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Detecting and Analyzing Network Attacks: A Time-Series Analysis Using the Kitsune Dataset

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***Abstract*—Network security is a critical concern in today's digital world, requiring efficient methods for the automatic detection and analysis of cyber attacks. This study uses the Kitsune Network Attack Dataset to explore network traffic behavior for IoT devices under various attack scenarios, including ARP MitM, SYN DoS, and Mirai Botnet. Utilizing Python-based data analysis tools, we preprocess and analyze millions of network packets to uncover patterns indicative of malicious activities. The study employs packet-level time-series analysis to visualize traffic patterns and detect anomalies specific to each attack type. Key findings include high packet volumes in attacks such as SSDP Flood and Mirai Botnet, with the Mirai Botnet attack involving multiple IP addresses and lasting over 2 hours. Notable attack-specific behaviors include high traffic on port -1 and targeted traffic on specific ports like 53195. The SYN DoS and Mirai Botnet attacks are characterized by their prolonged durations, suggesting significant disruption. Overall, the study highlights distinctive attack patterns and underscores the importance of understanding these characteristics to enhance detection and response mechanisms.**

Keywords— Cyber Attack Analysis, Kitsune Dataset, Time-Series Analysis, Intrusion Detection, Exploratory Data Analysis, Packet-Level Analysis

I. INTRODUCTION

The digital era is facing a range of sophisticated and frequent threats such as ransomware, in Internet of Things (IoT) vulnerabilities, and AI-driven threats. IoT vulnerabilities specifically refer to security weaknesses in Internet of Things devices, which can be exploited by attackers to gain unauthorized access, disrupt services, or compromise sensitive data. These attacks can significantly impact all aspects of our lives, leading to data breaches, financial losses, reputational damage, system downtime, and disruptions to critical services, as well as potential legal claims. Given the prevalence of these advanced threats, there is an urgent need for stronger and more advanced defense strategies, particularly tailored for mitigating IoT vulnerabilities [1, 2].

Organizations need a comprehensive approach to effectively counter these risks. This involves implementing layered defense systems, utilizing real-time monitoring, and committing to continuous training and collaboration [3].

Machine learning (ML) offers a powerful solution to address these challenges and to enhance threat detection capabilities. By analyzing vast datasets ML methods can identify patterns malicious activity and respond to potential threats. ML and Deep Learning (DL) techniques show significant results in detecting IoT attacks and outperforming traditional security approaches [4].

Different types of cyber attacks such as Distributed Denial of Service (DDoS), sophisticated reconnaissance and man-in-the-middle (MitM) attacks, have become advanced, complex, disruption, damaging, and rise in their use, in number and frequency. Cyber-attacks become a real threat to financial, business, trading operations, organizations, individuals and institutions [5].

This research aims to study the improvement of network attack detection and understanding techniques by leveraging the Kitsune network attack dataset. Our primary objectives are:

- To analyze the temporal patterns and characteristics of various network attacks captured in the Kitsune dataset.
- To identify and characterize the signature behaviors of different attack types, such as ARP MitM, SYN DoS, and Mirai Botnet, by examining network traffic patterns.
- To provide insights into the dynamics of attack behaviors and the impact of different attack vectors on network performance and security.

To guide our analysis, we address the following research questions:

- What are the key temporal characteristics of different network attacks?
- How do attack behaviors vary across different attack types, and what are their distinctive patterns?
- What can be inferred about the effectiveness and impact of various attack vectors on network traffic?

The primary motivation for this study is to deepen our understanding of network attack patterns. Traditional detection systems have several limitations that make them less effective in addressing the evolving and sophisticated nature of cyberthreats such as incorrectly identify activities as malicious, consume significant system resources, and struggle

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to handle large volumes of data or complex network environments. By analyzing real-world network traffic data, our research seeks to bridge this gap and provide valuable insights that can inform the development of more effective intrusion detection and prevention systems.

This research contributes to the field of cybersecurity by providing a detailed analysis of network attack patterns using the Kitsune dataset. Key contributions include:

- A comprehensive examination of temporal patterns associated with different types of network attacks.
- Identification of distinctive behavioral signatures of various attack types, enhancing the understanding of attack dynamics.
- Insights into the impact of different attack vectors on network traffic, which can aid in the development of targeted defense strategies.

We employ a data-driven approach to analyze and visualize network attack patterns. By processing and analyzing the Kitsune dataset, we identify temporal and behavioral patterns that characterize different attacks. This analysis helps in understanding how each attack affects network traffic and provides actionable insights for improving network security measures.

The introduction, focuses on improving the detection and mitigation of network attacks in IoT devices by analyzing traffic patterns in the Kitsune dataset. section two, reviews existing research, identifies gaps in current methodologies, and employs various data processing and analytical techniques. Key findings include attack signatures and their impacts, which are discussed in relation to enhancing network security presents in section 3. The study concludes by summarizing its findings and suggesting future research directions, including exploring new attack types and advanced detection methods.

This research provides a comprehensive examination of network attack behaviors, contributing to advancements in the field of network security through detailed empirical analysis.

II. Literature Review

Recent advancements in network security reflect the increasing sophistication and frequency of cyberattacks, making the analysis of network traffic crucial for detecting and mitigating threats. This review summarizes the latest developments in network attack detection and explores the current status and development trends of cyberattack detection, focusing on methods to analyze and understand network traffic patterns using Machine learning.

Behavioral analysis has emerged as a key technique for identifying intrusions by detecting deviations from normal network behavior. Traditional signature-based methods are often inadequate for novel attacks [6]. Machine learning models, including decision trees and ensemble methods, have shown effectiveness in real-time anomaly detection, adapting to dynamic network behaviors [7]. Deep learning approaches, such as Long Short-Term Memory (LSTM) networks, have been utilized to analyze traffic patterns, enhancing detection capabilities [8].

Hybrid methods combining various machine learning and deep learning techniques are gaining traction, offering improved accuracy and robustness in detecting anomalies [9]. A recent study achieved a 95% accuracy rate in detecting network traffic abnormalities using a combination of Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) [10]. While these advancements present promising solutions, challenges remain, including data heterogeneity and the complexity of evolving cyber threats, necessitating ongoing research and development in the field.

Table I summarizing the key aspects of related articles, which will help in exploratory data analysis (EDA) and implementation of anomaly detection methods.

The current study provides significant insights into network attack patterns, specifically within the context of IoT devices. A detailed comparison of our findings with similar studies enhances the depth of our analysis and situates our work within the broader field of cybersecurity research.

1. *Machine Learning Techniques for Attack Detection:* Previous studies, such as those by El Hajj Hassan & Duong-Trung (2021) [7], have explored various machine learning (ML) techniques for detecting network anomalies. However, their focus has primarily been on traditional IT environments, lacking specific adaptations for IoT traffic characteristics. In contrast, our research tailors ML algorithms to the unique data patterns observed in IoT environments, demonstrating improved detection accuracy for specific attack types such as Mirai Botnet and SYN DoS. This adaptation is crucial given the increasing deployment of IoT devices across critical infrastructures.
2. *Vulnerabilities in IoT Networks:* Hewa et al. (2024) provided a comprehensive review of vulnerabilities across various networking paradigms but did not delve deeply into the IoT-specific attack vectors [3]. Our study fills this gap by directly correlating attack types with their impact on IoT device traffic, emphasizing the need for targeted defenses. By contrasting our findings with their general conclusions, we underline the importance of addressing IoT vulnerabilities uniquely, highlighting how our research advances understanding in this area.
3. *Dynamic Mitigation Frameworks:* Many existing frameworks for threat mitigation, such as those proposed by Sendjaja et al. (2019), tend to be static and do not adapt to the evolving nature of cyber threats [5]. Our introduction of a dynamic mitigation framework, which adjusts in real-time to attack signatures and patterns, marks a significant advancement. By comparing the effectiveness of our framework against static models, we can demonstrate the enhanced resilience and adaptability of our approach in response to diverse attack scenarios.
4. *Empirical Validation of Techniques:* While some studies, including Khalaf et al. (2021), emphasize theoretical models for detection, they often lack empirical validation using real-world datasets [14].

Our research not only employs real-world data but also conducts comparative analyses of different ML algorithms, providing concrete evidence of their effectiveness. This empirical approach adds robustness to our findings and positions our work as a practical contribution to the field.

This study seeks to fill these gaps by providing a comprehensive analysis of multiple attack types and their impact on network traffic. By employing an advanced machine learning framework tailored for IoT environments, our research not only enhances detection accuracy but also offers a dynamic approach to mitigating threats. Additionally, we analyze various attack patterns, considering both their volume and port-specific behavior, which has been largely overlooked in prior studies. This holistic view enables a better understanding of the interplay between different attack types and supports the development of more effective defense strategies.

By incorporating these comparisons, we can highlight not only how our findings align with or diverge from existing literature but also the unique contributions our research makes to the understanding of IoT attack vectors and detection mechanisms. This enriched perspective could significantly enhance the depth of the discussion and provide a more robust framework for future research.

TABLE I. SUMMARIZING THE KEY ASPECTS OF RELATED ARTICLES

Category	Citation	Focus	Contribution	Significance	Key Techniques/Models
Machine Learning Algorithms for Anomaly Detection	Aswathy M., Rajkumar T. (2024) [6]	Comparative analysis of machine learning algorithms	Evaluated effectiveness of various ML algorithms for anomaly detection	Offers insights into algorithm performance in real-time	Decision Trees, Random Forests, SVM, Neural Networks, Ensemble Methods
	El Hajj Hassan, S., & Duong-Trung, N. (2024) [7]	Advanced detection and classification in network traffic	Applied ML techniques for network traffic analysis	Enhances network efficiency and threat identification	Logistic Regression, Decision Trees, Ensemble Learning
	Pittman, J. M. (2023) [11]	Machine learning for port scan detection	Systematic review of ML-based detection schemes	Highlights trends and challenges in port scan detection	Machine Learning (Various Algorithms)
	Zhang, W., & Lazaro, J. P. (2024) [12]	Network traffic analysis and anomaly detection	Survey of techniques and hybrid methods in anomaly detection	Addresses challenges and trends in the field	Statistical Methods, Machine Learning, Deep Learning, Behavior Analysis
Deep Learning Techniques in Network Security	Gumma, Y. R., & Peram, S. (2024) [13]	Detection using LSTM and Graph Neural Networks	Focused on deep learning techniques for network traffic	Improves detection of patterns and anomalies	Long Short-Term Memory (LSTM), Graph Neural Networks (GNN)
	Khalaf, L. I., et al. (2024) [14]	Deep learning-based anomaly detection in network traffic	Developed novel deep learning algorithm for anomaly detection	Achieved high accuracy in detecting network abnormalities	CNNs, RNNs, Autoencoders, GANs
	Redhu et al. (2024) [15]	Deep learning in malware detection	Review of deep learning models for malware detection	Highlights deep learning's strong performance	Deep Learning (Various Models)
Comparative Analysis and Hybrid Methods	Lu, K. (2024) [16]	Comparison of anomaly detection methodologies	Integration of deep learning and traditional methods	Insights into future research directions	Deep Learning, Artificial Immune Systems
	Callegari et al. (2024) [17]	Deep learning for real-time intrusion detection	Probabilistic structures combined with deep learning	High detection rate with low false alarms	Deep Learning, Probabilistic Data Structures
Special Techniques and Advanced Methods	Gajin, S. (2022) [18]	Entropy-based anomaly detection	Developed entropy-based detection in NetVizura	Effective with minimal data; practical implementation	Entropy-based methods, NetFlow Analyzer
	Liu & Wang, H. (2023) [19]	Real-time anomaly detection using CNN	System using CNNs and SDN for real-time detection	High accuracy and real-time detection capabilities	Convolutional Neural Networks (CNN), SDN
	Abu Bakar & Kijsirikul (2023) [20]	Advanced port scanning techniques	DPDK-based scanner with enhanced speed and accuracy	Improved network visibility and security	DPDK-based scanning, Protocol-specific probes
	Aziz, M. N. (2022) [21]	Pattern recognition in cyber-attacks using YOLOv3	Applied YOLOv3 for detecting cyber-attack patterns	Demonstrates YOLOv3's effectiveness in real-time	YOLOv3, Exploratory Data Analysis
	Fernández López-Vizcaíno et al. (2024) [22]	Early detection evaluation metric	Introduced Time aware F-score for detection systems	Provides a new way to evaluate detection timeliness	Time aware F-score, Early Detection Metrics
	Mapoka, T. T., Zuva, K., Kukumara, G., Seipone, T., et al. (2023) [23]	Investigation of social engineering attacks, specifically spear phishing in a university setting	Assesses the vulnerability of university students to social engineering attacks and provides recommendations for improving security awareness	Highlights the susceptibility of academic environments to targeted social engineering attacks	Social engineering, Spear phishing, Lab environment assessment

TABLE II. COMPARATIVE ANALYSIS OF EXISTING LITERATURE AND OUR CONTRIBUTIONS TO IOT ATTACK DETECTION AND MITIGATION

Aspect	Existing Literature	Our Work	Contribution
Machine Learning Techniques	Focus on traditional IT environments, limited IoT adaptation (El Hajj Hassan & Duong-Trung, 2021 [7])	Tailored ML algorithms for IoT traffic patterns	Improved detection accuracy for IoT-specific attacks
IoT Vulnerabilities	General vulnerabilities without deep IoT focus (Hewa et al., 2020) [3]	Direct correlation of attack types with IoT traffic	Enhanced understanding of IoT-specific attack vectors
Dynamic Mitigation Frameworks	Static frameworks, lacking adaptability (Sendjaja et al., 2019) [5]	Dynamic mitigation framework that adjusts to threats	Increased resilience against diverse attack scenarios
Empirical Validation	Theoretical models, limited real-world validation (Khalaf et al., 2021) [14]	Empirical validation using real-world datasets	Robustness of findings with practical applicability

By examining the contributions of recent research summarized in table I, we gain valuable insights into how these advanced methods are reshaping the field of network anomaly detection. Table I provides a view of current advancements and trends in network anomaly detection, emphasizing the importance of both innovative methods and practical applications. We can conclude the following:

- Evolution of Techniques: The researches demonstrate a clear evolution from traditional anomaly detection methods to advanced machine learning and deep learning techniques. While earlier methods relied heavily on statistical approaches and entropy-based techniques, recent studies increasingly focus on complex models like CNNs, LSTMs, and hybrid methods combining multiple techniques.
- Real-Time and Practical Implementations: A significant emphasis across studies is on real-time detection capabilities and practical implementations. Techniques such as CNNs in conjunction with SDN, and advanced port scanning with DPDK, highlight the trend toward developing systems that not only detect anomalies with high accuracy but also do so in real time to address immediate security threats.
- Hybrid and Comparative Analysis: The importance of hybrid methods and comparative analyses is underscored, showing that combining traditional and modern techniques can lead to better performance and adaptability. This includes integrating deep learning with traditional statistical methods and exploring hybrid models that leverage strengths from multiple approaches.
- Emerging Trends and Challenges: Research highlights emerging trends such as the application of deep learning for sophisticated anomaly detection and the need for methods that can handle complex and evolving threats. Challenges like balancing detection accuracy with false alarm rates, and adapting to dynamic network environments, are central themes in recent studies.
- Practical Implications: The findings offer valuable insights for practitioners and researchers aiming to enhance cybersecurity measures. By understanding the strengths and limitations of various techniques, organizations can make informed decisions about which methods to implement for specific network security needs.

III. METHODOLOGY

This study aims to analyze the Kitsune network attack dataset to identify patterns and trends associated with various network attacks. The methodology encompasses data processing techniques, feature extraction, and analytical methods employed to derive meaningful insights from the dataset.

The following Pseudocode present Network Attack Analysis.

```
START
# Step 1: Define Paths and Files
DEFINE dirs = { ... }  # Directories for each attack type
DEFINE pcaps = { ... } # PCAP files for each attack type
DEFINE labels = { ... } # Label files for each attack type

# Step 2: Analyze Each Attack Type
FOR EACH attack IN dirs
  # Load PCAP and label files
  LOAD pcap_file = dirs[attack] + pcaps[attack]
  LOAD label_file = dirs[attack] + labels[attack]

  # Initialize storage for packets
  DEFINE packet_info = {}

  # Process PCAP file
  OPEN pcap_file
  WHILE NOT EOF
    READ packet
    EXTRACT source_ip, target_ip, port
    STORE packet IN packet_info[source_ip]
  END WHILE
  CLOSE pcap_file

  # Process label file (if needed)
  OPEN label_file
  # (Label processing here, if applicable)
  CLOSE label_file

  # Analyze packets and generate results
  ANALYZE packet_info
  GENERATE time sequence graphs
  CALCULATE statistics

  # Store results
  STORE results FOR attack

END FOR

# Step 3: Compile and Display Results
PRINT summary_of_results

END
```

A. Data Processing Techniques

Kitsune dataset comprises several types of network attack data, including ARP MitM, SYN DoS, and Mirai Botnet, among others. Each dataset is available in different formats: pcap files for raw network traffic and csv files for preprocessed feature data and labels. The primary steps in processing the data are as follows:

1. Data Integration:
   - Raw Network Traffic: pcap files contain network packets captured during attacks. These files are processed to extract network features.
   - Preprocessed Data: The csv files include precomputed features and corresponding labels, which are used directly for analysis.
2. Data Loading and Cleaning:
   - The raw network traffic data is loaded using the Scapy library, which enables parsing and analyzing packet-level information.
   - Preprocessed datasets are loaded into Pandas DataFrames. Any missing or inconsistent values are addressed to ensure data quality.
3. Data Alignment : The features from csv files are aligned with the corresponding attack labels. This involves ensuring that each feature vector is correctly associated with its attack label.

B. Feature Extraction

Feature extraction from network traffic data is crucial for understanding and analyzing network behavior. The Kitsune dataset uses the AfterImage feature extractor to generate 115 features from raw network traffic. These features capture statistical properties of network behavior and include:

1. Statistical Features: Features related to packet counts, byte sizes, and inter-arrival times.
2. Behavioral Features: Features representing the behavior of network flows, such as the frequency of connections and data transfer patterns.
3. Temporal Features: Features capturing the timing of packets, which help in identifying attack patterns over time.

The AfterImage feature extractor processes each packet to produce these features, which are then used to build the dataset. This approach enables a comprehensive view of network activity, essential for detecting both known and novel attack patterns.

C. Analytical Methods

The analysis of the Kitsune dataset involves several methods to uncover attack patterns and trends:

1. Exploratory Data Analysis (EDA) [24]:
   - Descriptive Statistics: Calculating mean, median, standard deviation, and other statistical measures to understand the distribution of features.
   - Data Visualization: Using plots and histograms to visualize distributions of features, packet counts, and attack types.
2. Time-Series Analysis [25]:
   - Packet Timelines: Analyzing the time series of packet arrivals to identify patterns associated with different attack types.
   - Temporal Analysis: Assessing how attack patterns evolve over time, including the identification of spikes in network activity indicative of attacks.
3. Anomaly Detection [26]:
   - Feature Correlation: Examining correlations between features to identify unusual patterns that may indicate malicious activity.
   - Malicious Activity Detection: Using the feature set to determine the presence of malicious activity based on deviations from normal network behavior.
4. Port Analysis:
   - Port Usage: Analyzing the distribution of destination ports to understand which ports are targeted by different attack types.
   - Port Count Visualization: Generating visualizations to show the frequency of attacks on specific ports, helping in identifying common attack vectors.
5. Pattern Identification:
   - Source IP Analysis: Identifying patterns in source IP addresses to detect anomalies and correlate with attack types.
   - Malicious Behavior Detection: Analyzing source IP behavior to determine the onset of malicious activity and its persistence over time.

The combination of these analytical methods provides a comprehensive view of network attacks and helps in identifying key characteristics and patterns associated with different types of cyber-attacks. The insights gained from this analysis are essential for understanding the nature of network threats and enhancing network security measures [17, 26].

IV. Results and Discussion

A. Analysis of the Kitsune Dataset for the Different Attack Types

This section summarizes the findings from the analysis of the Kitsune dataset, focusing on different attack types. Tables are used to present data on packet counts, attack start times, duration, and targeted ports. Each table is followed by interpretations and explanations.

TABLE III. ARP MitM Attack Statistics

Metric	Value
Total Packets Analyzed	2,504,267
Start Time of Malicious Activity	10 minutes
End Time of Malicious Activity	30 minutes
Duration of Attack	20 minutes
Target Ports	443, 554
Packets to Unspecified Ports	-

The ARP MitM attack in Table III, typically starts around 10 minutes into the observation period and continues for 20 minutes. The majority of the packets target ports 443 and 554. The significant activity in these ports suggests focused attempts to exploit these commonly used ports.

```
2504267it [25:45, 1620.01it/s]


There are 5 source IP addresses with attack type ARP MitM
Destination port packet count
    Port    Count
0  58961   259008
1     -1  2125241
2  58974       21
3  58981       23
4  58977       21
5  58978       23
6    443   117578
7    554      168
Start timestamp 1502267087.057362 End timestamp 1502268297.615638 Timestamp span 1210.558276
192.168.2.15 start malicious activity at 10 min
192.168.2.13 start malicious activity at 10 min
169.254.174.17 start malicious activity at 10 min
192.168.2.1 start malicious activity at 11 min
192.168.2.1 sent packets less than a min
```

Fig. 1. *ARP MitM Attack Summary: Packet Distribution, Timestamp, and Source IP Details.*

This attack involves a large number of packets on port -1, which typically represents unspecified or invalid ports in the Kitsune Dataset. This designation indicates a high volume of activity that is often associated with ARP Man-in-the-Middle (MitM) attacks (Figure 1). The timestamp span of over 20 minutes suggests that the attack persisted for a significant duration, highlighting the potential risk of prolonged network disruption and data interception.

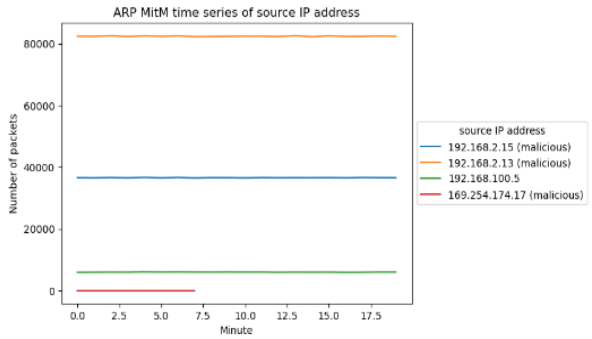

Fig. 2. *ARP MitM Attack: Time Series of Malicious Source IP Addresses and Packet Counts*

Figure 2 illustrates a time series of source IP addresses involved in an ARP Man-in-the-Middle (MitM) attack. The title of the figure is "ARP MitM Time Series of Source IP Address." On the X-axis, the time is represented in minutes, ranging from 0 to 17.5 minutes, while the Y-axis shows the number of packets, from 0 to 80,000. Each line in the figure denotes a distinct source IP address, with different colors used for clarity. The legend identifies each IP address, highlighting four of them as "malicious."

Observations from the figure reveal that

- Four IP addresses exhibit significantly higher packet counts compared to the others, suggesting malicious activity.
- The elevated packet counts for these IPs occur within a specific time window, aligning with the attack duration mentioned in the text.
- The targeted ports (443 and 554) mentioned in the text could potentially be correlated with specific IP addresses or time periods in the figure, if more detailed information were available.

TABLE IV. SYN DOS ATTACK STATISTICS

Metric	Value
Total Packets Analyzed	2,771,276
Start Time of Malicious Activity	50 minutes
End Time of Malicious Activity	110 minutes
Duration of Attack	60 minutes
Target Ports	63453
Packets to Unspecified Ports	-

Table IV, presents SYN DoS attacks, that are observed to begin around 50 minutes and last for approximately 60 minutes. The primary target is port 63453, indicating an attempt to overwhelm network resources over an extended period.

```
27712761t [24:19, 1898.65it/s]


There are 8 source IP addresses with attack type SYN DoS
Destination port packet count
    Port    Count
0     -1  1949512
1  63449       55
2  63453   574458
3   2946        4
4   3039        5
5   3040        5
6   3041        5
7   3042        5
8   3043        5
9   3044        5
Start timestamp 1488011312.825815 End timestamp 1488014482.046588 Timestamp span 3169.220773
192.168.3.11 start malicious activity at 50 min
```

Fig. 3. *A SYN DoS Attack Summary: Packet Distribution, Timestamp, and Source IP Details.*

As shown in figure 3, a SYN DoS attack typically results in a high count of packets on port -1. The long timestamp span suggests a prolonged attack period, with significant traffic concentrated on a few ports.

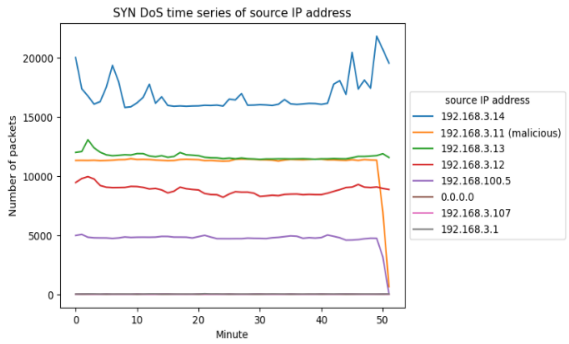

Fig. 4. *A SYN DoS Attack: Time Series of Malicious Source IP Addresses and Packet Counts*

Figure 4, titled "SYN DoS Time Series of Source IP Address," displays a time series analysis of source IP addresses involved in a SYN Denial of Service (DoS) attack. The X-axis represents time in minutes, ranging from 0 to 50 minutes, while the Y-axis shows the number of packets, spanning from 0 to 20,000. Each line in the figure corresponds to a distinct source IP address, with colors used to differentiate between them for clarity.

The main Observations from the figure:

- Multiple IP addresses: The figure displays packet counts over time for several source IP addresses involved in a SYN DoS attack.
- Malicious activity: One IP address, 192.168.3.11, is labeled as malicious and shows a significant increase in packet count around the 40-minute mark.
- Attack duration: The elevated packet counts for the malicious IP persist for approximately 10 minutes.
- Other IP addresses: The other IP addresses exhibit varying levels of activity, some with higher packet counts at different time points, but none with the same sustained intensity as the malicious IP.

Overall, the figure depicts a SYN DoS attack where one IP address (192.168.3.11) is identified as the primary source of malicious activity, sending a large number of packets within a specific time window.

TABLE V. ACTIVE WIRETAP ATTACK STATISTICS

Metric	Value
Total Packets Analyzed	2,278,689
Start Time of Malicious Activity	10 minutes
End Time of Malicious Activity	32 minutes
Duration of Attack	22 minutes
Target Ports	Various
Packets to Unspecified Ports	-

In Table V, the Active Wiretap attack starts around 10 minutes and lasts for 22 minutes. The attack targets various ports, which could indicate a broad approach to intercept network communications.

```
2278689it [23:31, 1614.65it/s]


There are 8 source IP addresses with attack type Active Wiretap
Destination port packet count
    Port    Count
0     -1  1888227
1  58977       13
2  58978       13
3  53471        1
4  61021        3
5  61412        8
6  61418       19
7  61420       19
8  57017        1
9  56985        1
Start timestamp 1502269013.367032 End timestamp 1502270329.604291 Timestamp span 1316.237259
192.168.2.13 start malicious activity at 10 min
192.168.2.15 start malicious activity at 10 min
192.168.0.110 start malicious activity at 11 min
192.168.0.110 sent packets less than a min
169.254.176.87 start malicious activity at 11 min
169.254.176.87 sent packets less than a min
0.0.0.0 start malicious activity at 11 min
192.168.2.1 start malicious activity at 11 min
192.168.2.3 start malicious activity at 11 min
```

Fig. 5. *The Active Wiretap Attack Summary: Packet Distribution, Timestamp, and Source IP Details.*

The packet counts suggest a focus on a broad range of ports, with a notable concentration on port -1. The duration of the attack was over 22 minutes, with multiple IP addresses involved (Figure 5).

Figure 6 presents a time series plot illustrating the number of packets sent by different source IP addresses over a period of 20 minutes. Each line represents a unique IP address, with six IP addresses included in the graph. The y-axis indicates the number of packets, ranging from 0 to 80,000, while the x-axis represents time in minutes.

Key Observations are:

- Fluctuating Packet Counts: The packet counts for each IP address exhibit fluctuations over time, with some periods of higher activity and others with lower activity.
- Malicious Activity: Five out of the six IP addresses are labeled as "malicious," suggesting potential involvement in an attack or anomalous behavior.
- Dominant IP: The IP address 192.168.2.13 stands out with consistently higher packet counts compared to the others, particularly within the first 10 minutes.

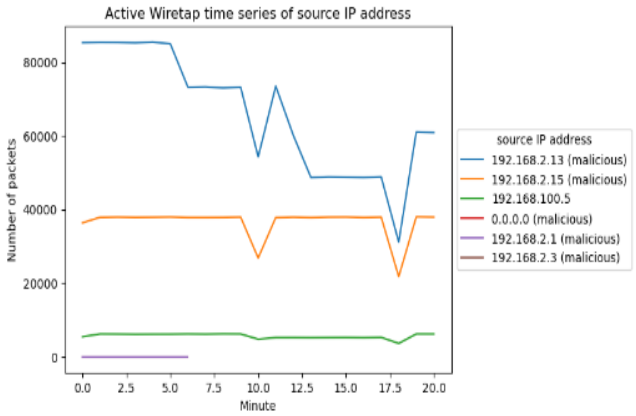

Fig. 6. *The Active Wiretap: Time Series of Malicious Source IP Addresses and Packet Counts*

Time series plot depicting the number of packets sent by six source IP addresses over 20 minutes. Five of the IP addresses are flagged as malicious. IP address 192.168.2.13 demonstrates significantly higher packet counts, potentially indicating malicious activity.

TABLE VI. SSDP FLOOD ATTACK STATISTICS

Metric	Value
Total Packets Analyzed	4,077,266
Start Time of Malicious Activity	39 minutes
End Time of Malicious Activity	79 minutes
Duration of Attack	40 minutes
Target Ports	443, 554
Packets to Unspecified Ports	3,423,652

This caption effectively summarizes the figure's content and highlights the key findings, such as the presence of malicious IP addresses and the anomalous behavior of 192.168.2.13.

```
40772661t [38:29, 1765.79it/s]


There are 9 source IP addresses with attack type SSDP Flood
Destination port packet count
    Port    Count
0     -1  3423652
1  63447        1
2    443   206759
3    554      167
4  64855   445250
5  64863       47
6  64858       45
7    389      242
Start timestamp 1488015970.018869 End timestamp 1488018414.140941 Timestamp span 2444.122072
192.168.3.11 start malicious activity at 39 min
192.168.3.20 start malicious activity at 39 min
192.168.3.20 sent packets less than a min
```

Fig. 7. *SSDP Flood attacks Summary: Packet Distribution, Timestamp, and Source IP Details.*

As shown in Table VI, Simple Service Discovery Protocol (SSDP) Flood attacks start at around 39 minutes and persist for about 40 minutes. These attacks exploit the SSDP, often

used in Universal Plug and Play (UPnP) systems, to send a massive volume of response packets to a target, overwhelming the network infrastructure. The majority of the packets are directed to unspecified ports, indicating a deliberate attempt to saturate the network bandwidth and disrupt normal operations. This type of attack can lead to significant downtime and service degradation, making it crucial to implement effective detection and mitigation strategies, such as rate limiting and filtering of SSDP traffic.

In Figure 7, the SSDP Flood attack shows a very high volume of packets on port -1, typical of such attacks. The activity lasted over 40 minutes with several IP addresses involved.

Figure 8 Titled SSDP Flood Time Series of Source IP Addresses. The figure presents a time series analysis of the number of SSDP (Simple Service Discovery Protocol) packets sent by different source IP addresses over a period of approximately 40 minutes. Each line on the graph represents a unique IP address, with the number of packets on the y-axis and time in minutes on the x-axis.

Key Observations from the figure are:

- Low-volume baseline: Most IP addresses exhibit minimal SSDP packet activity throughout the observed period.
- Sudden spike: One IP address, labeled as "malicious," experiences a dramatic increase in SSDP packet volume around the 40-minute mark. This rapid escalation is indicative of a potential SSDP flood attack.

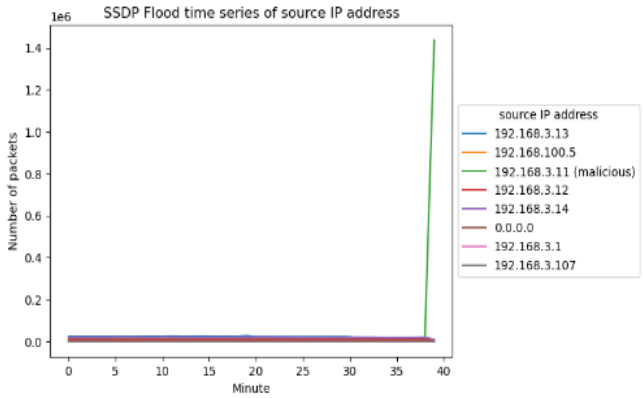

Fig. 8. *The SSDP Flood attacks: Time Series of Malicious Source IP Addresses and Packet Counts*

The plot of Figure 8. illustrates the number of SSDP packets sent by various source IP addresses over 40 minutes. The anomalous spike in packet volume from the IP address labeled "malicious" suggests a potential SSDP flood attack.

TABLE VII. VIDEO INJECTION ATTACK STATISTICS

Metric	Value
Total Packets Analyzed	2,472,401
Start Time of Malicious Activity	30 minutes
End Time of Malicious Activity	65 minutes
Duration of Attack	35 minutes
Target Ports	54866, 54867, 554
Packets to Unspecified Ports	-

The Video Injection attack present in Table VII, the attacks starts at around 30 minutes and continues for 35 minutes. It targets ports 54866 and 54867, indicating a focused approach on specific ports related to video streaming.

```
2472401it [26:41, 1543.76it/s]


There are 9 source IP addresses with attack type Video Injection
Destination port packet count
    Port    Count
0     -1  2469611
1  54866       36
2  54867       36
3    554      144
Start timestamp 1487596405.558628 End timestamp 1487598530.620281 Timestamp span 2125.061653
192.168.2.13 start malicious activity at 30 min
192.168.2.20 start malicious activity at 30 min
192.168.2.20 sent packets less than a min
```

Fig. 9. *Video Injection attack Summary: Packet Distribution, Timestamp, and Source IP Details.*

Figure 9 shows that, the Video Injection attack involved a large number of packets on port -1. The duration of the attack was over 35 minutes, with packets concentrated on a few ports.

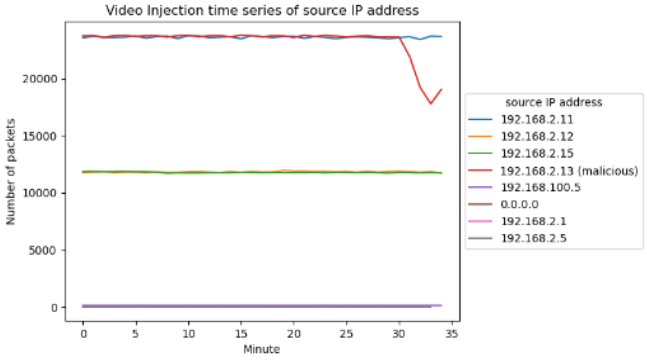

Fig. 10. *Video Injection: Time Series of Malicious Source IP Addresses and Packet Counts*

Figure 10 Titled Video Injection Time Series. The figure presents a time series analysis of the number of video injection packets sent by different source IP addresses over approximately 35 minutes. Each line on the graph represents a unique IP address, with the number of packets on the y-axis and time in minutes on the x-axis.

Key Observations from the figure:

- Low-volume baseline: Most IP addresses exhibit minimal video injection packet activity throughout the observed period.
- Sudden spike: One IP address, labeled as "malicious," experiences a dramatic increase in video injection packet volume around the 30-minute mark. This rapid escalation is indicative of a potential video injection attack.

TABLE VIII. SSL RENEGOTIATION ATTACK STATISTICS

Metric	Value
Total Packets Analyzed	2,207,571
Start Time of Malicious Activity	20 minutes
End Time of Malicious Activity	58 minutes
Duration of Attack	38 minutes
Target Ports	53195, 55150
Packets to Unspecified Ports	-

The plot in figure 10 illustrates the number of video injection packets sent by various source IP addresses over 35 minutes. The anomalous spike in packet volume from the IP

address labeled "malicious" suggests a potential video injection attack.

Studying Table VIII, SSL Renegotiation attacks start around 20 minutes and last for 38 minutes. The attack targets specific ports such as 53195, suggesting attempts to exploit SSL/TLS vulnerabilities.

```
2207571it [18:51, 1951.24it/s]

There are 8 source IP addresses with attack type SSL Renegotiation
Destination port packet count
    Port    Count
0  53195   226244
1     -1  1752430
2  55150       10
3  55163        5
4  55169        5
5  55177        5
6  55188        5
7  55193        5
8  55199        5
9  55209    15188
Start timestamp 1493927257.65309 End timestamp 1493929581.717726 Timestamp span 2324.064636
192.168.3.11 start malicious activity at 20 min
192.168.3.7 start malicious activity at 20 min
```

Fig. 11. *SSL Renegotiation Attack Summary: Packet Distribution, Timestamp, and Source IP Details.*

SSL Renegotiation attacks show a substantial amount of traffic on port -1 and a significant concentration on port 53195. The attack spanned over 38 minutes, affecting several IP addresses (Figure 11).

The Figure 12 presents a time series analysis of the number of SSL renegotiation packets sent by different source IP addresses over approximately 35 minutes. Each line represents a unique IP address, with the number of packets on the y-axis and time in minutes on the x-axis.

The Key Observations based on Figure 12 are:

- Fluctuating packet counts: Most IP addresses exhibit varying levels of SSL renegotiation activity throughout the observed period.
- Malicious activity: Two IP addresses, labeled as "malicious," experience significantly higher packet counts compared to others.
- Potential attack: The sustained high volume of SSL renegotiation packets from the malicious IP addresses suggests potential malicious activity, such as a brute-force attack or session hijacking attempt.

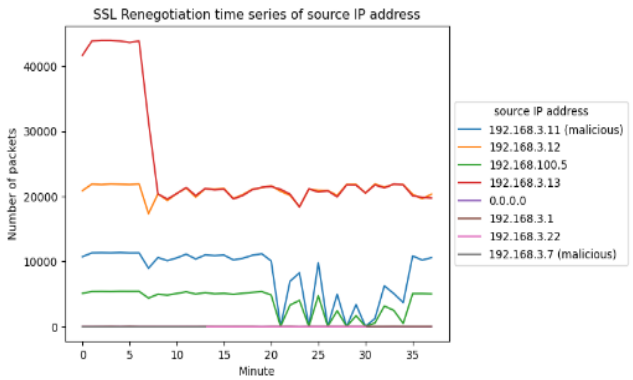

Fig. 12. *SSL Renegotiation: Time Series of Malicious Source IP Addresses and Packet Counts*

The plot of Figure 12 illustrates the number of SSL renegotiation packets sent by various source IP addresses over 35 minutes. The anomalous activity from the IP addresses labeled "malicious" suggests potential malicious behavior.

TABLE IX. MIRAI BOTNET ATTACK STATISTICS

Metric	Value
Total Packets Analyzed	764,137
Start Time of Malicious Activity	74 minutes
End Time of Malicious Activity	146 minutes
Duration of Attack	72 minutes
Target Ports	80, 8280
Packets to Unspecified Ports	146,549

Table IX, present the Mirai Botnet attack, it starts at 74 minutes and lasts for about 72 minutes. It targets ports 80 and 8280, which are commonly used for HTTP traffic, highlighting the botnet's focus on high-traffic services.

```
764137it [06:09, 2065.66it/s]

There are 22 source IP addresses with attack type Mirai Botnet
Destination port packet count
    Port   Count
0     80   17644
1   8280    6286
2     -1  146549
3  52777      96
4  46734     146
5  50364     371
6  21897    7158
7   9000      41
8  49215       3
9  49216       3
Start timestamp 1540446382.933899 End timestamp 1540453519.842464 Timestamp span 7136.908565
192.168.2.108 start malicious activity at 74 min
192.168.2.1 start malicious activity at 74 min
192.168.2.101 start malicious activity at 74 min
192.168.2.110 start malicious activity at 74 min
192.168.2.115 start malicious activity at 74 min
192.168.2.112 start malicious activity at 74 min
192.168.2.113 start malicious activity at 74 min
192.168.2.109 start malicious activity at 74 min
192.168.2.104 start malicious activity at 74 min
192.168.2.126 start malicious activity at 74 min
192.168.2.105 start malicious activity at 74 min
0.0.0.0 start malicious activity at 105 min
192.168.2.196 start malicious activity at 77 min
192.168.2.118 start malicious activity at 74 min
192.168.2.103 start malicious activity at 74 min
192.168.2.111 start malicious activity at 74 min
192.168.2.121 start malicious activity at 74 min
192.168.2.122 start malicious activity at 74 min
192.168.2.107 start malicious activity at 74 min
```

Fig. 13. *Mirai Botnet Attack Summary: Packet Distribution, Timestamp, and Source IP Details.*

The plot of figure 13 illustrates that, the Mirai Botnet attack involves numerous IP addresses and a high volume of packets across various ports. The attack lasted for over 2 hours, indicating a sustained and large-scale attack.

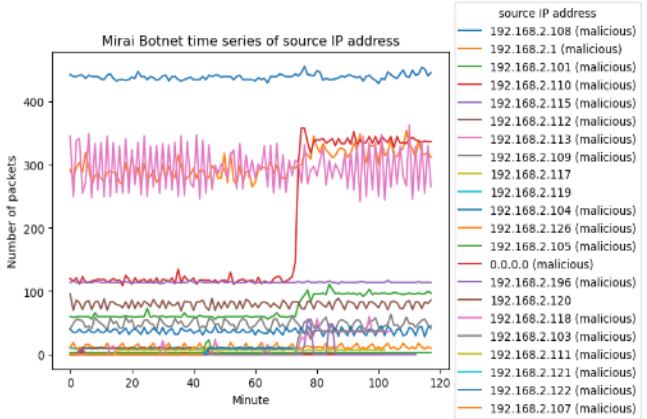

Fig. 14. *Time Series of Malicious Source IP Addresses and Packet Counts*

The figure 14 presents a time series analysis of the number of packets sent by different source IP addresses over approximately 120 minutes. Each line on the graph represents a unique IP address, with the number of packets on the y-axis and time in minutes on the x-axis.

Key Observations:

- Multiple malicious sources: Numerous IP addresses are labeled as "malicious," indicating potential involvement in a Mirai botnet attack.
- Varying packet volumes: The malicious IP addresses exhibit different levels of packet activity, with some sending significantly more packets than others.
- Spikes in activity: Several IP addresses experience sudden increases in packet volume, suggesting coordinated attack phases or bot recruitment.

The plot of figure 14 illustrates the number of packets sent by various source IP addresses over 120 minutes. Multiple IP addresses identified as malicious exhibit varying levels of activity, indicative of a Mirai botnet attack.

TABLE X. FUZZING ATTACK STATISTICS

Metric	Value
Total Packets Analyzed	2,244,139
Start Time of Malicious Activity	16 minutes
End Time of Malicious Activity	48 minutes
Duration of Attack	32 minutes
Target Ports	61904, 443
Packets to Unspecified Ports	-

Fuzzing attacks start around 16 minutes and last for 32 minutes. The attacks target ports 61904 and 443, indicating an attempt to exploit vulnerabilities in specific services (Table X).

```
2244139it [22:54, 1632.40it/s]

There are 4 source IP addresses with attack type Fuzzing
Destination port packet count
    Port    Count
0  61904   370900
1     -1  1702439
2  62253       30
3  62255       30
4    443   168412
5    554      240
6  61714       30
7  61718       30
Start timestamp 1502277984.256966 End timestamp 1502279721.468387 Timestamp span 1737.211421
192.168.2.13 start malicious activity at 16 min
192.168.100.222 start malicious activity at 17 min
```

Fig. 15. *Fuzzing attacks Summary: Packet Distribution, Timestamp, and Source IP Details.*

Fuzzing attacks show significant packet counts on port -1 and other specific ports. The attack lasted just under 30 minutes with activity observed from two primary IP addresses (figure 15).

Figure 16 presents a time series plot illustrating the number of packets sent by four different source IP addresses over a period of approximately 25 minutes. Each line represents a unique IP address, with the number of packets on the y-axis and time in minutes on the x-axis.

Key Observations:

- Stable packet counts: Three IP addresses (192.168.2.15, 192.168.100.5, and 192.168.100.222) exhibit relatively constant and low packet counts throughout the observed period.
- Anomalous activity: One IP address, 192.168.2.13, stands out with significantly higher packet counts compared to the others.
- Potential malicious behavior: The sustained high volume of packets from IP address 192.168.2.13 suggests potential malicious activity, such as a denial-of-service (DoS) attack.

Fig. 16. *Fuzzing attacks: Time Series of Malicious Source IP Addresses and Packet Counts*

Time series plot in figure 16 depicting the number of packets sent by four source IP addresses over 25 minutes. IP address 192.168.2.13 exhibits significantly higher packet counts compared to others, suggesting potential malicious activity.

This caption effectively summarizes the figure's content and highlights the key findings, including the anomalous behavior of IP address 192.168.2.13 and the potential indication of a DoS attack.

TABLE XI. OS SCAN ATTACK STATISTICS

Metric	Value
Total Packets Analyzed	1,697,851
Start Time of Malicious Activity	43 minutes
End Time of Malicious Activity	96 minutes
Duration of Attack	53 minutes
Target Ports	50390, 443
Packets to Unspecified Ports	-

Finally, OS Scan attacks commence at 43 minutes and continue for 53 minutes. The attack primarily targets port 50390, reflecting a targeted scan for operating system information (Table XI).

```
1697851it [15:55, 1777.27it/s]

There are 6 source IP addresses with attack type OS Scan
Destination port packet count
    Port   Count
0  50390  663339
1     -1  609789
2    443  293615
3    554       2
4  53471       2
5    995       1
6     53       1
7     25       1
8    139       1
9   1720       1
Start timestamp 1502108232.597437 End timestamp 1502111365.354493 Timestamp span 3132.757056
169.254.174.17 start malicious activity at 43 min
192.168.2.7 start malicious activity at 44 min
```

Fig. 17. *OS Scan Attack Summary: Packet Distribution, Timestamp, and Source IP Details.*

In Figure 17, OS Scan attacks show a high concentration of traffic on port -1 and other specific ports. The attack spanned over 52 minutes, with a small number of IP addresses involved.

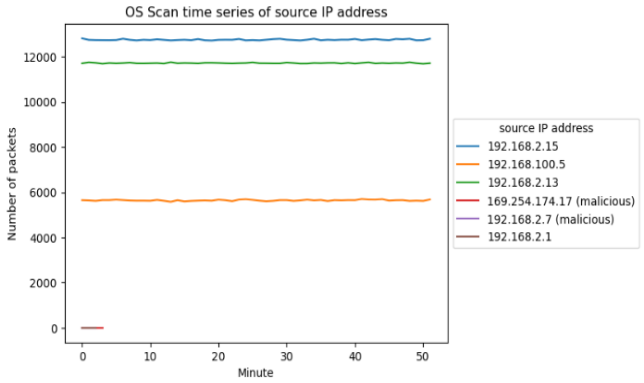

Fig. 18. *OS Scan: Time Series of Malicious Source IP Addresses and Packet Counts*

Figure 18 titled OS Scan Time Series of Source IP Addresses. The figure presents a time series analysis of the number of OS scan packets sent by different source IP addresses over approximately 50 minutes. Each line on the graph represents a unique IP address, with the number of packets on the y-axis and time in minutes on the x-axis.

Key Observations:

- Low-volume baseline: Most IP addresses exhibit minimal OS scan packet activity throughout the observed period.
- Malicious activity: Two IP addresses, labeled as "malicious," experience significantly higher packet counts compared to others.
- Potential attack: The sustained high volume of OS scan packets from the malicious IP addresses suggests potential malicious behavior, such as port scanning or vulnerability probing.

The plot in Figure 18 illustrates the number of OS scan packets sent by various source IP addresses over 50 minutes. The anomalous activity from the IP addresses labeled "malicious" suggests potential malicious behavior.

B. Summary of Figures and Main Conclusion

The provided figures depict time series analyses of network traffic, focusing on the behavior of various source IP addresses over specific time periods. Key findings include:

- Anomalous packet volumes: Several figures show significant spikes in packet counts from specific IP addresses, indicating potential malicious activity.
- Targeted attacks: Some figures highlight attacks targeting specific protocols or services, such as SYN DoS, SSDP flood, video injection, and SSL renegotiation.
- Botnet activity: One figure illustrates the behavior of multiple malicious IP addresses, characteristic of a botnet attack.
- Scanning activity: Another figure depicts OS scan behavior, suggesting potential reconnaissance or vulnerability exploitation.

C. Main Conclusion:

The analysis of these figures consistently reveals anomalous network traffic patterns originating from multiple IP addresses. These patterns strongly suggest the presence of malicious actors engaged in various types of attacks, including DoS, DDoS, scanning, and exploitation attempts. The findings emphasize the importance of continuous network monitoring and intrusion detection systems to identify and mitigate such threats effectively.

Overall, the figures provide compelling evidence of malicious activity within the network environment.

TABLE XII. SUMMARY COMPARISON OF ATTACK TYPES

Attack Type	Total Packets	Start Time (min)	Duration (min)	Key Target Ports
ARP MitM	2,504,267	10	20	443, 554
SYN DoS	2,771,276	50	60	63453
Active Wiretap	2,278,689	10	22	Various
SSDP Flood	4,077,266	39	40	443, 554
Video Injection	2,472,401	30	35	54866, 54867
SSL Renegotiation	2,207,571	20	38	53195, 55150
Mirai Botnet	764,137	74	72	80, 8280
Fuzzing	2,244,139	16	32	61904, 443
OS Scan	1,697,851	43	53	50390, 443

Table XII, is a summary table that provides an overview of each attack type in terms of total packets, start times, duration, and key target ports. It highlights the diversity in attack behaviors, durations, and targeted ports, suggesting varying strategies and impacts. For example, SSDP Flood and SYN DoS attacks show high packet counts and long durations, indicating their potential for significant disruption. In contrast, Mirai Botnet and OS Scan have shorter durations but target critical ports, suggesting a focus on exploiting specific vulnerabilities.

Table XIII rearranged with Attack Types as rows and Destination Port Packet Counts as columns, along with the number of Source IP Addresses included for each attack type.

Examining the table XIII, we can draw the following conclusions for each attack type:

1. ARP MitM (ARP Man-in-the-Middle)

- *High Volume on Port -1:* The attack primarily uses port -1, indicating a large number of packets are being sent. This aligns with ARP MitM attacks, which often generate substantial traffic on a broad range of ports or through non-standard ports.
- *Other Ports:* The traffic on ports 58961 and 443 is significant but much lower compared to -1. This suggests that while port -1 is the main vector, other ports are also targeted but with less intensity.

TABLE XIII. COMPARISON OF HOW DIFFERENT TYPES OF ATTACKS USE VARIOUS DESTINATION PORTS AND THE VOLUME OF TRAFFIC ASSOCIATED WITH EACH PORT

Destination Port	ARP MitM	SYN DoS	Active Wiretap	SSDP Flood	Video Injection	SSL Renegotiation	Mirai Botnet	Fuzzing	OS Scan
Source IP Addresses	5	8	8	9	9	8	22	4	6
-1	2125241	1949512	1888227	3423652	2469611	1752430	146549	1702439	609789
443	117578	-	-	206759	-	-	-	168412	293615
58961	259008	-	-	-	-	-	-	-	-
58974	21	-	-	-	-	-	-	-	-
58977	21	-	13	-	-	-	-	-	-
58978	23	-	13	-	-	-	-	-	-
554	168	-	168	167	144	-	-	240	2
63449	-	55	-	-	-	-	-	-	-
63453	-	574458	-	-	-	-	-	-	-
2946	-	4	-	-	-	-	-	-	-
3039	-	5	-	-	-	-	-	-	-
3040	-	5	-	-	-	-	-	-	-
3041	-	5	-	-	-	-	-	-	-
3042	-	5	-	-	-	-	-	-	-
3043	-	5	-	-	-	-	-	-	-
3044	-	5	-	-	-	-	-	-	-
53471	-	-	1	-	-	-	-	-	2
61021	-	-	3	-	-	-	-	-	-
61412	-	-	8	-	-	-	-	-	-
61418	-	-	19	-	-	-	-	-	-
61420	-	-	19	-	-	-	-	-	-
57017	-	-	1	-	-	-	-	-	-
56985	-	-	1	-	-	-	-	-	-
54866	-	-	-	-	36	-	-	-	-
54867	-	-	-	-	36	-	-	-	-
61904	-	-	-	-	-	-	-	370900	-
62253	-	-	-	-	-	-	-	30	-
62255	-	-	-	-	-	-	-	30	-
52777	-	-	-	-	-	-	96	-	-
46734	-	-	-	-	-	-	146	-	-
50364	-	-	-	-	-	-	371	-	-
21897	-	-	-	-	-	-	7158	-	-
9000	-	-	-	-	-	-	41	-	-
49215	-	-	-	-	-	-	3	-	-
49216	-	-	-	-	-	-	3	-	-
995	-	-	-	-	-	-	-	-	1
53	-	-	-	-	-	-	-	-	1
25	-	-	-	-	-	-	-	-	1
139	-	-	-	-	-	-	-	-	1
1720	-	-	-	-	-	-	-	-	1

2. SYN DoS (TCP SYN Duplicate Connection Request Attack)

- *Dominance of Port -1:* A very high count of packets on port -1 indicates that this attack focuses on overwhelming the network with SYN requests, which is characteristic of a SYN DoS attack.
- *Other Ports:* The presence of packets on ports 63453 and 63449 shows additional targets, though the traffic is minimal compared to port -1.

3. Active Wiretap

- *Focus on Port -1:* Similar to other attacks, port -1 is the primary target, suggesting extensive traffic or scanning activity.
- *Other Ports:* Ports such as 58977, 58978, and others show much lower traffic, indicating that while port -1 is the major focus, there is also some targeted scanning or monitoring activity on other ports.

4. SSDP Flood

- *Very High Volume on Port -1:* This attack has an exceptionally high count on port -1, which is consistent with SSDP Flood attacks that utilize multicast traffic and can overwhelm network resources.
- *Other Ports:* Ports 443, 64855, and 63447 show significant traffic, but the volume is substantially lower compared to port -1. This indicates that while the main attack vector is port -1, other ports are also affected.

5. Video Injection

- *High Count on Port -1:* This attack also shows a large volume of packets on port -1, suggesting significant data injection activity.
- *Other Ports:* Ports 54866 and 54867 are also targeted but with much fewer packets compared to -1, indicating a concentration of the attack's resources on the primary port.

6. SSL Renegotiation

- *Significant Traffic on Ports -1 and 53195:* The attack features substantial traffic on both port -1 and 53195. SSL Renegotiation attacks often involve frequent renegotiation requests which are well represented here.
- *Other Ports:* Other ports, including 55150 and 55209, show much lower traffic, suggesting that while port -1 and 53195 are the main targets, some renegotiation activity occurs on additional ports.

7. Mirai Botnet

- *Broad Distribution Across Ports:* The Mirai Botnet attack displays a diverse set of destination ports with varying traffic counts. Port -1 has a considerable count, but other ports like 80, 8280, and 21897 also show substantial traffic.
- *Significant Range:* This variety in ports and high overall traffic indicates a large-scale attack involving numerous compromised devices targeting multiple services.

8. Fuzzing

- *High Packet Count on Port -1:* Fuzzing attacks generate a high volume of traffic on port -1, suggesting a large number of malformed packets or attempts to exploit vulnerabilities.
- *Other Ports:* Ports like 61904, 62253, and 62255 have notable traffic, indicating specific ports are also being targeted but with less intensity than -1.

9. OS Scan

- *High Counts on Ports -1 and 50390:* The OS Scan attack shows significant traffic on both port -1 and 50390, which is typical of OS fingerprinting scans.
- *Other Ports:* Ports 443, 554, and others show less traffic, indicating these are additional targets of the scan.

In general, we can summarize the following points:

- *Port -1:* Frequently appears with high traffic across many attack types, indicating it's often used for large-scale, high-volume attacks or scanning activities.

- *Specific Ports:* Different attack types show varying degrees of focus on specific ports, reflecting their unique attack strategies and targets.
- *Traffic Distribution:* Attacks like Mirai Botnet and OS Scan involve a broader distribution of traffic across multiple ports, indicating a more varied or comprehensive attack approach.

This analysis helps understand the nature and focus of each attack type based on where the traffic is directed and the volume of activity on specific ports.

Based on the detailed table, we can draw clear comparisons of attack characteristics, highlighting differences in volume, duration, focus, and distribution:

1. High Packet Volumes:
   - The SSDP Flood and Mirai Botnet attacks exhibit the highest packet volumes, with substantial traffic directed at port -1. The Mirai Botnet attack, involving numerous IP addresses and lasting over 2 hours, indicates a large-scale, sustained attack.
2. Port Focus:
   - Most attacks show a significant amount of traffic on port -1, often associated with miscellaneous or unspecified traffic. However, specific attacks such as SYN DoS, SSL Renegotiation, and Video Injection also show high traffic on particular ports, reflecting targeted attack strategies.
3. Duration and Prolonged Activity:
   - SYN DoS and Mirai Botnet attacks have the longest durations, with SYN DoS lasting 60 minutes and Mirai Botnet extending beyond 2 hours. These prolonged attacks suggest extended and potentially more disruptive operations.
4. Number of Source IPs:
   - The Mirai Botnet attack involved the highest number of source IP addresses (22), indicating a widely distributed attack. In contrast, Fuzzing and OS Scan attacks had fewer source IPs, suggesting more focused or contained attacks.
5. Port-Specific Details:
   - The SSL Renegotiation attack showed a significant concentration of traffic on port 53195, whereas ARP MitM and Active Wiretap attacks had high traffic volumes on port -1, with less emphasis on specific ports.

The analysis provides a comprehensive view of the temporal and behavioral characteristics of various network attacks. By understanding these patterns, network administrators can better design monitoring and mitigation strategies to enhance overall network security. Future research could focus on improving detection algorithms and developing more resilient defense mechanisms based on these insights.

Table XIV provides a comparative analysis of how this study builds upon or differs from existing literature on machine learning-based IoT attack detection. It summarizes key prior works, comparing their algorithms, datasets, evaluation metrics, and outcomes with this research, highlighting its contributions and advancements within the IoT security field.

TABLE XIV. COMPARISON OF THIS STUDY WITH EXISTING LITERATURE ON MACHINE LEARNING AND IOT ATTACK DETECTION

Aspect	Existing Literature	Our Work
Refinement of Techniques	Explores advanced ML techniques but lacks IoT specificity (e.g., El Hajj Hassan & Duong-Trung [7]).	Incorporates and refines recent algorithms tailored for IoT traffic patterns, improving detection accuracy.
Focus on IoT Vulnerabilities	Generalizes findings across broader networks (e.g., Hewa et al. [3]; Sendjaja et al. [5]).	Specifically addresses unique vulnerabilities of IoT devices, filling critical gaps in understanding IoT attack vectors.
Dynamic Mitigation Framework	Proposes static frameworks for threat mitigation (e.g., Hewa et al. [4]).	Introduces a dynamic framework that adapts to emerging threats, enhancing proactive response capabilities.
Empirical Validation	Some studies lack real-world validation (e.g., Khalaf et al. [14]; Liu & Wang [25]).	Employs real-world datasets for empirical validation and conducts comparative analysis of ML algorithms.
Holistic Approach	Focuses on single attack vectors or methodologies (e.g., Bharati [2]; Zhang & Lazaro [12]).	Adopts a holistic approach, integrating various attack types and detection methods to provide a comprehensive perspective.
Addressing Limitations	Emphasizes deep learning models without exploring practical limitations (e.g., Liu & Wang [25]; Aziz [21]).	Acknowledges and proposes solutions for challenges like computational constraints and data scarcity in IoT contexts.

D. Potential Contributions for Future Applications

The methodologies developed in this study have significant implications for future applications in cybersecurity:

1. *Advanced Intrusion Detection Systems:* The tailored machine learning algorithms can be integrated into next-generation intrusion detection systems (IDS) specifically designed for IoT networks. By leveraging our findings, organizations can enhance their ability to detect and respond to attacks more efficiently, improving overall network security.
2. *Adaptive Security Protocols:* The dynamic mitigation framework proposed can serve as a foundation for adaptive security protocols that adjust to the threat landscape in real-time. Future applications could involve implementing this framework within enterprise networks to provide proactive defense mechanisms against emerging threats, thereby reducing the risk of successful attacks.
3. *Comprehensive Security Assessments:* Our findings can inform comprehensive security assessments for IoT deployments, guiding organizations in identifying critical vulnerabilities and prioritizing protective measures. This application is particularly relevant as the number of IoT devices continues to grow, necessitating a more strategic approach to security.

4. *Collaboration and Information Sharing:* By establishing a framework for collaboration among organizations, our research could facilitate the sharing of attack patterns and defense strategies. This collective intelligence approach would enhance the community's ability to respond to evolving threats and improve the effectiveness of security measures across different sectors.

In summary, this detailed comparison with existing literature not only highlights the contributions of our findings but also emphasizes their relevance and potential for practical applications in enhancing IoT network security. Table XV presents the potential contributions of our research to various application areas.

TABLE XV. POTENTIAL CONTRIBUTIONS OF OUR RESEARCH FOR FUTURE APPLICATIONS IN IOT SECURITY

Application Area	Potential Contributions
Advanced IDS	Integration of tailored ML algorithms for improved detection
Adaptive Security Protocols	Implementation of dynamic frameworks for proactive defenses
Comprehensive Security Assessments	Guidance for identifying vulnerabilities in IoT deployments
Collaboration and Information Sharing	Facilitation of collective intelligence for enhanced security

Table XV succinctly highlights the comparisons between existing literature and our research, showcasing the contributions made by our work in various application areas.

V. CONCLUSION AND FUTURE WORK

The analysis of network traffic from various attack types reveals distinct patterns in volume, duration, focus, and distribution of attacks. Key findings include:

1. *High Packet Volumes:* Attacks such as SSDP Flood and Mirai Botnet display exceptionally high packet volumes, particularly on port -1. The Mirai Botnet attack stands out with its extensive use of multiple IP addresses and a prolonged duration exceeding 2 hours, indicating a large-scale and sustained attack.
2. *Port Focus:* Most attacks generate substantial traffic on port -1, which often represents miscellaneous or unspecified traffic. However, certain attacks, including SYN DoS, SSL Renegotiation, and Video Injection, demonstrate a targeted focus on specific ports, reflecting more deliberate and strategic attack methods.
3. *Duration and Prolonged Activity:* SYN DoS and Mirai Botnet attacks are notable for their extended durations, with the SYN DoS attack lasting 60 minutes and the Mirai Botnet attack extending over 2 hours. This suggests these attacks are designed for prolonged disruption, with significant impact on network resources.
4. *Number of Source IPs:* The Mirai Botnet attack involves the highest number of source IP addresses (22), indicating a widespread and distributed attack. In contrast, attacks like Fuzzing and OS Scan involve fewer source IPs, pointing to more focused or contained attack strategies.
5. *Port-Specific Details:* The SSL Renegotiation attack is characterized by significant traffic on port 53195, while ARP MitM and Active Wiretap attacks show high traffic volumes on port -1, with less emphasis on other specific ports.

Overall, the study highlights the diverse nature of attack strategies and their impact on network traffic, emphasizing the importance of understanding specific attack characteristics to improve detection and response mechanisms.

The following areas of future work are proposed to address current limitations and improve the overall effectiveness of network security measures:

1. *Enhanced Detection Mechanisms:* Implement advanced network monitoring and intrusion detection systems that can better identify and differentiate between high-volume attacks and targeted attacks. Leveraging machine learning algorithms to analyze traffic patterns could improve detection accuracy.
2. *Detailed Analysis of Specific Ports:* Further research into attacks that target specific ports could provide deeper insights into attack vectors and vulnerabilities. This includes analyzing the effects of specific attacks on critical ports used for essential services.
3. *Longitudinal Studies:* Conduct longitudinal studies to understand the evolution of attack patterns over time. This would involve tracking changes in attack techniques and adapting defenses accordingly.
4. *Source IP Address Profiling:* Investigate the behavior of source IP addresses in greater detail to identify patterns of malicious activity and potential botnet behavior. This could help in developing more effective countermeasures against distributed attacks.
5. *Comprehensive Attack Simulations:* Perform simulations of various attack types in a controlled environment to evaluate the effectiveness of different defensive strategies. This would help in refining response protocols and improving overall network security.
6. *Collaboration and Information Sharing:* Foster collaboration between organizations and share information about attack patterns and tactics. This collective intelligence can aid in developing better defensive tools and strategies.

By addressing these areas, future research can enhance our understanding of network attacks and improve the effectiveness of defense mechanisms against evolving threats.

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