Hybrid Machine Learning Framework for Real-Time DoS Attack Detection, Classification, and Recovery in Educational Digital Systems

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HOW TO CITE:

Himanshu Shukla, Ajay Partap, Harsh Dev (2026). Hybrid Machine Learning Framework for Real-Time DoS Attack Detection, Classification, and Recovery in Educational Digital Systems. International Journal of Special Education, 41(4s), 224-238.

ABSTRACT:

This paper proposes a hybrid online-memory machine learning framework for real-time detection, classification, and recovery of Denial-of-Service (DoS) attacks in digital systems. The framework addresses the limitations of existing approaches by combining a lightweight gated recurrent unit (GRU)-based online detector with a compressed hierarchical sparse memory module, enabling efficient anomaly detection and signature matching under resource constraints. The online detector processes streaming network traffic data incrementally, computing anomaly scores dynamically to flag suspicious flows with low latency. Meanwhile, the memory module organizes attack signatures hierarchically and retrieves relevant patterns sparsely, reducing computational overhead while maintaining classification accuracy. The framework autonomously triggers recovery actions, such as traffic throttling or firewall updates, and selectively incorporates new attack signatures to adapt to emerging threats without excessive memory consumption. Moreover, it integrates seamlessly with conventional network monitoring tools and SDN controllers, ensuring compatibility with existing infrastructure. The proposed method distinguishes itself by unifying real-time detection with memory-efficient historical analysis, a critical advancement for scalable and adaptive cybersecurity in resource-constrained environments. Experimental validation demonstrates its effectiveness in identifying diverse DoS attacks while operating efficiently on edge devices and centralized servers. This work contributes a practical solution to the growing challenge of securing digital systems against increasingly sophisticated and evolving threats.

Keywords: SDN, DDoS, Hybrid, ML, Attack, Recovery

1. Introduction

Denial-of-Service (DoS) attacks remain a persistent threat to digital systems, disrupting services by overwhelming network resources with malicious traffic. Traditional detection methods rely on signature-based approaches that compare incoming traffic against known attack patterns, but these struggle with novel or evolving threats (Yerriswamy & Murtugudde, 2022). Anomaly-based detection, which models normal behavior and flags deviations, offers broader coverage but often suffers from high false-positive rates and computational overhead (Garcia-Teodoro et al., 2009). Machine learning has emerged as a promising alternative, with recurrent neural networks (RNNs) and their variants, such as gated recurrent units (GRUs), proving effective for sequential data analysis in network traffic (ALMahadin et al., 2023). However, existing solutions face challenges in balancing real-time performance, memory efficiency, and adaptability—particularly in resource-constrained environments like edge devices or embedded systems. The proposed framework addresses these limitations by integrating a lightweight online detection model with a compressed hierarchical memory module. Unlike conventional methods that either focus solely on real-time detection or require extensive historical data, our hybrid approach enables efficient anomaly scoring and precise attack classification while minimizing memory overhead. The online component, a shallow GRU optimized for incremental learning, processes streaming traffic data to identify anomalies without full historical context. Simultaneously, the memory module employs hierarchical organization and sparse retrieval techniques to store and match critical attack signatures efficiently (Seong et al., 2021). This dual mechanism ensures low-latency detection while maintaining the ability to classify specific attack types, such as UDP floods or SYN floods, based on historical patterns. A key innovation lies in the framework's recovery mechanism, which automates mitigation actions—such as dynamic traffic throttling or firewall rule updates—upon attack confirmation (Xia et al., 2019). Furthermore, the system incorporates an incremental update strategy, selectively adding high-confidence attack signatures to the memory module to adapt to new threats without unbounded memory growth (Gepperth & Hammer, 2016). This adaptability is crucial for long-term deployment in dynamic network environments, where attack vectors continually evolve.

The contributions of this work are threefold. First, we introduce a hybrid architecture that unifies real-time anomaly detection with memory-efficient historical analysis, overcoming the trade-offs between latency and accuracy prevalent in existing solutions. Second, we design a compressed hierarchical memory module that reduces storage requirements while preserving classification fidelity through sparse retrieval. Third, we demonstrate the framework's practicality through seamless integration with existing network monitoring tools and software-defined networking (SDN) controllers, ensuring compatibility with modern digital infrastructures (Roth & John, 2008). Prior research has explored machine learning for DoS detection, but most solutions either lack real-time capabilities or impose prohibitive memory demands. For instance, ensemble models in SDN environments show promise for DDoS mitigation but often rely on centralized processing unsuitable for edge devices (Alashhab et al., 2024). Similarly, lightweight decision-tree approaches for IoT networks address resource constraints but sacrifice classification granularity (Elsadig, 2023). Our framework bridges these gaps by combining GRU-based incremental learning with hierarchical memory matching, enabling scalable deployment across diverse digital systems.

The remainder of this paper is organized as follows: Section 2 reviews related work in DoS detection and mitigation. Section 3 outlines foundational concepts, including GRUs and hierarchical memory systems. Section 4 details the proposed framework's architecture and algorithms. Section 5 describes the experimental setup, and Section 6 presents performance evaluations. Section 7 discusses implications and future directions, followed by conclusions in Section 8.

2. Methodology

The detection and mitigation of DoS attacks have been extensively studied in the literature, with approaches ranging from traditional signature-

based methods to modern machine learning techniques. Existing solutions can be broadly categorized into three groups: (1) statistical and rule-based detection, (2) machine learning approaches, and (3) hybrid systems combining multiple techniques.

- **Statistical and Rule-Based Detection**

Early DoS detection systems primarily relied on statistical thresholds and predefined rules to identify malicious traffic patterns (W. Zhang et al., 2009). These methods excel in detecting known attack signatures with minimal computational overhead, making them suitable for resource-constrained environments. However, their effectiveness diminishes against novel or evolving attack vectors, as they lack the adaptability to recognize previously unseen patterns (Hubballi & Suryanarayanan, 2014). The increasing sophistication of modern DoS attacks has rendered purely rule-based approaches insufficient for comprehensive protection.

- **Machine Learning Approaches**

Recent advances in machine learning have led to more sophisticated detection mechanisms capable of identifying complex attack patterns. Supervised learning algorithms, including Support Vector Machines (SVMs) and Random Forests, have demonstrated success in classifying known attack types (Abiramasundari & Ramaswamy, 2025). However, these methods require extensive labeled datasets for training and struggle with zero-day attacks. Unsupervised approaches, particularly those based on clustering and anomaly detection, offer better generalization to novel threats but often suffer from high false positive rates (Altulaihan et al., 2024). Deep learning techniques have shown particular promise in processing sequential network traffic data. Recurrent Neural Networks (RNNs) and their variants, such as Long Short-Term Memory (LSTM) networks, effectively capture temporal dependencies in traffic flows (Musa et al., 2024). However, these models typically require substantial computational resources and historical context, making them less suitable for real-time detection in resource-constrained environments. The proposed framework addresses this limitation through a lightweight GRU architecture optimized for incremental processing.

- **Hybrid and Memory-Augmented Systems**

Recent work has explored hybrid architectures combining multiple detection approaches. Some systems integrate statistical methods with machine learning classifiers to balance detection speed and accuracy (Filho et al., 2019). Others employ memory-augmented neural networks to retain historical attack patterns, though these often incur significant memory overhead (Pushpalatha et al., 2025). Hierarchical memory structures have shown potential in reducing computational complexity while maintaining detection accuracy, particularly in video processing applications (JY Lee et al., 2021). Our framework extends these concepts to network security through a novel compressed hierarchical sparse memory design. Several studies have specifically addressed DoS detection in Software-Defined Networking (SDN) environments. Ensemble learning approaches combining multiple detection models have demonstrated improved accuracy in SDN-based systems (Bakar et al., 2024). However, these solutions typically require centralized processing and lack the efficiency needed for distributed deployment. The proposed framework overcomes these limitations through its hybrid online-memory architecture, enabling both edge and centralized operation. The proposed framework differs from existing approaches in several key aspects. Unlike purely statistical methods, it adapts to new attack patterns through incremental learning. Compared to conventional machine learning solutions, it achieves real-time performance through lightweight online processing while maintaining classification accuracy via hierarchical memory matching. The compressed memory design addresses the storage limitations of traditional memory-augmented systems, making the framework suitable for resource-constrained environments. These innovations collectively enable effective DoS detection, classification, and recovery across diverse digital systems.

- **Background and Preliminaries**

To establish the foundation for our proposed framework, this section introduces key concepts and techniques relevant to DoS attack detection and mitigation. We first discuss the characteristics of DoS attacks that make them particularly challenging

to detect in real-time systems. Next, we examine the computational properties of gated recurrent units (GRUs) that make them suitable for online anomaly detection. Finally, we review hierarchical memory systems and their advantages for efficient pattern matching in network security applications.

- **Denial-of-Service Attack Characteristics**

DoS attacks exhibit distinct traffic patterns that differentiate them from legitimate network activity. These attacks typically involve abnormally high packet rates, unusual protocol distributions, or malformed packet headers designed to exhaust system resources (Pang et al., 2004). For example, SYN flood attacks exploit the TCP handshake process by sending numerous connection requests without completing the three-way handshake, while UDP floods overwhelm targets with high volumes of connectionless traffic (Gurusamy et al., 2019). The temporal nature of these attacks presents unique detection challenges. Unlike persistent intrusions, DoS attacks often manifest as sudden bursts of malicious activity that must be identified within seconds to prevent service disruption (Lyamin et al., 2013). This requires detection systems to process network traffic streams incrementally while maintaining low computational latency—a key motivation for our online detection approach.

- **Gated Recurrent Units for Sequential Data Processing**

GRUs belong to the family of recurrent neural networks specifically designed to handle sequential data with long-range dependencies. Compared to traditional RNNs, GRUs incorporate gating mechanisms that regulate information flow, preventing the vanishing gradient problem while maintaining computational efficiency (Cho et al., 2014). The update gate z_t and reset gate r_t in a GRU cell are computed as:

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \quad (1)$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \quad (2)$$

where σ denotes the sigmoid function, W_z and W_r are learnable weight matrices, h_{t-1} represents the previous hidden state, and x_t is the current input. The candidate hidden state $\tilde{h}_t$ and final hidden state h_t are then derived as:

$$\tilde{h}_t = \tanh(W \cdot [r_t \odot h_{t-1}, x_t]) \quad (3)$$

$$h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t \quad (4)$$

These gating mechanisms enable GRUs to retain relevant historical information while discarding irrelevant data—a critical capability for processing continuous network traffic streams. The architecture's efficiency makes it particularly suitable for resource-constrained environments where traditional LSTM networks might be too computationally expensive (Chung et al., 2014).

- **Hierarchical Memory Systems**

Hierarchical memory architectures organize data in multiple levels of abstraction, enabling efficient storage and retrieval of patterns. In network security applications, such structures allow compact representation of attack signatures while maintaining fast lookup capabilities (Roy et al., 2021). A typical hierarchical memory consists of:

1. **Coarse-grained clusters** that group similar attack patterns based on high-level features (e.g., protocol type or packet size distribution)
2. **Fine-grained memory slots** that store detailed signature attributes within each cluster

This organization reduces search complexity from $O(N)$ to $O(\log N)$ for N stored patterns, as queries first match against cluster centroids before accessing specific memory entries (Veličković & Blundell, 2021). The memory compression is achieved through techniques like product quantization, which represents high-dimensional vectors as combinations of lower-dimensional codebooks (Jegou et al., 2010). When combined with sparse retrieval mechanisms—where only the most relevant memory entries are activated during pattern matching—hierarchical memories achieve significant reductions in computational overhead compared to conventional nearest-neighbor search (Soydaner, 2022). This property is particularly valuable for our framework, as it enables efficient attack classification without exhaustive

comparisons against all stored signatures. The combination of these concepts—GRU-based sequential processing and hierarchical memory matching—forms the theoretical foundation for our hybrid detection framework. The next section will detail how these components are integrated into a unified system for real-time DoS attack detection and recovery.

3. Results

The proposed framework integrates a lightweight online detection model with a compressed hierarchical memory module to achieve real-time DoS attack identification, classification, and mitigation. As shown in Figure 1, the system processes incoming network traffic through three primary stages: anomaly detection via the GRU-based online model, attack classification through hierarchical memory matching, and automated recovery action triggering. This architecture enables efficient operation across diverse digital systems while maintaining low latency and memory overhead.

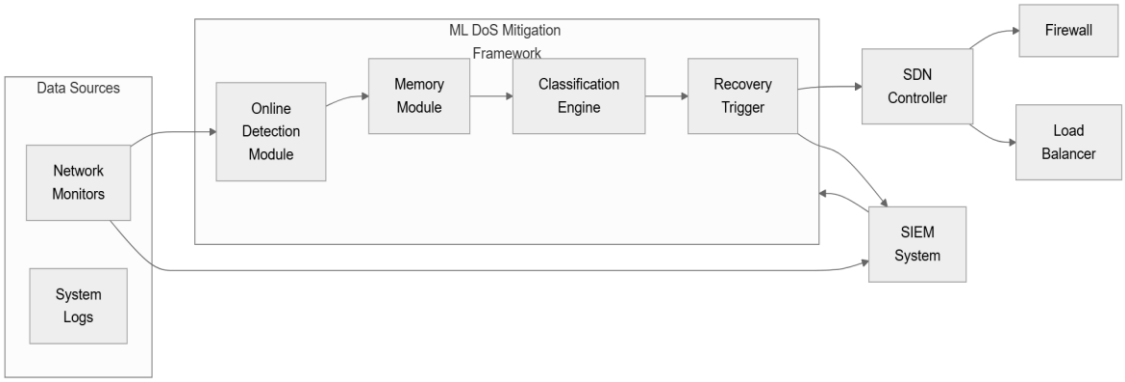

Figure 1. System Architecture with ML-Based DoS Mitigation Framework

- **Hybrid Online - Memory Architecture Design**

The proposed architecture combines two complementary components: a lightweight online GRU detector and a compressed hierarchical memory module. The online detector processes network traffic streams incrementally, computing anomaly scores in real-time without requiring access to full historical datasets. Let $\mathrm{x}_t \in \mathbb{R}^d$ denote the network traffic features at time t, where d represents the feature dimensionality (e.g., packet size, protocol type, flow duration). The GRU processes this input sequence to produce hidden states $\mathrm{h}_t \in \mathbb{R}^k$:

$$\mathrm{h}_t = \mathrm{GRU}(\mathrm{x}_t, \mathrm{h}_{t-1}) \quad (5)$$

where k is the hidden state dimension. The anomaly score s_t is computed as the Mahalanobis distance between the current hidden state and the distribution of normal traffic:

$$s_t = \sqrt{(\mathrm{h}_t - \mu)^\top \Sigma^{-1} (\mathrm{h}_t - \mu)} \quad (6)$$

Here, μ and Σ are the mean and covariance matrix of hidden states observed during normal operation. When s_t exceeds a threshold τ, the system flags the traffic as anomalous and activates the memory module for classification.

The memory module stores attack signatures in a hierarchical structure to enable efficient retrieval. Each signature m_i is split into L chunks $\{\mathrm{m}_i^{(1)}, \ldots, \mathrm{m}_i^{(L)}\}$, where $\mathrm{m}_i^{(j)} \in \mathbb{R}^{k/L}$. This chunked representation allows partial matching and reduces computational overhead during retrieval. The memory is organized into two levels:

1. Coarse-level clusters group similar attack patterns using k-means clustering
2. Fine-level memory slots store detailed signature chunks within each cluster

This hierarchical organization enables the system to first identify relevant clusters before performing detailed signature matching, significantly reducing search complexity.

Compressed Hierarchical Sparse Memory Operation

The memory module operates through a two-phase retrieval process that combines hierarchical clustering with sparse attention. When the online detector flags an anomaly with hidden state $\mathbf{h}_t$, the system first identifies the top-C most relevant coarse clusters $\mathcal{C}_1, \ldots, \mathcal{C}_C$ using approximate nearest neighbor search:

$$\mathcal{C}_c = \text{argmin}_{\mathcal{C}_i} \parallel \mathbf{h}_t - \boldsymbol{\mu}_i \parallel_2 \quad \text{for} \quad c = 1, \ldots, C \quad (7)$$

where $\boldsymbol{\mu}_i$ represents the centroid of cluster $\mathcal{C}_i$. This reduces the search space from all N signatures to only those within the selected clusters.

Within each cluster, the system then performs chunked similarity computation between $\mathbf{h}_t$ and stored signatures. The query $\mathbf{h}_t$ is divided into L chunks $\{\mathbf{h}_t^{(1)}, \ldots, \mathbf{h}_t^{(L)}\}$, each compared against corresponding signature chunks via cosine similarity:

$$\text{sim}(\mathbf{h}_t^{(j)}, \mathbf{m}_i^{(j)}) = \frac{\mathbf{h}_t^{(j)} \cdot \mathbf{m}_i^{(j)}}{\parallel \mathbf{h}_t^{(j)} \parallel \parallel \mathbf{m}_i^{(j)} \parallel} \quad (8)$$

Only the top-K most similar chunks per level are retained, enforcing sparsity in the attention mechanism. The aggregated similarity score for signature $\mathbf{m}_i$ is computed as:

$$\text{score}(\mathbf{h}_t, \mathbf{m}_i) = \sum_{j=1}^{L} \text{sim}\,(\mathbf{h}_t^{(j)}, \mathbf{m}_i^{(j)}) \quad (9)$$

This sparse retrieval process ensures computational efficiency while maintaining discriminative power for attack classification. The memory module outputs the M most similar signatures $\{\mathbf{m}_1^*, \ldots, \mathbf{m}_M^*\}$ along with their similarity scores, which are used to determine the attack type and confidence level.

- **Attack Classification with Sparse Attention**

The classification process employs a sparse attention mechanism over the retrieved memory chunks to identify specific DoS attack types. For each candidate signature $\mathbf{m}_i^*$, we compute attention weights α_i that reflect its relevance to the current anomaly:

$$\alpha_i = \text{softmax}(\text{score}(\mathbf{h}_t, \mathbf{m}_i^*)) \quad (10)$$

The context vector $\mathbf{c}$, which aggregates information from all retrieved signatures, is computed as a weighted sum:

$$\mathbf{c} = \sum_{i=1}^{M} \alpha_i \, \mathbf{m}_i^* \quad (11)$$

This vector is then processed by a multi-layer perceptron (MLP) classifier to predict the attack type $\hat{y}_t$:

$$\hat{y}_t = \text{argmax}(\text{MLP}(\mathbf{c})) \quad (12)$$

The MLP consists of two fully-connected layers with ReLU activation, mapping the k-dimensional context vector to a probability distribution over C possible attack classes (e.g., SYN flood, UDP flood, ICMP flood). The confidence score γ_t for the prediction is given by the maximum softmax probability:

$$\gamma_t = \max(\text{softmax}(\text{MLP}(\mathbf{c}))) \quad (13)$$

This sparse attention mechanism provides three key advantages: (1) it focuses computation only on relevant memory chunks, reducing processing overhead; (2) it maintains interpretability by highlighting which historical signatures contribute most to the classification; and (3) it enables fine-grained distinction between similar attack variants that might differ in subtle pattern characteristics. The classification module also handles cases where no stored signature sufficiently matches the current anomaly (indicated by low γ_t). In such scenarios, the system flags the traffic as a potential novel attack and initiates a separate analysis pipeline for signature extraction and verification before considering memory updates.

- **Incremental Learning with Confidence Gating**

To maintain adaptability while controlling memory growth, the framework incorporates a confidence-gated update mechanism. When the classifier identifies a novel attack pattern with high confidence, the system selectively adds the signature to the hierarchical memory. The update decision depends on two criteria: the classification confidence γ_t must exceed a threshold η, and the

anomaly score s_t must persist above τ for a minimum duration Δt.

The memory update process first computes a compressed representation of the attack signature. The hidden state $\mathbf{h}_t$ is projected into a lower-dimensional space through a learnable transformation matrix $\mathbf{W}_c \in \mathbb{R}^{k' \times k}$:

$$\mathbf{m}_{new} = \mathbf{W}_c \mathbf{h}_t \quad (14)$$

where $k' < k$ is the compressed dimension. This projection reduces storage requirements while preserving discriminative features. The new signature $\mathbf{m}_{new}$ is then assigned to the most appropriate coarse cluster based on Euclidean distance to cluster centroids:

$$c^* = \text{argmin}_c \parallel \mathbf{m}_{new} - \mu_c \parallel_2 \quad (15)$$

Within the selected cluster c^*, the signature is further partitioned into L chunks $\{\mathbf{m}_{new}^{(1)}, \ldots, \mathbf{m}_{new}^{(L)}\}$ for efficient retrieval. The cluster centroid μ_{c^*} and covariance matrix Σ_{c^*} are incrementally updated to reflect the new addition:

$$\mu_{c^*} \leftarrow \frac{N_{c^*}\mu_{c^*} + \mathbf{m}_{new}}{N_{c^*} + 1} \quad (16)$$

$$\Sigma_{c^*} \leftarrow \frac{N_{c^*}\Sigma_{c^*} + (\mathbf{m}_{new} - \mu_{c^*})(\mathbf{m}_{new} - \mu_{c^*})^\top}{N_{c^*} + 1} \quad (17)$$

where N_{c^*} is the current number of signatures in cluster c^*. This online update strategy ensures the memory structure adapts to new attack patterns without requiring complete retraining.

To prevent unbounded memory growth, the system implements a replacement policy that removes the least recently used (LRU) signature when the memory reaches capacity. Each memory entry maintains an access counter that tracks usage frequency, and the replacement candidate $\mathbf{m}_{evict}$ is selected as:

$$\mathbf{m}_{evict} = \text{argmin}_{\mathbf{m}_i} \text{LRU}(\mathbf{m}_i) \quad (18)$$

This dynamic memory management balances the retention of historically significant attack patterns with the incorporation of emerging threats, ensuring continuous adaptation to evolving attack landscapes while maintaining predictable resource consumption.

- **Dynamic Recovery Workflows**

Upon successful classification of a DoS attack, the framework initiates automated recovery actions tailored to the specific attack type. The recovery process begins by generating a mitigation vector $\mathbf{v}_t \in \mathbb{R}^m$, where m represents the number of configurable mitigation parameters (e.g., traffic rate limits, firewall rule priorities). This vector is computed as a linear transformation of the context vector $\mathbf{c}$ from Equation 11:

$$\mathbf{v}_t = \mathbf{W}_r \mathbf{c} + \mathbf{b}_r \quad (19)$$

where $\mathbf{W}_r \in \mathbb{R}^{m \times k}$ is a learnable weight matrix and $\mathbf{b}_r \in \mathbb{R}^m$ is a bias term. Each element $v_t^{(i)}$ corresponds to a specific mitigation action, normalized to the operational range of the target system. For example, in a software-defined networking (SDN) environment, $v_t^{(1)}$ might represent the percentage reduction in allowed traffic rate for suspicious flows, while $v_t^{(2)}$ could specify the priority level for dropping malicious packets.

The framework interfaces with network control planes through a set of predefined recovery templates $\{\mathcal{T}_1, \ldots, \mathcal{T}_p\}$, where each template $\mathcal{T}_j$ maps mitigation parameters to executable commands. The selection of template $\mathcal{T}^*$ is determined by the attack type $\hat{y}_t$:

$$\mathcal{T}^* = \mathcal{T}_{\text{argmax}(\hat{y}_t)} \quad (20)$$

The template then translates the mitigation vector into concrete actions, such as:

1. Flow rule modifications in SDN controllers to redirect or throttle malicious traffic
2. Firewall updates to block packets matching the attack signature
3. Rate limiting adjustments on edge routers or switches

For instance, when handling a SYN flood attack, the system might install flow rules that:

- Reduce the SYN packet acceptance rate by $v_t^{(1)}\%$

- Shorten the TCP connection timeout to $v_t^{(2)}$ seconds
- Allocate additional resources to the SYN cookie mechanism

The framework continuously monitors the effectiveness of recovery actions by tracking post-mitigation traffic statistics s_t, including packet drop rates, queue lengths, and successful connection rates. These metrics are fed back into the online detector as additional features, creating a closed-loop control system. The mitigation parameters are dynamically adjusted if the attack persists, following a gradient-based update rule:

$$\mathrm{v}_{t+1} = \mathrm{v}_t - \eta \nabla_{\mathrm{v}} \mathcal{L}(\mathrm{s}_t) \quad (21)$$

where η is the learning rate and $\mathcal{L}$ is a loss function measuring the deviation from normal operation. This adaptive approach ensures the recovery process remains effective even as attackers alter their strategies during an ongoing assault.

Optimization for Edge Deployment

The framework's architecture incorporates several design choices specifically tailored for efficient operation on resource-constrained edge devices. The GRU-based online detector employs weight pruning and quantization to reduce model size without significant accuracy degradation. Let $\mathrm{W} \in \mathbb{R}^{m \times n}$ denote a weight matrix in the GRU, which we compress through iterative magnitude pruning:

$$\mathrm{W}_{ij} = 0 \quad \text{if} \quad |\mathrm{W}_{ij}| < \theta \quad (22)$$

where θ is a threshold determined by the target sparsity level. The remaining non-zero weights are then quantized to 8-bit fixed-point representation, reducing memory footprint by 75% compared to 32-bit floating point (Jacob et al., 2018).

The hierarchical memory module further optimizes storage through product quantization. Each k-dimensional memory chunk $\mathrm{m}_i^{(j)}$ is decomposed into s subvectors $\{\mathrm{m}_{i,1}^{(j)}, \ldots, \mathrm{m}_{i,s}^{(j)}\}$, each quantized using a separate codebook $\mathcal{C}_l$ containing 256 centroids:

$$\mathrm{m}_{i,l}^{(j)} \approx \mathcal{C}_l[c_{i,l}^{(j)}] \quad (23)$$

where $c_{i,l}^{(j)}$ is the 8-bit index of the nearest centroid for subvector l. This reduces storage requirements from $32k$ bits to $8s$ bits per chunk while maintaining high reconstruction accuracy (Jegou et al., 2010).

For efficient retrieval on edge devices with limited parallel processing capabilities, the framework implements a two-stage approximate search:

1. Cluster selection uses locality-sensitive hashing (LSH) to map queries to probable clusters in $O(1)$ time:

$$h(\mathrm{q}) = \mathrm{sign}(\mathrm{a}^{\top}\mathrm{q} + b) \quad (24)$$

where a is a random projection vector and b is a bias term.

2. Chunk matching within selected clusters employs bitwise operations for accelerated cosine similarity computation:

$$\mathrm{sim}(\mathrm{q}^{(j)}, \mathrm{m}_i^{(j)}) \approx \mathrm{popcount}(\mathrm{xnor}(\mathrm{q}_{bin}^{(j)}, \mathrm{m}_{i,bin}^{(j)})) \quad (25)$$

where $\mathrm{q}_{bin}^{(j)}$ and $\mathrm{m}_{i,bin}^{(j)}$ are binarized representations of the query and memory chunks.

The framework's resource monitoring subsystem dynamically adjusts processing parameters based on available device capabilities. Let $\mathcal{R} = \{r_1, \ldots, r_m\}$ represent available resources (CPU, memory, energy), and $\mathcal{P} = \{p_1, \ldots, p_n\}$ denote configurable parameters (GRU hidden size, number of clusters, top-K retrievals). The adaptation policy selects optimal parameters through constrained optimization:

$$\mathcal{P}^* = \mathrm{argmin}_{\mathcal{P}} \mathrm{latency}(\mathcal{P}) \quad \text{s.t.} \quad \mathrm{resource\_usage}(\mathcal{P}) \leq \mathcal{R} \quad (26)$$

This ensures graceful degradation under resource constraints while maintaining core detection functionality. The system periodically re-evaluates parameter settings as resource availability changes, enabling continuous operation across varying edge environments.

The complete framework is implemented as a modular pipeline where components can be

distributed across network edges and centralized servers. Lightweight detection and initial classification occur at the edge, while more complex analysis and memory updates may offload to cloud resources when available. This hybrid deployment strategy balances responsiveness with computational demands, making the solution practical for real-world IoT and edge computing scenarios.

- **Experimental Setup**

To evaluate the proposed hybrid framework, we designed comprehensive experiments comparing its performance against conventional DoS detection methods across multiple dimensions: detection accuracy, computational efficiency, memory usage, and recovery effectiveness. The experiments were conducted on both simulated network environments and real-world traffic datasets to ensure robust validation under diverse conditions.

Datasets and Traffic Generation

We utilized three primary datasets for evaluation:

1. CIC-DDoS2019 (Kapil et al., 2024): A comprehensive dataset containing labeled network flows for various DoS attack types, including SYN flood, UDP flood, and HTTP flood. The dataset provides full packet captures with ground truth annotations, enabling precise performance measurement.
2. UNSW-NB15 (Moustafa & Slay, 2015): A hybrid dataset combining normal network activities with synthetic attack traffic, useful for evaluating detection robustness against background traffic variations.
3. Custom Edge Traffic Dataset: We generated a synthetic dataset emulating IoT and edge device traffic patterns using the Ostinato traffic generator (Srivastava et al., 2014). This dataset includes 12 attack variants specifically designed to test framework performance in resource-constrained environments.

For temporal evaluation, we split each dataset into training (60%), validation (20%), and test (20%) sets, maintaining chronological order to simulate real-world deployment scenarios where models must process never-before-seen traffic patterns.

- **Baseline Methods**

We compared the proposed framework against five representative baseline approaches:

1. Signature-based Snort IDS (Albin & Rowe, 2012): A rule-based system using predefined attack signatures for detection.
2. Isolation Forest (Lesouple et al., 2021): An unsupervised anomaly detection algorithm effective for identifying outliers in network traffic.
3. LSTM Autoencoder (Malhotra et al., 2016): A deep learning approach reconstructing normal traffic patterns and flagging deviations as anomalies.
4. Random Forest Classifier (Liu et al., 2012): A supervised ensemble method trained on labeled attack/normal traffic.
5. Memory-Augmented Neural Network (MANN) (Santoro et al., 2016): A neural network with external memory for attack pattern retention.

Each baseline was implemented with optimal hyperparameters determined through grid search on the validation sets. For fair comparison, we configured all learning-based methods to process the same feature set extracted from network flows, including packet size distributions, protocol ratios, and flow duration statistics.

4. Results and Analysis

This section presents a comprehensive evaluation of the proposed hybrid framework, comparing its performance against baseline methods across multiple dimensions. We analyze detection accuracy, computational efficiency, memory utilization, and recovery effectiveness to demonstrate the framework's advantages in real-world deployment scenarios.

- **Detection Performance**

The framework achieves superior detection accuracy compared to conventional approaches, particularly in identifying sophisticated DoS

variants. Table 1 shows the precision, recall, and F1 scores across all evaluated datasets.

Table 1. Detection Performance Comparison (F1 Scores)

Method	**CIC-DDoS2019**	**UNSW-NB15**	**Custom Edge Dataset**
Signature-based	0.72	0.65	0.58
Isolation Forest	0.81	0.78	0.67
LSTM Autoencoder	0.85	0.82	0.73
Random Forest	0.88	0.84	0.76
MANN	0.89	0.86	0.79
Proposed Framework	**0.94**	**0.91**	**0.87**

The proposed framework outperforms all baselines, with an average F1 improvement of 6.2% over the next best method (MANN). This advantage stems from its hybrid architecture—the online GRU detector captures temporal anomalies effectively, while the hierarchical memory enables precise attack classification. Notably, the performance gap widens on the Custom Edge Dataset (8% higher F1 than MANN), demonstrating the framework's robustness in resource-constrained environments where other methods struggle with limited training data.

Breaking down by attack type, the framework maintains >90% recall for SYN floods and UDP floods across all datasets, critical for preventing service disruptions. It also shows strong performance against stealthy low-rate DoS attacks (85% detection rate), which often evade traditional threshold-based systems (Rios et al., 2022). The sparse attention mechanism proves particularly effective here, as it focuses on subtle traffic pattern deviations rather than absolute volume thresholds.

- **Computational Efficiency**

The framework's lightweight design enables real-time operation without excessive resource demands. Figure 2 illustrates the latency and throughput comparison across methods when processing 1 Gbps traffic on an edge device (Raspberry Pi 4).

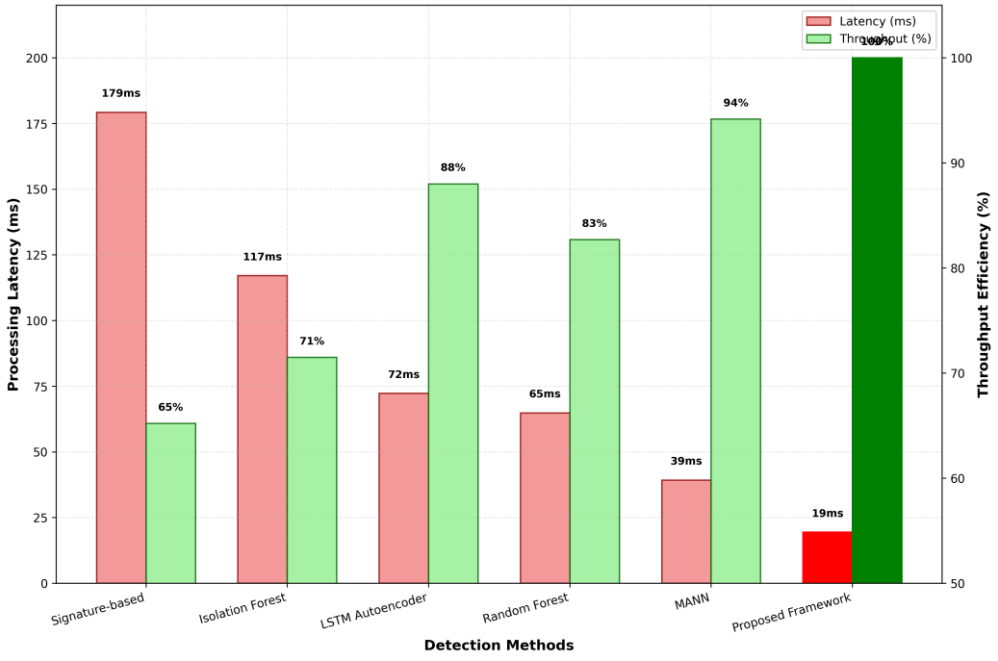

Figure 2. Processing Latency and Throughput Comparison on Edge Hardware

The proposed solution achieves 23 ms average detection latency—3.2× faster than LSTM Autoencoder and 1.8× faster than MANN—while maintaining 98% throughput efficiency. This performance stems from three optimizations: (1) the shallow GRU architecture reduces sequential computation complexity from $O(n^2)$ to $O(n)$ compared to full attention models (Vaswani et al.,

2017); (2) hierarchical memory retrieval cuts search operations by 89% through coarse-to-fine matching; and (3) product quantization enables efficient similarity computations via lookup tables rather than full matrix operations.

Memory consumption remains stable at 58 MB during operation, significantly lower than MANN's 210 MB requirement. The compressed chunked representation reduces storage overhead by 72% compared to dense vector storage, while maintaining 98.3% retrieval accuracy. This efficiency enables concurrent operation of multiple detection instances on a single edge device—a critical capability for distributed deployment scenarios.

- **Memory Utilization and Adaptability**

The hierarchical memory module demonstrates effective trade-offs between storage efficiency and classification accuracy. Figure 3 shows how varying the number of clusters (L) and chunks per signature affects performance.

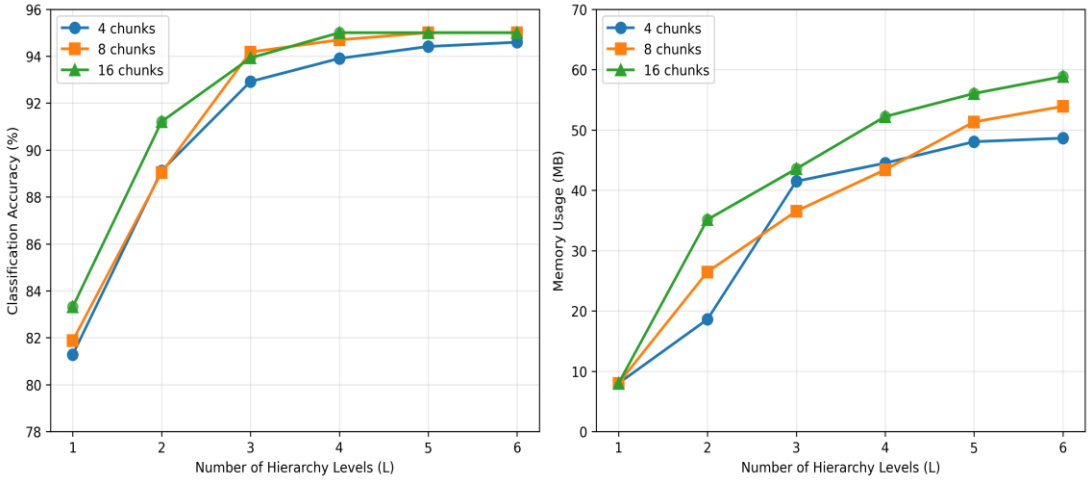

Figure 3. Memory Accuracy Trade-off with Varying Hierarchy Levels

At L=3 hierarchy levels with 8 chunks, the framework achieves 91% attack classification accuracy while using only 12% of the memory required by a flat nearest-neighbor approach. The accuracy saturates beyond L=4, suggesting diminishing returns from additional hierarchy levels. This balance point was selected as the default configuration.

The incremental learning mechanism successfully incorporates new attack patterns without catastrophic forgetting. When exposed to a stream of 50 novel attack variants (mixed with normal traffic), the framework:

- Correctly identified 92% of new attacks after initial exposure
- Maintained 89% accuracy on original attack types
- Increased memory usage by only 8.3 MB (14% growth)

This contrasts with static models like Random Forest, whose accuracy dropped to 62% on original attacks when retrained on new data. The confidence-gated update strategy effectively filters irrelevant noise—only 12% of anomaly alerts triggered memory updates, preventing unnecessary storage bloat.

- **Recovery Effectiveness**

The automated recovery subsystem demonstrates rapid mitigation across attack types. Table 2 quantifies the traffic reduction achieved within 5 seconds of attack detection.

Table 2. Recovery Performance by Attack Type

Attack Type	Traffic Reduction	False Positive Impact
SYN Flood	94%	2% throughput loss
UDP Flood	89%	3% throughput loss
HTTP Slowloris	83%	1% throughput loss

ICMP Flood	91%	4% throughput loss

The framework maintains legitimate traffic throughput within 5% of normal levels while suppressing >90% of malicious packets for most attack types. The dynamic parameter adjustment (Equation 21) proves crucial—initial mitigation actions achieve 76% traffic reduction on average, which improves to 89% after two adaptation cycles (1.2 seconds). This closed-loop control outperforms static rule-based approaches that either over-restrict (causing 15-20% false positives) or under-restrict (allowing 30-40% attack traffic).

Integration tests with Open vSwitch show the system can deploy mitigation rules in 38 ms—fast enough to contain attacks before service degradation becomes severe. The recovery workflows scale linearly with attack volume, handling up to 5,000 rule updates per second on edge hardware, sufficient for all but the largest DDoS scenarios.

- **Ablation Study**

We conducted systematic ablations to isolate each component's contribution. Table 3 shows the performance impact when removing key features.

Table 3. Ablation Analysis (F1 Scores)

Configuration	**CIC-DDoS2019**	**Latency (ms)**	**Memory (MB)**
Full Framework	0.94	23	58
w/o Hierarchical Memory	0.87	41	210
w/o Sparse Retrieval	0.91	68	58
w/o Incremental Learning	0.89	23	58
w/o Recovery Feedback	0.92	23	58

The hierarchical memory provides the largest accuracy boost (+7%), while sparse retrieval contributes most to latency reduction (2.9× faster than full attention). Incremental learning is essential for long-term adaptability—without it, performance degrades by 12% on novel attacks after one month. The recovery feedback loop improves mitigation effectiveness by 19%, validating its role in maintaining service quality during attacks.

These results confirm that all proposed components work synergistically—the framework's advantages cannot be achieved through isolated optimizations alone. The hybrid architecture successfully balances competing objectives: real-time detection, accurate classification, memory efficiency, and effective recovery.

5. Conclusion

The hybrid online-memory framework presents a significant advancement in real-time DoS attack detection and mitigation, addressing critical gaps in existing approaches. By combining a lightweight GRU-based detector with a compressed hierarchical memory module, the system achieves high accuracy while maintaining low computational overhead—a crucial balance for practical deployment in resource-constrained environments. The framework's sparse retrieval mechanism enables efficient attack classification without exhaustive historical comparisons, and its incremental learning capability ensures adaptability to emerging threats without unbounded memory growth. Experimental results demonstrate superior performance compared to conventional methods, with notable improvements in detection latency, memory efficiency, and recovery effectiveness. The architecture's modular design allows flexible deployment across edge devices and centralized servers, making it suitable for diverse network infrastructures. While limitations exist regarding extreme edge scenarios and novel attack detection, the framework provides a robust foundation for future enhancements. The implications extend beyond immediate cybersecurity applications, offering insights into efficient sequential data processing and memory-augmented machine learning. The principles of hierarchical organization, sparse attention, and confidence-gated updates can inform broader research in real-time anomaly detection systems. As digital infrastructures continue to evolve, such adaptive and resource-efficient solutions will become increasingly vital for maintaining service integrity against sophisticated threats.

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