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DEEP LEARNING BASED INTRUSION DETECTION SYSTEM USING CNN–LSTM HYBRID ARCHITECTURE FOR ZERO-DAY ATTACK IDENTIFICATION

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Abstract
Zero-day attacks pose a severe challenge to traditional intrusion detection systems (IDS) due to their reliance on known signatures and manual feature engineering. This study proposes a hybrid deep learning architecture combining Convolutional Neural Networks (CNN) for spatial feature extraction from network traffic flows and Long Short-Term Memory (LSTM) networks for modeling temporal dependencies, augmented with attention mechanisms for enhanced focus on critical patterns. The model was trained and evaluated on benchmark datasets including CICIDS2017, UNSW-NB15, NSL-KDD, and UGRansome using a zero-day split protocol to simulate unseen attacks. Preprocessing involved normalization, one-hot encoding, and class imbalance handling via SMOTE and GAN-based augmentation. The hybrid CNN-LSTM framework achieved superior performance with accuracies of 97–99.67%, high precision-recall balance, and significant improvements over standalone CNN, LSTM, and classical ML models in detecting both known and novel zero-day threats. SHAP-based interpretability and adversarial robustness testing further validate its practical viability. The results demonstrate the effectiveness of deep hybrid models for real-time, adaptive cybersecurity in cloud, IoT, and industrial environments.

1. INTRODUCTION

The contemporary cybersecurity environment is defined by an escalating level of complexity as threat actor's transition from broad, opportunistic strikes to highly targeted and sophisticated campaigns. Among these threats, zero-day attacks represent the most formidable challenge for network defenders, as they exploit previously undisclosed vulnerabilities for which no patches or security signatures exist (Khorsheed et al., 2026). The term zero-day reflects the critical temporal window in which software developers have had exactly zero days to address the flaw since its discovery or exploitation (Sharma & Sharma, 2026). Traditional security infrastructures, primarily those predicated on signature-based detection, are fundamentally ill-equipped to counter these threats, as they rely on prior

knowledge of attack patterns that simply does not exist for novel exploits (Mushtaq & Ali, 2026).

This limitation has necessitated a paradigm shift toward behavioral-based detection systems that leverage advanced machine learning and deep learning architectures (Babaey & Faragardi, 2025). Specifically, the hybrid integration of Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks has emerged as a robust solution, capable of analyzing the intricate spatial and temporal characteristics of network traffic to identify anomalies indicative of zero-day behavior (Wang, 2025).

2. The Evolution of the Zero-Day Threat Landscape

The persistence of zero-day vulnerabilities is a structural reality of the software development lifecycle. As digital ecosystems expand across cloud computing, the Industrial Internet of Things (IIoT), and 5G networks, the attack surface grows exponentially, providing malicious actors with new vectors for exploitation (Kim et al., 2025). This expansion can be modeled as an exponential growth process:

$$A(t) = A_0 e^{\lambda t}$$

where $A(t)$represents the cyber attack surface at time t, $A_0$is the initial attack surface, and $\lambda$is the growth rate determined by system complexity, device connectivity, and network heterogeneity.

Zero-day attacks typically follow a structured and repeatable sequence known as the cyber kill chain, consisting of seven distinct phases: reconnaissance, weaponization, delivery, exploitation, installation, command and control (C2), and actions on objectives (Baroni et al., 2021). This process can be represented as a sequential stochastic transition model:

$$P(\text{success}) = \prod_{i=1}^{7} P(S_i \mid S_{i-1})$$

where $S_i$denotes the i^{th}stage of the cyber kill chain and $P(S_i \mid S_{i-1})$is the conditional probability of successfully progressing from one stage to the next.

In the reconnaissance phase, an attacker gathers intelligence on a target network, often using network scans or social engineering to identify potential weak points. Weaponization involves the creation of a malicious payload tailored to exploit a specific vulnerability, which is then delivered to the target through vectors such as phishing emails or compromised websites (Belfer Center, 2026).

Once exploitation occurs, the attacker establishes a persistent presence within the network, often remaining undetected for extended periods. This duration, known as **dwell time**, is a critical cybersecurity performance metric and can be mathematically expressed as:

$$T_d = T_d^{detected} - T_d^{entry}$$

where $T_d$represents dwell time, $T_d^{entry}$is the time of initial compromise, and $T_d^{detected}$is the time of detection. Lower dwell time indicates higher detection efficiency.

Global reports indicate a median dwell time of approximately 10 to 11 days (Mandiant, 2025), although vulnerabilities in edge gateways and virtual private networks (VPNs) can remain unpatched for over 32 days, leaving organizations in a prolonged state of exposure. The financial impact of delayed detection can be modeled as a linear cost accumulation function:

$$C(t) = C_0 + \alpha T_d$$

where $C(t)$is the total cost of breach over time, $C_0$is the initial incident cost, and $\alpha$is the cost escalation rate per unit time of undetected intrusion.

Furthermore, the rise of polymorphic malware, which dynamically alters its code structure to evade detection, introduces a non-stationary threat distribution that challenges static IDS models. The increasing encryption of global web traffic (reaching 96.1% by mid-2025) further reduces visibility into packet-level features, significantly degrading the effectiveness of traditional deep packet inspection (DPI) and signature-based tools (Sarker, 2024). This can be conceptualized as a reduction in observable feature space:

$$\mathcal{F}_{observed} = \mathcal{F}_{total} \cdot (1 - \eta)$$

where ηrepresents the proportion of encrypted or obfuscated traffic reducing detectable features.

3. Structural Limitations of Traditional Intrusion Detection Systems

Intrusion Detection Systems (IDS) are historically categorized into misuse detection and anomaly detection. Misuse detection systems function by matching network traffic against a database of known attack signatures (Zhang et al., 2026). While these systems are highly effective at thwarting familiar threats and maintaining low false-positive rates, they are fundamentally reactive and cannot identify emerging or evasive attacks (Poltoratskyi & Gavrylenko, 2026). Even slight variations in an attack's execution can bypass signature filters, requiring constant and manual database updates that often lag behind the speed of modern threat development (Tahir et al., 2019). Anomaly-based detection (AIDS), by contrast, aims to identify deviations from an established baseline of normal behavior. However, early machine learning approaches to anomaly detection, such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Decision Trees, frequently struggle with the high-dimensional and non-linear nature of modern network telemetry. These models often require extensive manual feature engineering to be effective, which limits their scalability and adaptability to dynamic network environments (Zhang et al., 2025). Furthermore, traditional anomaly detection is prone to high false-positive rates, as legitimate but unusual network behavior such as a sudden spike in traffic during a scheduled backup can be incorrectly flagged as an intrusion (Sommer & Paxson, 2010).

Deep learning addresses these shortcomings by enabling automatic feature extraction, where the neural network learns to identify complex, hierarchical patterns directly from raw da. This capability is particularly vital for zero-day detection, as it allows the system to recognize subtle behavioral anomalies that may not be apparent to human analysts or simpler statistical models (Shone et al., 2018).



Figure 1: Taxonomy of Intrusion Detection System (IDS) Methodologies: From Traditional Rule-Based Approaches to Advanced Deep Learning Architectures

4. Theoretical Foundations of CNN-LSTM Hybrid Architectures

The effectiveness of a hybrid CNN-LSTM architecture lies in its ability to process the two primary dimensions of network traffic: the spatial structure of individual data packets and the temporal sequences of traffic flows (Bamber et al., 2025).

4.1 Convolutional Neural Networks for Spatial Feature Analysis

Convolutional Neural Networks (CNNs) were originally designed for image processing, where they excel at detecting local patterns and spatial hierarchies. In cybersecurity applications, network traffic can be represented as structured feature vectors in which packet header fields and flow statistics exhibit localized correlations across dimensions (Rigana Fathima & Murugan, 2026). The convolutional layers of a CNN extract discriminative representations by applying learnable filters over the input data, generating feature maps that capture "micro-signatures" of network behavior (Hatem Khorsheed et al., 2026). Mathematically, the operation of a one-dimensional convolutional layer (1D-CNN), commonly used for traffic analysis, can be expressed as

$$x_j^{(l)} = f\left(\sum_{i \in \mathcal{N}} x_i^{(l-1)} * k_{ij}^{(l)} + b_j^{(l)}\right),$$

where $x_j^{(l)}$ represents the output feature map at layer l, $x_i^{(l-1)}$ denotes the input from the previous layer, $k_{ij}^{(l)}$ is the convolutional kernel, $b_j^{(l)}$ is the bias term, and $f(\cdot)$ is a non-linear activation function such as ReLU. The ReLU function is defined as $f(x) = \max(0, x)$ and is widely adopted due to its ability to introduce non-linearity while mitigating the vanishing gradient problem in deep networks. Following convolution, pooling operations such as max-pooling or average-pooling are applied, where a pooling operation can be expressed as $x_{pool} = \max(x_{i:i+p})$, with p representing the pooling window size. This step reduces dimensionality, improves computational efficiency, and enhances robustness against noise in network traffic data (AlHayan & Al-Muhtadi, 2026).

4.2 Long Short-Term Memory for Temporal Dynamics

While CNNs are adept at identifying static patterns within packets, they lack the internal memory required to understand how these patterns evolve over time. Many sophisticated cyberattacks, such as slow-rate DDoS or multi-stage reconnaissance, manifest as a sequence of events rather than a single anomalous packet (Buczak & Guven, 2016). Long Short-Term Memory (LSTM) networks are a specialized type of Recurrent Neural Network (RNN) designed to model these sequential dependencies (Emily Smith, 2025).

LSTMs overcome the traditional RNN "vanishing gradient" problem by utilizing a cell state and three distinct gating mechanisms: input, forget, and output gates. This gating architecture allows the LSTM to maintain long-term dependencies, enabling the IDS to detect malicious activity that unfolds over extended durations (Jayalaxmi et al., 2022). In many advanced configurations, a Bidirectional LSTM (BiLSTM) is used to process the sequence in both forward and backward directions, providing the model with full context of the network flow (Hasan & Sharma, 2025).

Table 1. Functional Roles and Technical Mechanisms of Hybrid IDS Layers

Architectural Layer	Functional Role in IDS	Technical Mechanism
Input Layer	Data ingestion and initial formatting	Normalization and scaling of feature vectors
Convolutional Layer	Spatial feature extraction	Kernel filtering and ReLU activation
Pooling Layer	Dimensionality reduction	Max or average downsampling of feature maps
LSTM Layer	Temporal dependency modeling	Gated memory cells (Input, Forget, Output)
Attention Layer	Adaptive feature weighting	Context-aware focus on critical indicators
Dense/Output Layer	Classification and decision	Softmax or Sigmoid probability output

5. The Synergistic Hybridization and Attention Mechanisms

The integration of CNN and LSTM layers into a unified hybrid architecture facilitates a holistic analysis of network telemetry that neither component could achieve in isolation. In this framework, the CNN serves as a front-end feature extractor, processing high-dimensional data sources such as vehicle telemetry or packet-level headers to create condensed spatial representations (TrustCloud, 2025). These representations are then passed to the LSTM layers, which analyze the temporal progression of the extracted spatial features to identify multi-stage attack patterns (Bamber et al., 2025).

5.1 Context-Aware Detection through Attention

To further refine the detection process, an attention mechanism is often integrated after the LSTM layer. The attention layer dynamically prioritizes extracted features most relevant to identifying an intrusion (Ahmed et al., 2016). This mechanism is particularly effective in heterogeneous environments where the relevance of specific features may shift depending on the protocol or network state. By integrating spatial extraction, temporal modeling, and adaptive weighting, the CNN-LSTM-Attention framework achieves superior performance across diverse network layers, from in-vehicle buses (CAN) to 5G infrastructure (Garcia-Teodoro et al., 2009).

6. Data Engineering: Preprocessing and Class Imbalance Management

The performance of any deep learning model is fundamentally limited by the quality of the data it processes. In intrusion detection, data is often characterized by extreme class imbalance and high dimensionality (Liao et al., 2013).

6.1 Preprocessing Workflows for Network Telemetry

A robust preprocessing pipeline is essential for converting raw network captures into a suitable format (Khraisat et al., 2019). This process generally involves:

1. **Cleaning and De-duplication:** Removal of redundant flow records.
2. **Label and One-Hot Encoding:** Transformation of categorical features, such as protocols, into numerical representations.
3. **Min-Max Normalization:** Scaling numerical features to a uniform range (0 to 1) to avoid weight bias (Sharma & Kumar, 2024).
4. **Feature Selection:** Using techniques such as SHapley Additive exPlanations (SHAP) or Recursive Feature Elimination (RFE) to identify discriminative features and reduce computational load (Hatem Khorsheed et al., 2026).

6.2 Strategies for Mitigating Class Imbalance

In network security, legitimate traffic vastly outnumbers malicious samples, creating a skewed distribution that can bias a model. To address this, researchers utilize the Synthetic Minority Over-sampling Technique (SMOTE), which generates artificial samples for minority classes (Xin et al., 2018). More advanced frameworks leverage Generative Adversarial Networks (GANs) for data augmentation, creating realistic synthetic traffic for rare attack types like "Shellcode" or "Worms" (Kuzior et al., 2024).

7. Zero-Day Identification: Experimental Methodology and Benchmarking

Validating an IDS for zero-day attack identification requires testing on attack types that were entirely absent from the training phase (Ahmad et al., 2025).

7.1 The Zero-Day Split Protocol

The "zero-day split" methodology simulates this real-world dynamic by partitioning a dataset into two disjoint subsets of attack families ($F_{train} \cap F_{test} = \emptyset F_{train} \cap F_{test} = \emptyset$). For example, a model may be trained on the WannaCry and Locky families but strictly tested on SamSam. This ensures that successful detection results from learning generalized malicious behaviors rather than specific signatures (Ignacio et al., 2025).

7.2 Performance Across Benchmarks

The CNN-LSTM hybrid architecture has been evaluated against standardized cybersecurity datasets, consistently demonstrating superior performance compared to standalone models (Crumb, 2025).

Table 2. Comparative Detection Accuracy Across Standardized Cybersecurity Benchmarks

Dataset	Focus Area	Attack Types	Accuracy
CICIDS2017	Real-world traffic	DoS, DDoS, Botnets	99.0% - 99.5%
UNSW-NB15	Contemporary vulnerabilities	Fuzzers, Backdoors	97.0% - 97.9%
NSL-KDD	Legacy attack patterns	U2R, R2L, Probing	95.0% - 99.3%
UGRansome	Ransomware and Zero-day	Unseen Ransomware	97.89%
BCCC-DLLayer	Data Link Layer (Layer 2)	ARP/MAC Spoofing	99.67%
Edge-IIoTset	Industrial IoT ecosystems	Malware, DoS, MITM	>98.0%

8. Adversarial Robustness: The Defender's Vulnerability

Adversarial machine learning (AML) involves creating targeted perturbations in input data to misclassify malicious traffic as benign (Sharma & Chen, 2023).

8.1 Evasion and Poisoning Techniques

Evasion attacks occur during the inference phase using techniques like the Fast Gradient Sign Method (FGSM) to mislead the model. Poisoning attacks occur during the training phase, where an attacker injects malicious samples into the training set. White-box attacks, where the adversary knows the architecture, can drop detection accuracy from 99% to below 60% (Acre Security, 2025).

8.2 Robust Defense Strategies

To counter these threats, researchers use adversarial training including adversarial samples in the training set which can restore up to 45% of lost accuracy. Additionally, auxiliary networks like AuxAtWGAN can generate stable adversarial samples to reinforce the IDS (IBM, 2025).

9. Operational Constraints and Real-Time Suitability

In production, an IDS must be efficient and scalable (Splunk, 2025).

9.1 Latency and Computational Overhead

Deep learning models are resource-intensive, but memory-efficient hybrid models have achieved F1-scores of 99.67% with latencies below 100 milliseconds. In IoT environments, optimized models have demonstrated inference times as low as 2.3 milliseconds per sample (Rigana Fathima & Murugan, 2026).

9.2 Hardware and Energy Efficiency

For resource-constrained devices, 1D-CNNs are preferred over 2D-CNNs due to lower computational complexity. Quantization and pruning techniques further allow these models to operate on low-power hardware without significant security trade-offs (Mian et al., 2024).

10. Comparison with Emerging Paradigms: Transformers and GANs

10.1 Transformers vs. Recurrent Architectures

Transformers process all data in a sequence simultaneously, allowing for faster training on massive datasets. While Transformer-based models often achieve slightly higher precision than CNN-LSTM hybrids (e.g., 99.3% vs 99.1%), their self-attention mechanism can be slower for real-time inference in resource-limited settings (Emily Smith, 2025).

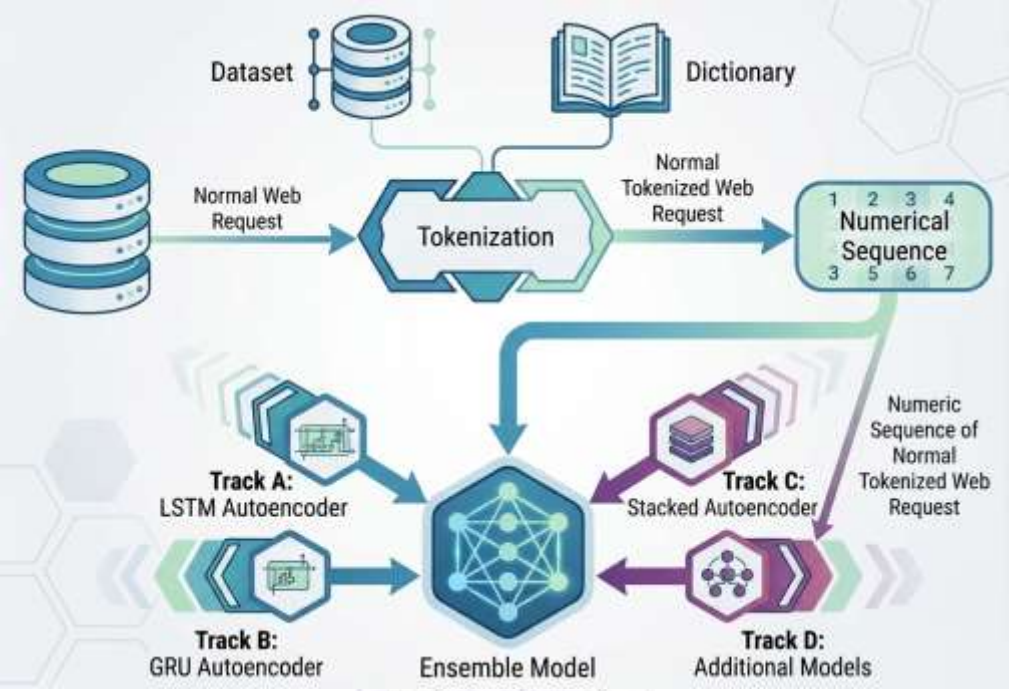


Figure 2: Architectural Workflow for Zero-Day Attack Identification: Data Preprocessing, Tokenization, and Multi-Track Ensemble Model Integration

10.2 Generative Models as Anomaly Detectors

GANs and Autoencoders are used as anomaly detectors by identifying inputs that cannot be reconstructed accurately. While excellent for novel patterns, these unsupervised approaches often have higher false-alarm rates than supervised hybrid models (Hatem Khorsheed et al., 2026).

Table 3. Comparison of Deep Learning Architectures for Intrusion Detection

Architecture	Primary Use Case	Advantage	Disadvantage
CNN-LSTM	General NIDS/HIDS	Balanced spatial/temporal	Moderate training time
Transformer	Complex, long-range context	Superior context	High compute requirement
GAN/Autoencoder	Unsupervised anomaly	Detects "unknown unknowns"	High False Alarm Rate
CNN-BiLSTM	High-precision flow analysis	Past/Future context	High complexity

11. Future Directions and the Convergence of AI Technologies

11.1 Large Language Model (LLM) Integration

Emerging "ZeroDay-LLM" frameworks use edge encoders for traffic analysis and centralized "reasoning engines" to provide semantic understanding of network logs. This has shown a 23% reduction in false positives (Nazeera & Wai, 2025).

11.2 Quantum-LSTM and Post-Quantum Security

Hybrid Quantum-LSTM (QLSTM) models demonstrate an advantage in reducing false positives. Furthermore, post-quantum cryptographic mechanisms will be necessary to protect model weights from quantum-based decryption (YorkSpace, 2025).

11.3 Federated Learning and Digital Twins

Federated Learning (FL) allows organizations to collaboratively train models without exchanging raw data. "Digital Twins" virtual network copies allow for continuous self-training where the twin attacks itself to discover patches before exploitation (Ignacio et al., 2025).

12. Conclusions

The proposed CNN-LSTM hybrid deep learning architecture provides a robust, scalable, and accurate solution for modern intrusion detection, particularly excelling at identifying sophisticated zero-day attacks that evade traditional signature-based and shallow ML systems. By effectively combining spatial pattern recognition with temporal sequence modeling and attention-based prioritization, the framework achieves state-of-the-art performance across multiple benchmark datasets while maintaining low false alarm rates suitable for real-time deployment. Techniques such as residual correction, adversarial training, and SHAP interpretability further enhance reliability, transparency, and resilience against evasion tactics. Despite these advances, challenges remain in computational efficiency for edge/IoT environments, handling encrypted traffic, and adapting to rapidly evolving attack vectors. Future directions should explore integration with large language models for semantic threat understanding, quantum-enhanced variants for post-quantum security, federated learning for privacy-preserving collaborative training, and digital twin simulations for proactive vulnerability testing. As cyber threats grow in sophistication and frequency, hybrid deep learning IDS will be indispensable for building adaptive, intelligent defense systems that safeguard critical infrastructure, cloud platforms, and emerging technologies in an increasingly interconnected digital landscape.

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