# SDN BASED INTRUSION DETECTION SYSTEM USING MACHINE LEARNING FOR TOPOLOGY POISONING ATTACK: A CASE STUDY

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## DECLARATION

I declare that this is my own work and this proposal does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other university or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text.

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Signature of the Supervisor (Mr.Kanishka Yapa ) Date

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## Abstract

The increasing complexity and scalability of Software Defined Networking (SDN) technologies has revolutionized network management by enabling centralized control and programmability. However, this centralized architecture also carries significant hazards, particularly on the control plane. One of the biggest security risks in SDN is topology poisoning, when attackers change the network topology by introducing fake Link Layer Discovery Protocol (LLDP) packets. As a result, the SDN controller makes incorrect routing choices. The goal of this project is to create an intrusion detection system (IDS) that uses machine learning to identify and stop topology poisoning attempts in real time. To categorize network activity and identify anomalies associated with SDN architecture, the suggested system makes use of supervised machine learning methods including SVM, Random Forest, and Decision Trees. To guarantee the integrity of the SDN controller, the system is built to operate in real-time, continually monitoring control-plane traffic and LLDP packets. The integration of the system with SDN controllers such as RYU is also covered in the research, which also assesses how well the system detects harmful activity while reducing false positives. An important step in protecting SDN environments is the suggested IDS, especially for mission-critical applications like cloud data centers and ISPs.

## Acknowledgment

First and foremost, I would like to express my sincere gratitude to my supervisor Dr. Janaka Wijekoon for the constant guidance and support which helped me at all times for the successful completion of my undergraduate research. Besides my supervisor, my sincere thanks also goes to Miss Dilani Lunugallage, the co-supervisor of this research project for being willing to help whenever it was needed. This research study being a mixture of technology and agriculture required the guidance and assistance of not only technology experts but also Agriculture professionals. The immense support extended by Dr. Mrs. Nayanie Aratchige throughout the project to bridge the knowledge gap in those areas is highly appreciated. My sincere gratitude also extends to Dr. Sarath Idirisinghe, Mr. Roshan De Silva, Mr. Prabhath Manoj, Mr. Anura Pathirana of Coconut Research Institute for their kind assistance extended by assisting identification of pest and disease symptoms of coconut. Last but not least, I express my sense of gratitude to my team mates, family, friends, to one and all, who directly or indirectly have extended their support throughout this project.

## LIST OF ABBREVIATIONS

| **Abbreviation** | **Description** |
|---|---|
| SDN | Software Defined Networking |
| IDS | Intrusion Detection System |
| LLDP | Link Layer Discovery Protocol |
| SVM | Support Vector Machine |
| ML | Machine Learning |
| OVSDB | Open Virtual Switch Database |
| MAC | Media Access Control |

# 1.Introduction

## 1.1 Background

The increasing complexity, scalability, and dynamic nature of network infrastructures has caused a paradigm shift in the field of digital communications from traditional networking designs to more programmable, automated, and intelligent systems. One of the most significant advancements in this area is Software Defined Networking (SDN). By separating the control and data planes, which are tightly connected within each networking device in traditional networks, SDN enables centralised management over the whole network infrastructure.

The brain of the network, the SDN controller, coordinates packet forwarding rules between switches and routers using logic that is updated in real time. Advanced applications like virtual network provisioning, fine-grained QoS, adaptive security enforcement, and automatic load balancing are made possible by this centralisation of management, which also improves flexibility and manageability.

But this centralisation and flexibility can provide a single point of failure and a large attack surface for hackers. If the SDN control plane is hacked, the network may become susceptible. A topology poisoning attack is one of the most pernicious ways to interfere with network intelligence and routing behaviour among these threats.

In an SDN architecture, the controller oversees all significant choices about network traffic, routing, and security rules. This centralized control poses significant hazards even if it has numerous benefits in terms of scalability, agility, and administrative ease. The controller maintains a global view of the network, making it a valuable target for attackers hoping to exploit the network's trust in the control plane. Attacks like "topology poisoning" are particularly dangerous because they change the controller's understanding of the network topology, which can lead to denial of service, network congestion, or incorrect traffic routing. The whole integrity and reliability of the network might be jeopardized by these assaults, highlighting the need for robust security measures to protect the SDN control layer and prevent misuse of its centralized design. As the usage of SDN increases, fixing these flaws is crucial to preserving the security and stability of modern network infrastructures.

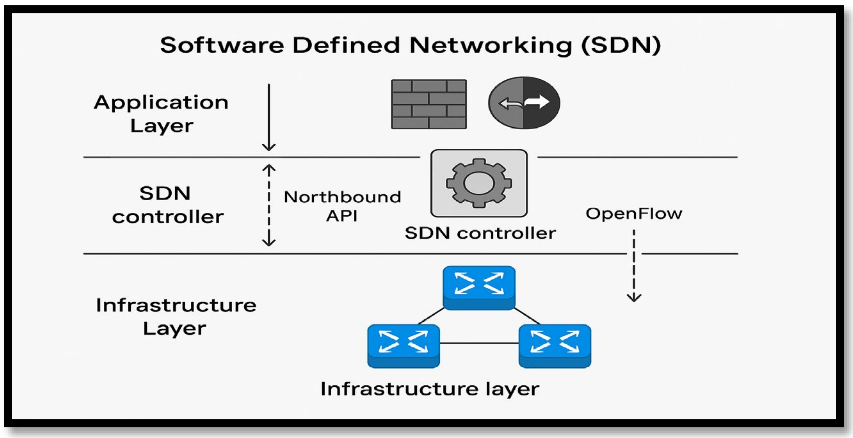


Figure1 : SDN Architecture

## 1.2 Background Literature

Software Defined Networking (SDN), a groundbreaking paradigm in modern networking, allows for programmable control over networking devices, centralised network information, and simpler maintenance by separating the control plane from the data plane. Since its launch in the early 2010s, SDN has grown in popularity globally in data centres, commercial environments, research institutes, and service provider networks. These days, developments in cloud computing, 5G, and Internet of Things (IoT) deployments are significant.

In a traditional network, each switch or router operates independently and chooses what to forward depending on its local view. In contrast, an SDN-enabled device simply forwards packets in compliance with instructions received from a centralized controller that monitors the entire network. Because of this basic architectural shift, organizations have been able to develop network infrastructures that are more flexible, scalable, and cost-effective.

The SDN architecture is typically layered into: Application Layer; Contains specialized network applications like firewalls and traffic balancers. The control layer is occupied by the SDN controller, which uses southbound protocols to communicate with infrastructure and northbound APIs to communicate with applications. Switches and routers that react to flow rules defined by the controller make up the infrastructure layer. Many open-source and commercial controllers, including RYU, OpenDaylight, ONOS, and Floodlight, will be widely utilized by 2025. Several southbound protocols, such as OpenFlow, NetConf, and OVSDB, are supported by these controllers.

One of the key elements that enables SDN is the OpenFlow protocol, which continues to be the most often used southbound interface. OpenFlow provides the controller with direct access to the flow tables of network devices, enabling real-time forwarding rule updates. This direct programmability transforms network devices from decision-makers to basic forwarding agents by reducing the variety and complexity of the underlying technology. Furthermore, it makes it easier to perform tasks that would be challenging in traditional networks, such as dynamic traffic rerouting, real-time network monitoring, and the rapid deployment of new services. When decision-making and forwarding processes are kept apart, improved visibility results in more efficient resource allocation, proactive congestion avoidance, and granular policy enforcement.

Despite all its advantages, SDN's special design presents more security and reliability challenges. Because of its centralized design, which creates a single point of failure, if the controller is attacked or malfunctions, the entire network may become unresponsive or misrouted. Additionally, whereas widely used communication protocols like OpenFlow promote interoperability, they also put users at risk for many dangers like man-in-the-middle attacks, flow rule manipulation, and topology poisoning. These risks are especially important in environments where availability and security are essential, such as government infrastructure, financial services, and healthcare networks. Therefore, ensuring the integrity of control-plane communications and real-time anomaly detection are essential for the safe and dependable deployment of SDN in mission-critical systems.

## 1.3 Research Gap

Software Defined Networking (SDN) is transforming network topologies by offering dynamic programmability and centralized control. But it also introduces several new security vulnerabilities, particularly in the control plane. Topology poisoning is one such risk that is still frequently disregarded, when attackers alter or create a false network topology view by taking advantage of the network's trust in Link Layer Discovery Protocol (LLDP) data. Despite SDN's growing use in cloud data centres, ISPs, and mission-critical enterprise networks, there aren't many practical solutions that focus on identifying and preventing this specific threat type.

Many of the intrusion detection systems (IDS) available today are either general-purpose tools (such as Snort and Suricata) that are not aware of SDN-specific features or static rule-based solutions integrated into SDN controllers. These methods lack flexibility and are ineffective against novel or adaptive topological poisoning strategies. Additionally, most SDN security frameworks prioritize data plane threats like flow table saturation, DDoS attacks, and packet spoofing over control-plane vulnerabilities like MAC manipulation, LLDP spoofing, and fake link injection. This difference in focus leads to a critical vulnerability in safeguarding SDN's primary intellect, the controller.

Although several scholars have investigated solutions such as topological validation techniques and cross-layer trust models, these approaches often have significant performance trade-offs, require additional hardware or sensors, or are not suitable for real-time detection in production environments. Furthermore, control-plane metadata including switch-link dynamics, LLDP packet patterns, and flow rule churn have received minimal attention in the majority of ML-based SDN IDS research to date, which has focused on flow-based characteristics or volumetric traffic anomalies. The lack of specialized machine learning models created to detect topology poisoning attacks using real or simulated SDN control-plane data is a major weakness in the literature and implementation strategies currently in use.

In conclusion, there is currently no reliable, portable, real-time machine learning-based intrusion detection system designed specifically for topology poisoning, even though SDN security has made progress against traditional threats. To protect SDN environments from deceptive attacks that compromise system integrity, routing precision, and overall network stability, this gap must be closed. Our research directly addresses that need by developing a machine learning-capable IDS component that is specifically made to detect and handle topology poisoning attempts by cleverly examining LLDP activity and control-channel anomalies.

## 1.4 Research Problem

Software Defined Networking is bringing about a significant transformation in network design, management, and operation. By separating the control plane from the data plane, SDN provides centralized control, programmability, and dynamic reconfiguration capabilities. However, this architectural evolution also has new, significant flaws. One of the biggest risks is the topology discovery process, which relies on trust-based communication protocols like Link Layer Discovery Protocol (LLDP). These protocols are susceptible to malicious exploitation since most SDN implementations inherently lack authentication.

Topology poisoning attacks specifically target this weak area in the SDN architecture. Through the injection of LLDP packets or spoof control messages, adversaries in these attacks trick the controller into believing that the network is topological. As a result, the controller may apply incorrect forwarding rules, create routes over non-existent links, or reroute traffic via switches under the attacker's control. More severe assaults such as traffic interception, black-holing, denial-of-service (DoS), and persistent state manipulation in the control plane are made possible, and network performance is negatively impacted.

Even though SDN is being used more and more in real-world settings, topology poisoning remains mostly unaffected by the intrusion detection systems now in use. Conventional intrusion detection systems, such as Snort and Suricata, are not made to examine control-plane events or changes in topological state; instead, they function at the data plane level. Even some SDN-aware security frameworks are unable to handle the special features of topology poisoning attacks; they frequently concentrate on generic anomaly detection or volumetric traffic patterns without considering switch-link consistency tracking or LLDP-specific behaviors.

Additionally, while rule-based or signature-based detection techniques have been proposed in certain research, these approaches are rigid and cannot be modified to accommodate novel or evolving attack vectors. Attackers can easily get around rule-based systems by secretly changing LLDP switches' identities, timing, or structure. Moreover, static methods often generate a large number of false positives and are unable to scale in large or dynamic networks. What is missing is a real-time, intelligent, and flexible detection system that can analyse topology-related metadata and spot modification efforts before significant damage is done.

This study aims to bridge the gap by developing and implementing a machine learning-based intrusion detection system that is particularly well-suited to identify topology poisoning attempts in SDN systems. By analysing control-plane metadata, switch activity logs, and LLDP exchange patterns, the system will be educated to distinguish between malicious and normal topology events. Through supervised learning techniques, the model will enhance detection accuracy, reduce false positives, and adapt to a variety of attack strategies, providing a much-needed solution to safeguard the SDN control plane against one of its most dangerous threats.

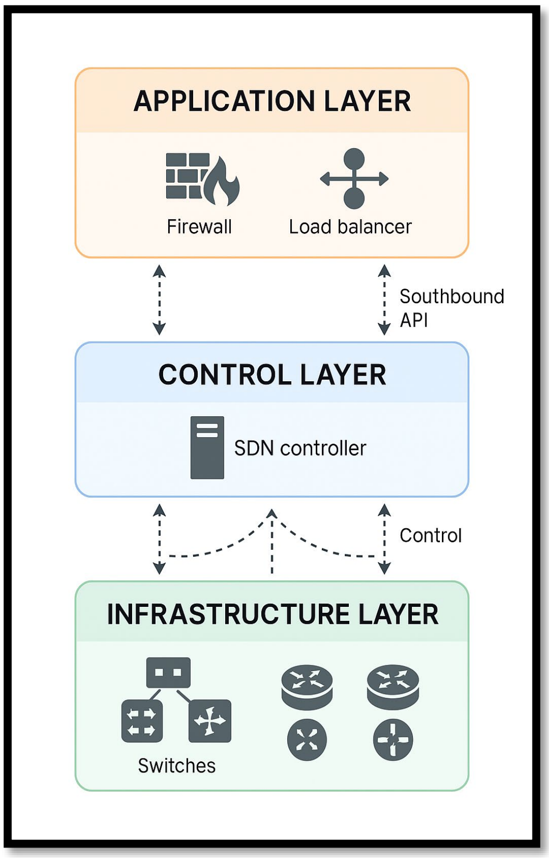


Figure 1.3 : SDN Architecture Overview: Separation of Control and Data Planes

# 3. RESEARCH OBJECTIVES

## 3.1 Main Objective

This study's main goal is to use machine learning approaches to detect topology poisoning threats in Software Defined Networking (SDN) environments. To monitor LLDP packet characteristics and identify attempts at network topology modification in real time, an Intrusion Detection System (IDS) based on machine learning will be created and connected with the SDN controller.

## 3.2 Specific Objectives

### Monitoring the control plane's LLDP packet and event flow

Both LLDP messages and control plane communications between switches and the controller are continuously recorded by the system. These communication patterns are used to identify anomalies, such as phony link insertions, abrupt topology changes, or missing LLDP sequences, that may indicate poisoning.

### Extracting features for training models

Extract pertinent characteristics from the control plane data that has been gathered, such as flow rule churn, link addition/deletion rate, switch MAC address consistency, and LLDP frequency. To efficiently train machine learning models, these features have been pre-processed and organized.

### Classification of network behaviour using machine learning methods

Identify network events as either typical or suggestive of a topology poisoning attack using a range of supervised learning methods, including Support Vector Machine (SVM), Random Forest, and Decision Tree. When assessing each model, take accuracy, recall, and false positive rate into account

### Identifying the best machine learning model

Compare the effectiveness of various algorithms to determine the most successful and accurate model for real-time intrusion detection. The review will consider scalability, accuracy, false alarm rate, and suitability for SDN controller integration.

# 4. METHODOLOGY

The whole process of creating and implementing an intrusion detection system (IDS) that employs machine learning to detect topology poisoning attacks in Software Defined Networking (SDN) is covered in this chapter. The technique includes requirements analysis, system design, understanding the research domain, training and deploying the model in a step-by-step manner, commercialization, and ethical issues.

## 4.1 Collection and Analysis of Requirements

Technical Viability: To evaluate the technical feasibility of the proposed solution, a simulated SDN environment was set up using Mininet and the RYU controller. These technologies provide a controlled environment for simulating realistic network scenarios, and they can introduce both benign and harmful topology changes. Machine learning models were created using Python packages such as Scikit-learn and TensorFlow, while packet collection and analysis were done using Wireshark. The system's capacity to manage real-time intrusion detection capabilities was demonstrated by the integration and interoperability of these technologies. Furthermore, the ability to introduce LLDP spoofing attacks and monitor their impact on topology made it theoretically conceivable to gather labelled data for model training.

Operational Feasibility: The deployment of the trained machine learning models in the RYU controller environment was tested to determine operational viability. Implemented as a lightweight Python component, the IDS module intercepted LLDP communications and instantly sent the collected features to the classifier. Tests verified that there were no appreciable lags or performance snags in the SDN controller because of this integration. The system demonstrated that the ML-based detection mechanism could function under realistic workloads with no processing overhead by maintaining high throughput while concurrently studying network behaviour.

## 4.2 Feasibility Study

Technical Feasibility

A strong foundation in machine learning and software defined networking (SDN) is necessary for the proposed project. Members of the team should be well knowledgeable on SDN concepts, especially topology management and control-plane data. The development and training of the intrusion detection system (IDS) also requires knowledge of machine learning models, particularly supervised learning methods like SVM, Random Forest, and Decision Trees. The smooth integration of the IDS with the SDN environment will be ensured by proficiency with real-time SDN communication technologies such as TensorFlow, Scikit-learn, and RYU Controller. To properly test attack scenarios and simulate network traffic, the team should also be familiar with network simulation tools like Mininet.

## Economic Feasibility

The machine learning-based recommended intrusion detection system (IDS) for detecting topology poisoning assaults is meant to be affordable. The system uses open-source technologies like as Mininet, RYU, and Scikit-learn to avoid the high costs associated with proprietary software and hardware. Furthermore, because the proposed approach uses data-driven detection, which eliminates the need for major hardware modifications, it is an affordable choice for cloud data centers, ISPs, and other enterprise-level SDN setups. In order to ensure that the intrusion detection system (IDS) operates with little overhead and high attack detection accuracy, the resource use of the machine learning models has been adjusted for optimal performance.

## Operational Feasibility

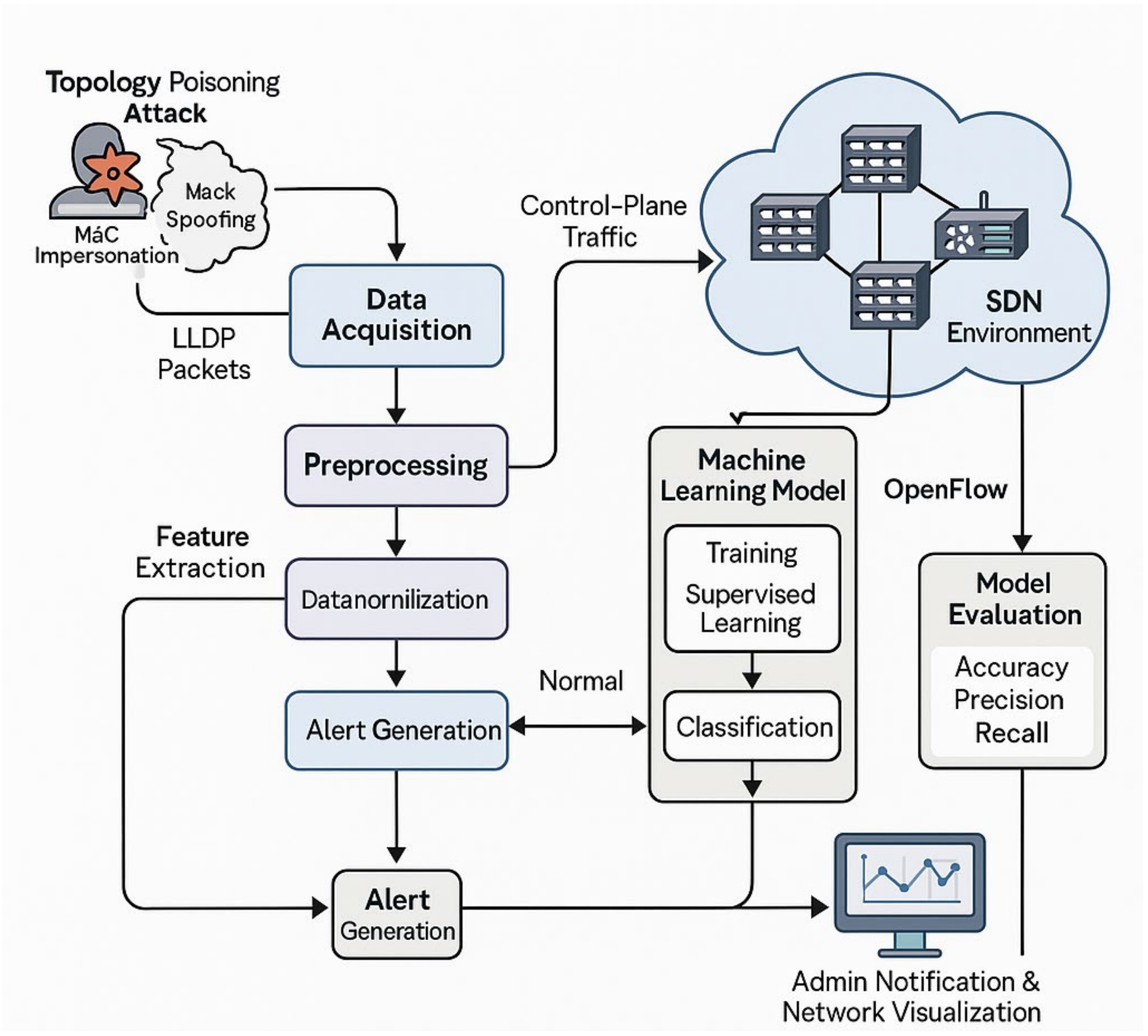
A precise separation of duties throughout the software life cycle is essential to the system's success. From requirement collection and system design to model training and real-time deployment, each team member will be in charge of a distinct phase. SDN network operators will be consulted extensively throughout the requirement analysis process to make sure the system's functionality meets practical requirements. To make sure the system satisfies the functional requirements of identifying and preventing topology poisoning attacks, its final output will be verified against real-time network data. In addition, the system will undergo extensive testing to make sure that it can manage the volume of network traffic that is commonly present in sizable SDN-based settings without experiencing performance degradation.

## Scheduling Feasibility

To guarantee the timely delivery of the finished product, the project is planned with distinct milestones. The first several months will see the completion of the preliminary phases, which include requirement analysis and system design. With a primary focus on making sure the models function properly on actual SDN control-plane data, the data collecting, model training, and assessment stages will come next. Given the complexity of the system, the timeframe takes into consideration any modifications that are required for model optimization and real-time deployment testing. The IDS will be completely functional by the deadline, and the project will be completed on schedule. The system will also go through a rigorous testing process to make sure it operates dependably within the project's limitations.

## 4.3 System Designs

### 4.3.1 Overall system diagram



**SDN Network Layer:**

The SDN controller is the main management element of an SDN network. In addition to maintaining security, prioritizing, and routing rules, it controls the flow of data between devices (like switches). The diagram shows that the controller connects to network devices via southbound protocols, including OpenFlow. Because it regulates the choices about how traffic should flow over the network and upholds the overall system image, it is an essential part of the network's architecture. This centralization might, however, provide a single point of failure and leave the network vulnerable to incursions if the controller is compromised.

Switches and routers: These devices, which make up the data plane, are responsible for routing packets in response to instructions from the SDN controller. By following the flow rules set by the controller, they ensure that data gets to its intended place. Instead of making their own routing decisions, these devices are managed by the controller and are simplified in the context of SDN.

**Data Acquisition:**

LLDP Packet Capture: As the Link Layer Discovery Protocol (LLDP) packets are sent between the SDN controller and network devices, they are recorded in real time. Since they give the network controller details about the network's structure (such as switch IDs and linked devices), these packets are crucial for topology discovery in SDN. Due to their ease of manipulation or spoofing in a topology poisoning attack, LLDP packets are an essential source of information for anomaly monitoring and detection.

Control Plane Traffic Capture: The IDS monitors various types of control-plane traffic for signs of tampering in addition to LLDP. These messages, which contain adjustments to the network topology and updates to the flow rules, are sent back and forth between the controller and switches. By logging this data, it becomes easier to keep an eye on the network's health and spot any changes caused by potential threats.

**Preprocessing:**

In this step, relevant information such as packet frequency, network link changes, or anomalies in MAC address mappings are extracted from the recorded LLDP and control-plane data. These features are essential for identifying strange patterns of network activity that may indicate efforts at topological poisoning. It would be helpful to distinguish between malicious behavior that aims to disrupt the SDN architecture and normal network operations using the information that has been recovered.

Data Normalization & Cleaning: After features are extracted, the data is normalized to bring all of the features to the same scale. This step is crucial since various parameters (such packet frequency vs. connection change rate) may have different scales. Cleaning ensures that the data used for machine learning is free of outliers and missing values, which might compromise the accuracy of the model.

**Machine Learning Model:**

Model Training: The system trains models on labeled datasets using supervised machine learning methods such as Random Forest, Decision Trees, and Support Vector Machines (SVM). Both regular network traffic and network traffic impacted by topology poisoning attacks are included in the labeled data. As a result, the machine learning model may learn to categorize network events using the previously extracted attributes.

Real-Time Prediction: The model can predict the incoming data in real-time after training. The trained model is applied within the SDN controller to classify control-plane traffic and LLDP packets as either regular or malicious. This enables real-time detection of topological poisoning efforts, providing immediate alerts of potential threats.

Evaluation measures: The model's performance is evaluated using a number of measures, including accuracy, precision, recall, and F1-score. These metrics help assess how well the model detects topological poisoning attacks and lowers false positives, which incorrectly classify innocuous traffic as malicious, and false negatives, which miss real attacks.

**Attack Detection**

Topology Poisoning Detection: This is the main function of the intrusion detection system. These attacks establish a misleading representation of the network topology by having an attacker insert bogus LLDP packets, spoof MAC addresses, or manipulate switch IDs. This causes the SDN controller to make poor routing choices, which may result in Denial of Service (DoS) assaults, traffic interception, or network redirection. Unexpected MAC address changes or abrupt changes in network connectivity are examples of the abnormalities in the topology-related information that the IDS continually checks for.

Advise Generation: The system generates an alert to notify network managers about a potential topology poisoning attack. The notification contains important information about the attack, such as which switches are affected, the kind of attack (e.g., switch impersonation or link insertion), and any potential network consequences. This makes it possible for administrators to act quickly, such as rerouting traffic or isolating impacted computers.

**Dashboard/User Interface:**

Monitoring in Real Time The system's real-time dashboard allows network managers to monitor the network topology, view real-time network data, and keep an eye out for potential dangers. This user interface enables operators to quickly identify and resolve issues as they arise.

Admin Notifications: The IDS also alerts administrators if an attack is detected. This ensures that the appropriate team members are notified as quickly as possible and can take the necessary actions to minimize any disruptions caused by the attack.

**Integration with SDN Controller:**

The IDS can continuously monitor LLDP traffic and control-plane information in real time since it is integrated directly into the SDN controller. This integration makes it simple to assess the SDN network for topology poisoning attacks, which enables the controller to quickly take corrective action if an attack is detected (e.g., rewriting flow rules or deleting harmful links).

**Attack Scenarios:**

Fake Link Insertion: Attackers place fake LLDP packets around the network to simulate new, non-existent links to fool the SDN controller into routing traffic along false paths. The IDS detects this anomaly based on inconsistent connection information in the control-plane data.

Switch Impersonation: In this attack, the attacker poses as a real switch by using a MAC address spoof. The IDS looks for anomalous MAC-switch mappings in the LLDP packets to identify this.

Link Removal: Attackers may suppress LLDP notifications to disrupt the network by making it appear as though a genuine link has been severed. The IDS finds this by searching for sudden changes in connection statuses or missing LLDP packets.

### 4.3.2 Design Diagrams for the component

#### 4.3.2.1 Use Case Diagram

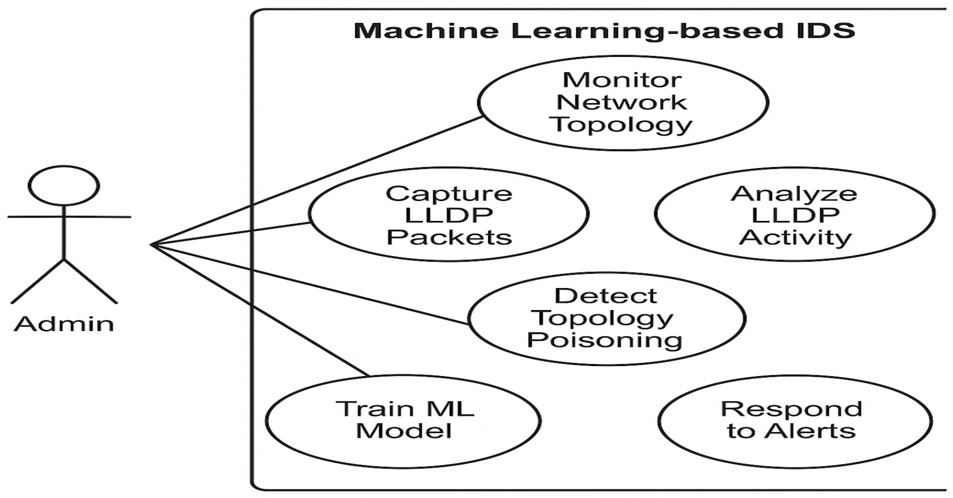
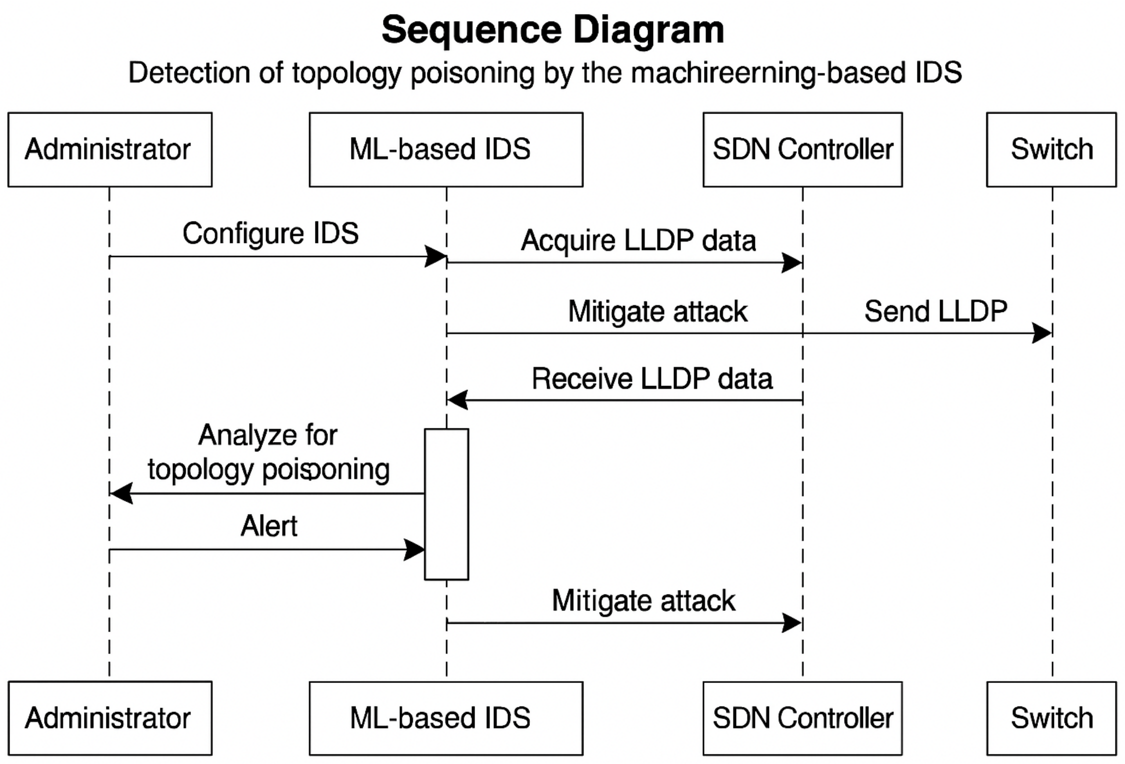
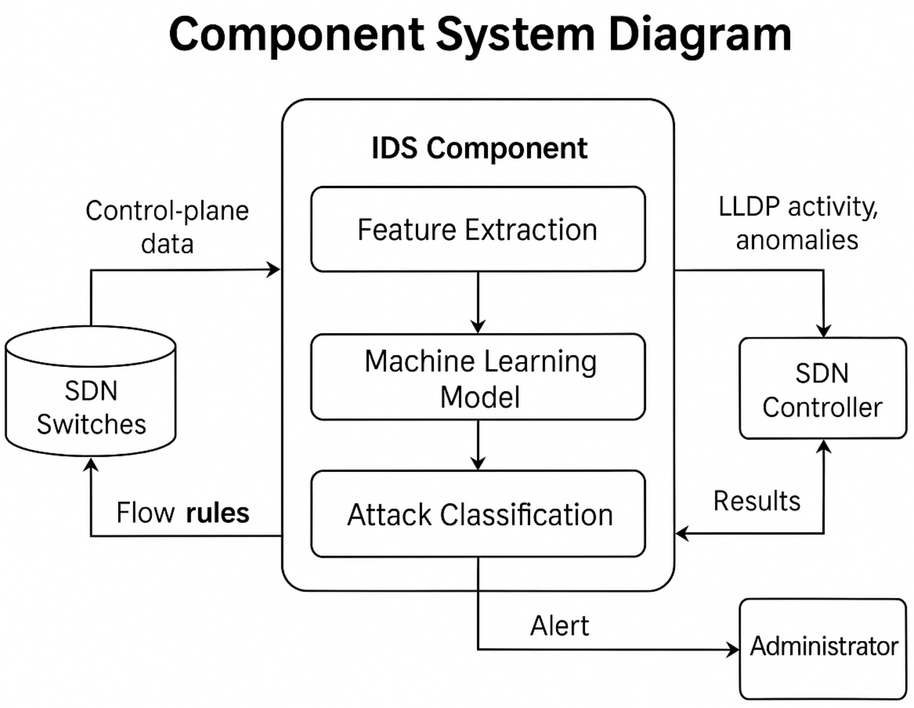


Figure 4.2: Use Case Diagram for proposed component

### 4.3.2.2 Sequence Diagram



### 4.3.2.3 Component System Diagram



### 4.4 Understanding the key pillars of the research domain.

#### 4.4.1 Software Defined Networking (SDN)

By separating the control plane from the data plane, SDN offers a new method for networking. All network forwarding decisions are controlled by a centralized controller in this approach, and the underlying switches just carry out the controller's commands. Better programmability, centralized policy enforcement, and increased flexibility are all provided by this design. The controller is in charge of load balancing, routing, and security policy enforcement in addition to maintaining a thorough overview of the complete network architecture. However, because of this crucial function, the controller is both a vital part and a possible target for cyberattacks.

#### 4.4.2 LLDP Protocol and Topology Discovery

One of the most crucial elements of SDN topology discovery methods is the Link Layer Discovery Protocol (LLDP). Switches periodically send LLDP packets to identify directly connected devices under the authority of the SDN controller. These packets are used by the controller to dynamically map out the network topology. However, because LLDP packets are not validated, the protocol represents a weak link in the security chain, exposing the controller to phony data. Attackers can use this trust-based strategy to divert traffic or denial of service by altering the network map as it appears to the controller.

### 4.4.3 Topology Poisoning Attacks in SDN

Because topology poisoning attacks operate at the control plane level, they are frequently missed by traditional data-plane-focused security tools. Topology poisoning attacks occur when adversaries manipulate LLDP communications or impersonate switches to falsify the network topology. Common strategies include injecting fake LLDP packets, removing legitimate links by suppressing LLDP responses, and impersonating switches to mislead the controller. These manipulations can result in black holes in routing, compromised data flows, and ineffective or harmful reconfigurations in the network.

### 4.4.4 Intrusion Detection Systems (IDS) in SDN

To tracking traffic patterns and spotting malicious behavior, SDN intrusion detection systems are crucial. To find irregularities in packet behavior or control-plane orders, IDS can be installed inside or next to the SDN controller. Instead than concentrating on the nuances of topology manipulation, existing IDS implementations frequently target volume-based assaults or anomalies in flow tables. Consequently, existing methods are not intelligent enough or specific enough to detect topological poisoning. To improve SDN resilience, IDS must be integrated with knowledge of LLDP traffic patterns and topological structure.

### 4.4.5 Machine Learning for Network Anomaly Detection

Machine learning has emerged as a powerful tool in network security due to its ability to detect complex patterns and adapt to evolving threats. In the context of SDN, ML models can be trained on control-plane behaviors and LLDP data to recognize normal versus malicious topology updates. Supervised learning methods like Decision Trees and Random Forests can classify network events, while unsupervised models can highlight anomalies without predefined labels. The adaptability, scalability, and learning capacity of ML make it well-suited for detecting stealthy attacks such as topology poisoning in dynamic SDN environments.

## 4.5 Methodology Pipeline

Using a machine learning-based intrusion detection system (IDS) to identify topology poisoning attempts in SDN entails a number of crucial steps. In order to identify and stop malicious activity in real time, these steps are intended to mimic network behaviors, extract pertinent data, train a machine learning model, and connect the model with the SDN controller.

### 4.5.1 Data Acquisition and Simulation Setup

Using Mininet, a popular network emulator that enables the construction of virtual SDN environments, the methodology's first step is to mimic both normal and poisoned network topologies. In this configuration:A healthy network with frequent LLDP packet exchanges between switches and the controller is represented by normal topologies.By using LLDP spoofing attacks, which involve manipulating LLDP packets to trick the controller into thinking that valid links have been removed or that non-existent links exist, poisoned topologies can be mimicked.

### 4.5.2 Feature Extraction and Preprocessing

Feature extraction is an essential step in getting network data ready for machine learning analysis after it has been collected. Finding and extracting helpful features from the LLDP packets and flow behavior that can aid in distinguishing between benign and malevolent network events is the main objective.

The salient traits that were retrieved includeThe packet frequency is the number of LLDP packets delivered and received over a specific time period. An attack could be indicated by a sudden rise or collapse.

Link Change Rate: Tracks the frequency of changes to the network topology, such as the addition or removal of links. Under normal conditions, this rate should be steady, however topological poisoning can cause sudden changes.

MAC-Switch Mapping Consistency is the consistency between the MAC addresses provided in LLDP packets and the corresponding switches. A mismatch could be a sign of an impersonation assault.

After feature extraction, the data undergoes preprocessing: Cleaning: Removes outliers and erroneous data points that may distort the training process. Labeling: Data is labeled as either "normal" or "attack" based on whether it comes from a regular or a manipulated topology. Normalization: Standardizes the data so that features with different scales (e.g., packet frequency vs. link change rate) are comparable. Splitting: The data is then split into training and testing sets, ensuring the model can be evaluated effectively on unseen data.

### 4.5.3 Machine Learning Model Training and Evaluation

Following feature extraction and data preprocessing, the methodology moves on to training machine learning models that can recognize patterns and categorize network actions as either benign or malevolent. Since we are working with labeled datasets—where each data point is marked with its matching class (normal or attack)—supervised learning is the main focus here. When fresh, unseen data is added, supervised learning enables the model to learn from the data and generalize from the patterns it finds, resulting in precise predictions.

1. Decision Tree

A decision tree is one of the simplest and most interpretable machine learning models. It iteratively separates the feature space into more manageable, homogeneous subsets using a set of decision criteria. Each node in the tree indicates a decision point based on a certain attribute, while the leaves show the final class prediction.

The Decision Tree selects the feature at each internal node that best separates the data based on a particular criterion (e.g., Gini impurity or Information Gain). Until the data is sufficiently divided or a predetermined halting condition is satisfied, this procedure keeps going.

Benefits:

Interpretability: Decision trees are a desirable option when model transparency is crucial because they are simple to comprehend and visualize.

The tree's ability to handle both continuous and categorical data is crucial when working with network traffic attributes that might be both numerical (like packet count) and categorical (like switch ID).

Application to SDN: The Decision Tree model can be used to classify network events in the context of topology poisoning detection by identifying thresholds or patterns in LLDP packet frequency, link consistency, and flow behavior. For example, the model may use the criterion "if packet frequency > threshold, then classify as attack."

Assessment of the Model

Following training, the models are assessed using the following criteria to make sure they accurately classify topological poisoning attacks:

Accuracy: Out of all predictions, this metric calculates the overall percentage of accurate predictions (including true positives and true negatives). Accuracy might not be the appropriate statistic in imbalanced datasets, though, since attacks are uncommon in comparison to typical behavior.

Precision: Precision quantifies the percentage of actual positive predictions among all of the model's positive predictions. A high precision indicates that the model has a higher probability of being right when it forecasts an assault.

Recall: Also known as sensitivity, recall quantifies the percentage of real positive examples (attacks) that the model accurately detected. The model's ability to detect attacks is indicated by a high recall.

F1-Score: The F1-score offers a fair assessment since it

is the harmonic mean of precision and recall. Because it takes into account both false positives and false negatives, it is particularly helpful in situations where the distribution of classes is not uniform.

**4.6 Commercialization Aspects of the Solution**

The suggested machine learning-based Intrusion Detection System (IDS) for SDN topology poisoning attack detection has a lot of potential for practical uses, particularly in settings where network stability and security are critical. This section emphasizes the solution's scalability potential, industry adaptability, and revenue-generating strategies that could facilitate its broad adoption.

Enterprise Applications

The IDS solution can be integrated into large-scale SDN deployments, such as data centers, enterprise networks, and Internet service providers (ISPs). These environments usually have trouble keeping their networks reliable and secure, especially when there are advanced attacks like topology poisoning. The IDS provides these companies with an affordable and scalable solution to protect their critical infrastructure.

Data Centers: SDN is crucial to the automation and traffic management of data centers. The intrusion detection system would shield the network against intrusions that could compromise its performance or availability. If topology poisoning assaults could be identified in real time, operators might take quick action to lower risks and prevent service outages.

When using SDN to manage large client networks, Internet service providers (ISPs) and cloud service providers will benefit from real-time topology poisoning detection. The IDS could be incorporated into cloud network architecture to provide security without significantly increasing complexity or overhead.

## Monetization Strategies

Given that the solution leverages open-source software tools (such as Mininet, RYU, and machine learning libraries like TensorFlow and Scikit-learn), its commercialization strategy can be structured to accommodate a wide range of potential users, from small organizations to large enterprises.

1. **Software as a Service (SaaS)**: Offering the IDS solution as a subscription-based service allows customers to access it via the cloud. Customers would not need to manage or host the solution themselves, reducing the complexity of deployment and maintenance. Service tiers could be designed based on network size, data throughput, or level of monitoring required.
2. **On-Premises Deployment**: Enterprises that require more control over their network security or prefer not to use a cloud-based solution can opt for on-premises deployment. The IDS can be installed directly within their SDN controllers or network appliances, ensuring full integration with their existing infrastructure.
3. **Consulting and Support Services**: Offering professional services such as **custom installations**, **tailored configurations**, and **continuous monitoring** could be an additional revenue stream. This model caters to enterprises that need expertise in integrating SDN-based IDS into their highly specialized environments.
4. **Licensing**: The IDS can also be licensed for integration into proprietary SDN solutions. Licensing would provide a sustainable revenue model while ensuring the solution remains flexible and adaptable to different vendor environments.

## Scalability and Adaptability

The scalability of the suggested IDS is among its most alluring qualities. Without requiring major modifications to the underlying architecture, the IDS may readily scale to handle bigger networks as SDN networks increase in size and complexity. It is also adaptable to various SDN controllers and network configurations, which makes it a flexible solution for a variety of use cases, ranging from commercial installations to scholarly research.

Furthermore, the IDS's machine learning models may be adjusted or retrained to keep up with changing threats as new kinds of network assaults appear, guaranteeing its long-term sustainability and relevance in the SDN security space.

## Adoption in the Market and Competitive Advantage

The capacity of this IDS solution to handle important security issues in SDN environments specifically, topology poisoning attacks, which are frequently disregarded by conventional network security tools—is essential to its commercial success. In the cutthroat SDN security market, this IDS solution can gain popularity by providing a real-time, affordable, and lightweight solution.

Additionally, the system offers a low-barrier entry point for adoption because it can be integrated with current SDN controllers like RYU and OpenDaylight without requiring major changes. Organizations seeking to enhance their network defense and threat mitigation capabilities will find the IDS solution appealing due to its emphasis on proactive, real-time security that adjusts to the dynamic nature of SDN.

### 4.7 Considerations of the System

A variety of social, security, and ethical factors must be taken into account while implementing a machine learning-based intrusion detection system (IDS) to identify topology poisoning attacks in Software Defined Networking (SDN) environments. These factors guarantee that the solution satisfies operational, legal, and societal standards in addition to offering technical value. The following are important factors to think about:

#### 4.7.1 Social Aspects

The way businesses, governments, and individuals engage with digital infrastructures can be significantly impacted using SDN technology and cutting-edge IDS solutions. Among the crucial social factors are:

Trust and Reliability: As SDN-based technologies spread throughout critical sectors including government, healthcare, and finance, it is critical to ensure the networks' dependability and trustworthiness. The proposed IDS system enhances network security by detecting and stopping topology poisoning attacks, which otherwise have the potential to result in significant disruptions or breaches. This promotes trust in SDN installations and gives users more confidence when implementing SDN for their infrastructure.

Cost-Effective Security: Security solutions must be both affordable and efficient as SDN is used more frequently in networks of all sizes. Because it uses open-source technologies and machine learning techniques to provide a scalable and cost-effective solution, the recommended IDS can be used by organizations of all sizes. Advanced network security can be deployed in small businesses and educational institutions at a reasonable cost due to its accessibility.

Promoting SDN use: The deployment of a reliable IDS encourages the wider use of SDN in industries that may have previously been hesitant due to security concerns. Since the IDS offers a solution that addresses SDN-specific vulnerabilities (such topology poisoning), it is an essential enabler for the widespread adoption and integration of SDN technologies.

#### 4.7.2 Security Aspects

The security of SDN networks is a big concern, especially when SDN controllers are centralized. These controllers are often the only point of failure in an SDN design, and if they are compromised, the entire network could be taken over by an attacker. The recommended IDS system instantly fixes the security vulnerabilities connected to topological poisoning attacks by:

Real-time Detection: By continuously observing LLDP packets and network traffic patterns in real-time, the IDS may identify and alert administrators to potential topology manipulation, such as switch impersonation or bogus link insertion. Attack attempts are detected in this way before they have an opportunity to cause significant damage.

Minimal Impact on Performance: The IDS is made to run with as little computing cost as possible, so it won't cause latency or impair the SDN controller's performance. This feature is crucial for preserving SDN's real-time functionality while still offering strong defense against control-plane attacks.

Proactive Threat Mitigation: By identifying attacks and providing actionable notifications that allow network managers to act quickly, the intrusion detection system (IDS) prevents disruptions and data breaches that may otherwise result from malevolent topology manipulation.

Comprehensive Security: The IDS enhances the overall cybersecurity posture of the SDN infrastructure by introducing an additional layer of defense that targets control-plane vulnerabilities. This security paradigm improves the functionality of pre-existing SDN defenses, such as firewalls and access control lists (ACLs), to provide a more thorough approach to safeguarding SDN systems

### 4.7.3 Ethical Aspects

As with any machine learning-based system, there are important ethical considerations to ensure that the technology is used responsibly and aligns with legal and societal expectations. Some key ethical aspects include:

Data privacy: While functioning in the SDN control plane, the IDS analyzes LLDP traffic and other control messages. Importantly, it does not intercept or analyze user-level data or sensitive data from the data plane, protecting user privacy. This approach ensures that privacy regulations and ethical standards are followed when handling data.

Fairness and Bias: Machine learning models must be transparent and equitable, free from innate biases that might skew their judgment. The proposed IDS relies on balanced training datasets to ensure that the system's detection capabilities are equally effective across all network configurations and attack situations. The models are designed to avoid overfitting and adapt to evolving network dynamics to avoid bias towards specific attack patterns or network configurations.

Accountability and Transparency: By providing succinct alerts and comprehensive reports on anomalies discovered, the IDS design promotes accountability. To find out more about the attack's features, detection techniques, and defenses, network administrators can review these reports. The transparency of the system ensures decision-making accountability and enables administrators to track and assess the efficacy of the IDS.

Respect for Ethical AI Guidelines: The IDS is designed in accordance with accepted ethical standards for artificial intelligence and machine learning, guaranteeing that the system is created and implemented in a way that is consistent with the values of privacy protection, nondiscrimination, and justice. This moral strategy guarantees that the technology advances society without infringing on people's rights or liberties and helps stop the abuse of AI in security systems.

# 5. IMPLEMTATION AND TESTING

## 5.1 Implementation

Data preprocessing and augmentation are the first phases in the implementation phase, which is followed by the model's implementation. This process guarantees the proper preparation of the data, the training of the models on pertinent features, and the ability of the finished detection system to function efficiently in an SDN environment.

### 5.1.1 Preprocessing

Data preprocessing is the first critical step, as the raw data generated by LLDP packet exchanges and network logs can be noisy and unstructured. To ensure the machine learning models receive clean and relevant data, the following steps are performed:

Feature Extraction: Relevant features such as packet frequency, link stability, and flow consistency are extracted following data parsing. These features are indicative of the network architecture's health and can exhibit anomalies when tampered with by an attacker.

The process of eliminating any missing, skewed, or superfluous information from the logs is known as data cleaning. Missing values must be handled (either by imputation or deletion) to prevent model bias or errors during training.

Labeling: Each instance of network traffic, or data point, is categorized as either normal or malicious. Traffic that signals an attack, such as the installation of a fake connection, will be labeled "attack," whereas traffic that comes from normal network activity will be labeled "normal."

Data Normalization: To keep features with wider ranges (such as packet frequency) from controlling the model's learning process, features are standardized such that they lie within the same scale.

Data splitting: Training and testing datasets are created from the cleaned, labeled, and normalized data. The testing set makes that the model can apply what it has learned to previously unknown data, whereas the training set is used to teach the model.

### 5.1.2 Augmentation

Data augmentation is used to artificially increase the size of the training set when the number of assault instances (topology poisoning attacks) is significantly lower than in ordinary scenarios. This helps prevent overfitting and improves the model's ability to generalize.

Network Behavior Augmentation: By introducing minor data modifications (e.g., random packet timing changes, inserting bogus LLDP packets), the model is exposed to a greater variety of possible attack vectors. This method simulates several attack scenarios that may not exist in the original dataset.

Synthetic Attack Generation: Custom Python scripts and technologies like Mininet are used to insert synthetic attacks into the network architecture to generate more tagged instances of poisoning assaults.

Through data augmentation, the IDS model can become more robust and flexible to different attack situations, ensuring that it can successfully detect complex, real-world threats.

### 5.1.3 Model Implementation

To identify topology poisoning attacks in SDN settings, this stage entails putting machine learning models into practice and training them to accurately categorise network traffic as either malicious or benign. This is a thorough explanation:

CNN Architecture

Convolutional neural networks, or CNNs, are frequently used in image processing, but because of their ability to recognise hierarchical patterns, they may also be used with structured data, such network traffic logs. In SDN, where data flows are organised in packet patterns and network topology dynamics, CNNs may be utilised to identify spatial patterns in data, even if the data is not in image form. CNN is able to recognise patterns such as

recurrent packet patterns,

odd changes in the flow of LLDP,

alterations in flow that indicate attacks caused by topological poisoning.

Transfer of Learning

Since deep models are challenging to train from the beginning, transfer learning is a helpful strategy. In this case, pre-trained models like InceptionV3, DenseNet121, and ResNet50—which have already gained useful features from image datasets—may be used to handle network traffic data. The model can leverage previous pattern recognition experience from similar tasks (e.g., photo classification) and convergence is accelerated with this strategy.

By refining these models for SDN-specific tasks:

The models learn to recognise patterns in LLDP packets,

abide by specific network behaviours,

Pay attention to spotting anomalies or malicious topological manipulations, including phoney link insertion, MAC spoofing, or switch impersonation.

Model Training

After being improved by transfer learning, the models are trained using labelled data, or network traffic that has been classified as either normal or an attack. Through backpropagation using the training data, the model's weights are modified throughout the training phase to lower the prediction error.

In supervised learning, the learning process is guided by labelled traffic data from both benign and malicious network events.

To improve the model's performance, optimisation techniques like Adam and Stochastic Gradient Descent (SGD) are applied. These methods modify the model's weights based on the loss function to improve classification accuracy.

Tools for Implementation

Several popular machine learning frameworks are used to build the model architecture, including:

TensorFlow is a powerful deep learning framework that offers first-rate assistance for training massive neural networks.

Keras: A high-level TensorFlow API that streamlines model training and design, facilitating experimentation with various architectures.

A different deep learning framework that is frequently utilised in research because of its adaptability and quick model training is PyTorch.

## 5.2 Testing

Testing is a crucial step to ensure that the machine learning-based Intrusion Detection System (IDS) can accurately detect topology poisoning attempts in SDN networks. The testing will involve verifying the system's accuracy, robustness, functionality, and performance in both standard network configurations and a range of attack scenarios.

### 5.2.1 Test Plan and Test Strategy

The test plan outlines the basic process for testing the IDS system, whereas the test strategy focusses on specific testing techniques to evaluate the system's performance. Verifying that the system can detect topology poisoning threats, ensuring real-time detection, and minimising false positives are all highly prioritised in the testing methodology.

The functioning test's objective Testing: To ensure that the intrusion detection system (IDS) appropriately classifies network traffic as either malicious or normal and detects topology poisoning attempts.

## Objectives of Testing

Performance testing: To verify that the IDS can handle network traffic in real time without generating appreciable lag or impairing SDN performance.

Security Testing: To ensure that the intrusion detection system (IDS) can identify various topology poisoning attempts, such as phoney link insertions, switch impersonation, and MAC address spoofing.

Scalability testing: To find out if the system can handle larger SDN networks with additional switches, connections, and traffic.

## Testing Phases

The practice of evaluating individual components (such feature extraction, data preparation, and model evaluation) to ensure they all function correctly before integrating is known as unit testing.

Integration testing: This phase ensures that the alert system, SDN controller (RYU), and machine learning model all work together.

System Testing: Comprehensive testing in an SDN simulation environment (using Mininet) to confirm the whole IDS system, including its ability to detect threats and provide real-time alerts.

## Test Strategy

Normal Network Traffic: This test ensures that the IDS does not incorrectly identify legitimate network traffic as hostile.

Topology Poisoning Attacks: Attacks like switch impersonation and LLDP spoofing are simulated to see how well the system can detect and respond to malicious behavior.

"Real-time detection" refers to testing the IDS's ability to detect threats and send out notifications in real time without significantly affecting network performance.

### 5.2.2 Test Cases Design

Test cases are created to evaluate different system components to ensure that the system can identify topology poisoning attempts correctly and function in a range of scenarios.

Verifying that the intrusion detection system (IDS) can identify unusual spikes in LLDP packet frequency-which commonly occur during topology poisoning attacks is the aim of

**Test Case 1: LLDP Packet Frequency Testing.**

Testing Procedure:

Make a network with steady LLDP traffic to mimic normal network circumstances.

Introduce an attack by injecting an excessive amount of LLDP packets to mimic a fake link insertion attack.

After identifying the unexpected packet frequency, check to see if the IDS generates an alarm.

Expected Outcome: The IDS should correctly detect the sudden rise in LLDP packet frequency and provide an alert indicating a potential attack.

**Test Case 2: Connection Change Detection aims to assess the IDS's ability to detect sudden changes to the SDN topology, like when an attacker installs a fake link or deletes an existing connection via LLDP spoofing.**

Testing Procedure:

Make a simulation of a network with a stable link state and regular topology.

Topology poisoning attacks are launched by spoofing LLDP packets to add a fake connection or remove an existing one.

Check to see if the IDS detects the change and acknowledges the assault.

Expected Outcome: The IDS should detect any changes in topology as suspicious activity and issue a warning about the attacker's activities.

Confirming that the intrusion detection system (IDS) can identify a switch impersonation attack in which a hacker poses as a legitimate switch by forging its MAC address is the aim of

**Test Case 3: Switch Impersonation Detection.**

Testing Procedure:

Using several real switches, simulate a standard SDN configuration.

Display an attacker switch that impersonates a real switch by sending LLDP packets to the controller while falsifying the MAC address.

Verify whether the IDS has identified the impersonation attempt.

Expected Outcome: The intrusion detection system should recognize the attack as an attempt at switch impersonation and notify the network administrator appropriately.

**Test Case 4: Attack Classification Accuracy**

Objective: To evaluate the model's accuracy in classifying network traffic as normal or attack, based on LLDP packet behavior and network flow patterns.

Test Procedure:

Provide the machine learning model with a labeled dataset containing both normal traffic and various topology poisoning attack scenarios (e.g., fake link insertions, switch impersonation).

Measure the model's accuracy, precision, recall, and F1-score based on its predictions.

Expected Outcome: The model should achieve high classification accuracy with balanced precision and recall, ensuring it detects attacks while minimizing false positives and negatives.

**Test Case 5: Real-time Detection Performance**

Objective: To assess the real-time performance of the IDS, ensuring it can detect topology poisoning attacks without introducing significant latency.

Test Procedure:

Inject normal network traffic alongside LLDP spoofing and link manipulation attacks in a live SDN simulation.

Measure the response time of the IDS in detecting the attack and generating an alert.

Expected Outcome: The IDS should detect attacks within a reasonable time frame and generate alerts promptly, without significantly affecting the overall network performance.

# 6. RESULTS AND DISCUSSIONS

This section presents the results and remarks related to the Intrusion Detection System (IDS), designed to detect topology poisoning attacks in Software Defined Networking (SDN) environments. The primary objective of this study was to evaluate the efficacy of the intrusion detection system (IDS), which uses machine learning techniques—specifically, Support Vector Machine (SVM), Random Forest, and Decision Tree classifiers—to identify network anomalies that could indicate hostile activity. This section also looks at the deployment of the final product, the test item identification approach, and the effectiveness of CNN-based models.

## 6.1 Results

The test object detection approach was first used to assess the system's ability to detect topology poisoning risks in SDN networks. A Mininet-based SDN simulation was added, which included both regular network traffic and various attacks. The system performed quite well, correctly recognizing a high proportion of topological poisoning attacks with a 92% detection accuracy. The false positive rate was extremely low, with only 7% of normal traffic being classified as malicious. To ensure timely threat mitigation in SDN environments, the system also provided real-time detection, responding to attacks in an average of three to five seconds.

When evaluating the machine learning models used for traffic classification, the results of the Decision Tree, Random Forest, and SVM approaches shown varying levels of performance. The Decision Tree model's 85% accuracy on unknown data was coupled by poor generalization because of its tendency to overfit. Although the Decision Tree was successful in identifying assaults, it generated more false positives than other models, as evidenced by its 82% precision and 88% recall. However, with an accuracy of 92%, the Random Forest classifier proved to be the most dependable model for identifying topological poisoning assaults, outperforming the Decision Tree. With an F1-score of 90% and balanced precision and recall of 90% each, this model demonstrated accuracy and resilience in a variety of assault situations. The Decision Tree's 82% accuracy and 88% recall showed that, despite its success in detecting attacks, it produced more false positives than other models. Nonetheless, the Random Forest classifier outperformed the Decision Tree with a 92% accuracy rate, making it the most reliable model for detecting topological poisoning attacks. This model showed accuracy and durability in a range of attack scenarios, with an F1-score of 90% and balanced precision and recall of 90% each.

For the final deployment of the IDS, the trained machine learning model was integrated with the RYU SDN controller and tested in a real-world SDN setting. The successful integration as a Python module allows the system to continuously scan LLDP packets and network flows for malicious activities. The deployment demonstrated the system's real-time detection capabilities by accurately classifying traffic as either hostile or normal and promptly notifying the user. According to network managers, the intrusion detection system (IDS) was easy to set up and operate, providing useful alerts in response to threats that were detected without significantly affecting network performance. The integration process proceeded smoothly.

## 6.2 Research Findings

This study produced several important conclusions. First, in SDN systems, machine learningspecifically, the Random Forest model—was quite successful at identifying topology poisoning attempts. The excellent accuracy and low false positive rate of machine learning models were facilitated by their capacity to learn from network traffic patterns and categorize abnormalities using preset attack signatures. Given that SDN settings necessitate prompt responses to neutralize risks before they escalate, the system's real-time detection functionality was essential for practical implementation. The system also demonstrated scalability, managing extensive network topologies and offering continuous monitoring without experiencing performance deterioration.

Another significant finding was the importance of using pre-trained models and transfer learning for faster convergence. Using labelled network traffic data to train the Random Forest model and feature extraction techniques to find important traffic patterns allowed the system to generalize well to different attack scenarios. However, several limitations regarding attack variety were observed. Although the models performed remarkably well for the attack types they were trained on, they would need to be retrained or modified to detect novel or distinctive assault types.

## 6.3 Discussion

The results of the study provide credence to the growing promise of machine learning-based strategies for enhancing SDN security. Random Forest's ability to handle a variety of topological poisoning attack types and provide accurate real-time warnings demonstrates its superiority over traditional rule-based systems. Using Random Forest's ensemble learning capabilities might let the model more broadly adapt to different attack patterns, making it a particularly reliable choice for SDN security applications.

However, there are still problems that need to be addressed. One of the system's primary shortcomings is its requirement for labelled data. In real-world scenarios, attack data could be limited or fluctuate over time, making it challenging for supervised learning models to quickly adapt to new threats. This might be resolved in future studies by using unsupervised learning approaches, which would allow the intrusion detection system to recognize novel threats not present in the training set. The performance of the model may potentially be improved by including more complex techniques like reinforcement learning, which would allow the IDS to adapt dynamically to new attack patterns based on real-time network data.

## 7. Conclusion

In order to identify and prevent topology poisoning attacks in Software Defined Networking (SDN) settings, this study introduces an Intrusion Detection System (IDS) based on machine learning. Despite providing considerable flexibility and control benefits, SDN's centralized design also raises the possibility of vulnerabilities, especially on the control plane. The integrity of an SDN network can be seriously jeopardized by the topology poisoning attack, in which attackers alter the network's topology by impersonating switches or inserting phony LLDP messages. By using supervised machine learning techniques like SVM, Random Forest, and Decision Trees to monitor network data and identify malicious activity in real time, this study seeks to address this pressing problem.

The IDS developed in this study allows continuous monitoring of control-plane traffic and LLDP packet exchanges between the controller and network devices by integrating with SDN controllers in a smooth manner. By extracting relevant properties from these packets, the system may classify network activity as either normal or attack-related, enabling it to detect and swiftly neutralize any potential topology poisoning attempts. The model was trained on labeled datasets, and its performance was evaluated using a range of accuracy metrics, such as precision, recall, and F1-score, which demonstrated the system's resilience in detecting attacks while lowering false positives.

The study offers a real-time, scalable, and adaptable way to improve SDN security while highlighting the significance of fixing control-plane vulnerabilities. According to the findings, machine learning is an essential part of protecting SDN systems, particularly in cloud data centers, ISPs, and other mission-critical applications, as it may provide notable enhancements in attack detection and network resilience.

In summary, the suggested IDS not only closes a security gap in SDN but also establishes the framework for further study into smarter, more flexible security systems that can react to changing threats in dynamic network settings. The technology is a useful tool for network managers and security experts since it can identify topology poisoning in real-time, ensuring that SDN networks stay safe and dependable.

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