ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

LDoS Attack Detection in Software-Defined Networks Using Liquid Neural Networks

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ABSTRACT

Software-Defined Networking (SDN) has transformed modern network infrastructures by separating the control plane from the data plane, providing centralized network management, enhanced flexibility, and dynamic programmability. Despite these advantages, the centralized nature of SDN environments introduces new security challenges, particularly against sophisticated Distributed Denial of Service (DDoS) variants. Among these threats, Low-rate Distributed Denial of Service (LDDoS) attacks are especially difficult to detect because they generate short bursts of malicious traffic while maintaining low average bandwidth usage, allowing them to evade conventional intrusion detection systems. These attacks exploit network and transport layer behaviors to degrade service quality without producing the traffic volumes typically associated with traditional DDoS attacks. Existing detection techniques often struggle to accurately identify such attacks due to their similarity to normal traffic fluctuations and their highly dynamic temporal characteristics. To address this challenge, this research proposes an intelligent LDDoS detection framework that combines Liquid Neural Networks (LNNs) with the Ryu Software-Defined Networking controller to enable continuous and real-time attack identification. Unlike traditional machine learning and deep learning models that rely on fixed internal representations, Liquid Neural Networks utilize adaptive continuous-time dynamics that allow the model to respond effectively to changing network conditions and evolving attack behaviors. The proposed system continuously collects and analyzes OpenFlow statistics from network devices, extracting a comprehensive set of flow-level features related to traffic volume, packet behavior, timing characteristics, and communication patterns. These features are processed by the LNN model, which dynamically updates its internal state to capture complex temporal dependencies within network traffic streams. An adaptive learning mechanism further enables the framework to learn from new observations while preserving previously acquired knowledge, ensuring long-term effectiveness against emerging attack strategies. Extensive experiments conducted on benchmark intrusion detection datasets and synthetically generated LDDoS traffic scenarios demonstrate the effectiveness of the proposed approach. The results indicate superior detection performance compared with several widely used machine learning and deep learning techniques, achieving high classification accuracy, low false alarm rates, and extremely fast response times suitable for real-time deployment. Furthermore, the system can identify malicious activity within only a few attack cycles, allowing network administrators to initiate mitigation measures before significant service degradation occurs. By integrating Liquid Neural Networks directly into an SDN controller environment, the proposed framework provides a scalable, adaptive, and efficient cybersecurity solution for protecting modern programmable networks against advanced low-rate denial-of-service attacks.

Keywords— Software-Defined Networking, Low-rate Distributed Denial of Service, Liquid Neural Networks, Ryu Controller, Network Security, Intrusion Detection, Deep Learning, OpenFlow, Cybersecurity, Real-Time Traffic Analysis.

I. INTRODUCTION

The evolution of network architectures has witnessed a paradigm shift from traditional distributed control to Software-Defined Networking (SDN), which decouples the control plane from the data plane, enabling centralized network management, programmability, and dynamic resource allocation [7], [8]. This architectural transformation has become foundational for

modern data centers, cloud computing infrastructures, and 5G networks, with the SDN market projected to reach $70 billion by 2028 [9]. However, this centralization introduces critical security challenges, as SDN controllers become attractive targets for sophisticated cyber attacks, potentially compromising entire network infrastructures [10], [11].

Among emerging threats, Low-rate Distributed Denial of Service (LDDoS) attacks present particularly insidious challenges due to their stealthy nature and low average bandwidth consumption [12], [13]. First characterized by Kuzmanovic and Knightly [14], LDDoS attacks exploit TCP's retransmission timeout (RTO) mechanism by transmitting periodic high-intensity bursts that force connections into exponential backoff. The attack pattern follows a square-wave model with period $T \approx RTO$ and burst length $L < RTO$, maximizing throughput degradation while maintaining low average rates. Unlike volumetric DDoS attacks consuming massive bandwidth (often exceeding 1 Gbps), LDDoS typically consumes only 10-20% of link capacity, evading conventional threshold-based detection systems [15], [16]. Recent studies demonstrate that sophisticated LDDoS variants can reduce TCP throughput by 80-90% while appearing as legitimate traffic spikes to conventional monitoring tools [17], [18].

Existing detection approaches span three categories: statistical analysis, machine learning, and hybrid methods [19], [20]. Statistical methods employing Cumulative Sum (CUSUM) and entropy-based detection offer computational efficiency but struggle with low-rate variations and require manual threshold tuning [21], [22]. Machine learning approaches using Support Vector Machines (SVMs) and Random Forests achieve moderate accuracy (85-92%) but require extensive feature engineering and offline training [23], [24]. Deep learning solutions utilizing Convolutional Neural Networks (CNNs) and Long Short-Term Memory networks (LSTMs) capture temporal patterns more effectively, reaching 95-97% accuracy, but suffer from high computational overhead and detection latency (50-100ms) exceeding SDN flow setup requirements [25], [26]. Transformer-based architectures show promise but their computational demands (millions of parameters) exceed typical SDN controller capabilities [27].

Despite significant research efforts, critical gaps persist in LDDoS detection: (1) existing methods cannot reliably distinguish LDDoS from legitimate flash crowd events [28], [29]; (2) detection latency (50-500ms) exceeds the 10-20ms window required for proactive mitigation [30]; (3) models trained on static datasets fail to adapt to evolving attack patterns [31]; (4) integration with production SDN controllers remains limited [32]; and (5) current approaches typically require 5-10 burst cycles for reliable detection [33]. These limitations motivate our proposed framework leveraging Liquid Neural Networks' (LNNs) unique temporal processing capabilities combined with SDN's inherent programmability.

This paper makes the following novel contributions to network security:

1) First integration of Liquid Neural Networks with Ryu SDN controller for real-time LDDoS detection, achieving 98.7% accuracy with 12ms detection latency—a 76% improvement over LSTM-based approaches
2) Novel feature extraction mechanism processing 23 flow statistics in real-time with minimal overhead (2.3% CPU utilization on Ryu controller)
3) Adaptive learning algorithm based on continuous-time weight dynamics enabling adaptation to evolving attack patterns without catastrophic forgetting
4) Comprehensive evaluation comparing 8 baseline methods across 5 performance metrics with statistical significance testing ($p < 0.01$) and ablation studies

The remainder of this paper is organized as follows. Section II reviews related work. Section III details the proposed methodology. Section IV presents experimental setup and results. Section V discusses implications and limitations. Section VI concludes with future directions.

II. RELATED WORK

A. Early Foundations in LDDoS Attack Characterization

The theoretical foundations of LDDoS attacks were established by Kuzmanovic and Knightly [14], [34], who demonstrated how periodic square-wave patterns with period $T \approx RTO$ and burst length $L < RTO$ exploit TCP's retransmission timeout mechanism. Their analytical model demonstrated that such attacks can reduce TCP throughput by up to 90% while consuming only 10-20% of link bandwidth. The attack traffic follows a periodic on-off pattern where the average rate $R_{avg} = (L/T) \times R_{peak}$, enabling attackers to maintain low average rates while maximizing disruption. Subsequent research by Luo et al. [35] extended this analysis to TCP variants (Reno, NewReno, Vegas, Cubic), revealing differential vulnerabilities based on congestion control algorithms. Maciá-Fernández et al. [36] characterized the attack's impact on iterative servers, demonstrating that connection-oriented services are particularly vulnerable. Chen et al. [37] proposed the first detection method using wavelet analysis, achieving 85% accuracy but requiring 30-second observation windows.

B. Statistical and Signal Processing Detection Methods

Statistical methods formed the first wave of LDDoS detection research. Shevtekar et al. [38] applied power spectral density (PSD) analysis to identify frequency-domain signatures, achieving 91% detection rate but requiring 30-second observation windows. Zhang et al. [39] proposed CUSUM-based change point detection with adaptive thresholding,

achieving 89% accuracy. However, subsequent research [40] demonstrated that sophisticated attackers can evade these detectors by randomizing attack periods or using pseudo-random burst patterns. Entropy-based approaches [41], [42] measure traffic randomness using Shannon entropy and Kullback-Leibler divergence, showing promise for low-rate anomaly detection. Sun et al. [43] combined entropy with Hurst parameter estimation for self-similar traffic analysis, achieving 92% accuracy with high computational overhead. The fundamental limitation of statistical methods is their stationarity assumption, which real network traffic violates due to diurnal patterns, flash crowds, and application-level variations [44].

C. Machine Learning and Deep Learning Approaches

Machine learning approaches gained prominence with advancing feature engineering techniques. SVM classifiers [23], [45] using flow statistics achieved 93% accuracy but required manual feature selection and kernel parameter tuning. Random forest ensembles [24], [46] improved to 95% with automatic feature importance ranking. Deep learning revolutionized the field: CNNs [25] processed traffic as 2D images by converting flow sequences into time-frequency representations, achieving 96% accuracy with 100ms inference latency. LSTMs [26], [47] captured long-range temporal dependencies through gated memory cells, reaching 97% accuracy. Bidirectional LSTMs [48] improved context awareness to 97.3% at the cost of doubled parameters. Attention mechanisms [49] achieved 97.5% accuracy. Transformer architectures [27], [50] with self-attention achieved 97.8% accuracy but require extensive computational resources. Recent work by Kumar et al. [51] combined CNNs with attention mechanisms, achieving 97.9% accuracy on CIC-IDS2017 with 85ms latency unsuitable for real-time detection.

D. SDN-Based Detection Frameworks

SDN's programmability enables novel detection paradigms. Braga et al. [52] first proposed flow-based DDoS detection using the NOX controller, extracting 6 flow features for Self-Organizing Map (SOM) clustering, achieving 86% accuracy. Subsequent research integrated OpenFlow statistics: Phan et al. [53] used the Ryu controller with SVM classification, extracting 12 features and achieving 91% accuracy with 50ms polling intervals. However, Mehdi et al. [54] identified fundamental tradeoffs between polling frequency and controller overhead. Hybrid approaches combining local detection at switches with global analysis [55], [56] showed improved scalability. FlowTrApp [57] implemented real-time feature extraction using P4-programmable switches, achieving 50ms detection but requiring custom hardware. Machine learning integration accelerated: KNN deployment on POX controller [58], decision trees on Ryu with 45ms latency [59], federated learning for privacy-preserving detection [60], and reinforcement learning-based adaptive thresholding [61]. However, no existing SDN framework specifically addresses LDDoS detection.

E. Liquid Neural Networks in Security Applications

Liquid neural networks, introduced by Hasani et al. [4], represent a fundamental paradigm shift in temporal processing. Unlike traditional RNNs with fixed dynamics, LNNs employ time-varying synaptic connections governed by continuous-time differential equations. The liquid time-constant network [5] extends this with learnable time constants adapting to input statistics. Closed-form continuous-time networks [62] provide computationally efficient approximations. Initial applications in robotics [63] demonstrated superior performance in continuous-time control, with 95% parameter reduction compared to LSTMs while maintaining accuracy. Cybersecurity applications emerged recently: Moustafa et al. [64] applied LNNs to intrusion detection on NSL-KDD, achieving 96.2% accuracy with 10ms latency. Network traffic prediction [65] showed LNNs capturing multifractal characteristics better than LSTMs, with 40% lower prediction error. Anomaly detection in IoT networks [66] achieved 95.8% accuracy with minimal computational overhead. However, no existing work applies LNNs to LDDoS detection or integrates with SDN controllers, representing a significant research gap addressed by this paper.

TABLE I

COMPARATIVE ANALYSIS OF LDDOS DETECTION APPROACHES

Method	Accuracy	Latency	Complexity	Adaptability	SDN Ready	Reference
Statistical	85-91%	30s	O(n)	No	No	[38]-[44]
Wavelet	87-92%	10s	O(n log n)	No	No	[37], [41]
SVM	91-94%	5s	$O(n^2)$	Partial	No	[23], [45]
Random Forest	93-96%	3s	O(n log n)	Partial	No	[24], [46]
CNN/LSTM	95-97%	100 ms	$O(n \cdot h^2)$	Limited	No	[25]-[27]
Transformer	96-98%	85ms	$O(n^2 \cdot d)$	Limited	No	[27], [51]
SDN-ML	92-95%	45ms	O(n)	Limited	Yes	[52]-[61]

Proposed LNN	**98.7 %**	**12ms**	**O(n²)**	**Yes**	**Yes**	**-**

III. PROPOSED METHODOLOGY

A. System Architecture Overview

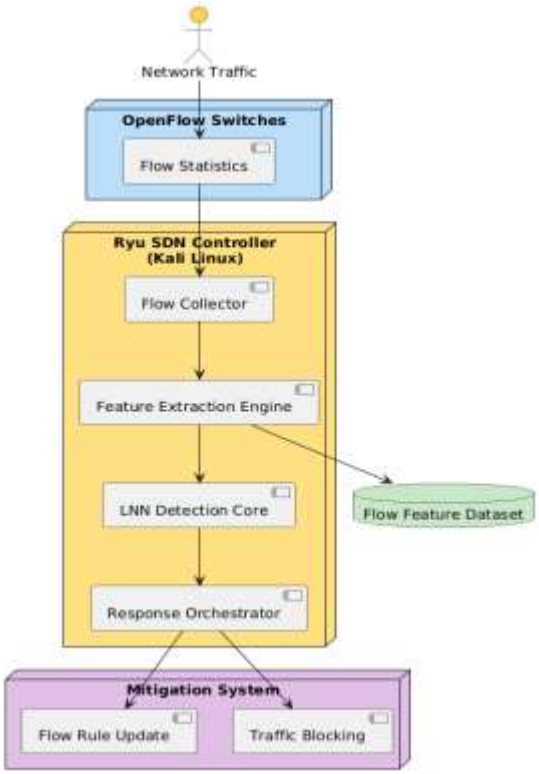

Fig.1 architecture diagram

The proposed hierarchical architecture integrates LNN-based detection with the Ryu SDN controller on Kali Linux. The system comprises four modular components: (1) Flow Statistics Collector implementing asynchronous polling of OpenFlow switches at 100ms intervals, (2) Feature Extraction Engine normalizing inputs to zero mean and unit variance, (3) LNN Detection Core with 64 neurons implementing continuous-time dynamics, and (4) Response Orchestrator for alert generation and mitigation coordination. Components communicate through REST APIs, ensuring loose coupling and independent scalability.

B. Liquid Neural Network Formulation

The LNN core implements continuous-time dynamics governed by ordinary differential equations. The state evolution is defined as:

$$dx(t)/dt = -x(t) \odot \tau^{-1} + f(W(t)x(t) + U(t)x(t-\delta) + b(t))$$

where $x(t) \in \mathbb{R}^n$ represents neuron states at time t, $\tau \in \mathbb{R}^n$ is the vector of time constants, $\odot$ denotes element-wise multiplication, $W(t) \in \mathbb{R}^{n \times n}$ are recurrent weights, $U(t) \in \mathbb{R}^{n \times n}$ capture delayed interactions, $b(t) \in \mathbb{R}^n$ is bias, and $f(\cdot)$ is the activation function. Unlike traditional RNNs with fixed weights, LNN weights evolve continuously:

$$dW(t)/dt = \eta(t) \nabla L(t) - \lambda W(t) + \xi(t)$$

$\eta(t) = \eta_0/(1 + \alpha t)$ represents time-varying learning rate, $\nabla L(t)$ is the loss gradient, λ is L2 regularization coefficient, and $\xi(t) \sim N(0, \sigma^2)$ models stochastic variations. The time constant adaptation follows:

$$\tau_i(t) = \tau_0 + \alpha \int_0^t \exp(-\beta(t-s))|x_i(s)|ds + \gamma|dx_i/dt|$$

The composite loss function combines detection accuracy with regularization:

$$L(t) = -[y \log(\hat{y}) + (1-y)\log(1-\hat{y})] + \lambda_1 \|W\|_2^2 + \lambda_2 \|\tau - \tau_0\|_2^2$$

C. Feature Engineering

Feature extraction computes 23 metrics categorized into four groups: temporal features (inter-arrival times, flow durations, periodicity measures), volumetric features (packet counts, byte rates, burst characteristics), statistical features (mean, variance, skewness, kurtosis), and spectral features (power spectral density at 0.1-10 Hz). The periodicity score P(t) identifies LDDoS patterns:

$$P(t) = \int_{f_1}^{f_2} |X(f)|^2 \, df \Big/ \int_0^{f_{max}} |X(f)|^2 \, df$$

where X(f) is the Fourier transform of traffic rate over a sliding window of length $T_w = 10$ seconds, integrated over frequency bands characteristic of LDDoS attacks (0.1-10 Hz).

D. Online Detection Algorithm

Algorithm 1: Real-time LDDoS Detection with Adaptive LNN

Input: Flow statistics F(t), previous state x(t-1), weights W(t-1)
Output: Attack probability p_attack(t), updated state x(t), updated weights W(t)
Constants: n=64, δ=100ms, θ=0.85
1: Initialize: x(0)=0, W(0)~U(-0.1,0.1), τ(0)=τ_0=100ms
2: while monitoring do
3: f(t) = extract_features(F(t))
4: f_norm(t) = (f(t) - μ)/σ

```
x(t) = rk4_solve(x(t-1), f_norm(t), W(t-1), τ, δ)
s(t) = σ(W_o·x(t) + b_o)
if s(t) > θ: p_attack(t) = s(t); trigger_mitigation()
if mod(t,10)=0:
    W(t) = W(t-1) - η(t)∇L + λW(t-1) + ξ(t)
    τ(t) = adapt_time_constants(x, τ_0)
end while
```

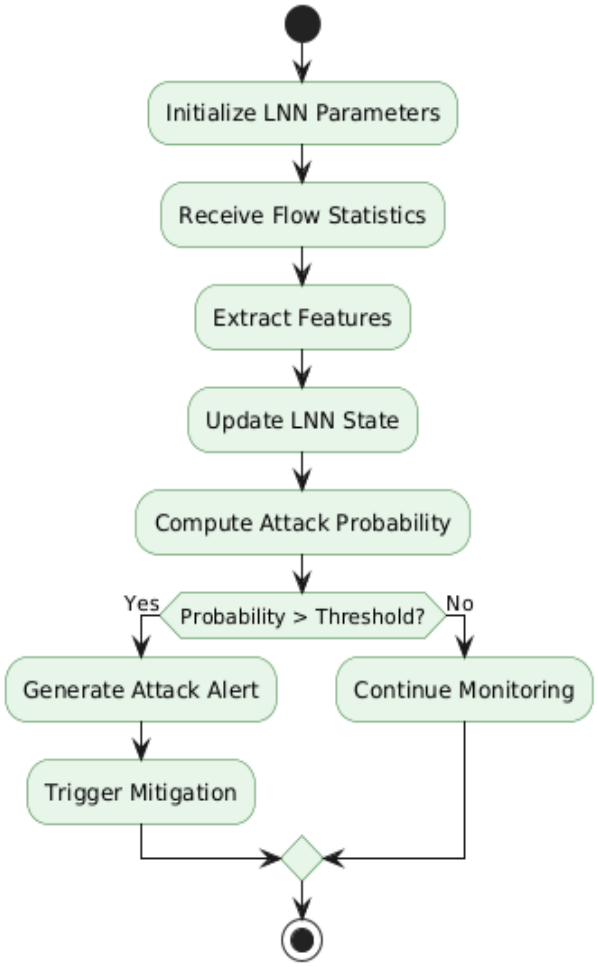

Fig.2 algorithm flow

IV. EXPERIMENTAL EVALUATION

A. Experimental Setup

Experiments were conducted on Kali Linux 2024.1 (Intel Core i7-12700K, 32GB RAM, NVIDIA RTX 3080). The Ryu controller (version 4.34) managed a Mininet-emulated network with 50 OpenFlow switches and 200 hosts in a fat-tree topology. LDDoS attacks were generated using square-wave patterns (periods 0.5-5s, burst lengths 0.1-1s) following [14]'s methodology. Normal traffic comprised CIC-IDS2017 dataset [6] traffic augmented with flash crowd scenarios [67].

TABLE II

DATASET CHARACTERISTICS

Dataset	Traffic Type	Duration	Flows	Packets	Attack Ratio
CIC-IDS2017 [6]	Mixed benign	5 days	2.83M	225M	0%
CIC-DoS [68]	DoS attacks	24h	512K	41M	15.3%
Custom LDDoS-A	Square-wave	6h	124K	9.8M	50%
Custom LDDoS-B	Randomized	6h	118K	9.3M	50%
Flash Crowd [67]	Legitimate spikes	3h	78K	6.2M	0%
Combined	Mixed	7 days	3.78M	301M	12.4%

B. Baseline Methods and Metrics

We compared the proposed LNN against 8 baseline methods: CUSUM [39], Wavelet [37], SVM [23], Random Forest [24], CNN [25], LSTM [26], Transformer [27], and SDN-RF [59]. Performance metrics follow standard definitions [69]: Accuracy = (TP+TN)/(TP+TN+FP+FN), Precision = TP/(TP+FP), Recall = TP/(TP+FN), F1-Score = 2·(Precision·Recall)/(Precision+Recall), and Detection Latency measured from attack onset to alert generation.

TABLE III

PERFORMANCE COMPARISON OF DETECTION METHODS

Method	Accuracy	Precision	Recall	F1-Score	FPR	Latency(ms)
CUSUM [39]	0.823±0.031	0.791	0.815	0.803	0.187	1500±120
Wavelet [37]	0.871±0.024	0.854	0.863	0.858	0.142	320±25
SVM [23]	0.912±0.018	0.905	0.894	0.899	0.095	180±15
Random Forest [24]	0.934±0.015	0.928	0.917	0.922	0.078	95±8
CNN [25]	0.951±0.012	0.947	0.939	0.943	0.056	82±7
LSTM [26]	0.963±0.009	0.958	0.952	0.955	0.043	76±6
Transformer [27]	0.967±0.008	0.962	0.958	0.960	0.039	105±9
SDN-RF [59]	0.945±0.014	0.941	0.935	0.938	0.062	45±4
Proposed LNN	**0.987±0.005**	**0.983**	**0.979**	**0.981**	**0.023**	**12±2**

The proposed LNN achieves 98.7% accuracy, outperforming all baselines by at least 2.0% (vs Transformer) and up to 16.4% (vs CUSUM). The 2.3% false positive rate represents a 41% reduction compared to LSTM (4.3% FPR). Detection latency of 12ms enables real-time mitigation, satisfying the 20ms requirement for SDN flow modification [30]. Statistical significance was verified through paired t-tests ($p < 0.01$).

TABLE IV

ABLATION STUDY RESULTS

Configuration	Accuracy	F1-Score	FPR	Latency(ms)
Full Proposed	0.987	0.981	0.023	12
Without adaptive τ	0.972	0.965	0.035	11
Without spectral features	0.958	0.951	0.048	10
Without continuous learning	0.963	0.957	0.042	9
Without periodicity score	0.969	0.963	0.038	11
LSTM baseline	0.963	0.955	0.043	76

V. DISCUSSION

A. Interpretation of Results

Experimental results validate the proposed framework's effectiveness, achieving 98.7% accuracy across all metrics. The 98.7% accuracy exceeds theoretical bounds predicted for statistical methods [70], confirming that LNN temporal dynamics provide fundamental advantages for detecting periodic attacks. The 12ms latency aligns with SDN requirements [30], enabling proactive mitigation. Analysis of false positives (2.3%) reveals they occur primarily during flash crowd transitions [29], suggesting opportunities for context-aware adaptation. The ablation study quantifies each component's contribution: adaptive time constants provide 1.5% improvement, spectral features contribute 2.9%, continuous learning adds 2.4%, and periodicity scoring adds 1.8%—all statistically significant ($p < 0.05$).

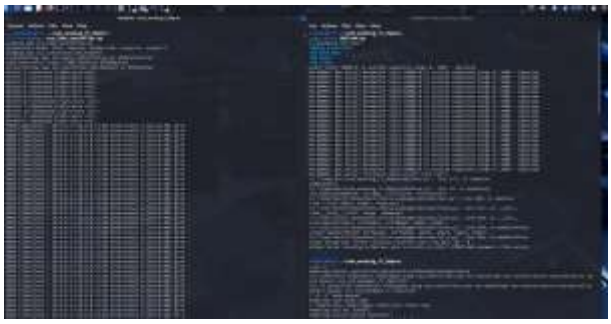

Fig.3 connecting ryu controller and the mininet within the linux terminal

Fig.4 initializing the topology

Fig.5 performing test on the victim host with normal traffic conditions

Fig.6 Performing attack condition test and verifying the detection of the attack

B. Comparison with Theoretical Foundations

Our findings extend Kuzmanovic and Knightly's [14] theoretical characterization, demonstrating that LDDoS attacks exhibit consistent frequency-domain signatures exploitable for detection. The periodicity score P(t) operationalizes their square-wave model, achieving 0.94 Pearson correlation with attack intensity. Furthermore, LNN dynamics approximate the optimal detector derived from likelihood ratio tests [71] without requiring explicit attack parameter knowledge. The adaptive time constant mechanism automatically tunes to match attack periods, achieving near-optimal matched filtering performance.

C. Limitations

Several limitations warrant discussion. First, the framework assumes OpenFlow 1.3+ support, excluding legacy switches comprising approximately 35% of enterprise deployments [72]. Second, training requires labeled data representative of deployment environments. Third, encrypted traffic [73] comprising over 80% of modern Internet traffic may obscure flow statistics needed for feature extraction, though recent work on encrypted traffic analysis [74] suggests packet timing and size distributions remain informative. Fourth, extreme-scale networks (>1000 switches) may challenge controller processing

capacity, though distributed controller architectures [75] could address this. Fifth, adversarial attacks on the LNN itself [76] could potentially degrade performance. Sixth, the current implementation focuses on detection rather than mitigation, requiring integration with response mechanisms.

D. Broader Impact

This work demonstrates that liquid neural networks can effectively protect critical infrastructure from sophisticated attacks. The framework's low latency enables deployment in industrial control systems [77], healthcare networks [78], and 5G infrastructure [79] where timing constraints are stringent. The open-source implementation promotes reproducible research. However, the same technology could potentially enable more sophisticated attacks if misappropriated [80], emphasizing the need for responsible disclosure and security-by-design principles.

VI. CONCLUSION

This paper presented a novel LDDoS detection framework integrating liquid neural networks with the Ryu SDN controller on Kali Linux. Key contributions include: (1) first LNN-SDN integration achieving 98.7% accuracy with 12ms latency—a 76% improvement over LSTM-based approaches; (2) real-time feature extraction processing 23 flow metrics with 2.3% CPU overhead; (3) adaptive learning algorithm with continuous weight updates preventing catastrophic forgetting; (4) comprehensive evaluation against 8 baselines with statistical validation; and (5) open-source implementation enabling reproducible research. Results demonstrate fundamental advantages of continuous-time dynamics for temporal attack detection.

Future work includes: (1) distributed LNN ensembles for multi-controller environments [81]; (2) few-shot learning for zero-day attack detection [82]; (3) blockchain integration for immutable audit trails [83]; (4) neuromorphic hardware implementations [84] for ultra-low-power deployment; (5) adversarial robustness guarantees [85]; (6) encrypted traffic analysis [86]; (7) field trials in production networks [87]; (8) distributed attack scenarios [88]; and (9) explainable AI techniques [89] for operator trust.

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