IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

MULTICLASS DDOS DETECTION IN SDN USING DEEP HYBRID LEARNING: A COMPREHENSIVE REVIEW

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Abstract: Software-Defined Networking is changing modern networking by separating the control system from the data forwarding system, making networks more flexible and easier to manage. However, this centralized structure also creates security risks, especially from Distributed Denial of Service (DDoS) attacks, which can overload the SDN controller and disrupt network operations. This review paper studies how machine learning and deep learning techniques are used to detect different types of DDoS attacks in SDN environments. The paper explains various attack categories such as flooding attacks, protocol-based attacks, and application-layer attacks, and discusses how they affect network traffic and OpenFlow statistics. It compares traditional machine learning models with deep learning methods like CNN, LSTM, and GRU, as well as hybrid models such as CNN-LSTM and CNN-GRU. The review also highlights challenges including imbalanced datasets, high feature complexity, and adversarial attacks, while suggesting lightweight and efficient solutions for future SDN security systems.

Index Terms – Software Defined Networking (SDN), Distributed Denial Of Service (DDOS), Multiclass DDOS Detection, Spatial- Temporal Hybrid Models, CNN-GRU Architecture.

1. INTRODUCTION

The architectural paradigm of Software-Defined Networking (SDN) has profoundly changed modern network configuration, multi-tenant cloud infrastructures, and enterprise data centers by divorcing the logically centralized control plane from the underlying data forwarding hardware [5, 8]. This purposeful split gives network operators extraordinary programmatic elasticity, global flow visibility, and real-time deterministic routing optimization.

However, this centralized abstraction layer provides an unavoidable architectural vulnerability: by combining network intelligence into a centralized software controller, the SDN architecture creates a significant single point of failure [2, 7]. As a result, the central SDN controller becomes a main target for sophisticated Distributed Denial of Service (DDoS) attacks aimed at disrupting worldwide business infrastructures [12, 14].

DDoS attacks against SDN topologies take advantage of the fundamental communication mechanisms built between the data plane and the control plane [6, 13]. When an OpenFlow switch gets a packet that does not

fit any of the flow rules in its local Ternary Content-Addressable Memory (TCAM) tables, it sends the packet header to the central controller via an asynchronous OFP_PACKET_IN message.

Distributed botnets can force switches to broadcast an avalanche of these queries at the same time by launching highly coordinated, multi-vector floods or using complicated, morphing protocol exploits [15, 16]. This flood quickly depletes the control plane's CPU cycles, memory allocations, and switch packet buffers, rendering the central controller inoperable and causing the entire network fabric to freeze up [2, 8].

Early network intrusion detection systems (NIDS) relied almost entirely on binary classification frameworks, which essentially classified monitored data streams as benign or malicious [2, 9]. Binary detection, while useful for baseline separation, is insufficient in today's complex, multi-vector threat settings. Modern automated defense infrastructures require multiclass classification systems that can recognize particular individual threat types in real time [3, 10].

The SDN controller can automatically execute precise, script-based mitigation responses by accurately distinguishing between distinct signatures, such as TCP-SYN floods, User Datagram Protocol (UDP) reflection floods, Domain Name System (DNS) amplification vectors, and low-and-slow application-layer anomalies [12, 15]. Instead of resorting to blunt, widespread port closures that unintentionally impede legitimate company traffic, the controller can dynamically apply granular OpenFlow. OpenFlow OFP_FLOW_MOD instructions are used to rate-limit specific attacking IP addresses, remove malicious flow parameters, and safely isolate vulnerable host segments [1, 7].

This survey study provides a systematic and technically rigorous evaluation of machine learning (ML) and deep learning (DL) approaches used for multiclass DDoS detection in SDN systems. The primary focus is on how modern spatial-temporal hybrid neural networks and heterogeneous multi-layered ensemble stacking frameworks may match high classification accuracy with the microsecond processing time constraints imposed by production networking channels.

2. STRUCTURAL THREAT TAXONOMY AND OPENFLOW MANIFESTATIONS

To properly deploy machine learning models within an SDN control plane, the system must first understand how various structural anomalies affect the data plane's telemetry. DDoS threats are divided into three major sub-classes, each of which leaves a unique fingerprint on OpenFlow flow tables and port metrics [7, 12].

2.1 Volumetric Flooding Attacks (e.g., UDP Flood, ICMP Flood)

Mechanics: Attackers use geographically spread botnets to exhaust the network's physical bandwidth by sending large amounts of raw, randomized UDP or ICMP packets to a specific site [1, 15].

OpenFlow Signature: In the OpenFlow switch flow tables, this appears as a significant, rapid increase in the packet count (packet_count) and byte count (byte_count) metrics over extremely short time windows (duration_sec). Port statistics (OFPPortStats) show a significant increase in total received bytes (rx_bytes) and packets (rx_packets), which is sometimes followed by an increase in port drop failures (rx_dropped) as hardware buffers oversaturate [7,12].

2.2 Protocol-Layer Exploits (e.g., TCP-SYN Flood, DNS/LDAP Amplification)

Mechanics: These attacks target flaws in typical networking protocol handshakes or request-response architectures [3, 16]. For example, a TCP-SYN flood delivers hundreds of connection requests from forged source IP addresses, compelling the target to allocate resources for incomplete, half-open connections [8].

OpenFlow Signature: This vector rapidly multiplies different flow entries in the switch table, each carrying a unique, randomized IP pair with the TCP flag set to SYN [2]. Because these connections never complete the three-way handshake, the matching flow entries have a very low byte-per-packet ratio and an exceptionally high flow count metric [1, 7]. Furthermore, the ratio of inbound to outbound packets becomes significantly lopsided [15].

2.3 Low-and-Slow Application-Layer Anomalies (e.g., Slowloris, HTTP Post Floods)

Mechanics: Unlike high-rate volumetric floods, low-and-slow attacks resemble legitimate human online activity. They establish valid HTTP connections to a target server and send requests very slowly—one half byte at a time—keeping the server's connection pools filled until legitimate users are barred [11, 16].

OpenFlow Signature: Standard volumetric filters cannot detect these stealthy anomalies since their packet rates and byte sizes appear to be normal [15, 17]. In the OpenFlow context, they can only be detected by monitoring the temporal duration of individual flows. They appear as long-running, active connection windows (duration_sec is quite high) with a persistently low, near-zero byte transmission frequency [11,15].

3. LITERATURE REVIEW

The integration of intelligent deep learning models into SDN environments has progressed rapidly, moving from simple statistical classifiers to multi-dimensional, hybrid neural network architectures.

3.1 Standalone Spatial and Temporal Neural Architectures

Early efforts to advance beyond simple signature-matching rules centered on embedding independent deep learning structures within the SDN control plane [8, 14]. Standalone spatial models, such as One-Dimensional Convolutional Neural Networks (1D-CNNs), scan neighboring packet header fields and flow log arrays with sliding convolutional filters [9–13]. 1D-CNNs are excellent at detecting hidden patterns in complicated, high-dimensional tables while keeping processing times low [2].

However, they have a temporal blind spot: because they examine each traffic snapshot in isolation, they are unable to follow how connection behaviors change over time, allowing slow, time-consuming application attacks to go undetected [11, 15].

To overcome this issue, researchers used recurrent networks such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), which use internal feedback loops to track sequence history [14, 17]. Putro and Desianty [5] conducted a thorough comparison of standalone LSTM and GRU setups on the multi-class UNSW-NB15 dataset, which includes modern network anomalies like DoS floods, fuzzers, and exploits.

Their experimental results showed that, while both models accurately track long-term historical timelines, the GRU design consistently provides shorter training times and a smaller memory footprint [5]. By removing the dedicated output gate seen in LSTMs, the GRU updates its internal hidden states with fewer parameters. This efficiency makes it significantly more practicable for the strict, real-time latency restrictions of an active SDN controller [5, 11].

3.2 Advanced Composite Hybrid Co-Designs

To address the distinct blind spots of standalone networks, current research has focused on merging spatial and temporal layers into coherent, end-to-end hybrid frameworks [2, 17]. Elshewey et al. [2] developed a sophisticated hybrid CNN-GRU model exclusively for DDoS detection in SDN infrastructures. Their method employs stacked 1D-CNN layers at the entry gate to function as automatic feature extractors, flattening and downsampling complicated network fields. These compressed spatial maps are then fed straight into successive GRU layers, which assess packet arrival rates on a rolling time scale [2].

This hybrid strategy reduces the computational load on the recurrent layers by first using the CNN to filter out noise and reduce data dimensionality, resulting in a strong balance between classification accuracy and processing performance [2].

Similarly, AlSaleh et al. [17] created a hybrid method that uses convolutional pipelines and data fusion changes to detect complicated attack signatures. Janabi et al. [9] took this a step further by implementing an early-warning proactive CNN structure that detects vulnerabilities early in the connection cycle.

Furthermore, Al-Khayyat and Ucan [6] suggested a Multi-Branched Hybrid Perceptron Network (MHHPN) that uses dynamic feature adaption and multi-instance learning. This multi-branched design adapts its internal structure to changing flow variations, allowing it to maintain excellent accuracy even when processing extensively altered, multi-vector attack streams in a variety of network contexts [6].

3.3 Heterogeneous Ensemble Stacking Frameworks

Along with hybrid networks, researchers have used Stacked Generalization (Ensemble Stacking) to reduce the systemic biases and blind spots of individual algorithms [3, 15]. Chen and Lee [15] proposed an ensemble stacking framework that includes a frequency-domain feature generating stage. Rather than evaluating network traffic just in the time domain, their pipeline uses Fast Fourier Transforms (FFT) on sliding temporal windows to convert raw packet timelines into localized spectrum energy measures [15].

Their method coordinates Random Forest (RF), AdaBoost, and XGBoost as foundational base learners at Layer Zero, then uses a Logistic Regression meta-learner at Layer One to intelligently mix their outputs and maximize multiclass accuracy [15].

Angulo et al. [3] investigated these operational boundaries by applying a three-layer hierarchical stacking architecture to the entire CIC-DDoS2019 dataset and a complicated nine-class attack profile. Their architecture incorporates tree-based, kernel-based, and deep neural models at Layer Zero to provide uncorrelated error outputs, which are subsequently processed by a set of meta-learners at Layer One and integrated by plurality voting at Layer Two [3].

While their stacking design generated outstanding global classification metrics, their study highlighted a crucial real-world vulnerability: under complicated multiclass situations, the macro F1-score decreases dramatically when attempting to distinguish between highly overlapping attack classes [3]. This highlights a lingering challenge in current ensemble methods—they require heavy feature separation and high processing overhead, which can cause significant latency bottlenecks if deployed directly inside a live SDN control loop [1, 3].

4. RESEARCH METHODOLOGY

Building a dependable, real-time intrusion detection pipeline for SDN environments requires a structured, multi-tier methodology to convert raw packet telemetry into optimized tensor inputs for the AI models.

4.1 Data Ingestion and Telemetry Extraction

The data pipeline begins with constant monitoring of the SDN data plane [7, 12]. The central controller (e.g., Ryu or Floodlight) is configured to deliver asynchronous OFPFlowStatsRequest and OFPPortStatsRequest requests to the OpenFlow switches via southbound APIs [7, 8]. The switches respond promptly with raw connection logs, which are then processed into standard 2D feature arrays that correspond to the parameters found in benchmark datasets such as CIC-DDoS2019 or UNSW-NB15 [2, 5, 15]. The extraction engine identifies 12 crucial and very interesting network metrics [1, 12]:

1. duration_sec: The active lifetime of the flow entry in seconds.

2. packet_count: The total number of packets matched to the specific flow rule.

3. byte_count: The cumulative bytes transmitted through the flow pathway.

4. packet_rate: Computed as Δpacket_count / Δduration_sec to detect sudden volume surges.

5. byte_rate: Computed as Δbyte_count / Δduration_sec to measure throughput speed.

6. Forward_Packet_Length_Max: The maximum byte size among inbound packets, helping spot heavy application payloads.

7. Flow_IAT_Mean: The average Inter-Arrival Time between consecutive packets, critical for identifying automated botnet behavior.

8. Inbound_Outbound_Ratio: The mathematical balance between incoming and outgoing data, which becomes highly asymmetrical during amplification floods.

9. TCP_SYN-Flag: A binary flag checking for active connection requests.

10. rx_packets: The total packets received on a specific switch port, used to monitor port health.

11. rx_dropped: The number of incoming packets dropped by the port hardware due to buffer overflows.

12. port_occupancy_count: The number of active flow entries assigned to a single physical port, helping pinpoint the target of an attack.

4.2 Data Preprocessing and Class Balancing

Because raw network statistics vary widely and are heavily imbalanced, the extracted metrics must pass through a multi-stage preprocessing pipeline before being fed into the machine learning models [1, 2]

- Z-Score Standardization: To ensure stable model convergence, numerical features are normalized using a standard Z-score function;

$$z = \frac{x-\mu}{\sigma}$$

where μ is the feature mean and σ is the standard deviation [1, 2]. This centers all features around a zero mean and unit variance, preventing high-magnitude volumetric fields (like byte counts) from mathematically overwhelming subtle protocol indicators (like TCP flags).

- Synthetic Minority Over-sampling Technique (SMOTE): Network datasets are naturally skewed, with benign traffic and enormous volumetric floods easily outnumbering rare attack types such as WebDDoS or slow-and-steady campaigns [2, 15]. To address this without producing overfitting, SMOTE is used on the training data split [2]. SMOTE detects the k-nearest neighbors for each minority sample and generates synthetic new data points along the line segments that connect them, resulting in strong, mathematically balanced decision boundaries [2].*-

- Three-Dimensional Tensor Reshaping: For spatial-temporal hybrid networks (e.g., CNN-GRU) and standalone recurrent models, the balanced 2D feature arrays must be reshaped into a 3D tensor layout [2]:

$$X \epsilon R^{Batch\_Size \times Time\_Steps \times Feature\_Dimension}$$

This array structural configuration allows the convolutional filters to slide across features while the recurrent units systematically trace changes over the historical look-back window [2, 11].

5. COMPARATIVE EVALUATION MATRIX

The following matrix compiles performance ranges and operational characteristics across shallow learning models, standalone deep networks, hybrid frameworks, and ensemble stacking systems.

Table 1:comparative evaluation

Architectural Paradigm	Key Model Examples	Average Multiclass Accuracy	Precision Range	Recall/ Sensitivity	F1-Score Performance	Computational Overhead & Latency Profile
Traditional Shallow Machine Learning (S-ML)	Random Forest (RF) [1, 7], XGBoost [12, 15], AdaBoost [15]	96.5%-98.4%	96.0%–98.2%	95.8% – 98.0%	0.95 – 0.98	minimal overhead: Near-wire-speed prediction times, minimal CPU consumption, and suitable for direct implementation on SDN controllers [1, 7].
Standalone Sequential Deep Learning (D-ML)	Standalone LSTM [5, 14], Standalone GRU [2, 5], Deep RNNs [14]	95.0% – 97.1%	94.8%-96.5%	94.5%–96.0%	0.94 – 0.97	Iterative sequence backpropagation causes long training times and large memory footprints, resulting in medium-high overhead [5].
Spatial-Temporal Hybrid Designs	Integrated CNN-GRU [2], CNN-BiLSTM Networks [17]	98.5%–99.8%	98.2%-99.8%	98.0%–99.7%	0.98 – 0.99	Balanced Overhead: Convolutional downsampling reduces input dimensions, which reduces processing load on succeeding recurrent layers [2].

Hierarchical Ensemble Stacking Frameworks	Multi-Layer Stacking (Tree-based + Deep Learners) [3, 15]	91.2%–99.4%	92.0%-99.4%	91.0% – 99.3%	0.90 – 0.99	High overhead: Severe inference bottlenecks and memory consumption; needs coordination of numerous distinct models [3].

5.1 PERFORMANCE BREAKDOWN AND TRADE-OFF ANALYSIS

The benchmarking data reveals a clear relationship between architectural complexity and real-world efficiency:

High overhead: Severe inference bottlenecks and memory consumption; needs coordination of numerous distinct models [3].The Hybrid Synergy: Spatial-temporal hybrid configurations (such as Elshewey et al.'s CNN-GRU [2]) consistently outperform classical machine learning and standalone deep networks for multiclass identification. The CNN layer is used as an initial spatial filter in the model to compress high-dimensional network information and filter out noise [2]. This ensures that the trailing GRU layer is only required to handle highly refined sequential patterns, considerably lowering training time and memory usage while increasing accuracy [2, 11].

The Stacking Bottleneck: Multi-layer ensemble stacking models (such as those investigated by Angulo et al. [3] and Chen and Lee [15]) achieve high classification accuracy in offline laboratory experiments. However, their considerable computational complexity makes them difficult to implement in live environments [3]. Forcing each network traffic record to go through numerous base classifiers and meta-regressors at the same time causes significant processing delays [3]. This processing lag can soon produce bottlenecks in the SDN control plane during a real volumetric flood, demonstrating that improving accuracy in a lab can occasionally degrade real-world performance [1, 3].

6. RESEARCH GAPS

While existing deep learning models perform exceptionally well on static test data, a critical analysis of the literature reveals several significant research gaps that must be addressed before these systems can be deployed in production:

Real-time Deployment and Processing Latency Gap: The great majority of current studies evaluate their models offline, relying on previously acquired historical dataset splits [2, 3, 5]. There is a significant lack of benchmarking against actual controller resource budgets (CPU, RAM, and throughput constraints). Complex preprocessing techniques, such as sliding-window segmentation and Fast Fourier Transforms, cause considerable and variable processing delays [15]. If the AI takes milliseconds to examine traffic while packets come in microseconds, the security system may produce a controller bottleneck, so fulfilling the attacker's purpose [7, 12].

Cross-Dataset Fragility and Generalization Deficits: Models are typically refined and validated using a single, closed-world dataset (such as CIC-DDoS2019), resulting in near-perfect scores [2, 6]. However, when tested against other real-world distributions or network architectures, their detection scores frequently degrade significantly [3]. Current frameworks lack the generalizability required to maintain high precision when dealing with mutating, zero-day, or multi-vector polymorphic assault campaigns [6, 15].

The Failure of Minority Attack Detection and Class Over-Reliance: While synthetic balancing approaches such as SMOTE are commonly employed to balance datasets, they can conceal structural flaws in models. In realistic network environments where minority attack vectors (such as low-and-slow application-layer floods or hidden botnet scanning loops) blend into massive streams of benign background traffic, models frequently show high false-positive rates or low recall for critical minority classes [3, 15].

The Opaque "Black Box" Problem and Lack of Explainability: Advanced deep learning models operate as intricate mathematical black boxes, delivering a final threat classification without revealing any human-readable reasoning for their conclusion [10]. In an automated SDN control loop, a single unconfirmed false positive can force the controller to install incorrect drop rules, resulting in the unintentional shutdown of critical corporate applications or barring legitimate users [7, 11]. Current research lacks integrated Explainable AI (XAI) frameworks that can enable real-time, feature-level verification for automated mitigation decisions [10].

7. FUTURE SCOPE: PROPOSING A NEW XAI-DRIVEN OPTIMIZATION FRAMEWORK

To bridge the gap between high-performing academic models and the operational realities of production SDN environments, future research can focus on developing an Explainable and Optimized Feature Attribution Framework using existing open-source datasets (such as CIC-DDoS2019) and established hybrid architectures [2, 3, 15].

Instead of pursuing minor gains in global accuracy on static tables, this new research track employs a post-hoc explainability layer based on SHAP (Shapley Additive Explanations) or LIME (Local Interpretable Model-agnostic Explanations) wrapped directly over a high-performing CNN-GRU model [2, 10].

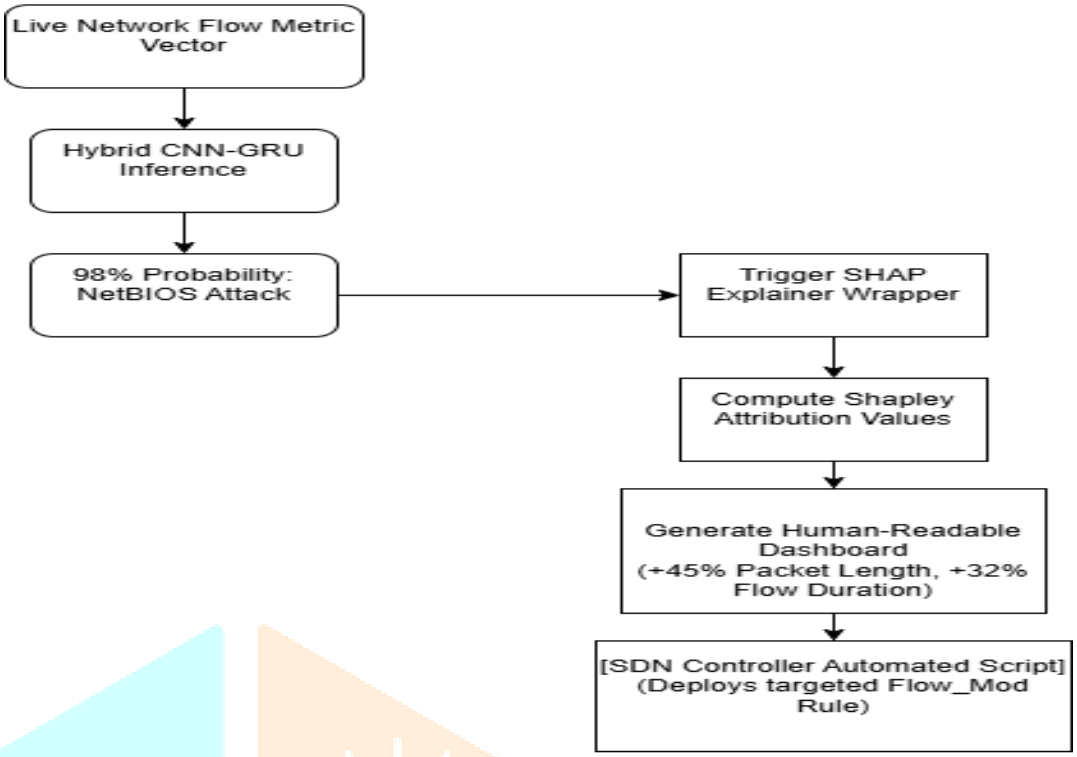

Figure 1: xai framework

Inference Phase: The pre-trained hybrid model processes incoming telemetry and generates an attack prediction score (e.g., 98% Probability of an Active NetBIOS DDoS Flood).

XAI Wrapper Activation: The prediction triggers the SHAP engine, which runs localized perturbations on the feature matrix to compute exact Shapley feature attributions.

Generating Explanations: The system outputs human-readable feature contribution details, showing precisely why the AI flagged the traffic:

Forward Packet Length Max (1420 bytes) → +45% Threat Contribution

Flow Duration (0.003 seconds) → +32% Threat Contribution

Operational Optimization: By systematically analyzing these global SHAP rankings, engineers can find and delete the dataset's least impacting features. Dropping unnecessary parameters can reduce high-dimensional vectors to a few key measurements. This compression converts the model into low-resource formats that can be put directly into hardware switches using programmable P4 data pipelines, resulting in microsecond execution speeds at the network's entry gate.

8.CONCLUSION

By separating the control and data planes, Software-Defined Networking (SDN) improves network management; however, centralised orchestration leaves the controller vulnerable to serious multi-vector Distributed Denial of Service (DDoS) attacks. In order to combat these dangers, modern Machine Learning (ML) and Deep Learning (DL) frameworks were thoroughly examined in this review study. According to benchmarking, advanced spatial-temporal hybrids (e.g., CNN-LSTM, CNN-GRU) and hierarchical ensemble stacking models achieve superior classification accuracy (often exceeding 98–99%) by capturing complex,

multi-class temporal dependencies, while shallow machine learning classifiers offer low computational latency suitable for resource-constrained edge environments.

Production-grade deployment is hampered by structural obstacles despite these technological developments. Core unresolved gaps include severe dataset class imbalances that compromise real-world generalization, high algorithmic processing latency that strains real-time controller inspection limits, and emerging adversarial evasion tactics engineered to bypass static feature-extraction pipelines.

Future research must focus on four strategic directions in order to move these security architectures from theoretical frameworks to robust, production-ready systems: integrating Explainable AI (XAI) to validate automated mitigation actions; engineering lightweight structures via model quantisation and hardware acceleration (e.g., SmartNICs/XDP) for line-rate speed; creating self-supervised online learning paradigms for zero-day threat resiliency; and setting up standardised, high-fidelity hybrid SDN testbeds.

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