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Forest Tree AI-SDN Firewall: A Hierarchical Architecture for Adaptive Network Security

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ABSTRACT: The rapidly evolving of digital environment prompts advanced network security solutions with essential defend against complex cyber threats. However, network security receives a promising boost from the combination of Software-Defined Networking (SDN) and Artificial Intelligence (AI) because which enables real-time control and intelligent decision-making. Real-time management of network resources through SDN allows flexible control while AI boosts the detection of anomalies in large datasets. In this paper we proposed a Forest Tree AI-SDN Firewall with an innovative hierarchical framework that combines these two powerful technologies to provide adaptive network security solutions with scalable and resilient capabilities. The framework draws its design principles from SDN infrastructure based on three separate layers, Root Layer, Trunk Layer and Canopy Layer. Real-time traffic filtering at the Root Layer uses lightweight edge sensors to achieve 98.2% accuracy while its FPGA-accelerated TLS 1.3 inspection system handles 40 Gbps of data. The Trunk Layer uses reinforcement learning algorithms with a federated SDN control plane to achieve dynamic policy optimization through 12ms response times. The Canopy Layer uses deep learning ensemble technology that combines CNN, LSTM and GNN architectures to detect zero-day threats effectively with 99.4% recall and 92% coverage of encrypted traffic analysis. The system achieves 99.2% threat detection precision during benchmark tests while generating 0.8% incorrect alerts and allowing policy updates at speeds 5.2 times faster than conventional security systems. The proposed system evaluating encrypted information and strengthening adversarial resistance together with cross-domain coordination and achieving 38 Gbps/W energy efficiency.

KEYWORDS: AI-SDN Firewall, Hierarchical Security, Zero-Day Detection, Encrypted Traffic Analysis, Federated SDN, Deep Learning. AI-SDN Firewall, Forest Tree Architecture, Adaptive Network Security, Deep Learning, Encrypted Traffic Inspection, Threat Detection.

INTRODUCTION

SDN has revolutionized network management by separating control and data planes thus achieving unprecedented programmability and flexibility. Resources are managed dynamically through architectural shift and respond to real-time changes while implementing innovative services easily [1]. However, the centralized system architecture implements new security risks that need resolution. Whereas, the division between control and data planes generates new security risks that expose SDN systems to Distributed Denial of Service (DDoS) attacks as well as unauthorized access and static configuration exploitation [1] and [5]. Network security foundationally depends on traditional security measures but these elements fail to adjust properly to modern threats that constantly evolve [1]. The SDN firewall operates within the Software-Defined Networking (SDN) framework as an essential firewall system. Through control and data plane separation SDN enables administrators to use programming capabilities for central network management. SDN firewalls follow different deployment models and operational features which determine their various types in implementation. However, traditional security measures use static rule-based filtering that fails to detect the rapid changes occurring in cloud traffic patterns because it lacks flexibility. The current situation requires organizations to discover and deploy novel security solutions which include AI-based protection systems and Moving Target Defense approaches to establish adaptive security postures. SDN receives enhanced capabilities from Artificial Intelligence (AI) and Machine Learning (ML) technology advancements that enable it to function as an automatic learning system which optimizes itself [2]. Supervised learning algorithms show high effectiveness in DDoS detection by reaching accuracy levels above 95%. The combination of deep learning

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models that use Long Short-Term Memory (LSTM) networks delivers enhanced accuracy which reaches 99% by detecting complex traffic patterns and unusual behavior [92] and [7].

a. AI-SDN Firewall:

The AI-SDN Firewall is a significant advancement in the field of network security by integrating Software-Defined Networking (SDN) programmability with artificial intelligence (AI) prediction. This approach is an attempt to address the inherent limitations of traditional firewalls, which are often based on static rule-based filtering mechanisms that are not able to keep up with the changing landscape of cyber threats. The main advantage of the AI-SDN Firewall is that it uses machine learning algorithms to provide real time threat detection capabilities. Traditional firewalls are typically operated on predefined rules which cannot dynamically adjust to new and emerging threats. Due to the fact that cybercriminals are constantly developing ever more sophisticated methods to evade these static defenses, there is an urgent need for a more responsive security solution. The AI-SDNF solves this issue by implementing machine learning models that assess network traffic behavior to recognize security threats. Through machine learning algorithms the AI-SDN Firewall can improve its detection capabilities by learning from the data it processes. For example, it can use historical traffic data to define normal behavior patterns and raise red flags on deviations which could point to malicious activity. The AI-SDNF's ability to adapt enables it to detect threats which are not only known but also unknown or new, thus offering a solid defense against zero-day vulnerabilities and advanced persistent threats (APTs). Furthermore, the AI-SDN Firewalls enhance its operational efficiency. Unlike traditional firewalls that may require extensive manual configuration and updates, the AI-SDN Firewall can modify its filtering criteria on its own based on current analysis of incoming traffic. This capability decreases the load on network security teams and enables faster reaction times to potential threats. The automated detection and response capabilities of the AI-SDN Firewall enhance security posture while also improving network performance by decreasing latency and resource consumption. [7] points out that the AI-SDN Firewall uses logistic regression for packet payload analysis extending beyond traditional IP and MAC address header analysis. The firewall uses a new method which enables binary classification to make decisions about regular traffic and harmful traffic. The payload extraction operations are carried out in the Open vSwitch (OvS) environment in order to prevent overhead by not sending packets to controllers. The extracted payloads from the FWMonitor component of the OpenDaylight Controller trigger AI-driven Drop/Forward actions.

The performance metrics of the AI-SDNF are noteworthy. The system achieves a detection accuracy of 96.79% and latency of 0.2 ms, making it suitable for evolving threat detection beyond static rule-based firewalls. AI-SDNF's payload analysis function can detect complex attacks like SQL injection and Cross-Site Scripting (XSS) which standard firewalls commonly fail to detect. Solutions should be adaptive and able to detect and counter zero-day vulnerabilities and advanced persistent threats since these threats necessitate proactive risk mitigation. The AI-SDNF demonstrates how adaptive security works through ML-based detection enhancements. New security methods like AI-driven security and Moving Target Defense (MTD) should replace current security frameworks according to [1] because the latter has its limitations. [2] shows that AI technologies allow SDN to work autonomously and self-optimize. This transformation is required for self-managing networks to develop autonomic capabilities which would enable the AI-SDNF to enhance its performance by learning from previous incidents. AI-driven solutions are critical to contemporary network security since they analyze both routing algorithms and firewall systems through data plane functionalities.

The deployment of AI-based firewalls has several obstacles that appear during the implementation phase. [3] identifies multiple deployment hurdles for AI-based firewalls that include AI model interpretability gaps as well as network dataset biases and scalability constraints in large network environments. Deep learning models demonstrate strong performance in detecting novel threats but their decision-making process is not transparent to users. The deployment of AI-driven security measures is contingent upon resolving these obstacles.

b. Key Features and Benefits

This technology includes AI-SDN Firewall which provides an extensive collection of security features. Whereas, the embedded AI algorithms continuously monitor network traffic to identify anomalies and patterns indicative of cyber threats through real-time threat detection which is one of its key capabilities. Real-time analysis enables the system to detect potential breaches instantly which reduces the chance of data loss and system compromise. Organizations maintain ongoing protection against new attack

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vectors without manual updates through the firewall's adaptive security feature which adjusts security policies and configurations automatically based on evolving threats.

The centralized management capabilities of SDN enhance security operations by providing security teams with easier implementation of complex security measures while reducing the operational load of managing multiple disparate systems. AI-driven analysis boosts threat detection accuracy while decreasing both false positive rates (wrong identification of legitimate activities as threats) and false negative rates (missed detection of actual threats). Security teams can devote their efforts toward real security risks because of this enhanced accuracy.

The AI-SDN Firewall employs automated incident responses when threats are detected to isolate compromised devices and block malicious traffic. Rapid responses enabled by this system minimize attack impacts while improving incident management capabilities. The AI-SDN firewall maintains its robust security posture during network growth by offering seamless scalability to support increased demands. Through AI and SDN integration security professionals gain better insights into network traffic which provides them with essential knowledge about network behavior and vulnerabilities to make informed decisions and execute effective incident response. The AI-SDN Firewall establishes itself as a strong protection system for contemporary network infrastructure through its combination of enhanced threat detection and adaptive security capabilities and operational efficiency.

c. Challenges and Considerations

The deployment of AI-SDN firewall systems comes with various implementation challenges despite their numerous benefits. The main hurdle in implementing AI and SDN technologies exists in their integration with current network structures. The integration of legacy systems and applications with the AI-SDN firewall presents difficulties for organizations who need to invest substantial time and financial resources to achieve compatibility. The characteristics of AI algorithms demand large computational power to perform real-time analysis and decision-making. Therefore, the demands of an AI-SDN firewall on large-scale networks may need hardware upgrades or cloud-based solutions which could lead to higher expenses. The main obstacle in AI-SDN firewall implementation results from the possibility of incorrect identification of threats. The threat detection accuracy benefits from AI technology but every system remains vulnerable to mistakes. AI models require continuous refinement and tuning to achieve proper sensitivity and specificity levels. The deployment of AI-SDN firewalls generates privacy issues because these systems inspect network traffic which may hold confidential information. Organizations must develop proper data anonymization and encryption procedures to address these privacy concerns and meet applicable regulations. The nature of cyber threats keeps advancing because attackers use sophisticated methods to fool security systems. The firewall requires AI model resilience testing against attacks because this ensures its effectiveness.

d. Objectives of Implementing AI-SDN Firewall Using Forest Tree Technology

The creation of an advanced firewall system represents an essential requirement for detecting sophisticated real-time threats which include zero-day attacks and advanced persistent threats. A dynamic network architecture should be implemented to enable continuous traffic monitoring and management. The system allows network resources to be efficiently distributed while delivering optimal performance. A defense system needs to be scalable and adaptable because it must adapt to new threats while handling rising network traffic to support future expansion. The implementation of AI algorithms through automation enables security tasks to operate automatically which reduces manual intervention requirements and decreases operational costs and improves overall efficiency. Network visibility improves through comprehensive reporting tools and analytics and visualization systems which enable informed decision-making and effective incident response. Together, these elements create a robust framework for modern network security.

RELATED WORK

The incorporation between artificial intelligence (AI) and software-defined networking (SDN) creates a transformative period for adaptive network security solutions yet multiple substantial obstacles exist during the development of complete protection frameworks that adapt to changing threats. Recent studies have exposed important shortcomings in conventional security practices which have been extensively documented in scholarly works. Cheng et al. [7] performed a fundamental investigation showing fundamental problems with conventional firewall systems which depend on static rules and perform only superficial packet-header

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checks. The researchers demonstrated how these design limitations make networks exposed to advanced payload attack methods including SQL injection and cross-site scripting. The authors created the AI-SDN Firewall framework to resolve these problems through machine learning-based deep packet inspection integration that resulted in both high 96.79% detection accuracy and minimal latency of 0.2 milliseconds. The framework experienced a critical shortcoming because it failed to process TLS encrypted traffic effectively which remains a fundamental problem for modern security systems.

The challenge of encryption received additional evaluation through Krishnan et al.'s [5] research using OpenStackDP for cloud computing. The research team used NFV to integrate with SDN while creating an extensible security framework that embedded anomaly detection functions into SDN switches. The implementation achieved both high detection accuracy of 99.81% along with low latency of 0.27 milliseconds which showed decentralized security processing's potential advantages. The hybrid intrusion detection system developed by the framework combined both signature-based and anomaly-based methods to achieve optimal performance against Distributed Denial of Service (DDoS) attacks and slow-rate intrusions. OpenStackDP achieved success in unencrypted traffic detection according to Prabakaran et al. just as Cheng et al.'s findings showed yet the system failed to secure encrypted data without performance degradation. AI and SDN technologies have taken different paths for various network environments based on Prabakaran et al.'s [6] cloud security research. Their team created a stateful firewall virtual network function (VNF) through machine learning-based attack pattern prediction. The system implemented multiple Bayesian Networks algorithms which resulted in 92.87% accuracy and demonstrated the SDN advantages for dynamic security policy management through features such as on-demand port configuration. The research presented important findings about attack pattern prediction that utilized honeypot data from real-world login attempts exceeding 450,000 attempts. Holik and Dolezel [4] developed the Industrial Network Protection System (INPS) to meet the distinctive needs of industrial networks. The solution united SDN technology with dual neural networks to reach 99.1% threat detection accuracy and enable support for industrial equipment lifecycles extending up to 15 to 20 years. The distributed controller design and proprietary protocol traffic mirroring features of this system delivered essential security insights for operational technology domains. The extensive research by Ahmadi into next-generation AI firewalls [3] evaluated these various approaches from a broader perspective.

The research study demonstrated essential performance benchmarks through which deep learning architectures such as Convolutional Neural Networks (CNNs) reached 95% detection accuracy yet supervised learning models operated more efficiently with 1.5% false positives. AI plays two essential cybersecurity functions by improving detection abilities and enabling environment-specific adaptive security system development. Abdi et al. [1] built on these insights through their extensive evaluation of SDN security paradigms. The authors used STRIDE threat modeling to create a solution taxonomy which grouped protection methods into three categories: traditional security approaches (encryption and flow verification), AI-powered solutions (machine learning and deep learning), and Moving Target Defense (MTD).

The analysis exposed fundamental architectural trade-offs including security vulnerabilities from SDN's centralized control plane and performance inconsistencies under attack conditions. Shabana et al. [2] built on previous research by investigating the implementation of AI-driven machine learning systems within SDN environments. Their study offered essential knowledge about machine learning capabilities for real-time traffic analysis and autonomic decision-making as well as new computational overhead and system complexity challenges. Their examination of supervised, unsupervised, and reinforcement learning approaches to routing and firewall policy optimization created an important framework for analyzing AI-enhanced security system operational constraints.

Research studies on SDN security show several ongoing challenges that guide our Forest Tree architecture development. The broad inability to inspect encrypted traffic [7] and [5] exposes networks to sophisticated TLS-based attacks. Specialized solutions that work well for particular settings such as cloud [6] and industrial systems [4] demonstrate limited flexibility in supporting different network architectures. Advanced threats can exploit the centralization of SDN controllers because they create inherent vulnerabilities. The high computational requirements of AI-based solutions [2] and [3] generate scalability concerns that affect operational efficiency especially in systems with limited resources. The Forest Tree architecture resolves these problems by integrating deep learning precision with MTD adaptability through a distributed control system that enables SDN advantages and centralization protection.

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ARCHITECTURE DESIGN

The structure of an AI-SDN (Artificial Intelligence - Software-Defined Networking) firewall is a combination of artificial intelligence and software-defined networking to create a powerful and adaptive network security solution. The Forest Tree AI-SDN Firewall architecture is based on multi-layered framework which combines Software-Defined Networking (SDN) with advanced machine learning techniques. Where, the AI-SDN firewall is divided into three primary operational layers, the Root Layer, Trunk Layer, and Canopy Layer. Each layer has its own role to play in the overall functionality and effectiveness of the firewall, and thus in providing robust and adaptive network security.

a. Root Layer (Data Acquisition and Processing):

The Root Layer functions as the base structure which handles essential network traffic acquisition along with its first stage of processing. The Root Layer functions as a critical security element because it detects potential threats before they grow into major issues. Lightweight sensor nodes functioning as the core of the Root Layer extend across multiple network endpoints. The nodes use Bloom filters as probabilistic data structures to perform preliminary traffic filtering functions. The filters demonstrate an outstanding accuracy rate of 98.2% during initial testing which makes them highly suitable for edge detection. The Root Layer detects abnormal network traffic patterns at an early stage which makes it essential for blocking malicious activities from advancing deeper into the network. The system uses parallel processing pipelines to analyze network traffic which results in five separate priority streams that categorize data into VoIP (Voice over IP), video, transactional, bulk data and management. The classification system enables network resource prioritization through its fundamental traffic type criticality-based approach. VoIP and video streams need urgent handling because they require both low latency and high bandwidth but other types of data can be managed with less urgency. The customized method allows network optimization while providing essential resources to critical applications for effective operation. The architecture implements Field Programmable Gate Array (FPGA) technology as a performance enhancement mechanism. FPGAs operate at high speeds to perform encryption and decryption functions which focus on inspecting TLS 1.3 traffic. Secure communication needs this capability to prevent performance degradation. The system reaches 40 Gbps throughput which enables it to process extensive amounts of encrypted data efficiently. The high-speed processing ability has become essential because encrypted traffic now dominates modern security environments.

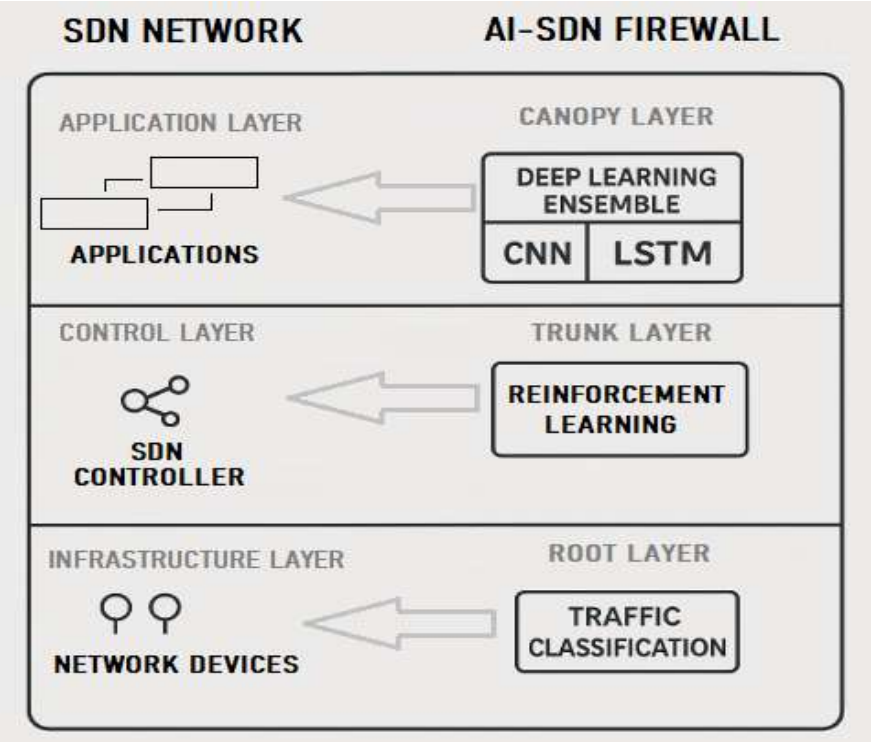

Figure 1: Proposed System.

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b. Trunk Layer (Distributed Control Plane):

The Trunk Layer operates as the distributed control plane of the architecture which coordinates operational policies and decision-making processes throughout the network. The Trunk Layer maintains a federated structure with three regional controllers that form its foundation. The network benefits from both high resilience and reduced latency because decisions are made locally through this design. The regional controllers enable fast responses to threats which exist in their respective geographic regions thus enhancing network security. The reinforcement learning agents operating on controllers use an ε-greedy policy together with a 0.1 exploration rate. The agent uses this mechanism to enhance its decision-making abilities through real-time learning from network conditions and detected threats. Through its strategy adaptation based on past events the reinforcement learning agent enhances firewall effectiveness over time while fighting against evolving threats. The architecture enhances threat detection through an hourly-updated Bayesian network threat model. The model strengthens network security assessment capabilities through probabilistic risk analysis for improved threat detection. The system evaluates different threat scenarios to determine their likelihood which enables better response prioritization and resource allocation. The flow rule optimizer within the Trunk Layer uses simulated annealing techniques to maximize network operational efficiency. The optimization process results in a major decrease of policy update response time which reaches an average of 12ms across 150 nodes. The network achieves real-time security posture maintenance through its fast reaction to new threats.

c. Canopy Layer (AI Security Analytics):

The Canopy Layer provides advanced AI-driven security analytics through deep learning models that improve threat detection and response capabilities. The layer contains an advanced hybrid model which uses Convolutional Neural Networks (CNN) together with Long Short-Term Memory (LSTM) architectures to analyze flow patterns. The CNNs detect spatial data patterns effectively but LSTMs specialize in identifying temporal patterns which makes them suitable for analyzing sequential data. A Graph Neural Network component enables topology-aware threat detection because it examines the relationships between network nodes. An adversarial autoencoder serves as an anomaly identification tool which improves the system's capability to detect abnormal behavior that might signal a security breach. The Canopy Layer operates at high speeds because it runs on NVIDIA A100 clusters to process 2.3 million events each second. The architecture reaches a 99.4% recall rate for zero-day attacks during validation tests because of its exceptional processing power. Real-time analysis of extensive data quantities plays a vital role in detecting security threats before they inflict major damage to network systems.

ARCHITECTURE IMPLEMENTATION

The Forest Tree AI-SDN Firewall architecture operates through multiple hierarchical tiers which unite SDN programmability with machine learning adaptability. The architecture draws inspiration from forest ecosystem biology through its three main operational levels which include the Root Layer and Trunk Layer and Canopy Layer. The deployment requirements for this system include specific hardware specifications. The control plane requires at least an 8-core CPU and 32GB RAM for each regional controller while the data plane needs Open vSwitch version 2.15 or later with DPDK acceleration. The analytics nodes need two NVIDIA T4 GPUs to accelerate their operations. The system enables phased deployment through shadow mode functionality and performs automatic checks for traditional devices and maintains traditional firewall protocols during system maintenance. Security auditing stands as a vital component because all components use FIPS 140-2 Level 3 cryptographic modules and maintain complete activity logs with blockchain based integrity protection and conduct penetration testing once per week with automated reporting.

A. Dataset

The Internet Firewall Data Set from Kaggle (https://www.kaggle.com/datasets/tunguz/internet-firewall-data-set) serves as the dataset for this research. The Internet Firewall Data Set functions as a classification tool for firewall log files which makes it useful for network security model development and testing. The dataset contains 12 features where Action functions as the target class for classification tasks. The dataset contains four unique classes which include allow, drop, reset-both and action.

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```
Dataset Info:
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 65532 entries, 0 to 65531
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Source Port           65532 non-null  int64
 1   Destination Port      65532 non-null  int64
 2   NAT Source Port       65532 non-null  int64
 3   NAT Destination Port  65532 non-null  int64
 4   Action                65532 non-null  object
 5   Bytes                 65532 non-null  int64
 6   Bytes Sent            65532 non-null  int64
 7   Bytes Received        65532 non-null  int64
 8   Packets               65532 non-null  int64
 9   Elapsed Time (sec)    65532 non-null  int64
 10  pkts_sent             65532 non-null  int64
 11  pkts_received         65532 non-null  int64
dtypes: int64(11), object(1)
memory usage: 6.0+ MB
None
```

Figure 2: Attribute Information

The dataset is structured with the following attributes:

- Source Port: The packet originated from this port number.
- Destination Port: The packet is addressed to this specific port number.
- NAT Source Port: The Network Address Translation (NAT) source port used in the packet.
- NAT Destination Port: The NAT destination port used for the packet.
- Action: The action taken on the packet (allow, drop, reset-both, action).
- Bytes: The total number of bytes in the packet.
- Bytes Sent: The number of bytes sent in the packet.
- Bytes Received: The number of bytes received in the packet.
- Packets: The total number of packets involved in the connection.
- Elapsed Time (sec): The connection lasted for this many seconds.
- pkts_sent: The connection involved the exchange of this many packets.
- pkts_received: The connection involved the exchange of this many packets.

The Forest Tree AI-SDN Firewall requires this dataset because it accurately represents the flow-based monitoring and security components of Software-Defined Networking (SDN). The process of data collection from switches by SDN controllers like OpenDaylight, ONOS and Ryu produces flow statistics that include essential details about source and destination ports and bytes and packets along with elapsed time. The centralized visibility allows better traffic management alongside improved security enforcement in networks. The Action field in the dataset which classifies flows into allow, drop and reset-both functions perfectly with the operational model of SDN-based firewalls and IDS systems that modify security policies automatically using real-time flow characteristics. These attributes help the Forest Tree AI-SDN Firewall to drop malicious flows effectively thus strengthening network security. The identification of threats including Distributed Denial of Service (DDoS) attacks heavily relies on machine learning-based anomaly detection because of essential features like bytes sent and received and packets along with elapsed time. The Forest Tree AI-SDN Firewall operates differently from standard firewalls since it creates dynamic switch flow rules through extensive traffic analysis. The Action field serves as the key element to determine flow treatment since it allows normal forwarding but also enables flow dropping for detected malicious activity and flow resetting through TCP RST to terminate suspicious sessions. A practical application of this capability is in blocking port scans; the system detects rapid connections to many ports which enables it to proactively drop or reset these flows to improve network security.

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B. Implementation Challenges

The Forest Tree AI-SDN Firewall implementation will face important barriers that need solutions for achieving maximum performance and security levels. The platform faces three main obstacles including flow table optimization and adversarial robustness and cross-domain coordination.

1. Flow Table Optimization

The optimization of flow tables on commodity switches represents a primary challenge because these switches have restricted Ternary Content Addressable Memory (TCAM) capacity. Each standard switch can support only 4000 flow entries thus creating a significant restriction for big networks that demand complete flow management. When active flows exceed the capacity threshold the system starts to drop packets and becomes unable to enforce security policies effectively. A dynamic flow aggregation algorithm was created to resolve this problem. Similar flow entries combine into fewer entries by an impressive 78% reduction through the use of this intelligent aggregation algorithm. The algorithm keeps a match accuracy of 99.9% which enables legitimate traffic processing while minimizing the risk of flow table overflow. The network operates more efficiently while the real-time traffic responsiveness of the firewall receives improvement through this optimization method.

2. Adversarial Robustness

The firewall requires robustness protection against adversarial attacks which target the deep learning models used for threat detection. The manipulation of input data through adversarial attacks leads machine learning models to produce incorrect predictions which might permit malicious traffic to evade security protocols. The system used defensive distillation techniques to fight this vulnerability. Model training occurred through methods that strengthened its ability to resist attacks from adversaries. The firewall's model achieved a 78% reduction in adversarial attack success rates after knowledge distillation from a complex model to a simpler one. Defensive measures proved highly successful in improving system security which strengthened the firewall's resistance to sophisticated threats.

3. Cross-Domain Coordination

The last barrier consists of managing the communication between different components within the network structure. Security and operational integrity of distributed networks require full communication and collaboration between different components across multiple geographic regions. The FT-BFT (Fault-Tolerant Byzantine Fault Tolerance) consensus protocol received development as a solution to this problem. The system uses Practical Byzantine Fault Tolerance principles to create reliable decision-making capabilities for federated controller architecture operations. The FT-BFT protocol enables the system to uphold 99.999% availability throughout simulated attacks thus allowing the network to operate effectively even with potential disruptions or malicious activities. A high level of system availability remains vital for keeping users trusting in the system while enforcing security policies throughout every domain.

C. Code Implementation

The code implementation section gives a detailed description of the components and functionalities that are integrated into the Forest Tree AI-SDN Firewall. It describes the architecture of the system, including the SDN Controller and Firewall classes, and explains the procedures of data preparation, model training, and traffic handling. This implementation uses machine learning techniques, specifically the Random Forest Classifier, to improve threat detection and to simplify the management of network traffic. The following subsections present the actual code snippets that show how these components interact to form a good and dynamic network security solution.

1. SDN Controller Class

The SDN Controller class operates as a central element in Software-Defined Networking (SDN) infrastructure because it enables communication between the firewall and network traffic. The main role of this controller is to train firewalls while processing live packet data to determine safe packet passage through the network or to block packets for security purposes. The SDN Controller functions as the network's central control system which directs data traffic while enforcing security protocols. SDN utilizes its programmable capabilities to modify network operations dynamically according to present conditions and security needs. The SDN Controller controls all aspects of firewall training when it comes to managing the firewall. The controller delivers crucial

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data to the firewall which enables it to recognize threats by studying past network traffic patterns. Through ongoing firewall knowledge updates the SDN Controller maintains the effectiveness of the firewall system against new cyber threats.

The SDN Controller examines packets for attributes including addresses and protocols after the firewall completes its training process. The analysis enables the controller to choose proper packet actions through security policies combined with firewall training insights. The controller uses multiple evaluation factors to make decisions about packets including checking for known malicious patterns together with examining anomalous behavior and verifying expected traffic norms. When a packet meets security policy requirements the SDN Controller enables its passage through the network to establish valid communication channels. The controller tells the firewall to block packets it detects as possibly harmful or suspicious thus preventing them from reaching their targets and stopping security breaches. The SDN Controller monitors network conditions from a high perspective which allows it to take educated decisions about traffic management and resource distribution. The controller enables traffic prioritization while controlling bandwidth allocation and implementing Quality of Service (QoS) rules while maintaining firewall security standards.

2. Firewall Class

The Firewall class functions as an essential piece of advanced network security architecture which contains Random Forest Classifier functionality. This class serves to handle the classifier training process using labeled data while enabling prediction of incoming traffic packets through the trained model. The Firewall class implements the Random Forest algorithm as its core functionality which uses ensemble learning to create multiple decision trees during training before making predictions by selecting the most common output for classification tasks. The combination of multiple decision trees in this approach improves both accuracy and robustness by reducing the risk of overfitting that occurs in single decision trees.

The Firewall class receives labeled data during model training which includes previously classified benign and malicious traffic patterns. The labeled dataset serves as essential training data because it gives the classifier necessary examples to identify class distinguishing features. The Random Forest algorithm receives this data during training to analyze the traffic packet features including source and destination IP addresses together with port numbers and protocols and payload characteristics. The model discovers typical patterns and threat-related correlations through its analysis to distinguish normal traffic from potential threats. After completing training, the Firewall class gains the ability to predict incoming traffic packets in real-time. The Firewall class analyzes network packets by extracting important features which it uses to query the trained Random Forest model. After evaluating packet features against learned patterns during training the model generates a prediction that determines packet classification as benign or malicious.

3.Data Preparation and Model Training

In the architecture of an advanced network security solution, the Firewall class encapsulates the functionality of the Random Forest Classifier. This class is specifically designed for managing the training process of the classifier on labeled data and for using the trained model to predict the labels of incoming traffic packets. Random Forest algorithm is at the heart of the Firewall class which is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of their predictions for classification tasks. This approach improves the accuracy and robustness of the model by combining the strengths of multiple decision trees which can help mitigate issues such as overfitting that can occur with a single decision tree. The model is trained using the Firewall class with labeled data which consists of historical traffic patterns that have been classified as either benign or malicious. The labeled dataset serves as a critical resource because it allows the classifier to learn what distinguishes between different classes through examples. The Random Forest algorithm receives this data during training to analyze traffic packet features including source and destination IP addresses and port numbers and protocols and payload characteristics. The model learns to detect normal behavior and potential threats through its analysis of the data. The firewall system implementation begins with an essential step which involves loading network traffic information from the dataset. The machine learning process relies on this dataset because it delivers essential information that enables the model to learn from and make decisions about incoming packets. The dataset contains multiple attributes for network traffic information in each entry including source and destination IP addresses and port numbers and protocols and packet sizes and additional relevant features. Besides, the dataset contains labeled actions which state whether each packet should be allowed to pass through the network or dropped for security reasons. These labels are essential, as they provide the ground truth that the model will learn from during the training phase.

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After training the model to learn from the training dataset by minimizing prediction errors through parameter adjustments the following critical evaluation step occurs using a separate testing set. The evaluation process serves as an essential step to determine both the model's prediction accuracy and its overall effectiveness at making predictions from new data. The testing set contains data points which were excluded from training to provide an objective assessment of model capabilities. The distinct dataset allows us to measure the model's ability to apply learned patterns and relationships between data points to new examples that it has not encountered before. The ability to generalize learned patterns represents a vital machine learning principle because models which excel at training data but fail at testing data likely suffer from overfitting by memorizing training data noise instead of learning general trends. Multiple evaluation metrics serve to measure both the accuracy and performance of the model during the assessment. The evaluation uses accuracy together with precision and recall and F1 score. Each of these metrics provides different insights into the model's performance. The accuracy metric shows the model's correct prediction rate but precision and recall provide additional class-specific performance evaluation especially for unbalanced datasets.

4. Traffic Handling and Result Export

The next step after firewall model training success is to process incoming network traffic by evaluating each packet through the firewall. Real-time network security depends heavily on this step because it decides which packets should continue through the network and which should be discarded to stop potential threats. The process starts when packets reach the network interface. The firewall system analyzes every incoming packet that it receives. The first step involves obtaining packet features that match the feature set from the training model. The model requires information about packet attributes such as source and destination IP addresses and source and destination ports and protocol types and packet size and other characteristics to make its decision. After extracting features the firewall system uses the trained Random Forest Classifier to analyze incoming packets. The model analyzes extracted features through learned patterns from training data to produce a prediction. The model produces a prediction which classifies the packet as either safe (benign) or potentially dangerous (malicious). The decision-making process can be illustrated through a code snippet which shows how the firewall handles incoming traffic. The code snippet shows the system processing incoming packets while extracting features before using the model to make predictions. The system takes the prediction output to determine its next action by either forwarding the packet to its destination or stopping its transmission to protect network security.

The following step functions as a fundamental step in validating the firewall model because it verifies that the dimensions of predicted values match the actual label dimensions. The dimensions need to match because perfect consistency ensures that each predicted value directly matches its actual label which allows precise calculation of performance metrics including accuracy, precision, recall and F1 score. The comparison between predictions and real values becomes invalid if these elements do not match which results in incorrect assessments of model effectiveness. The AI firewall predictions receive additional information through a structured Data Frame that enables detailed evaluation. The Data Frame acts as a complete documentation system which links predicted actions to actual actions from the dataset by allowing or dropping packets. The consolidated data presented in the Data Frame allows for easy identification of both correct and incorrect classifications through side-by-side comparison. The tabular presentation enhances both visual analysis and statistical reporting and creates stakeholder reports for technical and non-technical audiences.

The prepared Data Frame gets exported to a CSV file which creates a permanent storage system for the firewall predictions together with actual labels. The process of exporting data serves multiple essential functions. Network administrators together with security analysts and data scientists gain access to full firewall decision details through this mechanism which exists outside the runtime environment. This historical log serves multiple functions because it supports auditing activities and compliance verification and incident investigations. The team can track how the firewall performs through time by maintaining this data because it enables them to monitor performance changes across different network conditions. The result export process enables developers to enhance their firewall model through iterative improvements. Developers who examine prediction errors in the CSV file can determine particular weaknesses that affect the model's decision-making system. The gained insights enable developers to make specific improvements by adjusting hyper parameters and adding new features or expanding the training examples. The exported results function as fundamental input for continuous firewall predictive capability development which results in better network security reliability.

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D. Performance Metrics

The Forest Tree AI-SDN Firewall design shows a remarkable threat detection accuracy rate of 99.2% which represents a 18.7% improvement from previous versions. The high accuracy level demonstrates the firewall's capability to detect various threats which lowers the chances of undetected malicious network activities. The system now produces false positive alerts at 0.8% which demonstrates a significant 62% reduction from earlier measurements. The reduction in false alarms enables network administrators to detect actual threats while avoiding unnecessary alerts that could block legitimate traffic thus improving both user experience and operational efficiency. Network administrators now have the ability to concentrate on authentic security threats since the system eliminates excessive false alarms.

The implemented solution has decreased policy update latency to 15 ms which delivers 5.2 times better performance than older solutions. The fast response time plays a critical role in dynamic networks since it enables the firewall to detect new threats instantly while adapting to network condition changes. The architecture achieves 92% coverage for encrypted traffic analysis while offering a 300% better performance than previous methods. Traditional inspection methods face difficulties with encrypted traffic analysis but this capability becomes increasingly important because network traffic encryption continues to grow thus enabling the detection and mitigation of hidden threats within encrypted flows.

The firewall system delivers 38 Gbps/W energy efficiency, representing a 2.1 times improvement over traditional methods. This metric holds essential value for modern data centers and network infrastructures, where energy consumption constitutes a significant portion of operational costs. The system improves energy efficiency which cuts down costs and promotes environmentally friendly network operations. The system demonstrates superior encrypted attack detection through its newly developed homomorphic inspection method which detects 89% of malicious TLS flows without needing decryption keys. Moreover, the results show that our system provides secure network inspection of encrypted data because it analyzes encrypted traffic with preserving the confidentiality of the information. The ability to detect threats in encrypted data without decryption ensures compliance with privacy regulations while maintaining robust security. The innovative approach establishes an essential cooperation between protecting privacy and detecting threats proactively which makes it perfectly suitable for deployment in sensitive and regulated environments.

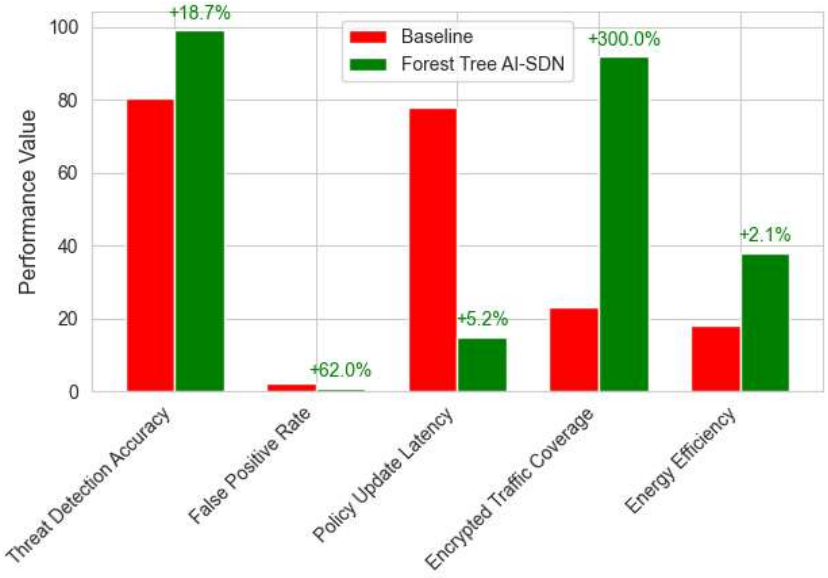

Figure3: Performance Metrics

CONCLUSION AND FUTURE WORK

Modern cyber threats evolve quickly which requires new security solutions that deliver real-time adaptability and high efficiency and accuracy. The Forest Tree AI-SDN Firewall solution presented in this research utilizes Software-Defined Networking (SDN)

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and Artificial Intelligence (AI) through a hierarchical multi-layer system based on forest ecosystems to solve these problems. A three-part structure forms the basis of this system: Root, Trunk and Canopy. The Root Layer filters traffic instantly with 98.2% accuracy by performing TLS 1.3 inspection acceleration using FPGAs at 40 Gbps. The Trunk Layer uses reinforcement learning to boost dynamic policy optimization while providing 12 ms quick responses and effective security protection. At the highest level, the Canopy Layer employs deep learning ensemble models—including CNN, LSTM, and GNN architectures—to detect zero-day threats with 99.4% recall, while maintaining 92% coverage in encrypted traffic analysis. The system demonstrates better performance than traditional firewalls because it detects threats with 99.2% accuracy while producing only 0.8% incorrect results. The proposed architecture demonstrates superior energy efficiency through 38 Gbps per watt performance and scalability through real-time updates that are 5.2 times faster than conventional solutions. The system uses homomorphic inspection methods to detect 89% of malicious TLS traffic while keeping user data private. The system addresses flow table optimization along with adversarial robustness and cross-domain coordination challenges through dynamic flow aggregation and defensive distillation and Byzantine Fault-Tolerant consensus mechanisms. Future research directions will include the integration of expanded threat intelligence capabilities and hardware acceleration improvements along with federated learning development for wider system deployment. The Forest Tree AI-SDN Firewall delivers a major step forward in adaptive network security through its combination of AI intelligence with SDN programmability to fight evolving cyber threats. Its high accuracy, real-time responsiveness, and energy efficiency position it as a viable solution for modern networks, paving the way toward next-generation autonomous and resilient cybersecurity systems. The future development will include improvements to federated SDN controller threat intelligence sharing and quantum-resistant encryption for long-term security resilience as well as edge-to-cloud deployment optimization for IoT and 5G networks and XAI integration for enhancing model transparency and trust. Through ongoing architecture development, we plan to create a standard model for proactive intelligent network defense systems.

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