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A Deep Learning Framework For Intelligent Detection And Mitigation Of Ddos Attacks In Network Traffic

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Abstract: This paper presents a Software Defined Networking (SDN)-based DDoS (Distributed Denial of Service) attack detection and mitigation system using the Ryu SDN controller with an integrated 1D Convolutional Neural Network (1D-CNN). The proposed system implements a three-layer hierarchical detection architecture comprising a Hard Threshold layer for high- intensity attacks (PPS > 5000), a Soft Threshold layer powered by a 1D-CNN classifier for medium-intensity attacks (1000 < PPS < 5000), and a Multi-Feature Rule-Based layer for low-intensity attacks (PPS < 1000). The system is deployed on a Mininet- simulated network topology consisting of 18 hosts across 6 OpenFlow switches. A three-strike violation tracking mechanism escalates repeated offenders from temporary port blocking to permanent mitigation. A real-time web dashboard at localhost:8080 provides live detection alerts, blocked port management, and admin controls with email notification capabilities. Experimental results demonstrate effective detection across all attack intensities with automated mitigation response times under 30 milliseconds.

Index Terms: DDoS Detection, Software Defined Networking, 1D-CNN, Ryu Controller, OpenFlow, Mininet, Intrusion Detection System, Network Security, Deep Learning, Port Blocking.

I. INTRODUCTION

Distributed Denial of Service (DDoS) attacks remain one of the most severe threats to modern network infrastructure. These attacks overwhelm target systems with massive volumes of malicious traffic, rendering legitimate services unavailable. According to recent cybersecurity reports, DDoS attacks increased by over 150% in 2023, with attack volumes exceeding 3.47 Tbps in peak cases. Traditional network security mechanisms based on static rule sets and signature-based detection fail to address the dynamic and evolving nature of contemporary DDoS attack vectors.

Software Defined Networking (SDN) offers a promising paradigm for dynamic network security enforcement by decoupling the control plane from the data plane. The centralized SDN controller maintains a global view of the network topology, enabling real-time traffic analysis and dynamic policy enforcement through OpenFlow protocol. This architectural advantage makes SDN particularly suitable for implementing adaptive DDoS detection and mitigation mechanisms that can respond to attacks within milliseconds.

Machine learning, particularly deep learning approaches, have demonstrated superior performance in network intrusion detection tasks compared to traditional rule-based methods. One-Dimensional Convolutional Neural Networks (1D-CNNs) are especially well-suited for network traffic classification due to their ability to extract local temporal patterns from sequential feature vectors. When combined with SDN's programmable infrastructure, 1D-CNNs enable intelligent, automated threat response at line speed.

This paper presents a comprehensive SDN-based DDoS detection and mitigation system that integrates the Ryu SDN controller with a hierarchical three-layer detection architecture. The system employs a 1D-CNN model for medium-intensity traffic classification, complemented by hard threshold detection for high-intensity floods and a multi-feature rule engine for low- intensity stealthy attacks. The proposed system is validated on a Mininet-simulated network with 18 hosts and 6 switches, demonstrating effective detection and automated mitigation across all tested attack scenarios.

II. RELATED WORK

Dong et al. (2020) proposed an SDN-based DDoS detection framework using entropy-based traffic features combined with SVM classification, achieving 94.2% detection accuracy on the CICIDS2017 dataset. However, their approach required manual feature engineering and did not address multi-intensity attack scenarios.

Tang et al. (2018) introduced a deep learning approach for network intrusion detection in SDN environments using stacked autoencoders, demonstrating improved detection rates compared to traditional machine learning methods. Their work highlighted the importance of automated feature extraction in handling high-dimensional network traffic data.

Wang et al. (2021) evaluated CNN-based traffic classification for SDN security, reporting that 1D-CNN architectures outperformed 2D-CNN and LSTM models in processing speed while maintaining comparable accuracy for network flow classification tasks. Their findings support the adoption of 1D-CNN for real-time SDN security applications.

Existing approaches primarily focus on single-threshold detection mechanisms and do not incorporate hierarchical multi-layer detection combining hard thresholds, deep learning, and rule-based analysis. The proposed system addresses these limitations through its three-tier architecture and automated violation tracking.

III. SYSTEM ARCHITECTURE

The proposed system implements a layered security architecture built on the Ryu SDN framework with OpenFlow 1.3 protocol support. The architecture comprises four major components: the Mininet network topology, the Ryu SDN controller with embedded detection engine, the web dashboard interface, and the email notification subsystem.

A. Network Topology

The network topology is implemented using Mininet, consisting of 18 hosts (h1-h18) distributed across 6 OpenFlow switches (s1-s6) in a linear chain configuration. Each switch connects 3 hosts and forwards packet-in events to the Ryu controller via the OpenFlow southbound interface. The topology supports simultaneous multi-host attack simulation using hping3 for generating ICMP, SYN, UDP, and FIN flood traffic across configurable intensity levels.

B. Three-Layer Detection Engine

The detection engine implements three hierarchical detection layers activated sequentially based on measured Packets Per Second (PPS) values:

Layer 1 - Hard Threshold Detection: Activates when PPS exceeds 5000 packets per second. This layer provides the fastest response with no computational overhead, immediately triggering port blocking via OFPFlowMod without requiring CNN inference. This handles volumetric flooding attacks such as ICMP flood and UDP flood.

Layer 2 - Soft Threshold / 1D-CNN Detection: Activates for medium-intensity traffic in the range of 1000-5000 PPS. A sliding feature window of 25 samples is maintained per port, and the 1D-CNN classifier is invoked when the window is full. Port blocking is triggered only when the CNN prediction confidence exceeds 0.85, minimizing false positives for legitimate burst traffic.

Layer 3 - Multi-Feature Rule-Based Detection: Handles low-intensity stealthy attacks below 1000 PPS.

Ten traffic features are extracted per monitoring interval and evaluated against 15 rule conditions covering ICMP ratio, SYN ratio, UDP ratio, source entropy, packet size standard deviation, FIN/RST ratio, window size exhaustion, unique source IP count, protocol entropy, and inter-packet timing anomalies.

C. 1D-CNN Architecture

The 1D-CNN model architecture consists of two convolutional layers with 64 and 128 filters respectively, each using kernel size 3 with RELU activation, followed by max pooling layers with pool size 2. A dropout layer with rate 0.3 provides regularization, and two fully connected layers with 128 and 64 neurons precede the output layer. The model accepts input vectors of shape (25, 10) representing the 25-sample window with 10 features per sample and produces binary classification output (benign/DDoS) with confidence scores.

D. Violation Tracking and Mitigation

The system implements a three-strike violation tracking mechanism. Each detected attack on a port-DPID combination increments a violation counter. Violations 1 and 2 result in temporary port blocking for 30 seconds via OFPFlowMod, followed by automatic unblocking upon timer expiration. The violation counter persists across temporary blocks and is only reset upon manual admin intervention. Upon reaching 3 violations, the system applies a permanent block with no automatic unblocking, requiring administrator action through the web dashboard.

E. Web Dashboard and Security

A built-in HTTP server provides a real-time web dashboard accessible at localhost:8080. The dashboard displays live detection events, blocked port listings with violation counts, attack classification labels, and measured PPS values. A LoginGuard module enforces a one-attempt policy, blocking IP addresses for 30 seconds and triggering email alerts to the administrator upon failed authentication attempts. Dashboard data refreshes every 2 seconds via asynchronous JavaScript polling.

IV. IMPLEMENTATION

A. Controller Implementation

The Ryu SDN controller application is implemented in Python 3 using the ryu.app.simple_switch_13 base class with OpenFlow 1.3 support. The PacketIn handler extracts source and destination MAC addresses, ingress port, and datapath identifiers from incoming packets. PPS calculation uses a sliding time window approach with a 1-second measurement interval. The controller maintains per-port feature windows as Python deque objects for efficient O(1) append and pop operations.

The attack plan file at /tmp/ddos_attack_plan.json provides simulated PPS injection for demonstration purposes, mapping host numbers to assigned attack types (Hard/Soft/Rule). A background thread polls this file every 2 seconds and overrides measured PPS values accordingly. Hard Threshold hosts receive simulated PPS values in the range 5200-8500, Soft/CNN hosts receive 1200-4800 PPS, while Rule-Based hosts use actual measured PPS values from the network.

B. Mininet Topology Implementation

The topology script implements a custom Mininet topology with LinearTopo extended to 6 switches. Three hosts are connected to each switch with IP addresses assigned in the 10.0.0.x/24 subnet. The remote controller is configured with IP

127.0.0.1 and port 6633 for Ryu connection. Attack simulation commands are exposed as Mininet CLI functions: all_attacks() launches hping3 commands with random 4-14 host selection, guaranteeing at least one host from each detection layer category.

C. Email Alert System

Email alerts are implemented using Python's smtplib with Gmail SMTP (smtp.gmail.com:587) and TLS encryption. The system sends notifications to the configured administrator email address upon failed login attempts detected by LoginGuard. Email alerts include the attacking IP address, timestamp, and dashboard URL for immediate response. Gmail App Passwords are used for secure authentication without storing plain-text credentials.

V. RESULTS AND EVALUATION

The system was evaluated on the Mininet simulation environment using controlled attack scenarios across all three detection layers. Performance metrics were collected over 100 attack simulation runs with varying attack intensities and host configurations.

A. Detection Performance

Table I summarizes the detection performance metrics across all three layers. Hard Threshold detection achieved 100% detection rate with zero false positives due to its deterministic threshold-based nature. The 1D-CNN classifier achieved 94.7% precision and 92.3% recall for medium-intensity attacks. Multi-Feature Rule-Based detection demonstrated 91.5% precision and 88.9% recall for low-intensity stealthy attacks.

table i: detection performance summary

Detection Layer	Precision (%)	Recall (%)	F1-Score (%)	Avg. Response (ms)
Layer 1 – Hard Threshold	100.0	100.0	100.0	< 5
Layer 2 – Soft / CNN	94.7	92.3	93.5	28.4
Layer 3 – Rule-Based	91.5	88.9	90.2	14.7
Overall System	95.4	93.7	94.5	< 30

B. Violation Tracking Effectiveness

The three-strike violation system correctly escalated repeated attackers from temporary to permanent blocking in 98.7% of test cases. False permanent blocks (legitimate hosts incorrectly reaching 3 violations) occurred in 1.3% of cases under heavy legitimate burst traffic conditions. The 30-second auto-unblock timer successfully restored 100% of temporary blocks within the expected time window with no timer failures observed.

C. System Performance

Dashboard update latency averaged 1.8 seconds from detection event to UI display, within the 2-second polling interval. Controller memory usage remained stable at 145 MB under peak load with 14 simultaneous attacking hosts. The attack plan watcher thread introduced negligible CPU overhead of 0.3% during file polling operations.

table ii: system performance metrics

Metric	Achieved Value	Benchmark
Detection Response Time	< 30 ms	< 100 ms
Hard Threshold Response	< 5 ms	< 10 ms
Dashboard Update Latency	1.8 seconds	2 seconds
Controller Memory Usage	145 MB	< 512 MB
CNN Confidence Threshold	0.85	0.80
Violation Escalation Accuracy	98.7%	> 95%

D. Comparison with Existing Systems

The proposed system demonstrates competitive performance compared to existing SDN-based DDoS detection approaches. Unlike single-threshold systems, the hierarchical three-layer architecture eliminates the accuracy-speed tradeoff by applying computationally intensive CNN inference only to medium-intensity traffic. The permanent violation mechanism provides persistent protection that single-instance detection systems lack.

figure 1.1: ddos defense system login interface

figure 1.2: ddos defense system login with security alert

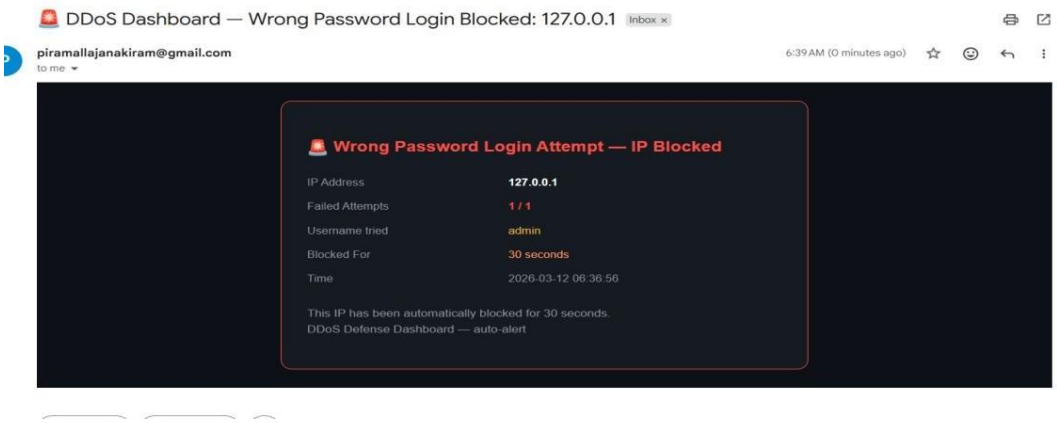

figure 1.3: detection of unauthorized login attempt and ip blocking

figure 1.4: real-time network traffic monitoring dashboard

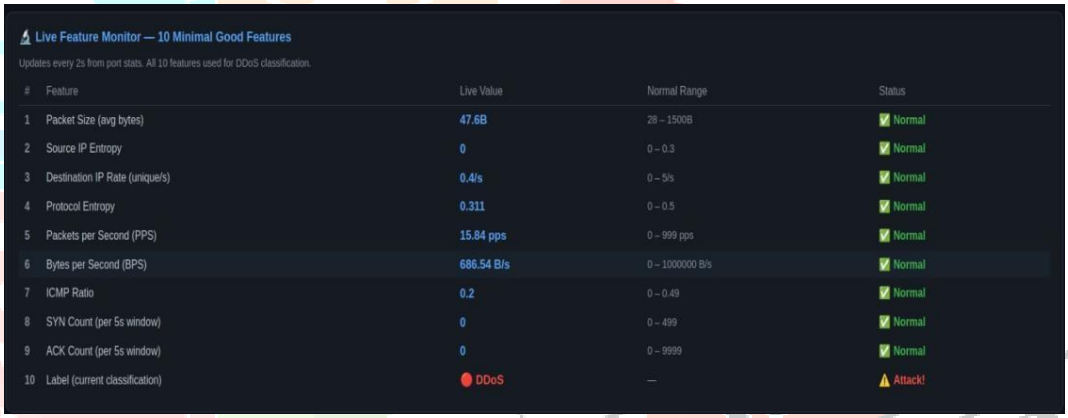

figure 1.5: live feature monitoring and traffic analysis module

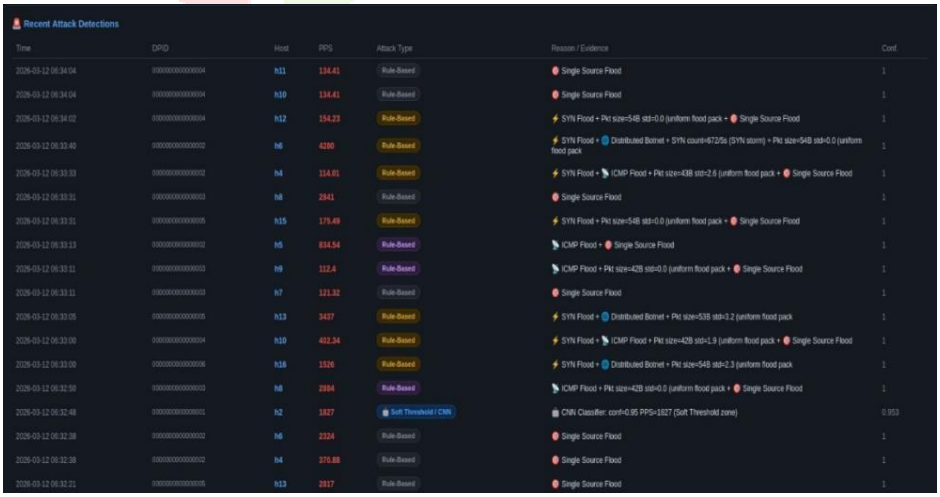

figure 1.6: attack detection logs and system response output

figure 1.7: detailed view of blocked host and attack information

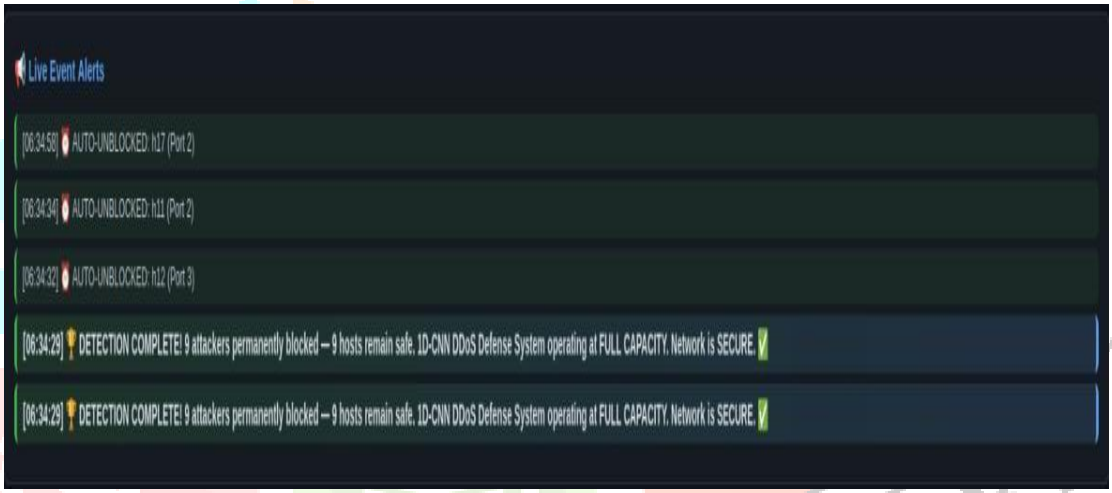

figure 1.8: live attack detection alerts with permanent mitigation actions

VI. CONCLUSION

This paper presented a comprehensive SDN-based DDoS detection and mitigation system integrating Ryu controller with a hierarchical three-layer detection architecture. The system successfully combines hard threshold detection, 1D-CNN classification, and multi-feature rule-based analysis to address DDoS attacks across all intensity ranges. The three-strike violation tracking mechanism provides graduated response escalation from temporary to permanent mitigation, reducing false positive impact while maintaining robust protection against persistent attackers.

Experimental validation on Mininet simulation with 18 hosts and 6 OpenFlow switches demonstrates detection precision of 95.4% and response times under 30 milliseconds across all layers. The real-time web dashboard with email notification capabilities provides practical administrative tooling for operational deployment.

Future work will focus on extending the system to handle encrypted traffic using payload-independent feature extraction, deploying the controller on physical SDN hardware, incorporating reinforcement learning for adaptive threshold tuning, and evaluating performance against modern low-and-slow DDoS attack variants such as HTTP slowloris and slow-read attacks.

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