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.

1. 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 2 gives the related works on IoT security and DDoS mitigation approaches. Section 3 explains the design, and implementation of our proposed framework. In Section 4, we provide experimental setup and results depicting the efficacy of our approach on practical applications. Section 5 wraps up the paper with ideas for future work.

2. LITERATURE SURVEY

2.1 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].

2.2 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].

2.3 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].

2.4 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].

2.5 NS3 Simulations for IoT Security

Dynamic fuzz testing has also been conducted in other attack scenarios, such as DDoS, on IoT security to check the resiliency of IoT networks[13]. 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 [14].

3. METHODOLOGIES

The methods applied in this project focus on IoT network security, which consists of detecting and mitigating DDoS attacks. It applies AI-driven techniques for the purpose mentioned above. This consists of the following major constituents:

3.1 Dynamic Fuzz Testing

Dynamic Fuzz Testing is an approach that simulates potential vulnerabilities in the IoT environment by introducing malformed or unexpected inputs into the IoT network[18]. The approach caused varied traffic patterns, which were either benign or malicious in nature, typically DDoS. A proper tag was assigned to the result to provide an extensive dataset to be used for training machine learning models[23].

3.2 Dataset Preparation

An NS3 simulation emitted a dataset of features including timestamps, source/destination IPs, packet sizes, and labels that the respective traffic was benign or a DDoS attack[24]. The XML output of the simulations were converted to CSV format for better compatibility with the machine learning tools. A careful labeling approach resulted in an almost balanced benign and attack traffic dataset, hence no biases were thereby introduced during training.

3.3 AI Model Training

A GNN was opted for the classification of network traffic because it could identify complex, node-wise relationships[22]. The model was trained on the labeled set and the hyperparameters were fine-tuned by running multiple iterations for best tuning and optimization of metrics in terms of accuracy, precision, recall, and F1-score[17]. The architecture of GNN presented the spatial and temporal dependencies of the traffic well, which made it possible to recognize patterns of DDoS attacks with accuracy. The validation process followed some simulated experiments by reproducing new, fresh data that tested whether the model could generalize and identify DDoS attacks in various scenarios.

3.4 Simulation Environment

NS3 was employed to emulate an IoT network built out of a set of devices, a router, and a server. In order to simulate the DDoS attacks, On-Off traffic generators were employed for both legitimate and malicious traffic whereas in the case of normal traffic, BulkSend was used. Results were visualized in NetAnim to understand the dynamics of the network under attack as well as how effectively was the mitigation strategy [25].

3.5 Mitigation Strategy

The proposed model of GNN classified malicious IPs, which were then blocked in real time within NS3. These results were to be studied with respect to network performance metric comparisons like delivery ratio and latency both before and after blocking. The iterations would lead to the final results of a robust efficient solution handling different attack scenarios.

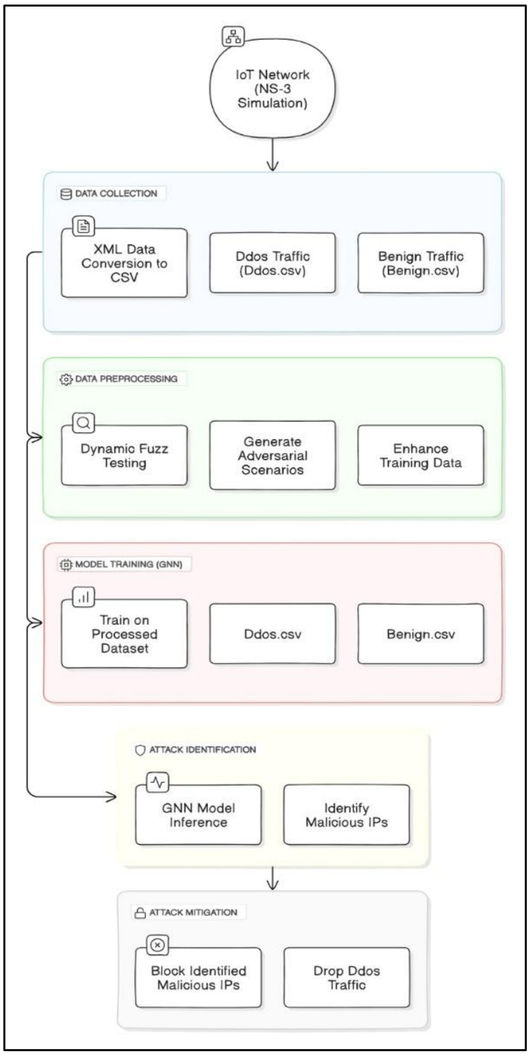

Fig. 1. Architecture Diagram

4. 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.

4.1 Simulation Setup in NS3

This network simulation mimicked real IoT conditions with 20 IoT devices generating benign traffic toward a central server. Five bot nodes flooded the server with high-rate traffic targeting a central router as a point of congestion[16]. It had benign traffic created by using the TCP BulkSend application, which reflected typical device-to-server communications while the bot nodes used On-Off traffic generators to create their DDoS pattern, which were defined as bursty. All nodes were static, having the ConstantPositionMobilityModel, which was more or less analog to most IoT deployment scenarios and relatively static. The experiment was visualized using NetAnim and graphically highlighted discrimination between benign and malicious flows, which analyzed the effect and efficiency of possible mitigation actions.

4.2 Dataset Generation

The traffic data, captured from the NS3 simulations, is in XML format: both benign IoT device traffic and malicious bot nodes traffic are logged. Utilizing custom scripts, these were then parsed into CSV files to be compatible with the different machine learning frameworks. From packets, features such as timestamp, source/destination IP, and packet size, were then extracted to later use in training AI models. These packets were labeled either "Benign" or "DDoS" based on where they came from[21]. The dataset was balanced out so as to ensure unbiased training, and there were equal instances of benign and malicious traffic.

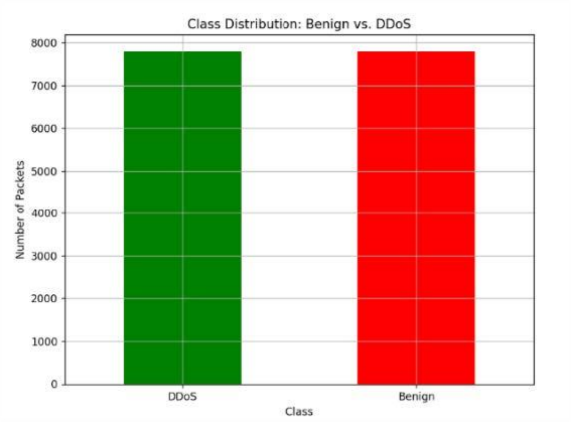

Fig. 2. Data Distribution Graph

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.

4.3 AI Model Training

This balancing provided nearly equal occurrences of each class during the training phase, a necessary component in any high-accuracy model with the task of identifying both benign and malicious traffic.

The AI model was constructed by designing a Graph Neural Network to be used in the detection process to fetch features from the dataset for the DDoS attack. The GNN architecture is rather adequate to serve for more complex relations that hold in network traffic data, and to which the learned hidden layers progressively differentiate benign from malicious activity. For instance, even fine-tuning achieved the best performance with modifications regarding the number of layers, batch size, and even learning rate. We do not want to overfit in the training time; therefore, using that independent dataset accuracy, precision, recall, and F1-score scores were monitored constantly during the run.

4.4 Real-time Mitigation in NS3

Real-time determination of malicious IP addresses in a real-time DDoS attack detection and mitigation setup through integration with the GNN model in the NS3 simulation environment. The framework dynamically up- updates a blocklist based on its analysis of network traffic that is then used to update the blocklist, thus effectively blocking malicious traffic from reaching the server at the router level, hence mitigating the attack. We have been tracking the performance metrics in terms of the packet delivery ratio, latency, and load at the server side not only for comparison before mitigation but also for comparison after mitigation. General comparisons between scenarios without and with mitigation will be helpful to quantify the benefits brought about by the AI-driven approach.

4.5 Flowchart for AI-Driven DDoS Detection and Mitigation Framework

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

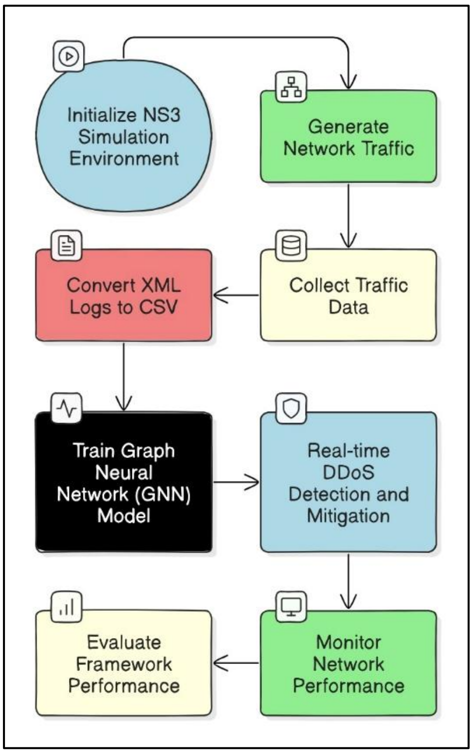
Initialize NS3 Simulation Environment
Generate Network Traffic
Convert XML Logs to CSV
Collect Traffic Data
Train Graph Neural Network (GNN) Model
Real-time DDoS Detection and Mitigation
Evaluate Framework Performance
Monitor Network Performance

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

4.6 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’

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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.
```

5. 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.

5.1 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.

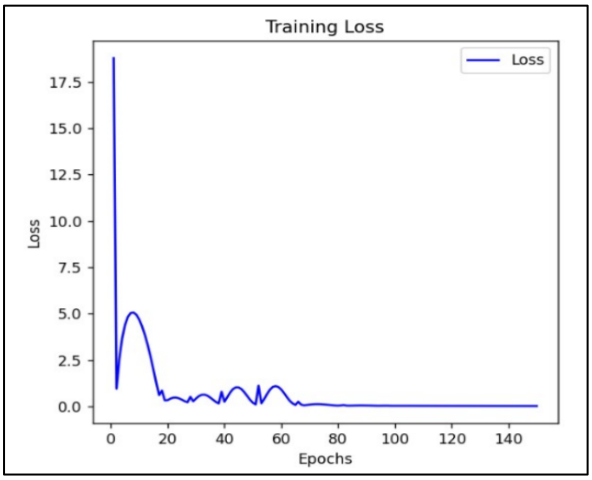

Fig. 4. GNN Model Training Loss

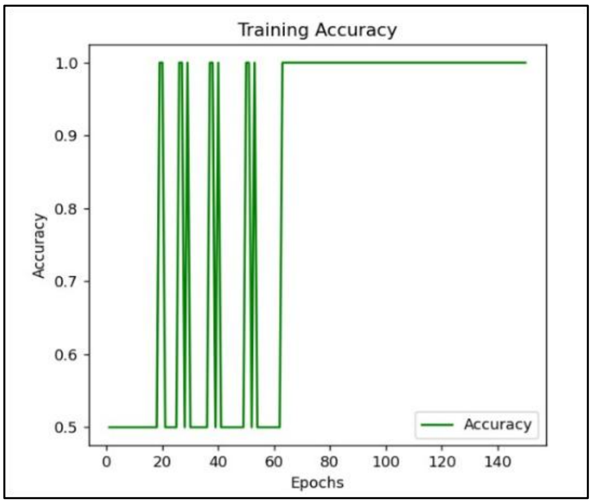

Fig. 5. GNN Model Training Accuracy

5.2 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.

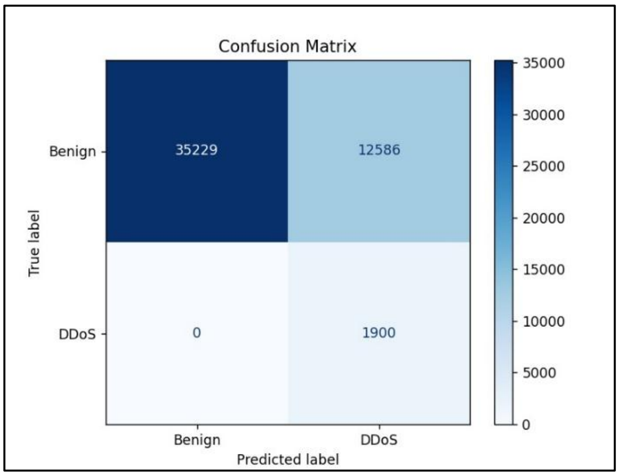

Fig. 6. Confusion Matrix

5.3 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.

5.4 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.

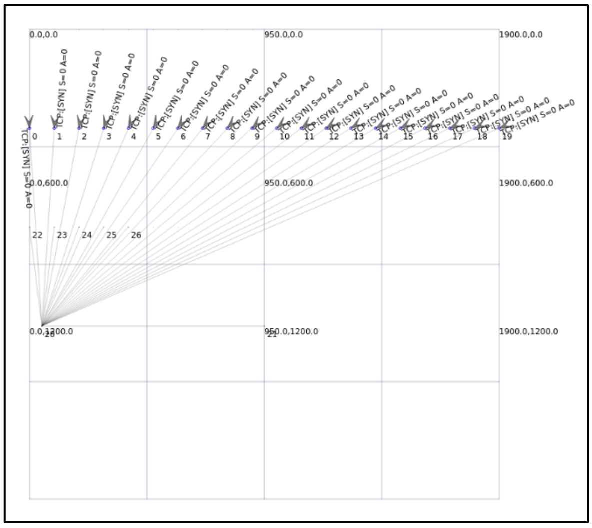

Fig. 7. Network Animation Simulation

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.

6. CONCLUSION AND FUTURE ENHANCEMENTS

6.1 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.

6.2 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.

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.

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.

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.

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.

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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