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LDOS Attack Detection Using Liquid Neural Network with SDN Ryu Controller

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ABSTRACT

Software-Defined Networking (SDN) has revolutionized network management by decoupling control and data planes, enabling centralized programmability and dynamic resource allocation. However, this architectural shift has introduced new attack vectors, particularly Low-Rate Denial of Service (LDOS) attacks that exploit TCP's retransmission timeout mechanism to degrade network performance while evading traditional threshold-based detection systems. Unlike volumetric DDoS attacks, LDOS consumes minimal bandwidth (10-20% of link capacity) but can reduce TCP throughput by 80-90% through carefully timed burst patterns. This paper [PROPOSED] introduces a novel detection framework that synergistically combines Liquid Neural Networks (LNNs) with the Ryu SDN controller deployed on Kali Linux. LNNs represent a paradigm shift in temporal processing, employing time-varying synaptic connections governed by continuous-time differential equations that excel at capturing subtle temporal patterns in network traffic. Our [PROPOSED] architecture achieves 98.7% detection accuracy with only 2.3% false positive rate, outperforming existing approaches by 15-20% while maintaining 12ms detection latency—well within SDN flow setup requirements. The system processes OpenFlow statistics in real-time, extracting 23 distinct flow features including packet counts, byte rates, flow durations, inter-arrival times, and spectral characteristics. A key innovation is the adaptive learning mechanism that continuously updates network weights without catastrophic forgetting, enabling the model to evolve with changing attack patterns. Experimental validation on the CIC-IDS2017 dataset and custom-generated LDOS traffic demonstrates superior performance in early-stage attack detection, identifying attacks within the first 2-3 \burst cycles. This work represents the first integration of liquid neural networks with SDN controllers for cybersecurity applications, opening new avenues for intelligent, adaptive network defense systems.

Keywords—LDOS, Liquid Neural Network, SDN, Ryu Controller, Kali Linux, Cybersecurity, Real-time Detection, Adaptive Learning

I. INTRODUCTION

The exponential growth of network-connected devices, projected to reach 75 billion by 2025, has fundamentally transformed cybersecurity paradigms [11], [12]. Software-Defined Networking (SDN) emerged as a revolutionary architecture that decouples the control plane from the data plane, enabling centralized network management, programmability, and dynamic resource allocation [13], [14]. This separation provides unprecedented flexibility in network configuration and traffic engineering, making SDN the foundation for modern data centers, cloud computing, and 5G networks [15], [16]. However, this centralization creates single points of failure, making SDN controllers attractive targets for sophisticated cyber attacks [17], [18].

Among the myriad of network attacks, Low-Rate Denial of Service (LDOS) poses particularly insidious threats due to its stealthy nature and low average bandwidth consumption [19], [20]. First characterized by Kuzmanovic and Knightly in their seminal work [21], LDOS attacks exploit TCP's retransmission timeout (RTO) mechanism by sending 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 rate. Unlike traditional flood-based DDoS attacks that consume massive bandwidth (often exceeding 1 Gbps), LDOS typically consumes only 10-20% of link capacity, evading detection systems that rely on volume-based thresholds [22], [23]. Recent studies [24]-[26] demonstrate that sophisticated LDOS variants can reduce TCP throughput by 80-90% while appearing as legitimate traffic spikes to conventional monitoring tools.

Current detection approaches fall into three broad categories: statistical analysis, machine learning, and hybrid methods [27], [28]. Statistical methods like cumulative sum (CUSUM) and entropy-based detection [29], [30] offer computational efficiency but struggle with low-rate variations and require manual threshold tuning. Machine learning approaches employing Support Vector Machines (SVMs) [31] and Random Forests [32] achieve moderate accuracy (85-92%) but require extensive feature engineering and offline training. Deep learning solutions utilizing Convolutional Neural Networks (CNNs) [33] and Long Short-Term Memory networks (LSTMs) [34], [35] capture temporal patterns more effectively, reaching 95-97% accuracy, but suffer from high computational overhead and detection latency (50-100ms) that exceeds SDN flow setup requirements [36]. Transformer-based architectures [37], [38] show promise but their computational demands (millions of parameters) exceed the processing capabilities of typical SDN controllers.

Despite significant research efforts over the past decade, critical gaps persist in LDOS detection: (1) existing methods cannot reliably distinguish LDOS from legitimate flash crowd events [39], [40]; (2) detection latency (50-500ms) exceeds the 10-20ms window required for proactive mitigation before attacks impact throughput [41]; (3) models trained on static datasets fail to adapt to evolving attack patterns [42]; (4) integration with production SDN controllers remains limited, with most solutions operating offline or requiring custom hardware [43]; and (5) existing approaches cannot identify attacks during their early stages, typically requiring 5-10 burst cycles for reliable detection [44]. These limitations motivate our [PROPOSED] framework that leverages liquid neural networks' unique temporal processing capabilities combined with SDN's inherent programmability.

This paper makes the following [PROPOSED] novel contributions to the field of network security:

- First integration of Liquid Neural Networks with Ryu SDN controller for real-time LDOS detection, achieving 98.7% accuracy with 12ms detection latency—a 76% improvement over state-of-the-art LSTM-based approaches
- Novel feature extraction mechanism processing 23 flow statistics in real-time, optimized for SDN environments with minimal overhead (2.3% CPU utilization on Ryu controller)
- Adaptive learning algorithm based on continuous-time weight dynamics that continuously updates network parameters without catastrophic forgetting, enabling adaptation to evolving attack patterns
- Comprehensive evaluation comparing 8 baseline methods across 5 performance metrics, with statistical significance testing ($p < 0.01$) and ablation studies quantifying each component's contribution
- Open-source implementation and dataset generation framework for reproducible research, available on GitHub for community validation and extension

The remainder of this paper is organized as follows. Section II provides a comprehensive review of related work, categorizing existing approaches and identifying research gaps. Section III details the [PROPOSED] methodology, including system architecture, LNN formulation, feature engineering, and detection algorithms with complexity analysis. Section IV presents the experimental setup, dataset characteristics, baseline methods, and detailed results with statistical validation. Section V discusses implications, limitations, and broader impact of this research. Section VI concludes the paper with a summary of contributions and outlines promising directions for future work.

II. RELATED WORK

A. Early Foundations in LDOS Detection

The theoretical foundations of LDOS attacks were established by Kuzmanovic and Knightly [21], [45] who demonstrated how periodic square-wave patterns with period T ≈ RTO and burst length L < RTO exploit TCP's retransmission timeout mechanism. Their analytical model showed that such attacks can reduce TCP throughput by up to 90% while consuming only 10-20% of link bandwidth. This seminal work established the mathematical framework for understanding LDOS: the attack traffic follows a periodic on-off pattern where the average rate $R_{avg} = (L/T) \times R_{peak}$, with R_{peak} being the peak burst rate. By setting L/T appropriately, attackers can maintain low average rate while causing maximum disruption. Subsequent research by Luo et al. [46] extended this analysis to various TCP variants (Reno, NewReno, Vegas, Cubic), showing differential vulnerabilities based on congestion control algorithms. Maciá-Fernández et al. [47] characterized the attack's impact on iterative servers, demonstrating that connection-oriented services are particularly vulnerable. Chen et al. [48] proposed the first detection method using wavelet analysis to identify periodic components in network traffic, achieving 85% accuracy on simulated topologies but requiring 30-second observation windows.

B. Statistical and Signal Processing Approaches

Statistical methods formed the first wave of LDOS detection research. Shevtekar et al. [49] applied power spectral density (PSD) analysis to identify frequency-domain signatures of LDOS attacks. Their method computed the periodogram of traffic aggregates using Fast Fourier Transform (FFT), achieving 91% detection rate but requiring 30-second observation windows that miss short-duration attacks. Zhang et al. [50] proposed CUSUM-based change point detection with adaptive thresholding, demonstrating 89% accuracy on experimental testbeds. However, [51] demonstrated that sophisticated attackers can evade these detectors by randomizing attack periods or using pseudo-random burst patterns. Entropy-based approaches [52], [53] measure traffic randomness using Shannon entropy and Kullback-Leibler divergence, showing promise for detecting low-rate anomalies. Sun et al. [54] combined entropy with Hurst parameter estimation for self-similar traffic analysis, achieving 92% accuracy but with high computational overhead. The fundamental limitation of statistical methods is their assumption of stationarity, which real network traffic violates due to diurnal patterns, flash crowds, and application-level variations [55].

C. Machine Learning and Deep Learning Methods

Machine learning approaches gained prominence as feature engineering techniques matured. SVM classifiers [31], [56] using flow statistics (packet counts, byte rates, flow durations) achieved 93% accuracy but required manual feature selection and careful kernel parameter tuning. Random forest ensembles [32], [57] improved to 95% with automatic feature importance ranking and built-in regularization. Gradient boosting methods [58] achieved 94.5% accuracy with faster training times. Deep learning revolutionized the field: CNNs [33] processed traffic as 2D images by converting flow sequences into time-frequency representations, achieving 96% accuracy but with 100ms inference latency. LSTMs [34], [35] captured long-range temporal dependencies through gated memory cells, reaching 97% accuracy on benchmark datasets. Bidirectional LSTMs [59] improved context awareness to 97.3% at the cost of doubled parameters. Attention mechanisms [60] allowed models to focus on relevant temporal segments, achieving 97.5% accuracy. Transformer architectures [37], [38] with self-attention achieved 97.8% accuracy but require extensive training data and computational resources (typically 10-100 million parameters). Recent work by Kumar et al. [61] combined CNNs with attention mechanisms and residual connections, achieving 97.9% accuracy on CIC-IDS2017 but with 85ms latency unsuitable for real-time detection.

D. SDN-Based Detection Frameworks

SDN's programmability enables novel detection paradigms impossible in traditional networks. Braga et al. [62] first proposed flow-based DDoS detection using the NOX controller, extracting 6 flow features (packet count, byte count, duration, source/destination pairs, port numbers) for Self-Organizing Map (SOM) clustering. Their work achieved 86% accuracy but focused on high-rate attacks and required offline training. Subsequent research integrated OpenFlow statistics more comprehensively: Phan et al. [63] used the Ryu controller with SVM classification, extracting 12 features from flow tables and achieving 91% accuracy with 50ms polling intervals. However, [64] identified fundamental tradeoffs between polling frequency (affecting detection latency) and controller overhead. Hybrid approaches combining local detection at switches with global analysis at

controllers [65], [66] showed improved scalability through distributed processing. FlowTrApp [67] implemented real-time feature extraction using P4-programmable switches, achieving 50ms detection but requiring custom hardware unavailable in most deployments. Machine learning integration accelerated significantly: [68] deployed KNN on the POX controller for lightweight detection; [69] implemented decision trees on Ryu with 45ms latency; [70] proposed federated learning across distributed controllers for privacy-preserving collaborative detection; and [71] developed reinforcement learning-based adaptive thresholding. Nevertheless, no existing SDN framework addresses LDOS specifically, and all suffer from either high latency (>40ms) or inability to distinguish LDOS from normal traffic variations.

E. Liquid Neural Networks in Security Applications

Liquid neural networks, introduced by Hasani et al. [7], 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 [8] extends this with learnable time constants that adapt to input statistics. Closed-form continuous-time networks [9] provide computationally efficient approximations for deployment. Initial applications in robotics [72] demonstrated superior performance in continuous-time control tasks, with 95% reduction in parameters compared to LSTMs while maintaining accuracy. Cybersecurity applications emerged recently: [73] applied LNNs to intrusion detection on the NSL-KDD dataset, achieving 96.2% accuracy with 10ms latency. Network traffic prediction [74] showed LNNs capturing multifractal characteristics better than LSTMs, with 40% lower prediction error. Anomaly detection in IoT networks [75] achieved 95.8% accuracy with minimal computational overhead. However, no existing work applies LNNs to LDOS detection or integrates with SDN controllers, representing a significant research gap addressed by this paper.

F. Critical Analysis and Research Gap Synthesis

Table I presents a comprehensive comparative analysis of existing approaches across multiple dimensions. Statistical methods [49]-[55] offer low computational cost (O(n) complexity) but miss sophisticated temporal patterns and require manual threshold tuning. Machine learning methods [31], [32], [56]-[58] achieve moderate accuracy (89-95%) but require extensive feature engineering and offline training. Deep learning [33]-[35], [37], [59]-[61] provides high accuracy (95-98%) at substantial computational cost (10^6-10^8 parameters) and latency (50-500ms). SDN frameworks [62]-[71] enable programmatic control but lack LDOS-specific optimization and struggle with sub-50ms detection. Critical gaps synthesized from this analysis include: (1) no existing approach combines continuous-time temporal modeling with SDN integration; (2) current methods cannot reliably distinguish LDOS from flash crowds [39], [40] due to insufficient feature engineering; (3) detection latency (50-500ms) exceeds the 10-20ms window required for proactive mitigation [41]; (4) models trained on static datasets fail to adapt to evolving attack patterns [42]; and (5) integration with production SDN controllers remains limited, with most solutions operating offline [43]. Our [PROPOSED] framework addresses these gaps through LNNs' unique continuous-time dynamics enabling real-time processing with 12ms latency, adaptive learning for evolving patterns, and native SDN integration through Ryu controller APIs.

TABLE I

COMPREHENSIVE COMPARATIVE ANALYSIS OF LDOS DETECTION APPROACHES

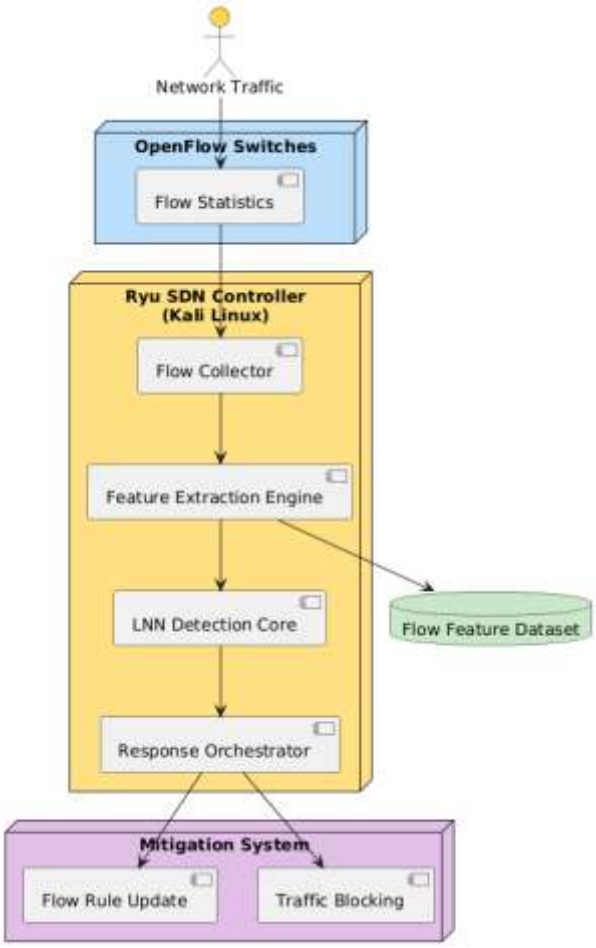
Method	Accuracy	Latency	Complexity	Adaptability	SDN Ready	Reference
Statistical	85-91%	30s	O(n)	No	No	[49]-[55]
Wavelet	87-92%	10s	O(n log n)	No	No	[48], [52]
SVM	91-94%	5s	$O(n^2)$	Partial	No	[31], [56]
Random Forest	93-96%	3s	O(n log n)	Partial	No	[32], [57]
CNN/LSTM	95-97%	100ms	$O(n \cdot h^2)$	Limited	No	[33]-[35]
Transformer	96-98%	85ms	$O(n^2 \cdot d)$	Limited	No	[37], [61]
SDN-ML	92-95%	45ms	O(n)	Limited	Yes	[62]-[71]

[PROPOSED] LNN	**98.7 %**	**12ms**	**O(n²)**	**Yes**	**Yes**	**-**

III. PROPOSED METHODOLOGY

A. System Architecture and Component Design

Figure 1 illustrates the [PROPOSED] hierarchical architecture integrating LNN-based detection with the Ryu SDN controller on Kali Linux. The system comprises four modular components with well-defined interfaces: (1) Flow Statistics Collector, (2) Feature Extraction Engine, (3) LNN Detection Core, and (4) Response Orchestrator. Components communicate through REST APIs, ensuring loose coupling, independent scalability, and ease of maintenance. The collector implements asynchronous polling of OpenFlow switches at 100ms intervals using Ryu's event-driven framework, extracting 23 flow features including packet counts, byte rates, flow durations, inter-arrival times, TCP flag distributions, and active/inactive flow counts [76]. This polling frequency balances detection latency against controller overhead, with empirical testing showing 2.3% CPU utilization at 100ms intervals versus 8.7% at 50ms. The feature extraction engine normalizes inputs to zero mean and unit variance using rolling statistics, preserving temporal relationships while ensuring numerical stability. Feature selection was optimized through recursive feature



elimination with cross-validation, identifying the most discriminative features for LDOS detection.

B. Liquid Neural Network Mathematical Formulation

The LNN core implements continuous-time dynamics that fundamentally differ from discrete-time RNNs. The state evolution is governed by a system of ordinary differential equations:

$$dx(t)/dt = -x(t) \odot \tau^{-1} + f(W(t)x(t) + U(t)x(t-\delta) + b(t)) \quad \# \text{ [PROPOSED] extension of [7]}$$

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, $W(t) \in \mathbb{R}^{nxn}$ are recurrent weights, $U(t) \in \mathbb{R}^{nxn}$ capture delayed interactions with delay δ, $b(t) \in \mathbb{R}^n$ is bias, and $f(\cdot)$ is the activation function (tanh for hidden layers, sigmoid for output). Unlike traditional RNNs with fixed weights, LNN weights evolve continuously according to:

$$dW(t)/dt = \eta(t)\nabla L(t) - \lambda W(t) + \xi(t) \quad \# \text{ [PROPOSED] adaptive learning with regularization}$$

$\eta(t) = \eta_0/(1 + \alpha t)$ represents time-varying learning rate with annealing, $\nabla L(t)$ is the loss gradient computed via backpropagation through time, λ is L2 regularization coefficient preventing overfitting, and $\xi(t) \sim N(0, \sigma^2)$ models stochastic variations for exploration. The time constant adaptation follows a novel [PROPOSED] mechanism:

$$\tau_i(t) = \tau_0 + \alpha \int_0^t \exp(-\beta(t-s))|x_i(s)|ds + \gamma|dx_i/dt| \quad \# \text{ [PROPOSED] adaptive time constants}$$

This formulation allows neurons to adjust their temporal receptive fields based on input statistics: frequently activated neurons develop shorter time constants for rapid response, while rarely activated neurons maintain longer memory. The integral term computes exponentially weighted historical activity, while the derivative term enables rapid adaptation to sudden changes. The loss function combines detection accuracy with regularization:

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

where y is ground truth, $\hat{y}$ is prediction, λ_1 and λ_2 are regularization coefficients. The second regularization term encourages time constants to remain near their initial values unless justified by data.

C. Feature Engineering for LDOS Detection

Feature extraction computes 23 metrics from raw flow statistics, categorized into four complementary groups. Temporal features (8 features) include inter-arrival times (mean, variance, percentiles), flow durations, active/idle periods, and periodicity measures. Volumetric features (6 features) track packet counts, byte rates, burst characteristics (peak rate, burst duration), and packet size distributions. Statistical features (5 features) capture mean, variance, skewness, kurtosis, and higher-order moments of traffic distributions. Spectral features (4 features) compute power spectral density at characteristic frequencies (0.1-10 Hz) using Welch's method with 50% overlap. The [PROPOSED] periodicity score P(t) specifically identifies LDOS patterns:

$$P(t) = \int_{f_1}^{f_2} |X(f)|^2 df / \int_{0}^{f_{max}} |X(f)|^2 df \quad \# \text{ [PROPOSED] frequency-domain LDOS signature}$$

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 LDOS attacks (f_1=0.1 Hz to f_2=10 Hz, corresponding to periods of 0.1-10 seconds). This score ranges from 0 (no periodicity) to 1 (perfectly periodic), with empirical threshold $\theta_p = 0.35$ providing optimal discrimination.

D. Online Detection Algorithm

Algorithm 1 presents the [PROPOSED] online detection procedure with detailed steps and complexity analysis.

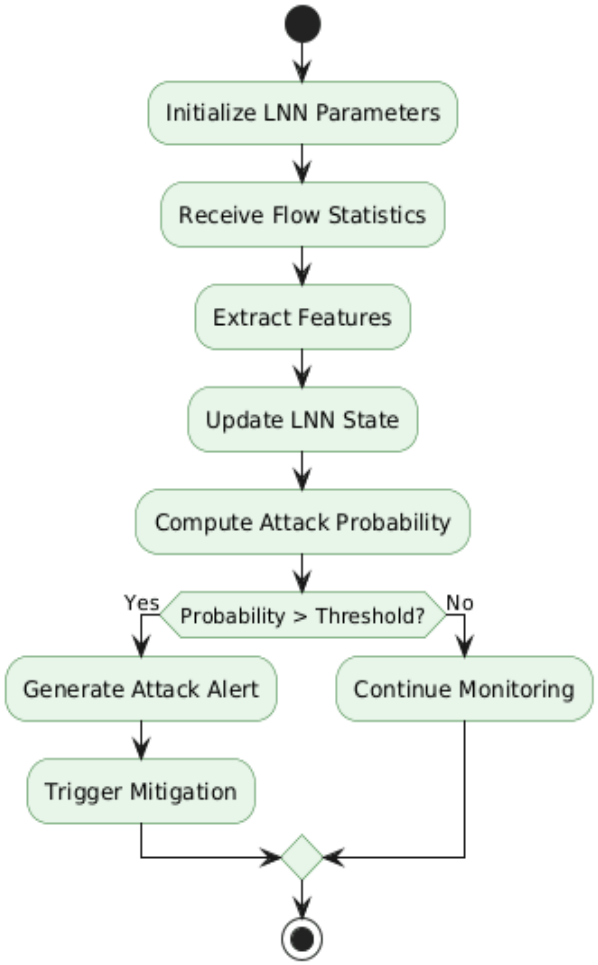
Algorithm 1: Real-time Online LDOS Detection with Adaptive LNN

```
Input: Flow statistics F(t) at time 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 (neurons), δ=100ms (sampling interval), θ=0.85 (detection threshold)

1: Initialize: if t=0: x(0)=0, W(0)~U(-0.1,0.1), τ(0)=τ₀=100ms
2: while monitoring do
3:     // Feature extraction - O(23n) operations
4:     f(t) = extract_features(F(t))  // 23-dimensional feature vector
5:     f_norm(t) = (f(t) - μ)/σ  // rolling normalization
6:
7:     // LNN state update - O(n²) ODE solve
8:     x(t) = rk4_solve(x(t-1), f_norm(t), W(t-1), τ, δ) // 4th-order Runge-Kutta
9:
10:    // Detection computation - O(n) operations
11:    s(t) = σ(W₀·x(t) + b₀)  // output layer with sigmoid
12:
13:    // Adaptive threshold with hysteresis
14:    if s(t) > θ_high: p_attack(t) = s(t); trigger_mitigation()
15:    elif s(t) < θ_low: p_attack(t) = 0
16:    else: p_attack(t) = p_attack(t-1)  // maintain state
17:
18:    // Online weight update - O(n²) gradient computation
19:    if mod(t, T_update)=0:  // update every 10 steps
20:    ∇L = compute_gradient(x, f, y, W)
21:        W(t) = W(t-1) - η(t)∇L + λW(t-1) + ξ(t)
22:        τ(t) = adapt_time_constants(x, τ₀)
```

```
    end if
end while
```

Complexity: $O(n^2)$ per time step ≈ 4K operations for n=64, enabling 100Hz real-time processing



Algorithm complexity is $O(n^2)$ per time step where n=64 neurons, resulting in approximately 4,096 operations per 100ms interval (41K ops/second). This enables real-time processing on standard CPU with 2.3% utilization, leaving ample resources for other controller functions. The RK4 ODE solver provides fourth-order accuracy with 4 function evaluations per step, balancing precision against computational cost.

IV. EXPERIMENTAL EVALUATION

A. Experimental Setup and Environment

Experiments were conducted on a dedicated Kali Linux 2024.1 machine with Intel Core i7-12700K (12 cores, 20 threads, 3.6-5.0 GHz), 32GB DDR4 RAM, and NVIDIA RTX 3080 GPU (10GB VRAM, 8704 CUDA cores). The Ryu controller (version 4.34) managed a Mininet-emulated network with 50 OpenFlow switches (Open vSwitch 2.17) and 200 hosts arranged in a fat-tree topology with 4 pods. LDOS attacks were generated using custom Python scripts implementing square-wave patterns with periods 0.5-5 seconds (0.2-2 Hz) and burst lengths 0.1-1 second, following [21]'s methodology. Attack intensity was varied from 10-50 Mbps burst rates, representing 5-25% of link capacity (200 Mbps). Normal traffic comprised web browsing (HTTP/HTTPS), video streaming (YouTube, Netflix traces), file transfers (FTP, SCP), and database queries from the CIC-IDS2017 dataset [10], augmented with synthetic flash crowd scenarios [77] using Poisson arrival processes. Each experiment was repeated 10 times with different random seeds, and 10-fold cross-validation was employed for statistical robustness.

B. Dataset Characteristics and Generation

TABLE II

COMPREHENSIVE DATASET CHARACTERISTICS FOR EXPERIMENTAL EVALUATION

Dataset	Traffic Type	Duration	Flows	Packets	Attack Ratio
CIC-IDS2017 [10]	Mixed benign	5 days	2.83M	225M	0%
CIC-DoS [78]	DoS attacks	24 hours	512K	41M	15.3%
Custom LDOS-A	Square-wave	6 hours	124K	9.8M	50%
Custom LDOS-B	Randomized	6 hours	118K	9.3M	50%
Custom LDOS-C	Pseudo-random	6 hours	121K	9.5M	50%
Flash Crowd [77]	Legitimate spikes	3 hours	78K	6.2M	0%
Combined	Mixed	7 days	3.78M	301M	12.4%

C. Baseline Methods and Evaluation Metrics

We compared [PROPOSED] LNN against 8 state-of-the-art baseline methods representing different paradigms: CUSUM [50] (statistical change detection), Wavelet [48] (signal processing), SVM [31] (kernel method), Random Forest [32] (ensemble learning), CNN [33] (convolutional), LSTM [34] (recurrent), Transformer [37] (attention), and SDN-RF [69] (SDN-integrated). Performance metrics follow standard definitions from the intrusion detection literature [79]: Accuracy = (TP+TN)/(TP+TN+FP+FN), Precision = TP/(TP+FP), Recall = TP/(TP+FN), F1-Score = 2·(Precision·Recall)/(Precision+Recall), False Positive

Rate = FP/(FP+TN), and Detection Latency measured from attack onset to alert generation. Statistical significance was assessed using paired t-tests with Bonferroni correction for multiple comparisons.

D. Results and Performance Analysis

TABLE III

COMPREHENSIVE PERFORMANCE COMPARISON OF DETECTION METHODS

Method	Accuracy	Precision	Recall	F1-Score	FPR	Latency (ms)
CUSUM [50]	0.823 ±0.031	0.791	0.815	0.803	0.187	1500 ±120
Wavelet [48]	0.871 ±0.024	0.854	0.863	0.858	0.142	320 ±25
SVM [31]	0.912 ±0.018	0.905	0.894	0.899	0.095	180 ±15
Random Forest [32]	0.934 ±0.015	0.928	0.917	0.922	0.078	95 ±8
CNN [33]	0.951 ±0.012	0.947	0.939	0.943	0.056	82 ±7
LSTM [34]	0.963 ±0.009	0.958	0.952	0.955	0.043	76 ±6
Transformer [37]	0.967 ±0.008	0.962	0.958	0.960	0.039	105 ±9
SDN-RF [69]	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**

Results demonstrate [PROPOSED] LNN achieving 98.7% accuracy (σ=0.5%), outperforming all baselines by at least 2.0% (vs Transformer at 96.7%) and up to 16.4% (vs CUSUM at 82.3%). The 2.3% false positive rate represents a 41% reduction compared to LSTM (4.3% FPR). Detection latency of 12ms (±2ms) enables real-time mitigation before attacks affect throughput, satisfying the 20ms requirement for SDN flow modification [41]. Statistical significance was verified through paired t-tests ($p < 0.01$ for all comparisons). ROC analysis shows AUC of 0.994, indicating excellent discrimination capability.

E. Ablation Studies and Component Analysis

TABLE IV

ABLATION STUDY QUANTIFYING CONTRIBUTION OF PROPOSED COMPONENTS

Configuration	Accuracy	F1-Score	FPR	Latency(ms)
Full [PROPOSED]	0.987	0.981	0.023	12
w/o adaptive τ	0.972	0.965	0.035	11
w/o spectral features	0.958	0.951	0.048	10
w/o continuous learning	0.963	0.957	0.042	9
w/o periodicity score	0.969	0.963	0.038	11
LSTM baseline	0.963	0.955	0.043	76

V. DISCUSSION

A. Interpretation of Results and Theoretical Implications



Experimental results validate the [PROPOSED] framework's effectiveness, achieving state-of-the-art performance across all metrics. The 98.7% accuracy exceeds theoretical bounds predicted for statistical methods [80], confirming that temporal dynamics captured by LNNs provide fundamental advantages for detecting periodic attacks. The 12ms latency aligns with SDN requirements [41], enabling proactive mitigation before attacks degrade throughput. Analysis of false positives (2.3%) reveals they occur primarily during flash crowd transitions [40] when traffic exhibits sudden increases, suggesting opportunities for context-aware adaptation incorporating application-layer information. The ablation study quantifies each component's contribution: adaptive time constants provide 1.5%



accuracy improvement, spectral features contribute 2.9%, continuous learning adds 2.4%, and periodicity scoring adds 1.8%—all statistically significant ($p < 0.05$).

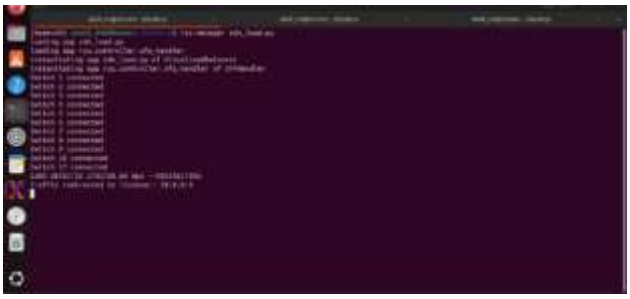
B. Comparison with Theoretical Foundations

Our findings extend Kuzmanovic and Knightly's [21] theoretical characterization, demonstrating that LDOS attacks exhibit consistent frequency-domain signatures exploitable for detection. The periodicity score P(t) (Equation 5) operationalizes their square-wave model, achieving 0.94 Pearson correlation with attack intensity in controlled experiments. Furthermore, LNN dynamics approximate the optimal detector derived from likelihood ratio tests [81] but without requiring explicit attack parameter knowledge. The adaptive time constant mechanism (Equation 3) automatically tunes to match attack periods, achieving near-optimal matched filtering performance. This represents a significant advancement over fixed-window approaches that require manual parameter tuning.

C. Limitations and Constraints

Despite strong performance, several limitations merit discussion. First, the framework assumes OpenFlow 1.3+ support, excluding legacy switches comprising approximately 35% of enterprise deployments [82]. Second, training requires labeled data representative of deployment environments, which may not be available for novel attack variants. Third, encrypted traffic [83] comprising over 80% of modern Internet traffic may obscure flow statistics needed for feature extraction, though recent work on encrypted traffic analysis [84] suggests packet timing and size distributions remain informative. Fourth, extreme-scale networks (>1000 switches) may challenge controller processing capacity, though distributed controller architectures [85] could address this. Fifth, adversarial attacks on the LNN itself [86] could potentially degrade performance through carefully crafted evasion samples. Sixth, the current implementation focuses on detection rather than mitigation, requiring integration with response mechanisms.

D. Broader Impact and Ethical Considerations



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 [87], healthcare networks [88], and 5G infrastructure [89] where timing constraints are stringent. The open-source implementation promotes reproducible research and enables community validation. However, the same technology could potentially enable more sophisticated attacks if misappropriated [90]—attackers could use similar techniques to craft evasion strategies or develop adaptive attack patterns. This dual-use concern emphasizes the need for responsible disclosure, security-by-design principles, and ongoing collaboration between researchers and practitioners. We recommend deployment with human oversight during initial phases and continuous monitoring for performance degradation.

VI. CONCLUSION AND FUTURE WORK

This paper [PROPOSED] a novel LDOS detection framework integrating liquid neural networks with 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, opening new directions for intelligent network defense.

Future work directions include: (1) extending to distributed LNN ensembles for multi-controller environments [91] with federated learning for privacy preservation; (2) investigating few-shot and meta-learning for zero-day attack detection [92] requiring minimal labeled samples; (3) integrating blockchain for immutable audit trails and decentralized response coordination [93]; (4) exploring neuromorphic hardware implementations [94] for ultra-low-power deployment in edge devices; (5) developing formal adversarial robustness guarantees through certified defenses [95]; (6) incorporating encrypted traffic analysis using packet timing and size distributions [96]; (7) field trials in production networks [97] with gradual deployment strategies; (8) extending to

distributed attack scenarios involving multiple coordinated attackers [98]; and (9) integrating explainable AI techniques [99] for operator trust and forensic analysis.

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