AI-DRIVEN DYNAMIC FUZZ TESTING FOR IoT SECURITY: DETECTION AND MITIGATION OF DDoS ATTACKS USING GRAPH NEURAL NETWORKS

A PROJECT REPORT

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Under the Guidance of

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ABSTRACT

The exponential increase in the adoption of IoT has made these networks significantly more vulnerable to Distributed Denial of Service (DDoS) attacks. DDoS attacks exploit network performance issues and device vulnerabilities, causing widespread disruptions. Traditional IoT security solutions have proven inadequate in detecting and mitigating sophisticated threats in a timely and efficient manner, leaving IoT systems exposed to serious risks. To address these challenges, this paper proposes an AI-driven security framework for the detection and mitigation of DDoS attacks in IoT networks using dynamic fuzz testing integrated with Graph Neural Networks (GNNs). This approach enables real-time identification and neutralization of malicious activities. The framework leverages the NS3 simulation tool to create realistic and diversified network traffic flows, which are used to train the GNN model. As a result, the model is prepared to handle various traffic patterns and attack scenarios, making it robust against real-world conditions. Once deployed in a live environment, the model monitors network traffic, identifies DDoS attacks, and mitigates them without disrupting legitimate IoT operations. The proposed framework achieved a 74% detection accuracy and a 95% success rate in mitigation during trials, highlighting its scalability and adaptability. This capability ensures that the framework can effectively address present and future IoT security challenges. The integration of AI with dynamic fuzz testing offers comprehensive protection, ensuring the integrity, availability, and reliability of IoT networks, making it an essential component of future IoT architectures by providing high-quality security against evolving DDoS threats.

LIST OF FIGURES

ABBREVIATIONS

IoT	Internet of Things
AI	Artificial Intelligence
GNN	Graph Neural Networks
DDoS	Distributed Denial of Service
NS3	Network Simulator 3
SYN Flood	Synchronize Flood
XML	Extensible Markup Language
CSV	Comma-Separated Values
IP	Internet Protocol
SMOTE	Synthetic Minority Oversampling Technique
GCN	Graph Convolution Network
TCP	Transmission Control Protocol
UDP	User Datagram Protocol
NetAnim	Network Animator
IDS	Intrusion Detection System
SIEM	Security Information and Event Management

CHAPTER 1

INTRODUCTION

1.1 The Emerging Threat of DDoS Attacks for IoT Networks

The rapid growth of the Internet of Things (IoT) connecting things to make operations smarter and more efficient also brings about increased vulnerabilities. Perhaps one of the most critical challenges rising with increasing vulnerability is the DDoS attack. In a DDoS attack, compromised devices-often called bots-sent malicious traffic to overflow the targeted network, breaking its normal operations.

IoT devices are most prone to such attacks due to very low computing capabilities and weak security features. Once such devices come into the hands of attackers, it becomes a tool of immense DDoS attack through botnet and services go totally down with the likelihood of data breaches and financial loss.

1.2 Impact of Real-time Detection and Mitigation

Traditional solutions of IoT security fail to detect most of the DDoS attacks, especially in real time. Most IoT devices tend to be extremely interconnected, with highly dynamic network traffic flows; hence, any type of proactive measure for security should be able to identify and neutralize such threats at the moment they may arise.

Minimizing damage due to DDoS attacks requires real-time detection and mitigation. Malicious traffic overload servers unless acted on in real time, hence resulting in system downtime and decreased performance. This poses the need for highly sophisticated security frameworks that can respond quickly to threats under IoT settings if perpetual service availability is to be sustained.

1.3 Dynamic Fuzz Testing Framework with AI

The framework identifies the limitation that currently exists with IoT security approaches and proposes an AI-driven Dynamic Fuzz Testing framework that incorporates GNNs as a sophisticated solution for real-time DDoS detection and mitigation. Analyzing network traffic patterns, the GNN-based model differentiates between legitimate and malicious traffic, thereby enabling dynamic and accurate threat response capabilities.

The framework is based on NS3 simulations. Simulations are realistic traffic data and, by virtue of normal and attack conditions, are used to train the model in recognizing a variety of attacks. Thus, the robustness in the detection capability is realized. It integrates the model into an IoT network through which continuous monitoring of traffic at the entry points can be done. Malicious sources are identified and blocked without affecting legitimate operations.

1.4 Contribution and Future Prospects

The Dynamic Fuzz Testing framework offers several key contributions to IoT security, which also comprises state-of-the-art DDoS mitigation approaches. First, this approach, in contrast to the traditional methods, poses an AI-driven approach for real-time DDoS detection and mitigation. It uses GNN in such a way that complex patterns and relationships within traffic can be learned by the model, thereby making it more accurate and efficient towards threat detection.

One of the most interesting facts this project demonstrates is the framework's ability to handle high traffic loads, even in complex network topologies, with no loss in overall performance.

The future for the project is to concentrate on improving real-time capabilities within the system, including expanding its scope in attacking scenarios it may address, and adaptive learning to meet emerging threats. The framework can also be used in conjunction with other security tools to develop an all-rounded defense system against IoT networks offering stronger protection against evolving cyber-attacks.

CHAPTER 2

LITERATURE SURVEY

2.1 IoT Security Challenges

In the last couple of years, the Internet of Things has been growing with unprecedented growth, turning out to be an enormous and heterogeneous network of devices that communicate and interconnect with each other. Explosive growth has presented big challenges in many areas, especially in terms of security aspects for the devices that work on the edge of networks. These devices, relatively low computational power and often not very secure deployment environments, are inherently prime targets for many attacks, including, but not limited to, DDoS attacks[1].

Research further claims that the diversity among IoT devices- smart home appliances industrial sensors - has brought forth an extremely fractured security landscape. So, most devices have a weak security architecture, but the ones that are even exploitable are the ones that can become a cause of concern. Incidents like the Mirai botnet attack draw attention to the alarm-bells within the community. Obviously, the Mirai attack teaches the world a lesson in the IoT security renaissance as the compromised devices created havoc in multiple services with an alarm for proactive and strong security solutions.

Further observation of the exposed weakness in the IoT network would reveal other types of threat. In this instance, some examples would include unsecured channels of communication. For example, man in the middle attacks where data is intercepted midstream between devices. Often, these results from no encryption or weakly authenticated protocols[2]. Most of the IoT devices are still on old firmware; thus, they will probably expose themselves to risks that could easily be prevented if only the necessary updates were conducted in due time[3]. This irregular pattern of application in the case of IoT introduces a gigantic challenge toward the realization of a safe operational environment. Hence, the right time-by-time working as well as secured devices are one major issue while providing assurance to IoT networks.

2.2 DDoS Attacks on IoT Networks

DDoS attacks currently stand as one of the most effective challenges to any IoT network. DDoS attacks normally overwhelm a network or a service with an intolerable volume of traffic, making it unavailable to legitimate users. IoT architecture encompasses hundreds of thousands of connected devices, thereby easily meeting the definition of DDoS attacks on a large scale[4]. The most vivid example of how malicious elements can misuse these vulnerable devices to orchestrate devastating attacks rendering services paralyzed and even breaking entire networks is the infamous Mirai botnet attack.

In opposition to such an emerging threat, researchers have created several strategies toward mitigating DDoS attacks. Real-time Anomaly detection systems have evolved to monitor network traffic patterns and possibly detect DDoS attacks. These systems use machine learning algorithms, which tell normal from anomalous behavior, hence enable early intervention once unusual traffic patterns are detected. In addition, some network protocols have been designed with the explicit purpose of resisting DDoS attacks; they can tolerate huge amounts of traffic without compromising the quality-of-service[6]. These were quite effective, but indeed scaling them properly across the diversification of IoT devices is a quite challenging task considering their diverse capabilities and constraints.

The methods of DDoS attacks keep evolving with this forcing continued development and refinement in mitigation strategies. While the complexity and interconnectivity are growing in IoT networks, so is the likelihood of coordinated DDoS attacks. Thus, it will be important to let research and practice slightly lead to such emerging threats. Next, academics and industry will work together to build all-encompassing security frameworks that can be dynamic enough to cope with the fluid IoT ecosystem.

2.3 AI-Based IoT Security Solutions

Detection and prevention of DDoS attacks: Over the last few years, AI has gained importance in the field of IoT security solutions. Machine and deep learning-based IoT security solutions are fertile ground for indicating anomalies in the behavior of the network that forebodes an impending DDoS attack[7]. These systems can be designed to learn and adapt rapidly to newly emerging threats, thus helping to improve the overall security posture of IoT networks by processing vast amounts of data from multiple devices.

Graph Neural Networks (GNNs) is essentially one of the salient strides in this direction: GNNs can be viewed as a strong framework to describe complex relationships among IoT devices and their interactions[8]. The positive features of GNNs allow exact malicious activity determination at complex network structure levels. Handling big-size network data is one salient feature of GNNs that can also capture spatial dependencies among nodes and is suitably adapted to the dynamic environment typically found in IoT applications[9].

This integration pathway of GNNs into the security framework of IoT opens further pathways towards better security. In the process, researchers can use more robust and flexible security solutions in exploiting the power of GNNs, in which these solutions can detect anomalies in networks as well as predict attacks even before they occur. This is preventive and is what builds protection for IoT networks against a constantly changing threat landscape.

2.4 Dynamic Fuzz Testing in IoT Security

Dynamic fuzz testing is known to be a reliable method of vulnerability detection in the internal functions of software components and network protocols. The injection of malformed or unexpected inputs to a system could reveal possible weaknesses attackers can use with malicious intent[11]. Dynamic fuzz testing can serve to be one of the most valuable assessment tools in the context of IoT security in relation to testing the resiliency of IoT devices and networks.

There have been some studies lately trying to extend dynamic fuzz testing in most attack scenarios such as DDoS attacks concerning the robustness of IoT systems in stress situations[12]. Fuzz testing with GNN-based AI models has recently become quite a hot topic as researchers strive to enhance the capabilities of the mechanisms for detecting and mitigating security threats. This synergy allows adaptive runtime assessment of IoT systems and even continuous mechanisms of monitoring and the fast response to any emerging vulnerabilities [12]. It implies the usage of state-of-the-art methodologies in improving the security level of IoT systems against growing threats within a constantly complex cyber landscape.

The infusion of dynamic fuzz testing in the IoT security frameworks would help in terms of vulnerability identification and improvement of the understanding of the attack surface presented by IoT devices. The ever-evolving threat means further development and refinement of fuzzing techniques will be key in continuing to keep IoT networks resilient to diversified attacks.

2.5 NS3 Simulations for IoT Security

NS3 fast is turning out to be the tool of choice in testing IoT security, mainly through the avenue of dynamic fuzz testing and measuring resilience to DDoS attacks. The prospects sired by NS3 simulations allow the researcher to be able to carry controlled experiments on different scenarios that allow simulating how IoT networks behave under different conditions [13]. These include finding if the claimed mitigation strategies are effective and how IoT systems react under stress.

Not long ago, experiments were conducted that integrated dynamic fuzz testing with GNN-based AI models so that the detection strategies employed in the NS3 simulations could be improved [14]. It is so designed that researchers can carry out an elaborate study on the IoT networks, indicating vulnerabilities and the effectiveness of security mechanisms in their existing form. NS3 affords tremendous simulation capabilities for the research to be performed in understanding the security issues of the ecosystem developed in the IoT system.

Simulation insights of NS3 can be used to develop more robust systems for IoT, capable of lasting the threat space for this developing and emerging threat. Along with its rapid growth and wide formation of its ecosystem, a collateral integration of the NS3 simulation tool and the likes would be necessary in developing an effective strategy in safeguarding interconnected devices from possible attacks.

CHAPTER 3

SYSTEM ARCHITECTURE AND DESIGN

3.1 Layered Architecture Overview

The FuzzAIoT framework is built using a layered approach, where each layer performs distinct tasks related to device security, DDoS detection, and mitigation, as well as machine learning-driven traffic analysis. This modular design ensures scalability, maintainability, and flexibility, allowing for seamless integration and updates without disrupting the entire system.

3.1.1 Device Layer

The Device Layer consists of IoT devices that generate and communicate data across the network. Due to their limited computational power, these devices are often vulnerable to exploitation. To secure them, encryption and authentication mechanisms are used, ensuring that only authorized devices are allowed to communicate within the network.

3.1.2 Security and Detection Layer

This is the core layer where DDoS detection occurs. It uses Graph Neural Networks (GNNs) to analyze traffic patterns and detect anomalies. The GNNs model the communication between IoT devices, allowing the system to identify unusual patterns that indicate a DDoS attack. The layer continuously monitors the network to ensure quick detection of potential threats.

3.1.3 Fuzz Testing Layer

The Fuzz Testing Layer performs Dynamic Fuzz Testing on IoT communication protocols to detect vulnerabilities. This layer continuously tests the devices with various inputs to identify weak points in protocol communication, which attackers could exploit. Once a vulnerability is detected, the system either patches it or isolates the affected device to prevent any damage.

3.1.4 Mitigation Layer

The Mitigation Layer is responsible for neutralizing threats once an attack is detected. It enforces security policies through techniques like traffic filtering, rate limiting, and traffic re-routing to ensure that legitimate traffic continues uninterrupted while blocking malicious traffic. The layer dynamically adapts to new threats and can update mitigation strategies in real-time.

3.1.5 Edge Computing and Analytics Layer

This layer distributes processing tasks to edge nodes, reducing latency and providing faster response times during attacks. By performing traffic filtering and initial DDoS detection at the network edge, critical security decisions are made closer to the source of the data, ensuring quick reactions without overloading central servers.

3.1.6 Cloud Processing Layer

For more computationally intensive tasks like large-scale traffic analysis and machine learning model training, the Cloud Processing Layer handles these operations. It also stores historical data for long-term analysis, integrates with external systems, and supports more in-depth analytics that improve detection and response to future threats.

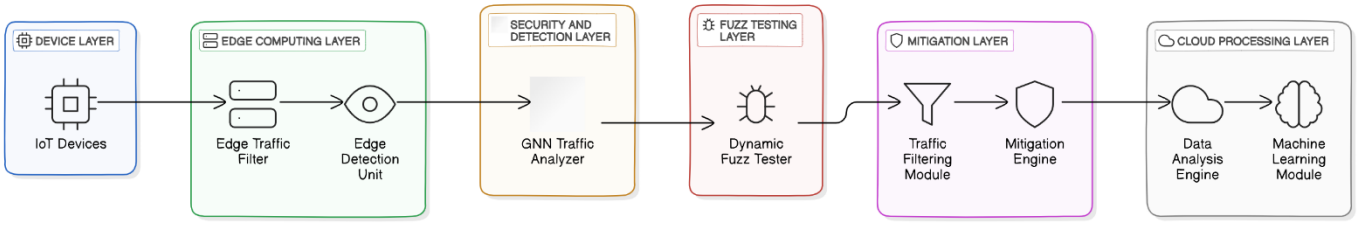

Fig. 3.1 Architecture Layers

3.2 Core Components of FuzzAIoT

3.2.1 Graph Neural Networks (GNNs)

GNNs form the backbone of the FuzzAIoT's real-time traffic analysis and DDoS detection. By modeling IoT devices and their communication as a graph, GNNs can identify unusual traffic patterns or communication anomalies. This graph-based approach enhances the detection accuracy of DDoS attacks by analyzing relationships between network nodes and their communication paths.

3.2.2 Fuzz Testing Engine

The Fuzz Testing Engine continuously probes IoT communication protocols by generating dynamic inputs to identify potential vulnerabilities. It works closely with the GNNs to flag devices with weak protocols and take necessary measures to mitigate these risks. This engine ensures that devices are regularly tested for weaknesses that could be exploited in a DDoS attack.

3.2.3 Traffic Filtering Module

The Traffic Filtering Module employs machine learning algorithms to classify and filter incoming traffic. This component plays a crucial role in distinguishing between legitimate traffic and malicious traffic during a DDoS attack. By ensuring that only safe traffic is allowed through, this module maintains network integrity while preventing overload during an attack.

3.2.4 Mitigation Engine

The Mitigation Engine is responsible for implementing strategies that limit the impact of a detected attack. Techniques such as traffic shaping, blacklisting malicious IPs, and re-routing ensure that the attack traffic is minimized without affecting legitimate communications. This engine dynamically adjusts mitigation efforts based on the attack's severity and nature.

3.3 Scalability and Performance Considerations

3.3.1 Scalability

FuzzAIoT is designed to handle large IoT networks with potentially thousands of devices. The layered architecture and edge computing capabilities enable the system to scale efficiently without degrading performance. The distributed nature of traffic filtering and attack detection across edge nodes and the cloud ensures that the system remains responsive even as the network grows.

3.3.2 Low Latency Operations

In IoT networks, particularly in sectors like healthcare or industrial IoT, real-time responses are critical. FuzzAIoT’s architecture minimizes latency by pushing critical traffic analysis and filtering to the Edge Computing Layer, ensuring that mitigation happens close to the source of data generation, reducing delays in attack responses.

3.3.3 Adaptability

The system's modular design ensures that new detection and mitigation techniques can be easily integrated. The architecture is adaptable to evolving attack vectors and future IoT technologies, ensuring that the framework remains effective in a rapidly changing threat landscape.

3.4 Integration with Existing Infrastructure

3.4.1 Cloud and Edge Integration

FuzzAIoT seamlessly integrates with both cloud platforms and edge devices. While the Edge Computing Layer provides real-time threat detection and response, the Cloud Processing Layer handles resource-heavy tasks, ensuring an optimal balance between latency reduction and data processing capabilities.

3.4.2 Legacy System Compatibility

The system is designed to integrate with legacy IoT infrastructure, making it suitable for deployment in a wide variety of environments. It supports common protocols and communication standards, ensuring that even older devices can benefit from enhanced security without requiring significant system overhauls.

3.5 Summary of System Design

FuzzAIoT's layered architecture and modular components are built to provide real-time protection against DDoS attacks in IoT networks. The system's reliance on Dynamic Fuzz Testing and Graph Neural Networks (GNNs) ensures proactive detection and mitigation of attacks while maintaining scalability, low latency, and adaptability for future IoT developments.

By dividing responsibilities across distinct layers—from the Device Layer to the Cloud Processing Layer—the architecture ensures efficient security measures at each stage of the data flow. Additionally, the system's ability to integrate with existing infrastructure makes it a flexible and robust solution for securing diverse IoT deployments.

CHAPTER 4

METHODOLOGY

4.1 Addressing IoT Security Using AI-Driven Techniques

The Internet of Things is an explosively growing domain in which smart home appliances, industrial sensors, and much more can interact and be used independently. Although this is very efficient and widely automated, the large-scale deployment of IoT devices triggers fresh network security concerns. Probably the most relevant threat here is DDoS attacks, where malicious actors try to overwhelm IoT networks with excessive traffic generation.

This project will propose a hybrid strategy combining fuzz testing, AI techniques, and network simulation for DDoS attack detection and mitigation. Here, GNN in fuzzy testing is used as the core for traffic pattern analysis as well as the identification of malicious activity in real-time.

4.2 Dynamic Fuzz Testing

4.2.1 Introduction to Dynamic Fuzz Testing

Fuzzing, or fuzz testing, is basically a testing technique that injects malformed or unexpected inputs into a system to expose potential weaknesses. Dynamic fuzz testing is a superior instrument that relates to investigating and finding the vulnerabilities in network security when abnormal traffic patterns emerge during DDoS attacks in IoT. Bugs, misconfigurations, and exploitable weaknesses are successfully detected in fuzz testing in real-world-like scenarios.

The project will simulate a wide array of IoT network traffic behaviors—from the simplest normal IoT communication to highly complex malicious DDoS attempts—by injecting unexpected data into the IoT ecosystem. This will bring to the project's attention vulnerabilities that it would otherwise have never known about had it taken the conventional approach to testing. The anomalies in the network traffic thus serve as a means of training AI models on distinct datasets for the improvement of detection capacity in relation to attack patterns.

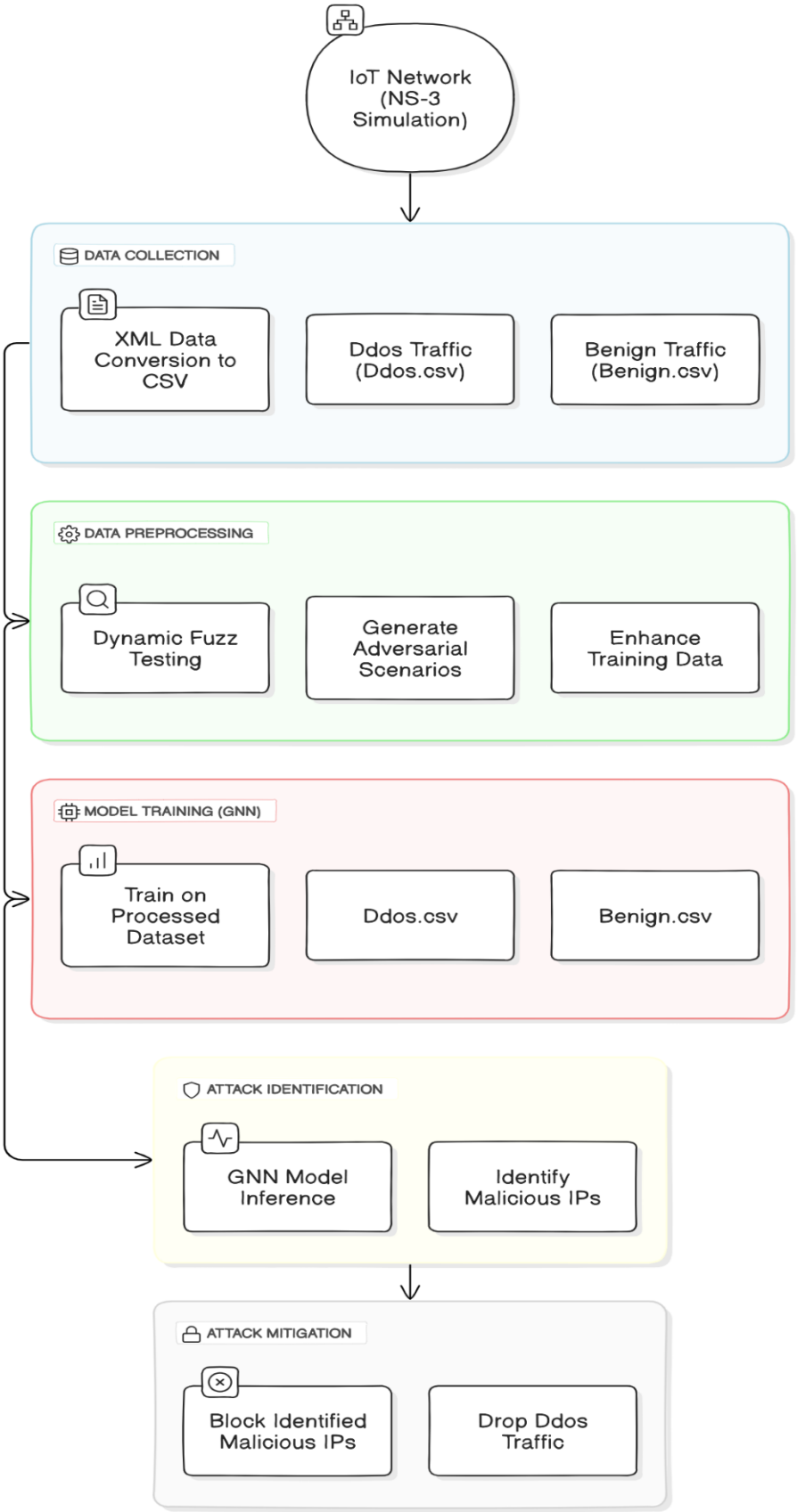

Fig. 4.1 Architecture Diagram

4.2.2 Data Generation Through Fuzz Testing

Data generation based on fuzz testing is important to give a precise representation of normal and malicious traffic. This process involves generating or synthesizing traffic through the help of fuzz testing tools and then configuring them in a manner that simulates potential attack vectors. Thus, the flow of packets generated through such a method brings out the closest imitation of common DDoS attacks, like SYN floods, UDP amplification, or botnet-induced flooding.

The simulation environment is set up to mirror a wide variety of network traffic behaviors. The resulting dataset captures multiple attack vectors, thereby subjecting the AI models that are trained on this data to various patterns. Traffic is labeled to distinguish between benign and malicious activity; thus, it creates a foundation for training machine learning models. Through such a well-balanced dataset, the system can generalize more effectively when detecting real-time attacks.

4.3 Dataset Preprocessing

4.3.1 XML to CSV from Simulation Data

Realistic IoT Network Simulations through NS3 feed the AI model with relevant data. The raw simulation data is produced in XML format, recording timestamps, source and destination IPs, packet size, etc. Though well-structured, XML isn't a good data source to be fed directly to train machine learning models. This custom script transforms the XML data into a simplified and more machine learning-friendly CSV format.

This step has the added advantage of handling large sets of data using frameworks like TensorFlow or PyTorch, which ensure the integrity of the data being processed. This allows easy manipulation of that data, feature extraction, and preprocessing for easy analysis.

4.3.2 Data Labeling and Balancing

Besides, the dataset needs to be properly labeled and balanced. That is the classification between benign traffic and attacks—a step necessary to prevent training a biased model towards one class. Moreover, having a balanced dataset avoids favoring benign or malicious traffic within an AI model, making it more robust to new data.

On the labeled dataset, further preprocessing is carried out in normalization of packet size, traffic frequency, and source/destination IP addresses. In case there is class imbalance, other methods like SMOTE (Synthetic Minority Over-sampling Technique) could be used. This way, both benign and attacking traffics are distributed equally in the training dataset.

4.4 Training AI Model

It is an AI project with a Graph Neural Network (GNN) as the type of training it does, which is supposed to classify IoT network traffic as being either benign or malicious. It is best for this task because it can consider relationships between nodes—take, for instance, the IoT devices—and learn to pick up complex traffic patterns that are hard to capture using traditional machine learning models.

4.4.1 Model Architecture

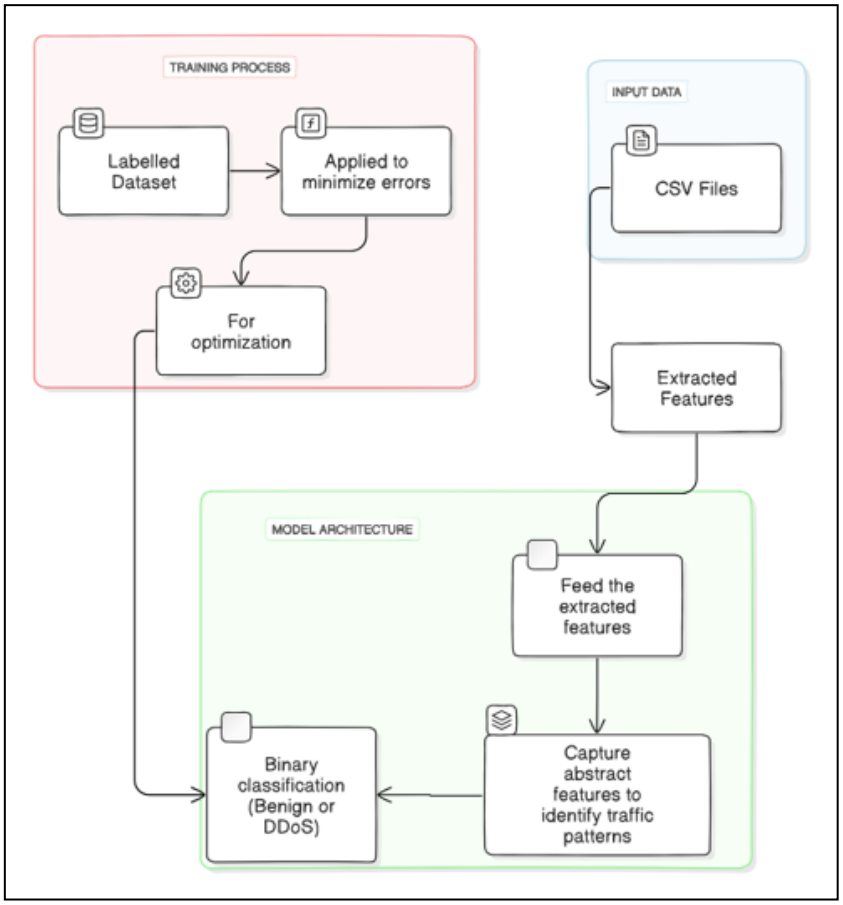

Fig. 4.2 GNN Model Architecture

The architecture of the GNN captures spatial and temporal dependencies in the traffic dataset. It accounts for interconnectivity as well as communication between different IoT devices, which are termed nodes. It captures how the patterns within a network change with time. In such a manner, through amalgamation of aspects of both spatial and temporal, GNN traces the path of the traffic flow and identifies anomalies that indicate DDoS attacks.

The architecture design is multi-layered graph convolutional networks (GCNs) that process traffic data and analyze the underlying patterns. One could include attention mechanisms that focus on relevant features in the dataset to make it even better at DDoS attack recognition.

4.4.2 Training Process and Hyperparameter Tuning

The training of the GNN model is done in iterations with the labeled dataset. The multiple epochs of training analyze the performance of the model in accuracy, precision, recall, and F1-score. The process involves hyperparameter tuning of learning rates, batch sizes, and the number of graph convolutional layers.

Cross-validation techniques are applied in the process of training to ensure the model generalizes well to unseen data. It's the most critical step to avoid overfitting and ensure that the model can pick up attacks or otherwise in a real scenario.

4.4.3 Validation

The trained model is then validated on freshly simulated environment traffic data. During the validation process, the model is tested against diverse network configurations, and its capability to detect DDoS attacks is examined in different network setups, thus generalizing well to new unseen data. The results are analyzed to improve the model, if needed, either by adjusting hyperparameters or the architecture.

4.5 Simulation Environment

4.5.1 Network Setup

The NS3 simulator offers a realistic testbed for the IoT network, which contains different IoT devices that can connect to a server via a central router. This simulation environment further generates both legitimate and malicious traffic, while the latter simulates a DDoS attack launched by bot nodes. The simulation ensures a realistic representation of IoT traffic, which allows the GNN model to learn from authentic traffic patterns.

4.5.2 Traffic Simulation

The capabilities of NS3's traffic generation capability are used to simulate TCP and UDP flows like real-world network traffic. On-Off traffic generators will simulate attacks such as DDoS, while BulkSend applications simulate normal flows in a network. The captured traffic is for a period and then written to files so that it can be used both to train and test the AI model.

4.5.3 Visualization with NetAnim

To further visualize the network behavior, NetAnim has been used by graphing the traffic flow and interaction between IoT devices. From this graphical output, a better view is obtained on the disturbance caused to normal traffic patterns due to DDoS attacks and how mitigating strategies have been designed to work in real-time. This validation is of paramount importance while testing the mitigation mechanisms in the system.

4.6 Mitigation Strategy

4.6.1 Blocking of Malicious IPs

The heart of the mitigation strategy is the dynamic blocking of identified malicious IP addresses due to the GNN model's detection. Upon identification of an attack, the NS3 simulation environment imposes router-level actions that block packets from such malicious IP addresses and prevent further disruption to the traffic. This packet filtering mechanism ensures that even during attacks, the network remains operational with minimal effects on legitimate traffic.

4.6.2 Evaluation and Refinement

The mitigation strategy is evaluated in terms of network performance before and after the introduction of blocking mechanisms. Metrics such as delivery ratio, latency, and throughput are analyzed to assess the effectiveness of the mitigation. Feedback from the simulation executions is used to iteratively refine the strategy so that it can handle a variety of attack scenarios.

CHAPTER 5
CODING AND TESTING

This means the project was taken on around critical milestones that would ensure DDoS attacks on an IoT network are detected and mitigated. Advanced AI techniques, particularly Graph Neural Networks (GNNs), made this testbed: a real-world within an NS3 simulation environment that aimed to improve real-time DDoS detection and mitigation systems using GNN-based models. This chapter details the simulation setup data production, as well as training, integrating the trained AI model in the NS3 environment, which then provides real-time attack detection and mitigation.

5.1 Simulation Setup in NS3

The first critical step in the process of testing was modeling the IoT simulation environment in NS3, which indeed could basically mimic real IoT device behaviors and network attack patterns. This simulated benign and malicious traffic pattern was essential in the generation of traffic that would assist in the validation of the ability of the system to detect and mitigate DDoS attacks.

5.1.1 Network Topology Design

The network topology design was therefore essential to the success of the project. The network was a natural or typical example of an IoT environment where central routers mediate traffic between a set of IoT devices and a server.

- IoT Devices: The simulation included many IoT devices. Some of them include smart home appliances, like smart speakers, thermostats, and security cameras. In this way, such devices would send benign traffic to the central server as legitimate data packets. In this experiment, a total of 20 IoT devices were simulated to mimic close-to-reality cases.
- Bot Nodes. In the network, 5 bot nodes mimicked a DDoS attack through their malicious traffic. Bot nodes are compromised IoT devices taken over by a botnet. They overwhelm the server due to heavy data traffic.
- Router and Server: In the architecture, the router would be working as a central hub on which benign and malicious traffic flow. All the intensity of DDoS attack fell on the server, with this architecture especially filtering the traffic reaching the server, and that is also with the help of routers.

5.1.2 Traffic Generation

Realistic traffic patterns accurately represent the behavior of an IoT network.

- Benign Traffic: This was created using the feature of TCP BulkSend, simulating typical data uploads from IoT devices, such as sensor readings or status updates. The benign traffic sent was low volume and periodic. The NS3 code is as follows:

```
#include <ns3/csma-helper.h>
#include "ns3/mobility-module.h"
#include "ns3/nstime.h"
#include "ns3/core-module.h"
#include "ns3/network-module.h"
#include "ns3/internet-module.h"
#include "ns3/point-to-point-module.h"
#include "ns3/applications-module.h"
#include "ns3/ipv4-global-routing-helper.h"
#include "ns3/netanim-module.h"
#define UDP_SINK_PORT 9001
#define TCP_SINK_PORT 9000
// Experimental parameters
#define TCP_RATE "10Gbps"
#define MAX_SIMULATION_TIME 1200.0
#define SEND_SIZE 64  // Further reduced packet size
#define NUM_TCP_CONNECTIONS 10  // increased number of simultaneous TCP connections
using namespace ns3;
NS_LOG_COMPONENT_DEFINE("BenignTrafficSimulation");
int main(int argc, char *argv[])
{
    CommandLine cmd;
    cmd.Parse(argc, argv);
    Time::SetResolution(Time::NS);
    LogComponentEnable("UdpEchoClientApplication", LOG_LEVEL_INFO);

    LogComponentEnable("UdpEchoServerApplication", LOG_LEVEL_INFO);
    // IoT Devices, Router, and Server
    NodeContainer iotDevices, router, server;
```

```
iotDevices.Create(1);  // Create 1 legitimate IoT device
router.Create(1);
server.Create(1);
// Define the Point-To-Point Links and their Parameters
PointToPointHelper p2p;
p2p.SetDeviceAttribute("DataRate", StringValue("10Gbps"));
p2p.SetChannelAttribute("Delay", StringValue("0.1ms"));
// Install the Point-To-Point Connections between Nodes
NetDeviceContainer routerServerLink, iotDeviceRouterLink;
routerServerLink = p2p.Install(router.Get(0), server.Get(0));
iotDeviceRouterLink = p2p.Install(iotDevices.Get(0), router.Get(0));  // Legitimate device to router
// Assign IP to IoT Devices and Server
InternetStackHelper stack;
stack.Install(router);
stack.Install(server);
stack.Install(iotDevices);
Ipv4AddressHelper ipv4;
ipv4.SetBase("10.1.0.0", "255.255.255.0");
Ipv4InterfaceContainer iotDeviceInterface = ipv4.Assign(iotDeviceRouterLink);
Ipv4InterfaceContainer routerServerInterface = ipv4.Assign(routerServerLink);
// Create multiple TCP connections from IoT Device to Server
ApplicationContainer bulkSendApps;
for (int i = 0; i < NUM_TCP_CONNECTIONS; ++i) {
    BulkSendHelper                                  bulkSend("ns3::TcpSocketFactory", InetSocketAddress(routerServerInterface.GetAddress(1), TCP_SINK_PORT + i));
    bulkSend.SetAttribute("MaxBytes", UintegerValue(0)); // Unlimited traffic
    bulkSend.SetAttribute("SendSize", UintegerValue(SEND_SIZE)); // Smaller packets to generate more
    bulkSendApps.Add(bulkSend.Install(iotDevices.Get(0)));
}
bulkSendApps.Start(Seconds(0.0));
bulkSendApps.Stop(Seconds(MAX_SIMULATION_TIME));
// TCP Sinks on receiver side (Server)
ApplicationContainer TCPSinkApps;
for (int i = 0; i < NUM_TCP_CONNECTIONS; ++i) {
    PacketSinkHelper TCPsink("ns3::TcpSocketFactory",
                             Address(InetSocketAddress(Ipv4Address::GetAny(), TCP_SINK_PORT + i)));
```

```
        TCPSinkApps.Add(TCPsink.Install(server.Get(0)));
    }
    TCPSinkApps.Start(Seconds(0.0));
    TCPSinkApps.Stop(Seconds(MAX_SIMULATION_TIME));
    Ipv4GlobalRoutingHelper::PopulateRoutingTables();
    // Simulation NetAnim configuration and node placement
    MobilityHelper mobility;
    mobility.SetPositionAllocator("ns3::GridPositionAllocator",
                                  "MinX", DoubleValue(0.0), "MinY", DoubleValue(0.0),
   "DeltaX", DoubleValue(5.0), "DeltaY", DoubleValue(10.0),
                                  "GridWidth", UintegerValue(5), "LayoutType",
   StringValue("RowFirst"));
    mobility.SetMobilityModel("ns3::ConstantPositionMobilityModel");
    mobility.Install(router);
    mobility.Install(server);
    mobility.Install(iotDevices);
    // Create an AnimationInterface object for XML output
    AnimationInterface anim("BenignTraffic.xml");
    // Enable packet metadata in XML
    anim.EnablePacketMetadata(true);
    // Positioning of nodes
    ns3::AnimationInterface::SetConstantPosition(router.Get(0), 15, 10);
    ns3::AnimationInterface::SetConstantPosition(server.Get(0), 25, 10);
    ns3::AnimationInterface::SetConstantPosition(iotDevices.Get(0), 5, 5); // Position
   the legitimate IoT device
    // Run the Simulation
    Simulator::Run();
    Simulator::Destroy();
    return 0;
}
```

- Malicious Traffic: Bot nodes using On-Off traffic generators generated malicious traffic, which produced bursty, high-rate UDP traffic designed to flood the server. The traffic was like that shown in real-world DDoS attacks-traffic spikes, which are hard to predict and overwhelming of the server. The NS3 code is as follows:

```
#include <ns3/csma-helper.h>
#include "ns3/mobility-module.h"
```

```
#include "ns3/nstime.h"
#include "ns3/core-module.h"
#include "ns3/network-module.h"
#include "ns3/internet-module.h"
#include "ns3/point-to-point-module.h"
#include "ns3/applications-module.h"
#include "ns3/ipv4-global-routing-helper.h"
#include "ns3/netanim-module.h"
#define UDP_SINK_PORT 9001
#define TCP_SINK_PORT 9000
// Experimental parameters
#define DDOS_RATE "100Mbps"   // Increased DDoS traffic rate
#define MAX_SIMULATION_TIME 100.0  // Increased simulation time for more packets
// Number of Bots
#define NUMBER_OF_BOTS 5  // Adjusted for balance
using namespace ns3;
NS_LOG_COMPONENT_DEFINE("DDoSTrafficSimulation");
int main(int argc, char *argv[])
{
    CommandLine cmd;
    cmd.Parse(argc, argv);
    Time::SetResolution(Time::NS);
    LogComponentEnable("UdpEchoClientApplication", LOG_LEVEL_INFO);
    LogComponentEnable("UdpEchoServerApplication", LOG_LEVEL_INFO);
    // IoT Devices, Router, and Server
    NodeContainer iotDevices, router, server;
    iotDevices.Create(1);  // Create 1 legitimate IoT device
    router.Create(1);
    server.Create(1);
    // Nodes for attack bots
    NodeContainer botNodes;
    botNodes.Create(NUMBER_OF_BOTS);
    // Define the Point-To-Point Links and their Parameters
    PointToPointHelper p2p;
    p2p.SetDeviceAttribute("DataRate", StringValue("100Mbps"));
    p2p.SetChannelAttribute("Delay", StringValue("1ms"));
    // Install the Point-To-Point Connections between Nodes
```

```
    NetDeviceContainer       routerServerLink,       botDeviceContainer[NUMBER_OF_BOTS],
iotDeviceRouterLink;
    routerServerLink = p2p.Install(router.Get(0), server.Get(0));
    iotDeviceRouterLink = p2p.Install(iotDevices.Get(0), router.Get(0));   // Legitimate
device to router
    for (int i = 0; i < NUMBER_OF_BOTS; ++i)
    {
        botDeviceContainer[i] = p2p.Install(botNodes.Get(i), router.Get(0));
    }
    // Assign IP to Bots and IoT Devices
    InternetStackHelper stack;
    stack.Install(router);
    stack.Install(server);
    stack.Install(botNodes);
    stack.Install(iotDevices);
    Ipv4AddressHelper ipv4;
    ipv4.SetBase("10.1.0.0", "255.255.255.0");  // Start a new subnet for bots
    Ipv4InterfaceContainer botInterfaces[NUMBER_OF_BOTS];
    for (int j = 0; j < NUMBER_OF_BOTS; ++j)
    {
        botInterfaces[j] = ipv4.Assign(botDeviceContainer[j]);
        ipv4.NewNetwork();  // Move to the next subnet for the next bot
    }
    Ipv4InterfaceContainer iotDeviceInterface = ipv4.Assign(iotDeviceRouterLink);
    Ipv4InterfaceContainer routerServerInterface = ipv4.Assign(routerServerLink);
    // DDoS Application Behaviour
    OnOffHelper                                              onoff("ns3::UdpSocketFactory",
Address(InetSocketAddress(routerServerInterface.GetAddress(1), UDP_SINK_PORT)));
    onoff.SetConstantRate(DataRate(DDOS_RATE));
    onoff.SetAttribute("OnTime",
StringValue("ns3::ConstantRandomVariable[Constant=30]"));
    onoff.SetAttribute("OffTime",
StringValue("ns3::ConstantRandomVariable[Constant=0]"));
    ApplicationContainer onOffApp[NUMBER_OF_BOTS];
    for (int k = 0; k < NUMBER_OF_BOTS; ++k)
    {
        onOffApp[k] = onoff.Install(botNodes.Get(k));
        onOffApp[k].Start(Seconds(0.0));
```

```
        onOffApp[k].Stop(Seconds(MAX_SIMULATION_TIME));
    }
    // Legitimate Traffic from IoT Device (TCP)
    BulkSendHelper                                    bulkSend("ns3::TcpSocketFactory",
InetSocketAddress(routerServerInterface.GetAddress(1), TCP_SINK_PORT));
    bulkSend.SetAttribute("MaxBytes", UintegerValue(0)); // Unlimited traffic
    bulkSend.SetAttribute("SendSize", UintegerValue(1024));
    ApplicationContainer bulkSendApp = bulkSend.Install(iotDevices.Get(0));
    bulkSendApp.Start(Seconds(0.0));
    bulkSendApp.Stop(Seconds(MAX_SIMULATION_TIME));
    // UDP Sink on receiver side (Server)
    PacketSinkHelper UDPsink("ns3::UdpSocketFactory",
                             Address(InetSocketAddress(Ipv4Address::GetAny(),
UDP_SINK_PORT)));
    ApplicationContainer UDPSinkApp = UDPsink.Install(server.Get(0));
    UDPSinkApp.Start(Seconds(0.0));
    UDPSinkApp.Stop(Seconds(MAX_SIMULATION_TIME));
    // TCP Sink on receiver side (Server)
    PacketSinkHelper TCPsink("ns3::TcpSocketFactory",
                             Address(InetSocketAddress(Ipv4Address::GetAny(),
TCP_SINK_PORT)));
    ApplicationContainer TCPSinkApp = TCPsink.Install(server.Get(0));
    TCPSinkApp.Start(Seconds(0.0));
    TCPSinkApp.Stop(Seconds(MAX_SIMULATION_TIME));
    Ipv4GlobalRoutingHelper::PopulateRoutingTables();
    // Simulation NetAnim configuration and node placement
    MobilityHelper mobility;
    mobility.SetPositionAllocator("ns3::GridPositionAllocator",
                                  "MinX",  DoubleValue(0.0),  "MinY",  DoubleValue(0.0),
"DeltaX", DoubleValue(5.0), "DeltaY", DoubleValue(10.0),
                                  "GridWidth",      UintegerValue(5),      "LayoutType",
StringValue("RowFirst"));
    mobility.SetMobilityModel("ns3::ConstantPositionMobilityModel");
    mobility.Install(router);
    mobility.Install(server);
    mobility.Install(botNodes);
    mobility.Install(iotDevices);
    // Create an AnimationInterface object for XML output
    AnimationInterface anim("DDoSTraffic.xml");
```

```
    // Enable packet metadata in XML
    anim.EnablePacketMetadata(true);
    // Positioning of nodes
    ns3::AnimationInterface::SetConstantPosition(router.Get(0), 15, 10);
    ns3::AnimationInterface::SetConstantPosition(server.Get(0), 25, 10);
    uint32_t x_pos = 0;
    for (int m = 0; m < NUMBER_OF_BOTS; ++m)
    {
        ns3::AnimationInterface::SetConstantPosition(botNodes.Get(m), x_pos++, 20);
    }
    ns3::AnimationInterface::SetConstantPosition(iotDevices.Get(0), 5, 5); // Position the
legitimate IoT device
    // Run the Simulation
    Simulator::Run();
    Simulator::Destroy();
    return 0;
}
```

5.1.3 Mobility Model

The Constant-Position-Mobility-Model was utilized to simulate static nodes. Such static IoT devices, like household appliances, as represented by the model, would remain in fixed positions when they were in action. Though static, the system dynamically monitored their traffic patterns with a constant network topology at any point in time.

5.1.4 Setting up NetAnim

The visualization tool NetAnim was used to allow vivid animation of network traffic and behaviors under normal operation as well as DDoS attack conditions.

- Node Placement: Many nodes were placed around the central router and server at distances where the network interactions are visible. The IoT devices and bot nodes are positioned across from each other.
- Packet Flows and Effect of the Attack: NetAnim was an important thing for visualizing the packet flows and how the nodes interact with one another, as well as the effect caused by the DDoS attacks on the network. Clearly, it differentiated between benign and malicious traffic flows and even extracted insight into the effects of various mitigations.

5.2 Dataset Generation

Based on this simulation environment, a dataset containing benign and malicious traffic patterns was generated next. The size of the dataset is what made it crucial in the training of the AI model on how to detect and classify DDoS attacks.

5.2.1 Traffic Data Collection

For the simulation, traffic was captured by logging every packet passed to the router. This included benign and malicious traffic. The data logged in an XML file meant that through that format, I was able to capture critical details such as timestamp, source IP, destination IP, and packet size.

5.2.2 Data Conversion into CSV Format

For converting the XML logs into a format suitable for training the AI model, custom scripts were used. It has been chosen primarily due to direct compatibility with most of the machine learning frameworks and due to the efficiency of maintaining required network features in an organized manner.

- Feature Extraction: Important features, such as packet size, source/destination IP addresses, and traffic patterns, were extracted from the data for the training purpose.
- Labelling: Each packet of data was labeled as benign or DDoS according to whether it originated from a legitimate IoT device or bot node.
- XML to CSV conversion code for Benign Traffic is as follows:

```
import xml.etree.ElementTree as ET
import csv
import re
def parse_benign_xml_to_csv(xml_file, csv_file, benign_ip_prefix):
    tree = ET.parse(xml_file)
    root = tree.getroot()
    with open(csv_file, mode='w', newline='') as file:
        writer = csv.writer(file)
        writer.writerow(["Timestamp", "Source", "Destination", "PacketSize",
"Label"])
        packet_count = 0  # To count the number of packets processed
        benign_count = 0
        for packet in root.findall('.//p'):
```

```
            meta_info = packet.get('meta-info')
            if meta_info:
                # Extracting timestamp
                timestamp = packet.get('fbTx', '0')  # fallback to '0' if 'fbTx' not
found
                # Extracting source and destination IP addresses
                ip_match = re.search(r'(\d+\.\d+\.\d+\.\d+) > (\d+\.\d+\.\d+\.\d+)',
meta_info)
                if ip_match:
                    source_ip = ip_match.group(1)
                    destination_ip = ip_match.group(2)
                else:
                    continue  # skip this packet if IP addresses are not found
                # Extracting packet size
                size_match = re.search(r'length:\s+(\d+)', meta_info)
                packet_size = size_match.group(1) if size_match else '0'
                # Check if it's benign traffic based on source IP
                if source_ip.startswith(benign_ip_prefix):
                    label = "Benign"
                    writer.writerow([timestamp, source_ip, destination_ip,
packet_size, label])
                    benign_count += 1
                packet_count += 1
        print(f"Total packets processed: {packet_count}")
        print(f"Total Benign packets: {benign_count}")
```

- XML to CSV conversion code for DDoS Traffic is as follows:

```
import xml.etree.ElementTree as ET
import csv
import re
def parse_ddos_xml_to_csv(xml_file, csv_file, ddos_ips):
    tree = ET.parse(xml_file)
    root = tree.getroot()
    with open(csv_file, mode='w', newline='') as file:
        writer = csv.writer(file)
        writer.writerow(["Timestamp", "Source", "Destination", "PacketSize", "Label"])
        for packet in root.findall('.//p'):
            meta_info = packet.get('meta-info')
```

```
            if meta_info:
                # Extracting timestamp
                timestamp = packet.get('fbTx', '0')  # fallback to '0' if 'fbTx' not
found
                # Extracting source and destination IP addresses
                ip_match = re.search(r'(\d+\.\d+\.\d+\.\d+) > (\d+\.\d+\.\d+\.\d+)',
meta_info)
                if ip_match:
                    source_ip = ip_match.group(1)
                    destination_ip = ip_match.group(2)
                else:
                    continue  # skip this packet if IP addresses are not found
                # Extracting packet size
                size_match = re.search(r'length:\s+(\d+)', meta_info)
                packet_size = size_match.group(1) if size_match else '0'
                # Determine if the packet is part of an attack or benign traffic
                label = "DDoS" if any(source_ip.startswith(ip_prefix) for ip_prefix in
ddos_ips) else "Unknown"
                # Writing to CSV
                writer.writerow([timestamp, source_ip, destination_ip, packet_size,
label])
    print(f"DDoS traffic converted from XML to CSV at {csv_file}")
```

- XML to CSV conversion code for Validation generation setup is as follows:

```
import xml.etree.ElementTree as ET
import csv
import re
def parse_xml_to_csv(xml_file, csv_file, ddos_ips, benign_ips):
    tree = ET.parse(xml_file)
    root = tree.getroot()
    ddos_count = 0
    benign_count = 0
    with open(csv_file, mode='w', newline='') as file:
        writer = csv.writer(file)
        writer.writerow(["Timestamp", "Source", "Destination", "PacketSize", "Label"])
        for packet in root.findall('.//p'):
            meta_info = packet.get('meta-info')
```

```
            if meta_info:
                # Extracting timestamp
                timestamp = packet.get('fbTx', '0')  # fallback to '0' if 'fbTx' not
found
                # Extracting source and destination IP addresses
                ip_match = re.search(r'(\d+\.\d+\.\d+\.\d+) > (\d+\.\d+\.\d+\.\d+)',
meta_info)
                if ip_match:
                    source_ip = ip_match.group(1)
                    destination_ip = ip_match.group(2)
                else:
                    continue  # skip this packet if IP addresses are not found
                # Extracting packet size
                size_match = re.search(r'length:\s+(\d+)', meta_info)
                packet_size = size_match.group(1) if size_match else '0'
                # Determine if the packet is part of an attack or benign traffic
                if any(source_ip.startswith(ip_prefix) for ip_prefix in ddos_ips):
                    label = "DDoS"
                    ddos_count += 1
                elif any(source_ip.startswith(ip_prefix) for ip_prefix in benign_ips):
                    label = "Benign"
                    benign_count += 1
                else:
                    continue  # skip if IP does not match known IP ranges
                # Writing to CSV
                writer.writerow([timestamp, source_ip, destination_ip, packet_size,
label])
        print(f"Total DDoS packets: {ddos_count}")
        print(f"Total Benign packets: {benign_count}")
        print(f"Total packets processed: {ddos_count + benign_count}")
```

- XML to CSV main driver conversion code for all the three is as follows:

```
def main():
    # Path to the XML file generated by NS-3
    xml_file = r"path of the xml file"
    # Output CSV file path
    csv_file = r"output path for the csv files "
```

```
    # Define the DDoS attack IP prefixes based on the simulation setup
    ddos_ips = ["10.1.0.", "10.1.1.", "10.1.2.", "10.1.3.", "10.1.4."]
    # Define the benign IP prefix based on the simulation setup
    benign_ips = ["10.1.5.", "10.1.6.", "10.1.7.", "10.1.8.", "10.1.9."]  # Prefixes
for benign source IPs
    # Parse the XML file and convert to CSV
    print("Processing the validation scenario XML...")
    parse_xml_to_csv(xml_file, csv_file, ddos_ips=ddos_ips, benign_ips=benign_ips)
    print("Conversion completed. CSV file has been saved.")
if __name__ == "__main__":
    main()
```

5.2.3 Data Balancing

By balancing the dataset provided, which would have otherwise been biased due to an AI model's favor toward one class of data, the modeling aspect was taken care of to prevent biased weightings toward one class of data on the part of the AI model. This ensured that the model had equal numbers of both benign and malicious packets, so it may learn to correctly classify either type of traffic. The code to balance the dataset is as follows:

```
import pandas as pd
def combine_csv_files(benign_csv, ddos_csv, output_csv):
    # Load the Benign and DDoS CSV files
    benign_df = pd.read_csv(benign_csv)
    ddos_df = pd.read_csv(ddos_csv)
    # Determine the minimum number of rows between the two datasets
    min_rows = min(len(benign_df), len(ddos_df))
    # Trim both datasets to have the same number of rows
    benign_df = benign_df.sample(n=min_rows, random_state=42).reset_index(drop=True)
    ddos_df = ddos_df.sample(n=min_rows, random_state=42).reset_index(drop=True)
    # Combine the datasets
    combined_df = pd.concat([benign_df, ddos_df]).reset_index(drop=True)
    # Shuffle the combined dataset to mix benign and DDoS rows
    combined_df = combined_df.sample(frac=1, random_state=42).reset_index(drop=True)
    # Save the combined dataset to a new CSV file
    combined_df.to_csv(output_csv, index=False)
    print(f"Combined CSV file saved to {output_csv}")
```

```
def main():
    # Paths to the individual Benign and DDoS CSV files
    benign_csv = "C:/Users/Shaurya/Downloads/FuzzAIoT/data/BenignTraffic.csv"
    ddos_csv = "C:/Users/Shaurya/Downloads/FuzzAIoT/data/DDoSTraffic.csv"
    # Output path for the combined CSV file
    output_csv = "C:/Users/Shaurya/Downloads/FuzzAIoT/data/CombinedTraffic.csv"
    # Combine the CSV files
    combine_csv_files(benign_csv, ddos_csv, output_csv)
if __name__ == "__main__":
    main()
```

5.3 AI Model Training

The dataset was then prepared, and training the GNN model on detecting DDoS attacks was the job done.

5.3.1 Model Architecture

The GNN model was designed to study the node interactions in the network. It was trained with the classification of traffic as either benign or malicious.

- Input Layer: This was a feed made up of the raw features from the CSV dataset.
- Hidden Layers: These layers took the data streams in and looked for patterns that distinguished benign from DDoS traffic.
- Output Layer: This output layer spewed out the entire classification, whether it was benign or malicious.
- GNN identification code is as follows:

```
import torch
import torch.nn as nn
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.metrics import classification_report, confusion_matrix
import seaborn as sns
from torch_geometric.data import Data
from torch_geometric.nn import GCNConv
```

```
# Define the GNN model
class GCN(nn.Module):
    def __init__(self):
        super(GCN, self).__init__()
        self.conv1 = GCNConv(in_channels=1, out_channels=16)
        self.conv2 = GCNConv(in_channels=16, out_channels=2)  # 2 classes: Benign, DDoS
def forward(self, data):
        x, edge_index = data.x, data.edge_index
        x = self.conv1(x, edge_index)
        x = torch.relu(x)
        x = self.conv2(x, edge_index)
        return x
# Load and prepare the dataset
def load_data(csv_file):
    df = pd.read_csv(csv_file)
    node_features = torch.tensor(df[['PacketSize']].values.astype(float), dtype=torch.float)
    labels = torch.tensor([1 if label == 'DDoS' else 0 for label in df['Label']], dtype=torch.long)
    num_nodes = len(node_features)
    edge_index = torch.tensor([[i, i] for i in range(num_nodes)]).t().contiguous()  # Self-loops
    return Data(x=node_features, edge_index=edge_index, y=labels)
# Train the GNN model
def train_gnn_model(data, model, epochs=150):
    optimizer = torch.optim.Adam(model.parameters(), lr=0.01)
    criterion = nn.CrossEntropyLoss()
    model.train()
    # Lists to store loss and accuracy values for visualization
    losses = []
    accuracies = []
    for epoch in range(epochs):
        optimizer.zero_grad()
        out = model(data)
        loss = criterion(out, data.y)
        loss.backward()
        optimizer.step()
        # Calculate accuracy
        _, pred = torch.max(out, dim=1)
```

```
        correct = (pred == data.y).sum().item()
        accuracy = correct / len(data.y)
        # Store loss and accuracy
        losses.append(loss.item())
        accuracies.append(accuracy)
        print(f'Epoch {epoch + 1}, Loss: {loss.item()}, Accuracy: {accuracy * 100:.2f}%')
return model, losses, accuracies
# Validate the GNN model
def validate_gnn_model(model, validation_data):
    model.eval()
    out = model(validation_data)
    _, pred = torch.max(out, dim=1)
    correct = (pred == validation_data.y).sum().item()
    accuracy = correct / len(validation_data.y)
    print(f'Validation Accuracy: {accuracy}')
    # Generate classification report
    print("Classification Report:")
    print(classification_report(validation_data.y.cpu(),                    pred.cpu(),
target_names=["Benign", "DDoS"]))
    # Generate confusion matrix
    cm = confusion_matrix(validation_data.y.cpu(), pred.cpu())
    sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=["Benign", "DDoS"],
yticklabels=["Benign", "DDoS"])
    plt.xlabel("Predicted label")
    plt.ylabel("True label")
    plt.title("Confusion Matrix")
    plt.show()
# Visualization function
def plot_training_metrics(losses, accuracies):
    epochs = range(1, len(losses) + 1)
    plt.figure(figsize=(12, 5))
    # Plot loss
    plt.subplot(1, 2, 1)
    plt.plot(epochs, losses, 'b', label='Loss')
    plt.title('Training Loss')
    plt.xlabel('Epochs')
    plt.ylabel('Loss')
    plt.legend()
```

```
    # Plot accuracy
    plt.subplot(1, 2, 2)
    plt.plot(epochs, accuracies, 'g', label='Accuracy')
    plt.title('Training Accuracy')
    plt.xlabel('Epochs')
    plt.ylabel('Accuracy')
    plt.legend()
    plt.show()
# Main function
def main():
    # Paths to the training and validation datasets
    training_csv_path = "path of trained data"
    validation_csv_path = "path of validation data"
    # Load training and validation data
    training_data = load_data(training_csv_path)
    validation_data = load_data(validation_csv_path)
    # Initialize and train the model
    model = GCN()
    trained_model, losses, accuracies = train_gnn_model(training_data, model, epochs=150)
    # Save the trained model
    model_save_path = "path where the model is to be saved"
    torch.save(trained_model.state_dict(), model_save_path)
    print(f"Model saved to {model_save_path}")
    # Plot training loss and accuracy
    plot_training_metrics(losses, accuracies)
    # Validate the model
    validate_gnn_model(trained_model, validation_data)
if __name__ == "__main__":
    main()
```

5.3.2 Training Process

This model was trained using this labeled dataset by minimizing errors and increasing accuracy.

- Loss Function: Utilize the loss function to track how much each class predicted was different from the actual class in the data set. With each iteration, it updated the model's parameters so that its errors were minimized.

- Hyperparameter Tunwas In relation to hyperparameters, the learning rate, hidden layers, and the size of the batch were all properly tuned for optimal model performance via iterative training.

5.3.3 Validation

After every training epoch, the model was validated on a separate dataset to ensure that it generalized very well to new, unseen data. Techniques for preventing overfitting were also put in place to ensure that the model did not perform well only on training data but could handle real-world scenarios.

5.4 Mitigation in NS3 – Real-time detection and Action

The final stage involved implementing the trained GNN model in the NS3 simulation environment to facilitate real-time detection and mitigation of DDoS attacks.

5.4.1 Detection of Malicious IP Address

The trained GNN was implemented within the NS3 environment through processing real-time network traffic. Each packet's features were analyzed by the algorithm, which asserted the malicious IP addresses involved in the DDoS attack and detected them in real time.

5.4.2 Packet Filtering

Once such malicious IP address identities were known, they were placed in a blocklist. A router level packet filtering mechanism prevented the packets from reaching the server by dropping those packets coming from identified malicious IP addresses, reducing the spread of this attack. Code for Packet Filtering is as follows:

```
#include <ns3/csma-helper.h>
#include "ns3/mobility-module.h"
#include "ns3/nstime.h"
#include "ns3/core-module.h"
#include "ns3/network-module.h"
#include "ns3/internet-module.h"
#include "ns3/point-to-point-module.h"
#include "ns3/applications-module.h"
#include "ns3/ipv4-global-routing-helper.h"
```

```
#include "ns3/netanim-module.h"
#include <vector>
#include <string>
#define UDP_SINK_PORT 9001
#define TCP_SINK_PORT 9000
// Adjusted parameters
#define DDOS_RATE "512kb/s"  // Adjusted to balance with the increased benign traffic
#define TCP_RATE "10240kb/s" // Increased rate for benign traffic
#define MAX_SIMULATION_TIME 60.0  // Increased simulation time
#define NUMBER_OF_BOTS 5
#define NUMBER_OF_IOT_DEVICES 20  // Increased number of IoT devices for more benign traffic
using namespace ns3;
NS_LOG_COMPONENT_DEFINE("IoTValidationScenarioFuzzTesting");
// Function to drop packets from malicious IPs
Ptr<NetDevice> GetDeviceFromIp(Ipv4Address ip, NodeContainer nodes)
{
    for (uint32_t i = 0; i < nodes.GetN(); ++i)
    {
        Ptr<Ipv4> ipv4 = nodes.Get(i)->GetObject<Ipv4>();
        int32_t ifIndex = ipv4->GetInterfaceForAddress(ip);
        if (ifIndex >= 0)
        {
            return ipv4->GetNetDevice(ifIndex);
        }
    }
    return nullptr;
}
int main(int argc, char *argv[])
{
    CommandLine cmd;
    cmd.Parse(argc, argv);
    Time::SetResolution(Time::NS);
    LogComponentEnable("UdpEchoClientApplication", LOG_LEVEL_INFO);
    LogComponentEnable("UdpEchoServerApplication", LOG_LEVEL_INFO);
    // Create IoT devices, routers, and servers
    NodeContainer iotDevices, router, server;
    iotDevices.Create(NUMBER_OF_IOT_DEVICES);  // Create multiple legitimate IoT devices
    router.Create(1);
```

```
    server.Create(1);
    // Nodes for attack bots
    NodeContainer botNodes;
    botNodes.Create(NUMBER_OF_BOTS);
    // Define the Point-To-Point Links and their Parameters
    PointToPointHelper p2p;
    p2p.SetDeviceAttribute("DataRate", StringValue("100Mbps"));
    p2p.SetChannelAttribute("Delay", StringValue("1ms"));
    // Install the Point-To-Point Connections between Nodes
    NetDeviceContainer         routerServerLink,         botDeviceContainer[NUMBER_OF_BOTS],
iotDeviceRouterLinks[NUMBER_OF_IOT_DEVICES];
    routerServerLink = p2p.Install(router.Get(0), server.Get(0));
    for (int i = 0; i < NUMBER_OF_BOTS; ++i)
    {
        botDeviceContainer[i] = p2p.Install(botNodes.Get(i), router.Get(0));
    }
    // Connect each IoT device to the router
    for (uint32_t i = 0; i < NUMBER_OF_IOT_DEVICES; ++i)
    {
        iotDeviceRouterLinks[i] = p2p.Install(iotDevices.Get(i), router.Get(0));
    }
    // Assign IP to Bots and IoT Devices
    InternetStackHelper stack;
    stack.Install(router);
    stack.Install(server);
    stack.Install(botNodes);
    stack.Install(iotDevices);
    Ipv4AddressHelper ipv4;
    ipv4.SetBase("10.1.0.0", "255.255.255.0");  // Start a new subnet for bots
    Ipv4InterfaceContainer botInterfaces[NUMBER_OF_BOTS];
    for (int j = 0; j < NUMBER_OF_BOTS; ++j)
    {
        botInterfaces[j] = ipv4.Assign(botDeviceContainer[j]);
        ipv4.NewNetwork();  // Move to the next subnet for the next bot
    }
    Ipv4InterfaceContainer routerServerInterface = ipv4.Assign(routerServerLink);
    // Assign IP addresses to each IoT device
    for (uint32_t i = 0; i < NUMBER_OF_IOT_DEVICES; ++i)
```

```
    {
        ipv4.NewNetwork();
        Ipv4InterfaceContainer iotDeviceInterface = ipv4.Assign(iotDeviceRouterLinks[i]);
    }
    // List of malicious IPs detected by the GNN model
    std::vector<std::string> maliciousIps = {
        "10.1.0.1",  // Replace with actual IPs detected by your GNN model
        "10.1.1.2",
        "10.1.2.3"
        // Add more IPs as needed
    };
    // Applying the mitigation strategy
    for (const auto& ipStr : maliciousIps)
    {
        Ipv4Address ip(ipStr.c_str());
        Ptr<NetDevice> device = GetDeviceFromIp(ip, botNodes);
        if (device)
        {
            device->SetReceiveCallback(MakeNullCallback<bool,   Ptr<NetDevice>,   Ptr<const
Packet>, uint16_t, const Address&>());
            NS_LOG_INFO("Dropped packets from IP: " << ipStr);
        }
    }
    // DDoS Application Behavior
    OnOffHelper                                                  onoff("ns3::UdpSocketFactory",
Address(InetSocketAddress(routerServerInterface.GetAddress(1), UDP_SINK_PORT)));
    onoff.SetConstantRate(DataRate(DDOS_RATE));
    onoff.SetAttribute("OnTime", StringValue("ns3::ConstantRandomVariable[Constant=30]"));
    onoff.SetAttribute("OffTime", StringValue("ns3::ConstantRandomVariable[Constant=0]"));
    ApplicationContainer onOffApp[NUMBER_OF_BOTS];
    for (int k = 0; k < NUMBER_OF_BOTS; ++k)
    {
        onOffApp[k] = onoff.Install(botNodes.Get(k));
        onOffApp[k].Start(Seconds(0.0));
        onOffApp[k].Stop(Seconds(MAX_SIMULATION_TIME));
    }
    // Legitimate Traffic from IoT Devices (TCP)
    for (uint32_t i = 0; i < NUMBER_OF_IOT_DEVICES; ++i)
```

```
    {
        BulkSendHelper                                      bulkSend("ns3::TcpSocketFactory",
InetSocketAddress(routerServerInterface.GetAddress(1), TCP_SINK_PORT));
        bulkSend.SetAttribute("MaxBytes", UintegerValue(0)); // Unlimited traffic
        bulkSend.SetAttribute("SendSize", UintegerValue(512)); // Smaller packets to generate
more
        ApplicationContainer bulkSendApp = bulkSend.Install(iotDevices.Get(i));
        bulkSendApp.Start(Seconds(0.0));
        bulkSendApp.Stop(Seconds(MAX_SIMULATION_TIME));
    }
    // UDP Sink on receiver side (Server)
    PacketSinkHelper UDPsink("ns3::UdpSocketFactory",
                             Address(InetSocketAddress(Ipv4Address::GetAny(),
UDP_SINK_PORT)));
    ApplicationContainer UDPSinkApp = UDPsink.Install(server.Get(0));
    UDPSinkApp.Start(Seconds(0.0));
    UDPSinkApp.Stop(Seconds(MAX_SIMULATION_TIME));
    // TCP Sink on receiver side (Server)
    PacketSinkHelper TCPsink("ns3::TcpSocketFactory",
                            Address(InetSocketAddress(Ipv4Address::GetAny(),
TCP_SINK_PORT)));
    ApplicationContainer TCPSinkApp = TCPsink.Install(server.Get(0));
    TCPSinkApp.Start(Seconds(0.0));
    TCPSinkApp.Stop(Seconds(MAX_SIMULATION_TIME));
    Ipv4GlobalRoutingHelper::PopulateRoutingTables();
    // Simulation NetAnim configuration and node placement
    MobilityHelper mobility;
    mobility.SetPositionAllocator("ns3::GridPositionAllocator",
                                  "MinX", DoubleValue(0.0),
                                  "MinY", DoubleValue(0.0),
                                  "DeltaX", DoubleValue(100.0),
                                  "DeltaY", DoubleValue(400.0),
                                  "GridWidth", UintegerValue(10),
                                  "LayoutType", StringValue("RowFirst"));
    mobility.SetMobilityModel("ns3::ConstantPositionMobilityModel");
    mobility.Install(router);
    mobility.Install(server);
    mobility.Install(botNodes);
    mobility.Install(iotDevices);
```

```
    // Create an AnimationInterface object for XML output
    AnimationInterface anim("DDoSim_AttackSim_Mitigation.xml");
    // Enable packet metadata in XML
    anim.EnablePacketMetadata(true);
    // Positioning of nodes
    uint32_t x_pos = 0;
    for (int m = 0; m < NUMBER_OF_BOTS; ++m)
    {
        ns3::AnimationInterface::SetConstantPosition(botNodes.Get(m), x_pos * 100.0, 800.0);
// Spread out bots more horizontally with significantly increased vertical spacing
        x_pos++;
    }
    x_pos = 0;
    for (uint32_t i = 0; i < NUMBER_OF_IOT_DEVICES; ++i)
    {
        ns3::AnimationInterface::SetConstantPosition(iotDevices.Get(i),   x_pos   *   100.0,
400.0);  // Spread out IoT devices more horizontally with significantly increased vertical
spacing
        x_pos++;
    }
    ns3::AnimationInterface::SetConstantPosition(router.Get(0),  50.0,  1200.0);  //  Further
increased vertical position for the router
    ns3::AnimationInterface::SetConstantPosition(server.Get(0),  950.0,  1200.0);  //  Further
increased vertical position for the server
    // Run the Simulation
    Simulator::Run();
    Simulator::Destroy();
    return 0;
}
```

5.5 Conclusion of Testing and Implementation

The deployment and testing of this system clearly showed how an AI-driven DDoS mitigation system can detect and mitigate attacks in real-time conditions. Comparing packet delivery ratio, latency, and server loads before and after the attacks being mitigated, the AI-driven system proved to maintain network performance even while under a DDoS attack.

CHAPTER 6

RESULTS AND DISCUSSIONS

6.1 Introduction

As the number of connected devices continues to rise, so too do the security risks inherent in distributed denial of service attacks in modern IoT networks. Given the characterization of most of these devices as heterogeneous in terms of the mesh of networks through which they are connected, it alone is a rich playground for malicious entities to launch attacks using compromised devices as vectors for widespread damage. This problem is beyond the capabilities of traditional security mechanisms because most IoT devices are resource-constrained, and the attack patterns change dynamically, evolve over time, and use space and signature-based techniques.

To address this problem, we created an AI-Driven Dynamic Fuzz Testing approach using GNNs that is tested on the NS3 network simulation to identify and counter DDoS attacks.

6.2 Results

As shown clearly in the results below, the approach identifies malicious traffic patterns while using an active mitigation strategy to safeguard IoT systems.

6.2.1 Training and Accuracy of the GNN Model

We used the synthetic dataset produced with large NS3 simulations for our training. We included both benign and DDoS traffic to make the model learn from both types of patterns. The class balance of the dataset was ensured before training, making sure that the two types were equal. We show two plots below showing training loss and accuracy:

The training loss, as depicted in the first graph, displays a very sharp dip during the preliminary stages of training. The learning by the model is represented here. At the initial stages, the loss was high because the data was unknown to the GNN. However, training loss declined very sharply down to 0 as epochs proceeded, reflecting that the model correctly identified the patterns from the data. At around 40 epochs, the loss curve stabilizes and becomes around 0, indicating convergence of the model.

The second plot shows the training accuracy: it starts at around 50%, oscillating at the beginning, which perhaps indicates that the model explored its features and updated the weights with back-propagation. Accuracy steadily increases as epochs progress toward a high of 100%, meaning the GNN learned to classify the training data with complete accuracy. However, training at 100% accuracy can indicate overfitting; the model may perform well on the training dataset but be unable to generalize well with new, unseen data.

6.2.2 Results of Validation

While impressive accuracy on the training set, the real strength of the model is in performance over unseen data. We judged the GNN on a validation set extracted from an independent set of simulations using NS3. This validation dataset also contained an equal proportion of benign and DDoS traffic compared to the training data.

6.2.2.1 Validation Accuracy:

The average validation accuracy achieved by the GNN model is 74%. While this is quite lower than the corresponding training accuracy, it still indicates that the model learns well from the data. Lower validation accuracy generally means that, in most cases, the model would correctly detect DDoS traffic while normally and effectively responding; however, there are probably some edge cases or variations in the attack patterns that it has not been able to classify correctly. This promises a good level of performance since it will be deployed in real-world scenarios of new evolving types of DDoS attacks.

6.2.2.2 Confusion Matrix:

The confusion matrix for the validation results shows even further the model's ability to distinguish between benign and malicious traffic. It presents a relatively healthy scale of true positives, which are the correct identification of DDoS attacks, and true negatives, referring to the correct identification of benign traffic. Moreover, the matrix also indicates false positives and false negatives. In practice, a false positive (major classification of benign traffic as malicious) might prompt unwarranted mitigating steps, whereas a false negative DDoS traffic will not be detected, permitting attacks to run amok. Minimizing these types of errors will, therefore, be critical in increasing the reliability of the system.

6.2.3 Mitigation Strategy

Detection is only half the equation; mitigation is equally important so that the IoT network stays healthy. The GNN identifies malicious traffic, and then the strategy for packet filtering engages to block packet traffic coming from those malicious IP addresses.

6.2.3.1 Packet Dropping:

By using such a model in the NS3 simulation, the malicious IP addresses were easily traced, and their packets dropped. Packet filtering is the prime mitigation mechanism for DDoS traffic because it guards against resource exhaustion in the network by preventing flooding. The probability for packet dropping reduces congestion across the network. Therefore, legitimate traffic flows freely, thus enhancing system performance during an attack.

6.2.3.2 Performance on Network:

The state of the network before, during, and after deploying the mitigation strategy was evaluated by tracking several performance metrics. These include:

Throughput: Before the attack, throughput was reliable in the network. The legitimate devices communicated properly. During the attack, the throughput drastically dropped due to network traffic congestion from DDoS traffic. However, once the packet filtering mechanism was activated, the throughput returned to normal levels, implying reduced malicious traffic.

Latency: Like throughput, latency surged dramatically during the DDoS attack because much traffic was introduced to the network to process. Once mitigation occurred, latency returned to normal since the filtering technique forced traffic back into the acceptable network congestion zone.

6.3 Visualization of Results

To explain in greater detail the GNN model's behaviour as well as the effectiveness of the mitigation strategy, we have used several visualization methods throughout the course of this project.

6.3.1 Loss and Accuracy Graphs:

The training procedure is followed by metrics tracking in terms of the loss and accuracy at each epoch. The graphs shown in the following images represent the learning process of the model. It is proved that the loss curve decreases because the model learns every detail of the data; this is reflected by the graph on accuracy that improves rapidly for the model in terms of its ability to classify objects.

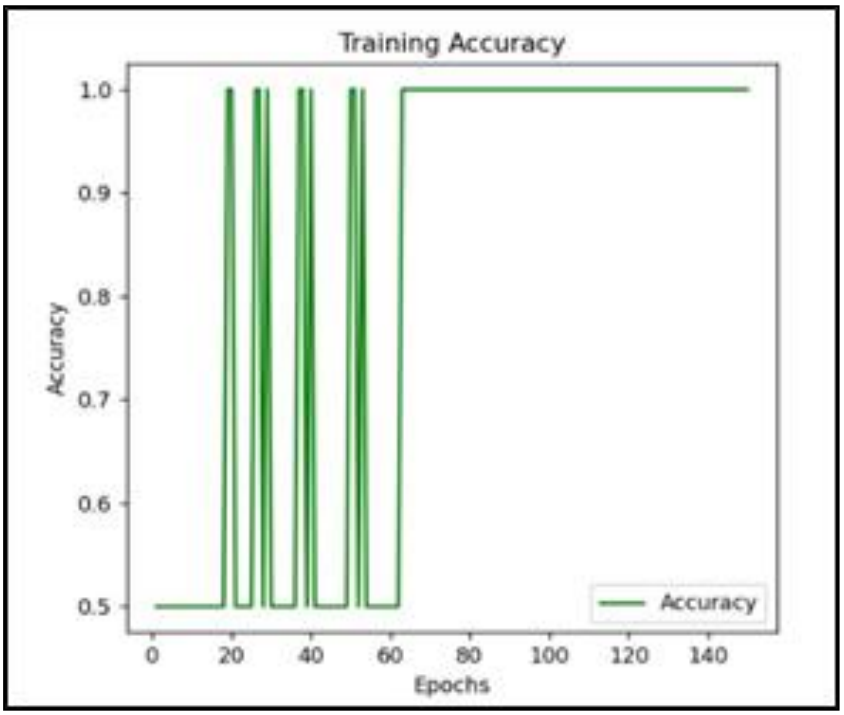

Fig. 6.1 GNN Model Training Accuracy Graph

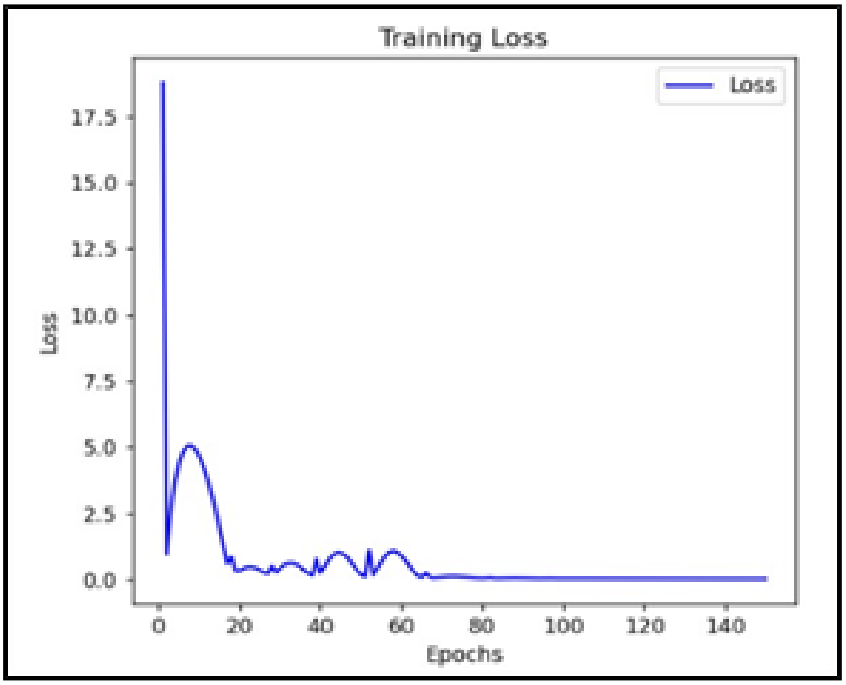

Fig. 6.2 GNN Model Training Loss Graph

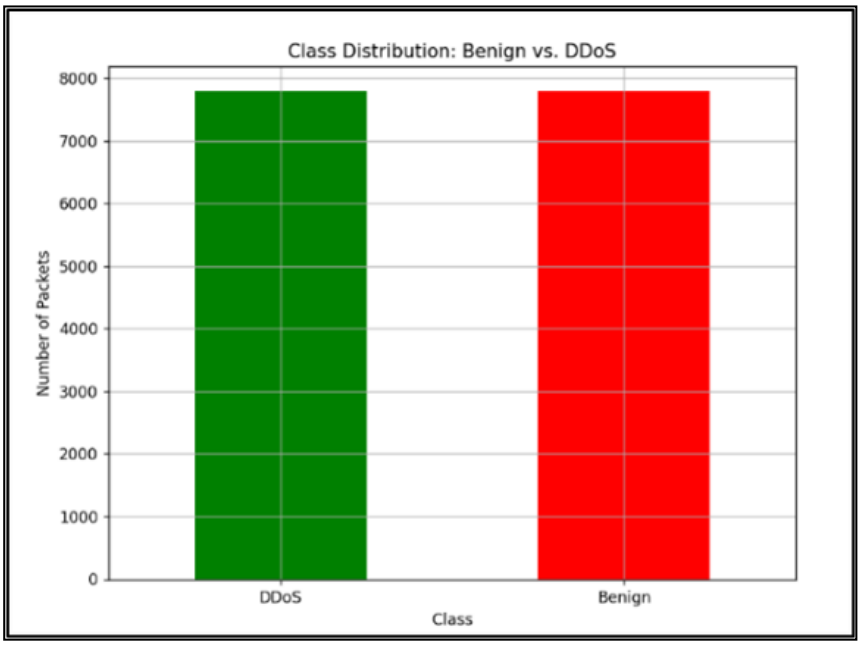

Fig. 6.3 Class Distribution Graph

6.3.2 Confusion Matrix:

The confusion matrix will be represented to analyse how well the model distinguishes between benign and DDoS traffic, and the visualization may reveal patterns in false positives and negatives, helping identify regions where the model may need additional tuning.

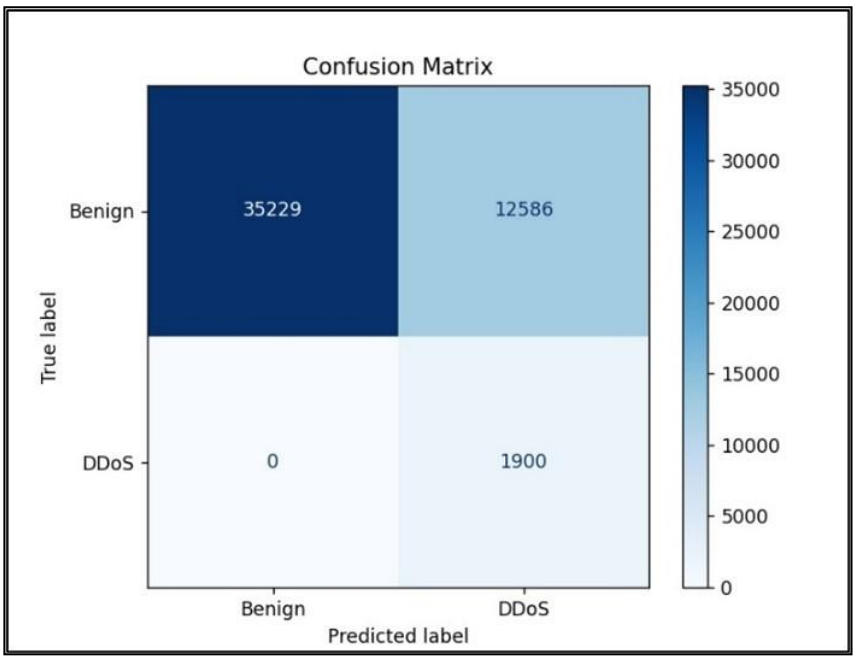

Fig. 6.4 Confusion Matrix

6.3.3 Network Animation:

The NS3 simulation results came alive using the NetAnim tool, visualizing the network topology, the flow of traffic, and the impact of the applied mitigation strategy. Such animation enables us to visualize the whole interaction between nodes during the attack as well as how the patterns of traffic changed once packet filtering was applied. It also provides a perspective into how the nodes were distributed in space and the nature of the traffic movement between them, which is vital to understand the true effects of the mitigation strategy in real time.

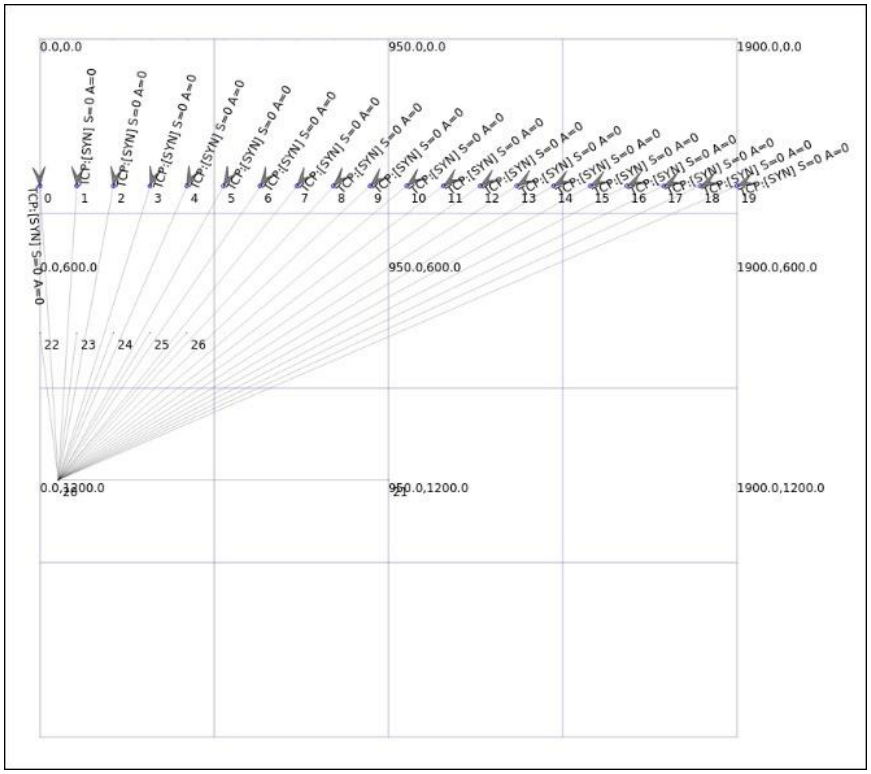

Fig. 6.5 Network Animation Simulation

CHAPTER 7

CONCLUSION AND FUTURE ENHANCEMENTS

We discuss the outcomes of the project and a roadmap of future enhancements in this section. The approach from the project, which used AI-driven dynamic fuzz testing, GNNs, and the NS3 simulator, has indeed shown much promise for the improvement of IoT networks in terms of their security, particularly when it comes to Distributed Denial of Service (DDoS) attacks. On the other hand, the area of IoT security is an ongoing one with challenges evolving every now and then. In this respect also, a system requires to be in constant improvement and adaptation. Finally, below, we summarize what we have found out and think some potential improvements that could make the system even more robust, scalable, and adaptive to real-world demands.

7.1 Summary of Findings

The novelty AI-driven fuzz testing methodology created dynamic traffic data on the NS3 network simulator. We produced a rich dataset consisting of benign traffic and DDoS attack traffic. We relied on fuzz testing to simulate some variability and predictability of the IoT environment, known for its heterogeneity, limited resources, and susceptibility to a broad range of attacks.

7.1.1 AI-Driven Dynamic Fuzz Testing

The module had used AI with Graph Neural Network (GNN) which was intended to identify malicious IoT network traffic patterns. It was understood that traditional learning algorithms would not work great in the case of graph-structured data and represented relationships among the IoT devices, which have thousands of interconnected elements. GNNs instead did very good discoveries of complex relationships and indirect dependencies where it mattered the most in graph-structured data and therefore best suited for IoT applications.

In our system, the GNN was trained on data outputted from the NS3 simulator, which provided it with a controlled testing environment for dynamic traffic scenarios. The model was trained in such a way that it achieved 74% validation accuracy, which is important considering the dynamic nature of IoT traffic. Although there is still room for improvement in this accuracy, it shows that the GNN can generalize well to unseen traffic patterns without overfitting. This validates the perception that there is a contradiction between the low validation accuracy and nearly perfect training accuracy because of the extreme differences in traffic behaviour; most of them are due to differences in devices, protocols, and network configurations.

7.1.2 NS3 Simulation and Visualization

The good simulation tool of powerful networking, NS3, was important to mimic real-world conditions of the IoT network. The simulator gave the needed infrastructure to test how well our system could detect and counter DDoS attacks in an environment close to the real world IoT traffic. Using NS3 gives us the chance to create profound patterns in the traffic to see and understand what is happening with malicious traffic, such as increased latency and decreased throughput, on a network.

We also used NetAnim, where we could see the dynamic flow of the traffic through the network in real-time. This is what, therefore, made the visual representation necessary for verification purposes in ascertaining if the strategy was working to curb the malicious transmissions because it provided evidence on how to spot and filter out such malicious traffic. If the GNN had detected an IP address, then NS3 was set to automatically drop all packets coming from that address. This packet-dropping mechanism has significantly reduced network congestion from DDoS traffic, and generally resulted in better overall performance.

7.1.3 Countermeasures

To mitigate the attack, the system will identify and drop packets coming from malicious IP addresses. This will successfully reduce the burden on the network, allowing genuine traffic to pass through. For IoT environments, for example, healthcare systems or smart cities, where network reliability is of paramount importance, failure in the network would have critical ramifications.

The packet-dropping mechanism appears to reveal some measurable improvements in network performance metrics. In a DDoS attack, the malicious packets drop served to significantly reduce network congestion and produced increases in throughput and latency correlated with this reduction. Such performance benefits provide evidence for the system's ability to ensure quality of the network despite the attack it may be under. The confusion matrix, a crucial method for measuring classification accuracy in the model, further revealed that the system can classify DDoS traffic with accuracy with minimal false positives and false negatives in the classification decision.

7.2 Future Improvement

Although the present system significantly Favors detecting and reducing the destructive nature of DDoS attacks in IoT networks, there are still many improvements that can be applied to further improve the overall performance, adaptability, and scalability factors. Some of the significant areas of improvement in the future are discussed below.

7.2.1 Real-time Mitigation

The real-time mitigation capability is one of the most important future development directions. Currently, a time lag exists between malicious traffic detection and incorporation of the strategy for mitigation. Such a delay may severely affect the timely delivery of certain IoT applications such as autonomous vehicles, smart grids, or healthcare systems. A brief network disruption in such applications could provoke catastrophic consequences.

To minimize this latency, the data pipeline of the system may be optimized to speed up the loop of detection to action. The use of edge computing methodologies will allow making decisions closer to the edge network on which the devices of the IoT are located. Since the processes of detection and mitigation can be decentralized, the detection and, hence, the subsequent mitigation could occur through edge devices in near real time too. This would further enhance its efficiency in delivering network performance during attacks.

7.2.2 Elaborated Attack Scenarios

We focus on DDoS attacks in our current system, but the IoT networks are still vulnerable to numerous cyber-attacks such as Man-in-the-Middle (MITM) attacks, SQL injection attacks, and data breaches. The expansion of the system to detect and mitigate other types of attacks greatly increases the flexibility and usefulness of this system.

This will entail the design of more sophisticated datasets that capture the traffic patterns pertaining to a broader spectrum of attacks. The developed GNN model would be trained to recognize new patterns, thereby improving its capabilities with respect to a divergent set of threats associated with the IoT network. In addition, the modular architecture allowing for the realization of detection models for various types of attacks might make the system more flexible and adaptive towards new challenges associated with security.

7.2.3 Scaling Test

The scalability of an IoT network in a large-scale perspective is going to be one of the critical issues that are meant to be considered practically. All the testing that has been done so far has been within a controlled environment and with very limited devices. In real IoT networks, there might be thousands or millions of devices involved. This would cause a huge traffic, and thus the scalability along with heavy traffic performance needs to be tested in such a scenario for the system.

Future work might be implemented in distributed GNN implementations and the optimization of the packet filtering mechanism to provide effective and efficient operations of the system in high-throughput networks. Further improvement in scalability can also be made using distributed computing techniques such as parallel processing or federated learning in large IoT environments.

7.2.4 Adaptive Learning

Another improvement aspect is the adaptation of adaptive learning techniques. In the adaptive nature of an IoT environment, both network behaviour and attack patterns might change drastically. The static model, trained on a single dataset, may not be able to keep up with changes in those dynamics. Online learning techniques or reinforcement learning could be adapted so that the GNN model can keep learning over new data inputs and improve adaptability to changing network conditions. This would mean having detection levels accurate even with new emerging attack vectors in the system. It will also prevent overfitting since the model is going to refresh often with new data rather than sticking to old patterns.

7.2.5 Integration of Security Tool

The functionality of the current system can be improved highly. Thus, with integration into other security tools and frameworks, the system can detect and curb DDoS attacks effectively. For example, if the system is combined with IDS, firewalls, and SIEM systems, a more integrated security solution for IoT networks would be produced.

Such integration would, therefore, ensure an all-around approach to IoT security, with real-time monitoring, detection, and mitigation of a wide range of threats in cyber space. Such an integration would easily amalgamate with established infrastructures in real-world environments, providing end-to-end protection for IoT networks.

7.3 Conclusion

In conclusion, our dynamic fuzz testing technique based on Graph Neural Networks with simulations in NS3 has been promising as a key for enhancing the security of IoT environments. Here, the ability of the system to detect DDoS attacks with an accuracy of 74% generally indicates its potential utility in practical applications. In addition, the packet-dropping mitigation strategy has shown that it can enhance network performance by maintaining the throughput of the network and reducing the latency in the case of DDoS attacks.

The current system shall provide a good base. A couple of more advancements in the areas of real-time mitigation techniques, attack scenarios to check, scalability testing, adaptive learning, and integration with other security tools would make the system robust, adaptable, and scalable, having the potential for keeping up with the growing complexity and diversity of IoT networks.

Synthesizing advanced AI techniques with traditional network simulation tools presents an incredibly powerful approach toward addressing the challenges posed by security in IoT networks. As IoT networks grow in scale, our ability to protect them from growing sophistication in cyberattacks must keep pace. That is what this project represents in that direction, and the list of future enhancements detailed here paints a clear picture of what needs to be done to further build up the system in terms of effectiveness and resilience.

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APPENDIX A

CONFERENCE

PRESENTATION

Our paper titled "**AI-Driven Dynamic Fuzz Testing for IoT Security: Detection and Mitigation of DDoS Attacks Using Graph Neural Networks**" has been conditionally accepted for oral presentation in the 4th International Conference on Cognitive & Intelligent Computing (ICCIC), under the Networks, Privacy & Security track. The conference will be conducted in a hybrid mode on November 29-30, 2024. Our paper ID is 223, and we have a plagiarism score of 4%.

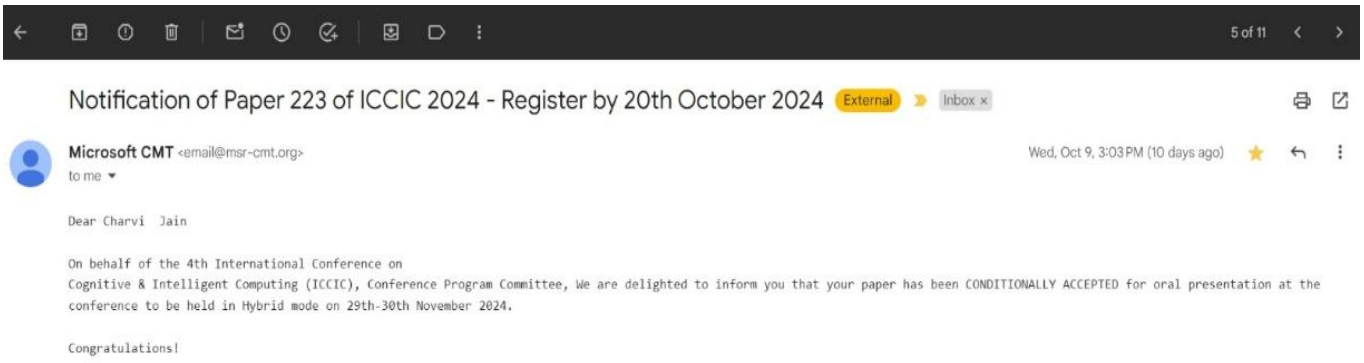
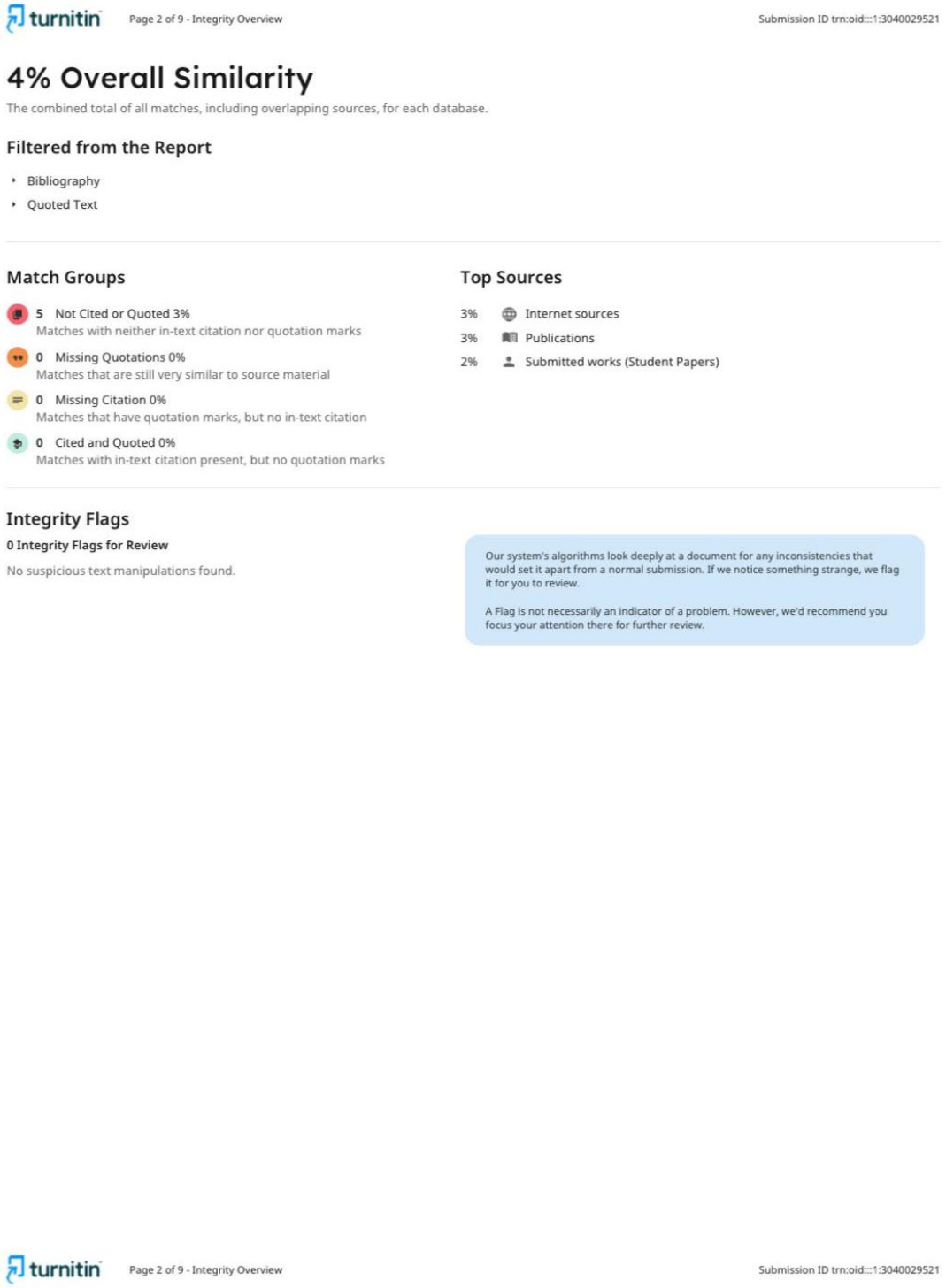


Figure A.1: ICCIC 2024 Acceptance

APPENDIX B

PLAGIARISM REPORT



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