 4/20
```

```
Epoch 17: val_accuracy did not improve from 0.97603
38269/38269 [==============================] - 98s 3ms/step - loss: 1.2297e-05 - accuracy: 0.8807 - val_loss: 9.928
4e-06 - val_accuracy: 0.8245
Epoch 18/20
38258/38269 [============================>.] - ETA: 0s - loss: 1.2391e-05 - accuracy: 0.8539
Epoch 18: val_accuracy did not improve from 0.97603
38269/38269 [==============================] - 102s 3ms/step - loss: 1.2389e-05 - accuracy: 0.8539 - val_loss: 8.92
45e-06 - val_accuracy: 0.9486
Epoch 19/20
38267/38269 [============================>.] - ETA: 0s - loss: 1.2514e-05 - accuracy: 0.8910
Epoch 19: val_accuracy improved from 0.97603 to 0.99153, saving model to /Users/tharun/Desktop/FYP/DATASET/best_mod
el_CNN.h5
38269/38269 [==============================] - 96s 3ms/step - loss: 1.2514e-05 - accuracy: 0.8910 - val_loss: 1.293
0e-05 - val_accuracy: 0.9915
Epoch 20/20
38268/38269 [============================>.] - ETA: 0s - loss: 1.1610e-05 - accuracy: 0.8798
Epoch 20: val_accuracy did not improve from 0.99153
38269/38269 [==============================] - 98s 3ms/step - loss: 1.1610e-05 - accuracy: 0.8798 - val_loss: 9.542
0e-06 - val_accuracy: 0.9339
```

Fig 6.19 TRAINED SCAE – shows accuracy of each epoch during training

```
[ ]

    # Save only the encoder_2 weights to a file
    encoder_2.save_weights('/content/drive/MyDrive/FYP/encoder_2_weights.h5')
```

```
    # Create a new Model object with only the encoder_2 layer
    # Extract the encoder layers
    encoder_1 = tf.keras.models.Model(inputs=input_layer, outputs=encoder_1)
    encoder_2 = tf.keras.models.Model(inputs=encoder_1.input, outputs=encoder_2)
```

+ Code + Text

```
[ ] encoder_2.load_weights('/content/drive/MyDrive/FYP/encoder_2_weights.h5')

    # use the trained encoder to make predictions on new data
    encoded_data = encoder_2.predict(X_val)

    6697/6697 [==============================] - 12s 1ms/step
```

Fig 6.20(a) SAVING AND LOADING THE WEIGHTS– Lading the best weights for auto encoder

```
[ ] # Test the model
    test_loss, test_acc = best_model.evaluate(X_test, X_test)
    print(f"Test loss: {test_loss:.4f}")
    print(f"Test accuracy: {test_acc:.4f}")

    9568/9568 [==============================] - 11s 1ms/step - loss: 1.2930e-05 - accuracy: 0.9915
    Test loss: 0.0000
    Test accuracy: 0.9915
```

```
[ ]
```

```
[ ] # Extract the encoder layers
    encoder_1 = tf.keras.models.Model(inputs=input_layer, outputs=encoder_1)
    encoder_2 = tf.keras.models.Model(inputs=encoder_1.input, outputs=encoder_2)
```

```
[ ] encoded_train = encoder_2.predict(X_train)
    encoded_test = encoder_2.predict(X_test)

    38269/38269 [==============================] - 74s 2ms/step
    9568/9568 [==============================] - 10s 1ms/step
```

Fig 6.21(b) ACCURACY AND PREDICTIONS – shows testing accuracy and 32 features are extracted as output from data

PSO - FEATURE SELECTION:

```
[ ] # error rate
    def error_rate(xtrain, ytrain, x, opts):
        # parameters
        fold = opts['fold']
        xt = fold['xt']
        yt = fold['yt']
        xv = fold['xv']
        yv = fold['yv']
        # number of instances
        num_train = np.size(xt, 0)
        num_valid = np.size(xv, 0)
        # Define selected features
        xtrain = xt[:, x == 1]
        ytrain = yt.reshape(num_train)
        xvalid = xv[:, x == 1]
        yvalid = yv.reshape(num_valid)
        # Training
        mdl     = LinearRegression()
        mdl.fit(xtrain, ytrain)
        # Prediction
        ypred   = mdl.predict(xvalid)
        error   = mean_squared_error(yvalid, ypred, squared=False)

        return error
```

Fig 6.22 ERROR RATE FUNCTION - calculate the error of PSO

```
[ ] # Error rate & Feature size
    def Fun(xtrain, ytrain, x, opts):
        # parameters
        alpha = 0.99
        beta = 1 - alpha
        # original feature size
        max_feat = len(x)
        # Number of selected features
        num_feat = np.sum(x == 1)
        # Solve if no feature selected
        if num_feat == 0:
            cost = 1
        else:
            # Get error rate
            error = error_rate(xtrain, ytrain, x, opts)
            # Objective function
            cost = alpha * error + beta * (num_feat / max_feat)

        return cost
```

Fig 6.23 OBJECTIVE FUNCTION – calculate the cost during each iteration

```
[ ] def init_position(lb, ub, N, dim):
        X = np.zeros([N, dim], dtype='float')
        for i in range(N):
            for d in range(dim):
                X[i,d] = lb[0,d] + (ub[0,d] - lb[0,d]) * rand()

        return X
```

Fig 6.24 INITIAL POSITION FUNCTION – defines the position of a particle

```
[ ] def init_velocity(lb, ub, N, dim):
        V    = np.zeros([N, dim], dtype='float')
        Vmax = np.zeros([1, dim], dtype='float')
        Vmin = np.zeros([1, dim], dtype='float')
        # Maximum & minimum velocity
        for d in range(dim):
            Vmax[0,d] = (ub[0,d] - lb[0,d]) / 2
            Vmin[0,d] = -Vmax[0,d]

        for i in range(N):
            for d in range(dim):
                V[i,d] = Vmin[0,d] + (Vmax[0,d] - Vmin[0,d]) * rand()

        return V, Vmax, Vmin
```

6.25 INITIAL VELOCITY FUNCTION – defines the velocity of the particle

```
[ ] def binary_conversion(X, thres, N, dim):
        Xbin = np.zeros([N, dim], dtype='int')
        for i in range(N):
            for d in range(dim):
                if X[i,d] > thres:
                    Xbin[i,d] = 1
                else:
                    Xbin[i,d] = 0

        return Xbin
```

Fig 6.26 BINARY CONVERION – of value of particle

```
[ ]  def boundary(x, lb, ub):
         if x < lb:
             x = lb
         if x > ub:
             x = ub

         return x
```

Fig 6.27 DEFINING BOUNDARIES – for particle

```
[ ] def jfs(xtrain, ytrain, opts):
        # Parameters
        ub    = 1
        lb    = 0
        thres = 0.5
        w     = 0.9    # inertia weight
        c1    = 2      # acceleration factor
        c2    = 2      # acceleration factor

        N        = opts['N']
        max_iter = opts['T']
        if 'w' in opts:
            w    = opts['w']
        if 'c1' in opts:
            c1   = opts['c1']
        if 'c2' in opts:
            c2   = opts['c2']

        # Dimension
        dim = np.size(xtrain, 1)
        if np.size(lb) == 1:
            ub = ub * np.ones([1, dim], dtype='float')
            lb = lb * np.ones([1, dim], dtype='float')

        # Initialize position & velocity
        X              = init_position(lb, ub, N, dim)
        V, Vmax, Vmin = init_velocity(lb, ub, N, dim)

        # Pre
        fit   = np.zeros([N, 1], dtype='float')
        Xgb   = np.zeros([1, dim], dtype='float')
        fitG  = float('inf')
        Xpb   = np.zeros([N, dim], dtype='float')
        fitP  = float('inf') * np.ones([N, 1], dtype='float')
        curve = np.zeros([1, max_iter], dtype='float')
        t     = 0
```

Fig 6.28 (a)

```
while t < max_iter:
    # Binary conversion
    Xbin = binary_conversion(X, thres, N, dim)

    # Fitness
    for i in range(N):
        fit[i,0] = Fun(xtrain, ytrain, Xbin[i,:], opts)
        if fit[i,0] < fitP[i,0]:
            Xpb[i,:]  = X[i,:]
            fitP[i,0] = fit[i,0]
        if fitP[i,0] < fitG:
            Xgb[0,:]  = Xpb[i,:]
            fitG      = fitP[i,0]

    # Store result
    curve[0,t] = fitG.copy()
    print("Iteration:", t + 1)
    print("Best (PSO):", curve[0,t])
    t += 1

    for i in range(N):
        for d in range(dim):
            # Update velocity
            r1     = rand()
            r2     = rand()
            V[i,d] = w * V[i,d] + c1 * r1 * (Xpb[i,d] - X[i,d]) + c2 * r2 * (Xgb[0,d] - X[i,d])
            # Boundary
            V[i,d] = boundary(V[i,d], Vmin[0,d], Vmax[0,d])
            # Update position
            X[i,d] = X[i,d] + V[i,d]
            # Boundary
            X[i,d] = boundary(X[i,d], lb[0,d], ub[0,d])


# Best feature subset
Gbin       = binary_conversion(Xgb, thres, 1, dim)
Gbin       = Gbin.reshape(dim)
pos        = np.asarray(range(0, dim))
```

```
pos        = np.asarray(range(0, dim))
sel_index  = pos[Gbin == 1]
num_feat   = len(sel_index)
# Create dictionary
pso_data = {'sf': sel_index, 'c': curve, 'nf': num_feat}

return pso_data
```

Fig 6.29(b)

Fitness function – update the initial position and initial velocity for each iteration

```
[ ] c1   = 2          # cognitive factor
    c2   = 2          # social factor
    w    = 0.9        # inertia weight
    k      = 5      # k-value in KNN
    N      = 20     # number of population
    T      = 5    # maximum number of iterations
    opts = {'k':k, 'fold':fold, 'N':N, 'T':T, 'w':w, 'c1':c1, 'c2':c2}
```

Fig 6.30 INITIALIZING FACTORS – constant values

```
[ ] # perform feature selection
    start_time = time.time()
    fmdl   = jfs(fea_train, tar_train, opts)
    print("Run Time --- %s seconds ---" % (time.time() - start_time))

    sf     = fmdl['sf']

    # model with selected features
    num_train = np.size(xtrain, 0)
    num_valid = np.size(xtest, 0)
    x_train   = xtrain[:, sf]
    y_train   = ytrain.reshape(num_train)  # Solve bug
    x_valid   = xtest[:, sf]
    y_valid   = ytest.reshape(num_valid)  # Solve bug

    mdl       = LinearRegression()
    mdl.fit(x_train, y_train)

    # accuracy
    y_pred    = mdl.predict(x_valid)
    RMSE       = mean_squared_error(y_valid, y_pred, squared=False)
    print("RMSE:", RMSE)

    # number of selected features
    num_feat = fmdl['nf']
    print("Feature Size:", num_feat)

    # plot convergence
    curve    = fmdl['c']
    curve    = curve.reshape(np.size(curve,1))
    x        = np.arange(0, opts['T'], 1.0) + 1.0

    fig, ax = plt.subplots()
    ax.plot(x, curve, 'o-')
    ax.set_xlabel('Number of Iterations')
    ax.set_ylabel('Fitness')
    ax.set_title('PSO')
    ax.grid()
    plt.show()
```

Fig 6.31 Performing feature selection and calculating RMSE for each and every iteration and storing the selected features in a variable

```
[272] features = [1,  2,  3,  5,  6,  7,  8, 10, 11, 12, 13, 14, 16, 17, 19, 22, 23,
          24, 26, 27, 28, 29, 30, 31]

[247] type(fea_train)

      pandas.core.frame.DataFrame

[331] # Convert the NumPy array to a pandas DataFrame
      fea_train = pd.DataFrame(fea_train)
      fea_test = pd.DataFrame(fea_test)

[354] val_fea_train=pd.DataFrame(val_fea_train)

[333] fea_train1= fea_train[features]
      fea_test1=fea_test[features]

[355] val_fea_train1= val_fea_train[features]
```

Fig 6.32 Creating the dataset with the selected features

PSO - Hyper parameter selection:

```
[ ]  import numpy as np

     class Particle:
         def __init__(self, n_params, bounds):
             self.position = np.random.uniform(bounds[0], bounds[1], n_params)
             self.velocity = np.zeros(n_params)
             self.best_position = self.position.copy()
             self.best_error = float('inf')

         def update_best(self, error):
             if error < self.best_error:
                 self.best_position = self.position.copy()
                 self.best_error = error

         def update_velocity(self, global_best, w, c1, c2):
             r1, r2 = np.random.rand(2)
             cognitive = c1 * r1 * (self.best_position - self.position)
             social = c2 * r2 * (global_best - self.position)
             self.velocity = w * self.velocity + cognitive + social

         def update_position(self, bounds):
             self.position += self.velocity
             # enforce bounds
             self.position = np.maximum(self.position, bounds[0])
             self.position = np.minimum(self.position, bounds[1])
```

Fig 6.33 Creating the particle class with position, velocity and error

```python
class PSO:
    def __init__(self, n_params, bounds, n_particles, n_iterations, fitness_fn, w=0.5, c1=1, c2=1):
        self.n_params = n_params
        self.bounds = bounds
        self.n_particles = n_particles
        self.n_iterations = n_iterations
        self.fitness_fn = fitness_fn
        self.w = w
        self.c1 = c1
        self.c2 = c2

        self.global_best_position = None
        self.global_best_error = float('inf')

        self.particles = [Particle(n_params, bounds) for _ in range(n_particles)]

    def run(self):
        for i in range(self.n_iterations):
            for particle in self.particles:
                error = self.fitness_fn(particle.position)
                particle.update_best(error)
                if error < self.global_best_error:
                    self.global_best_position = particle.position.copy()
                    self.global_best_error = error
            for particle in self.particles:
                particle.update_velocity(self.global_best_position, self.w, self.c1, self.c2)
                particle.update_position(self.bounds)

        return self.global_best_position, self.global_best_error
```

Fig 6.34 Creating the PSO class and updating for each iteration

```python
from sklearn.model_selection import cross_val_score
from sklearn.tree import DecisionTreeClassifier

# define fitness function
def fitness_fn(params):
    max_depth, min_samples_split = params
    clf = DecisionTreeClassifier(max_depth=int(round(max_depth)), min_samples_split=int(round(min_samples_split)))
    scores = cross_val_score(clf, fea_train, tar_train, cv=5)
    return 1 - np.mean(scores)


# define bounds for hyperparameters
bounds = [(1, 10), (2, 20)]

# create PSO object and run algorithm
pso = PSO(n_params=2, bounds=bounds, n_particles=10, n_iterations=50, fitness_fn=fitness_fn)
best_params, best_score = pso.run()

print("Best hyperparameters:", best_params)
```

```
Best hyperparameters: [ 1.86594353 10.30765563]
```

Fig 6.35 Finding the best hyper parameters

LSTM MODEL:

```
[ ] model3 = models.Sequential()
    model3.add(layers.LSTM(50, input_shape = (32,1), activation = 'tanh', return_sequences = True, recurrent_activation='sigmoid', recurrent_dropout = 0.0, unro
    model3.add(layers.Dropout(0.15))
    model3.add(layers.LSTM(50, activation = 'tanh', return_sequences = True,recurrent_activation='sigmoid',recurrent_dropout = 0.0,unroll=False ,use_bias=True))
    model3.add(layers.Dropout(0.25))
    model3.add(layers.LSTM(50, activation = 'tanh', return_sequences = True,recurrent_activation='sigmoid',recurrent_dropout = 0.0,unroll=False ,use_bias=True))
    model3.add(layers.Dropout(0.35))
    model3.add(layers.LSTM(50, activation = 'tanh',recurrent_activation='sigmoid',recurrent_dropout = 0.0,unroll=False ,use_bias=True))
    model3.add(layers.Dropout(0.45))
    model3.add(layers.Flatten())
    model3.add(layers.Dense(50,activation = 'relu'))
    model3.add(layers.Dropout(0.04))
    model3.add(layers.Dense(15,activation = 'softmax'))
    optimizer = tf.keras.optimizers.Adam(learning_rate=1e-5)
    model3.compile(loss = tf.keras.losses.SparseCategoricalCrossentropy(),
                optimizer = 'adam',
                metrics = ['accuracy'])
    model3.summary()
```

Fig 6.36 LSTM MODEL – Creating Layers for LSTM

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 32, 50)            10400

 dropout (Dropout)           (None, 32, 50)            0

 lstm_1 (LSTM)               (None, 32, 50)            20200

 dropout_1 (Dropout)         (None, 32, 50)            0

 lstm_2 (LSTM)               (None, 32, 50)            20200

 dropout_2 (Dropout)         (None, 32, 50)            0

 lstm_3 (LSTM)               (None, 50)                20200

 dropout_3 (Dropout)         (None, 50)                0

 flatten (Flatten)           (None, 50)                0

 dense (Dense)               (None, 50)                2550

 dropout_4 (Dropout)         (None, 50)                0

 dense_1 (Dense)             (None, 15)                765

=================================================================
Total params: 74,315
Trainable params: 74,315
Non-trainable params: 0
_________________________________________________________________
```

Fig 6.37 MODEL SUMMARY – shows the details of Layers

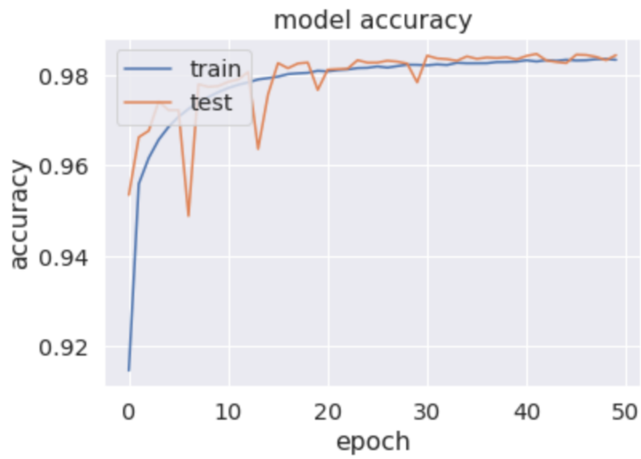
```
es = EarlyStopping(monitor='val_loss', mode='min', verbose=1, patience=15)
mc = ModelCheckpoint('/Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5', monitor='val_accuracy', mode='max', verbose=1, save_best_only=True)
# Train the model
history = model3.fit(fea_train.reshape(fea_train.shape[0], fea_train.shape[1], 1), tar_train, validation_data=(fea_test, tar_test), epochs=50, batch_size=12
```

```
Epoch 1/50
9566/9568 [============================>.] - ETA: 0s - loss: 0.2482 - accuracy: 0.9146
Epoch 1: val_accuracy improved from -inf to 0.95349, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5
9568/9568 [==============================] - 136s 14ms/step - loss: 0.2482 - accuracy: 0.9146 - val_loss: 0.1157 - val_accuracy: 0.9535
Epoch 2/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.1163 - accuracy: 0.9560
Epoch 2: val_accuracy improved from 0.95349 to 0.96629, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5
9568/9568 [==============================] - 135s 14ms/step - loss: 0.1163 - accuracy: 0.9560 - val_loss: 0.0882 - val_accuracy: 0.9663
Epoch 3/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.0991 - accuracy: 0.9617
Epoch 3: val_accuracy improved from 0.96629 to 0.96771, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5
9568/9568 [==============================] - 134s 14ms/step - loss: 0.0991 - accuracy: 0.9617 - val_loss: 0.0783 - val_accuracy: 0.9677
Epoch 4/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.0903 - accuracy: 0.9657
Epoch 4: val_accuracy improved from 0.96771 to 0.97419, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5
9568/9568 [==============================] - 141s 15ms/step - loss: 0.0903 - accuracy: 0.9657 - val_loss: 0.0693 - val_accuracy: 0.9742
Epoch 5/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.0842 - accuracy: 0.9686
Epoch 5: val_accuracy did not improve from 0.97419
9568/9568 [==============================] - 140s 15ms/step - loss: 0.0842 - accuracy: 0.9686 - val_loss: 0.0720 - val_accuracy: 0.9723
Epoch 6/50
9568/9568 [==============================] - ETA: 0s - loss: 0.0794 - accuracy: 0.9708
Epoch 6: val_accuracy did not improve from 0.97419
9568/9568 [==============================] - 142s 15ms/step - loss: 0.0794 - accuracy: 0.9708 - val_loss: 0.0679 - val_accuracy: 0.9723
Epoch 7/50
9568/9568 [==============================] - ETA: 0s - loss: 0.0757 - accuracy: 0.9726
Epoch 7: val_accuracy did not improve from 0.97419
9568/9568 [==============================] - 143s 15ms/step - loss: 0.0757 - accuracy: 0.9726 - val_loss: 0.1153 - val_accuracy: 0.9488
Epoch 8/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.0725 - accuracy: 0.9740
Epoch 8: val_accuracy improved from 0.97419 to 0.97801, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5
9568/9568 [==============================] - 132s 14ms/step - loss: 0.0725 - accuracy: 0.9740 - val_loss: 0.0618 - val_accuracy: 0.9780
Epoch 9/50
```

```
9568/9568 [==============================] - 138s 14ms/step - loss: 0.0458 - accuracy: 0.9833 - val_loss: 0.0423 - val_accuracy: 0.9843
Epoch 42/50
9566/9568 [============================>.] - ETA: 0s - loss: 0.0461 - accuracy: 0.9831
Epoch 42: val_accuracy improved from 0.98436 to 0.98475, saving model to /Users/tharun/Desktop/FYP/DATASET/best_model_LSTM1.h5
9568/9568 [==============================] - 132s 14ms/step - loss: 0.0461 - accuracy: 0.9831 - val_loss: 0.0411 - val_accuracy: 0.9847
Epoch 43/50
9568/9568 [==============================] - ETA: 0s - loss: 0.0455 - accuracy: 0.9834
Epoch 43: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 141s 15ms/step - loss: 0.0455 - accuracy: 0.9834 - val_loss: 0.0438 - val_accuracy: 0.9833
Epoch 44/50
9565/9568 [============================>.] - ETA: 0s - loss: 0.0459 - accuracy: 0.9832
Epoch 44: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 131s 14ms/step - loss: 0.0459 - accuracy: 0.9832 - val_loss: 0.0473 - val_accuracy: 0.9829
Epoch 45/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.0453 - accuracy: 0.9834
Epoch 45: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 140s 15ms/step - loss: 0.0453 - accuracy: 0.9834 - val_loss: 0.0473 - val_accuracy: 0.9827
Epoch 46/50
9566/9568 [============================>.] - ETA: 0s - loss: 0.0455 - accuracy: 0.9833
Epoch 46: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 132s 14ms/step - loss: 0.0455 - accuracy: 0.9833 - val_loss: 0.0413 - val_accuracy: 0.9846
Epoch 47/50
9565/9568 [============================>.] - ETA: 0s - loss: 0.0453 - accuracy: 0.9833
Epoch 47: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 139s 14ms/step - loss: 0.0453 - accuracy: 0.9833 - val_loss: 0.0414 - val_accuracy: 0.9845
Epoch 48/50
9567/9568 [============================>.] - ETA: 0s - loss: 0.0448 - accuracy: 0.9836
Epoch 48: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 130s 14ms/step - loss: 0.0448 - accuracy: 0.9836 - val_loss: 0.0419 - val_accuracy: 0.9841
Epoch 49/50
9565/9568 [============================>.] - ETA: 0s - loss: 0.0446 - accuracy: 0.9836
Epoch 49: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 132s 14ms/step - loss: 0.0446 - accuracy: 0.9836 - val_loss: 0.0436 - val_accuracy: 0.9834
Epoch 50/50
9566/9568 [============================>.] - ETA: 0s - loss: 0.0447 - accuracy: 0.9834
Epoch 50: val_accuracy did not improve from 0.98475
9568/9568 [==============================] - 136s 14ms/step - loss: 0.0447 - accuracy: 0.9834 - val_loss: 0.0424 - val_accuracy: 0.9845
```

Fig 6.38 TRAINED LSTM MODEL – Shows accuracy of each epoch while training

```
[ ] sns.set_context('notebook', font_scale= 1.3)
    plt.plot(history.history['accuracy'])
    plt.plot(history.history['val_accuracy'])
    plt.title('model accuracy')
    plt.ylabel('accuracy')
    plt.xlabel('epoch')
    plt.legend(['train', 'test'], loc='upper left')
    plt.show()
```




```
[ ] model3.save('/content/drive/MyDrive/FYP/DATASET/LSTM.h5')
```

Fig 6.39 LSTM MODEL ACCURACY – the graph depicts the accuracy of epochs ranging from 0 to 50

```
# Apply the softmax activation function to the output tensor
from scipy.special import softmax
pred_probs = softmax(lstm_pred1, axis=0)

# Get the class with the highest probability
#pred_class = np.argmax(pred_probs, axis=0)
sns.set_context('notebook', font_scale= 1.3)
fig, ax = plt.subplots(1, 2, figsize = (25,  8))
ax1 = plot_confusion_matrix(tar_test, lstm_pred1, ax= ax[0], cmap= 'YlGnBu')
#ax2 = plot_roc(tar_test, pred_class, ax= ax[1], plot_macro= False, plot_micr
```

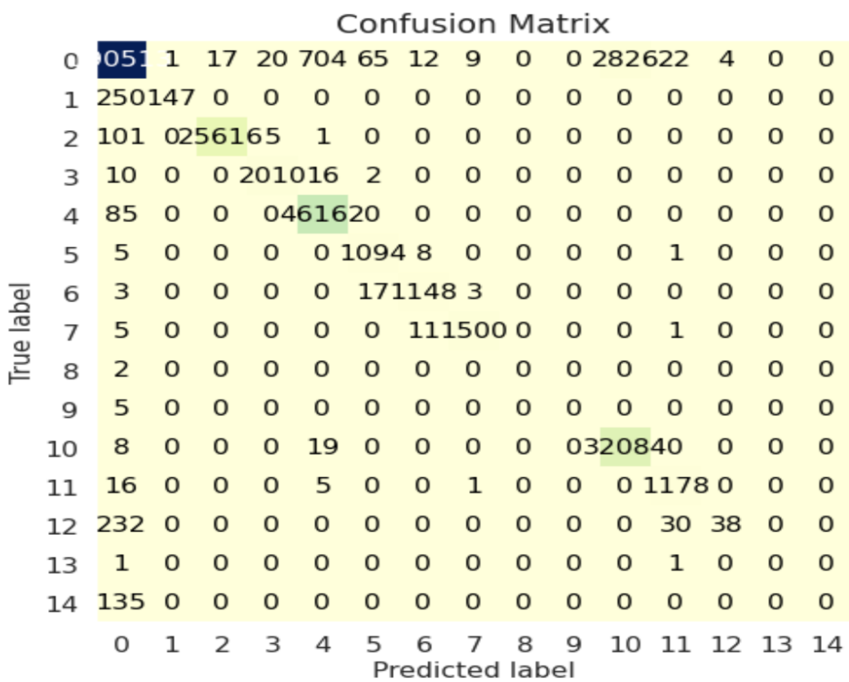


Fig 6.40 LSTM MODEL CONFUSION MATRIX

```
[ ] # Compute initial ensemble accuracy
    dt_pred1 = dt.predict(fea_test)
    lstm_pred_prob = model3.predict(fea_test)
    lstm_pred1 = np.argmax(lstm_pred_prob, axis=1)

    9568/9568 [==============================] - 54s 5ms/step
```

```
[ ] # Calculate precision and recall
    precision, recall, _, _ = precision_recall_fscore_support(tar_test, lstm_pred1, average='weighted')

    # Display or save the precision and recall
    print(f'Precision: {precision:.3f}, Recall: {recall:.3f}')

    Precision: 0.985, Recall: 0.985
```

Add text cell

Fig 6.41 PRECISION AND RECALL OF LSTM MODEL

DECISION TREE:

```
[ ] from keras.models import load_model
    model3=load_model('/content/drive/MyDrive/FYP/DATASET/LSTM.h5')
```

```
[ ] dt = DecisionTreeClassifier(random_state=42)
    dt.fit(fea_train,tar_train)

    DecisionTreeClassifier(random_state=42)
```

```
[ ] dt_pred_test=dt.predict(fea_test)
```

```
[ ] accuracy1 = accuracy_score(tar_test, dt_pred_test)
    accuracy1

    0.994685594269457
```

```
[ ] # Calculate precision and recall
    precision, recall, _, _ = precision_recall_fscore_support(tar_test, dt_pred_test, average='weighted')

    # Display or save the precision and recall
    print(f'Precision: {precision:.3f}, Recall: {recall:.3f}')

    Precision: 0.995, Recall: 0.995
```

Fig 6.42 PRECISION AND RECALL OF DECISION TREE MODEL – Creating decision tree model and depicting its accuracy, precision and recall

```python
y_prob = dt.predict_proba(fea_test)
sns.set_context('notebook', font_scale= 1.3)
fig, ax = plt.subplots(1, 2, figsize = (25,  8))
ax1 = plot_confusion_matrix(tar_test, dt_pred_test, ax= ax[0], cmap= 'YlGnBu')
ax2 = plot_roc(tar_test, y_prob, ax= ax[1], plot_macro= False, plot_micro= False, cmap= 'winter')
```

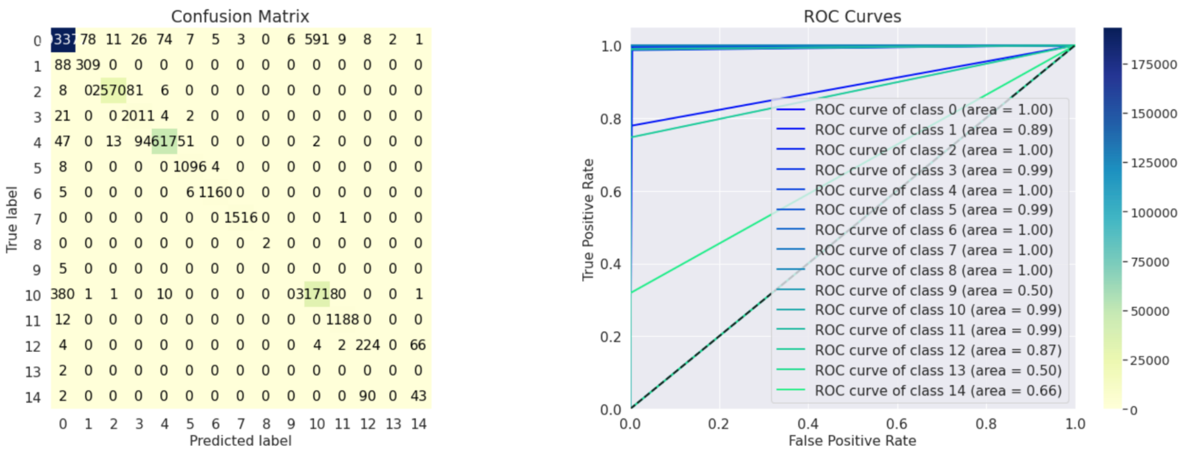


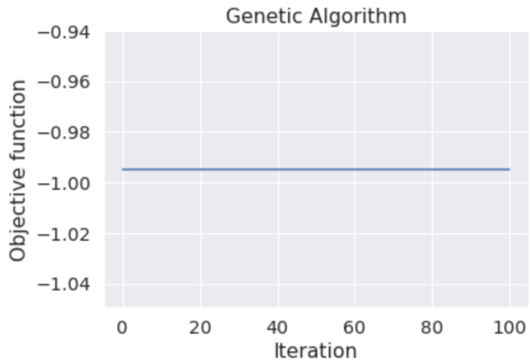
Fig 6.43 CONFUSION MATRIX AND ROC CURVE OF DECISION TREE MODEL

ENSEMBLE MODEL:

```python
import numpy as np
from geneticalgorithm import geneticalgorithm as ga

# Define the fitness function that calculates the accuracy of the ensemble model
def fitness_function(weights):
    # Combine the predictions using the weights
    weighted_pred = weights[0] * dt_pred1 + weights[1] * lstm_pred1

    # Round the prediction to the nearest integer
    final_pred = np.round(weighted_pred)

    # Calculate the accuracy of the final prediction
    accuracy = accuracy_score(tar_test, final_pred)

    # Return the negative accuracy (since the genetic algorithm minimizes the objective function)
    return -accuracy

# Define the bounds for the weights (between 0 and 1)
bounds = [(0, 1), (0, 1)]
bounds = np.array(bounds)
algorithm_param = {'max_num_iteration': 100,\
                   'population_size':100,\
                   'mutation_probability':0.1,\
                   'elit_ratio': 0.01,\
                   'crossover_probability': 0.5,\
                   'parents_portion': 0.3,\
                   'crossover_type':'uniform',\
                   'max_iteration_without_improv':None}
# Create the genetic algorithm object
ga_model = ga(function=fitness_function, dimension=2, variable_type='real', variable_boundaries=bounds, algorithm_parameters=algorithm_param)
# Run the genetic algorithm for 100 generations with a population size of 20
ga_model.run()
# Get the best weights found by the genetic algorithm
weights = ga_model.best_variable
```

Fig 6.44 GENETIC ALGORITHM – finding best fit of weights for ensemble model

```
The best solution found:
[0.98098415 0.0231155 ]

Objective function:
-0.994685594269457
```




```
In [56]: ensemble_pred1 = np.average([dt_pred1, lstm_pred1], axis=0, weights=weights)
         initial_score = np.mean(ensemble_pred1 == tar_test)
         print("Initial ensemble accuracy: {:.2f}%".format(initial_score*100))

         Initial ensemble accuracy: 93.40%

In [57]: ensemble_pred2 = np.average([dt_pred_val1, lstm_pred_val1], axis=0, weights=weights)
         initial_score = np.mean(ensemble_pred2 == tar_val)
         print("Initial ensemble accuracy: {:.2f}%".format(initial_score*100))

         Initial ensemble accuracy: 93.38%
```

Fig 6.45 ACCURACY AND PREDICTION OF ENSEMBLE MODEL – Shows the best fit weight and the accuracy of the model using those weights.

```
In [59]: y_pred_ensemble = np.array([np.argmax(np.bincount([dt_pred1[i], lstm_pred1[i]])) for i in range(len(dt_pred1))])
         from collections import Counter
         count = Counter(y_pred_ensemble)

         print(count)

         Counter({0: 293784, 4: 69183, 10: 48386, 2: 38643, 3: 2920, 7: 1883, 5: 1624, 6: 1584, 11: 869, 1: 347})

In [61]: y_pred_ensemble1 = np.array([np.argmax(np.bincount([dt_pred_val1[i], lstm_pred_val1[i]])) for i in range(len(dt_pred
         from collections import Counter
         count = Counter(y_pred_ensemble1)

         print(count)

         Counter({0: 137542, 4: 32224, 10: 22321, 2: 17809, 3: 1324, 7: 1032, 5: 754, 6: 743, 11: 400, 1: 155})
```

Fig 6.46 OUTCOMES OF ENSEMBLE MODEL – Shows the predicted classes and no of instances in their respective class.

```
[ ] sns.set_context('notebook', font_scale= 1.3)
    fig, ax = plt.subplots(1, 2, figsize = (25,  8))
    ax1 = plot_confusion_matrix(tar_test, y_pred_ensemble, ax= ax[0], cmap= 'YlGnBu'
```

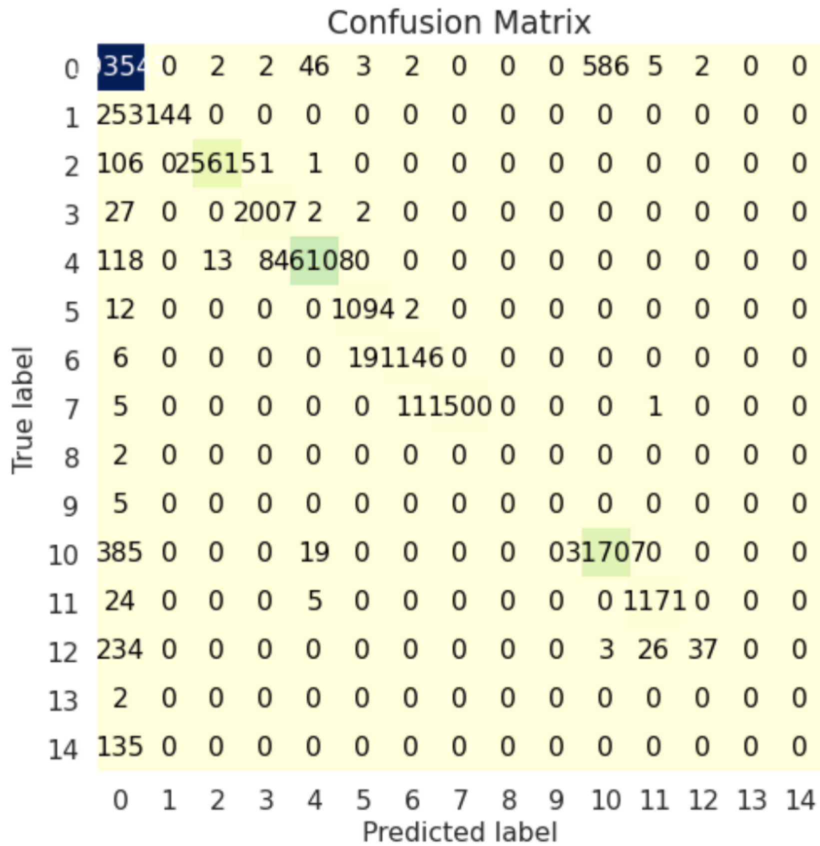


Fig 6.47 CONFUSION MATRIX OF ENSEMBLE MODEL

```
[12] from sklearn import preprocessing
     label_encoder = preprocessing.LabelEncoder()
     label_encoder.fit(df[' Label'])
     cn = dict(zip(label_encoder.classes_, label_encoder.transform(label_encoder.classes_)))

     for i in cn:
       print(i + '\n')
```

```
BENIGN

Bot

DDoS

DoS GoldenEye

DoS Hulk

DoS Slowhttptest

DoS slowloris

FTP-Patator

Heartbleed

Infiltration

PortScan

SSH-Patator

Web Attack � Brute Force

Web Attack � Sql Injection

Web Attack � XSS
```

Fig 6.48 CLASSES IN THE DATASET

CHAPTER 7
METRICS FOR EVALUATION

THRESHOLD METRICS:

- **Classification Rate (CR):** Classification rate is a metric that measures the accuracy of a classifier, or how well it can predict the correct class label of a data point.

Classification Rate = Number of Correct Predictions / Total Number of Predictions

- **F Measure (FM):** F-measure is a metric used to measure the accuracy of a classification model. It is a harmonic mean between precision and recall.

F-measure = 2 * (Precision * Recall) / (Precision + Recall)

RANKING METRICS:

- **Accuracy:** It is the percentage of correctly predicted labels out of all instances in the dataset.

Accuracy = (Number of Correct Predictions) / Total Number of Predictions

- **Recall:** Recall measures the proportion of actual positive instances that are correctly identified by the model as positive.

$$\textbf{Recall} = \textbf{True Positives} / (\textbf{True Positives} + \textbf{False Negatives})$$

- **Precision (PR):** Precision is a measure of the accuracy of a measurement or a system that produces measurements.

Precision = (Number of correctly estimated measurements / Total number of measurements) x 100

- **Area Under ROC Curve (AUC):** AUC, or Area Under the Receiver Operating Characteristic Curve, is a metric used to measure the performance of a binary classifier. It is a way to measure the accuracy and power of a classifier. AUC measures the area under the ROC curve, which is a graph of the true positive rate against the false positive rate.

$$\mathbf{AUC} = \int_{0}^{1} \mathbf{ROC}(t)\,dt$$

PROBABILITY METRICS:

- **Root Mean Square Error (RMSE):** Root Mean Square Error (RMSE) is a measure of how well a model fits a dataset. It is the average of the squared differences between the observed values and the predicted values.

$$\mathbf{RMSE} = \sqrt{\left(\sum (\text{predicted} - \text{observed})^2 / n\right)}$$

CHAPTER 8
TEST CASES

TEST CASE NUMBER	INPUT DATASET	ENSEMBLE MODEL'S ACCURACY	CLASSIFICATION RATE	RESULT
1	test_dataset.csv	93.4%	0.98	passed
2	Val_data.csv	92%	0.95	passed
3	Val_data1.csv	70%	0.79	30% failed

In 3rd test case, this model got less correct predictions because that dataset contains some of the classes which has less instances when the model trained.

CHAPTER 9
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