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Customizable DDoS attack data generation in SDN environments for enhanced machine learning detection models.

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Customizable DDoS Attack Data Generation in SDN Environments for Enhanced Machine Learning Detection Models

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***Abstract*—Distributed Denial of Service (DDoS) attacks are a critical threat to the security and reliability of Software-Defined Networking (SDN) environments. Existing datasets for training machine learning (ML) models, such as KDDCup '99 and CICIDS 2017, are either outdated or fail to capture SDN-specific characteristics, limiting their effectiveness in detecting modern DDoS attacks. This paper proposes a framework for generating a comprehensive, SDN-specific dataset using a virtual environment that integrates Mininet, the Ryu controller, and Python-based automation. The dataset incorporates advanced flow-level metrics, including SYN counts, queue lengths, and real-time traffic dynamics, reflecting contemporary attack scenarios such as ICMP floods, TCP SYN floods, and UDP floods. By addressing the limitations of traditional datasets, this custom dataset enhances ML model training for DDoS detection in SDN environments, providing improved accuracy and adaptability. Contributions include a scalable SDN-based dataset generation framework, enriched feature sets for ML training, and a comprehensive approach to capturing both legitimate and malicious traffic dynamics. This study highlights the potential of SDN programmability in advancing security research and offers a robust tool for the development of reliable DDoS detection mechanisms.**

***Index Terms*—DDoS detection, Software-Defined Networking (SDN), dataset generation, machine learning, network security.**

I. Introduction

The rising threat of Distributed Denial of Service (DDoS) attacks poses a significant challenge to the security and reliability of Software-Defined Networking (SDN) environments. These attacks can impact network functionality, causing downtime, degraded service, and financial losses. With advancements in attack techniques, DDoS attacks have become more sophisticated, scalable, and difficult to mitigate. This makes robust detection and mitigation mechanisms crucial to maintaining the reliability and security of SDN, which offers centralized and programmable control but remains vulnerable to various attack vectors [1].

A key challenge in DDoS detection is distinguishing between legitimate and malicious traffic, as these attacks often mimic normal patterns, complicating traditional systems without disrupting regular services.

Outdated detection models relying on inadequate datasets fail to capture modern DDoS attack characteristics, hindering the training of machine learning (ML) models for real-time traffic differentiation. Legacy datasets, such as KDDCup '99 and NSL-KDD, fail to represent the complexity of contemporary DDoS scenarios, particularly within SDN environments. These datasets lack comprehensive features for modern ML models and fail to simulate diverse attack vectors or unique SDN vulnerabilities, such as flow table manipulation and control channel saturation [2].

To address these limitations, generating custom attack data in SDN environments is critical. SDN's programmability enables researchers to control traffic and simulate evolving threats, producing datasets tailored to specific research goals. This allows the incorporation of SDN-specific features like flow rules and controller interactions, improving the accuracy of ML-based DDoS detection models [3]. This research develops a method to generate a comprehensive SDN dataset, addressing the limitations of existing datasets and enhancing DDoS detection by capturing unique vulnerabilities like flow table manipulation and control plane saturation.

The contributions are as follows:

1) SDN-Based Dataset Generation Framework: This study offers a structured method for simulating a range of DDoS attacks in an SDN environment, allowing precise control over attack parameters like type, volume, and target, producing realistic attack data.
2) Enhanced ML Model Training: By generating data enriched with SDN-specific features—such as flow statistics and control plane interactions—this research provides a more robust foundation for training effective ML-based DDoS detection models.
3) Addressing Traditional Dataset Limitations: Unlike existing datasets, this generated data set accurately reflects modern DDoS attack patterns in SDN, supporting the development of more reliable and adaptable detection mechanisms.

These contributions highlight the value of SDN-based data generation in advancing ML-driven DDoS detection, paving the way for future improvements in network security.

II. Literature Review

The existing research on synthetic data generation, datasets, and methodologies reveals significant gaps in DDoS detection within SDN environments. Both traditional and modern approaches are examined to emphasize the need for a flexible and comprehensive SDN-specific dataset to support advanced machine learning models for DDoS detection.

A. Existing Datasets for DDoS Detection

Legacy datasets like KDDCup '99 and NSL-KDD have been extensively used for training DDoS detection models. However, they are increasingly viewed as outdated due to their limited scope and simplistic attack scenarios, rendering them less suitable for training robust machine learning models in contemporary contexts [1]. Modern datasets, such as CICIDS 2017, CSE-CIC-IDS 2018, and TON-IoT, have introduced more advanced features and attack scenarios, including a variety of modern DDoS techniques. These datasets aim to capture real-world attack vectors and provide an improved foundation for machine learning-based anomaly detection [2]. However, they still face limitations in capturing SDN-specific network characteristics [3] [4]. The InSDN dataset, proposed as a comprehensive intrusion dataset specifically for SDNs, addresses some of these gaps by including unique SDN attack scenarios such as flow table saturation and control plane attacks [22]. Similarly, advanced feature selection methods for DDoS detection, such as those highlighted in [21], further emphasize the necessity of tailoring datasets to SDN-specific threats. The differences between legacy and modern datasets highlight a significant gap in existing research. While newer datasets have made strides in diversity and richness of features, there remains a critical need for datasets specifically tailored for SDN environments, incorporating features related to SDN controller activities and dynamic flow statistics [5]. Network emulation tools like Mininet are used to generate synthetic traffic in virtual environments that simulate both normal and attack scenarios, providing a controlled setup ideal for reflecting real-time dynamics [6]. Simulation tools such as OMNeT++ and NS-3 also create synthetic datasets for networking research, but they lack SDN-specific features, limiting their effectiveness in SDN-based DDoS detection [7]. Hybrid approaches, which mix real traffic with synthetic data, enhance dataset richness but may lack the consistency necessary for SDN-specific research, especially in terms of flow rules and interactions [8]. Adversarial learning has also been used for synthetic dataset generation by creating datasets with adversarial attacks. While promising, their application to SDN contexts remains largely unexplored [9].

B. Challenges in Synthetic Dataset Creation

Challenges in creating synthetic datasets include capturing diverse attack vectors, ensuring realism in generated data, and addressing scalability [10]. Moreover, creating datasets that include SDN-specific elements like flow modifications and controller communication has remained a significant hurdle [11]. Additionally, challenges related to real-time anomaly detection using flow metrics have been identified, emphasizing the difficulty of handling real-time stream processing effectively [12].

C. Current Research Gaps

Existing datasets often fail to include SDN-specific features, such as flow-level metrics from the controller, making them unsuitable for SDN environments where DDoS attacks can exploit flow rules and controller interactions [13]. The lack of real-time metrics in many datasets limits their applicability in real-world detection systems, which need to operate in dynamic environments where network behavior changes rapidly [14]. Another significant gap is the lack of adaptability in existing datasets to emerging attack vectors. Modern threats evolve quickly, requiring datasets that can be updated to include new attack scenarios, particularly in programmable environments like SDN [15]. Many existing dataset generation methods lack the ability to scale to larger topologies or reproduce specific network conditions, limiting their applicability for researchers working with diverse network environments [16]. The identified gaps in existing datasets and generation methods point towards the need for a custom SDN-based dataset creation framework. Such a framework should be capable of emulating both benign and malicious traffic in an SDN environment, allowing for real-time metrics, flexibility in attack type simulation, and a comprehensive feature set suitable for modern DDoS detection models [17]. This review highlighted limitations in current datasets, including the lack of real-time metrics, SDN-specific features, and adaptability to emerging attack vectors [18]. Future work should focus on frameworks with real-time SDN metrics, advanced simulation, and industry collaboration for real-world validation [19].

III. METHODOLOGY

A. Overview of the Dataset Generation Framework

The proposed approach focuses on generating a comprehensive dataset for DDoS attack detection within an SDN environment. By leveraging the programmability and centralized control features of SDN, we simulate both benign and malicious traffic to capture a wide range of network behaviors. The process involves setting up a virtual network topology using Mininet, controlling network operations with the SDN controller, and utilizing Python scripts for automation. This setup allows precise control over network parameters and traffic patterns, enabling the simulation of various DDoS attack vectors alongside normal network traffic. Flow statistics and network metrics are collected from the SDN environment to create a dataset enriched with features relevant to DDoS detection. The collected data undergoes preprocessing and labeling to prepare it for training machine learning models aimed at enhancing DDoS detection capabilities in SDN networks.

The choice of SDN as the foundation for our data generation environment is justified by several key advantages.

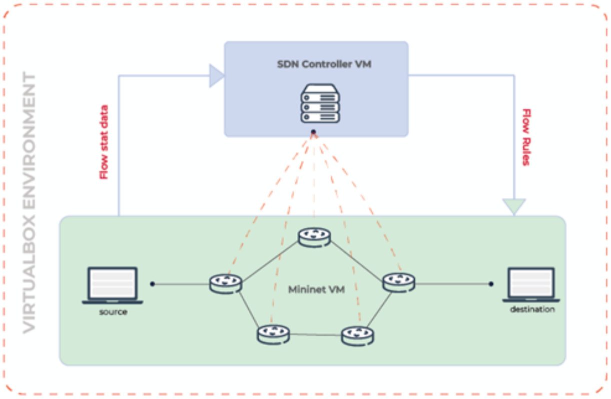

Fig. 1. SDN-Based Synthetic Data Generation Architecture

First, SDN's decoupling of control and data planes enables centralized management, simplifying the implementation of policies and the simulation of attack scenarios. Additionally, the programmability of SDN allows for dynamic adjustments to network configurations, traffic flows, and the injection of varied traffic types, which is essential for comprehensive traffic simulation. Finally, SDN's centralized controller offers enhanced monitoring, providing real-time flow statistics and detailed network visibility, making it ideal for capturing relevant data for DDoS detection. Thus, using SDN creates a flexible, controlled environment that addresses the limitations of existing datasets and produces data tailored specifically for detecting DDoS attacks in modern networks.

B. *SDN Testbed Setup and Configuration*

As shown in Fig. 1 to create an effective SDN environment for data generation, we utilized several tools and technologies. Mininet, an open-source network emulator, enabled the creation of a virtual network comprising hosts, switches, and links on a single machine, providing a realistic platform for testing network protocols and simulating complex topologies. We also employed the Ryu controller, a component-based SDN framework that offers a logically centralized control plane. The Ryu controller facilitated communication with network devices via the OpenFlow protocol, allowing for centralized network management and data collection. Virtual Box was used for virtualization, creating virtual machines (VMs) to run the Mininet and Ryu environments. Additionally, Python was employed for scripting and automation, providing the necessary flexibility and control throughout the data generation process.

C. *Network Topology Design and Architecture*

The network topology in this research was designed to create a realistic simulation environment for both benign and DDoS attack traffic, enhancing the detection capabilities for malicious versus legitimate activities. Using Mininet, we built a topology featuring multiple layers of switches and hosts, managed by an OpenFlow-enabled SDN controller. This setup represents a typical small-to-medium enterprise network, providing a realistic testbed for network analysis.

The topology includes multiple switches connected hierarchically, with each switch managing several hosts. This cascading structure allows network traffic to traverse different paths, simulating real-world complexities like congestion points and varying link utilizations, which are critical for replicating DDoS challenges.

Key Components:

- **Switches**: OpenFlow 1.3 compliant switches form the network backbone, managed by the Ryu SDN controller, which dynamically controls traffic flows and gathers flow statistics for training and evaluation.
- **Hosts**: Each switch manages several hosts (with IPs in the 10.0.0.0/24 subnet), serving as clients or servers to create diverse traffic patterns, emulating typical operational roles or targets for simulated attacks.
- **Links**: Connections between switches and hosts are configured with Traffic Control (TC) to simulate various link conditions, such as limited bandwidth and latency, replicating typical data center spine-leaf configurations for diverse traffic scenarios.

This setup maintains a manageable level of complexity while providing realistic emulation for network analysis.

D. *Benign Traffic Generation*

In order to create a comprehensive and realistic dataset that includes both legitimate and malicious network behavior, it is essential to simulate benign traffic that mirrors typical user activity. This involved using a range of tools to generate various types of network traffic, reflecting common activities. Ping was utilized to create ICMP traffic, simulating connectivity checks and latency measurements, which are typical for health checks and diagnostics. Iperf generated both TCP and UDP streams to test throughput and emulate data transfers, while Wget simulated HTTP traffic for browsing and file downloads, mimicking client-server interactions. Additional tools were used to increase traffic diversity: Curl was employed to handle HTTP/HTTPS requests, simulating API calls; Scapy was used for generating custom packet streams to represent complex interactions; and Netcat simulated lightweight TCP/UDP connections for inter-host communication, contributing to the diversity and realism of the traffic.

These traffic patterns included browsing and web requests (simulated by Wget), file transfers (via Iperf for TCP/UDP streams), API calls and lightweight connections (Curl and Netcat for HTTP/HTTPS requests and simple TCP/UDP connections), and inter-host communication (using Ping for diagnostics and connectivity checks). This combination of diverse tools and traffic types provided a realistic representation of typical network activity, which was essential for effectively training machine learning models for DDoS detection.

These simulated benign traffic activities provide a diverse representation of normal network behavior, ensuring that the dataset includes a wide range of legitimate traffic patterns. This diversity is critical for effectively training machine learning

Algorithm 1 Benign Traffic Generation

```
Require: Set of hosts $H$, set of switches $S$, controller instance, traffic duration $T$
Ensure: Generated benign traffic dataset
Initialize Network
Create topology with hosts $H$ and switches $S$
Connect the controller to the network
Start network net
Configure Services
for each host $h_i \in H$ do
    Start HTTP server on $h_i$ port 8080
    Start TCP and UDP Iperf servers on $h_i$
end for
Generate Benign Traffic
for time $t = 1$ to $T$ do
    Randomly select source host $h_{\text{src}} \in H$ and destination host $h_{\text{dst}} \in H$
    if $h_{\text{src}} \neq h_{\text{dst}}$ then
        Generate ICMP traffic
        Generate TCP traffic
        Generate HTTP traffic
    end if
end for
End Traffic Generation
Stop all running services on hosts
    return Benign traffic dataset
```

models to distinguish between normal and malicious activities, thereby enhancing the robustness of DDoS detection mechanisms.

E. DDoS Attack Traffic Generation

To create a robust and comprehensive dataset for training machine learning models capable of detecting DDoS attacks, diverse types of DDoS attack traffic were simulated, including ICMP Floods, TCP SYN Floods, UDP Floods, LAND Attacks, and TCP ACK Floods. The ICMP Flood overwhelms the target with Echo Request packets, consuming resources and potentially disrupting the network. TCP SYN Floods send numerous SYN packets without completing the handshake, burdening the server with half-open connections [20]. UDP Floods target random ports with large volumes of packets, exhausting resources by forcing the target to verify listening applications. The LAND Attack uses identical source and destination IPs and ports to confuse the target system, while TCP ACK Floods overload the network by sending high volumes of acknowledgment packets, degrading performance.

Hping3 was employed to generate attack traffic due to its ability to craft precise TCP, UDP, and ICMP packets. Its flexibility in adjusting parameters like packet rate and source addresses made it ideal for simulating realistic DDoS scenarios and analyzing their impact on SDN components.

These attacks were chosen for their prevalence and the distinct network layers they target. ICMP and UDP Floods tested bandwidth and processing capacity, while TCP SYN Floods explored vulnerabilities in connection-oriented protocols. The LAND Attack evaluated SDN resilience to spoofed packets, and TCP ACK Floods tested resource management under high acknowledgment traffic. This comprehensive approach ensured the dataset captured diverse attack vectors, enabling effective machine learning model training and enhancing SDN resilience against real-world threats.

Algorithm 2 DDoS Attack Traffic Generation

```
Require: Set of hosts $H$, set of switches $S$, controller instance, attack duration $T$, attack types (ICMP Flood, TCP SYN Flood, UDP Flood, LAND Attack, TCP ACK Flood)
Ensure: Generated DDoS attack traffic dataset
Initialize Network
Create topology with hosts $H$ and switches $S$
Connect the controller to the network
Start network net
Select Attackers and Targets
Randomly choose attacker hosts $H_{\text{att}} \subset H$
Randomly choose target hosts $H_{\text{tgt}} \subset H$
Generate Attack Traffic
for time $t = 1$ to $T$ do
    for each attacker $h_{\text{att}} \in H_{\text{att}}$ do
        Randomly select target $h_{\text{tgt}} \in H_{\text{tgt}}$
        Generate attack packets using hping3 based on attack type:
            – Flood attacks: hping3 -1 --flood --rand-source $h_{\text{tgt}}$
    end for
end for
End Attack Generation
Stop all attack scripts
    return DDoS attack traffic dataset
```

F. Data Collection and Feature Extraction

In the data collection phase, the Ryu controller gathered flow statistics from network switches using the OpenFlow protocol. The controller requested flow information every ten seconds, capturing both short-lived and persistent flows. This periodic collection tracked real-time changes in the network activity, crucial for distinguishing benign from malicious patterns.

To create a comprehensive dataset, we extracted features relevant to diverse traffic behaviors, as shown in Table I. Basic features like source/destination IPs, ports, and protocol types identified traffic nature, while statistics such as packet counts, byte counts, and flow durations provided insights into intensity and persistence. Advanced metrics like SYN packet counts, active flow counts, and queue lengths highlighted anomalies indicative of DDoS attacks. This combination of features offered a detailed view of network behavior, forming the foundation for effective detection and enabling feature engineering tailored to DDoS traffic characteristics.

To capture more nuanced data for DDoS detection, modifications were made to the Ryu controller scripts. Specifically,

TABLE I
EXTRACTED FEATURES

Feature Category	Features Extracted
Basic Features	Source IP, Destination IP, Source Port, Destination Port, Protocol Type
Traffic Statistics	Packet Count, Byte Count, Flow Duration
Advanced Features	SYN Packet Counts, Active Flow Counts, Queue Lengths

the scripts were extended to collect additional features such as SYN counts, queue lengths, and active flow counts. These enhancements were essential for distinguishing between normal bursts of traffic and malicious attempts to overwhelm network resources. By focusing on these features, we aimed to make our dataset more suitable for training machine learning models capable of detecting DDoS attacks with greater precision and recall.

G. Dataset Description

The generated dataset contained thousands of records, equally representing benign and malicious traffic, providing a balanced foundation for machine learning. It included a diverse range of features for DDoS detection, from basic identifiers like IP addresses and ports to advanced metrics such as packet count, flow duration, SYN packet counts, and queue lengths. This combination offered a holistic perspective of network behaviors, enabling the detection model to identify both known and emerging attack patterns effectively. Furthermore, preliminary evaluations demonstrate that the dataset works well with various machine learning models, achieving high accuracy and robustness in detecting DDoS attacks. This validates the effectiveness of the proposed method for generating test data tailored for modern security challenges.

IV. DISCUSSION

A. Advantages of Custom Data Generation in SDN

The use of SDN for custom data generation offers unmatched flexibility, enabling tailored simulations of specific network scenarios, such as ICMP and TCP SYN floods. Its programmable nature allows fine-tuning of parameters like traffic rates, attack intensities, and flow durations, making it possible to closely emulate real-world conditions and stay relevant to emerging threats.

Leveraging the Ryu controller, our environment gathered a richer set of flow-level statistics compared to existing datasets, including basic metrics (e.g., packet count) and advanced metrics (e.g., SYN packet counts, queue lengths). These features captured nuanced malicious behavior, enhancing real-time anomaly detection. The combination of Mininet, Ryu, and Python scripts ensures reproducibility and scalability, allowing other researchers to recreate or extend experiments. This scalability supports realistic simulations and effective training of machine learning models on larger data volumes.

B. Addressing Limitations of Existing Datasets

The limitations of existing datasets are evident when comparing traditional, synthetic, and the Custom SDN Dataset, as shown in TABLEII. Traditional datasets like CICIDS2017 and NSL-KDD lack SDN-specific features and fail to address the requirements of modern SDN environments. Synthetic datasets, such as TON_IoT and UNSW-NB15, often introduce noise or artifacts due to oversimplified traffic models and do not capture critical SDN dynamics, such as flow rule updates, queue lengths, and control plane interactions. In contrast, the Custom SDN Dataset, generated using Mininet and the Ryu controller, addresses these gaps by providing advanced SDN-specific features and real-time flow statistics. Its adaptable framework allows for simulating diverse attack scenarios and evolving threats, making it a robust foundation for training machine learning models tailored to DDoS detection in SDN contexts.

TABLE II
COMPARISON OF DATASETS WITH EMPHASIS ON SDN RELEVANCE

Dataset Name	Traffic Type	Attack Types Covered	Volume (Samples)	Feature Set	Applicability to SDN
CICIDS2017	Benign, DoS, DDoS	HTTP Flood, UDP Flood, etc.	$\sim$2.5 million	Traditional network features	Limited applicability
NSL-KDD	Benign, DoS, Others	Basic DoS attacks	$\sim$125,973	Limited feature engineering	Not specific to SDN
TON_IoT	IoT traffic (Benign, DoS, DDoS, etc.)	DDoS, Data Exfiltration, Reconnaissance	$\sim$500,000+	Diverse IoT-specific features	Not applicable to SDN
UNSW-NB15	Benign, DoS, Others	Fuzzers, DDoS, Reconnaissance, etc.	$\sim$2.5 million	Advanced synthetic features, including flow-based and packet-based data	Not applicable to SDN
Custom SDN Dataset	Benign, DDoS	ICMP Flood, UDP Flood, SYN Flood, LAND Attack	$\sim$1 million+ (balanced)	Advanced SDN-specific metrics, such as flow rules, queue lengths, and control plane interactions	Fully tailored for SDN research

C. Potential Impact on Machine Learning Models

The quality and richness of the custom dataset directly impact the effectiveness of machine learning models trained for DDoS detection. By incorporating diverse features—ranging from basic flow-level statistics to advanced metrics indicative of specific attacks—the dataset offers a more informative training resource, leading to models with improved detection accuracy and robustness. The enhanced dataset also supports the application of different ML algorithms, including supervised, unsupervised, and ensemble methods. The ability to experiment with feature-rich data allows for model comparisons and improvements in feature selection, boosting both the precision and recall of detection models.

D. Preliminary Machine Learning Evaluation

To validate the efficacy of the Custom SDN Dataset, a preliminary evaluation was conducted using a Random Forest classifier. The dataset, comprising both benign and malicious traffic, was split into 80% for training and 20% for testing. The classifier achieved an overall accuracy of 98.60%, with precision, recall, and F1-score values of 0.99 for both benign and malicious traffic. The support for benign and malicious traffic was 57,040 and 46,639, respectively, ensuring balanced representation in the dataset. These results highlight the dataset's robustness and its ability to support reliable DDoS detection in SDN environments.

E. Limitations and Challenges

Despite the strengths of the SDN-based data generation approach, there are inherent limitations. The primary concern is the difference between simulated traffic and real-world traffic. In practice, network conditions are affected by countless unpredictable variables, while simulations often provide idealized scenarios. As such, the performance of models trained on simulated data may differ when deployed in actual networks. Furthermore, there are resource constraints; even though Mininet provides an effective emulation tool, the capacity to simulate very large networks is limited by hardware resources. Finally, simulating highly sophisticated or stealthy attacks remains challenging. Attacks that adapt dynamically to the target environment or utilize advanced evasion techniques are particularly difficult to replicate in a controlled SDN simulation.

V. Conclusion

This research demonstrated the feasibility and advantages of using Software-Defined Networking (SDN) to generate custom DDoS attack data. The SDN environment provided comprehensive control, allowing the simulation of various attack scenarios and benign traffic. Leveraging SDN controllers, a rich dataset was created, addressing the limitations of existing datasets and enhancing adaptability to modern DDoS vectors. Importantly, the dataset has been validated by cybersecurity experts, ensuring its practical relevance and quality. This dataset serves as a robust foundation for training machine learning models to detect diverse DDoS attacks effectively in dynamic environments. Preliminary evaluations using a Random Forest classifier achieved an accuracy of 98.60, demonstrating the dataset's robustness for machine learning-based DDoS detection. The adaptability of this framework allows researchers to generate data for any desired attack type, ensuring its ongoing relevance for research.

A. Future Work

In future work, the dataset will be used to evaluate a variety of machine learning models, including neural networks and ensemble methods, to further validate its applicability for real-time DDoS detection. Also future improvements to this data generation framework could focus on incorporating more advanced and diverse attack scenarios, such as low-rate stealthy attacks, application-layer threats, and complex multi-vector assaults. Enhancing the simulation environment to better reflect real-world conditions is also critical—by introducing background traffic and varying congestion levels, the system can better account for the complexity that might obscure malicious activity. Additionally, collaborations with industry partners could provide invaluable real-world validation. Testing models with actual enterprise data in production-like environments would enhance the robustness and applicability of the detection mechanisms, strengthening their reliability for real-world deployment.

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