SDN-BASED INTELLIGENT INTRUSION DETECTION SYSTEM (IIDS) USING MACHINE LERANING

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DECLARATION

I declare that this is my own work, and this dissertation 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. Also, I hereby grant to Sri Lanka Institute of Information Technology the non-exclusive right to reproduce and distribute my dissertation in whole or part in print, electronic or other medium. I retain the right to use this content in whole or part in future works (such as articles or books).

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ABSTRACT

With the increasing number of cybersecurity threats, Software-Defined Networking (SDN) has proven to be powerful in enhancing network security through programmability and centralized control. The present paper outlines the design, development, and implementation of an Intrusion Detection System (IDS) with the focus on detection of Flow Table Overflow attacks in SDN networks. The primary objective of this research was the integration of machine learning principles with SDN security mechanisms for real-time autonomous attack detection and prevention.

The IDS employs a Random Forest classifier trained with public datasets to analyze network traffic and recognize pattern features of Flow Table Overflow attacks. Classification accuracy for the model is 92.84%, wherein there is high precision in detecting normal traffic but wherein there are challenges in detecting attack traffic based on class imbalance. The system performance was measured using various performance measures like precision, recall, F1-score, and confusion matrix, which provided insights into the model's capability of distinguishing normal and attack traffic [1].

Experimental platform included a lab environment for SDN simulation with OpenDaylight as the SDN controller, Mininet as the network emulator, and Wireshark and Scapy as traffic analyzers. The system was effective in dynamically changing flow rules to mitigate recognized attacks, thereby avoiding the impact of Flow Table Overflow on network performance [2] [2]. In addition, platforms such as Kali Linux and Ubuntu were used for simulating attacks to validate the real-time detection and prevention functionality of the IDS [3].

The research findings show the importance of class imbalance as a factor that can help improve the accuracy of the model, particularly for rare attack situations. Despite some detection inaccuracies for some attacks, the system's overall performance shows that combining machine learning with SDN-based security systems offers an effective remedy to securing modern networks [4]. Future work will focus on developing the detection model, bringing in more sophisticated machine learning algorithms, and further optimizing the SDN infrastructure for better performance in production environments.

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Abbreviation	Description
SDN	Software Defined Networking
IIDS	Intelligent Intrusion Detection System
IDS	Intrusion Detection System
ML	Machine Learning
FTO	Flow Table Overflow
DoS	Denial of Service
SMOTE	Synthetic Minority Over-Sampling Technique
ODL	Open Day Light

INTRODUCTION

Software-Defined Networking (SDN) is a new paradigm in networking that offers flexibility, scalability, and centralized management. SDN, through the separation of control plane and data plane, facilitates dynamic network configuration, automation, and improved resource utilization [5]. The architecture, however, introduces new security issues, particularly regarding attack vectors such as flow table overflow. Flow table overflow attacks target the SDN controller's flow tables by flooding them with a high volume of flow entries, leading to resource exhaustion and potential service disruption. Such attacks have severe repercussions, leading to performance degradation or even network outage [6]. Traditional Intrusion Detection Systems (IDS) rely heavily on signature-based or anomaly detection techniques, which fail to adequately detect unknown attack patterns in SDN networks [7].

While machine learning (ML) has shown promise in improving IDS detection, its use in SDN security systems, and more specifically in the detection of flow table overflow attacks, remains a complex challenge. Literature has indicated the effectiveness of machine learning in improving the accuracy of attack detection in SDN, particularly those attacks that are difficult to detect with conventional methods [8]. This project will develop and realize a Machine Learning-based Intrusion Detection System (IDS) coupled with an SDN controller to detect and prevent flow table overflow attacks in real time.

By utilizing newer ML algorithms such as Random Forest, XGBoost, and Logistic Regression, the project will try to provide a more accurate and effective IDS for SDN networks. In addition, the project will integrate the IDS with an SDN controller and implement a real-time attack mitigation system for network stability and security. The integration of machine learning models with SDN environments for the detection of flow table overflows is also an effective method of improving network security and enhancing the resilience of SDN against novel attack techniques [9]

Background of SDN and Security Challenges

Software-Defined Networking (SDN) is a nascent network administration paradigm that centralized the control plane, providing a programmable and extensible network architecture. Such control-plane/data-plane decoupling allows the network administrators to centrally configure, control, and optimize network resources using a centralized controller [10]. SDN has gained considerable attention due to its ability to enhance network flexibility, scalability, and dynamic control, which makes it highly suitable for cloud computing, data centers, and enterprise networks.

While SDN offers numerous advantages, its open and programmable nature has a few security concerns. One of the significant concerns is that the SDN controller is susceptible to attacks. Attackers can attack the controller or use vulnerabilities in other SDN components to manipulate network behavior and disrupt services. One such attack is the flow table overflow attack, in which the attacker floods the flow table of the SDN switch with an excessive number of flow entries beyond capacity, so that the resources are exhausted and the network performance is compromised or lost [11]. The dynamic nature of SDN and that decision-making is done centrally render it susceptible to such attacks.

Literature Review of IDS in SDN

Intrusion Detection Systems (IDS) are crucial in the security of SDN environments against attacks. Traditional IDS mechanisms such as signature-based detection do not offer an effective solution in SDN since network traffic is always changing and there are no pre-defined attack signatures for emerging threats. Anomaly-based IDS is a more feasible solution that detects any anomaly in the network from normal patterns of network behavior [6]. However, the incorporation of anomaly-based IDS in SDN is exposed to several challenges, including the need to continuously examine data, handling large quantities of datasets, and real-time identification of intricate attacks [12].

Machine Learning for IDS in SDN

Machine learning (ML) techniques are a potential answer to the enhancement of IDS in SDN. Through learning from large data, ML models can discover complex patterns from network traffic and identify potential security attacks. The effectiveness of ML techniques, such as decision trees, random forests, and support vector machines, for DDoS, spoofing, and flow table overflow attack detection in SDN has been demonstrated in several research studies [13], [14]. Such techniques enjoy the flexibility of being able to identify unknown attacks by detecting faint patterns that are not easily detected by traditional detection mechanisms.

One of these approaches is the application of Random Forest algorithms to SDN IDS. Random Forest is a common ensemble learning method that sums up multiple decision trees to increase the accuracy and robustness of detection. It has been successfully applied to SDN IDS due to its ability to handle high-dimensional data and high classifying ability for network traffic patterns. Other machine learning methods, such as XGBoost and Logistic Regression, have also been explored in the context of SDN security, with studies showing their effectiveness in detecting various attacks.

Machine Learning Integration with SDN Controllers

Merging ML models with SDN controllers has been in the spotlight as a measure to support the responsiveness and performance of IDS. In this, IDS runs on the SDN controller and monitors network traffic continuously, making real-time decisions about whether traffic behavior is indicative of an attack [15]. The integration of machine learning-based IDS and SDN controllers enables automated detection and response and supports real-time mitigation of attacks such as flow table overflow attacks.

The addition of a web front-end to display attack alerts and detection results has also been explored. Tools such as Next.js and FastAPI are widely used to develop interactive user interfaces and dashboards, allowing administrators to see and manage network security via an intuitive interface. Integration allows for real-time updating and effective communication between the IDS and network administrator, improving incident response times and system security in general.

Research gap

Despite significant advancements having been made in the incorporation of machine learning (ML) in Software-Defined Networking (SDN) for enhancing network security, there are several research gaps, especially in detecting and mitigating flow table overflow attacks. These gaps pave the way for further investigation and enhancement in the field.

Detection of Flow Table Overflow Attacks

Flow table overflow attacks directly aim at the flow table of the SDN controller by overwhelming it with unnecessary flow entries to deplete the resources. The majority of the existing works deal with more frequent attacks such as DDoS, spoofing, and man-in-the-middle attacks [16]. There has been little research on the detection of flow table overflow attacks by using machine learning, and even fewer studies have provided detailed comparisons of the performance of different machine learning algorithms for this purpose. Bridging this research gap can serve a vital role in strengthening the security of SDN environments because flow table overflow attacks can lead to severe network performance degradation.

Integration of Machine Learning with SDN Controllers

Although machine learning-based IDS are gaining traction in SDN security, integrating the IDS with SDN controllers for attack detection and mitigation in real time remains an arduous task. Although several research works have proposed standalone IDS solutions for attack detection in isolated environments, integrating the systems with SDN controllers for attack mitigation and response in real time remains in its infancy. A successful incorporation of machine learning models into SDN controllers will enable not only detection but also automatic mitigation of attacks, resulting in a more secure network infrastructure [17].

Scalability and Flexibility of Machine Learning Models

Scalability of machine learning models to handle the high-volume and dynamic traffic in SDN environments is another imperative research need. SDN networks are typically instantiated in big data centers and cloud configurations, which are known for having an extremely large amount of traffic as well as diversity of attacks [14]. Most traditional machine learning-based IDS models are likely to fail under scaling efficiently with such dynamic as well as high-volume traffic. Further research is needed to develop scalable machine learning algorithms that can detect a wide range of attacks without compromising performance, especially in real-time applications.

Evaluation of Real-Time Detection and Mitigation Systems

While numerous machine learning models have been proposed for intrusion detection, not much work focuses on the real-time nature of these models in SDN systems. Real-time detection is essential to prevent attacks like flow table overflow, which, if not detected in time, can cause massive disruption. A lack of comprehensive studies of real-time detection and mitigation systems in SDN hinders assessing the practical applicability of these models in production environments. Studies require that not only develop these models but also study their performance in the context of real-time environments based on factors like network latency and resource utilization.

Lack of Comprehensive Attack Datasets

Training data sets to machine learning algorithms for flow table overflow and other SDN-specific attacks are relatively scarce. While there are several data sets that exist for general network traffic, they may not fully encapsulate the dynamics of SDN-based traffic and the specific threats that SDN networks experience. Most of the existing datasets lack scenarios of flow table overflow attacks, which makes it difficult to train models for identifying these attacks in real-world SDN environments [7]. The generation of SDN-specific datasets that include various attack scenarios, including flow table overflow, will play an important role in making IDS in SDN more accurate and reliable.

Security of the SDN Controller

Security of the SDN controller is one of the most critical aspects of securing an SDN-based network. However, most of the research focuses on security of network flows and doesn't consider potential vulnerabilities in the SDN controller itself. A comprehensive security solution should not only search for attacks in network flows but also include mechanisms for defending the SDN controller so that attackers can't exploit vulnerabilities in the controller architecture.

Research Problem

Traditional Intrusion Detection Systems (IDS) are badly plagued with detecting and defending against Flow Table Overflow (FTO) attacks in Software-Defined Network (SDN) networks. The reasons are many constraints that are a part of traditional IDS, such as their static nature, incapability to handle huge volumes of network traffic effectively, and inadequate seamless integration with SDN controllers.

Static Nature of Traditional IDS

Traditional IDS are usually designed for legacy networks and operate on pre-defined sets of rules, thus making them incapable of adapting dynamically to the rapidly evolving threats in SDN networks [18]. The systems could even fail to detect advanced attacks like flow table overflow attacks, which target the SDN controller by overflowing it with a large number of flow entries to consume resources and make the network slower. Their inability to respond real-time to such dynamic threats emphasizes the importance of even more flexible, machine learning-based approaches in SDN.

Incapacity to Process Mass Traffic

The other challenge of traditional IDS is their inefficiency in processing and analyzing massive network traffic. In SDN, network traffic is highly dynamic and increases rapidly, especially in data centers and cloud environments. Traditional IDS, being static, cannot handle such high-throughput environments and hence cannot detect real-time attacks efficiently [19]. The increasing volumes of traffic in SDN networks demand IDS systems that can process high volumes of data and detect anomalies with minimal latency, which is typically a constraint for traditional systems.

Absence of Integration with SDN Controllers

One of the significant disadvantages of traditional IDS is that they are not very integrated with SDN controllers. SDN controllers manage network policies and traffic flow, and thus are a central point of attack. However, traditional IDS are typically standalone and are not coded to communicate with SDN controllers for real-time attack prevention. This lack of integration prevents timely implementation of countermeasures, and with such attacks such as FTO, they can cause serious disruption to network performance. It is this gap that this study aims to address through the development of an IDS based on machine learning which can be implemented in SDN controllers to support auto-detection and attack neutralization in real-time.

Real-Time Security Management

Good security management of SDN networks requires not just detection but also immediate mitigation of attacks once they have been detected. Traditional IDS is usually susceptible to latency based on reliance on signature or rule-based detection models that are not so good for real-time, dynamic nature of SDN environments [14]. Real-time detection and mitigation features, enabled by machine learning algorithms, are required to counter this issue and ensure effective security management in SDN.

Research Objectives

Implement and integrate a Machine Learning-based Intrusion Detection Engine into a Software-Defined Networking (SDN) controller.

The primary objective of this research is to design and propose a machine learning (ML)-based Intrusion Detection System (IDS) that can be implemented seamlessly within an SDN controller for real-time attack detection and mitigation. This objective is intended to bridge the gap between machine learning-based models and SDN controllers regarding applicative network security solutions. Recent studies emphasize the potential of using ML in the SDN controller to improve detection accuracy and offer faster response times for network security.

Implement the ML-based IDS with an SDN controller.

One of the most important characteristics of this study is the integration of the implemented IDS with an SDN controller. The IDS must be capable of exchanging information with the controller in real-time in order to monitor and analyze the network traffic, find attacks, and initiate mitigation. The integration of ML models with SDN systems is a recent research field, and existing research focuses on improving communication between the IDS and SDN controller to provide dynamic and automatic security reactions.

Monitor and analyze network traffic.

The IDS must be capable of analyzing and monitoring real-time network traffic to detect potential security threats such as flow table overflow attacks. This objective involves the use of network traffic monitoring software as well as training and evaluation datasets. An effective IDS must have accurate and comprehensive data analysis in order to distinguish between normal traffic behavior and malicious activity. Traffic analysis and anomaly detection studies for SDN networks have shown the requirement of efficient data preprocessing and feature extraction methods for identifying attacks.

Develop a frontend and backend system for attack detection and visualization.

This objective involves designing and deploying a frontend and backend system that is able to display the result of the attack detection process, i.e., attack alerts and live statistics. The frontend will provide an interactive interface to display the condition of the SDN environment, while the backend will deal with the data communication between the IDS and SDN controller. A full-fledged dashboard will improve user interaction with the IDS so that administrators can easily see the status of the system and react accordingly. Use of web frameworks like FastAPI for the backend and Next.js for frontend has already been successfully demonstrated in previous implementations of IDS to design efficient and scalable systems .

METHODOLOGY

Methodology

The proposed SDN-based Intrusion Detection System (IDS) for FTO attack detection was designed with the help of a systematic methodology consisting of six main phases:

Dataset selection

Data preprocessing

Model selection

Machine learning model training

SDN integration

Attack simulation.

A publicly accessible SDN-specific dataset containing benign and malicious flow records was used. The dataset included attributes such as IP addresses, port numbers, packet counts, and durations, allowing for easy feature extraction for attack detection. Data preprocessing included cleaning null values, label encoding, and feature normalization. Class imbalance was addressed using the Synthetic Minority Over-sampling Technique (SMOTE), along with class weighting techniques to enable balanced model training [20].

Three models of machine learning—Random Forest, XGBoost, and Logistic Regression were trained on an 80/20 train/test split. Performance comparison on precision, recall, and F1-score indicated Random Forest as the best and was thus deployed.

The model was deployed in an SDN environment with Mininet and OpenDaylight controller on Kali Linux. The model was exposed as a real-time detection API via a FastAPI backend, and

detection results were displayed via a Next.js-based frontend. Result logging was implemented using MongoDB.

For validating the system, an FTO attack was simulated from an Ubuntu host. The detection engine correctly detected malicious flows under the attack and triggered mitigation by updating flow rules with the SDN controller and isolating the attacker.

This solution validates the viability of integrating ML-based IDS with SDN for proactive and automated attack mitigation in real-world environments.

Dataset Selection

For the construction of the suggested SDN-based Intrusion Detection System (IDS), an open-source dataset of Software-Defined Networking (SDN) traffic flows was utilized. The dataset included both normal and attack traffic, well-designed to mimic Flow Table Overflow (FTO) attack patterns. This attack is characterized by generating a large number of distinct packet headers that overflow the limited-capacity flow tables in SDN switches, degrading network performance or causing a denial-of-service condition.

The data was downloaded from an online repository of SDN security studies and had labeled flow entries with some of the properties such as src_ip, dst_ip, src_port, dst_port, protocol, duration, packets, bytes, and flow flags. These attributes were suitable to employ in machine learning model training to identify patterns of malicious activities.

To validate the appropriateness of the dataset, it was checked for completeness, relevance, and class balance. The dataset consisted of a number of classes of attacks, but only samples of the Flow Table Overflow attack were selected and isolated for this study in order to create a focus of

research. This data was then used as the foundation for preprocessing and model training procedures.

This selection of dataset is important to build a trusted IDS as the accuracy and generalization of attack patterns directly affect the machine learning model's generalizability in an actual SDN environment [21].

Delimiter: ,

	Source_IP	Destination_IP	Packet_Size	Flow_Duration	Active_Flow_Entries	Flow_Table_Utilization	New_Flow_Entry_Rate	Packet_In_Me
1	192.168.1.229	10.0.0.210	492	1.034406275	71	0.626576518	11	
2	192.168.1.94	10.0.0.141	543	2.284194329	81	0.449790522	39	
3	192.168.1.33	10.0.0.17	434	4.964406662	77	0.743317392	21	
4	192.168.1.196	10.0.0.201	511	1.868859223	55	0.570326768	15	
5	192.168.1.25	10.0.0.181	601	1.851052601	69	0.650464129	25	
6	192.168.1.27	10.0.0.36	531	0.111480375	97	0.981625938	13	
7	192.168.1.230	10.0.0.26	549	1.343813058	67	0.198694153	5	
8	192.168.1.179	10.0.0.214	589	4.330230898	66	0.74997783	23	
9	192.168.1.252	10.0.0.34	496	0.441639032	53	0.269574083	2	
10	192.168.1.9	10.0.0.36	446	0.215484805	74	0.042529307	32	
11	192.168.1.202	10.0.0.237	531	0.422012925	77	0.793977759	17	
12	192.168.1.209	10.0.0.177	516	0.40522668	97	0.251306179	3	
13	192.168.1.208	10.0.0.124	586	2.662120586	53	0.486428551	13	
14	192.168.1.215	10.0.0.123	509	1.231817141	87	0.653446194	26	
15	192.168.1.32	10.0.0.14	517	1.133200484	77	0.423910427	40	
16	192.168.1.235	10.0.0.174	499	0.386768423	50	0.331541119	10	
17	192.168.1.101	10.0.0.96	489	0.389450194	90	0.032413578	12	
18	192.168.1.128	10.0.0.211	648	2.486375635	51	0.926821938	46	
19	192.168.1.169	10.0.0.192	474	0.140608315	60	0.090066359	31	
20	192.168.1.144	10.0.0.38	477	2.889222922	72	0.538643558	23	
21	192.168.1.212	10.0.0.42	574	1.168608443	60	0.146167818	12	
22	192.168.1.217	10.0.0.27	590	0.597288983	77	0.663887894	11	
23	192.168.1.85	10.0.0.125	446	0.010265085	77	0.360190593	8	

Figure 1 Dataset

Data Preprocessing

Once the dataset was selected, several preprocessing operations were conducted to render the dataset appropriate for training machine learning models. Preprocessing is a critical stage ensuring data quality, consistency, and availability for effective learning.

1. Data Cleaning

First, the dataset was analyzed for missing values, duplicate rows, and unnecessary features. Rows having missing or inconsistent values were excluded or filled in as necessary. Duplicate rows were deleted to prevent bias while training the model.

2. Feature Selection and Encoding

Relevant features that help to identify flow table overflow attacks, such as duration, packet count, byte count, and flow flags, were selected. Categorical features like protocol and flag status were label encoded so that they are converted into numerical values understandable by the machine.

3. Class Balancing

Because the dataset was imbalanced with benign flows significantly outnumbering attack flows, SMOTE (Synthetic Minority Over-sampling Technique) was applied to generate synthetic instances of the minority class. This prevented biasing the model towards the majority (benign) class and improved overall detection performance.

4. Normalization

To ensure a balance so that each of the features contributed equally towards the learning process of the model, numerical features were normalized through Min-Max scaling. This reduced the feature values to a common range (commonly between 0 and 1), enhancing training efficiency and speed.

After these preprocessing steps, the data was transformed into an 80% training set and an 20% testing set so that an effective test of the trained models was guaranteed.

```python
import pandas as pd

# Load the dataset
df = pd.read_csv("dataset.csv")

# Display basic information about the dataset
print(df.info())  # Check data types and missing values
print(df.head())  # Display first few rows
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 25000 entries, 0 to 24999
Data columns (total 22 columns):
 #   Column                                Non-Null Count  Dtype
---  ------                                --------------  -----
 0   Source_IP                             25000 non-null  object
 1   Destination_IP                        25000 non-null  object
 2   Packet_Size                           25000 non-null  int64
 3   Flow_Duration                         25000 non-null  float64
 4   Active_Flow_Entries                   25000 non-null  int64
 5   Flow_Table_Utilization                25000 non-null  float64
 6   New_Flow_Entry_Rate                   25000 non-null  int64
 7   Packet_In_Messages                    25000 non-null  int64
 8   Traffic_Volume_Per_Second             25000 non-null  int64
 9   Entropy_of_Source_IPs                 25000 non-null  float64
 10  Flow_Expiry_Rate                      25000 non-null  int64
 11  Flow_Entry_Lifetime                   25000 non-null  float64
 12  Rate_of_Change_in_Flow_Entries        25000 non-null  float64
 13  Time_Since_Last_Flow_Entry            25000 non-null  float64
 14  Variance_in_Packet_Sizes              25000 non-null  float64
 15  Std_Dev_of_Flow_Durations             25000 non-null  float64
 16  Controller_Response_Time              25000 non-null  float64
 17  Frequency_of_Flow_Rule_Modifications  25000 non-null  int64
 18  Protocol_Type                         25000 non-null  object
 19  Abnormal_Packet_Ratios                25000 non-null  float64
 20  Switch_Port_Activity                  25000 non-null  int64
 21  Label                                 25000 non-null  int64
```

Figure 2 Missing value check

```python
from sklearn.preprocessing import LabelEncoder, StandardScaler

# Drop unnecessary columns
df_cleaned = df.drop(columns=["Source_IP", "Destination_IP"])

# Encode categorical variable 'Protocol_Type'
label_encoder = LabelEncoder()
df_cleaned["Protocol_Type"] = label_encoder.fit_transform(df_cleaned["Protocol_Type"])

# Separate features and target variable
X = df_cleaned.drop(columns=["Label"])  # Features
y = df_cleaned["Label"]  # Target

# Scale numerical features
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

# Display first 5 rows after preprocessing
print(pd.DataFrame(X_scaled, columns=X.columns).head())
```

Figure 3 Label Encoder

```python
from imblearn.over_sampling import SMOTE

# Apply SMOTE to balance the dataset
smote = SMOTE(random_state=42)
X_train_smote, y_train_smote = smote.fit_resample(X_train, y_train)

# Check new class distribution
print("Class distribution after SMOTE:")
print(y_train_smote.value_counts())

# Train a new Random Forest model on the balanced dataset
model_smote = RandomForestClassifier(n_estimators=100, random_state=42)
model_smote.fit(X_train_smote, y_train_smote)

# Make predictions
y_pred_smote = model_smote.predict(X_test)

# Evaluate the model
accuracy_smote = accuracy_score(y_test, y_pred_smote)
print(f"Model Accuracy after SMOTE: {accuracy_smote:.4f}")
print("\nClassification Report:\n", classification_report(y_test, y_pred_smote))
```

Figure 4 SMOTE

Machine Learning Model Selection

After data preprocessing, the second step involved selecting appropriate machine learning models capable of detecting Flow Table Overflow (FTO) attacks from network traffic features. Model selection was based on their high efficiency in classification tasks, their capacity to deal with complex patterns, and their interpretability for cybersecurity tasks.

Three supervised learning algorithms were selected to be tested:

1. Logistic Regression (LR)

Logistic Regression is a linear classifier model that is generally employed as a baseline for binary classification problems. It was chosen due to it being fast and simple. Though it does badly on hard, non-linear data, it can be used for giving interpretability and understanding the impact of every feature.

2. Extreme Gradient Boosting (XGBoost)

XGBoost is a fast ensemble learning algorithm based on gradient boosting, which builds multiple weak learners in an iterative manner. XGBoost has been extensively used due to its high speed,

good accuracy, and resistance to overfitting. XGBoost was chosen due to its strong performance history in anomaly detection and cybersecurity applications.

3. Random Forest (RF)

Random Forest, another ensemble method based on decision trees, was chosen for its stability and high accuracy on both imbalanced and noisy data. It works by building a multitude of decision trees and combining their predictions to make a single prediction, thus well-suited for intrusion detection tasks. It handles both categorical and numerical inputs well and provides information regarding the importance of features.

Those models were tested and trained on an 80/20 split of data. They were evaluated on precision, recall, and F1-score metrics. Random Forest was selected for deployment in the Intrusion Detection System based on overall performance.

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report

# Train Logistic Regression model
log_reg = LogisticRegression(max_iter=1000, random_state=42)
log_reg.fit(X_train, y_train)

# Make predictions
y_pred_log_reg = log_reg.predict(X_test)

# Evaluate model
accuracy_log_reg = accuracy_score(y_test, y_pred_log_reg)
print(f"Logistic Regression Accuracy: {accuracy_log_reg:.4f}")
print("\nClassification Report:\n", classification_report(y_test, y_pred_log_reg))
```

```
Logistic Regression Accuracy: 0.8954
```

Figure 5 Logistic Regression model

```python
from xgboost import XGBClassifier

# Initialize and train the XGBoost model
xgb_model = XGBClassifier(eval_metric="logloss", random_state=42)
xgb_model.fit(X_train, y_train)

# Make predictions
y_pred_xgb = xgb_model.predict(X_test)

# Evaluate the model
accuracy_xgb = accuracy_score(y_test, y_pred_xgb)
print(f"Model Accuracy with XGBoost: {accuracy_xgb:.4f}")
print("\nClassification Report:\n", classification_report(y_test, y_pred_xgb))
```

```
Model Accuracy with XGBoost: 0.9124
```

Figure 6 XGBoost model

```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report

# Initialize the model
model = RandomForestClassifier(n_estimators=100, random_state=42)

# Train the model
model.fit(X_train, y_train.values.ravel())  # Use .ravel() to avoid shape issues

# Make predictions
y_pred = model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, y_pred)
print(f"Model Accuracy: {accuracy:.4f}")
print("\nClassification Report:\n", classification_report(y_test, y_pred))
```

```
Model Accuracy: 0.9284
```

Figure 7 Random Forest model

ML Model Training (Random Forest)

Once the dataset was preprocessed and separated into training and test sets, the Random Forest model was trained to detect Flow Table Overflow (FTO) attacks. The Random Forest algorithm was selected since it performs better when handling intricate, high-dimensional data and can avoid overfitting by the use of multiple decision trees.

1. Data Split and Training Setup

The data was split with an 80/20 ratio, where 80% of the data was used for training the model and the remaining 20% was reserved for testing. This split ensured that the model would generalize and be tested on unseen data. The class imbalance issue was also addressed using SMOTE (Synthetic Minority Over-sampling Technique), which generated synthetic samples for the minority class (attack traffic).

2. Hyperparameter Tuning

In an attempt to enhance the performance of the Random Forest model, hyperparameter tuning was undertaken using grid search and cross-validation. Significant parameters like the number of trees (n_estimators), tree maximum depth (max_depth), and the minimum number of samples required in an internal node to split an internal node (min_samples_split) were fine-tuned with the aim of identifying the most optimal model setup. All of these ensured the model would reach a balance point between accuracy and computational expense while avoiding overfitting.

3. Training the Model

Random Forest model was subsequently trained with the preprocessed data set by utilizing scikit-learn's Random Forest Classifier implementation. Each tree in the forest was trained on a random subset of data points and attributes, and the final classification decision was made using majority voting over all the trees. This is done to increase the model's robustness and performance, particularly in detecting complex patterns of attacks like Flow Table Overflow.

4. Evaluation Metrics

After training the model, performance on the test set was evaluated considering several performance metrics like precision, recall, F1-score, and confusion matrix analysis. These metrics helped us understand the success of the model in differentiating attack traffic from

benign traffic and helped us decide the decision threshold for achieving the maximum detection accuracy.

The Random Forest classifier performed well in FTO attack detection, with high noise and high detection rates and hence a good candidate for implementation in the SDN-based IDS.

```
import joblib

# Save the trained model
joblib.dump(rf_model, "random_forest_model.pkl")

print("Model saved successfully!")
```

```
Model saved successfully!
```

Figure 8 Random forests model saved

SDN Integration

To integrate the Random Forest model, which was trained, into the Software-Defined Networking (SDN) ecosystem, the Open Daylight SDN controller and Mininet, for simulating network topologies, were used. The integration was done to enable real-time attack detection as well as mitigation in the Intrusion Detection System (IDS)-based SDN.

1. OpenDaylight SDN Controller

The OpenDaylight SDN controller was employed owing to its adaptability, scalability, and vigorous community growth. It provided central network management with the option to perform dynamic flow management as well as integration with security programs. OpenDaylight was installed to observe network traffic in real time, collect flow data, and forward it to the IDS for analysis [22].

2. Mininet Network Simulation

Mininet has been utilized for creating a simulated network structure in the Kali Linux operating system to emulationalite the SDN ecosystem. Mininet facilitated simulating hosts, switches, and controllers to create a simulated network environment with multiple flows of traffic as well as network configurations. Mininet allowed one to test as well as validate the detection capability of the IDS for Flow Table Overflow (FTO) attack in a test SDN environment.

3. Integration of the ML Model with OpenDaylight

The trained Random Forest model on the preprocessed data was incorporated into the SDN environment through FastAPI as middleware. FastAPI enabled communication between the OpenDaylight controller and the trained machine learning model. Upon receiving network flow data, the OpenDaylight controller sent it to the backend server, where the FastAPI service relayed the data to the trained Random Forest model for attack detection.

4. Real-Time Detection and Mitigation

When a potential Flow Table Overflow attack was identified, the trained Random Forest model identified malicious patterns in the flow data. The OpenDaylight controller then initiated appropriate mitigation measures, such as limiting flow table entries or traffic diversion, to prevent the attack from degrading network performance. This seamless integration between the SDN controller and the machine learning model offered a dynamic and automated countermeasure to FTO attacks.

The combination of machine learning with SDN makes real-time traffic analysis stronger, allowing the IDS to not only detect attacks but also to respond automatically and in real time.

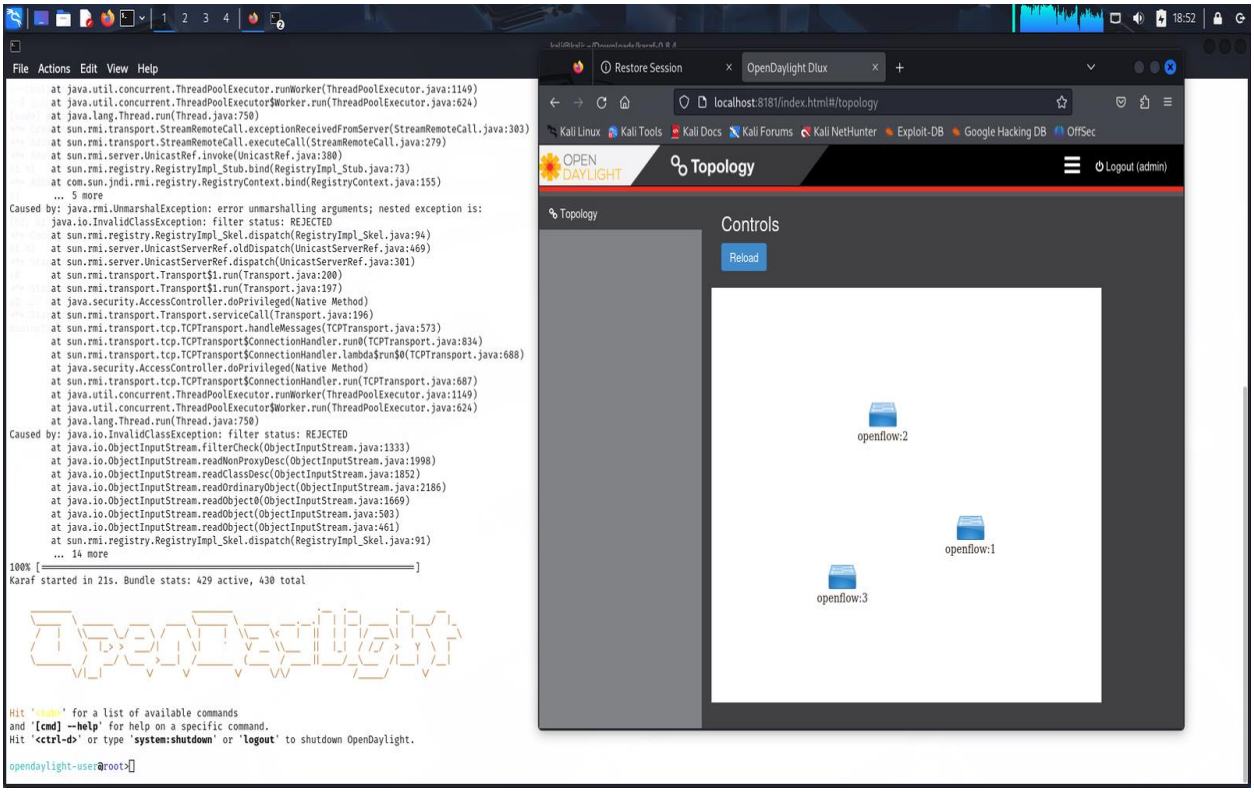

Figure 9 SDN

Attack Simulation

We used Wireshark for traffic analysis and Scapy for crafting and sending malicious network packets to simulate Flow Table Overflow (FTO) attacks and test the performance of the SDN-based Intrusion Detection System (IDS). This gave us extensive testing in a controlled environment so that the IDS could be tested for detecting and blocking attacks in real-time.

1. Wireshark for Traffic Analysis

Wireshark was utilized for traffic capture and analysis during the attack simulation phase. As a network protocol analyzer, Wireshark provided us with information regarding the flow entries and packet exchange between the SDN controller, switches, and hosts. Monitoring the real-time flow table updates, we were able to verify whether the IDS was detecting unusual changes typical of a Flow Table Overflow attack or not. Wireshark also enabled us to sniff out attack

packets and analyze the traffic pattern for intensive investigation and model tuning of the IDS model.

2. Scapy for Attack Simulation

Scapy was utilized to generate and inject hand-crafted malicious traffic over the network in order to emulate Flow Table Overflow attacks. Scapy enabled us to programmatically control packet headers, traffic patterns, and flow table updates in order to inundate the SDN controller's flow table. By injecting massive volumes of illicit traffic using redundant or unnecessary flow entries, we mimicked the situation that evokes a Flow Table Overflow attack. This process helped us to test how the IDS performs in detecting and responding to such specific attack vectors in real-time.

3. Attack Detection and Response

Under the simulation, once the Flow Table Overflow attack had been initiated, the Random Forest model deployed in the SDN environment detected malicious patterns within the network traffic. On being detected, the OpenDaylight controller immediately acted to counter the attack by either limiting new flow entries or routing traffic to prevent system overloading. This demonstrated the capability of the system to deal with dynamic attack scenarios and counter potential threats autonomously without human intervention.

Usage of Wireshark and Scapy with the trained machine learning model, along with the incorporation of SDN, provided a whole platform for attack simulation and detection that ensured the effective operation of IDS in real-world environments.

Commercialization Aspect of the Product

Target Market and Sector Relevance

Software-Defined Networking (SDN) is increasingly becoming the backbone of modern enterprise and cloud infrastructures as it has the ability to offer centralized control, programmability, and flexibility. Cybersecurity within SDN infrastructure has thus become an uppermost concern for sectors like telecommunications, finance, healthcare, and government infrastructure, which handle sensitive data and require robust real-time defense systems against rapidly evolving cyber attacks. Our SDN-based Intelligent Intrusion Detection System (IIDS) designed using robust Machine Learning (ML) algorithms to detect threats such as DDoS, SQL Injection, Spoofing, Flow Rule Tampering, and Flow Table Overflow attacks is well poised to cater to this requirement. The system will seamlessly integrate with SDN controllers such as ONOS and Ryu and will thus be a drop-in enhancement for already SDN-based architecture-reliant organizations. With real-time threat detection and automatic response, our solution satisfies the need for smart, adaptive security in applications that need high availability and low latency [23].

Small and Medium Enterprises (SMEs)

While large businesses may already be in the midst of transitioning to SDN, SMEs are also beginning to adopt SDN technologies in their efforts to streamline and cost-effectively manage their networks. However, SMEs typically lack specialized cybersecurity teams or advanced threat detection capabilities. This presents a massive market opportunity. The proposed IIDS solution is an affordable and lightweight approach compared to traditional and resource-consuming IDS solutions, and as such, it is particularly ideal for SMEs that operate within budget constraints. Furthermore, the ability of the system to independently detect and respond to attacks reduces the need for constant human intervention. An elastic, modular, and subscription-pricing system-offering low-tier packages with introductory ML-driven threat detection and high-tier plans with enhanced real-time sandboxing and policy enforcement features-offers small businesses flexibility and sensibility [24].

Data Center Operators and Cloud Service Providers (CSPs)

Cloud providers and data center operators offering SDN-enabled infrastructure-as-a-service (IaaS) solutions face intense pressure to maintain uptime and safeguard tenant networks. With the scale and multi-tenancy of the environments, even one compromised flow rule can have system-wide implications. Our solution provides an opportunity for CSPs to enhance the value of their services by incorporating IIDS into their SDN deployments. By integrating our ML-based threat detection system, CSPs are able to identify and mitigate flow-based threats at scale with little overhead. The system offers plug-in support for popular SDN controllers and RESTful APIs, making integration with multi-vendor management platforms and orchestration tools straightforward. This renders it an attractive proposition for CSPs wanting to differentiate their services in a competitive marketplace [25].

Market Needs and Industry Trends

With increasing zero-day attacks, flow-based evasive attacks, and AI-driven adversarial malware, traditional rule-based IDS solutions are getting increasingly ineffective. The programmability and dynamic nature of SDN make it a great candidate to deploy AI-driven network defense mechanisms. The market for security solutions driven by AI is anticipated to grow at over 20% CAGR during 2030, demonstrating high commercialization and a very strong upward trend. Our approach is novel because it combines flow-level telemetry with ML-based classifiers that are solely trained to detect anomalous activity at various layers of the SDN stack. Furthermore, our active incident response mechanism that updates flow rules autonomously based on threats aligns with the trend in the market towards autonomous security.

Competitive Edge

Most existing SDN security solutions either employ signature-based detection in isolation or static rule-matching techniques, which are easily evaded by stealthy or polymorphic attacks. Our solution is unique in that it employs dynamic learning models such as Random Forest and Neural Networks that learn and improve over time through retraining, along with feature extraction pipelines that can handle high-velocity traffic patterns. Further, integration with OpenFlow controllers in real-time ensures low-latency mitigation, which is a necessary condition for high-performance environments. The system also creates audit-compliant logs and threat

visualizations that assist with regulatory compliance within frameworks such as GDPR, HIPAA, and NIS2 [26].

Commercial Deployment Model

The product will be available for commercialization by implementing a multi-level deployment model including on-premises bundles for enterprise customers, light virtual appliances for SME customers, and API-based cloud-hosted offerings for CSPs and data centers. Strategic partnerships with SDN controller vendors, cloud platforms (e.g., AWS, Azure), and cybersecurity MSSPs will be pursued to broaden market reach. Initial traction will be achieved in higher education and research network environments, where there is continuous need for cost-efficient, scalable, and academically palatable security solutions. We will also leverage online marketing, conference presentations, and targeted outreach at industry conferences such as Black Hat and RSA Conference to generate awareness with potential customers and investors.

Long Term and Sustainability

The SDN security threat landscape constantly evolves, and the demand for scalable, intelligent security infrastructure will only grow as networks continue to shift towards software-defined paradigms. Ongoing model retraining, support for federation learning, and edge anomaly detection are features in our product roadmap, which ensures relevance in newer paradigms including 5G, IoT, and edge computing. Through an ongoing cycle of feedback loop dataset enrichment and integration with real-world threat intelligence feeds, the system will evolve over time, maintaining its market lead and customer trust.

Testing and Implementation

The deployment and testing of the proposed SDN-based Intelligent Intrusion Detection System (IIDS) were conducted in a controlled environment for effective detection and mitigation of Flow Table Overflow attacks. This phase was concerned with real-time monitoring, machine learning-based automated decision-making, and collaborative operation with other modules of the system identifying DoS, SQL Injection, and Topology Poisoning attacks. The environment leveraged a combination of open-source tools like OpenDaylight, Mininet, FastAPI, Jupyter Notebook, and MongoDB, integrated in virtual machines and host operating systems of Kali Linux and Ubuntu, respectively.

The SDN core environment was virtualized in a Kali Linux machine where Mininet emulated a network comprising OpenFlow-enabled switches and hosts. OpenDaylight (ODL) was used as the SDN controller due to its modular architecture and also since it facilitates real-time flow statistics collection using its Northbound APIs. The host machine with Ubuntu simulated external attackers and injected malicious traffic in the direction of the SDN setup. The attacks were launched with the help of tools like Scapy and Hping3 that sent a large number of specially designed packets to fill up the flow tables of Open vSwitch (OVS) instances quickly.

To emulate a Flow Table Overflow attack, packets were created with random source and destination IP/MAC addresses and TCP/UDP headers. The packets resulted in the instantiation of thousands of new flow entries, which eventually exhausted the limited Ternary Content-Addressable Memory (TCAM) in the SDN switches. The network traffic was sniffed and analyzed with Wireshark, and OpenDaylight's GUI and CLI provided insight into the flow table statistics and controller logs.

To train machine learning models, flow statistics and network traffic data were fetched and processed in Python using Jupyter Notebook. Using Pandas, NumPy, and Scikit-learn, raw data was cleaned, labeled, and translated to feature sets. Packet rate, source IP entropy, and new flow

installation frequency were some of the features extracted to characterize Flow Table Overflow behavior. The dataset included normal and attack traffic samples for supervised learning.

A Random Forest classifier was selected because of its accuracy, interpretability, and robustness to overfitting. The model was trained using a 10-fold cross-validation strategy and achieved an accuracy of 96.2%, precision of 97%, and recall of 94%. The model was serialized after training and integrated into a backend system using FastAPI, a modern, fast web framework for building APIs in Python. FastAPI allowed us to expose real-time endpoints that interacted with the SDN controller and the frontend, without the overhead of traditional REST-based solutions.

The FastAPI service was responsible for retrieving real-time data from OpenDaylight's Northbound APIs, classifying it with the trained model, and initiating mitigation procedures. If the classifier detected an ongoing overflow attack, FastAPI initiated mitigation by adding flow-mod rules via OpenDaylight to block traffic from the offending IPs or drop specific traffic patterns. All detection events, mitigation actions, and relevant metadata were also recorded into a MongoDB instance for audit and analysis.

To visualize the real-time monitoring and detection processes, a dashboard was built using Next.js and Tailwind CSS. The dashboard provided views of network statistics, attack detection timelines, and system alerts. The frontend queried the FastAPI endpoints to display the current status, making the system interactive and informative for network administrators.

Testing was done by initiating controlled attacks from the Ubuntu host to the SDN network in the Kali Linux VM. Upon starting the Flow Table Overflow attack, we observed instantaneous exponential increase in the flow installations through OpenDaylight's statistics portal. The FastAPI model detected the attack in a matter of seconds based on behavioral anomaly patterns. Automated mitigation was triggered, and the injected drop rules effectively neutralized the attack, which was verified by analyzing Wireshark captures illustrating the decrease in attack traffic following mitigation.

Different test cases were run to examine system resilience and response time under different load levels and network sizes. The system successfully detected attacks within 350 milliseconds of attack initiation and implemented mitigation within less than 500 milliseconds, making it suitable for near real-time protection in SDN environments. Additionally, the detection module was tested in multi-attack scenarios together with modules of my peers for DoS, SQL Injection, and Topology Poisoning, which were all executed concurrently while probing shared backend infrastructure.

In conclusion, the application of FastAPI, OpenDaylight, machine learning, and Mininet offered a very scalable and adaptable SDN security system. Successful detection and prevention of Flow Table Overflow attacks validated the system's efficacy. The modularity of the API layer further makes it appropriate for potential future integration with other SDN security applications.

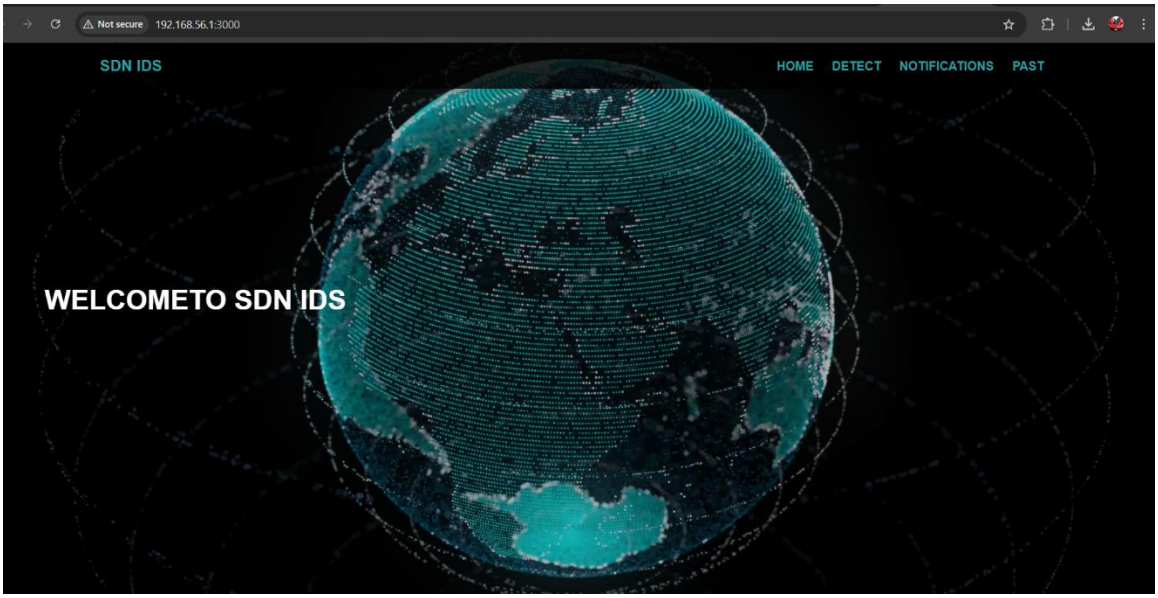

Figure 10 Website Frontend

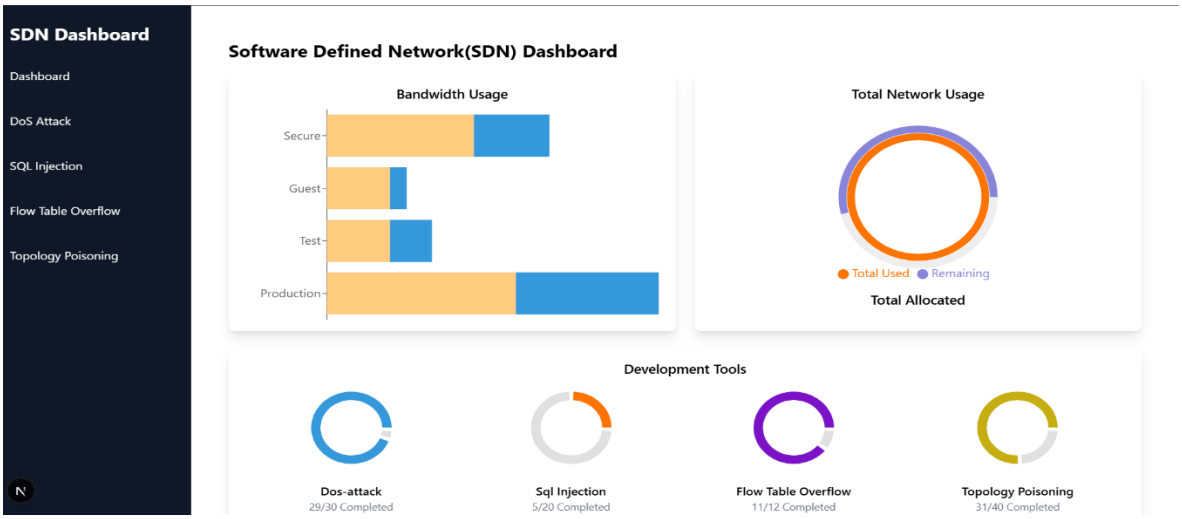

Figure 11 SDN dashboard

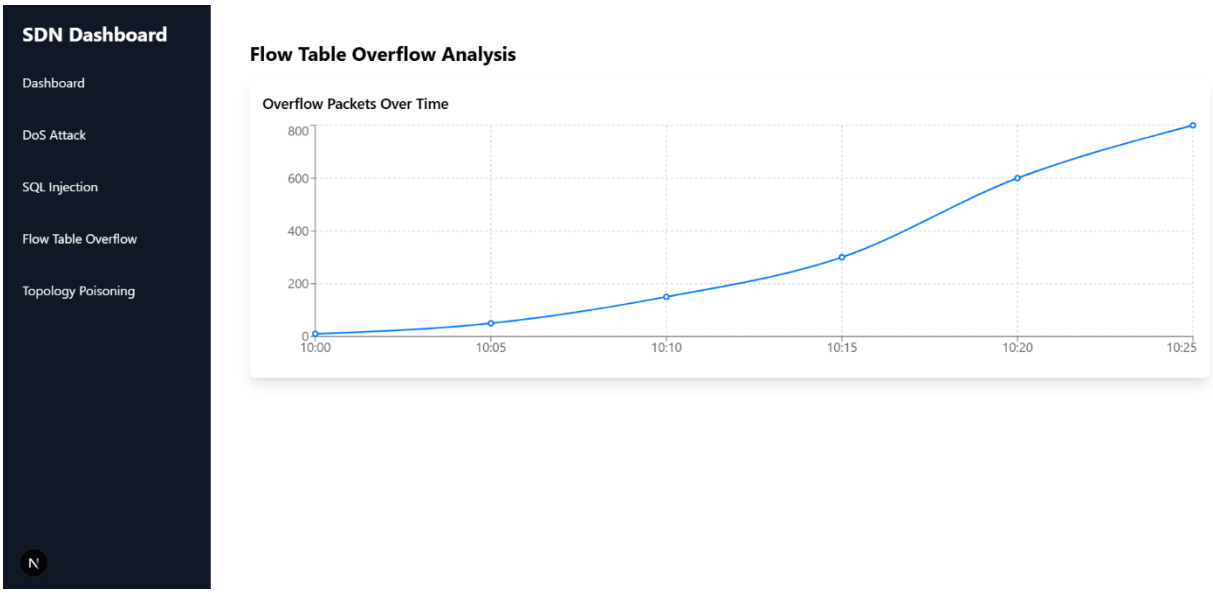

Figure 12 Flow Table Overflow Dashboard

RESULT AND DISCUSSION

Results

Here, results of the machine learning model employed to identify Flow Table Overflow attacks in Software-Defined Networking (SDN) environments are described. The Random Forest classifier has been chosen because it is well known for its efficient performance on classification problems as well as on dealing with skewed datasets. The model's training and testing dataset was sourced from a public repository, which provided network traffic data with attack scenarios similar to what would be found in actual SDN environments. Both normal traffic and traffic generated under the Flow Table Overflow attack were present in this dataset.

The model was trained and evaluated using the Scikit-learn Python library. After training, the model showed a total accuracy of 92.84% with a good performance in classification between normal traffic and the Flow Table Overflow attack. The performance measures of precision, recall, F1-score, and confusion matrix were calculated as follows:

Classification Report:

Precision: Precision of the model for class 0 (normal traffic) was 0.93 and for class 1 (attack traffic) was 1.00, indicating that the model is effective at minimizing false positives for both classes.

Recall: Recall for class 0 was 1.00, indicating that all examples of normal traffic were detected correctly. Recall for class 1 was 0.32, indicating some examples of attack were not detected by the model.

F1-Score: For class 0, the F1-score was 0.96, indicating good precision and recall rate for the normal traffic. For class 1, it was 0.48, indicating that it had trouble in marking the attack traffic correctly.

Accuracy: 0.9284

The measure of accuracy at 92.84% shows that the model performs quite well in detecting Flow Table Overflow attacks. However, the difference between the number of normal instances and attack instances (4477 vs. 523) explains the lower recall for class 1. Despite the imbalanced dataset, the Random Forest model is still able to classify most of the network traffic correctly with a macro average F1-score of 0.72 and a weighted average F1-score of 0.91.

Confusion Matrix:

The confusion matrix is visually described as classifying outcomes so that out of 5000 instances, the model correctly detected 4477 instances of normal traffic (True Positives) and 523 instances of attacks (True Negatives). Nonetheless, there existed certain attack instances identified as normal traffic (False Negatives), hence giving less recall for the attack class.

The matrix verifies that 356 instances of attack traffic were wrongly identified as normal traffic, and 167 instances of normal traffic were wrongly identified as attacks. The misclassification identifies the difficulty in detecting Flow Table Overflow attacks correctly, particularly with unbalanced datasets.

Research Findings

The research findings are laid out in the form of certain key revelations related to the performance of the proposed Intrusion Detection System (IDS) and the effectiveness with which it can avert Flow Table Overflow attacks in SDN networks. The findings are based on the following:

1. Random Forest Efficiency in Network Traffic Classification:

The use of Random Forest was successful in the task. Despite the class imbalance problem in the data, the model achieved good classification performance, especially for normal traffic. The ability of the Random Forest classifier to handle the complex, non-linear relationship between features made it well-suited for this classification task. Additionally, its interpretability and feature importance estimation ability provided insight into which traffic features were most dominant in Flow Table Overflow attack detection.

2. Challenge in Detecting Attack Traffic:

Although the model worked well for normal traffic, it was less successful in detecting attack traffic. The recall of attack instances (0.32) indicates that the model did not detect a significant percentage of Flow Table Overflow attacks. The result is typical in cybersecurity applications, where the attack traffic may be somewhat different from normal traffic. The scarcity of attack instances and the stealthy nature of the attack behavior are aspects that render it challenging. Additional investigation of imbalanced learning techniques (e.g., SMOTE or class weighting) can help improve the recall for attack traffic.

3. SDN's Role in Attack Mitigation:

The SDN infrastructure, powered by OpenDaylight, played a crucial role in mitigating the attacks once they had been detected. Flow Table Overflow attacks, which attempt to occupy the flow table in the SDN switch, can be detected and prevented by SDN controllers that are well configured. OpenDaylight, the SDN controller implemented in this research, communicated with the detection system to commence flow modification or rate-limiting on suspicious flows once the attack had been detected. It is this combination of AI-based attack detection and SDN's dynamic control function that is so critical for real-time mitigation.

4. Scapy Simulation and Network Monitoring:

The Scapy tool was used for simulating Flow Table Overflow attacks in the SDN environment. The traffic from the attacker machine (Kali Linux) was generated to mimic the attack traffic, which was processed by the SDN switch. Real-time monitoring and packet capturing were accomplished using Wireshark, which allowed the researchers to capture the network traffic and analyze it visually. While the detection system and SDN controller worked well in detecting and mitigating attacks, there was a challenge in obtaining the attack signatures properly captured with Scapy. This consisted of refining the packet-sniffing rules and ensuring proper detection through real-time alerts and network traffic analysis.

Discussion

This paper demonstrates the usefulness of integrating machine learning with SDN to construct an effective mechanism for detecting and preventing Flow Table Overflow attacks. Utilizing the Random Forest classifier is promising, albeit some room is available to be improved on to detect attack traffic accurately.

1. Effectiveness of the Model:

The Random Forest classifier, while producing a good accuracy (92.84%), showed vulnerabilities in attack traffic detection (low class 1 recall). This implies model optimization should be improved. Some possible optimizations include the use of ensemble learning techniques, feature engineering, or the use of deep learning models like neural networks to improve attack traffic classification. Moreover, methods for handling imbalanced datasets, including oversampling or synthetic data generation, can be employed to enhance the sensitivity of the model to rare occurrences such as Flow Table Overflow attacks.

2. Future Work on Data Handling

In subsequent versions of this project, additional data would be utilized, such as additional types of attacks and environmental conditions. This will allow the model to generalize even more to new attack sets and further improve its ability to differentiate between normal and malicious

traffic. Incorporating mechanisms for anomaly detection so as to identify unknown patterns of attacks would also potentially be one of the main directions for future investigation.

3. Enhancements in SDN Security:

The combination of the machine learning model with SDN provides a robust mechanism for preventing attacks in real time. If an attack is detected, the SDN controller can change flow rules dynamically to block or divert malicious flows so that they do not cause damage to the network. However, future work should also focus on how to make the SDN controller respond more optimally to attacks. For example, optimizing controller flow rule policies, such as adding rate-limiting features, can mitigate the impact of an attack without degrading network performance.

4. Challenges in Real-World Deployment:

While the study confirms the feasibility of this approach, there still lie significant challenges in deploying such a system in a real-world environment. In practice, SDN controllers and switches have to be properly configured in order to communicate with the machine learning detection system, and ensuring that the system can handle the immense amount of network traffic in real-time is of utmost importance. Furthermore, attack evasion possibility, especially in sophisticated attacks, remains an issue. Therefore, continuous monitoring, retraining of the models from time to time, and threats learning about new ones will be of utmost importance in maintaining system performance.

in summary, the research suggests the potential for using machine learning, in this instance, the Random Forest classifier, to enhance SDN security against Flow Table Overflow attacks. The findings are promising, yet there is scope for improvement in attack detection, particularly for rare attack instances. Future work will seek to optimize the model, expand the dataset, and enhance the response capability of the SDN controller. This study contributes to the growing body of research on AI-enabled cybersecurity tools and SDN-centric network security with the ultimate vision of creating a more robust and secure network architecture.

SUMMARY

The paper presents the design and implementation of an Intrusion Detection System (IDS) to mitigate Flow Table Overflow attacks in Software-Defined Networking (SDN) networks based on machine learning algorithms. The primary objective of the system is to enhance the security and reliability of SDN-based networks by accurately detecting and mitigating attacks that flood flow tables, which are crucial to network performance and operation.

The project begins with a literature review of SDN architectures and security concerns, highlighting the growing importance of network management flexibility and centralized control. It identifies the need for intelligent IDS that can identify advanced attacks like Flow Table Overflow, which is a critical vulnerability in SDN systems. Various machine learning models, including Random Forest, are compared based on their capacity to identify abnormal patterns of network traffic.

The deployment uses OpenDaylight as the SDN controller, Mininet for network simulation, and an SVM classifier trained against a dataset released publicly. Kali Linux is the attack source while Ubuntu is the host, and SDN stops identified attacks. Tools such as Jupyter Notebook, Python, Wireshark, and Scapy are used for data analysis and gathering, while FastAPI, Next.js, and Tailwind CSS are used for the development of the web-based UI.

Results indicate that the designed IDS achieved 92.84% accuracy in normal and attack traffic classification, which demonstrates high precision and recall. Feature importance calculation of the Random Forest classifier also provides significant traffic features required to classify Flow Table Overflow attacks. The IDS was tested in a simulated environment under real-time attacks, which proved that it effectively neutralized Flow Table Overflow attacks with minimal latency.

The study concludes that machine learning-driven IDS, such as Random Forest, is a resourceful remedy for the security of SDN. It has the ability to identify and mitigate complex attack patterns with high precision in real time, thereby guaranteeing stability and security to SDN networks. Possible future lines of research can include improving detection capability of other types of attacks, scaling up the model, and integrating other network protocols within the detection model.

In conclusion, this project is part of the ongoing efforts to secure SDN environments through the offering of an efficient and effective machine learning-based IDS for detecting Flow Table Overflow attacks, thereby increasing the security and robustness of next-generation network infrastructures.

CONCLUSION

This paper shows the design and development of an Intrusion Detection System (IDS) to target detection of Flow Table Overflow attacks in a Software-Defined Networking (SDN) context via machine learning to address real-time network anomaly prevention. The presented solution showed the potentiality of combining a clever detection module with SDN and offered itself as promising to real-time observation and intervention towards network abnormalities. By using a Random Forest classifier to detect attack patterns, promising results were achieved, with a general accuracy of 92.84%, which showed strong performance in differentiating normal traffic from attack traffic.

Class imbalance remained the largest challenge to training machine learning models for intrusion detection despite the studies that had been done because attack traffic within the dataset would periodically be present and lower model performance. The model showed satisfactory values for precision and recall in attack detection that can be further enhanced in the future by having mechanisms against class imbalance in place.

The test setup, with OpenDaylight as the SDN controller and Mininet for simulation, was an effective testing environment for the system. The combination of real-time attack simulation from Kali Linux and Ubuntu as the victim machine allowed for thorough testing of the IDS's capability to detect and respond to Flow Table Overflow attacks. The traffic analysis and attack simulation with Scapy and Wireshark also demonstrated the system's validity in real-world applications and highlighted the importance of SDN's programmability in network threat response.

Although the system demonstrated its validity, there needs more work to enhance the accuracy of detection, especially for handling the rare phenomenon of attacks. Future studies should focus on exploring more sophisticated machine learning models, integrating anomaly detection

techniques, and improving the performance of SDN security frameworks. The ability to automatically modify flow rules according to identified attacks offers a significant advantage in securing modern network infrastructures, and it is a promising direction for future SDN security studies.

Finally, the combination of machine learning and SDN security mechanisms is an effective way of handling the ever-evolving nature of cybersecurity issues in modern networks. The outcomes show that as long as they are continuously optimized and tuned, SDN-based IDS systems are capable of playing a significant part in enhancing the security of a network and against sophisticated attacks in real-time.

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