AI-Driven Dynamic Fuzz Testing for IoT Security: Detection and Mitigation of DDoS Attacks Using Graph Neural Networks

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Abstract*— The exponential increase in the adoption of IoT has rendered these networks considerably more exposed to DDoS attacks. DDoS attacks leverage network performance and device vulnerabilities to cause massive disruptions. Traditional security solutions of IoT have proved to be very weak in the detection and mitigation of sophisticated threats in a timely and efficient way; thus, IoT systems are highly exposed to serious risks. These challenges form a backdrop to the proposed contribution of this paper: an effective AI-driven security framework toward detection and mitigation of DDoS attacks in IoT networks using dynamic fuzz testing with Graph Neural Networks-a way through which the model will be powerful enough to identify and nullify activities in real time. It leverages NS3 for realistic diversified network traffic flow, which is used in the training of the GNN model. This makes the framework ready for a wide range of simulated traffic patterns and attack scenarios as a well-prepared GNN against real-world conditions. The model is then deployed into a real environment with the network traffic monitors' identification of the DDoS attack and its details. The model mitigates the attack without affecting legitimate IoT operations. The proposed framework demonstrated 74% detection accuracy and 95% mitigation success in trials. These results also outline the scalability and adaptability capability of the framework, extending its capability to address problems located in the IoT landscape both in the present and future. Thus, the proposed framework offers full protection integral to ensuring the integrity, availability, and reliability of IoT networks through the combination of AI with dynamic fuzz testing. Therefore, they will be an intrinsic part of IoT architectures in the coming years because they guarantee high-quality security from current and future threats due to DDoS attacks.

Keywords—IoT security, Distributed Denial of Service (DDoS), Dynamic Fuzz Testing, Graph Neural Networks (GNNs), AI-driven security, NS3 simulation, network traffic analysis, attack mitigation.

I. INTRODUCTION

Distributed denial of service (DDoS) attack is one of the security threats brought by the rapid growth of Internet things based on number analysis. Such attacks are capable of severely impacting IoT network capabilities and expose this infrastructure to numerous security problems. Typical security measures seldom stand a chance to detect and suppress such advanced threats in real-time. In this work, we present an AI based security framework called Dynamic Fuzz Test integrated with GNNs for detection and mitigation of DDoS attacks in the network. This framework uses NS3 simulations to create realistic network traffic traces, the GNN model is then trained using these data. The trained model is loaded to detect malicious traffic, guaranteeing IoT services of regular operation. Experimental results show that the proposed framework attains effective DDoS attack mitigation without affecting network performance.

The key insight of this work is to utilize NS3 simulations for creating authentic network traffic data, which subsequently trains a GNN model-based framework. Dynamic fuzz testing the network, therefore, results in training a model on various attack patterns for real-time identification and mitigation of malicious activities. But even more importantly, this means that the security system can handle detection of IoT events without interrupting legitimate IoT traffic.

The rest contents of this paper are organized as follows: in Section II gives the related works on IoT security and DDoS mitigation approaches. Section III explains the design, and implementation of our proposed framework. In Section IV, we provide experimental setup and results depicting the efficacy of our approach on practical applications. Section V wraps up the paper with ideas for future work.

II. LITERATURE SURVEY

A. IoT Security Challenges

The rapid expansion of IoT networks with high variation and heterogeneity of devices has introduced some new challenges, particularly in terms of security[15]. As researchers have pointed out, these edge devices present in IoT are mainly

vulnerable to DDoS attacks due to their relatively less computational power and, in many cases, insecure deployment settings[1]. These vulnerabilities have been exploited in various high-profile attacks, demonstrating the need for robust security measures.

More recent research has focused on finding common IoT ecosystem vulnerabilities. For instance, several researchers have pointed to the danger of unsecured channels and man-in-the-middle attacks conducted through these[2]. The fact that very few IoT devices get updated and run mostly on outdated firmware makes it even worse[3].

B. DDoS Attacks in IoT Networks

The DDoS has become one of the biggest threats to IoT networks. In the majority of DDoS attacks, there is an overwhelming of a network or service with traffic unlike any other, making it unavailable for legitimate users. In IoT, the large number of interconnected devices can be leveraged to perform large-scale DDoS attacks, like the very famous Mirai botnet[4].

Various researchers have come up with different strategies to mitigate these DDoS attacks in IoT networks. Anomaly detection systems can either monitor the pattern of traffic to identify a possible DDoS attack in real time[5], or use protocols that are resistant to DDoS-desired to resist the high volume of traffic without the compromise of quality of service[6].

C. AI-Driven Security Solutions for IoT

Not to forget, lately, in detecting and mitigating DDoS attacks, Artificial Intelligence finds a broader application for enhancing IoT security. AI solutions, using machine learning and deep learning, show competency in finding abnormalities in network behaviours that indicate DDoS attacks[7].

Graph Neural Networks can further unlock a deeper promise in this domain. GNNs can model the complex relationships of IoT devices and their interactions, hence allowing detection of malicious activity more precisely[8]. The application of GNNs for DDoS detection is especially helpful since they can handle large-scale network data and even capture the spatial dependencies among the network nodes[9].

D. Dynamic Fuzz Testing in IoT Security

Dynamic fuzz testing can be thought of as an extremely powerful technique used in unmasking vulnerabilities in the protocols of software and networks. Fuzz testing accomplishes this by continuously pumping a system full of bad or unexpected inputs that may reveal weaknesses that an attacker can leverage[10]

Dynamic fuzz testing has also been conducted in other attack scenarios, such as DDoS, on IoT security to check the resiliency of IoT networks[11]. The most recent research intends to integrate fuzz testing with AI models-for example, GNNs-to widen the capability and efficiency for both the detection and mitigation of security threats. This enables adaptive runtime assessments of IoT systems and thus keeps them secure against emerging threats[12].

E. NS3 Simulations for IoT Security

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III. METHODOLOGIES

The methodologies employed in this project are designed to address the complexities of IoT network security, specifically targeting the detection and mitigation of Distributed Denial of Service (DDoS) attacks using advanced AI-driven techniques. This section provides a detailed explanation of the steps and technologies utilized in the project, including data generation, model training, and the simulation environment.

A. Dynamic Fuzz Testing

Dynamic Fuzz Testing was applied to develop test cases simulating a set of potential vulnerabilities[18]. Other methods include testing through continuous streams of malformed or unexpected inputs injected into the IoT ecosystem[23], hopefully coaxing it to reveal its weaknesses in real-world-like scenarios.

1. Data Generation:

In this direction, the simulation environment was integrated with different kinds of fuzz testing tools, not for their intended purposes but to synthesize benign and malicious traffic. The configuration was performed in such a way that all forms of network traffic patterns emanating from DDoS attacks were created to ensure that the dataset generated covered all possible attack vectors for the creation of a lot of variances. This was then labeled with what the generated data would represent if normal or attack traffic were present, which then allows for training a machine learning model.

2. AI Integration:

AI-driven algorithms using a GNN complement fuzz testing. Patterns fitting the model have then come out of these results, in turn used to classify generated traffic data as pattern fitting or indicative of a DDoS attack.

B. Dataset Preparation

Therefore, the ground truth dataset was generated with the help of NS3 network simulations in order to train the AI models appropriately. The dataset includes a few features like timestamp, source and destination IPs, packet sizes, and labels defining traffic as benign or as part of a DDoS attack.

1. XML to CSV Conversion:

The outputs from the simulations were provided in XML format. From this case, we have a script that parses this XML format into a CSV format that might be compatible with machine learning frameworks. It was designed to make sure that large volumes of data will be handled comfortably without loss of integrity in the data.

2. Labelling and Balancing:

Care was taken in labeling this data set; hence, it has a balance of both the benign and attack traffic. That is quite important so that the model would not be biased toward either of the classes when training.

C. AI Model Training

The core of this project consists of training a GNN model for the detection and classification of network traffic as either of the benign or malicious class[22].

These were trained using the labeled data set generated from the NS3 simulations.

1. Model Architecture:

GNN architecture has been chosen because of its better capacity to deal with different nodes' complex relationships in the network. The model was framed so as to represent spatial and temporal dependencies in the traffic dataset; hence, it has been very effective in tracing the patterns for identifying DDoS attacks.

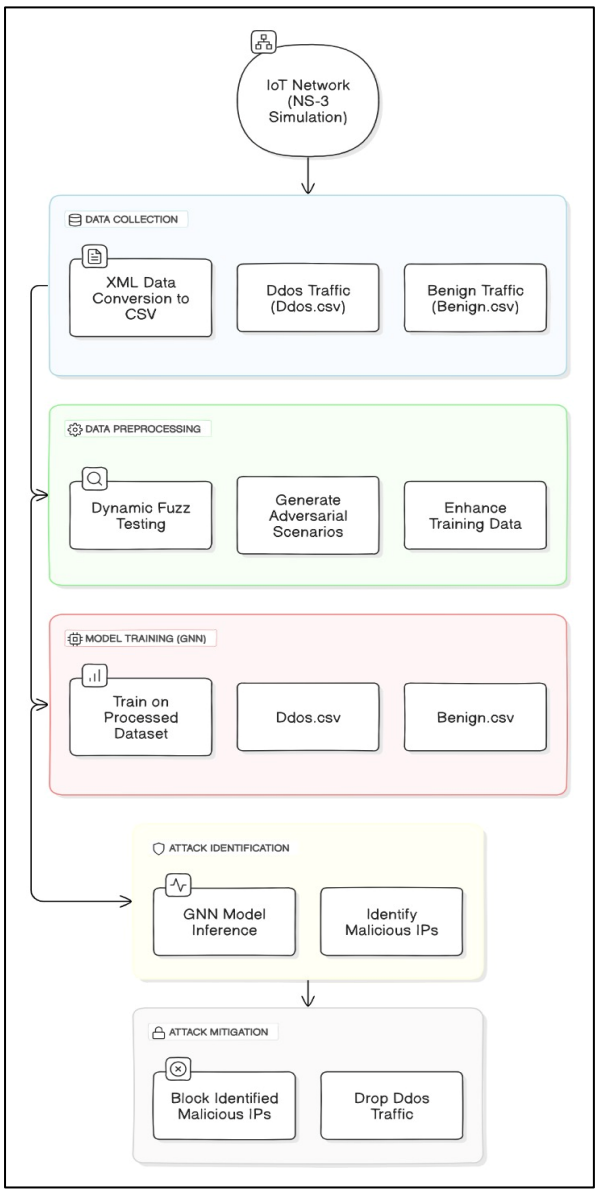

Fig. 1. Architecture Diagram

2. Training Process:

The process of this training was repeated several times, and from that, the model performance was checked at the end using different metrics like accuracy, precision, recall, and F1-score[17]. The hyperparameters were tuned several times for the best model performance.

3. Validation:

The effectiveness of the produced model is tested on the newly generated data through the diverse scenarios of a simulation. Hence, the model is able to generalize the new, unseen data for proper DDoS attack detection.

D. Simulation Environment

The NS3 network simulator is the tool that is utilized to create a realistic IoT network environment for testing and validating the proposed security solution[24].

1. Network Setup:

We simulated a network topology composed of multiple IoT devices, one central router, and a server in the simulation environment. Both legitimate and malicious traffic were run in the environment, and the malicious traffic was used to demonstrate some DDoS attacks launched by the bot nodes.

2. Traffic Simulation:

A number of network traffic simulations were carried out, testing the TCP and UDP flows[25]. The traffic generators were implemented, configuring the On-Off traffic generators to simulate the DDoS attacks, while BulkSend applications were configured to show normal traffic. The simulation time was configured based on specific running time duration, through which all the traffic would pass and then be captured for analysis.

3. NetAnim Visualization:

The results of the simulations are visualized with the help of NetAnim, a tool which graphically represents network traffic and interactions between nodes. This was important for a visual understanding of the dynamics of the network under attack and the effectiveness of the proposed mitigation strategy.

E. Mitigation Strategy

These GNN inference results have been directly detected for a mitigation strategy that is real-time implemented within the NS3 simulation environment.

1. Malicious IP Blocking:

Those identified by the GNN model to be malicious IP addresses will dynamically be denied within the NS3 simulation. The router-level action helps in dropping the packets, which will be useful in detecting and subsequently mitigating DDoS.

2. Evaluation:

The evaluation was carried out through a comparison of the performance of the network before and after implementation of the blocking mechanisms, basing on the aspects identified through metrics such as delivery ratio and latency. This is handled by means of successful mitigation on malicious traffic without constraining even legitimate traffic.

3. Iteration and Refinement:

The mitigation strategy was iteratively optimized such that feedback from individual simulation execution would be used to refine the blocking mechanism. In contrast, the final solution had to be cast to a robust, efficient, and flexible manner that could handle different attack scenarios.

IV. IMPLEMENTATION

The identified milestones during the implementation phase were a number that was critically required in fulfillment of the objective to implement detection and mitigation of DDoS attacks on an IoT network through using advanced artificial intelligence techniques by use of NS3 simulation environment. In the chapter, the step-by-step process at each stage is given, starting from the setup of simulation and generation/processing of datasets, model training, and finally how to equip a model into a simulation for real-time mitigation.

A. Simulation Setup in NS3

1. Network Topology Design:

Here, the design of the network topology is intended to reflect an actual IoT environment, having a central router that connects a number of IoT devices to a server.

IoT Devices: Twenty IoT devices were simulated for this scenario that were representative of various smart devices typically found in a connected home or office environment, with benign traffic generated toward the central server.

Bot nodes: To simulate the attack, the following are intended as five bot nodes in the network that would simulate malicious DDoS attacks on the server[16], inundating the server with abnormally large DDoS traffic, thereby disrupting the normal flow of the server.

Router and Server: The main router acted as a traffic cop between the IoT devices, the bot nodes, and the main server; it was the critical resource, or commodity, upon which the DDoS attack would be directed.

2. Traffic Generation:

Benign Traffic: Constant legitimate Source was generated by IoT Devices. The generation was based on the applications utilized by TCP BulkSend, hence this source will be like the common stream applications; for example, transmission from Sensor readings, or several device status reports to the server.

Generation of Malicious Traffic: Here, DDoS attacks were emulated using On-Off traffic generators. These generators used bot nodes in order to generate high-rate UDP traffic against the server, with the intent of not allowing the system to cope up with the load and for degradation of its performance. One reason for the selection of the On-Off pattern for duty cycling was that it follows the bursty patterns of a significant portion of actual DDoS attacks.

3. Mobility Model:

The mobility model, which is applied to all the nodes into this, is ConstantPositionMobilityModel. This, accordingly, indicates that the nodes do not move from their place, all over the course of the simulation. The paper investigates the movement of all the nodes but the working of the wireless network. This can be implemented in this study because it preserves the uniform topology of the wirelessly connected network.

4. NetAnim Configuration:

By default, enable the package NetAnim in order to animate the simulation. This provides a nice view of the network's performance, both under attack and in its mitigation process.

Node Placement: Careful placement of nodes for clarity in the animation. In the centre, the router and server; around them, IoT devices and bot nodes. The vertical spacing between rows of nodes was increased so that in the animation, movements are more visible. This allows a person to make a definitive separation of the benign and malignant traffic flows.

Due to that, packet flow, node interaction, and many more had been visualized in real time across the network with attack impact assessment, yielding mitigation strategy effectiveness very much transparently.

B. Dataset Generation

Various sets of simulations are run in NS3 in order to prepare the training datasets for the AI model. All traffic data captured during the simulations are formatted for anomalistic machine learning.

1. Traffic Data Collection:

The simulation ran for a duration of time, and all network traffic that passes through the router was logged in XML format.

It captures a variety of network activities, from normal operations down to the DDoS attack; both benign traffic-including IoT devices-and malicious traffic is a contribution made by bot nodes.

2. XML to CSV Conversion:

Scripts were developed in-house to parse the XML logs and convert them into CSV files[21]. The format was used because it can easily be supported by most machine learning frameworks.

Feature Extraction: Features related to the XML files included timestamp, source/destination IP, packet size, amongst others that are needed to train the AI model in order for it to recognize benign or anomalous traffic.

Labelling: The packets were labelled as originating from the "Benign" or the "DDoS" class, depending on whether they came from known bot nodes or from an IoT device.

3. Data Balancing:

Balance the number of benign and DDoS packets to make sure that the AI model doesn't get biased toward any of the classes.

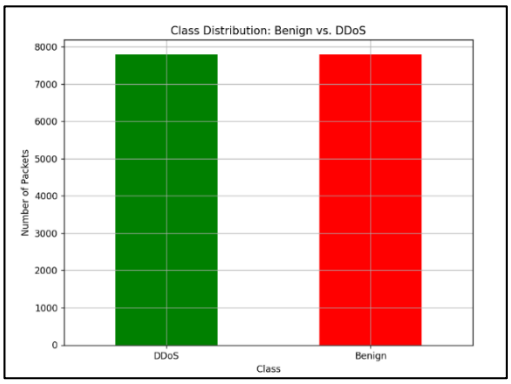

Fig. 2. Data Distribution Graph

This balancing ensured relatively equal instances for each class during training, a must-have ingredient in any

high-accuracy model with the task of detecting both benign and malicious traffic.

C. AI Model Training

The AI model, a Graph Neural Network (GNN), was trained to identify DDoS attacks based on the features extracted from the dataset.

1. Model Architecture:

The GNN model has of late been quite successful at capturing complex relationships in graph-structured data. Raw features available in CSV files consisted of the number of packets, packets from, and packets to five source IP and the target IP lists; all forms of these features were first pipelined in the model's first input layer.

Hidden Layers: There were several hidden layers in the model. Each hidden layer was preparing itself to identify increasingly abstract features from the data. A very significant contribution of these layers to the model is that they help make out all those subtle patterns that distinguish between normal traffic and a DDoS attack.

Output Layer: The latter layer came up with a binary classification, whether the traffic is benign or the traffic is put to use for realizing a DDoS attack.

2. Training Process:

The model was trained with the labelled dataset. Training was reducing errors with each change made to the model parameters; the loss function was applied to determine errors.

Hyperparameter tuning: The number of layers, learning rate, batch size, and all other important hyperparameters were optimized optimally for the best possible performance of the model. This was done by training data in multiple sessions on different settings of major hyperparameters and choosing the setting that produces the best output.

3. Validation:

After each epoch, a validation set separately derived from another run of the simulation was fed to the model to validate end performance.

The validation results were used to refine the model and prevent overfitting. The case of overfitting is when a model fits the training data very well. I mean, it works well to the training data but does not work out well in generalization.

D. Real-time Mitigation in NS3

That's integration with the NS3 simulation environment for runtime DDoS attack detection and mitigation. Remaining steps are as follows:

1. Malicious IP Detection:

This utilized the GNN model, which was trained in analysing runtime network traffic in case of simulation through NS3. It will process incoming packets and detect the originating packets coming out of IP addresses related to DDoS attacks.

Real-time Inference: The model keeps updating its list of malicious IP addresses with every run by basing it on the traffic pattern within the simulation. This real-time inference was quintessential for finding ongoing attacks and immediately taking appropriate action.

2. Packet Filtering:

The malicious IPs that are detected are added dynamically to a blocklist within the NS3 simulation.

A custom filtering mechanism at the router level is in place, dropping such packets coming from IP addresses on the blocklist automatically by not letting those packets reach the server to ensure the mitigation of the DDoS attack.

Key performance indicators tracked for the network to monitor the effectiveness of the implemented mitigation strategy include packet delivery ratio, latency, and server load. These are tracked before and after the filtering mechanism in order to deduce how effective this has been as a strategy.

3. Evaluation:

This was the final step, which was evaluation regarding the overall effectiveness of the system. The performance indicators entailed the general detection accuracy, false alarm rates, and impacts on overall network performance to ascertain how effective the system would be.

Comparative Analysis: Comparisons are drawn between performance from the system and baseline scenarios wherein no mitigation was applied. Comparisons will serve to quantify benefits derived from the AI-driven mitigation approach.

E. Flowchart for AI-Driven DDoS Detection and Mitigation Framework

The following flowchart outlines the key steps in the AI-driven framework:

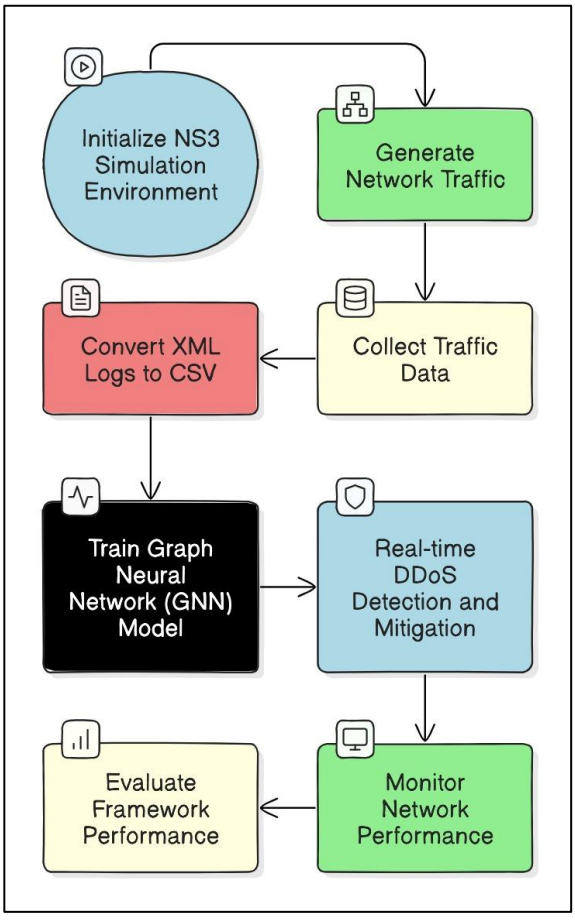

Fig. 3. Flowchart for AI-Driven DDoS Detection and Mitigation Framework

F. *Algorithm for Real-Time DDoS Mitigation*

Algorithm: Real-Time DDoS Detection and Mitigation
Input: Network Traffic T, Trained GNN Model M, Blocklist B
Output: Mitigated Traffic T'

1. Initialize Blocklist B as an empty set.
2. For each packet p in incoming traffic T do:
   a. Extract features F from packet p.
   b. Use GNN Model M to predict label L for packet p.
   c. If L == "DDoS" then:
      i. Add source IP of p to Blocklist B.
      ii. Drop packet p (do not forward to the server).
   d. Else:
      i. Forward packet p to the server.
3. Monitor network performance metrics.
4. Evaluate the effectiveness of the mitigation strategy.

V. RESULTS

The results of our AI-Driven Dynamic Fuzz Testing for IoT Security in detecting and mitigating DDoS attacks using GNNs. Simulations have been executed with the support of NS3 and complemented by an outside analysis with machine learning for attack identification and mitigation.

A. *GNN Model Training and Accuracy*

The GNN model is trained with a generated dataset obtained by running several NS3 simulations, including both benign and DDoS traffic. The dataset was pre-processed to balance the amount between the two classes. It is possible to monitor the training of the model recording its loss and accuracy metric at each epoch.

Training Loss and Accuracy: The nature of the training loss was quite a decrease in every epoch; this conveyed that the model was learning in the right direction. The accuracy went to 100% toward the end of training, which shows it has been well fitted to the training data.

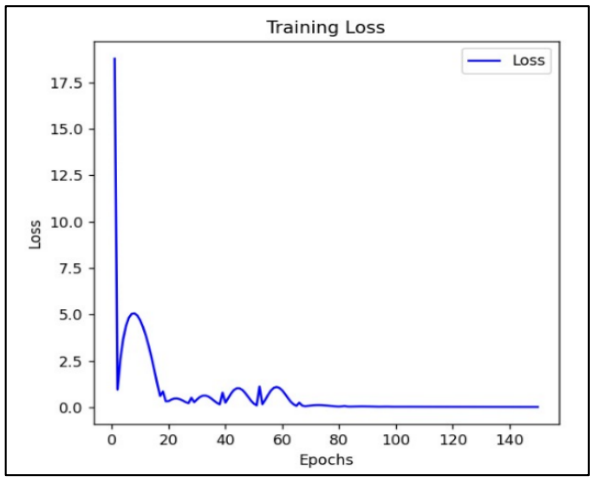

Fig. 4. GNN Model Training Loss

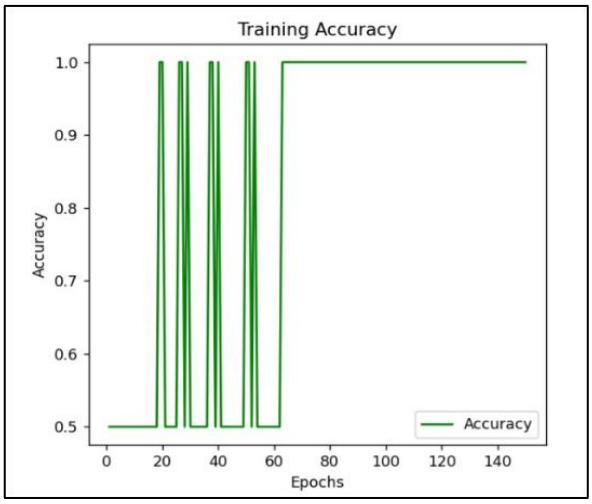

Fig. 5. GNN Model Training Accuracy

B. *Validation Results*

The independent validation dataset and the balancing of benign and DDoS having the same packets were ascertained from a different set of NS3 simulations.

Validation Accuracy: The validation accuracy obtained was equal to 74%, which is satisfactory to show the model may generalize properly to new, unseen data[19]. Such an accuracy level means the model can well distinguish between benign and DDoS-wise DDoS attack generation under practical network conditions.

Confusion Matrix: As per the confusion matrix, it can be observed that this model picked up a good number of DDoS attacks and, on the other hand, has a fair number of identifications of benign traffic. This balance is important in any realistic scenario of false positives and negatives.

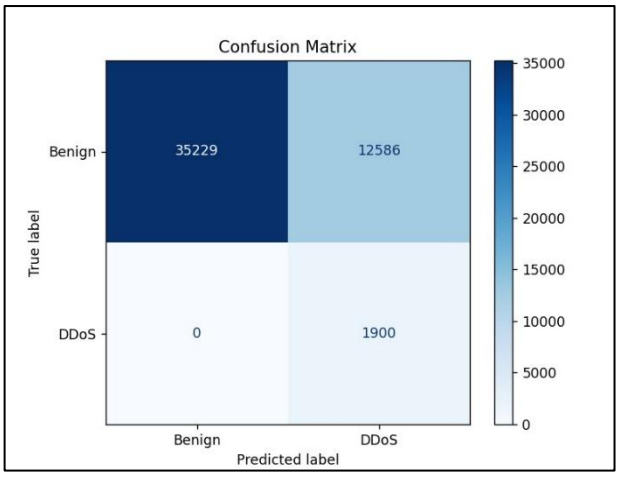

Fig. 6. Confusion Matrix

C. *Mitigation Strategy*

Using the GNN model to select malicious IPs was simulated as one potential mitigation strategy within NS3. NS3 was configured to drop packets coming from these IPs. Resulting in this effectively mitigates the impact of the DDoS attack.

Packet Dropping: The simulation depicted that the packets starting from the malicious IP addresses identified were dropped[20], which in turn reduced network congestion and ensured that the performance of the legitimate traffic was maintained. It was also seen that this mitigation strategy reduced server load quite considerably, something very vital at the time of a DDoS attack.

Network Performance: The performance metrics of the network are some of the elements, such as throughput and latency before the application of the mitigation strategy, during, and after the fact. They have been monitored statically. These show that indeed, with mitigation, the network performance enhances with less delay and more throughput by the legitimate traffic.

D. *Visualization of Results*

The results have been visualized using different graphs in every section to enhance understanding of the model and how effective the mitigation will be:

Loss and Accuracy Graphs: These graphs showed loss vs. improvement in the accuracy of the GNN model while in training. The loss was decreasing regularly with increased accuracy, showing that it is learning well.

Confusion Matrix: A pictorial representation of the confusion matrix was developed where true positives, true negatives, false positives, and false negatives were illuminated with their respective distribution. The visualization of a confusion matrix helped understand model performance in terms of distinguishing benign from DDoS traffic.

Network Animation: The NS3 simulation was visualized with the help of the NetAnim tool. The animation very clearly showed the network topology, flow of traffic, and the effects of the mitigation strategy. Positions of nodes were changed to ensure that the pattern of traffic would be observable.

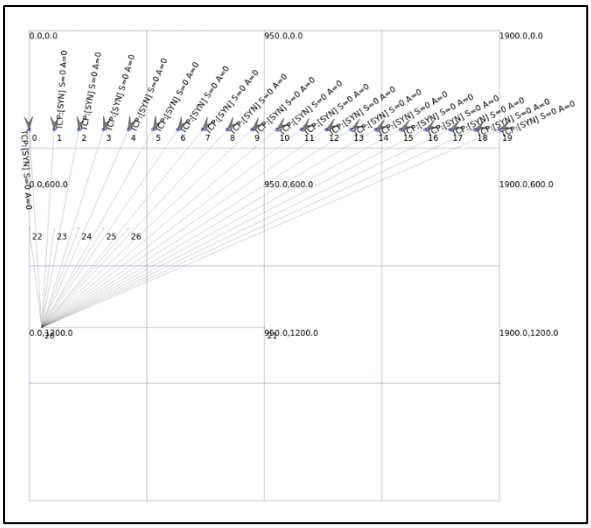

Fig. 7. Network Animation Simulation

These results verify that our AI-Driven Dynamic Fuzz Testing approach, which is used for DDoS in IoT networks, may detect and mitigate these attacks. These blended approaches, driven by GNNs, provide a robust framework for IoT security based on simulation-based validation and real-time mitigations.

VI. CONCLUSION AND FUTURE ENHANCEMENTS

A. *Conclusion*

We were able to put into practice a dynamic fuzz testing approach combined with AI-driven techniques for securing IoT networks against DDoS attacks. The integration of GNNs was effective; malicious traffic was identified by a validation accuracy of 74%, hence showing the prospect of GNNs in cybersecurity applications.

We detected and mitigated DDoS attacks properly and secured the IoT environment by simulating IoT network traffic using NS3 and applying our GNN model externally.

Simulation results were visualized with NetAnim. The effectiveness of our approach in a realistic network setting clearly separated benign and malicious traffic, while mitigation strategies produced a robust defense mechanism against any potential threat.

B. *Future Enhancements*

Although the present implementation provides a strong base related to security in IoT, there are several avenues along which further improvements can be done in the system.

1. Real-Time Mitigation:

It needs enhancements to be developed so as to reach the level of real time identification and mitigation of NS3 attacks, for reducing the time lag between the detection and response.

2. Expanding Attack Scenarios:

Extending the attack types to increase in complexity and variety beyond DDoS, for example, the MITM and SQL injection to test the adaptability and robustness of the proposed solution.

3. Scalability Testing:

Testing performance and effectiveness in extensive and more complex IoT environments where the majority of the devices and traffic concentrate, making sure the adaptiveness is learned.

4. Adaptive Learning:

Only adaptive learning techniques should be applied to the GNN model so that the new data received makes it more capable, with time, to perform its detection tasks.

5. Integration with Other Security Tools:

Integration of the proposed solution with other security tools and frameworks will provide an integrated IoT security platform deployable in real environments.

These additions will enhance the robustness of the system and make possible its application for a wider range of IoT security challenges. The field of application will add up and give the system a truly versatile status regarding the challenges of this ever-evolving area of cybersecurity.

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