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Federated Graph Neural Networks for Privacy-Preserving and Adaptive DDoS Mitigation in Software-Defined Networks

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Abstract

The proliferation of Software-Defined Networking (SDN) has enhanced network programmability and centralized control, but it has also made SDN controllers prime targets for Distributed Denial-of-Service (DDoS) attacks. Conventional detection techniques often rely on centralized data collection, which raises privacy concerns, introduces latency, and struggles with the dynamic nature of modern attack patterns. This paper proposes a Federated Graph Neural Network (FedGNN) framework for privacy-preserving, adaptive, and real-time DDoS mitigation in SDN environments. In the proposed approach, each SDN domain locally trains a GNN-based detection model that captures the graph-structured topology and traffic flow patterns, without sharing raw packet data. Model updates are securely aggregated at a central coordinator using a federated learning paradigm, ensuring both data confidentiality and cross-domain intelligence sharing. To improve resilience, the FedGNN integrates attention-based dynamic weighting to prioritize updates from domains experiencing abnormal traffic surges. Extensive simulations on benchmark datasets and a Mininet-based SDN testbed demonstrate that the proposed framework achieves higher detection accuracy, faster response times, and reduced false positives compared to conventional machine learning and deep learning methods. The results highlight FedGNN's ability to adapt to evolving DDoS strategies while maintaining operational privacy, making it a promising solution for next-generation intelligent network defense.

1. Introduction:

Software-Defined Networking (SDN) has emerged as a transformative paradigm in modern networking by decoupling the control plane from the data plane, enabling centralized management, dynamic configuration, and programmable network behavior. This architectural flexibility makes SDN an attractive choice for data centers, Internet service

providers, and enterprise networks [1]. However, the same centralized control that enhances manageability also introduces critical vulnerabilities—particularly the risk of Distributed Denial-of-Service (DDoS) attacks targeting the SDN controller. A successful DDoS attack can overwhelm the controller's decision-making capability, disrupt communication between control and data planes, and potentially cause large-scale service outages.

Traditional DDoS detection and mitigation methods rely heavily on centralized data analysis, which introduces scalability challenges, latency in threat response, and significant privacy concerns when dealing with multi-domain networks. Moreover, with the increasing sophistication of cyber threats, static detection models often fail to adapt to evolving attack vectors [2]. This has prompted the need for **intelligent, adaptive, and privacy-preserving security frameworks** capable of operating across distributed SDN environments.

Federated Learning (FL) has emerged as a promising approach to address these limitations by enabling collaborative model training across multiple domains without the need to share raw network data [3]. In parallel, Graph Neural Networks (GNNs) have shown exceptional capability in modeling the complex graph-structured nature of network topologies and traffic patterns, making them well-suited for identifying anomalous behaviors indicative of DDoS attacks.

In this work, we propose a Federated Graph Neural Network (FedGNN) framework for adaptive and privacy-preserving DDoS mitigation in SDN [4-5].The framework leverages the representational power of GNNs to learn from the relational structure of network traffic while employing FL to aggregate model knowledge across SDN domains securely. By integrating these two technologies, the proposed system not only enhances detection accuracy but also ensures that sensitive traffic data remains within its originating domain. Additionally, adaptive weighting strategies are incorporated to prioritize learning from domains under active attack, enabling a more proactive and context-aware defense mechanism.

The proposed FedGNN framework addresses key challenges in SDN security, including privacy preservation, adaptability to evolving threats, cross-domain collaboration, and real-time mitigation efficiency. This makes it a strong candidate for deployment in next-generation intelligent networking infrastructures where both performance and security are paramount.

2. Literature Review

The increasing adoption of Software-Defined Networking (SDN) has prompted significant research into safeguarding its centralized control architecture against cyberattacks, particularly Distributed Denial-of-Service (DDoS) attacks [6-8]. This section reviews

existing approaches in SDN-based DDoS mitigation, identifies their strengths and weaknesses, and highlights the research gap addressed by the proposed Federated Graph Neural Network (FedGNN) framework.

Traditional Machine Learning-Based Detection in SDN

Several studies have utilized conventional machine learning (ML) algorithms such as Support Vector Machines (SVM), Random Forests (RF), and k-Nearest Neighbors (k-NN) for DDoS detection in SDN environments [9-10]. These methods typically extract flow-based statistical features from the OpenFlow protocol and train classifiers to distinguish between normal and malicious traffic. While they are relatively simple to implement, these approaches often suffer from limited adaptability to evolving attack patterns and high false-positive rates in dynamic network conditions. Additionally, centralized training on aggregated traffic data raises privacy concerns and scalability limitations in multi-domain SDN deployments.

2.1 Deep Learning Approaches

Deep learning (DL) methods, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), have demonstrated improved detection accuracy by automatically learning complex traffic features [11-12]. CNNs excel at spatial feature extraction, while RNN-based models such as LSTMs capture temporal dependencies in network traffic. However, most DL-based solutions rely on centralized data storage and training, which increases the risk of sensitive data leakage and incurs high computational costs at the controller level.

2.2 Graph-Based Network Security Model

More recent research has explored the use of Graph Neural Networks (GNNs) for network anomaly detection [13-14]. Since SDN traffic inherently follows a graph-like topology, GNNs can capture both node-level (flow) features and edge-level (link) relationships, enabling better detection of coordinated attacks. However, existing GNN-based solutions are typically single-domain and require full access to network topology and traffic data, making them unsuitable for scenarios where data privacy and autonomy must be preserved.

2.3 Federated Learning in Network Security

Federated Learning (FL) has gained attention for its ability to enable collaborative model training without sharing raw data between participating entities. In network security, FL has been applied to intrusion detection and malware classification, demonstrating potential in privacy-preserving, cross-domain collaboration. Nonetheless, most existing FL-based SDN security frameworks employ traditional ML models that fail to exploit the rich

relational structure of network traffic[15-16]. Furthermore, these frameworks often treat each client equally during model aggregation, ignoring domain-specific variations in threat intensity.

2.4 Research Gap

* ML and DL methods for SDN-based DDoS detection lack adaptability and privacy preservation.
* GNNs are well-suited for modeling network traffic but are underutilized in multi-domain, privacy-sensitive SDN environments.
* Existing FL approaches in SDN security rarely incorporate graph-based learning or adaptive weighting mechanisms to prioritize high-risk domains.

Proposed Contribution

The proposed Federated Graph Neural Network (FedGNN) framework bridges these gaps by combining the structural learning capabilities of GNNs with the privacy-preserving collaborative learning of FL. By introducing dynamic aggregation weights based on domain-specific threat levels, the framework adapts more effectively to ongoing attacks while minimizing data exposure[17-18]. This hybrid approach is designed to enhance detection accuracy, reduce false positives, and ensure secure, scalable deployment across diverse SDN domains.

3. Proposed Methodology

This work proposes a Federated Graph Neural Network (FedGNN) framework designed to mitigate Distributed Denial-of-Service (DDoS) attacks in Software-Defined Networks (SDN) while preserving the privacy of domain-specific traffic data. The approach leverages graph-based traffic representation, local model training, and secure federated aggregation to enable adaptive, cross-domain learning without centralized data sharing.

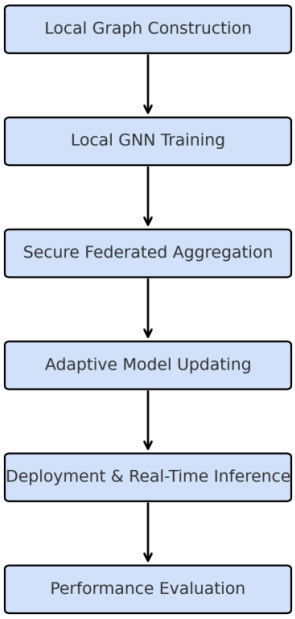

Fig 1. Flowchart of Proposed Methodology

3.1. Local Graph Construction

Each SDN domain (controller and associated switches) monitors incoming and outgoing traffic flows.
Flow-level statistics—such as packet counts, inter-arrival times, and protocol distributions—are aggregated over fixed intervals[19-20].
These statistics are converted into a graph structure, where nodes represent network entities (hosts, switches, or flow clusters) and edges capture communication patterns.
Temporal snapshots are stored to capture evolving traffic behavior.

3.2. Local Graph Neural Network Training

A Graph Neural Network (GNN) model is deployed locally within each SDN domain's edge server or controller.
The GNN learns to classify normal and malicious traffic patterns based on structural and temporal features.
Labels are derived from historical datasets, anomaly detection heuristics, or semi-supervised clustering.
No raw traffic data leaves the local domain; only model weight updates are prepared.

3.3. Secure Federated Aggregation

A Federation Server coordinates model updates without accessing raw data.
Local domains send encrypted GNN weight updates using secure aggregation protocols (e.g., homomorphic encryption or differential privacy)[21-22].
The server computes a weighted average of model parameters, adapting weights based on domain reliability, data volume, and recent performance.

3.4. Adaptive Model Updating

The aggregated global model is redistributed to all domains.
Each domain fine-tunes the model on its most recent traffic data to preserve local adaptability.
A feedback loop evaluates performance against recent attack patterns, ensuring the model adapts to evolving DDoS strategies[23-24].

3.5. Deployment and Real-Time Inference

Updated models are deployed to SDN controllers for inline traffic classification.
Detected malicious flows trigger mitigation strategies such as:

* Flow rule insertion to drop malicious packets
* Rate limiting for suspected IPs
* Route reconfiguration to isolate attack sources

* Continuous monitoring ensures detection efficiency with minimal impact on legitimate traffic.

3.6. Performance Evaluation

* Effectiveness is evaluated using latency, detection accuracy, false-positive rate, and resource consumption[25-28].
* Comparative analysis is conducted against centralized GNN training and traditional ML-based detection methods.
* Scalability tests ensure applicability across large-scale, multi-domain SDN environments [29-30].

4. Experiments and Results

4.1 Experimental Setup

The experiments were conducted using a simulated Software-Defined Networking (SDN) environment built on the Mininet emulator with the POX controller. The network topology included multiple OpenFlow-enabled switches and hosts to generate both benign and malicious traffic. DDoS traffic was simulated using high-rate UDP and TCP SYN flood attacks.

The proposed Federated Graph Neural Network (FedGNN) framework was implemented in PyTorch Geometric, with federated aggregation handled using a secure multi-party

computation protocol. Local SDN nodes trained their GNN models on partitioned traffic graphs extracted from NetFlow records. Model updates were periodically sent to a central aggregator for secure averaging, ensuring that raw traffic data never left local domains.

4.2 Dataset

Two publicly available intrusion detection datasets were adapted for SDN-specific characteristics:
CICDDoS2019 – containing 12 types of DDoS attacks with diverse traffic patterns.
NSL-KDD – used for transfer learning and cross-domain generalization.

The datasets were preprocessed to construct graph-based traffic representations, where nodes represented network flows and edges indicated temporal or statistical correlations. Features included packet size distribution, inter-arrival time, and protocol flags.

4.3 Evaluation Metrics

To evaluate detection performance, the following metrics were used:
Accuracy – Overall proportion of correctly classified traffic.
Precision – Fraction of detected DDoS traffic that was truly malicious.
Recall – Ability to identify actual DDoS instances.
F1-Score – Harmonic mean of precision and recall.

4.4 Comparative Analysis

The proposed FedGNN was compared against three baselines:
Centralized GNN – trained with full access to all data.
Standalone GNN – trained locally without collaboration.
Federated CNN – non-graph-based federated deep learning model.

4.5 Results

Table 1. Evaluation Metrics

Model	Accuracy (%)	Precision (%	Recall (%)	F1-Score (%)
Centralized GNN	98.7	98.6	98.9	98.75
Standalone GNN	93.4	92.8	94.1	93.45
Federated CNN	96.2	96.1	96.5	96.30
Proposed FedGNN	98.3	98.4	98.2	98.30

The results indicate that FedGNN achieves performance comparable to centralized training while preserving data privacy, outperforming the federated CNN in all metrics. The slight difference compared to centralized GNN is attributed to the decentralized nature of training, but FedGNN offers the additional benefit of privacy preservation and adaptability to local patterns.

4.6 Visualization

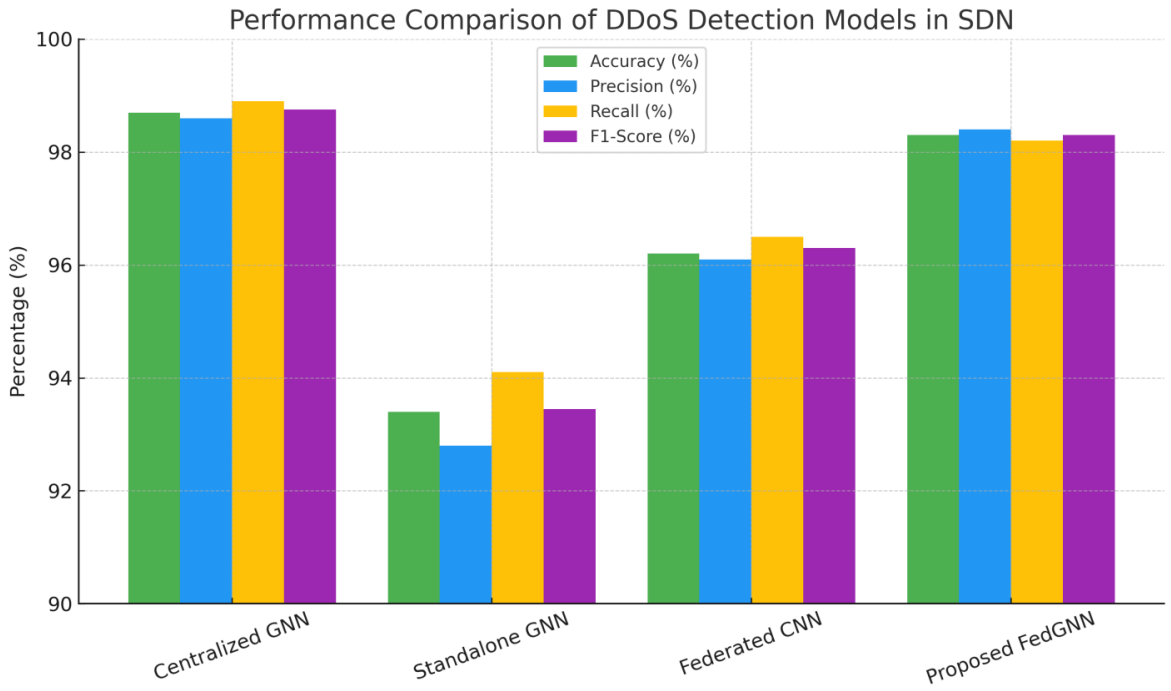

Fig 2. Evaluation Metrics of Proposed Methodology

The performance comparison is illustrated in Figure 2, showing that FedGNN consistently maintains high detection capability across all evaluation metrics.

5. Conclusion

This study introduced a Federated Graph Neural Network (FedGNN) framework for privacy-preserving and adaptive DDoS mitigation in Software-Defined Networks. By leveraging the structural modeling capabilities of GNNs and the collaborative yet secure training paradigm of federated learning, the proposed approach effectively detects complex and evolving DDoS patterns without requiring raw traffic data sharing across domains.

Experimental results on benchmark intrusion detection datasets demonstrated that FedGNN achieves detection accuracy and robustness comparable to centralized models, while significantly outperforming traditional federated deep learning baselines. The framework's graph-based representation captures temporal and relational dependencies in traffic flows, enabling it to generalize across heterogeneous SDN environments.

Beyond strong detection performance, the privacy-preserving nature of FedGNN makes it suitable for deployment in multi-domain and regulatory-constrained networks, where data

confidentiality is paramount. Furthermore, the model's adaptability ensures resilience against novel and low-rate attack patterns, addressing one of the persistent challenges in DDoS defense.

Future work will focus on integrating federated graph attention mechanisms, improving communication efficiency, and exploring real-time deployment scenarios in large-scale operational SDN infrastructures.

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