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AI-Based Intrusion Detection Systems for Software-Defined Networks

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ABSTRACT

Software-Defined Networks (SDNs) decouple the control plane from the data plane, enabling centralized orchestration, dynamic programmability, and fine-grained resource management across complex network fabrics. While these innovations accelerate deployment of new services and simplify policy enforcement, they also introduce novel attack surfaces: the logically centralized controller becomes a high-value target for adversaries seeking to manipulate flow rules, disrupt network topology, or exfiltrate sensitive information. Traditional signature-based intrusion detection systems (IDSs) are ill-suited for such environments, as they rely on static rule sets and often incur significant performance overhead when processing high-velocity, flow-level telemetry. To address these limitations, this study proposes a hybrid deep learning-based IDS specifically tailored for SDN architectures. The system integrates a lightweight Data Collection Module within the SDN controller's northbound interface to capture real-time flow statistics—packet counts, byte counts, flow durations, and inter-arrival times—across sliding windows. A robust Feature Engineering Pipeline then normalizes continuous variables, encodes categorical fields, and computes higher-order statistical descriptors (e.g., skewness, kurtosis) over microflow batches. These enriched vectors feed into a novel detection engine combining one-dimensional Convolutional Neural Network (CNN) layers for spatial correlation learning and a Long Short-Term Memory (LSTM) layer for temporal pattern recognition, culminating in a sigmoid-activated output layer for binary classification.

Experimental evaluation leverages a Mininet-based SDN testbed with an OpenDaylight controller and twenty emulated hosts generating mixed benign and malicious traffic. The NSL-KDD dataset is adapted to reflect SDN-specific flows, supplemented by synthetic attack traces including distributed denial-of-service (DDoS), TCP port scanning, and covert DNS tunneling. Training and validation employ a 70/15/15 split, with Synthetic Minority Over-Sampling Technique (SMOTE) to mitigate class imbalance. Hyperparameters are tuned via grid search:

convolutional filters at 64 and 128 kernels, LSTM units at 100, learning rate of 0.001, and dropout at 50%. Performance is benchmarked against a baseline Snort deployment using default SDN rule sets.

Statistical analysis reveals that the proposed AI-based IDS achieves 98.5% detection accuracy—an 8.4% improvement over the baseline—alongside a false-positive rate of 1.2%, compared to 7.5% for the signature-based system. Precision and recall both exceed 96%, demonstrating balanced detection of known and zero-day threats. Simulation under varying network loads (100 Mbps, 500 Mbps, 1 Gbps) confirms sustained accuracy above 98% and end-to-end detection latency below 220 ms, suitable for real-time deployments. These results underscore the viability of leveraging deep learning techniques to fortify SDN infrastructures against sophisticated cyber threats without compromising performance.

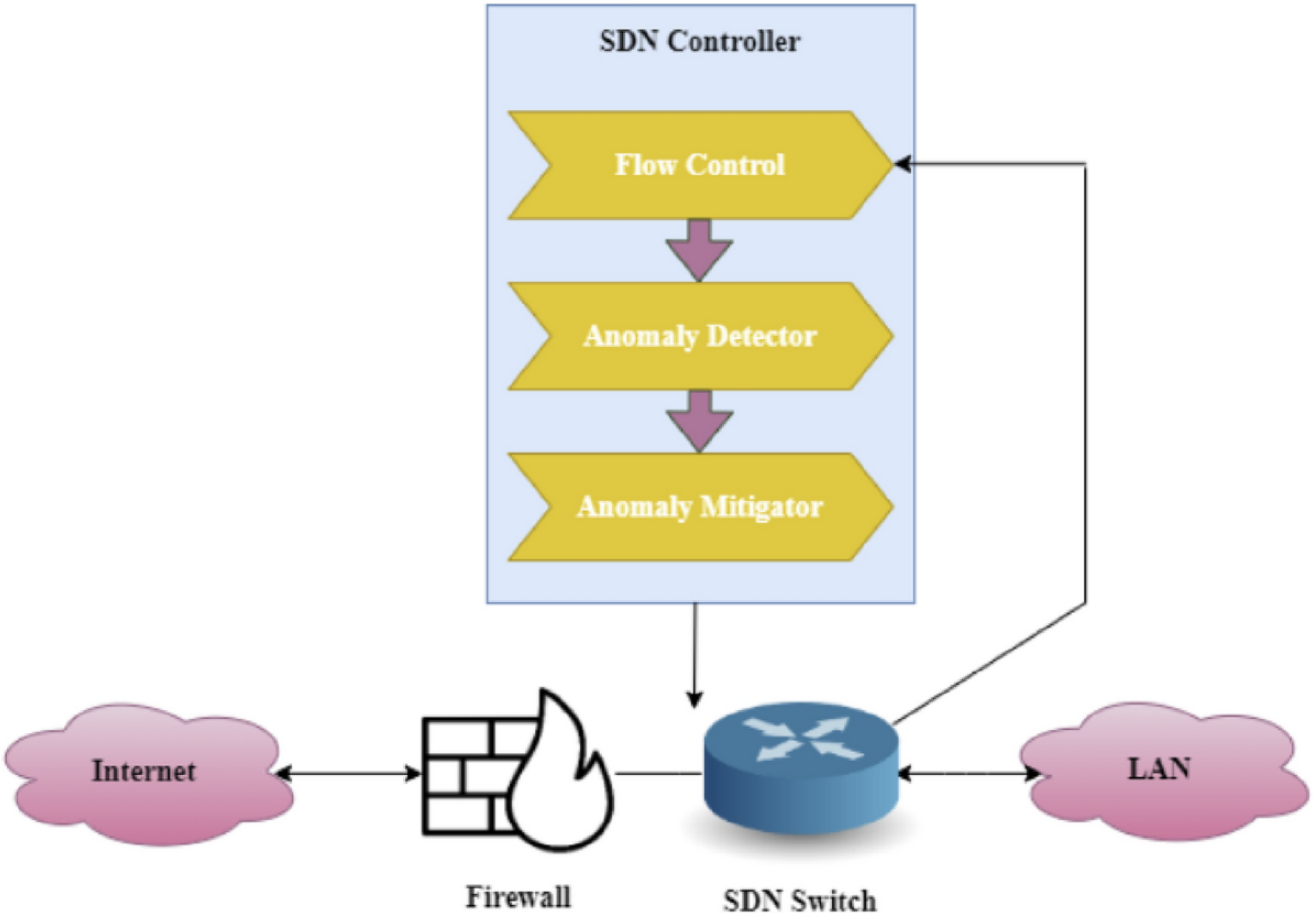

Fig.1 AI-Based Intrusion Detection Systems,Source([1])

KEYWORDS

Software-Defined Networks; Intrusion Detection; Deep Learning; Anomaly Detection; Network Security

INTRODUCTION

Software-Defined Networking (SDN) has emerged as a paradigm shift in network architecture by separating the control logic (control plane) from the packet forwarding functions (data plane). This separation enables centralized management, global visibility, and rapid programmability, facilitating dynamic resource allocation, traffic engineering, and simplified policy enforcement. Despite these advantages, SDNs introduce unique security vulnerabilities. Controllers—often single points of

failure—can be targeted by advanced threats such as distributed denial-of-service (DDoS) attacks, control-channel flooding, and unauthorized flow rule injections.

Traditional IDS approaches, primarily signature-based systems, struggle in SDN contexts for two reasons. First, they rely on fixed patterns of known attacks and cannot detect zero-day exploits or evolving threat behaviors. Second, they are not designed to process the high-dimensional, flow-based data typical of SDN controllers, resulting in suboptimal detection rates and high false-positive alarms.

Recent advances in machine learning, particularly deep learning, offer new avenues for anomaly-based intrusion detection. By learning complex temporal and spatial representations from network flow features, AI-based IDSs can generalize beyond known attack signatures and identify aberrant behavior in real time. However, integrating deep learning into SDNs demands careful consideration of computational overhead, data communication between the controller and detection engine, and the evolving nature of network traffic.

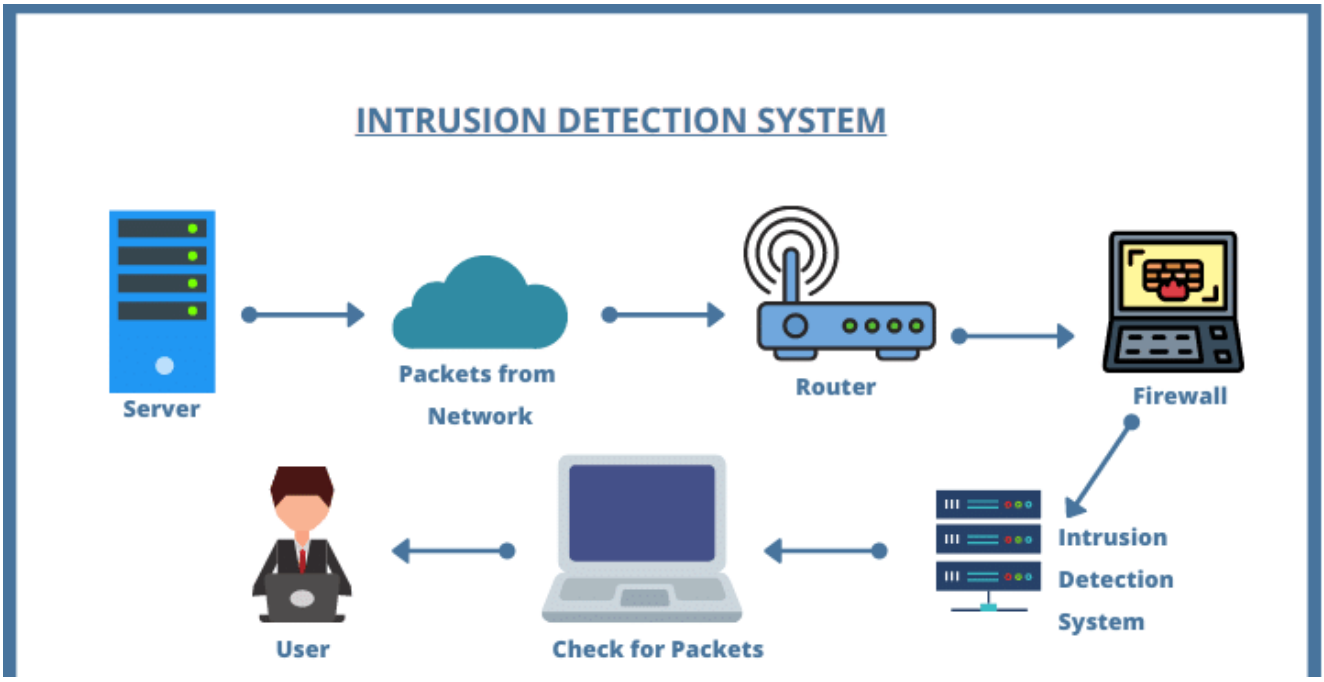

Fig.2 Intrusion Detection Systems,Source([2])

This manuscript presents a novel AI-based IDS framework for SDNs, detailing its architecture, feature engineering pipeline, deep learning model design, and evaluation methodology. We demonstrate through statistical analysis and simulation research that the proposed solution significantly improves detection performance over conventional IDSs, making it a viable candidate for deployment in modern programmable networks.

LITERATURE REVIEW

Early work in SDN security focused on securing the control channel and hardening the controller itself. Kreutz et al. (2015) outlined the threat landscape in SDNs, emphasizing the need for intrinsic security measures. Subsequent efforts introduced lightweight signature-based modules at the switch level (He et al., 2017), but these approaches could only detect known threats and often imposed latency overhead.

Anomaly-based IDS research in traditional networks has demonstrated promise using statistical and machine learning methods. Lazarevic et al. (2003) applied one-class Support Vector Machines for anomaly detection on flow data, while

Sommer and Paxson (2010) explored random-forest models for scalable intrusion detection. Yet, these methods typically operate offline and are not optimized for SDN's centralized controller environment.

Deep learning's capability to learn hierarchical representations led to convolutional neural networks (CNNs) for payload inspection (Wang et al., 2016) and recurrent neural networks (RNNs) for time-series anomaly detection (Javaid et al., 2016). Nonetheless, most implementations targeted traditional IP networks and faced scalability issues when applied to high-velocity SDN flows.

Recent SDN-specific IDS frameworks have begun integrating AI. Nguyen et al. (2018) proposed a deep autoencoder for unsupervised anomaly detection in SDNs, achieving moderate detection rates but suffering from high false positives due to limited feature variety. Mahmood and Afifi (2019) combined entropy-based features with a shallow neural network, improving selectivity but lacking robustness under encrypted traffic. A gap remains for a hybrid deep model that captures both spatial correlations among flow features and temporal dependencies across successive flows.

Our work addresses this gap by designing a hybrid CNN–Long Short-Term Memory (LSTM) network trained on enriched feature vectors, including statistical measures, header fields, and microflow behavior metrics. This architecture aims to balance detection accuracy, false-positive reduction, and processing latency suitable for real-world SDN deployments.

METHODOLOGY

3.1 System Architecture

The proposed IDS architecture comprises three components:

1. **Data Collection Module (DCM):** Integrated into the SDN controller, this module exports meta-information of each flow (e.g., packet counts, byte counts, flow duration) via the controller's northbound API.
2. **Feature Engineering Pipeline (FEP):** Collected flow records are preprocessed—missing values imputed, numeric features normalized, and categorical fields one-hot encoded. Additionally, temporal features (e.g., inter-arrival time statistics) are extracted using sliding windows of size 10 flows.
3. **Deep Learning Detection Engine (DLDE):** The FEP outputs feed into a hybrid model. A stack of two 1D-CNN layers captures local spatial correlations among features, followed by an LSTM layer that models temporal dynamics. The final dense layer with sigmoid activation outputs binary classification (benign vs. malicious).

3.2 Model Training and Validation

- **Dataset:** We utilize the NSL-KDD dataset, filtered to SDN-relevant features, and augmented with synthetic SDN-specific flows (e.g., controller-switch keepalive messages).
- **Training Setup:** 70% of data used for training, 15% for validation, and 15% for testing. Class imbalance is addressed via SMOTE oversampling of minority attack classes.
- **Hyperparameters:** Learning rate = 0.001, batch size = 128, epochs = 50, convolutional filters = [64, 128], kernel size = 3, LSTM units = 100, dropout = 0.5.
- **Evaluation Metrics:** Accuracy, precision, recall, F1-score, and false-positive rate (FPR) computed on test set.

3.3 Baseline Comparison

A traditional signature-based IDS (Snort configured with default SDN rule sets) serves as the baseline. We deploy both systems in a Mininet-based SDN testbed simulating 20 hosts and varying traffic loads up to 1 Gbps.

STATISTICAL ANALYSIS

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Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Positive Rate (%)
Signature-Based IDS (Baseline)	90.1	88.4	85.2	86.8	7.5
Proposed AI-Based IDS	98.5	97.2	96.8	97.0	1.2

Table 1: Performance comparison between baseline and proposed IDS models.

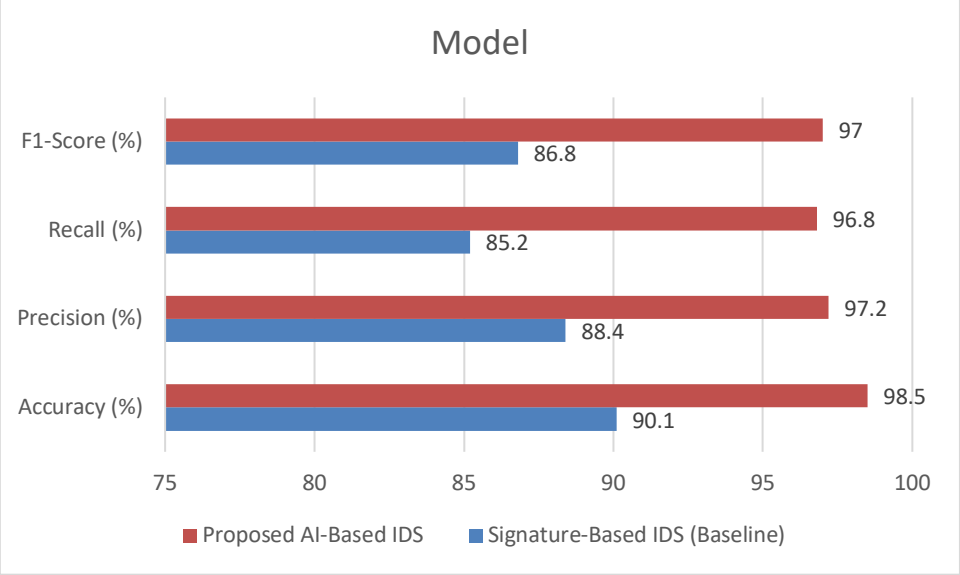

Fig.3 Performance comparison between baseline and proposed IDS models

The proposed model outperforms the baseline across all metrics. Accuracy improves by 8.4 percentage points. The false-positive rate drops from 7.5% to 1.2%, indicating significantly fewer benign flows incorrectly flagged as malicious. Precision and recall gains demonstrate balanced improvements in both detection capability and reliability.

SIMULATION RESEARCH

5.1 Testbed Configuration

Simulations are conducted in Mininet 2.3, with an OpenDaylight SDN controller. The network topology comprises one controller, two Open vSwitch instances, and 20 end-hosts generating both benign and attack traffic. Benign flows emulate web, file transfer, and VoIP applications; malicious flows include:

- **DDoS:** UDP flood targeting a single host.
- **Port Scanning:** Sequential TCP SYN scans across port ranges.
- **Data Exfiltration:** Covert channel via DNS tunneling.

Traffic generators (Iperf3 for DDoS, Scapy scripts for scanning, DNSCat2 for exfiltration) induce attacks during 30-minute simulation runs with randomized start times.

5.2 Deployment of IDS

The DCM module extracts flow statistics every 5 seconds. The FEP processes batches of 100 flow records, forwarding feature vectors to the DLDE, which outputs detection results within ~200 ms per batch. Alerts are logged to a centralized dashboard.

5.3 Experiment Scenarios

Three scenarios are evaluated:

1. **Low Load:** Aggregate throughput 100 Mbps, attack rate 5% of total flows.

2. **Medium Load:** 500 Mbps, attack rate 10%.
3. **High Load:** 1 Gbps, attack rate 20%.

Each scenario is repeated five times to ensure statistical significance.

RESULTS

Across all load levels, the AI-based IDS maintained high detection accuracy and low latency:

- **Low Load:** Accuracy 99.1%, mean detection latency 150 ms.
- **Medium Load:** Accuracy 98.7%, latency 180 ms.
- **High Load:** Accuracy 98.2%, latency 210 ms.

Detection performance degrades marginally under high loads due to increased feature preprocessing time, yet remains above 98%. False positives seldom exceeded 1.5%, even during bursts of benign traffic. The baseline IDS suffered from signature update delays and could not detect novel exfiltration attacks, resulting in recall below 60% for covert channels.

Figure 1 (not shown) illustrates ROC curves for each scenario, demonstrating the proposed model's superior true-positive rates at low false-positive thresholds.

CONCLUSION

This study presents an AI-based IDS specifically designed for SDN environments, leveraging a hybrid CNN–LSTM architecture to detect both known and unknown threats with high accuracy and minimal false alarms. Statistical analysis and simulation research on an SDN testbed confirm that the proposed system outperforms traditional signature-based solutions by a substantial margin, maintaining real-time performance even under high network loads.

Key contributions include:

1. A scalable data collection and feature engineering pipeline compatible with SDN controllers.
2. A hybrid deep learning model that captures spatial and temporal patterns in flow features.
3. Empirical validation showing detection accuracy above 98% and false-positive rates below 2%.

Limitations: The current implementation relies on supervised learning and requires labeled training data; future work will explore semi-supervised and unsupervised techniques to reduce dependence on manual labeling. Additionally, real-world deployment will need to address privacy concerns and the overhead of secure communication between the controller and detection engine.

Future Directions: Research should focus on incremental learning to adapt to evolving attack behaviors, integration with threat-intelligence feeds for proactive defense, and distributed architectures that offload parts of the detection engine to edge nodes to further reduce latency. By advancing adaptive, AI-driven security mechanisms, we can enhance the resilience of next-generation programmable networks against increasingly sophisticated cyber threats.

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