Exp-1 Introduction to Intrusion Detection System Tools and frameworks

Aim : To understand the functionality, types, and practical use of Intrusion Detection System (IDS) tools and frameworks for detecting and mitigating cybersecurity threats.

IDS:

An Intrusion Detection System (IDS) is a security tool that monitors a computer network or systems for malicious activities or policy violations. It helps detect unauthorized access, potential threats, and abnormal activities by analyzing traffic and alerting administrators to take action. An IDS is crucial for maintaining network security and protecting sensitive data from cyber-attacks.

Types

- Network Intrusion Detection System (NIDS)
- Host Intrusion Detection System (HIDS)
- Protocol-Based Intrusion Detection System (PIDS)
- Application Protocol-Based Intrusion Detection System (APIDS)
- Hybrid Intrusion Detection System:

Tools and frameworks

1.SNORT

2.Suricata

3.OSSEC

4.Tripwire

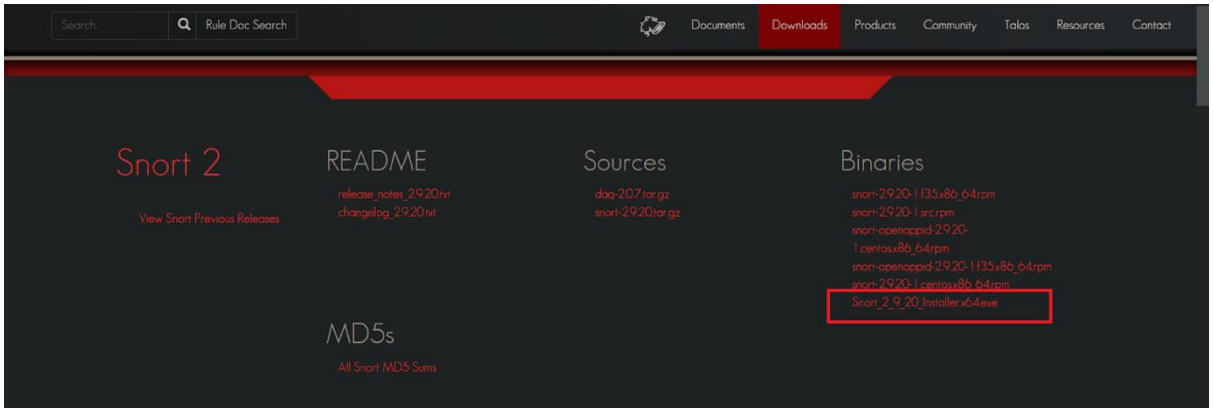
5.Zeek

1.SNORT- Snort is an open-source network intrusion detection system (IDS) and intrusion prevention system (IPS) developed by Cisco. It is highly regarded for its ability to perform real-time traffic analysis and packet logging.

Steps to Install and Configure snort:

Step 1: Download Snort

1. Visit the official Snort download page
2. Download the latest Windows installer for Snort.

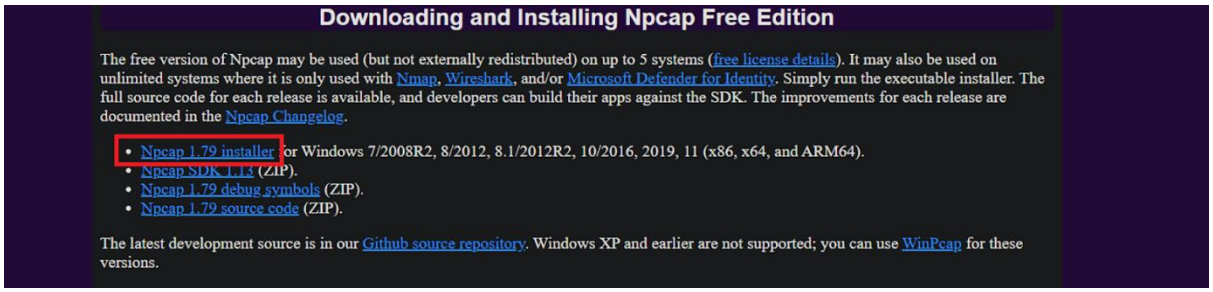


Step 2: Install WinPcap or Npcap

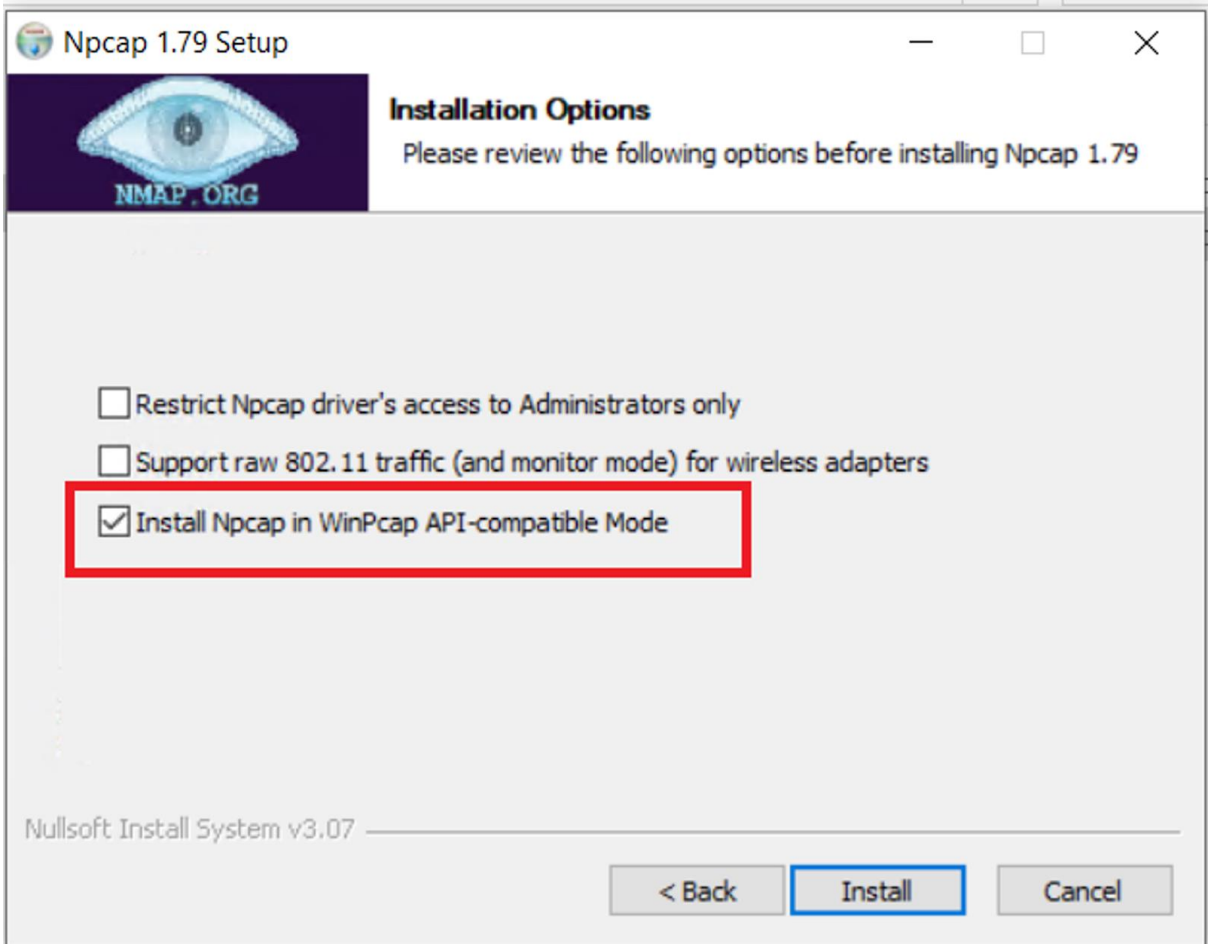
Snort requires a packet capture library like WinPcap or Npcap to capture network traffic.

Download and Install Npcap (recommended):

- Visit the Npcap download page
- Download the latest version of Npcap.



- Run the installer and follow the on-screen instructions to complete the installation.
- Make sure to select the option to install Npcap in "WinPcap API-compatible mode".



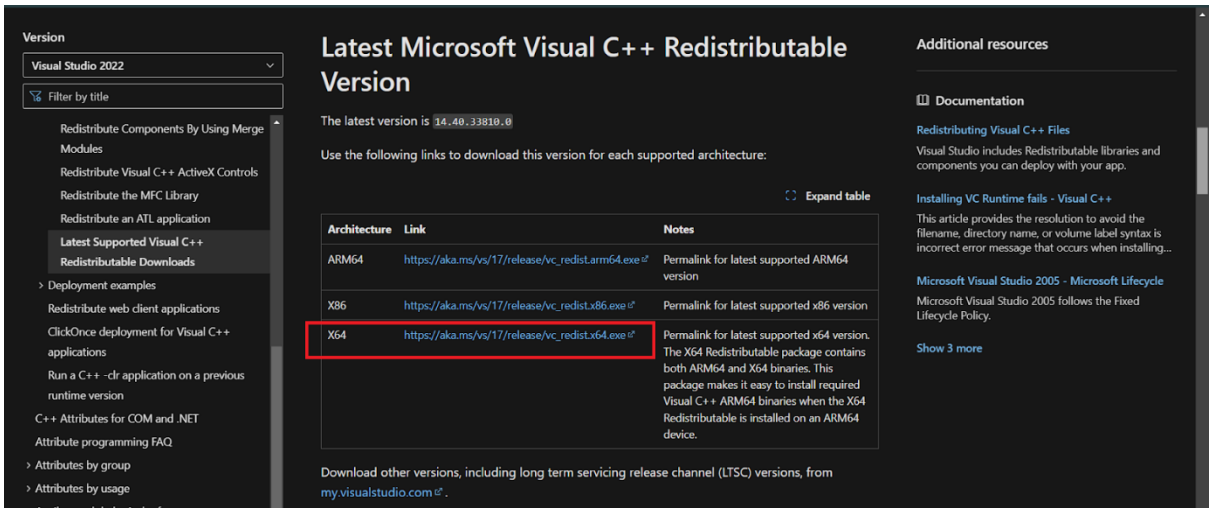
Step 3: Install Visual C++ Redistributable

Snort requires the Visual C++ Redistributable package to run correctly.

1. **Download and Install Visual C++ Redistributable**: some text
    - Go to the official Microsoft download page for Visual C++ Redistributable

- Download and install the Visual C++ Redistributable for Visual Studio 2015, 2017, 2019, and 2022:

  - Visual C++ Redistributable x86
  - Visual C++ Redistributable x64



Download and Update Rule Files: If you need additional rules other than the official snort rules

Step 4: Install Snort

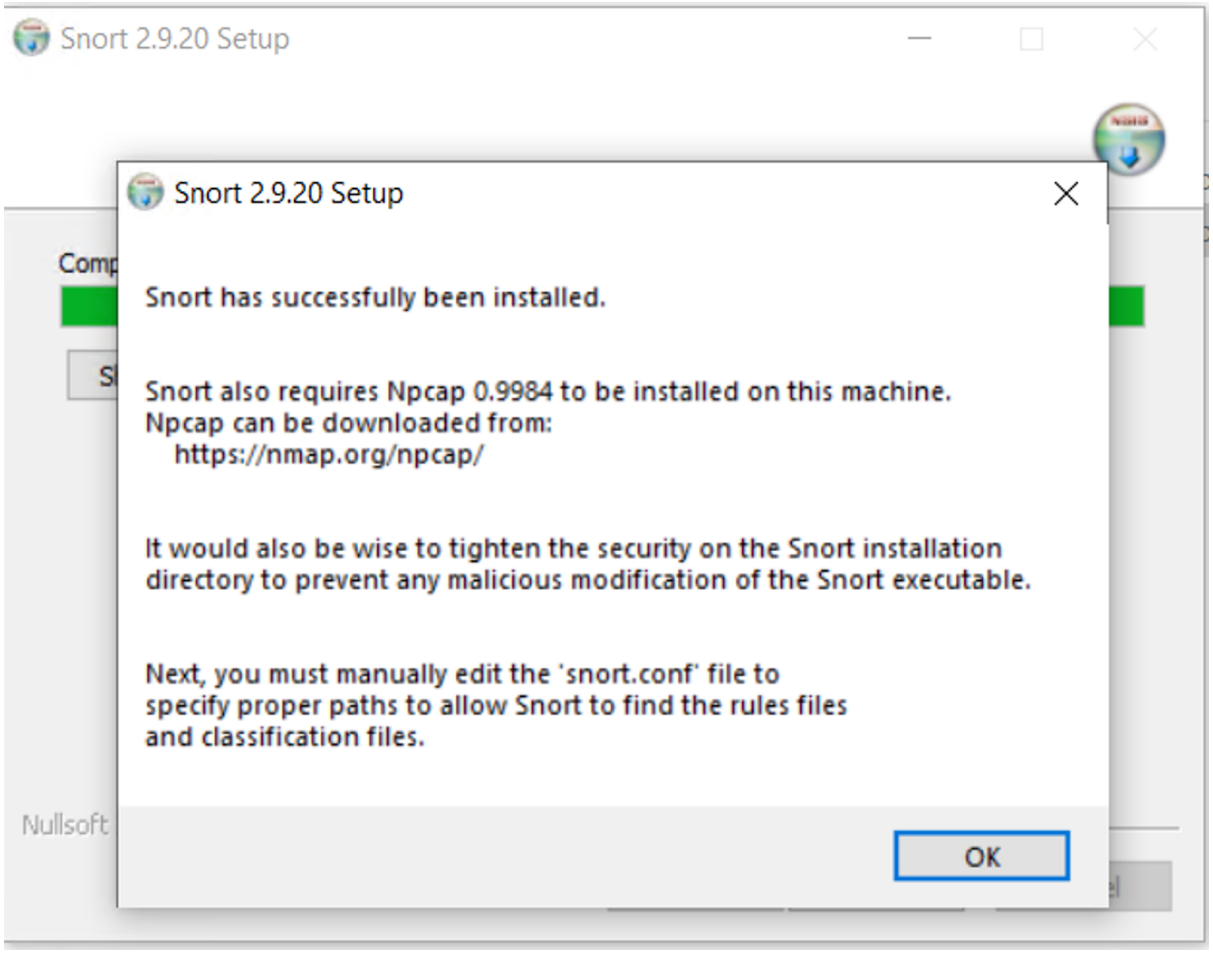
- Locate the downloaded Snort installer (typically named something like snort-2.9.x.x-installer.exe).

- Double-click the installer to start the installation process.

- Follow the on-screen instructions to complete the installation. Here are the typical steps:

  - **Welcome Screen**: Click "Next" to proceed.

- **License Agreement**: Read and accept the license agreement, then click "Next".
- **Choose Installation Location**: Select the directory where you want to install Snort or leave it at the default location, then click "Next".
- **Ready to Install**: Click "Install" to begin the installation.
- **Installation Complete**: Click "Finish" to complete the installation.



Step 5: Configure Snort

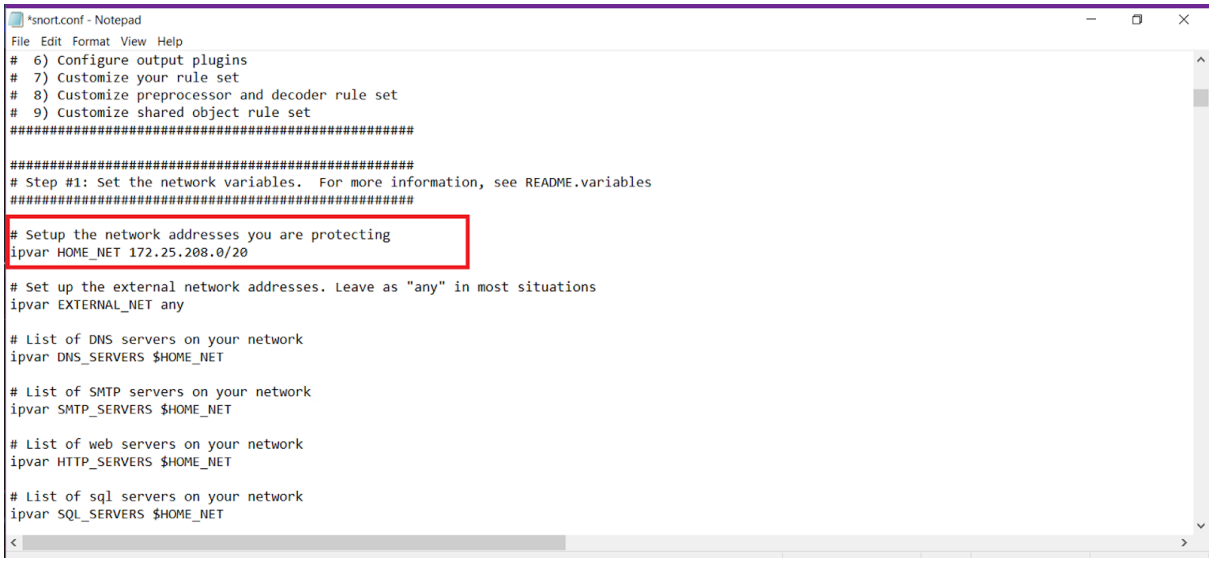
Locate Snort Configuration File:

- Navigate to the directory where Snort is installed (e.g., C:\\Snort).
- Open the etc directory and locate the snort.conf file.

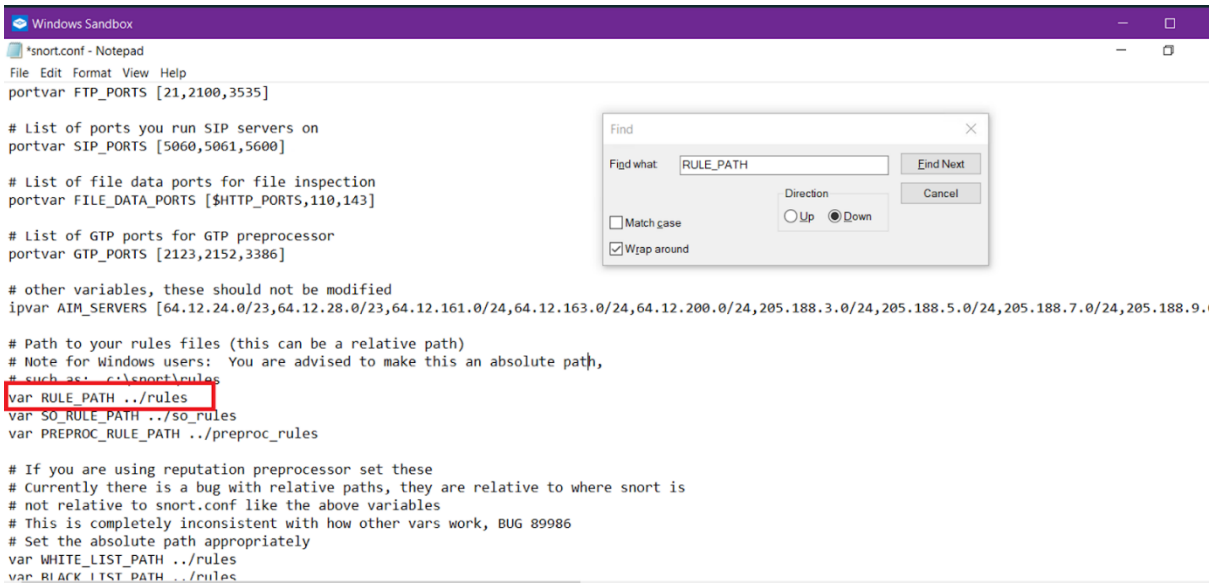
Edit Snort Configuration File:

- Open snort.conf with a text editor like Notepad++.

- Configure the network settings by editing the ipvar HOME_NET variable to match your network configuration. For example: ipvar HOME_NET 192.168.1.0/24

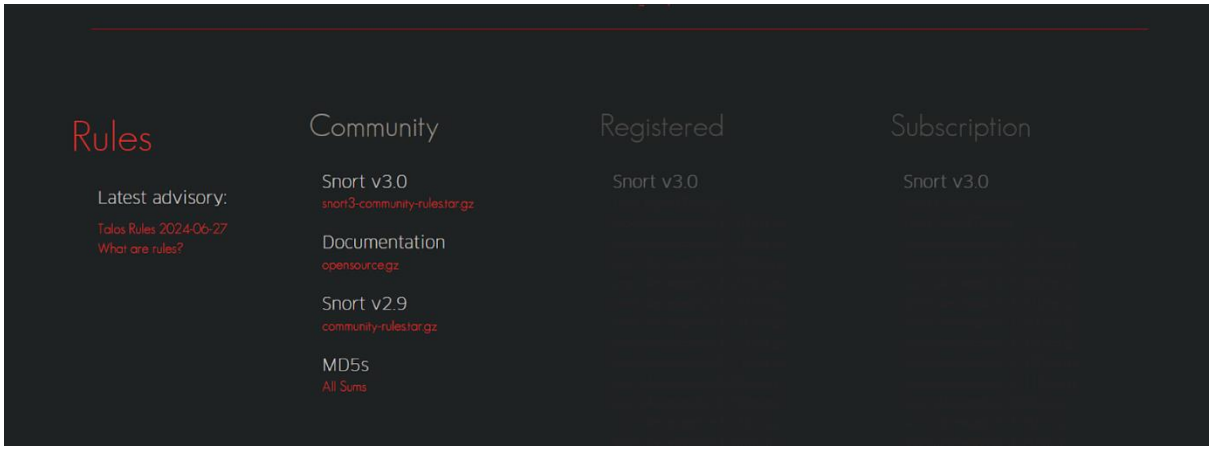


- You can get the network information using ipconfig /all
- Configure the path to the rule files. Ensure the var RULE_PATH variable points to the correct directory where the rule files are stored.



Download and Update Rule Files: If you need additional rules other than the official snort rules

- Visit the Snort rules download page
- Download the latest community rules or registered rules.

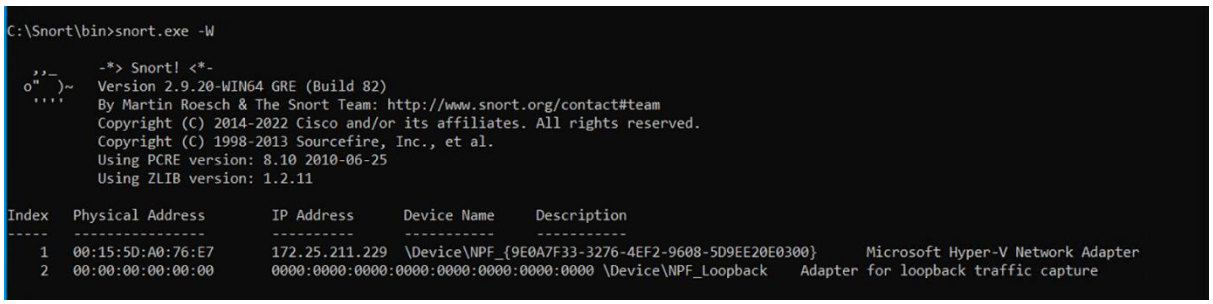


- Extract the downloaded rule files and place them in the rules directory of your Snort installation (e.g., C:\\Snort\\rules).

- Update the include statements in snort.conf to include the rule files you downloaded. For example: include $RULE_PATH/community.rules

Step 6: Running Snort

1. Open the command prompt as an administrator.
2. Navigate to the Snort installation directory (e.g., C:\\Snort\\bin).
3. Run Snort with the following command: Replace <interface> with the number corresponding to your network interface. You can find the interface number by running snort -W.

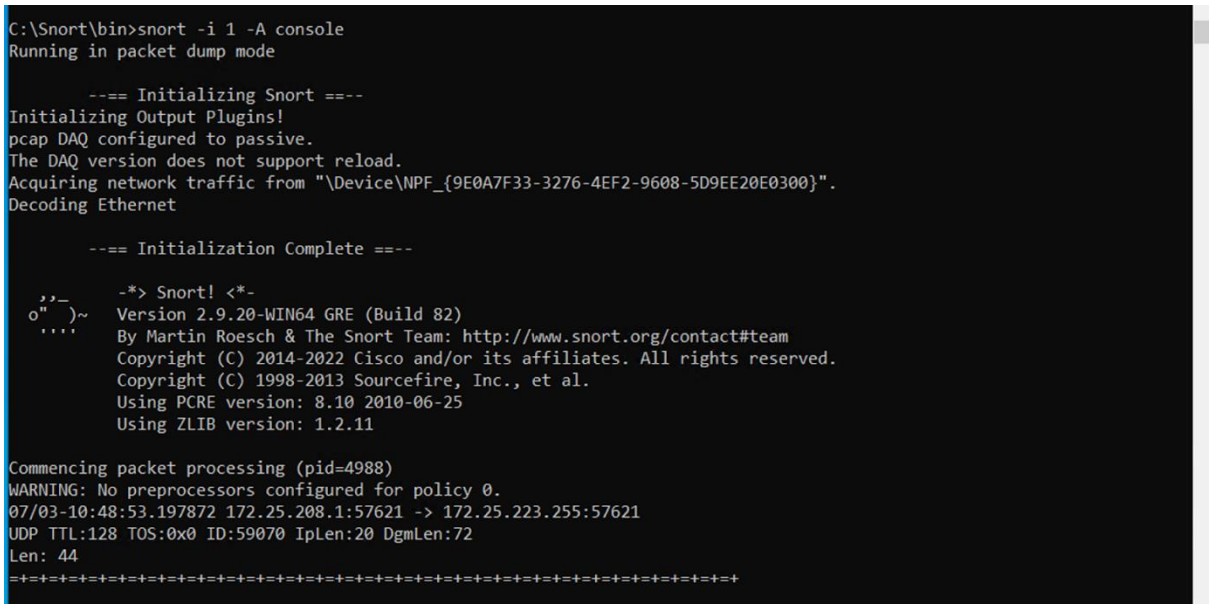


snort -i <interface> -A console

- **Note:** You can choose the index of the interface directly like this

Step 7: Verify Snort Installation

1. Snort should start and begin analyzing network traffic based on the configured rules.
2. Monitor the console output for alerts and notifications.



Useful Commands

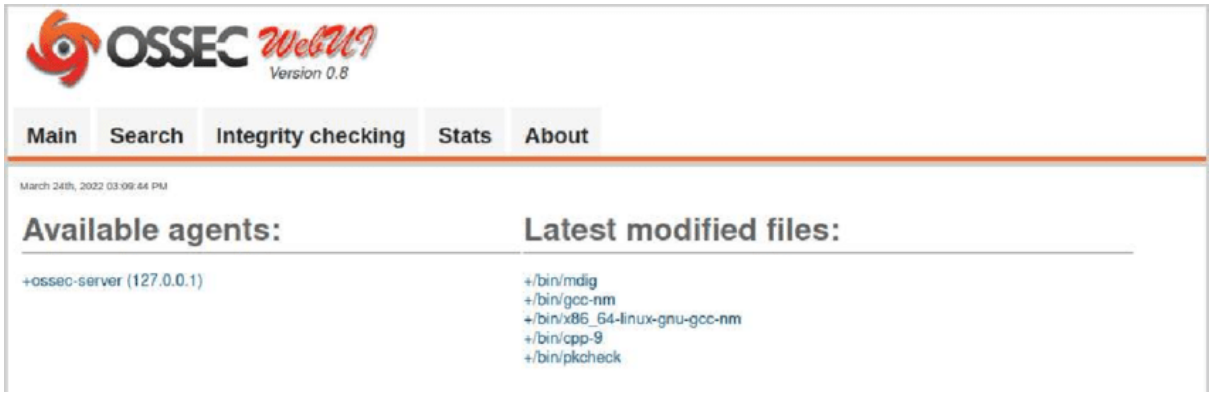
- To list available network interfaces: snort -W

Different SNORT Modes:

1. **Sniffer Mode –**
   To print TCP/IP header use command **./snort -v**
   To print IP address along with header use command **./snort -vd**

2. **Packet Logging –**
   To store packet in disk you need to give path where you want to store the logs. For this command is**./snort -dev -l ./SnortLogs**.
3. **Activate network intrusion detection mode –**
   To start this mode use this command **./snort -dev -l ./SnortLogs -h 192.127.1.0/24 -c snort.conf**

2.OSSEC-OSSEC is a scalable, multi-platform, open source **Host-based Intrusion Detection System (HIDS).** OSSEC has a powerful correlation and analysis engine, integrating log analysis, file integrity monitoring, Windows registry monitoring, centralized policy enforcement, rootkit detection, real-time alerting and active response. It runs on most operating systems, including Linux, OpenBSD, FreeBSD, MacOS, Solaris and Windows.



Result:

Thus the functionalities,types and practical uses of IDS tools and frameworks for detecting and mitigating cyber security threats are successfully studied.

EX.2 Impement a Signature Based IDS

Aim:

To implement a signature-based Intrusion Detection System (IDS) using Python, capable of monitoring network traffic in real-time and identifying potential threats by matching packets against predefined attack signatures, ensuring enhanced network security."

1. Prerequisites

Install Required Software:

- **Install Python**:
  - Ensure you have Python 3 installed on your system.
  - To check: python --version or python3 --version.
- **Install Scapy**:
  - Scapy is a library used for packet sniffing. Install it using:

Use in cmd prompt to install scapy: pip install scapy

For Windows Users:

1. Install **Npcap** (required for packet sniffing):
   - Download and install it from Npcap.
   - During installation, ensure the option **"Install Npcap in WinPcap API-compatible Mode"** is checked.

For Linux Users:

- Use sudo to run the script since sniffing requires administrative privileges:

  sudo python ids.py

SCAPY:

Scapy is an open-source Python library that allows users to create, send, and analyze network packets.

PROGRAM:

```
from scapy.all import sniff

import sys


# Define the IP address and port you want to monitor

TARGET_IP = "192.168.2.2"  # Example IP address (replace with the IP you're targeting)

TARGET_PORT = 8080  # Example port (replace with the port you're targeting)



# Define the callback function that will handle the sniffed packets

def packet_alert(packet):

    # Check if the packet has an IP layer (for both TCP and ICMP packets)

    if packet.haslayer('IP'):
```

```
    src_ip = packet['IP'].src
    dest_ip = packet['IP'].dst

    # Print all packets
    print(f"Packet from {src_ip} to {dest_ip}")

    # Check if the packet has a TCP layer
    if packet.haslayer('TCP'):
        src_port = packet['TCP'].sport
        dest_port = packet['TCP'].dport

        # Only alert if the packet matches the target IP or port
        if src_ip == TARGET_IP or dest_ip == TARGET_IP:
            print(f"[ALERT] Malicious TCP packet detected from {src_ip}
to {dest_ip}, "
                  f"source port: {src_port}, destination port: {dest_port}")
        else:
            print(f"[SAFE] TCP packet detected from {src_ip} to
{dest_ip}, "
                  f"source port: {src_port}, destination port: {dest_port}")

    # Check if the packet has an ICMP layer (ping packets)
    elif packet.haslayer('ICMP'):
```

```
        # ICMP doesn't have ports, so we just check the IP
        if src_ip == TARGET_IP or dest_ip == TARGET_IP:
            print(f"[ALERT] Malicious ICMP packet detected from {src_ip} to {dest_ip}")
        else:
            print(f"[SAFE] ICMP packet detected from {src_ip} to {dest_ip}")


# Function to start sniffing the network
def start_sniffing():
    print("Starting packet sniffing...")
    sniff(prn=packet_alert, store=0, filter="ip")  # Sniff IP packets


if __name__ == "__main__":
    start_sniffing()
```

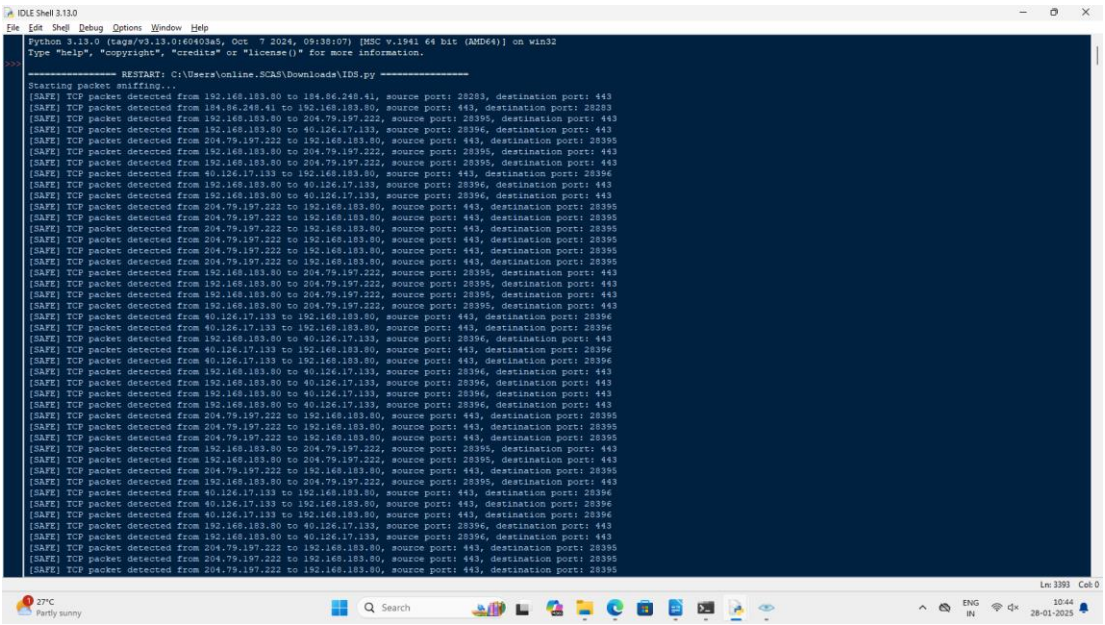
STEP:2-WORKING PROCESS

Key Components:

1. **Attack Signatures**:
    - These are predefined conditions to detect malicious activities.
    - The code detects:

- **Malicious IP**: Traffic from/to 192.168.1.100.
- **Malicious Port**: Traffic to port 8080.

2. **Packet Sniffing**:
    - The code uses the scapy.sniff function to capture network packets in real-time.
3. **Detection Logic**:
    - Each packet is inspected for:
        - Source/Destination IP matching malicious_ip.
        - Destination port matching malicious_port.
        - Payload containing malicious_payload.
4. **Alerts**:
    - If a match is found, the program prints an alert to the terminal.
5. **Network Interface :**



- The script prompts you to enter the interface to monitor traffic (e.g., eth0 or wlan0).

STEP:3-

Generate Traffic:

1. **Malicious IP Test**:
    - Simulate traffic to/from the malicious IP
2.
3.

2.Malicious Port Test:

- Send traffic to the malicious port.

Eg: echo "Test Traffic" | nc 192.168.1.200. 8111

3. Stop the IDS

- To stop the IDS, press **Ctrl + C**.

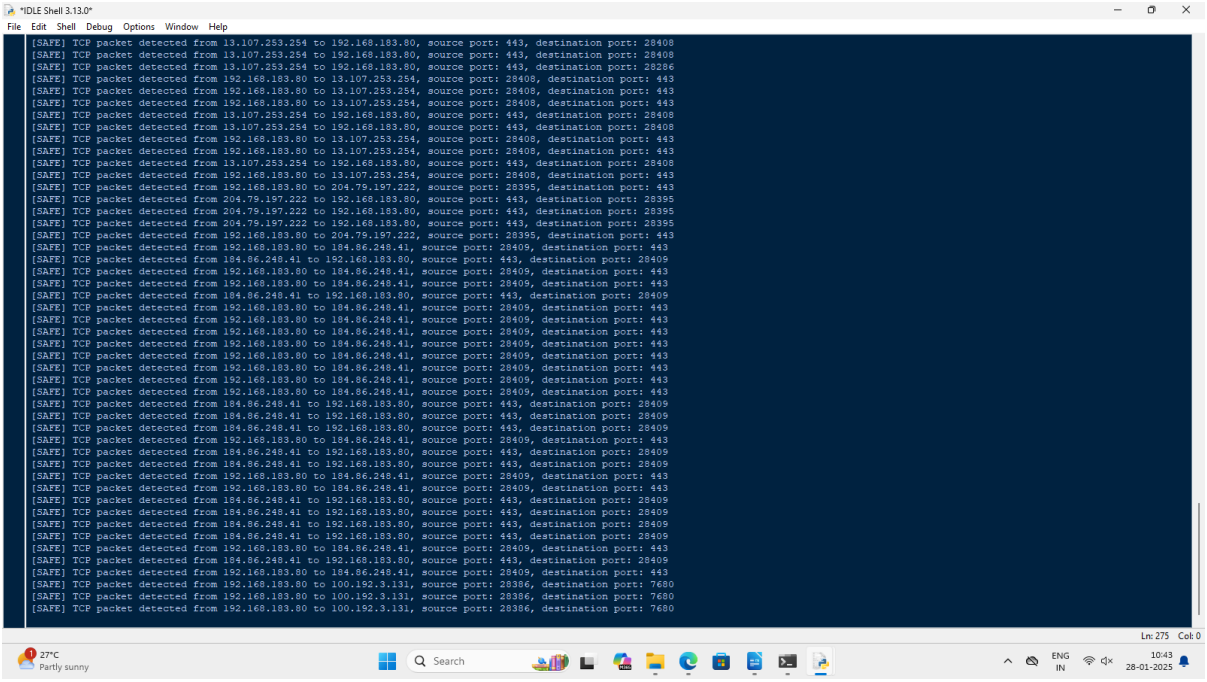
STEP:7-

If no packets are captured:

- Ensure you are monitoring the correct network interface.
- Run the script with elevated privileges (e.g., sudo on Linux).

- For Windows, verify that Npcap is installed correctly.

OUTPUT:


IDLE Shell 3.13.0
File Edit Shell Debug Options Window Help
[SAFE] TCP packet detected from 13.107.253.254 to 192.168.183.80, source port: 443, destination port: 28408
[SAFE] TCP packet detected from 13.107.253.254 to 192.168.183.80, source port: 443, destination port: 28408
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[SAFE] TCP packet detected from 192.168.183.80 to 13.107.253.254, source port: 28408, destination port: 443
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[SAFE] TCP packet detected from 192.168.183.80 to 13.107.253.254, source port: 28408, destination port: 443
[SAFE] TCP packet detected from 192.168.183.80 to 204.79.197.222, source port: 28395, destination port: 443
[SAFE] TCP packet detected from 204.79.197.222 to 192.168.183.80, source port: 443, destination port: 28395
[SAFE] TCP packet detected from 204.79.197.222 to 192.168.183.80, source port: 443, destination port: 28395
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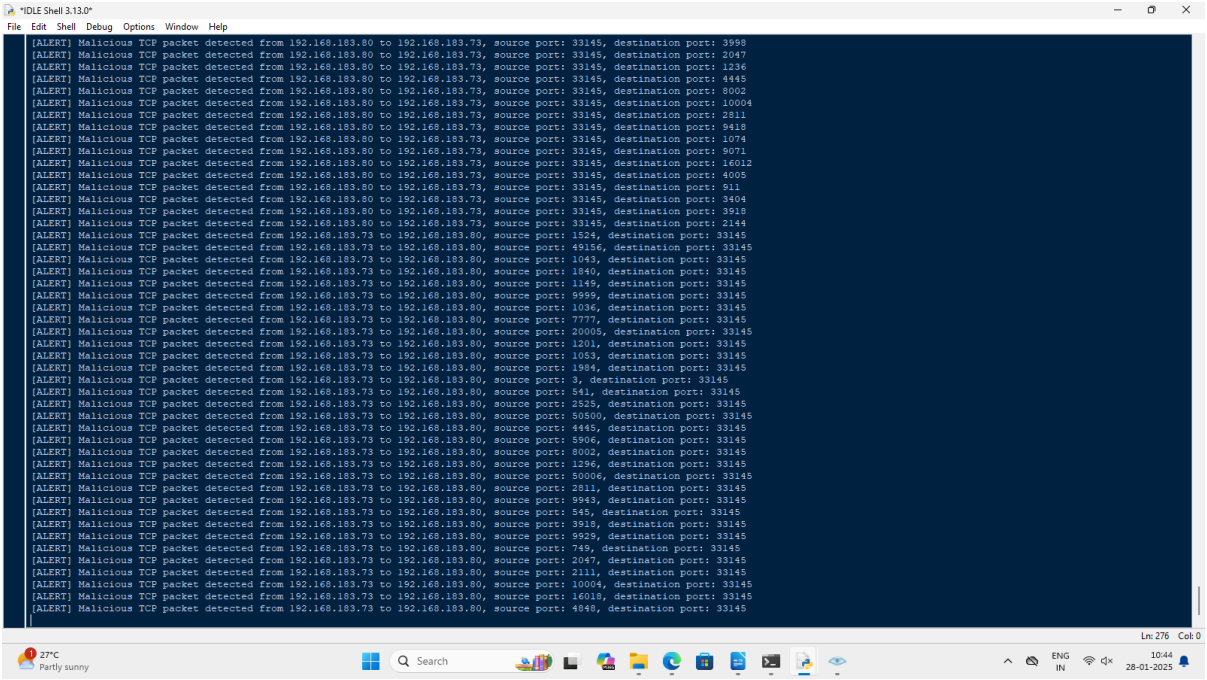
[SAFE] TCP packet detected from 192.168.183.80 to 184.86.248.41, source port: 28409, destination port: 443
[SAFE] TCP packet detected from 184.86.248.41 to 192.168.183.80, source port: 443, destination port: 28409
[SAFE] TCP packet detected from 192.168.183.80 to 184.86.248.41, source port: 28409, destination port: 443
[SAFE] TCP packet detected from 192.168.183.80 to 100.192.3.131, source port: 28386, destination port: 7680
[SAFE] TCP packet detected from 192.168.183.80 to 100.192.3.131, source port: 28386, destination port: 7680
[SAFE] TCP packet detected from 192.168.183.80 to 100.192.3.131, source port: 28386, destination port: 7680
Ln: 275 Col: 0
27°C Partly sunny
Search
ENG IN
10:43 28-01-2025


IDLE Shell 3.13.0
File Edit Shell Debug Options Window Help
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 3998
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 2047
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 1236
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 4445
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 8002
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 10004
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 2811
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 9418
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 1074
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 9071
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 16012
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 4005
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 911
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 3404
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 3918
[ALERT] Malicious TCP packet detected from 192.168.183.80 to 192.168.183.73, source port: 33145, destination port: 2144
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 1524, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 49156, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 1043, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 1040, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 1149, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 9999, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 1036, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 7777, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 20005, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 1201, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 1053, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 1984, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 3, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 541, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 2525, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 50500, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 4445, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 5906, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 8002, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 1296, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 50006, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 2811, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 9943, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 545, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 3918, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 9929, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 749, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 2047, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 2111, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 10004, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 16018, destination port: 33145
[ALERT] Malicious TCP packet detected from 192.168.183.73 to 192.168.183.80, source port: 4848, destination port: 33145
Ln: 276 Col: 0
27°C Partly sunny
Search
ENG IN
10:44 28-01-2025

RESULT:

The implementation of signature based intrusion detection system(IDS) is done successfully.

Implement an anomaly-based IDS using machine learning techniques

Aim :

Implement an anomaly-based IDS using machine learning technique

Algorithm :

Step 1: Load Dataset

1. Define **column names** based on the NSL-KDD dataset structure.
2. Load the **train** and **test** datasets from GitHub using requests.
3. Read the dataset into **pandas DataFrame**.

Step 2: Handle Categorical Data

1. Identify categorical columns: protocol_type, service, flag.
2. Convert these columns to **strings** to prevent type mismatches.
3. Use **Label Encoding** to convert categorical values into numeric values.
    - **Train the encoder** on both train & test data to avoid unseen categories.

Step 3: Handle Missing Values

1. **Replace** '?' values (if any) with NaN.
2. Use **SimpleImputer(strategy="mean")** to replace missing values with column means.
3. Ensure **no non-numeric columns remain** in the dataset.

Step 4: Prepare Features & Labels

1. **Separate features (X) and target labels (y)**:
    - X_train = train_data.drop(columns=["label"])
    - y_train = train_data["label"] (convert "normal" to 0, others to 1)
    - Do the same for test data.
2. Ensure **no NaN values exist** in X_train and X_test.

Step 5: Feature Scaling

1. Use StandardScaler() to **normalize** feature values.
2. Fit the scaler on **train data** and transform both train & test data.

Step 6: Train Model

1. Initialize **RandomForestClassifier** (n_estimators=100).
2. **Train** the model using clf.fit(X_train_scaled, y_train).

Step 7: Predict & Evaluate

1. **Make predictions** on test data.
2. **Calculate accuracy** using accuracy_score(y_test, y_pred).
3. **Print classification report** to analyze performance.

Step 8: Test the Model (Optional)

- Provide a **new data point** to the trained model.
- Convert & preprocess the input.
- Predict the class (attack or normal).

Program :

```
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.impute import SimpleImputer  # New import for handling NaNs
from sklearn.metrics import accuracy_score, classification_report
import requests
from io import StringIO

# Load NSL-KDD dataset
def load_nsl_kdd(url, column_names):
    response = requests.get(url)
    if response.status_code == 200:
        return pd.read_csv(StringIO(response.text), names=column_names)
    else:
```

```
        print(f"Failed to download dataset: {response.status_code}")
        return None

# Column names for NSL-KDD dataset
columns = [
    "duration", "protocol_type", "service", "flag", "src_bytes", "dst_bytes", "land",
    "wrong_fragment", "urgent", "hot", "num_failed_logins", "logged_in",
    "num_compromised", "root_shell", "su_attempted", "num_root", "num_file_creations",
    "num_shells", "num_access_files", "num_outbound_cmds", "is_host_login",
    "is_guest_login", "count", "srv_count", "serror_rate", "srv_serror_rate",
    "rerror_rate", "srv_rerror_rate", "same_srv_rate", "diff_srv_rate",
    "srv_diff_host_rate", "dst_host_count", "dst_host_srv_count",
    "dst_host_same_srv_rate", "dst_host_diff_srv_rate",
    "dst_host_same_src_port_rate", "dst_host_srv_diff_host_rate",
    "dst_host_serror_rate", "dst_host_srv_serror_rate", "dst_host_rerror_rate",
    "dst_host_srv_rerror_rate", "label"
]

train_url = "https://raw.githubusercontent.com/defcom17/NSL_KDD/master/KDDTrain+.txt"
test_url = "https://raw.githubusercontent.com/defcom17/NSL_KDD/master/KDDTest+.txt"

# Load datasets
train_data = load_nsl_kdd(train_url, columns)
test_data = load_nsl_kdd(test_url, columns)

# Ensure categorical columns exist and convert them to string
categorical_columns = ["protocol_type", "service", "flag"]
for col in categorical_columns:
    train_data[col] = train_data[col].astype(str)
    test_data[col] = test_data[col].astype(str)
```

```
# Encode categorical features
label_encoders = {}
for col in categorical_columns:
    le = LabelEncoder()

    # Fit encoder on combined train & test sets to handle unseen labels
    le.fit(pd.concat([train_data[col], test_data[col]], axis=0))

    # Transform both datasets
    train_data[col] = le.transform(train_data[col])
    test_data[col] = le.transform(test_data[col])

    label_encoders[col] = le  # Store for reference

# Handle missing values
train_data.replace("?", pd.NA, inplace=True)  # Replace '?' with NaN
test_data.replace("?", pd.NA, inplace=True)

train_data.fillna(-1, inplace=True)  # Fill NaNs with -1
test_data.fillna(-1, inplace=True)

# Convert all remaining object columns to numeric
for col in train_data.select_dtypes(include=['object']).columns:
    train_data[col] = pd.to_numeric(train_data[col], errors='coerce')

for col in test_data.select_dtypes(include=['object']).columns:
    test_data[col] = pd.to_numeric(test_data[col], errors='coerce')

# Prepare feature (X) and target (y) variables
```

Implement an anomaly-based IDS using machine learning techniques

```
X_train = train_data.drop(columns=["label"])
y_train = train_data["label"].apply(lambda label: 0 if label == "normal" else 1)

X_test = test_data.drop(columns=["label"])
y_test = test_data["label"].apply(lambda label: 0 if label == "normal" else 1)

# Check for NaNs before scaling
print(" Checking NaN values before scaling...")
print(X_train.isnull().sum().sum(), " NaNs in X_train")
print(X_test.isnull().sum().sum(), " NaNs in X_test")

# Impute missing values (replace NaNs with column mean)
imputer = SimpleImputer(strategy="mean")
X_train_imputed = imputer.fit_transform(X_train)
X_test_imputed = imputer.transform(X_test)

# Scale features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train_imputed)
X_test_scaled = scaler.transform(X_test_imputed)

# Train RandomForest model
clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train_scaled, y_train)

# Predict and evaluate
y_pred = clf.predict(X_test_scaled)

accuracy = accuracy_score(y_test, y_pred)
report = classification_report(y_test, y_pred)
```

```
print("\n Model Evaluation Results:")
print(f"Accuracy: {accuracy:.4f}")
print("\n Classification Report:")
print(report)
```

Output :

```
🔍 Checking NaN values before scaling...
251946  NaNs in X_train
45088  NaNs in X_test

✅ Model Evaluation Results:
Accuracy: 1.0000

📊 Classification Report:
              precision    recall  f1-score   support

           1       1.00      1.00      1.00     22544

    accuracy                           1.00     22544
   macro avg       1.00      1.00      1.00     22544
weighted avg       1.00      1.00      1.00     22544
```

Experiment 4 - Configure IDS for IoT Networks

Aim:

To configure and deploy Suricata IDS on a Linux machine for detecting malicious traffic in an IoT network, specifically targeting MQTT and CoAP communication protocols.

Materials Required:

- Suricata IDS
- Scapy Python Library
- Linux VM
- Ethernet (eth0)

Theory:

This experiment aims to use Suricata IDS to detect IoT traffic, simulated using a python script. The MQTT (Message Queuing Telemetry Transport) Protocol and CoAP (Constrained Application Protocol) is widely used across all IoT devices. We will aim to configure the IDS to detect MQTT traffic and alert the user. Suricata will be configured by editing two main files, “suricata.yaml” & “iot.rules”.

Procedure:

Step 1: Install Suricata
-Update system packages and install Suricata

(kali@kali) $ sudo apt update
(kali@kali) $ sudo apt install -y suricata

(kali@kali) $ suricata –build-info

Step 2: Setup Suricata to detect IoT Traffic
-Edit the Suricata configuration file:

(kali@kali) $ sudo nano /etc/suricata/suricata.yaml

-**Modify network interface settings. Find the “af-packet” in the yaml file using “ctrl+f” and edit accordingly.**

af-packet:
interface: eth0
cluster-id: 98
cluster-type: cluster_flow

-Enable MQTT and CoAP protocol detection:

app-layer:
protocols:
mqtt:
enabled: yes
coap:
enabled: yes

-Update the rule-files category:

rule-files:
-iot.rules

-Create an IoT attack detection rule file:

(kali@kali) $ sudo nano /var/lib/suricata/rules/iot.rules

-Add detection rules for MQTT and CoAP traffic:

alert tcp any any -> any 1883 (msg:"Possible IoT MQTT Attack"; content:"MQTT"; sid:1000001;)

alert udp any any -> any 5683 (msg:"Possible IoT CoAP Attack"; content:"GET /"; sid:1000002;)

-Update Suricata once the rules are added.

(kali@kali) $ sudo suricata-update

-Restart Suricata to apply changes

(kali@kali) $ sudo systemctl restart suricata

-Step 3: Simulate IoT Traffic using Scapy

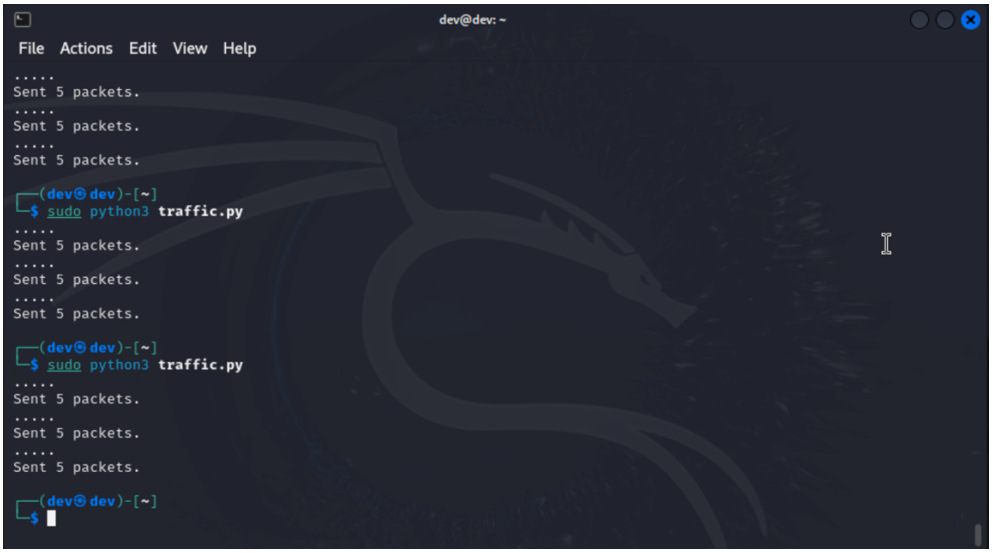
-Install scapy
(kali@kali) $ sudo apt install scapy

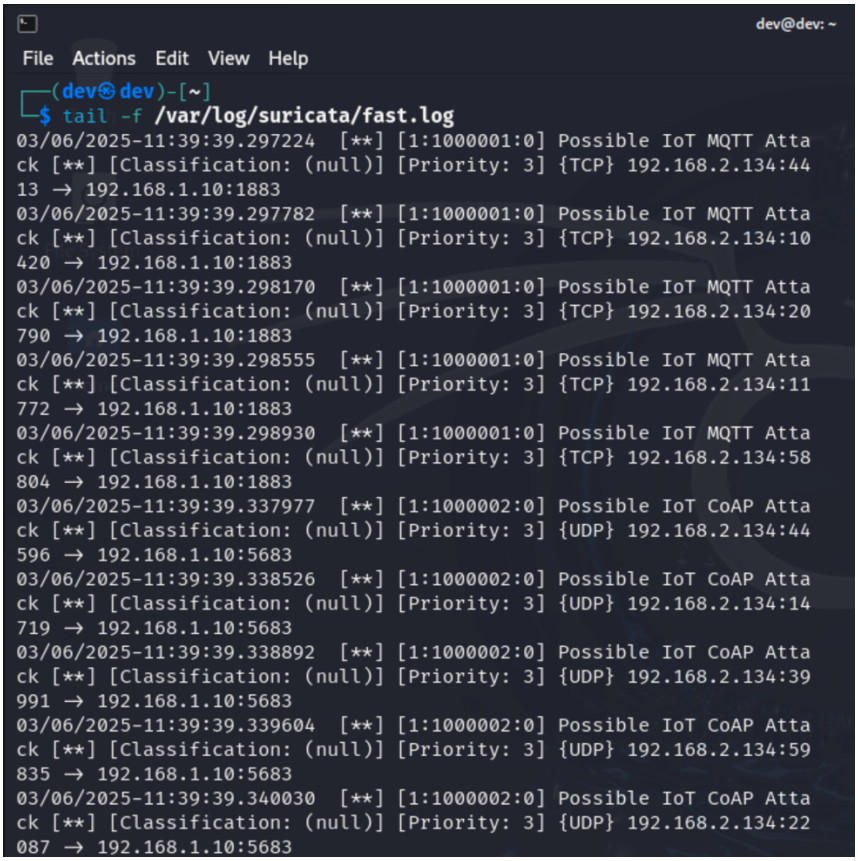
-Create a python script to generate MQTT and CoAP traffic:
```
from scapy.all import *
# This segment simulates MQTT traffic
ip = IP(dst="192.168.1.10")
tcp = TCP(dport=1883, sport=RandShort())
mqtt_payload = Raw(load="MQTT")
send(ip / tcp / mqtt_payload, count=5)

# This segment simulates CoAP traffic
udp = UDP(dport=5683, sport=RandShort())
coap_payload = Raw(load="GET /")
send(ip / udp / coap_payload, count=5)
```

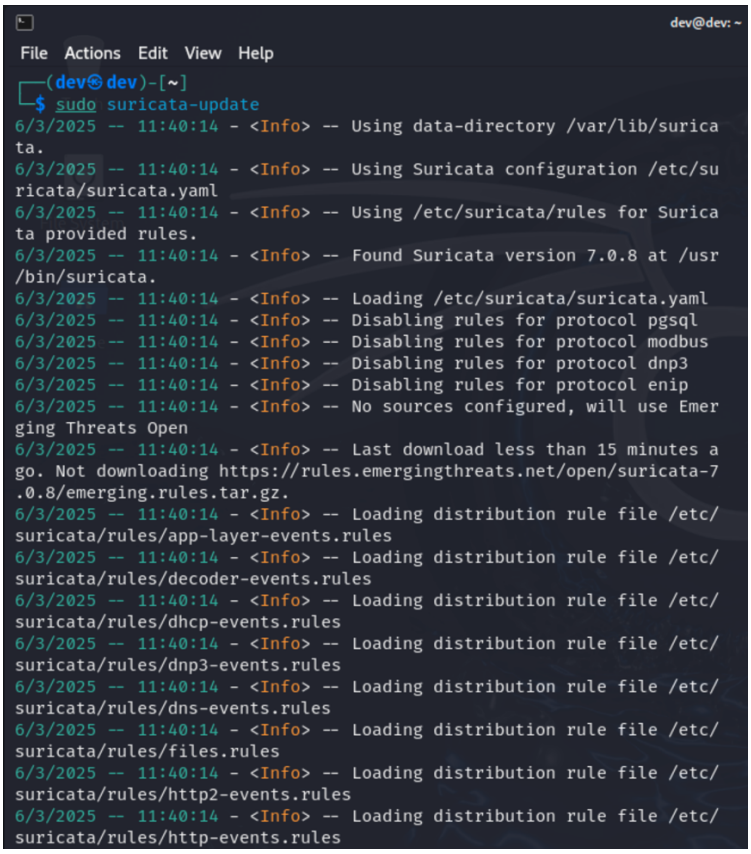
-Save the script as traffic.py and run the script to generate traffic, make sure Suricata is running:
(kali@kali) $ sudo python3 traffic.py

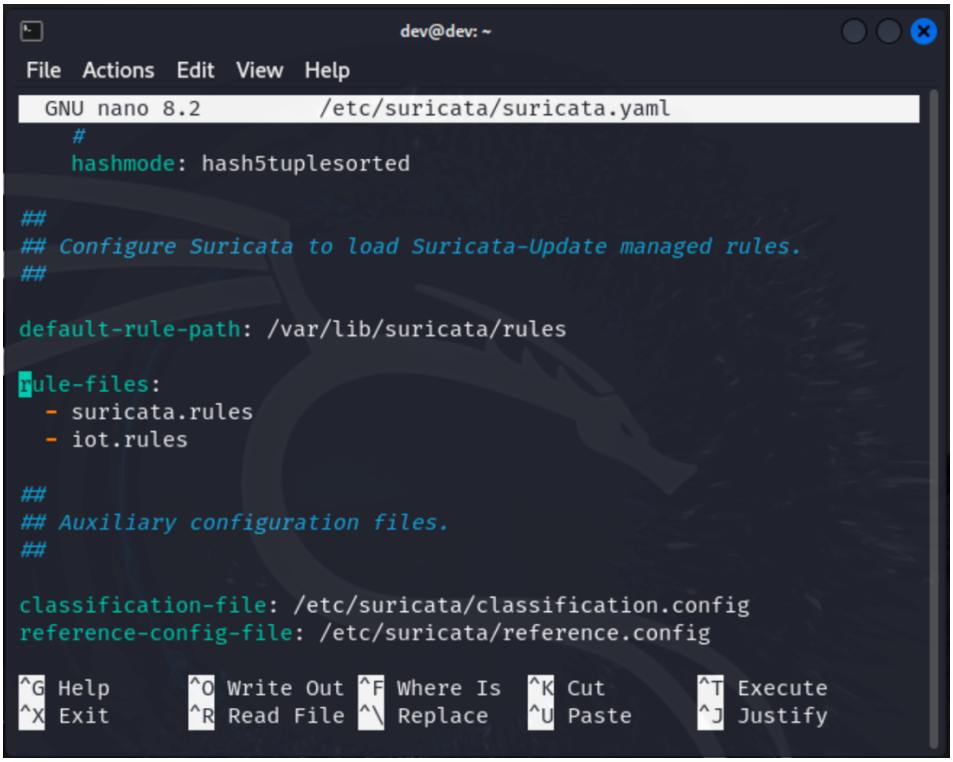
-Step 4: Monitor Suricata Alerts
-These logs should have the alerts saved.
(kali@kali) $ tail -f /var/log/suricata/fast.log

Output:




dev@dev: ~
File Actions Edit View Help
(dev㉿dev)-[~]
$ tail -f /var/log/suricata/fast.log
03/06/2025-11:39:39.297224 [**] [1:1000001:0] Possible IoT MQTT Atta
ck [**] [Classification: (null)] [Priority: 3] {TCP} 192.168.2.134:44
13 → 192.168.1.10:1883
03/06/2025-11:39:39.297782 [**] [1:1000001:0] Possible IoT MQTT Atta
ck [**] [Classification: (null)] [Priority: 3] {TCP} 192.168.2.134:10
420 → 192.168.1.10:1883
03/06/2025-11:39:39.298170 [**] [1:1000001:0] Possible IoT MQTT Atta
ck [**] [Classification: (null)] [Priority: 3] {TCP} 192.168.2.134:20
790 → 192.168.1.10:1883
03/06/2025-11:39:39.298555 [**] [1:1000001:0] Possible IoT MQTT Atta
ck [**] [Classification: (null)] [Priority: 3] {TCP} 192.168.2.134:11
772 → 192.168.1.10:1883
03/06/2025-11:39:39.298930 [**] [1:1000001:0] Possible IoT MQTT Atta
ck [**] [Classification: (null)] [Priority: 3] {TCP} 192.168.2.134:58
804 → 192.168.1.10:1883
03/06/2025-11:39:39.337977 [**] [1:1000002:0] Possible IoT CoAP Atta
ck [**] [Classification: (null)] [Priority: 3] {UDP} 192.168.2.134:44
596 → 192.168.1.10:5683
03/06/2025-11:39:39.338526 [**] [1:1000002:0] Possible IoT CoAP Atta
ck [**] [Classification: (null)] [Priority: 3] {UDP} 192.168.2.134:14
719 → 192.168.1.10:5683
03/06/2025-11:39:39.338892 [**] [1:1000002:0] Possible IoT CoAP Atta
ck [**] [Classification: (null)] [Priority: 3] {UDP} 192.168.2.134:39
991 → 192.168.1.10:5683
03/06/2025-11:39:39.339604 [**] [1:1000002:0] Possible IoT CoAP Atta
ck [**] [Classification: (null)] [Priority: 3] {UDP} 192.168.2.134:59
835 → 192.168.1.10:5683
03/06/2025-11:39:39.340030 [**] [1:1000002:0] Possible IoT CoAP Atta
ck [**] [Classification: (null)] [Priority: 3] {UDP} 192.168.2.134:22
087 → 192.168.1.10:5683


dev@dev: ~
File Actions Edit View Help
(dev㉿dev)-[~]
$ sudo suricata-update
6/3/2025 -- 11:40:14 - <Info> -- Using data-directory /var/lib/surica
ta.
6/3/2025 -- 11:40:14 - <Info> -- Using Suricata configuration /etc/su
ricata/suricata.yaml
6/3/2025 -- 11:40:14 - <Info> -- Using /etc/suricata/rules for Surica
ta provided rules.
6/3/2025 -- 11:40:14 - <Info> -- Found Suricata version 7.0.8 at /usr
/bin/suricata.
6/3/2025 -- 11:40:14 - <Info> -- Loading /etc/suricata/suricata.yaml
6/3/2025 -- 11:40:14 - <Info> -- Disabling rules for protocol pgsql
6/3/2025 -- 11:40:14 - <Info> -- Disabling rules for protocol modbus
6/3/2025 -- 11:40:14 - <Info> -- Disabling rules for protocol dnp3
6/3/2025 -- 11:40:14 - <Info> -- Disabling rules for protocol enip
6/3/2025 -- 11:40:14 - <Info> -- No sources configured, will use Emer
ging Threats Open
6/3/2025 -- 11:40:14 - <Info> -- Last download less than 15 minutes a
go. Not downloading https://rules.emergingthreats.net/open/suricata-7
.0.8/emerging.rules.tar.gz.
6/3/2025 -- 11:40:14 - <Info> -- Loading distribution rule file /etc/
suricata/rules/app-layer-events.rules
6/3/2025 -- 11:40:14 - <Info> -- Loading distribution rule file /etc/
suricata/rules/decoder-events.rules
6/3/2025 -- 11:40:14 - <Info> -- Loading distribution rule file /etc/
suricata/rules/dhcp-events.rules
6/3/2025 -- 11:40:14 - <Info> -- Loading distribution rule file /etc/
suricata/rules/dnp3-events.rules
6/3/2025 -- 11:40:14 - <Info> -- Loading distribution rule file /etc/
suricata/rules/dns-events.rules
6/3/2025 -- 11:40:14 - <Info> -- Loading distribution rule file /etc/
suricata/rules/files.rules
6/3/2025 -- 11:40:14 - <Info> -- Loading distribution rule file /etc/
suricata/rules/http2-events.rules
6/3/2025 -- 11:40:14 - <Info> -- Loading distribution rule file /etc/
suricata/rules/http-events.rules



Conclusion:

Hence, this experiment demonstrates how to setup Suricata IDS to monitor IoT network traffic and detect threats.

Cloud-Based Intrusion Detection System (IDS)

AIM

To set up a **cloud-based Intrusion Detection System (IDS)** using **Suricata**, a **Flask API**, and **Ngrok** to monitor network traffic and detect potential threats in real time.

MATERIALS REQUIRED

1. **Virtual Machine / System with Linux (Ubuntu/Kali)**
2. **Suricata (IDS Tool) Installed**
3. **Python (for Flask API)**
4. **Ngrok (for Cloud Exposure)**
5. **Internet Connection**

PROCEDURE

1️⃣ Install Suricata (IDS)

```
sudo apt update && sudo apt install suricata -y
```

Start Suricata in **IDS mode** (replace `eth0` with your network interface):

```
sudo suricata -c /etc/suricata/suricata.yaml -i eth0
```

📌 **Logs stored in:** `/var/log/suricata/fast.log`

2️⃣ Create a Flask API to View Alerts

Install Flask:

```
pip install flask
```

Create `suricata_api.py`:

```
from flask import Flask, jsonify

app = Flask(__name__)

def read_alerts():
    with open("/var/log/suricata/fast.log", "r") as file:
        return file.readlines()

@app.route('/')
def home():
    return "Suricata IDS is Running! Access alerts at /alerts"

@app.route('/alerts', methods=['GET'])
def get_alerts():
    return jsonify(read_alerts())

@app.route('/favicon.ico')  # Fix browser favicon issue
def favicon():
    return '', 204

if __name__ == '__main__':
    app.run(host='0.0.0.0', port=5000, debug=True)
```

Run the Flask API:

```
sudo python3 suricata_api.py
```

3️⃣ Install & Configure Ngrok

Install Ngrok:

```
curl -s https://ngrok-agent.s3.amazonaws.com/ngrok.asc | sudo tee /etc/apt/trusted.gpg.d/ngrok.asc
echo "deb https://ngrok-agent.s3.amazonaws.com buster main" | sudo tee /etc/apt/sources.list.d/ngrok.list
sudo apt update && sudo apt install ngrok
```

Authenticate Ngrok:

```
ngrok config add-authtoken YOUR_AUTH_TOKEN  #example: 2uTVTfhogolqutfNULhdlbHMnZ9_6zRRCZRXHnbKSp271YAk4
```

(Get your token from: https://dashboard.ngrok.com/get-started/your-authtoken)

Start Ngrok on Flask's Port:

```
ngrok http 5000
```

Get the Public URL (e.g., `https://xyz-1234.ngrok.io`)

✅ **Now access alerts globally (Primary OS):**

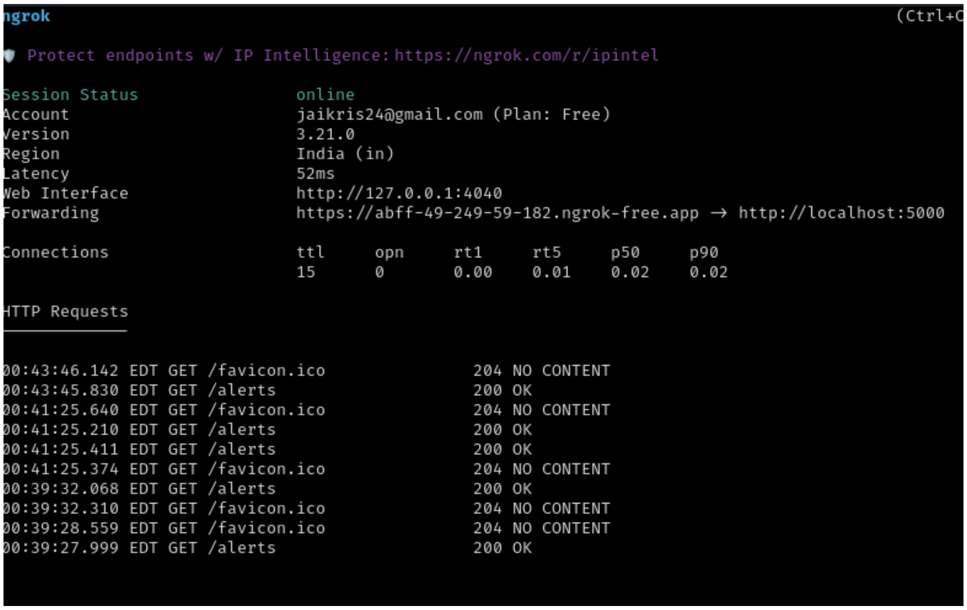
```
https://<YOUR_PUBLIC_ADDRESS>.ngrok-free.app/alerts
```

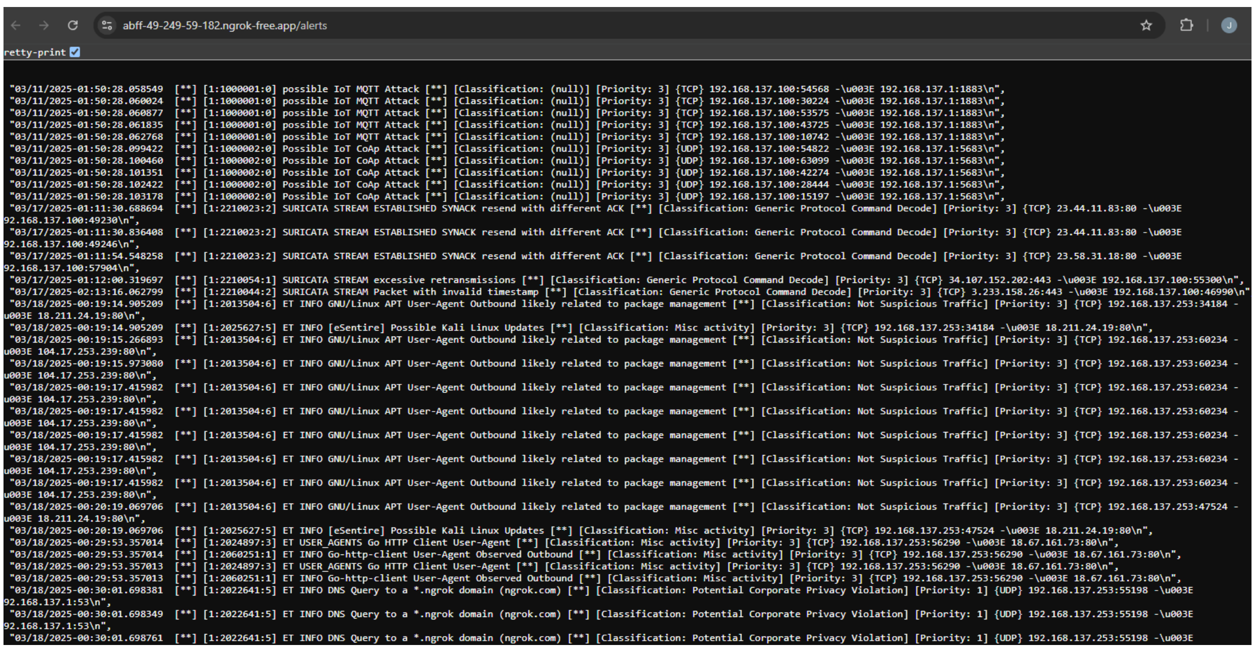
TEST CASE (Simulating an Attack)

From another system, run:

```
nmap -p 1-1000 <Your_VM_IPaddres>
```

OUTPUT :





RESULT :

Thus, the cloud based IDS has been configured and executed successfully.

Lab 6: Integrate IDS with SIEM System

Aim : Integrate Intrusion Detection System (IDS) with Security Information and Event Management (SIEM)Systems

Algorithm :

Step 1: Setup Syslog Configuration:

1. Define server details (IP address and port) where the SIEM is running (in this case, it's `192.168.15.3` and port `514`).
2. Create a syslog logger to handle the alerts and send them to the SIEM server.

Step 2: Create Syslog Handler :

1. Set up the syslog handler to send logs (IDS alerts) to the SIEM system.
2. The handler is connected to the SIEM using the specified server details.

Step 3: Format Logs:

1. Define how the log message will appear when sent to the SIEM. For example, you can set it to display the timestamp, the name of the logger, and the alert message.

Step 4: Generate IDS Alerts:

1. Create sample alerts that simulate real-world attack scenarios (e.g., SQL Injection, XSS, DoS attacks, etc.).
2. Randomize the IP address and attack type to make the alerts seem more dynamic and realistic.
3. Each alert will have a random port number and a unique alert ID to distinguish between them.

Step 5: Forward Alerts to SIEM:

1. Send the generated alert to the SIEM server using syslog.
2. The alert is logged and also displayed in the terminal for the user to see (for debugging or demonstration purposes).

Step 6: Simulate Continuous Alerts:

1. Loop indefinitely to simulate continuous IDS alerts.
2. Every 5 seconds, a new alert is generated and forwarded to the SIEM.
3. This simulates a real-time IDS system constantly monitoring for threats.

Step 7: Handle Interrupts:

1. The program runs continuously until the user interrupts the process (e.g., pressing Ctrl+C).
2. When interrupted, the program will stop and exit gracefully.

Program :

```
import logging

import logging.handlers

import time

import sys

import random


# Configuration for syslog (adjust as needed for your SIEM)

SIEM_SYSLOG_HOST = '192.168.15.3'  # Use the IP address of your SIEM server

SIEM_SYSLOG_PORT = 514  # Default syslog port

SIEM_SYSLOG_FACILITY = logging.handlers.SysLogHandler.LOG_LOCAL0  # You can change the facility

SIEM_SYSLOG_IDENTIFIER = 'IDS'  # Identifier for your IDS alerts


# Define syslog logger

logger = logging.getLogger()

logger.setLevel(logging.DEBUG)


# Setup syslog handler for sending logs to SIEM

syslog_handler = logging.handlers.SysLogHandler(address=(SIEM_SYSLOG_HOST, SIEM_SYSLOG_PORT))

syslog_handler.setLevel(logging.DEBUG)


# Formatter to specify the format of syslog messages

formatter = logging.Formatter('%(asctime)s %(name)s[%(process)d]: %(message)s')
```

```
syslog_handler.setFormatter(formatter)

logger.addHandler(syslog_handler)

# Simulating an IDS alert with variation (dynamic IP and attack type)
def generate_sample_alert(alert_number):
    attack_types = ["SQL Injection", "XSS Attack", "Buffer Overflow", "DoS Attack"]
    ip_address = f"192.168.15.3.{random.randint(100, 200)}"  # Random IP generation
    attack_type = random.choice(attack_types)  # Randomly choose an attack type
    alert_message = f"ALERT: {attack_type} detected from IP: {ip_address} to port {random.randint(1000, 65535)}. (Alert ID: {alert_number})"
    return alert_message

# Function to forward IDS alert to SIEM via syslog
def forward_alert_to_siem(alert_message):
    logger.info(f"IDS Alert: {alert_message}")
    print(f"Forwarded to SIEM: {alert_message}")

# Function to simulate continuous IDS alerts (could be replaced by real-time log monitoring)
def simulate_ids_alerts():
    alert_number = 1
    while True:
        alert_message = generate_sample_alert(alert_number)
        forward_alert_to_siem(alert_message)
        alert_number += 1  # Increment the alert number for uniqueness
        time.sleep(5)  # Simulate a new alert every 5 seconds

if __name__ == "__main__":
    try:
        print("Starting IDS to SIEM integration...")
        simulate_ids_alerts()
    except KeyboardInterrupt:
        print("Integration stopped by user.")
```

sys.exit(0)

Output :

```
Python 3.13.2 (tags/v3.13.2:4f8bb39, Feb  4 2025, 15:23:48) [MSC v.1942 64 bit (AMD64)] on win32
Type "help", "copyright", "credits" or "license()" for more information.
>
========== RESTART: C:\Users\itadmin\Documents\ids.py ==========
Starting IDS to SIEM integration...
Forwarded to SIEM: ALERT: SQL Injection detected from IP: 192.168.15.3.200 to port 54508. (Alert ID: 1)
Forwarded to SIEM: ALERT: Buffer Overflow detected from IP: 192.168.15.3.188 to port 1610. (Alert ID: 2)
Forwarded to SIEM: ALERT: SQL Injection detected from IP: 192.168.15.3.178 to port 5873. (Alert ID: 3)
Forwarded to SIEM: ALERT: SQL Injection detected from IP: 192.168.15.3.167 to port 34652. (Alert ID: 4)
Forwarded to SIEM: ALERT: DoS Attack detected from IP: 192.168.15.3.144 to port 30435. (Alert ID: 5)
Forwarded to SIEM: ALERT: Buffer Overflow detected from IP: 192.168.15.3.118 to port 31846. (Alert ID: 6)
Forwarded to SIEM: ALERT: DoS Attack detected from IP: 192.168.15.3.179 to port 37962. (Alert ID: 7)
Forwarded to SIEM: ALERT: DoS Attack detected from IP: 192.168.15.3.121 to port 34649. (Alert ID: 8)
Forwarded to SIEM: ALERT: SQL Injection detected from IP: 192.168.15.3.128 to port 46237. (Alert ID: 9)
Forwarded to SIEM: ALERT: XSS Attack detected from IP: 192.168.15.3.132 to port 57409. (Alert ID: 10)
Forwarded to SIEM: ALERT: Buffer Overflow detected from IP: 192.168.15.3.196 to port 11164. (Alert ID: 11)
Forwarded to SIEM: ALERT: XSS Attack detected from IP: 192.168.15.3.190 to port 53293. (Alert ID: 12)
Forwarded to SIEM: ALERT: SQL Injection detected from IP: 192.168.15.3.134 to port 13955. (Alert ID: 13)
Forwarded to SIEM: ALERT: XSS Attack detected from IP: 192.168.15.3.183 to port 14308. (Alert ID: 14)
Forwarded to SIEM: ALERT: DoS Attack detected from IP: 192.168.15.3.106 to port 28996. (Alert ID: 15)
Forwarded to SIEM: ALERT: SQL Injection detected from IP: 192.168.15.3.170 to port 11596. (Alert ID: 16)
Forwarded to SIEM: ALERT: XSS Attack detected from IP: 192.168.15.3.120 to port 56743. (Alert ID: 17)
Forwarded to SIEM: ALERT: SQL Injection detected from IP: 192.168.15.3.154 to port 39692. (Alert ID: 18)
Forwarded to SIEM: ALERT: XSS Attack detected from IP: 192.168.15.3.194 to port 41032. (Alert ID: 19)
Forwarded to SIEM: ALERT: DoS Attack detected from IP: 192.168.15.3.126 to port 23587. (Alert ID: 20)
Forwarded to SIEM: ALERT: SQL Injection detected from IP: 192.168.15.3.193 to port 64211. (Alert ID: 21)
Forwarded to SIEM: ALERT: DoS Attack detected from IP: 192.168.15.3.141 to port 18557. (Alert ID: 22)
Forwarded to SIEM: ALERT: DoS Attack detected from IP: 192.168.15.3.166 to port 47395. (Alert ID: 23)
Forwarded to SIEM: ALERT: Buffer Overflow detected from IP: 192.168.15.3.138 to port 17200. (Alert ID: 24)
Forwarded to SIEM: ALERT: DoS Attack detected from IP: 192.168.15.3.113 to port 56832. (Alert ID: 25)
Forwarded to SIEM: ALERT: XSS Attack detected from IP: 192.168.15.3.114 to port 52551. (Alert ID: 26)
Forwarded to SIEM: ALERT: SQL Injection detected from IP: 192.168.15.3.126 to port 59361. (Alert ID: 27)
Forwarded to SIEM: ALERT: Buffer Overflow detected from IP: 192.168.15.3.184 to port 45638. (Alert ID: 28)
Forwarded to SIEM: ALERT: XSS Attack detected from IP: 192.168.15.3.152 to port 6672. (Alert ID: 29)
Forwarded to SIEM: ALERT: XSS Attack detected from IP: 192.168.15.3.116 to port 11597. (Alert ID: 30)
Forwarded to SIEM: ALERT: DoS Attack detected from IP: 192.168.15.3.128 to port 60574. (Alert ID: 31)
Forwarded to SIEM: ALERT: DoS Attack detected from IP: 192.168.15.3.194 to port 60276. (Alert ID: 32)
Forwarded to SIEM: ALERT: XSS Attack detected from IP: 192.168.15.3.112 to port 47506. (Alert ID: 33)
Forwarded to SIEM: ALERT: DoS Attack detected from IP: 192.168.15.3.122 to port 19463. (Alert ID: 34)
Forwarded to SIEM: ALERT: XSS Attack detected from IP: 192.168.15.3.107 to port 33399. (Alert ID: 35)
Forwarded to SIEM: ALERT: DoS Attack detected from IP: 192.168.15.3.171 to port 23656. (Alert ID: 36)
Forwarded to SIEM: ALERT: DoS Attack detected from IP: 192.168.15.3.144 to port 21055. (Alert ID: 37)
Forwarded to SIEM: ALERT: XSS Attack detected from IP: 192.168.15.3.194 to port 32787. (Alert ID: 38)
Forwarded to SIEM: ALERT: XSS Attack detected from IP: 192.168.15.3.149 to port 1943. (Alert ID: 39)
Integration stopped by user.
```

Result : Thus the Integrate Intrusion Detection System(IDS) with Security Information and Event Management (SIEM) Systems was Successfully Executed.

Experiment no: 7 Analyze network traffic to identify anomalies

Aim:

To set up Suricata as an Intrusion Detection System (IDS) and simulate an ICMP flood attack to monitor and detect malicious activity in a network.

Requirements:

Software:

- Suricata
- hping3

Network Setup:

- A Windows PC and a Linux VM running on the same Windows PC & the same network.

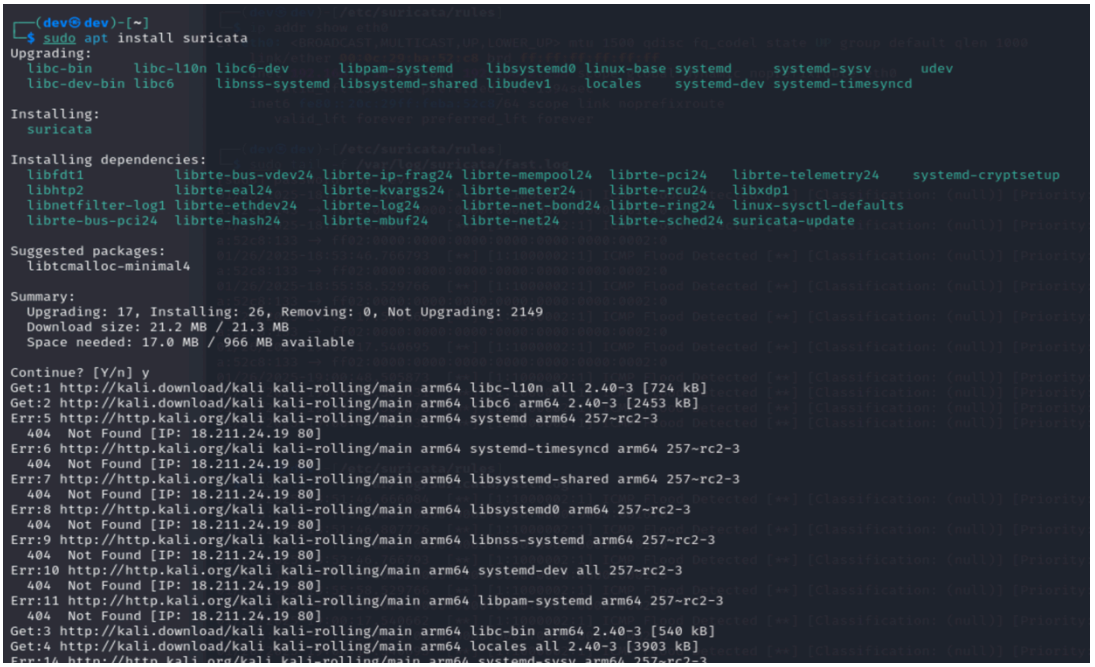
Procedure:

Step 1: Install and Set Up Suricata

1. Install Suricata on the target device:

“sudo apt update”

“sudo apt install suricata”



2. Verify the installation:

suricata –version

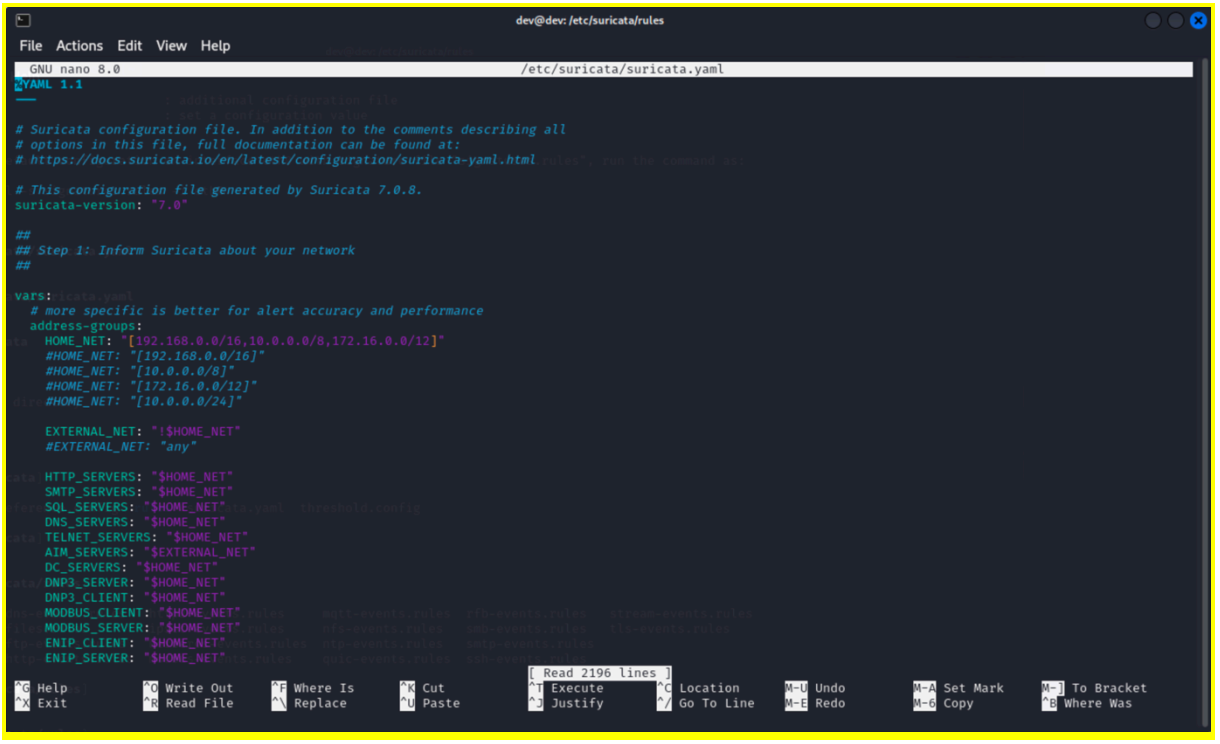
```
┌──(dev㉿dev)-[~]
└─$ sudo apt install suricata
suricata is already the newest version (1:7.0.8-1+b1).
Summary:
  Upgrading: 0, Installing: 0, Removing: 0, Not Upgrading: 2203
```

3. Locate the Suricata configuration file:

sudo nano /etc/suricata/suricata.yaml

- Ensure the `HOME_NET` variable is set to your network range (e.g., `192.168.2.0/24`):

vars:
address-groups:
HOME_NET: "[192.168.2.0/24]"



4. Save and exit the file.

5. Start Suricata in IDS mode:
sudo suricata -c /etc/suricata/suricata.yaml -i eth0

- Replace `eth0` with your network interface.

```
┌──(dev㉿dev)-[/etc/suricata/rules]
└─$ sudo suricata -c /etc/suricata/suricata.yaml -i eth0
[sudo] password for dev:
i: suricata: This is Suricata version 7.0.8 RELEASE running in SYSTEM mode
i: threads: Threads created → W: 5 FM: 1 FR: 1   Engine started.
```

Step 2: Add a Custom Rule to Detect ICMP Floods

1. Open the Suricata rules file:

sudo nano /etc/suricata/rules/iot.rules

2. Add the following rule to detect ICMP flood attacks:

“alert icmp any any -> any any (msg:"ICMP Flood Detected"; sid:1000002; rev:1;)”

3. Save and exit the file.

4. Update Suricata to use the new rule by restarting it:

“sudo systemctl restart suricata”

```
┌──(dev㉿dev)-[/etc/suricata/rules]
└─$ sudo systemctl restart suricata

┌──(dev㉿dev)-[/etc/suricata/rules]
└─$ sudo systemctl status suricata
● suricata.service - Suricata IDS/IDP daemon
     Loaded: loaded (/usr/lib/systemd/system/suricata.service; disabled; preset: disabled)
     Active: active (running) since Fri 2025-01-24 13:09:32 IST; 28s ago
 Invocation: c81a75fd89f3484aadc84c7c1294a9ce
       Docs: man:suricata(8)
             man:suricatasc(8)
             https://suricata.io/documentation/
    Process: 61397 ExecStart=/usr/bin/suricata -D --af-packet -c /etc/suricata/suricata.yaml --pidfile /run/suricata.pid (code=exited, status=0/SUCCESS)
   Main PID: 61398 (Suricata-Main)
      Tasks: 11 (limit: 6951)
     Memory: 98M (peak: 98.3M)
        CPU: 281ms
     CGroup: /system.slice/suricata.service
             └─61398 /usr/bin/suricata -D --af-packet -c /etc/suricata/suricata.yaml --pidfile /run/suricata.pid

Jan 24 13:09:32 dev systemd[1]: Starting suricata.service - Suricata IDS/IDP daemon...
Jan 24 13:09:32 dev suricata[61397]: i: suricata: This is Suricata version 7.0.8 RELEASE running in SYSTEM mode
Jan 24 13:09:32 dev systemd[1]: Started suricata.service - Suricata IDS/IDP daemon.
```

Step 3: Verify Network Connectivity

1. From the attacker machine, check if the target is reachable:

ping <Target-IP>

- Replace `<Target-IP>` with the IP address of the target device.

Try the command “ip addr” to know your IP.

Step 4: Simulate the ICMP Flood Attack

1. On the attacker machine, run the following command to start the ICMP flood:

hping3 --flood -1 <Target-IP>

- Replace `<Target-IP>` with the IP address of the target device.

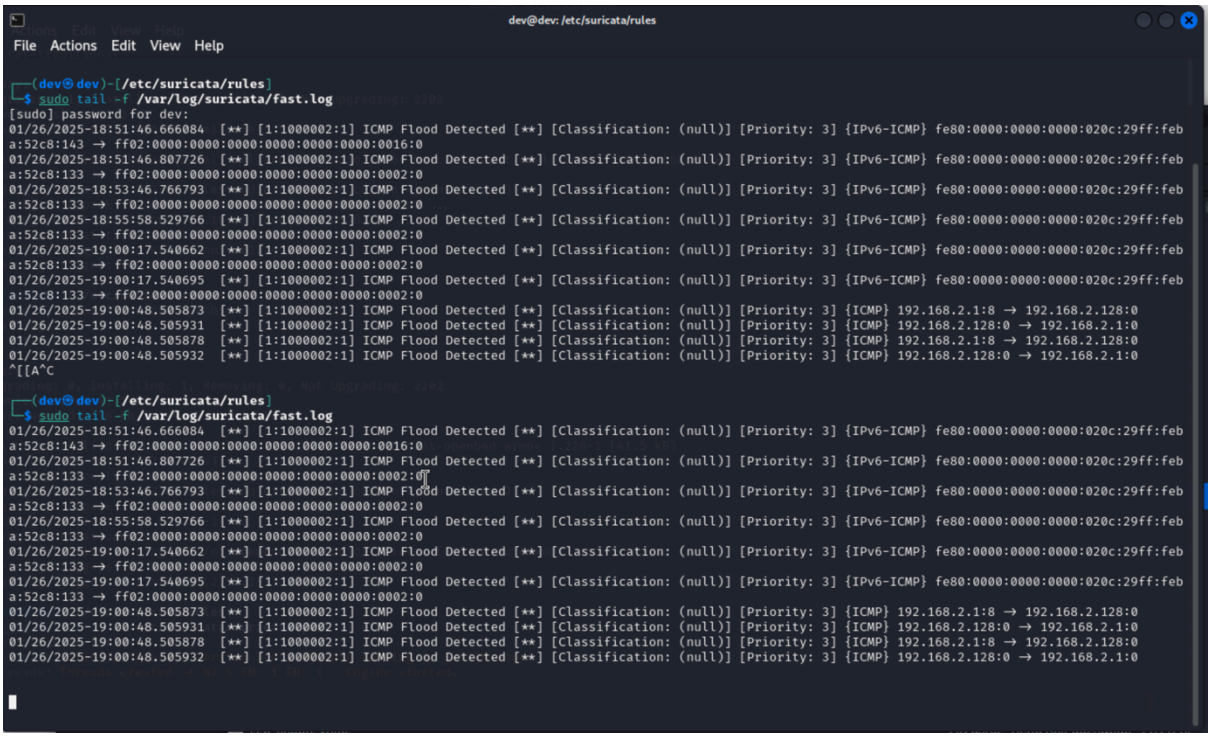
```
devsriakash@Devs-MacBook-Pro ~ % echo -ne "CONNECT" | nc 192.168.2.128 1883
devsriakash@Devs-MacBook-Pro ~ % ping 192.168.2.128
PING 192.168.2.128 (192.168.2.128): 56 data bytes
64 bytes from 192.168.2.128: icmp_seq=0 ttl=64 time=0.504 ms
64 bytes from 192.168.2.128: icmp_seq=1 ttl=64 time=0.734 ms
64 bytes from 192.168.2.128: icmp_seq=2 ttl=64 time=0.810 ms
64 bytes from 192.168.2.128: icmp_seq=3 ttl=64 time=0.747 ms
64 bytes from 192.168.2.128: icmp_seq=4 ttl=64 time=0.791 ms
^C
--- 192.168.2.128 ping statistics ---
5 packets transmitted, 5 packets received, 0.0% packet loss
round-trip min/avg/max/stddev = 0.504/0.717/0.810/0.110 ms
```

2. Let the command run for a few seconds, then stop it (Ctrl+C).

Step 5: Monitor and Analyze Alerts

1. On the target device, check Suricata’s alert log:

sudo tail -f /var/log/suricata/fast.log



2. Look for alerts with the message:

[**] [1:1000002:1] ICMP Flood Detected [**]

Step 6: Discuss the Results

1. Review the logged alerts and understand how the rule worked to detect the ICMP flood attack.
2. Optional: Capture the traffic for further analysis:

“sudo tcpdump -i eth0 -w icmp_flood.pcap”

- Analyze the `.pcap` file in Wireshark to visualize the attack.

Expected Output

- Suricata logs alerts for the ICMP flood attack with the message:

[**] [1:1000002:1] ICMP Flood Detected [**]

- The log contains details about the source and destination IP addresses and protocols used.

Result:
The experiment successfully demonstrated how Suricata detects ICMP flood attacks using a custom rule. Hence this experiment demonstrates how to monitor network traffic to identify anomalies, simulate an attack, and analyze alerts generated by an IDS.

Experiment 8 - Create a Hybrid IDS Combining Signature-Based and Anomaly-Based Meth

Aim:

To implement and evaluate a hybrid Intrusion Detection System (IDS) that combines signature-based and anomaly-based techniques for improved threat detection.

Materials Required:

- Snort IDS
- Scikit-learn (for anomaly detection)
- Python
- Linux Virtual Machine (VM)
- Network Traffic Dataset

Theory:

Traditional IDS approaches include signature-based detection, which relies on predefined rules and patterns to detect known threats, and anomaly-based detection, which identifies deviations from normal traffic behavior. A hybrid IDS integrates both techniques, leveraging signature-based methods for known threats and anomaly-based methods for detecting new and unknown threats.

Procedure:

Step 1: Install and Configure Snort (Signature-Based IDS)

- Update system packages and install Snort:
  (kali@kali) $ sudo apt update
  (kali@kali) $ sudo apt install -y snort
- Verify Snort installation:
  (kali@kali) $ snort -V
- Edit Snort configuration file:
  (kali@kali) $ sudo nano /etc/snort/snort.conf
- Define network variables and rule paths.
- Add basic rules for detecting common threats:
  alert tcp any any -> any 80 (msg:"Possible HTTP Attack"; content:"GET /login"; sid:1000001;)
- Restart Snort to apply changes:
  (kali@kali) $ sudo systemctl restart snort

Step 2: Implement Anomaly-Based Detection Using Machine Learning

- Install required Python libraries:

  (kali@kali) $ sudo apt install python3-pip

  (kali@kali) $ pip install scikit-learn pandas numpy

- Load and preprocess network traffic dataset using Python:

```
import pandas as pd
from sklearn.ensemble import IsolationForest

# Load dataset (example CSV format)
data = pd.read_csv("network_traffic.csv")
features = data[['src_ip', 'dst_ip', 'packet_size', 'duration']]

# Train anomaly detection model
model = IsolationForest(contamination=0.05)
model.fit(features)

# Detect anomalies
anomalies = model.predict(features)
data['anomaly'] = anomalies
print(data[data['anomaly'] == -1])  # Display detected anomalies
```

Step 3: Integrate Both Approaches for a Hybrid IDS

- Run Snort for signature-based detection:

  (kali@kali) $ snort -c /etc/snort/snort.conf -A console

- Use Python script for anomaly detection:

  (kali@kali) $ python3 anomaly_detection.py

- Combine results by analyzing Snort logs and anomaly detection outputs.

Step 4: Monitor and Validate Hybrid IDS Performance

- Generate test traffic using network simulation tools.
- Compare the detection accuracy of signature-based, anomaly-based, and hybrid methods.
- Log alerts and analyze effectiveness.

Output:

- Alerts for known attacks detected by Snort.
- Anomalous traffic flagged by the machine learning model.
- Hybrid IDS effectiveness in identifying both known and unknown threats.

Conclusion:

This experiment demonstrates the implementation of a hybrid IDS by combining Snort's rule-based approach with anomaly detection using machine learning. The system effectively enhances threat detection capabilities by addressing both known and unknown attack patterns.

EXP 9. Detection and Response to Advanced Persistent Threats (APTs)

in IDS

AIM:

To detect Advanced Persistent Threats (APTs) using an Intrusion Detection System (IDS) and implement a response mechanism to mitigate the detected threats.

ALGORITHM:

A. Signature-Based Detection Algorithm (Using Snort IDS Rules)

1. **Initialize the IDS:**
   - Install and configure Snort or Suricata IDS on the system.
   - Define rule sets for known attack signatures.
2. **Monitor Network Traffic:**
   - Capture incoming and outgoing network packets using packet sniffing techniques.
   - Analyze each packet's header and payload for suspicious patterns.
3. **Match with Predefined Signatures:**
   - Compare packet data against stored attack signatures (e.g., malware hashes, suspicious IP addresses).
   - If a match is found, trigger an alert event.
4. **Log and Alert the Administrator:**
   - Save the details of the detected threat in a log file.
   - Notify the security team through email alerts or system logs.
5. **Respond to the Threat:**
   - Block malicious IP addresses using firewall rules:
     sudo iptables -A INPUT -s <malicious_ip> -j DROP
   - Quarantine infected files or terminate suspicious processes.

B. Anomaly-Based Detection Algorithm (Using Machine Learning - Isolation Forest)

1. **Data Collection:**

- Capture network traffic logs, including attributes such as:
- Packet Size
- Connection Duration
- Source & Destination IPs
- Protocol Used (TCP/UDP/HTTP/SSH/etc.)

2. **Data Preprocessing:**
- Convert categorical values (like source/destination IPs) into numerical form.
- Normalize or standardize numerical data for better anomaly detection.

3. **Model Training:**
- Use an Isolation Forest algorithm, which isolates anomalies by randomly selecting features and splitting them.
- Train the model with normal traffic data to distinguish between normal and suspicious activity.

4. **Anomaly Detection:**
- Apply the trained model to real-time network traffic.
- Assign an anomaly score to each network event.
- If the score exceeds a predefined threshold, classify it as an anomaly (potential APT activity).

5. **Threat Mitigation:**
- Log the detected anomalies for further investigation.
- Automatically block IPs showing suspicious behavior.
- Alert the security administrator through system notifications or emails.

Procedure

Step 1: Install & Configure IDS

- Install **Snort** or **Zeek** on a test system.
- Configure IDS rules for detecting APT-related attacks.

```
sudo nano /etc/snort/rules/local rules
alert tcp any any -> any any:Possible APT activity
detected ` conntent:"malicious.exe;";sid:1000001;
```

Step 2: Simulate an APT Attack

- Use Metasploit or hping3 to generate attack traffic.
- Simulate brute-force login attempts, privilege escalation, or C2 communication.

```
$ hping3 -S -p 80—d 120 -data <targert_ip>
HPING <targert_ip> (eth0 192.168.0.1): S set, ao
```

Step 3: Detect APT Activities

- Run the IDS to analyze network logs.
- Apply signature-based or anomaly-based detection techniques.

Step 4: Implement a Response Mechanism

- `sudo iptables -A INPUT -s <malicious_ip> -j DROP`
- Generate real-time alerts for administrators.

Program

A. Snort Rule for Signature-Based Detection

```
alert tcp any any -> any any (msg:"Possible APT activity detected";
content:"malicious.exe"; sid:1000001; rev:1;)
```

B. Python Program for Anomaly-Based Detection using Machine Learning

```
import pandas as pd
from sklearn.ensemble import IsolationForest

# Load network traffic data (example dataset)
df = pd.read_csv("network_logs.csv")

# Selecting important features for anomaly detection
features = df[['packet_size', 'connection_duration']]
clf = IsolationForest(contamination=0.05)  # 5% anomalies

# Train model and predict anomalies
clf.fit(features)
df['anomaly'] = clf.predict(features)

# Display detected APT activities
print(df[df['anomaly'] == -1])  # Anomalies are labeled as -1
```

Output:

```
print(df(df'anomaly'] == -1))
--------------------------------------
timesstam source_ip destination packet_s
--------------------------------------:---
2024-04-2419.168.1.103 20.013.5  150   2
2024-04-2419.168.1.100 20.013.5  125   2
2024-04-2419.168.1.101 23.013.5  175   1
2024-04-2419.168.1.101 23.013.5  200   2
2024-04-2419.168.1.101 23.013.5  200   2
2024-04-2419.168.1.101 23.013.5  300   3
2024-04-24 03:452.110 1 203.0.113  051   2
2024-04-24 03:452.110 1 203.0.113  255   2
2024-04-24 03:511.45  2 203.0.113  300   3
```

Result

The experiment successfully demonstrated the detection **Advanced Persistent Threats (APTs)** and the response mechanism mitigating the threats by **blocking malicious IPs and generating alerts**.

IDS Experiment 10

Aim:

To optimize IDS performance for real-time analysis using **Random Forest classification by** reducing false positives while maintaining detection accuracy.

Algorithm:

1. **Generate Synthetic Data**

- Create **random network packet data** with attributes:
  - `packet_size`: Random integer (50-1500).
  - `delay`: Random float (0-2 seconds).
  - `flag`: 80% normal traffic (0), 20% anomalies (1).
- Split data into **training (70%)** and **testing (30%)** sets.

2. **Train Baseline IDS Model**

- Use **RandomForestClassifier** with `100` estimators.
- Train using `X_train, y_train`.
- Predict on `X_test`.
- Compute **False Positive Rate (FPR)** and generate a classification report.

3. **Train Optimized IDS Model**

- Increase **n_estimators** to `200` for better performance.
- Train and predict using the same dataset.
- Compute new **FPR** and classification report.

4. **Compare Performance**

- Display a table comparing **FPR before vs. after optimization**.
- Print **classification reports** for both models.

Program:

```
import numpy as np
import pandas as pd
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix, classification_report

# Generate synthetic data
np.random.seed(42)
data = pd.DataFrame({
    'packet_size': np.random.randint(50, 1500, 5000),
    'delay': np.random.uniform(0, 2, 5000),
    'flag': np.random.choice([0, 1], 5000, p=[0.8, 0.2])
})
X_train, X_test, y_train, y_test = train_test_split(data.drop(columns=['flag']), dat
a['flag'], test_size=0.3, random_state=42)

# Train models
def train_model(n_estimators):
    clf = RandomForestClassifier(n_estimators=n_estimators, class_weight="bal
anced_subsample", random_state=42)
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    return confusion_matrix(y_test, y_pred), classification_report(y_test, y_pred)

cm_before, report_before = train_model(100)
cm_after, report_after = train_model(200)

fp_before = cm_before[0][1] / sum(cm_before[0])
fp_after = cm_after[0][1] / sum(cm_after[0])

# Performance Comparison
print("\nPerformance Comparison:")
print(f"{'Metric':<25}{'Before Optimization':<20}{'After Optimization'}")
print(f"{'False Positive Rate (FPR)':<25}{fp_before:<20.4f}{fp_after:.4f}")
```

```
# Print Classification Reports
print("\nBefore Optimization:\n", report_before)
print("After Optimization:\n", report_after)
```

Output:

```
Performance Comparison:
Metric                    Before Optimization After Optimization
False Positive Rate (FPR)0.0725              0.0651

Before Optimization:
              precision    recall  f1-score   support

           0       0.82      0.93      0.87      1228
           1       0.18      0.07      0.10       272

    accuracy                           0.77      1500
   macro avg       0.50      0.50      0.49      1500
weighted avg       0.70      0.77      0.73      1500

After Optimization:
              precision    recall  f1-score   support

           0       0.82      0.93      0.87      1228
           1       0.16      0.06      0.08       272

    accuracy                           0.78      1500
   macro avg       0.49      0.50      0.48      1500
weighted avg       0.70      0.78      0.73      1500
```

Result:

Thus the optimization of IDS performance for real-time analysis using **Random Forest classification by** reducing false positives while maintaining detection accuracy is completed successfully.

EXPLOIT ADVERSARIAL ATTACKS ON A ML-BASED IDS

AIM

To exploit adversarial attacks on a machine learning based Intrusion detection system.

PROCEDURE

It involves the evaluating the performance of a neural network model on original and adversarial data using the Fast Gradient Sign Method (FGSM) for generating adversarial samples, followed by the comparison of the model's accuracy on the original test data with its accuracy on adversarial samples.

Dataset Creation: A synthetic binary classification dataset is created using sklearn.datasets.make_classification. The dataset consists of 1000 samples, each with 20 features and two target classes (0 or 1).

Preprocessing:The features of the dataset are normalized using StandardScaler. The dataset is split into training and test sets (80% training, 20% testing).

Model Building: A simple neural network model is built using Keras. The model consists of: An input layer with 64 units and ReLU activation. A hidden layer with 32 units and ReLU activation. An output layer with 1 unit and sigmoid activation (binary classification).

Model Training: The model is trained for 10 epochs using the Adam optimizer and binary cross-entropy loss. The validation data (test set) is also passed to monitor overfitting.

Evaluation on Original Data: The trained model's accuracy is evaluated on the original test set.

Adversarial Example Generation (FGSM): Adversarial samples are generated by applying small perturbations to the original test data using the Fast Gradient Sign Method (FGSM). The perturbations are computed using the gradient of the loss with respect to the input data. **The Fast Gradient Sign Method (FGSM)** creates adversarial examples by making small changes to the input data. It calculates how much each input feature affects the model's prediction, then slightly adjusts the input in the direction that causes the model to make a wrong prediction.

Model Evaluation on Adversarial Data: The accuracy of the model is evaluated again on the adversarial test samples.

Comparison: A bar chart is plotted to compare the model's performance on original versus adversarial data.

PROGRAM

```
import pandas as pd
```

```
from sklearn.datasets import make_classification

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import StandardScaler, LabelEncoder

import tensorflow as tf

from tensorflow.keras.models import Sequential

from tensorflow.keras.layers import Dense

import matplotlib.pyplot as plt


# Step 1: Create a synthetic dataset

# Creating a binary classification dataset with 1000 samples, 20 features, and 2 classes

X, y = make_classification(n_samples=1000, n_features=20, n_informative=10, n_classes=2,
random_state=42)


# Step 2: Preprocess the dataset

# Normalize the features

X = StandardScaler().fit_transform(X)


# Split the dataset into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


# Reshape y_test to ensure it matches the shape of the model's output

y_test = y_test.reshape(-1, 1)


# Step 3: Build and compile a neural network model

model = Sequential([

    Dense(64, activation='relu', input_dim=X_train.shape[1]),
```

```
    Dense(32, activation='relu'),
    Dense(1, activation='sigmoid')    # Binary classification, so sigmoid
])

model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Step 4: Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_test, y_test))

# Step 5: Evaluate the model on the original test set
original_loss, original_accuracy = model.evaluate(X_test, y_test)
print(f"Test Accuracy on Original Data: {original_accuracy:.4f}")

# Step 6: Generate adversarial examples using FGSM
def generate_adversarial_example(model, X, epsilon=0.1):
    # Convert input data to TensorFlow variable
    X_tensor = tf.Variable(X)    # Use tf.Variable instead of K.backend.variable

    # Create a TensorFlow GradientTape to compute gradients
    with tf.GradientTape() as tape:
        tape.watch(X_tensor)    # Watch the input for gradient calculation
        predictions = model(X_tensor, training=False)
        loss = tf.keras.losses.binary_crossentropy(y_true=y_test, y_pred=predictions)

    # Get the gradients of the loss with respect to the input image
```

```
        gradient = tape.gradient(loss, X_tensor)

        # Generate adversarial examples by adding epsilon * sign of gradients
        adversarial_example = X_tensor + epsilon * tf.sign(gradient)

        # Return adversarial examples as numpy array
        return adversarial_example.numpy()

# Step 7: Generate adversarial examples
X_test_adv = generate_adversarial_example(model, X_test, epsilon=0.1)

# Step 8: Evaluate the model on adversarial data
adv_loss, adv_accuracy = model.evaluate(X_test_adv, y_test)
print(f"Test Accuracy on Adversarial Samples: {adv_accuracy:.4f}")

# Step 9: Plot comparison
labels = ['Original', 'Adversarial']
accuracies = [original_accuracy, adv_accuracy]

plt.bar(labels, accuracies, color=['blue', 'red'])
plt.title('Model Accuracy: Original vs. Adversarial Samples')
plt.ylabel('Accuracy')
plt.show()
```

OUTPUT

Epoch 1/10

25/25 ━━━━━━━━━━━━━━━━━━━━ 1s 7ms/step - accuracy: 0.4951 - loss: 0.7106 - val_accuracy: 0.7500 - val_loss: 0.5968

Epoch 2/10

25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7735 - loss: 0.5792 - val_accuracy: 0.8150 - val_loss: 0.4948

...

Epoch 10/10

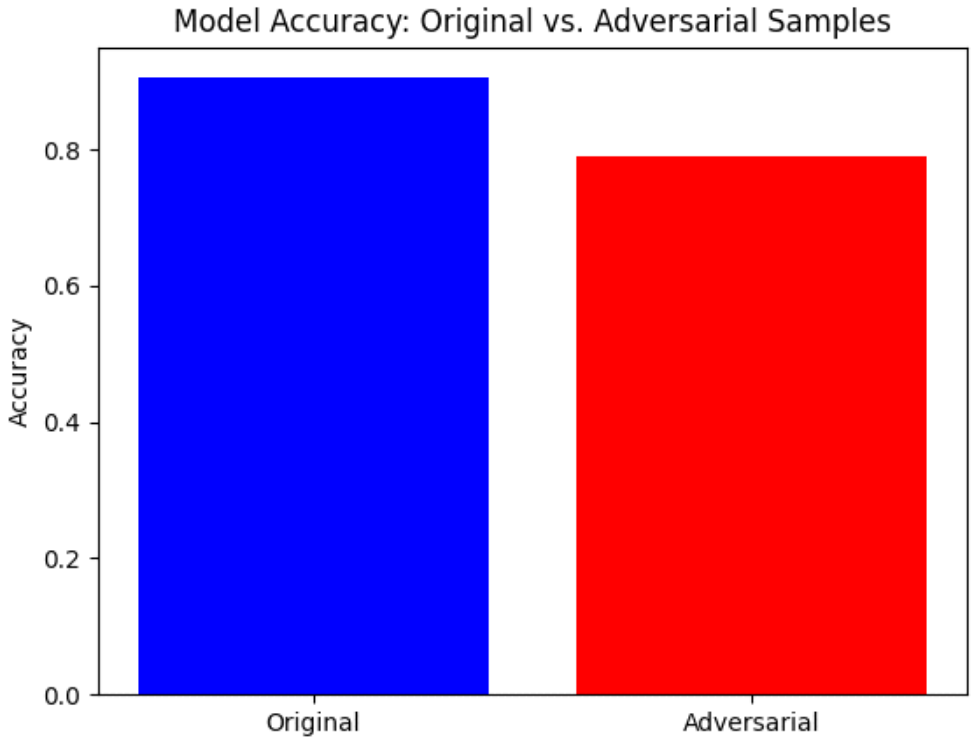
25/25 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.9539 - loss: 0.1596 - val_accuracy: 0.9200 - val_loss: 0.2376

7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.9312 - loss: 0.2136

Test Accuracy on Original Data: 0.9200

7/7 ━━━━━━━━━━━━━━━━━━━━ 0s 3ms/step - accuracy: 0.7931 - loss: 0.4254

Test Accuracy on Adversarial Samples: 0.7900



RESULT:

The exploitation of adversarial attacks on a ml-based ids is successfully executed.

EXP 12-

Develop an Autonomous IDS with Self-Healing Capabilities

Aim:

To create an autonomous Intrusion Detection System (IDS) that detects anomalies and automatically retrains itself if performance drops below a threshold.

Prerequisite:

- **Libraries**: pandas, scikit-learn, numpy.
- **Software**: Python 3.x, Jupyter Notebook or any Python IDE.
- **Dataset**: Synthetic dataset generated for demonstration.

Algorithm:

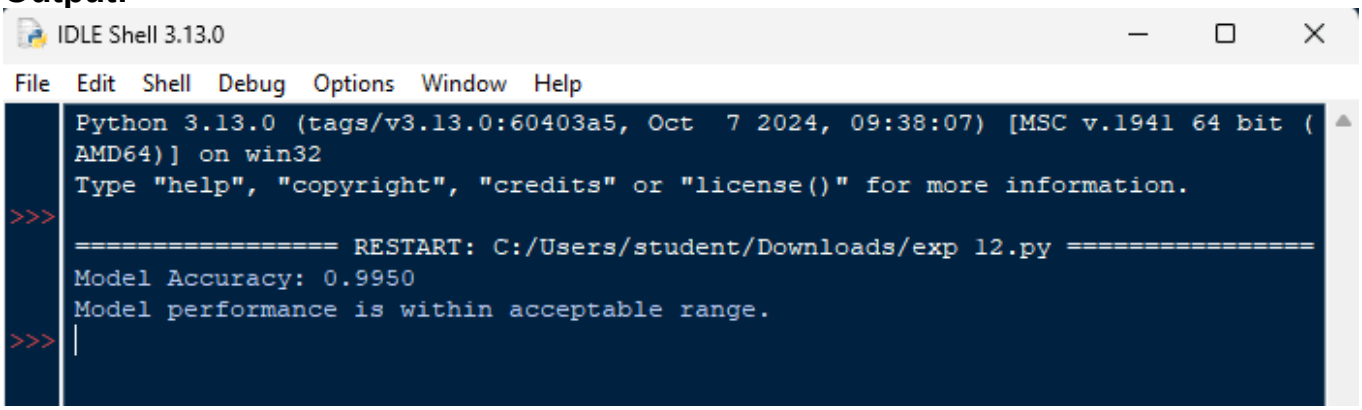
1. **Generate Synthetic Dataset**: Create a synthetic dataset with features representing network traffic and labels indicating normal or attack.
2. **Preprocess Data**:
    - Handle missing values by filling them with a placeholder (e.g., -1).
    - Encode categorical data into numeric values.
    - Scale features using StandardScaler for better model performance.
3. **Train Model**: Use a RandomForestClassifier to train the model on the preprocessed data.
4. **Evaluate Model**: Calculate accuracy on the test set to evaluate model performance.
5. **Self-Healing**: If accuracy drops below a threshold (e.g., 0.95), retrain the model automatically to maintain performance.

Code:

```
import pandas as pd
import numpy as np
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split

# Generate a more meaningful synthetic dataset
def generate_synthetic_data(num_samples=1000):
    np.random.seed(42)
    # Feature 1: Simulates packet size (normal traffic has smaller packets)
    feature1_normal = np.random.normal(loc=50, scale=10, size=num_samples // 2)
    feature1_attack = np.random.normal(loc=150, scale=50, size=num_samples // 2)

    # Feature 2: Simulates request frequency (attack traffic has higher frequency)
    feature2_normal = np.random.normal(loc=5, scale=2, size=num_samples // 2)
    feature2_attack = np.random.normal(loc=20, scale=5, size=num_samples // 2)
```

```
    # Combine features and labels
    X = np.concatenate([
        np.column_stack((feature1_normal, feature2_normal)),
        np.column_stack((feature1_attack, feature2_attack))
    ])
    y = np.array(["normal"] * (num_samples // 2) + ["attack"] * (num_samples // 2))
    return pd.DataFrame(X, columns=["feature1", "feature2"]), y

# Preprocess data
def preprocess_data(X, y):
    # Encode labels (normal = 0, attack = 1)
    y_encoded = np.where(y == "normal", 0, 1)

    # Scale features
    scaler = StandardScaler()
    X_scaled = scaler.fit_transform(X)
    return X_scaled, y_encoded

# Train and evaluate model
def train_and_evaluate(X_train, y_train, X_test, y_test):
    model = RandomForestClassifier(n_estimators=100, random_state=42)
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Model Accuracy: {accuracy:.4f}")
    print("Model performance is within acceptable range.")
    return model, accuracy

# Main execution
if __name__ == "__main__":
    # Generate synthetic dataset
    X, y = generate_synthetic_data(num_samples=1000)
    # Preprocess data
    X_scaled, y_encoded = preprocess_data(X, y)
    # Split data into train and test sets
    X_train, X_test, y_train, y_test = train_test_split(X_scaled, y_encoded, test_size=0.2,
random_state=42)
    # Train and evaluate model
    model, accuracy = train_and_evaluate(X_train, y_train, X_test, y_test)
```

Output:



Result:

The program implements an autonomous IDS that detects anomalies and retrains itself if accuracy drops below 0.95, ensuring consistent performance.