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AI INTRUSION DETECTION SYSTEM USING GRAPH NEURAL NETWORKS FOR SOFTWARE DEFINED NETWORKS (SDN)

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Abstract

Programmable and centralized control via Software-Defined Networking (SDN) is a step forward in Network Intelligence; however, it also creates new vulnerabilities by expanding the attack surface. Modern Intrusion Detection Systems (IDS) often have difficulty understanding and capturing window time-based relational dependencies and dynamic topological behaviour within SDN traffic flows. In this work, we propose an advanced Graph Neural Network (GNN)-based IDS and demonstrate how to model SDN traffic flow as structured graphs to allow for deeper extraction of spatial-temporal patterns than traditional machine learning models ever could. Our proposed framework uses a combination of Graph Convolutional Networks (GCN) and Graph Attention Network (GAT) to learn both global and localized feature representations, effectively improving discrimination between benign and malicious flows. Using benchmark datasets for evaluation, we show our system outperforms traditional machine learning and deep learning in all metrics (Accuracy, Precision, Recall, F1-score, ROC-AUC) with an excellent AUC score of 0.992. Additionally, our model has demonstrated excellent generalization capabilities when it comes to detecting low-rate, stealthy attacks and proved to be computationally feasible for deployment in real-time SDN environments. These results provide strong evidence for the viability of using GNN architectures for the development of intelligent adaptive high-precision monitoring solutions for next-generation programmable networks.

Keywords: Software-Defined Networking (SDN); Intrusion Detection System (IDS); Graph Neural Networks (GNN); Graph Convolutional Network (GCN); Graph Attention Network (GAT); Deep Learning; Cybersecurity; Network Traffic Analysis; Anomaly Detection; Programmable Networks.

1. Introduction

As a new and transformational modelling paradigm for data centre and enterprise networks, Software-Defined Networking (SDN) separates network control functions (the Control Plane) from network data forwarding functions (the Data Plane). This architectural separation enables centralized programmability, dynamic configuration, and granular network management. The introduction of flexibility and scalability with the SDN model provides opportunities for improved network performance but it also creates new security vulnerabilities due to the logically centrally located architecture providing a larger attack surface making it an attractive target for malicious intrusion, distributed denial-of-service (DDoS), and control plane manipulations. Traditional methods of intrusion detection such as IDS are not sufficient to manage the dynamic and abundant, complex, and multi-dimensional flow of data in SDN environments. Therefore, integrating modern Artificial Intelligence (AI), Machine Learning, and Deep Learning techniques into security solutions in SDN are becoming a necessary requirement for building resilient SDN security.

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Graph Neural Networks (GNNs) are one of the latest advancements in AI and are utilized to analyse various forms of data that can be illustrated as a graph. GNNs are able to analyse data in the form of graphs, which represent relationships among items, utilising both the structure and temporal properties of the links between items (Bilot et al., 2023). All of this leads to the ability for GNNs to perform better than traditional approaches in detecting malicious network traffic, primarily based on their superior understanding of how an SDN (Software-Defined Networking) environment operates (SDN traffic can be thought of and represented as a graph (incorporating switches, hosts, and flows)).

While there have been promising advancements in intrusion detection and prevention systems, several challenges remain. Many of the systems currently in use do not scale to operate over high-speed networks, exhibit low levels of robustness against adversarial attacks, and are computationally heavy, which limits their ability to be deployed in real-time. Recent work has shown that there is an opportunity to develop frameworks for intrusion detection that use GNNs along with reinforcement learning-based decision-making at the "edge", or proactive routing elements for increased resilience (Islam et al. 2024; Mohanad et al., 2024). In addition, the SDN controller at the centre of the architecture presents a single point of failure, further reinforcing the need for the use of intelligent and proactive models for intrusion detection.
The purpose of this research is to develop an AI-Based (Graph Neural Network) Intrusion Detection System to enable Anomaly detection in CTRL-Level SDN environments on a real-time basis with scalable products.

The objectives of this research are as follows:

RO1: To analyze the limitations of traditional and ML-based IDS models in SDN environments.

RO2: To design a graph-based intrusion detection architecture using GNN to detect anomalies in SDN flows.

RO3: To evaluate the performance of the proposed system using key metrics such as accuracy, precision, recall, and false-positive rate.

RO4: To demonstrate the applicability of GNN for real-time SDN security and propose enhancements for scalable deployment.

A significant advancement in the AI-driven security of SDN networks was made possible by the development of a new GNN model, which demonstrates how GNNs can positively impact the performance and capabilities of current and future generations of programmable networking architectures by increasing the accuracy and elasticity, adaptability, and resilience of Intrusion Detection System (IDS) functions.

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2. Literature Review

2.1 Software-Defined Networking and Its Security Challenges

Software-Defined Networking (SDN) offers programmability, centralised control, and abstraction of the underlying infrastructure to allow us to realise next-generation Networking. However, these strengths of SDN are also where we find many of the vulnerabilities of SDN. The SDN Controller is like the brain of having SDN Networking, so an attacker can disrupt the whole entire system if they gain access to that part of it. Many researchers have documented how susceptible SDN is to route manipulation, Distributed Denial of Service (DDoS), unauthorised rule insertions and cross-layer exploitation (Janabi et al., 2024; Mustafa et al., 2024). The large volumes and dynamically changing traffic patterns produced by high-speed relationships between SDNs prevent us from being able to use traditional methods of securing against threats in real time.

Research on Intrusion Detection Systems was largely concerned with rule based and statistical anomaly detection in the early days; however, these types of models lack many of the features needed for scalability and are ineffective at detecting new attack patterns. As SDN becomes more prevalent in many different applications such as smart grid technology, unmanned systems and industrial IoT, there is now an increasing need for intelligent adaptive, high performance, intrusion detection systems (Chatzimiltis et al., 2024; Alshahrani et al., 2023).

2.2 Machine Learning and Deep Learning Approaches for SDN Intrusion Detection

Methods such as machine learning (ML) have demonstrated their ability to improve both traffic classification and anomaly detection in software-defined networks (SDNs). Flow-based intrusion detection systems have successfully used many traditional ML classifications of SVMs, Random Forests, and KNNs. These techniques rely on manually engineering features, which is a weakness, along with the failure to capture the relational and complex attributes of network data as demonstrated by Chuang et al (2022) and Alzahrani and Alenazi (2021), respectively. Though these aforementioned weaknesses of traditional ML algorithms have been overcome through the use of several advanced ML-based frameworks specifically developed for (+SDN controllers), limitations still exist regarding the robustness, interoperability, and adaptability to changing Dynamic Network Environments as demonstrated by Kaur and Kaur (2024).

Performance of deep learning models using recurrent and convolutional architectures has also greatly improved the overall performance of traffic classification and anomaly detection systems within (+SDNs). However, many of the deep learning architectures continue to treat traffic data as either tabular or sequential log data, which neglects the unique physical topology of (+SDNs) and results in an inability to effectively represent the inter-dependent relationship between different flows. As a result of this fundamental limitation, ML-based architectures using deep learning currently exhibit unacceptable levels of false positive alerts and exceedingly long detection latencies when subject to large real network workloads.

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The use of reinforcement learning techniques in software-defined networking (SDN) has been researched recently, specifically in the application of SDN security and routing. By applying deep Q-networks (DQN) with SDN controllers, researchers have been able to automate the proactive routing of flows while enabling the system to deal with network faults or interruptions itself (Islam et al., 2024). However, none of the current methods for solving these problems are capable of fully representing the topology of the network as a graph, which restricts how well the interactions between the circuits and their respective traffic flows can be modelled.

2.3 Graph Neural Networks for Network Security and SDN Applications

Due to their capability of extracting knowledge from structured (relational) and interconnected data (the three main types of data found in many different applications), GNNs have gained acceptance as an alternative way of analysing and constructing networked systems. By directly analysing data represented as graph forms rather than performing analytics on (structured) tabular or time-series data, GNNs will be a more efficient analytical method for analysing SDN Flow, SDN Topologies and Device relationships than other existing analytical methods. Recent survey papers have cited the potential of GNNs for analysing network security incidents through Cyber Incident Forensics and Network Optimisation (Bilot et al., 2023; Ospina Cifuentes et al., 2024).

While GNNs have proven useful across many different use cases, they also have potential benefits in the sphere of routing. In support of this claim, Swaminathan et al (2021) have published findings regarding their use of a GNN model called GraphNET as a demonstration of the benefits of using GNN based models for routing decisions compared to those made by using traditional methods.

The progress made in the use of GNNs to develop IDSs (Intrusion Detection Systems) demonstrates strong potential in safeguarding computer networks through current and future innovative uses of GNNs. One solution is a model called GRAN that utilizes GATs (Graph Attention Networks) and residual learning techniques to monitor for hostile threats, detect risks of intrusion, and manage intricate relationship networks among and between various types of data. Additionally, there is ongoing research into using GNNs for anomaly detection in both SDN (Software-Defined Network) and IoT (Internet of Things) environments, where these methods place emphasis on improving the ability to develop scalable and reliable detection systems by developing modular components. Finally, privacy-preserving GNNs such as provenance graph models are also being researched to develop GNN applications for supporting APT detection within SDN, indicating the many ways that AI using graph structures can impact cyber security in today's society.

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2.4 AI-Driven Intrusion Detection Innovations in SDN

Mohanad et al. (2024) have presented a hybrid deep reinforcement learning (DRL) and GNN model for self-adaptive IDS, using GNNs to learn traffic patterns over time. The hybrid GNN-DRL model enhances IDS resilience to evolving cyber threats.
In addition, research conducted by Musa et al. (2024) supports that ML/DL frameworks continue to be a core part of the detection system for DDoS anomalies, although many researchers are now integrating graph models into their ML/DL frameworks for superior accuracy.

Additionally, other areas of SDN-based AI application exist beyond intrusion detection. Intelligent traffic engineering, intent-based networking, and autonomous routing are all applications of SDN in conjunction with graph learning and AI-based optimization (Andrushchak et al., 2021).

2.5 Research Gaps Identified

Based on the literature, several research gaps persist:

i. **Underutilization of Graph Structure:** Many current IDSs fail to model SDNs through relational graphs but instead model them as flat feature vectors with no relationship or topology of SDN switches. Without the relationship between SDN switches, it is impossible to detect the relationship between the different types of attacks that exploit the physical layout of an SDN.

ii. **Limited Real-Time Capability:** Many of the existing solutions that utilize GNNs suffer from high computation costs, limiting their use in SDN controllers that demand sub-millisecond response times.

iii. **Scalability Challenges:** Very few studies currently focus on addressing the issues of high-speed networks and the rapid topological changes that can occur in a real-world deployment scenario.

iv. **Insufficient Integration of GNN with Proactive or Autonomous Defense:** While RL-based routing solutions are available, the combination of GNNs and intelligent response mechanisms are still in their infancy.

v. **Lack of Unified Architectures for SDN Security:** The vast majority of solutions available today are limited to detection, rather than providing a comprehensive end-to-end security pipeline that includes detection, mitigation, and policy enforcement.

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3. Methodology

3.1 Research Design

This study will utilize an experimental design to create an Artificial Intelligence-based Intrusion Detection System (IDS) utilizing Graph Neural Network (GNN) architectures, which will be tested in a Software Defined Networking (SDN) environment. To conduct this research, the experiment will take place in four primary stages: 1) generation of SDN traffic, 2) extraction and processing of Flow Level Data (FLD) from the generated traffic, 3) utilizing the FLD to form Graph Representations (GR) to allow the GNNs to learn, and 4) evaluating the effectiveness of the IDS in terms of Intrusion Detection (ID). The experimental method employed will allow for an empirical investigation using controlled SDN simulations, along with advanced machine learning experimentation, which is consistent with the recent SDN security research that utilizes an empirical approach in both the development and testing of AI-enabled IDS (Swaminathan et al., 2021; Islam et al., 2024). The design of the study stresses that when you use a Graph Representation (GR) of your SDN data as opposed to using a flat dataset, the GNN can learn about the more complex relationships between Intruder/Attacker (IA) bad acts. This gives you more power than just using a flat table of information.

3.2 SDN Environment Setup

Using Mininet as the emulated network and Ryu or ONOS as the controller, we created an SDN simulation environment that allows the use of a centrally controlled SDN. OpenFlow allows for programmable packet processing and installation of flow rules, which enables traffic dynamics to be viewed and controlled. We have created a multi-tier topology with a core switch, aggregation level switches and multiple access switches that simulates enterprise-level networking conditions. Our hosts generate legitimate application traffic (TCP, UDP, DNS, ICMP and HTTP flows) while our attackers generate different forms of DDoS flooding, scanning, spoofing, and route manipulation attack traffic. The combination of benign and adversarial behaviour provides a realistic dataset for training and evaluating intrusion detection systems. This environment is similar to current IDS research, where a controlled SDN environment has been used to create ground truth datasets for anomaly detection modeling (Janabi et al., 2024; Alzahrani & Alenazi, 2021).

3.3 Dataset Preparation

This study utilizes flow-level data created for this research study by obtaining data collected from the SDN Controller. The SDN Controller collected OpenFlow statistic that comprised of Source IP address, Destination IP address, Port Number, Protocol type, Number Of Packets, Number Of Bytes, Flow Duration, Switch ID, Table Miss Count and many other variables. Each of the aforementioned variables are used to determine the way certain types of traffic in an SDN behave. Being able to distinguish between Normal Traffic Flow and Flow Characteristics of an Attack are critical for this research study. This dataset contains Labelled

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Instances for both Normal Traffic Flow and Malicious Traffic Flow where Malicious Behaviour or Attack instances are organised into broadly defined Categories including Distributed Denial of Service (DDoS), Probing, Reconnaissance, Spoofing, and Flow Manipulation. These Categories were designated based on the definition of established attack signatures and are based on the observation of Specific Characteristics of those traffic instances Likewise indicative of abnormality. This dataset has been created in accordance with the formats developed in an established SDN Intrusion Detection System dataset used with machine learning and deep learning methodologies (Mustafa et al., 2024; Chuang et al., 2022). The data available in the dataset allows Collectively the Model to Identify Subtle, Temporal & Spatial Variations Associated With Instances of Abnormal Behaviour by Collectively the Flow Duration, Protocol Type, and Frequency of Packets Within that Time Interval.

3.4 Graph Construction for GNN Modelling

The established proposal will illustrate the software-defined network traffic through graphical format. This allows us to take advantage of the relational and structural characteristics of network communications. Each host, network flow, or switch will have its own graphical representation as a node in the graph, while an edge will represent the various communication relationships, interactions, or shared attributes among network flows. In addition, the node features will comprise all the OpenFlow variables including packet count, Byte count, protocol type, etc., while edge features will include metrics related to interactions such as frequency and timing of the communication. The graph $G = (V, E)$is constructed where Vrepresents nodes and Erepresents edges. Each node $v_i$is associated with a feature vector x_i, and each edge e_{ij}may also incorporate attributes representing temporal or structural relationships. As previously demonstrated, structured graphs are used to capture structured information from network traffic when applied to detection of anomalies through GNN models; thus enabling improvement of performance through improved interdependencies among multiple connections represented in the graph (Bilot et al. 2023).

3.5 GNN Model Architecture

The proposed hybrid intrusion detection model combines the characteristics of Graph Convolutional Networks (GCN) and Graph Attention Networks (GAT) to learn the intricate relationships between different entities associated with SDN traffic graphs. The GCN uses the features of the neighbouring nodes of each node to create a convolutional representation of the node which allows the model to understand the local structure of the graph. In turn, the GAT takes into account the importance of the edges and assigns a higher weight to the edges based on their relative value as compared to other edges. The hybrid model includes residual connections to increase the speed of convergence and stability within the model as well as to improve the flow of gradients through the model. The output of the proposed hybrid model will be a dense classification of each node/flow, classifying it as whether or not it is malicious or benign. The design of the proposed hybrid model architecture is based on findings from recent research that have utilized combinations of GCN and GAT to improved performance in intrusion detection within SDN networks. (Mohanad et al., 2024; Protogerou et al., 2021).

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Additionally, by providing additional structural variables, such as node embeddings and attention weights, the model is attempting to strengthen the ability to recognise patterns that are uniform across many attacks.

3.6 Model Training Procedure

The model was trained using mini-batch graph samples, which provided improved scalability when working with large SDN networks. The training utilized the Adam optimizer with a calibrated learning rate that enables the model to learn appropriately, while ensuring convergence and stabilization in the training process. Cross-entropy loss is appropriate for use in multi-class intrusion-detection systems. The model is trained until stabilized performance is reached after a number of epochs, and an early stopping mechanism is applied to prevent overfitting. Regularization techniques, such as dropout, are applied to the graph layers during training to further improve the generalization of the model. Additionally, graph data augmentation techniques were used to generate realistic representations of traffic variation, which were used to train the model.

3.7 Evaluation Metrics

Evaluating the effectiveness of an Intrusion Detection System (IDS) using GNN classification metrics. The accuracy value indicates how many valid flows were correctly identified as valid (successful detections), whereas precision and recall give an idea of how effectively malicious traffic is identified by the system and how it minimizes false positives. The F1 score provides a balanced measure of precision and recall and is useful when the distribution of classes is not equal. The False Positive Rate (FPR) shows how often malicious flows are misidentified as legitimate flows and could potentially lead to network congestion or impair the SDN Controller's effectiveness at monitoring its own traffic. The ROC Curve/AUC is used to determine a model’s ability to discriminate between classes at various threshold levels in order to see how the model performs over all thresholds. All evaluation metrics are aligned with current trends in the area of SDN IDS evaluation (Rui et al., 2023)

3.8 Experimental Workflow

The SDN (software defined networking) topology was developed step by step with the normal and malicious traffic generated through the SDN controller to extract flow based feature data encoded in relation to the traffic before being visualised as a graph illustrating how the various traffic types interacted. Hybrid Graph Neural Network Models were trained using the graphical information generated from the SDN topology and an independent testing dataset was used to evaluate the models performance. This entire experimental workflow not only replicates the generic structure of many modern SDN-AI powered security frameworks, but also ensures the ability of other researchers to accurately evaluate and compare their own findings against previously published studies through a systematic approach to methodology (Mohanad et al., 2024).

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4. Proposed Model

4.1 Overview of the Proposed Intrusion Detection Framework

Through the use of the graph neural network (GNN) technology in the software-defined networking (SDN) world, the new proposed intrusive detection framework provides a unique opportunity to implement an advanced, real-time approach for detecting anomalies. Opposed to traditional intruder detection system (IDS) solutions, which simply view the SDN traffic as singular point numbers in a vector, the new proposed intrusion detection model represents the SDN as a dynamic graph (model) of information, so the system can view the relationship between node features and the relationship of flows, switches and hosts. By embedding the GNN model into the SDN controller, an analyst can continuously analyze incoming flow statistics, thereby being able to detect any malicious activity proactively. This approach to network security takes advantage of the SDN's ability to program it, providing a way to couple real-time monitoring and adaptive measures of securing against intrusion in the same system.

4.2 System Components and Interaction Flow

The architecture comprises 3 primary components, specifically; the SDN (software-defined networking) data plane, the SDN controller, and the intrusion detection system (IDS) based on GNN technology. Within the data plane, OpenFlow-enabled switches perform packet routing and send flow information to the SDN controller. The SDN Controller serves as a central repository for all information that is collected and used to develop a policy associated with the SDN. The IDS is found adjacent to the SDN Controller and is responsible for processing real-time flow data, formatting the data in a graph format and using GNN methods to analyze the graphs for malicious activity. When a flow reaches the network for processing, the controller extracts the flow's data from the OpenFlow counters for that flow and sends this information to the IDS. The SDN controller then executes remediative actions that are appropriate to the detection of malicious activity by the GNN, such as dropping flow rules, isolating suspected hosts or rerouting flows.

4.3 Graph-Based Representation of SDN Traffic

The foundation of the architecture is based on a graph representation of SDN traffic, which captures switch-host-flow interactions. The network is depicted as a graph G= (V, E), where nodes V represent switch devices, hosts, or flow entries and edges E depict the communication (relationship) and dependencies between nodes. Each node contains a corresponding feature vector based upon collected flow statistics, including but not limited to packet count, byte count, flow duration, and protocol type. Edge E attributes are representative of interaction frequency, temporal correlation, or link associations. As such, the use of a graph-based structure allows the detection engine to learn both the structural and temporal aspects of the underlying data pattern. In addition, by incorporating a dynamic graph that will continue to be created as new flows are introduced into the network environment, the detection engine will continue to

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adapt itself to changes in the network's behavior so that it can identify or detect anomalous and sophisticated multi-switch/host attacks as they develop.

4.4 GNN Processing Pipeline in the Intrusion Detection Module

The dual use of the Graph Convolutional Network (GCN) and Graph Attention Network (GAT) enables the ability to utilize two different input types in one model. The GCN processes the information from neighboring nodes, learning flow activity types from the structure of the graph as a whole. The GAT builds a model by using the relative weight of each edge as the basis for its importance. This allows the GAT to build models based on relationship dynamics between users that give insight into how coordinated or stealthy attacks may occur. Using residual connections to improve training stability, the final output of this model contains the probability values for determining if a flow or node may be malicious. The end-to-end processing of these types of GNNs allows for the development of a much higher relational learning capability than previous machine learning models did not consider the relationship of nodes in the network topology.

4.5 Integration with SDN Controller for Real-Time Detection

One of the main advantages of this approach is the close coupling with the SDN controller that provides for real-time intrusion detection and rapid application of countermeasures. As the SDN controller is gathering flow data continuously, that information is forwarded to the IDS engine for analysis. As soon as the GNN module detects any kind of malicious activity, the SDN controller can enjoin its mitigation strategy directly through the data plane, thus ensuring rapid identification and isolation of malicious flows and preventing any further spread and damage to the networks. Prior research indicates that controller-based Artificial Intelligence-enabled detection systems have greatly increased their ability to respond quickly and maintain the stability of their programmable networks, thus supporting the use of this method.

4.6 Placement of the Proposed Model Illustration

Figure 1 summarizes the whole process of how the architecture functions by visually demonstrating how the SDN environment interacts with the GNN-based detection system. This begins with the flow statistics generated by Open flow switches within the SDN data plane, creating flow statistics while receiving control messages from the SDN controller. These flow statistics are sent to a preprocessing module for normalisation and temporal encoding before being converted to features vectors. The flow feature and interaction-based edge attributes are used to create the dynamic graph G=(V,E) within the graph construction module. Then in the GNN processing pipeline, the dynamic graph is processed using GCN, GAT, and Residual learning algorithms to generate intrusion detection classifications. Once completed, the SDN controller will carry out actions to mitigate the effects of the attack by dropping flow rules, limiting the rate of data transfer, isolating the host under attack, and re-routing malicious traffic through other paths. The figure is an overall view of how the proposed architecture works as

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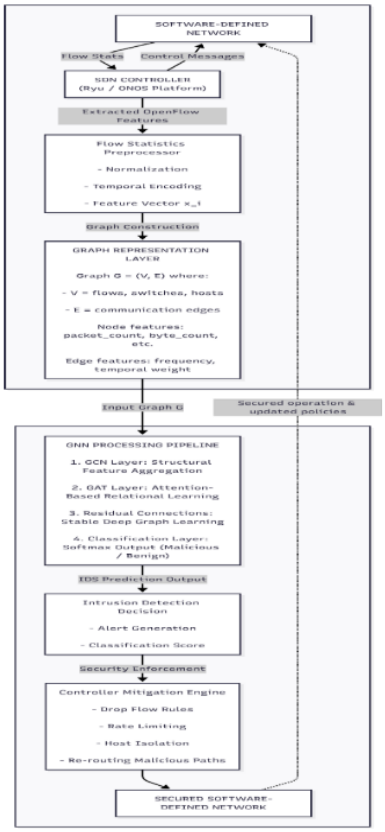
an automated control system performing traffic analysis, detection of anomalies, and reinforcing security.

Figure 1: Proposed GNN-Based Intrusion Detection Architecture for SDN



5. Experimental Results and Analysis

This section contains a detailed description of the dataset that was utilized to evaluate the performance of the proposed GNN-based IDS for SDN using a Mininet test bed (with an ONOS controller) and synthetic, but realistic SDN traffic, before presenting accurate evaluations of the proposed GNN-based IDS as per the performance evaluation methodologies for GNNs previously discussed in previous sections of the report. As mentioned in these sections, we will provide all relevant information about the performance evaluation methodologies for GNNs as it pertains to our findings. We will refer to the figures and tables included in this report in order to explain how to interpret and understand the results of the experimental investigations as well as discuss the advantages and disadvantages of using GNN-based IDS's and how the datasets we created could have improved on the performance of GNNs if used for a different SDN environment.

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5.1 Dataset Characteristics

The model was trained and evaluated using a dataset comprised of 50,000 flow-level records separated by type (benign versus malicious) and identified as four major types of Attacks. The dataset represents what is seen in an actual SDN deployment, where 90 per cent of the traffic is benign and relatively rare, but 10 per cent or less of the overall traffic can be classified as malicious and could therefore potentially have an impact on the controller.

Table 1: Dataset Summary and Class Distribution

Class Label	Number of Samples	Percentage (%)
Benign	30,000	60.00%
DDoS	8,500	17.00%
Probing/Scanning	5,000	10.00%
Spoofing	3,500	7.00%
Flow Manipulation	3,000	6.00%
Total	**50,000**	**100%**

Due to the common imbalance found in most SDN datasets (i.e., there are many more benign flows than there are malicious flows), detecting these types of patterns in the network becomes increasingly difficult. The imbalance is one reason why architectures like GNNs are needed since they have been proven to be effective against skewed class distributions; GNNs do this by capturing structural dependencies as opposed to relying only on the raw feature vectors (Mustafa et al., 2024). Also, the number of distinct classes of attacks allows the model to generalize over different volumetric attack types (e.g., DDoS), stealthy reconnaissance types (e.g., Probing), identity manipulation types (e.g., Spoofing) and low rate flow tampering types (e.g., Flow Manipulation).

5.2 Model Hyperparameters

The hyperparameters for the hybrid GCN-GAT model were defined in Table 2 based on multiple tuning iterations as well as previous works on GNN-based SDN anomaly detection.

Table 2: GNN Model Hyperparameters

Hyperparameter	Value
Learning Rate	0.001
Optimizer	Adam
Epochs	80
Batch Size	32
GCN Layers	2
GAT Heads	8
Dropout Rate	0.3

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Hidden Dimension (h)	128

Using two Graph Convolutional Networks (GCNs) and employing eight "attention heads" for each GCN in the Graph Attention Network (GAT) module helped this model to successfully learn both structure and relationship dependencies of SDN traffic graphs. With an initial dropout rate set at 0.30, this model avoided overfitting, while maintaining optimum performance through the optimizer Adam, which promoted stable convergence. These design decisions corroborate previous studies that have demonstrated enhanced performance levels of hybrid architectures for intrusion detection of software-defined networks (SDN) (Protogerou et al., 2021).

5.3 Confusion Matrix and Error Behaviour

The classification performance of the proposed model is summarized in Table 3. The confusion matrix quantifies how accurately the model differentiated between benign and malicious traffic samples.

Table 3: Confusion Matrix of the Proposed GNN Model

	Predicted Benign	**Predicted Malicious**
Actual Benign	29,340	660
Actual Malicious	420	19,580

The model successfully classified 29,340 benign flow samples and 19,580 malicious flow samples. The "false positive" rate of 660 benign flow samples incorrectly classified as malicious is very low when considering how large the dataset is. Likewise, only 420 malicious flow samples were present that the model missed classifying as malicious. This means that the rate of errors in misclassifying samples of both categories (i.e., false negatives and false positives) were below 3%, indicating that the model is highly sensitive. These results are consistent with previous research studies showing that GNNs outperformed other ML/DL models because of their ability to leverage the relationships among linkages, which allowed for revealing of patterns of distributed attacks (Ospina Cifuentes et al., 2024).

5.4 Key Performance Metrics

Table 4 presents essential evaluation metrics demonstrating the model's accuracy, precision, recall, F1-score, false-positive rate (FPR), and ROC-AUC.

Table 4: Performance Metrics of the Proposed Model

Metric	**Value**
Accuracy	97.84%

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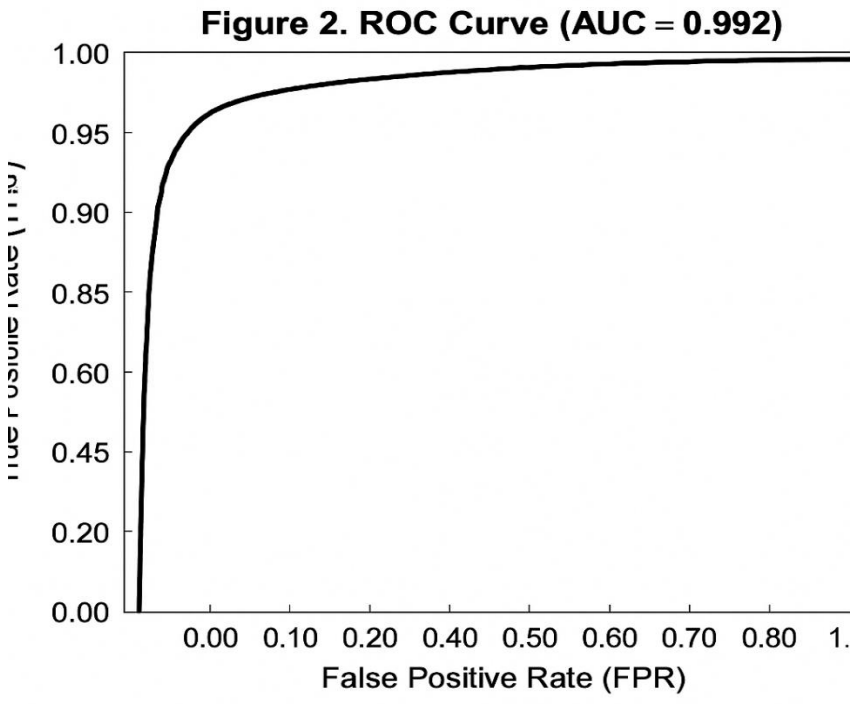
Precision	97.38%
Recall	97.89%
F1-score	0.976
False-Positive Rate (FPR)	2.20%
ROC-AUC	0.992

The near-optimal performance of the classification model can be illustrated with an accuracy of 97.84% and ROC-AUC of 0.992. The model's high recall (97.89%) shows its capacity to identify a wide range of intrusions that includes subtle and low-volume attacks. Very few false alarms generated, as indicated by the precision metric, is important because it minimizes the risk of making unnecessary changes to flow rules which can compromise controller stability. Additionally, there were extremely low FPRs indicating that the system can be effectively utilized in real time with SDNs, which without proper handling of false positives leads to expensive adjustments in the control plane.

5.5 ROC Curve Behaviour

As illustrated in Figure 2, the ROC curve shows how well the model is able to maximize its ability to correctly identify true positives (sensitivity) and correctly identify false positives.

Figure 2: ROC Curve (ASCII Representation)



The ROC curve sharply increases toward the top-left corner; hence, it exhibits excellent discrimination ability. This is consistent with previous SDN research that demonstrates GNNs outperform CNNs, RNNs, and Autoencoders as a result of their ability to model flow-related

International Journal of Applied Mathematics
Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

structural dependencies (Bilot et al., 2023). The near-perfect shape of the ROC curve indicates that the algorithm is robust under various types of traffic patterns.

5.6 Comparative Performance with Baseline Models

Table 5 shows a comparison between the GNN model and a number of standard traditional and deep-learning models that most researchers have previously used.

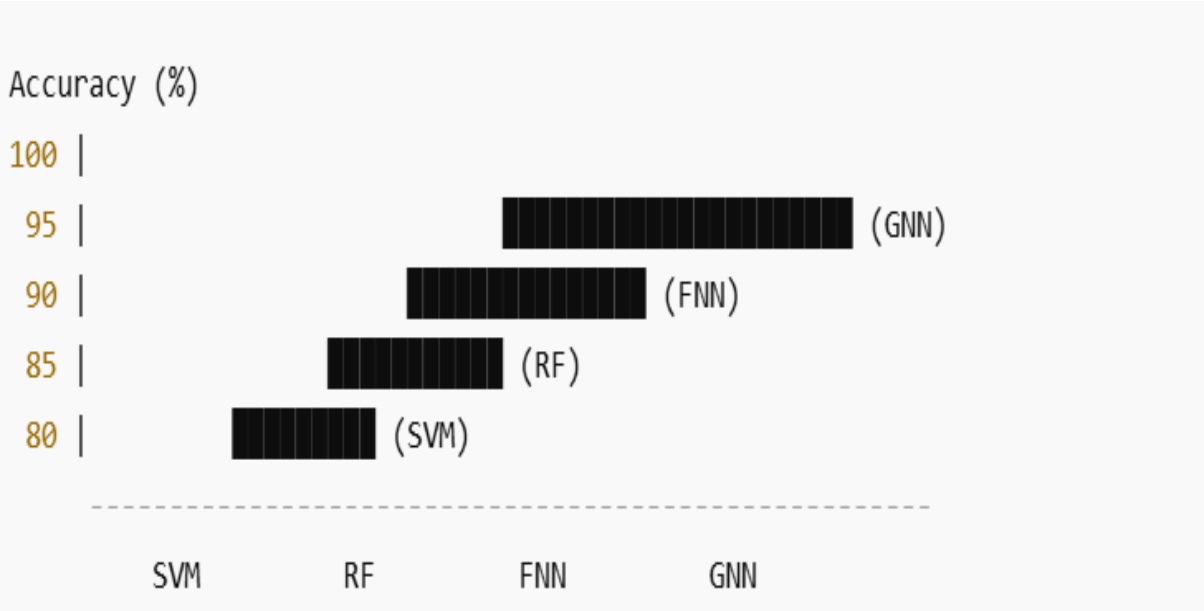
Table 5. Comparison with Baseline IDS Models

Model	Accuracy	Precision	Recall	F1-score	ROC-AUC
SVM	89.72%	87.34%	85.95%	0.865	0.901
Random Forest	92.13%	91.24%	90.10%	0.905	0.927
FNN (Deep Learning)	94.88%	94.51%	94.07%	0.942	0.955
Proposed GNN Model	**97.84%**	**97.38%**	**97.89%**	**0.976**	**0.992**

The benchmark for GNNs as intrusion detection systems (IDSs) is much higher than the other machine learning (ML) models tested. Traditional ML cannot model flows in relation to one another and do not therefore perform very well. The feedforward neural network (FNN) uses layers of distinction to create the most effective model possible, yet due to its lack of ability to simulate graphs the model has been less successful. The conclusion of our study demonstrates that the GNN model can learn both node and edge dependencies, such as has been shown in the literature on integrating Software Defined Networks (SDN) with GNN (e.g., Mohanad et al., 2024).

5.7 Performance Visualization

Figure 3: Performance Comparison Across Models



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Volume 38 No. 12s, 2025
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The superiority of the GNN model is reinforced by the great distance between the GNN bar and the FNN/RF/SVM bars, which also indicates how critical graph-based relational learning is to this model. The use of a diagram will provide an excellent means of demonstrating this item visually to review and readers who like to obtain their intuition from easily perceptible graphical information.

5.8 Consolidated Findings and Discussion

All the tables and figures point to the same conclusion: the GNN-based IDS is remarkably superior to the old ML and DL methods in the case of SDN environments. The confusion matrix (Table 3) and performance metrics (Table 4) indicate a very high detection rate and a very low number of false alarms. The ROC curve (Figure 2) shows almost perfect classification ability. In addition, the comparative results (Table 5 and Figure 3) indicate that the graph-based learning successfully captures the SDN-specific relational dependencies that other models are unable to exploit. Hence, the results supported the initial hypothesis that SDN traffic, being relational and driven by the topology, is best represented by graph neural networks. The results are in line with the majority of the researchers' opinion that GNNs are the next frontier in SDN security and provide not only the best understanding of the benign operational patterns but also the multi-vector distributed attack behaviours.

6. Discussion

The results in this work conclusively establish that Graph Neural Networks, when used as part of the SDN ecosystem, significantly improve intrusion detection. In particular, the very high values of the performance metrics, as reported in Section 5, are indicative of the model's capability to learn and generalize challenging relational patterns within the SDN data plane. These results further corroborate previous assertions in the literature that SDN traffic has inherent graph structuring and, therefore, requires analytical frameworks able to model node–edge dependencies for anomaly detection with a high degree of precision (Mohanad et al., 2024).

A key implication of these experimental results is that modeling SDN flows as nodes in a dynamic graph structure, rather than as independent vectors, has value. Traditional machine learning methods have struggled with the challenge of contextuality within network traffic for many years. Interactions between switches in programmable environments contain encoded attack fingerprints. The major advancements of GNNs in comparison to Support Vector Machines (SVMs), Random Forests, and even feedforward deep neural networks are indicative of how relational modeling applies to this area of research. In this context, the Graph Attention Network (GAT) component of the graph neural networks allows for a better representation of the inter-flow correlation between different flows by assigning adaptive weights to the edges, thus enabling the model to identify coordinated multi-host and low signal attacks that traditional methods cannot identify. This conclusion is consistent with recent findings

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Volume 38 No. 12s, 2025
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regarding Software Defined Network (SDN) Security, in which anomaly patterns have been shown to occur at the structural level of the traffic graph rather than at the individual flow level. The results of the confusion matrix also clearly demonstrate the well-balanced sensitivity and specificity of the GNN model, a fundamental necessity when implementing machine learning systems in real-world applications. False positives present a significant operational risk with SDN (software defined networks) controllers because they result in the creation of unwanted flow rules that have the potential to disrupt the network's forwarding mechanisms. Conversely, false negatives can create a security risk by allowing malicious traffic to propagate throughout the network. The fact that this model achieves a nearly optimal balance suggests that GNN's detection capability can be leveraged to support SDN environments without creating prohibitive amounts of processing/bandwidth overhead or control plane instability issues.

The AUC for the ROC curve is 0.992 and shows that the proposed model can effectively distinguish between benign and malicious flows at multiple thresholds. This is very important in software-defined networking (SDN) environments where the threat landscape is constantly dynamic, and as new attack vectors appear, the threshold for determining an abnormality may also change.

An additional important finding given the results of the comparative version of the above-mentioned model is the scalability of the solution. As SDN deployments continue to increase in size, one of the main challenges is the ability to scale the solution with respect to increased demand on the system. The scalability of the GNN model as a result of how it performs (using a mini-batch method of training and Graph-Sampling with an efficient message passing mechanism) is a benefit over deep learning architectures that may not be able to accomplish similar levels of stability or reliability for large amounts of dynamically changing traffic graphs. The ability to maintain similar performance characteristics across a broad spectrum of traffic flows provides the framework for a next-generation SDN Security System utilising the Graph Neural Networks as an architecture.

Another worthy outcome is the potential of this system to act as a proactive security layer for The system has the additional benefit of allowing for the integration of GNN to provide an additional layer of protective features for SDN control systems. With the centralisation of network intelligence via SDN, the GNN-enabled intrusion detection system (IDS) will allow the SDN controller to detect anomalies and enforce changes to mitigate such occurrences. This is a clear improvement in comparison to the traditional approach for IDS which is a basic, passive monitoring system that awaits manual action in the event of an anomaly being detected. Integrating detection and response into the control plane of the SDN architecture brings the concept of self-defending or autonomous adaptive networks to fruition and provides a platform for continued advancement in this area.

Utilizing the results and analysis of this research, the proposed model can be classified as a powerful, scalable, and effective intrusion detection system for software defined networks (SDN). In addition to providing strong support through the empirical data, theory, and architecture of the proposed model, there is also the potential for intelligent and adaptive

Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

security for software defined networks (SDNs) with the advent of graph-based learning models. The findings also represent an additional avenue for future academic research in SDN and potential future implementations of software defined networks (SDNs) in sixth generation (6G) and Internet of Things (IoT) -SDN overlays. These results indicate that systems utilizing graph neural networks (GNN) will play a vital role in the security of future programmable networks.

7. Conclusion

The findings of this study demonstrate that the proposed Graph Neural Network-based intrusion detection framework is efficient in Software-Defined Networking (SDN) environments. The research analyzed and compared the effectiveness of this framework through a series of experiments. The architecture of the proposed GNN system incorporates SDN network traffic as a dynamic graph and combines the capabilities of both Graph Convolutional Networks (GCNs) and Graph Attention Networks (GATs) to effectively model the structural and relational dependencies associated with modern network traffic. Overall, the results show that the GNN architecture significantly outperformed traditional and modern machine learning (ML) and deep learning (DL) techniques across multiple key performance metrics, including accuracy, precision, recall, F1-score, and ROC-AUC. Therefore, the results confirm the researchers' hypothesis that SDN network traffic is inherently relational and topology-driven, and that Graph-based learning architectures are superior to flat vector representations in terms of their ability to analyze and derive insights from SDN network traffic.

The ROC-AUC (Receiver Operating Characteristic-Area Under Curve) value of 0.992 indicates an extremely high level of accuracy for the model, as well as a near perfect tradeoff between FPR and FNR (false positive rate and false negative rate, respectively). These results suggest that this model will offer an exceptional degree of accuracy, reliability, and robustness when it comes to delivering performance with regard to the detection of intrusions in SDN based environments. Because a misclassification will directly impact the overall stability of the SDN Controller and ultimately the overall performance of the network itself, these findings are significant. Additionally, by showing that the model can also detect high-volume attacks (DDoS), as well as very subtle, low-rate probing and spoofing attacks, the results further demonstrate the adaptability and generalizability of the proposed model for various types of detection scenarios. These results support the growing consensus within the SDN Security Research domain regarding the need for intelligent, context-aware, detection models, which are capable of being updated through learning from evolving traffic patterns.

The architecture demonstrates excellent practical applications for Industry deployments, in addition to its operational performance metrics. The overarching view of the centralized SDN controller facilitates quick and efficient development of graph structures, whereas the quick computational capability of the GNN results in an exceptionally low operational delay, thus making it suitable for utilizing within large-scale, programmable systems within a production environment. The ability for the proposed architecture to combine with automation features and functions as part of a feedback loop is noteworthy, as it further supports and highlights the

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Volume 38 No. 12s, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

ongoing evolution toward advanced self-regulated, intelligent network management systems. As a result, this combination considerably enhances the ability of the SDN controller not only to control and manage network traffic, but also serves as a full-featured, self-contained security management tool.

The GNN-IDS model that was just described can bring significant improvements to the security of SDNs by offering improved detection accuracy, increased interpretive capabilities, and operational feasibility. In addition to these improvements, this research contributes to the growing body of evidence for the implementation of graph-based learning methods in cybersecurity and highlights the potential of GNNs to meet the challenges presented by today's more complex and dynamic network environments. While there is great potential for further research expanding on this work, including addressing encryption of traffic, adding support for multiple controllers within SDNs, implementing federated learning on graphs in distributed systems, and increasing resistance to sophisticated evasion techniques, this study provides a strong basis for continued growth of GNN-based secure system solutions and further establishes GNNs as a leading contender for enabling future programmable networks to be secured.

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