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Behavioral Anomaly Detection in Big Data Streams: An Attention-Enhanced LSTM Approach for Privacy-Aware Zero-Day Attack Detection

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Abstract:
Zero-day attacks become a serious threat for today's Big Data Stream, which their behaviors are unknown and there exists not predefined signatures about them. Such new attacks are not detected by the classical signature-based intrusion detection systems (IDS). A Deep Learning Based Method for Zero-Day Attack Detection through the Behaviour Analysis inBig Data Stream. This article presents a system-level framework that adopts deep learning technique using for the detection of zero-day attack. We use the recently published CIC-IDS2023 data set which offers realistic zero-day attack simulations and a wide range of system telemetry. Our approach utilizes a Long Short-Term Memory (LSTM) network combined with attention mechanisms to model temporal behavior patterns from process, network, and file system activities. Experimental results demonstrate that the proposed model achieves 98.7% accuracy, 97.4% precision, 96.9% recall, and an F1-score of 97.1% in detecting zero-day attacks, outperforming existing machine learning and deep learning baselines. The study also includes ablation studies and feature importance analysis, confirming the efficacy of behavioral features and temporal modeling. This work contributes to advancing proactive cybersecurity through AI-driven behavioral anomaly detection.

Keywords: Zero-day attack detection, behavioral analysis, deep learning, LSTM, attention mechanism, CIC-IDS2023, intrusion detection system.

1. Introduction

The increasing number, diversity, and dynamic nature of cyber threats has resulted in zero-day attacks becoming commonplace. Among the 2023 breaches, a significant 18% of breaches used 0-day virus attack is reported, which is 40% higher than previous year[1]. Signature- based IDS (such as Snort) is not suitable to prevent such attacks because the patterns are unknown [2]. Therefore, there is an acute demand for behavior-related detection-tech that can check abnormal behaviors that represent the working principles of zero-day attacks. Behavioral characterization observes the activity of systems, like the execution of processes, connection on a network, and access of files.

Behavioral analysis focuses on monitoring system activities such as process execution, network connections, and file access patterns. By modeling normal behavior, deviations can be flagged as potential threats. Deep learning models, particularly Recurrent Neural Networks (RNNs) and their variants, have shown promise in capturing temporal dependencies in system behavior.

Recent advancements in attention-based architectures, such as Transformers, have further enhanced the capability to model complex system behaviors.Somar.,Alqahtani and Kim et al. proposed a self-attention-enhanced model for host-based intrusion detection, achieving superior performance on the CICIDS2017 dataset by capturing both temporal and contextual relationships in network traffic[3],[4]. In another study, Luo et al. developed a multi-modal deep learning framework that integrates system logs, network flows, and process behaviors using a hybrid CNN-LSTM architecture, significantly improving detection accuracy for zero-day attacks [5].

Moreover, unsupervised and self-supervised learning approaches are gaining traction due to the scarcity of labeled attack data. S. Hochreiteret al. introduced the Deep Support Vector Data Description (Deep SVDD) method, which learns a compact representation of normal behavior and detects anomalies based on deviation from this learned manifold [6]. This approach was later adapted by L.Gato et al. for

cybersecurity applications, demonstrating robustness in detecting previously unseen attack patterns in enterprise environments [7].

Federated learning has also emerged as a promising paradigm for privacy-preserving behavioral modeling across distributed endpoints. Nguyen et al. presented a federated anomaly detection framework using LSTM networks, enabling collaborative model training across multiple devices without sharing raw system data, thus preserving user privacy while maintaining high detection efficacy [8].

In parallel, research into explainability and interpretability of deep learning-based IDS has intensified, as trust and transparency are crucial for deployment in real-world settings. Arrieta et al. emphasized the importance of explainable AI (XAI) in cybersecurity, proposing integration methods such as SHAP and LIME to interpret model decisions and improve analyst confidence [9]. This line of work was extended by L. Ruff et al., who developed an explainable recurrent neural network for intrusion detection that provides actionable insights into detected anomalies, facilitating faster incident response [10].

These studies collectively underscore the shift from signature-based to behavior-driven, deep learning-powered intrusion detection systems. As zero-day threats continue to grow in sophistication, integrating advanced neural architectures with explainability, privacy preservation, and multi-modal data fusion will be pivotal in building resilient and adaptive cybersecurity defenses.

This paper presents a deep learning framework for zero-day attack detection using behavioral analysis. We utilize the CIC-IDS2023 dataset—a recent, comprehensive dataset that includes simulated zero-day attacks—and propose an attention-enhanced LSTM model to detect anomalies in system behavior. Our contributions are:

1. A deep learning architecture combining LSTM and attention mechanisms for temporal behavioral modeling.
2. Evaluation on the CIC-IDS2023 dataset with a focus on zero-day attack detection.
3. Comprehensive experimental results and ablation studies validating the model's performance.
4. Visualization of attention weights and feature importance to enhance interpretability.

2. Related Work

Conventional IDS, such as Snort and Suricata, based on signature matching is not efficient when it comes to the detection of zero-day attacks. Anomaly-based approaches such as statistical models or machine learning (SVM, Random Forest, etc.) have been investigated, but they also tend to produce high false alarms rates [11]. Recent work has also used deep learning for behavioral analysis. Nguyen, T. T., et al. [12] applied autoencoders to identify anomalies in system call sequences. However, their model did not address temporal context. Arrieta et al. [13] introduced a CNN-LSTM hybrid model for network traffic analysis, but it does not concentrate on zero-day attacks. The dataset CIC-IDS2023 [14] is an extension of the previous ones such as CIC-IDS2017 and UNSW-NB15 with real world attack simulations such as zero-days as Log4Shell and new Ransomware. Thus it is well suited for testing the new generations of IDS. Our work enhances previous work on cyber threat detection by improving one class of deep learning model known as LSTM (Long Short-Term Memory) and achieving better detection accuracy. LSTMs are capable of learning patterns in these sequences of system behavior, including the order in which processes are run or network connections are established. Yet in long sequences, they may occasionally overlook vital information. We addressed this by using an attention mechanism in the LSTM. Attention can be thought of like shining a spotlight — it allows the model to focus on the most relevant parts of the behavior sequence when making decisions. For instance, when a suspicious application makes an unexpected connection to a new external server, the attention mechanism assists the model to focus on this event so it can better identify true threats. We evaluated our enhanced model (LSTM-Aligned) on a contemporary and realistic dataset which consists of real-world cases of zero-day attacks based on previously unknown zero-day

vulnerabilities, hence they are particularly difficult to recognize. Several previous works are based on obsolete or synthetic data, while our work is based on a recent labeled dataset with real zero-day situations, and our results will be more reliable and practical to real-world security systems. Our contribution to the body of research is the synthesis of LSTM and attention and testing of the approach on high-quality and recent data, which are representative of real world cybersecurity tasks.

3. Dataset and Behavior Features

Our work focuses on a recent and realistic dataset which record detailed system-level behaviors, which is an ideal environment for zero-day attacks detection through behavioral analysis. The dataset contains detailed logs of process executions, system calls, file access patterns, and network connections, recorded at real enterprise environments in normal operations and under attacks. these behavioral profiles, and can then mode l the normal actions of users and systems over time, such that significant departure such as a suspect script is spawning off a hidden process, or strange outbound network traffic can be flagged as a potential threat. Most importantly, the dataset presents labeled zero-day attacks, i.e. the attacks that happened before becoming publicly known: thus, we are able to assess the model's potential in the detection of previously unknown threats without using the traditional attack signatures. Because our approach is centered around behavior-based characteristics that reflect real, deployed system dynamics, it enables us to rapidly detect such behavior patterns without any prior knowledge of the attack itself challenges.

By focusing on behavioral features that reflect actual system dynamics, our approach supports timely and accurate detection of malicious activities, even when the specific attack technique has never been seen before.

3.1. CIC-IDS2023 Dataset

The CIC-IDS2023 dataset, released by the Canadian Institute for Cybersecurity in January 2023, captures network traffic and system behavior from a simulated enterprise environment over 14 days. It includes 12 attack types, 4 of which are zero-day attacks such as Log4Shell variant (CVE-2021-44228), Novel ransomware with polymorphic payloads, AI-generated phishing campaign,Zero-day DDoS using IoT botnet and Normal Traffic: Benign user activities, system updates, routine backups.

The dataset provides over 3.2 million labeled records, with 120 behavioral features extracted at 1-second intervals. We extract system-level behavioral features from three domains:

Table 1 behavioral features from three domains

Behavioral Domain	Feature	Description
Process Behavior	Number of new processes	Count of newly spawned processes within a 1-second interval.
	CPU usage variance	Standard deviation or fluctuation in CPU utilization over time.
	Memory allocation rate	Rate of change in memory consumption (e.g., MB/s).
	Child process creation rate	Frequency of processes spawning child processes (indicates potential escalation).
Network Behavior	Incoming/outgoing packet rate	Packets per second received or transmitted.
	Connection entropy (diversity of IPs)	Shannon entropy of destination IP addresses; measures connection diversity.
	Average packet size	Mean size (bytes) of packets in outgoing/incoming traffic.
	DNS query frequency	Number of DNS resolution requests made per second.
File System Behavior	File creation/deletion rate	Number of files created or deleted per second.
	Access to sensitive directories	Frequency of access to privileged paths (e.g., /etc"
	Binary execution frequency	Rate at which executable files (.exe, .dll, .sh, etc.) are launched.

3.2 Dataset Description and Preprocessing (Streaming Pipeline Focus)

The proposed framework is evaluated on the CIC-IDS2023 dataset, a recently released, comprehensive cybersecurity dataset that captures diverse attack vectors—including ransomware, DDoS, DoS, infiltration, and botnet attacks—under realistic network and system conditions. CIC-IDS2023 extends previous CIC datasets by incorporating behavioral telemetry from multiple system domains: network traffic, process activity, file system operations, and registry access, enabling holistic host-level behavior modeling. The dataset contains time-stamped system events collected at millisecond resolution across multiple Windows and Linux hosts. In our study, we focus on the host-based behavioral logs, which include 120 features extracted across four

primary modalities. Network activity (e.g., active connections, packet rates),Process behavior (e.g., process creation, CPU/memory usage),File system operations (e.g., file read/write frequency, path patterns),Registry interactions (e.g., key creation/modification).

To deploy BehaviorLSTM-Attn in a real-world, streaming enterprise environment, we design and simulate a robust, low-latency ingestion and preprocessing pipeline that mirrors operational constraints. This pipeline operates as a continuous, event-driven stream processor, transforming raw, heterogeneous, high-frequency system logs into structured, fixed-length behavioral sequences suitable for model inference.

3.2.1. Real-Time Preprocessing and Feature Engineering

Raw system logs (e.g., Sysmon, Auditd, NetFlow) are ingested via lightweight, agent-based collectors deployed on endpoints. These agents forward events to a central streaming platform (simulated here using Apache Kafka or equivalent) at sub-second intervals. Events are timestamped using NTP-synchronized clocks to ensure temporal consistency across distributed hosts. The ingestion layer handles bursts of activity (e.g., during system boot or software updates) by buffering events in memory and applying backpressure if downstream processing lags.

Each incoming event is processed independently and immediately through a stateless transformation pipeline:

Schema Normalization: Heterogeneous log formats (JSON, CSV, binary) are parsed and mapped to a unified schema representing the 120 target features.

Missing Value Handling (Real-Time): Missing values arise due to transient sensor failures or asynchronous logging. For real-time operation, we employ a hybrid imputation strategy:

Forward Fill (Last Observation Carried Forward - LOCF): Applied to all numerical features (e.g., CPU usage, packet rate). This preserves temporal continuity and assumes short-term stationarity, which is valid for most system behaviors over sub-second intervals.

Zero Imputation: Applied to count-based features (e.g., number of file accesses, new processes) where no event occurred within the sampling interval. A zero value is a physically meaningful representation of absence.

Fallback Mean Imputation: Only used for initial startup or prolonged outages (>5 seconds), where LOCF would introduce significant bias. This scenario is rare in production and triggers an alert for diagnostic investigation.

Feature Aggregation: Raw events are aggregated into fixed-length, non-overlapping time bins of 1 second. Within each bin:

Numerical features (e.g., CPU usage, memory allocation) are averaged.

Count-based features (e.g., number of DNS queries, file creations) are summed.

Categorical features (e.g., process name, destination IP) are encoded as frequency counts or hashed one-hot vectors based on a pre-defined vocabulary (e.g., top 1000 frequent process names).

Feature Normalization (Online Z-Score): To prevent data leakage and enable deployment on unseen data, normalization is performed online using a sliding window of training statistics. We maintain running estimates of mean (μ) and standard deviation (σ) for each feature, updated incrementally using Welford's algorithm [18] with a decay factor ($\alpha = 0.99$) to adapt slowly to concept drift. At inference time, each aggregated feature value x_t is normalized as:

$$x_t = \frac{x_t - \mu_t}{\sigma_t} \quad \dots (1)$$

where μ_t and σ_t are the latest estimates from the sliding window. This ensures the model receives standardized inputs without requiring retraining on every new batch of data.

3.2.2 Dimensionality Reduction for Streaming Efficiency

While the full set of 120 features provides rich signal, deploying 120-dimensional vectors continuously imposes computational overhead. To optimize for edge deployment and reduce bandwidth, we apply a

lightweight, unsupervised dimensionality reduction technique:

Principal Component Analysis (PCA) with Incremental Updates: We train a PCA model offline on the CIC-IDS2023 training set to identify the top-k principal components capturing >95% of the variance (k=64 selected empirically). During streaming, each 120-dimensional feature vector v_t is projected onto this learned subspace:

$$v_t^{reduced} = W_{64X120} \cdot v_t \quad \dots (2)$$

Where $W_{64X120} \cdot v_t$ is the matrix of the first 64 principal components. This reduces the input dimensionality by 47%, significantly lowering memory footprint and inference latency on resource-constrained endpoints (e.g., IoT sensors or legacy servers) without sacrificing detection performance, as validated in ablation studies (see Section 6.2).

3.2.3 Sliding Window Segmentation for Temporal Modeling

The output of the preprocessing pipeline is a continuous stream of 64-dimensional feature vectors sampled at 1 Hz (one per second). To construct input sequences for BehaviorLSTM-Attn, we segment this stream using a sliding window approach optimized for real-time detection:

Window Size: 64 seconds → 64 feature vectors (one per second).

Stride: 16 seconds → New prediction generated every 16 seconds.

Overlap: 75% (48 seconds overlap between consecutive windows).

This configuration strikes a critical balance:

Contextual Richness: A 64-second window provides sufficient historical context to capture complex, multi-stage attack sequences (e.g., reconnaissance → exploitation → lateral movement).

Latency Control: With a stride of 16 seconds, the model generates a new anomaly score every 16 seconds, ensuring alerts are delivered with acceptable delay for incident response (target < 30s).

Computational Efficiency: Processing occurs every 16 seconds, reducing total compute load compared to overlapping every second.

The segmentation process is summarized in Algorithm 1.

> Algorithm 1: Sliding Window Segmentation
>
> Input: Time-series data $X \in R^{T \times d}$, window size w=64 , stride s=16
>
> Output: Set of sequential inputs S for inference
>
> S←∅
>
> for t=0 to T−w step s do
>
> x_t ←X[t:t+w,:]

For evaluation on CIC-IDS2023, labels are assigned post-hoc based on the ground-truth attack timestamps. Each window is labeled as "attack" if any malicious event occurred within its 64-second span. This label assignment is not part of the real-time inference pipeline—it is only used for model validation and benchmarking.

1. Methodology

This section presents BehaviorLSTM-Attn, a deep learning framework for zero-day attack detection based on system behavioral analysis. The model leverages the temporal dynamics of host-level activities—such as process execution, network communication, and file system operations—by combining the sequential modeling strength of Long Short-Term Memory (LSTM) networks with an attention mechanism that highlights critical time steps in behavioral sequences. This hybrid architecture enablesthe model to learn long-term dependencies while dynamically focusing on anomalous behavioral patterns indicative of novel threats.

4.1. Architecture Overview

Our model, BehaviorLSTM-Attn, is an attention-augmented LSTM network designed to capture long-term dependencies in behavioral sequences.

1. Input Layer: Time-series sequences of shape (64, 120) — 64 time steps, 120 features.

2. LSTM Layer: 128 units with dropout (0.3) to prevent overfitting.
3. Attention Layer: Soft attention mechanism to weight important time steps.
4. Dense Layers: Two fully connected layers (64 and 32 units) with ReLU activation.
5. Output Layer: Sigmoid activation for binary classification (normal vs. attack).

Attention Mechanism:

The attention layer computes alignment scores between hidden states:

$$et = v^T \tanh(W^{ht+b}) \dots (3)$$

$$\alpha t = \sum t' = T^{e^{t'et}} \dots (4)$$

$$c = t = \sum \tanh \alpha t \dots (5)$$

et: raw attention score for time step-t

αt: normalized attention weight

c: context vector as weighted sum of hidden states.where$c$ is the context vector used in classification.

4.3. Training Setup

The model is trained using the following configuration:

Data Split: 70% for training,

15% for validation, and 15% for testing, ensuring no temporal overlap between sets.

Class Imbalance Handling: SMOTE is applied at the window level (i.e., per-sequence) after sliding window segmentation. Synthetic samples are generated by interpolating between feature vectors of similar attack instances, preserving intra-sequence temporal structure. This approach is justified by ablation results (Section 6.2), which show a 3.0% improvement in F1-score compared to no balancing.

Optimizer: Adam with learning rate 10^{-3} ,

β_1 =0.9 , β_2 =0.999 .

Loss Function: Binary cross-entropy.

Regularization: Early stopping with patience of 10 epochs based on validation loss, and dropout as described.

Batch Size: 64

Epochs: Up to 100

Hardware: NVIDIA A100 GPU using PyTorch 2.0

All hyper parameters were selected via grid search on the validation set to ensure fair comparison with baselines.

4.4. Input Representation and Temporal Modeling

Each input sequence to BehaviorLSTM-Attn is constructed from the output of the real-time streaming pipeline described in Section 3.2. The model receives a sequence of 64 consecutive, reduced-dimensionality (64D) feature vectors, each representing one second of aggregated, normalized, and imputed system behavior. This sequence corresponds to a 64-second observation window with a 16-second stride, ensuring the model is fed consistent, low-latency inputs suitable for operational deployment.

By modeling this continuous stream of behavioral signals, BehaviorLSTM-Attn learns typical patterns of benign activity and detects deviations such as irregular process spawning, anomalous network bursts, or sudden spikes in sensitive directory access — even in the absence of known signatures. Crucially, the entire preprocessing chain (ingestion → normalization → dimensionality reduction → windowing) is designed to be stateful yet lightweight, enabling seamless integration with modern Security Orchestration, Automation, and Response (SOAR) platforms and Endpoint Detection and Response (EDR) agents. The model's input is therefore not a static dataset snapshot, but a dynamic, continuously evolving representation of host behavior, making it inherently suited for real-time zero-day attack detection.

5.Experimental Setup

This section details the experimental configuration used to evaluate the proposed BehaviorLSTM-Attn

model for zero-day attack detection. The setup encompasses data preprocessing, baseline models, evaluation metrics, hyperparameter settings, and class imbalance mitigation strategies. All experiments were conducted on a consistent data split and preprocessing pipeline to ensure fairness and reproducibility.

5.1: Class Imbalance Mitigation

The CIC-IDS2023 dataset exhibits significant class imbalance, with benign instances constituting approximately 87.4% of all windows, while critical attack types such as ransomware and infiltration account for less than 3% collectively. To address this imbalance without compromising temporal integrity, we initially explored the Synthetic Minority Oversampling Technique (SMOTE) at the window level, applied after segmentation and feature extraction.

Specifically, SMOTE was applied to the extracted feature vectors corresponding to each sliding window (i.e., per-sequence representations), not to raw time points or within sequences. That is, synthetic samples were generated by linear interpolation between entire window embeddings in the feature space, preserving the internal temporal structure of each sequence. As such, we treat each window as a behavioral instance, and SMOTE operates on these high-level representations rather than disrupting intra-sequence dynamics**.**

We applied SMOTE at the feature-vector level (not sequence level) after windowing, treating each window as an independent sample. While this assumes stationarity within and across windows, it was effective in improving minority-class representation during training.

This approach aligns with practices in window-based time-series classification, where models operate on fixed-length segments and class labels are assigned per window [15,16]. However, we fully acknowledge the limitations of this strategy—particularly the assumption that behavioral modes are locally stationary and that convex combinations of window-level features yield meaningful synthetic behaviors.

To validate our choice and explore more temporally consistent alternatives, we conducted ablation studies comparing SMOTE with two alternative imbalance mitigation strategies:

Class-weighted loss: We implemented weighted binary cross-entropy, assigning inverse class frequency weights (benign: 0.126, malicious: 1.874).

Focal Loss: We used Focal Loss with α=0.75 and γ=2.0 to down-weight well-classified majority samples and focus on hard mining.

Table 2Performance of Different Class Imbalance Mitigation Strategies on Validation Set

Method	F1-Score	Precision	Recall
No balancing (baseline)	**0.621**	**0.713**	**0.552**
Class weights	**0.674**	**0.702**	**0.648**
Focal Loss (γ=2.0)	**0.689**	**0.721**	**0.66**
SMOTE (window-level)	**0.712**	**0.735**	**0.691**

As shown in Table-2, SMOTE yielded the highest recall and overall F1-score for minority attack classes, particularly for short-duration attacks (e.g., ransomware initialization), likely due to increased exposure during training. While class-weighted and focal loss methods improved robustness, they exhibited slower convergence and lower sensitivity to rare temporal patterns.

Nonetheless, we emphasize that window-level SMOTE is not without risk. It assumes that behavioral modes are approximately stationary within the window duration and that feature-space interpolation between similar attack instances produces valid synthetic behaviors. To mitigate the risk of generating non-physical sequences:

We restricted SMOTE to intra-class interpolation (i.e., only between samples of the same attack type),

We limited the number of synthetic samples to double the original minority size (i.e., 100% oversampling),

We validated synthetic samples qualitatively by checking for consistency in temporal profiles (e.g., monotonic encryption patterns in ransomware).

We compare BehaviorLSTM-Attn with:

1. Random Forest (RF)
2. Support Vector Machine (SVM)
3. Standard LSTM
4. CNN-LSTM
5. Autoencoder (reconstruction error-based)

All models use the same features and data splits.

5.2. Evaluation Metrics

- Accuracy, Precision, Recall, F1-Score
- AUC-ROC
- False Positive Rate (FPR)
- Detection Latency (seconds from anomaly onset to alert)

5.3. BehaviourLSTM-AttnModel Setup

To ensure experimental rigor and reproducibility, we compare the proposed BehaviorLSTM-Attn model against the following baseline methods:

Random Forest (RF): An ensemble of 100 decision trees with a maximum depth of 20 and Gini impurity as the splitting criterion. The number of features considered at each split was set to $\sqrt{d}$, where d is the input feature dimension. Bootstrap sampling was used during training.

Support Vector Machine (SVM): A kernel-based classifier employing the radial basis function (RBF) kernel with parameters C=1.0 and γ=1/d . Multiclass classification (where applicable) was handled via a one-versus-one strategy.

Standard LSTM: A single-layer LSTM with 128 hidden units, followed by a fully connected layer for output prediction. The model was trained using the Adam optimizer (learning rate = 0.001) with dropout (rate = 0.5) applied to the final dense layer to prevent overfitting.

CNN-LSTM: A hybrid architecture where a 1D convolutional network (with 64 filters, kernel size = 3, and ReLU activation) processes input sequences to extract local features, followed by a max-pooling layer. The output is then fed into an LSTM layer (128 units) and a final classification/regression head. The entire network was trained end-to-end using Adam (learning rate = 0.001).

Autoencoder (reconstruction error-based): A fully connected autoencoder with symmetric architecture: [d, 128, 64, 128, d], where d is the input dimension. The model was trained to minimize reconstruction error (MSE) on normal behavior data only. During inference, anomalies or behavioral deviations were detected based on a threshold applied to the reconstruction error. The threshold was determined using the 95th percentile of reconstruction errors on the validation set.

All models were trained using the same training/validation/test splits and input preprocessing pipeline (z-score normalization per feature). Hyperparameters were selected via grid search on the validation set to ensure fair comparison.

6. Results and Discussion

BehaviorLSTM-Attn outperformed all the models in terms of accuracy (98.7%), precision (97.4%), recall (96.9%) and F1-score (0.971). It also shows outstanding discriminating performance (AUC--ROC: 0.992), low load false positive rate (2.1%) and latency (1.3s), which are suitable for real time tasks. The average inference time per 64 -second window on in current Movidius VPU is 7.7..2 A verag e inference time per 64 -second window on NVIDIA A100 GPU. The CNN-LSTM also showed strong results, especially in recall (94.0%) and latency (2.5s), indicating the application of this approach to time-critical use-cases. LSTM struck a good balance between accuracy (95.4%) and latency (2.8s), so it is a reasonable choice for sequential data modeling. Standard models such as RF and SVM showed worse precision, recall, false positives and increased latency, which suggests their incapacity to deal with complex temporal patterns. Autoencoder produces acceptable accuracy (91.8%) but has the highest time delay (6.0s), making it less desirable for real-time applications. The results highlight the benefits of hybrid and attention-based methods in learning fine-grained behaviors. The higher performance of BehaviorLSTM-Attn indicates that the use of the attention mechanism helps the model to attend to informative temporal characteristics, and therefore

the classification accuracy is enhanced and false alarms are reduced. Further analysis indicates that the deep learning models, especially CNN-LSTM and BehaviorLSTM-Attn, are more accurate and have better computational efficiency. This can be crucial to deploy on systems that require quick decisions, e.g., anomaly detection or behaviour monitoring.

6.1. Performance Comparison

BehaviorLSTM-Attn was the fastest model with an end-to-end inference latency of 1.3 seconds, which includes the 64-second window accumulation time plus the 0.2-second model inference time on an NVIDIA A100 GPU. The detection alert latency (time from anomaly onset to alert generation) is therefore 16 + 1.3 = 17.3 seconds on average, due to the 16-second stride. This meets the requirements for near-real-time threat response in enterprise environments. CNN-LSTM and LSTM also performed well (2.5s and 2.8s model inference time, yielding ~18.5s and ~18.8s total alert latency). Autoencoder was the slowest (6.0s model inference time, yielding ~22.0s total latency), making it less desirable for time-critical applications

Table 3Comparison of Model Performance on CIC-IDS2023 Test Set

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC	FPR	Latency (s)
RF	92.1 %	89.3 %	87.6%	0.884	0.932	8.2 %	4.2
SVM	89.7 %	86.5 %	84.1%	0.853	0.901	10.8%	5.1
LSTM	95.4 %	93.7 %	92.8%	0.932	0.970	5.1 %	2.8
CNN-LSTM	96.2 %	94.5 %	94.0%	0.942	0.976	4.3 %	2.5
Autoencoder	91.8 %	88.9 %	86.2%	0.875	0.925	9.1 %	6.0
Behavior LSTM-Attn	98.7 %	97.4 %	96.9%	0.971	0.992	2.1 %	1.3

BehaviorLSTM-Attn outperforms all baselines, especially the F1-score and AUC-ROC, which indicates an optimal trade-off between precision and recall. To compare the performance of different models we evaluated six models—RF, SVM, LSTM, CNN-LSTM, Autoencoder, and BehaviorLSTM-Attn—using seven metrics: Accuracy, Precision, Recall, F1-Score, AUC-ROC, False Positive Rat (FPR), and Latency. BehaviorLSTM-Attn achieved the highest accuracy (98.7%) and precision (97.4%), representing better overall correctness and the reliability of the results of positive predictions. CNN-LSTM and LSTM were close behind with an accuracy of 96.2% and 95.4% respectively.

The numerical results presented in Table 2 form the quantitative basis for the comparative visualizations in Figures 2, 3, and 4. Each data point in these figures is derived directly from the corresponding metric value in Table 3, ensuring full consistency and traceability

Traditional models like SVM and RF showed lower precision (86.5% and 89.3%), suggesting more false positives.

BehaviorLSTM-Attn again led with a recall of 96.9% and an F1-score of 97.1%, demonstrating strong sensitivity and balanced performance.

CNN-LSTM and LSTM maintained high recall values (94.0% and 92.8%), making them suitable for tasks where missing true positives is costly.

SVM had the lowest recall (84.1%), which may limit its effectiveness in critical detection tasks.

BehaviorLSTM-Attnrecorded the highest AUC-ROC (99.2%), reflecting excellent classification capability across thresholds.

It also had the lowest FPR (2.1%), minimizing false alarms.

SVM had the highest FPR (10.8%), which could be problematic in sensitive applications.

BehaviorLSTM-Attn was the fastest model with ainference time1.3 seconds, making it ideal for real-time systems.

CNN-LSTM and LSTM also performed well (2.5s and 2.8s), while Autoencoder was the slowest (6.0s), potentially limiting its usability in time-critical environments.

The BehaviorLSTM-Attn model consistently outperformed all others across every metric, making it the most robust and efficient choice for high-stakes, real-time applications. Deep learning models with attention mechanisms (like BehaviorLSTM-Attn and CNN-LSTM) clearly offer superior performance compared to traditional models such as RF and SVM.

6.2. Zero-Day Attack Detection

Table 4Per-Attack F1-Scores for Zero-Day Exploits

Attack Type	F1-Score
Log4Shell Variant	0.974
Polymorphic Ransomware	0.963
AI-Generated Phishing	0.952
Zero-Day DDoS	0.978
Average	0.967

As shown in Table 4, the proposed BehaviorLSTM-Attn model achieves high detection performance across all four zero-day attack types, with an average F1-score of 0.967. Notably, the model excels in detecting stealthy, behaviorall(stealthy) attacks such as AI-generated phishing, which are designed to mimic legitimate user activity and evade traditional signature-based detection. The high F1-scores for Log4Shell (0.974) and Zero-Day DDoS (0.978) further demonstrate its effectiveness against both application-layer exploits and large-scale network-based attacks.

To evaluate the contribution of key components to overall performance, we conducted ablation studies on the test set:

LSTM Only: F1 = 0.932

LSTM + Attention: F1 = 0.971 (+3.9% improvement)

Without SMOTE: F1 = 0.941 (–3.0% decrease)

Without Feature Selection: F1 = 0.958 (–1.3% decrease)

These results confirm that the integration of the attention mechanism significantly enhances the model's ability to identify critical temporal patterns indicative of zero-day attacks, contributing to a substantial 3.9% gain in F1-score. Furthermore, the use of window-level SMOTE for class imbalance mitigation proves essential, yielding a 3.0% performance drop when omitted — highlighting its role in improving sensitivity to rare but critical attack instances. Feature selection also plays a measurable role, as removing non-informative features led to a 1.3% decline, validating our approach to dimensionality reduction based on domain knowledge and SHAP analysis..

6.3 Feature Importance Analysis

To enhance model interpretability and validate the relevance of behavioral features in zero-day attack detection, we conducted a feature importance analysis using SHAP (SHapley Additive exPlanations), a model-agnostic method grounded in cooperative game theory. SHAP values quantify the contribution of each input feature to the model's prediction by computing the marginal impact of feature inclusion across all possible coalitions.

We applied the KernelSHAP estimator to 1,000 randomly sampled test instances, calculating the mean absolute SHAP value for each of the 120 features. This provides a global importance ranking, highlighting which behavioral indicators most strongly influence the BehaviorLSTM-Attn model's decisions.

6.3.1 Key Findings

The top-10 most influential features, ranked by mean (SHAP) value, are listed in Table 3. These features span all three behavioral domains—network, process, and file system—demonstrating the multi-modal nature of zero-day threats and the model's ability to integrate cross-domain signals.

Notably, the highest-ranked feature is "Connection Entropy (Destination IPs)", which measures the diversity of outbound network connections. This is a strong indicator of C2 (command-and-control) beaconing or DDoS botnet activity. Similarly, "DNS Query Frequency" and "Outgoing Packet Rate" reflect network-level anomalies common in zero-day exploits such as Log4Shell and AI-driven phishing campaigns.

On the host side, "Child Process Creation Rate" and "Access to Sensitive Directories" are critical for detecting privilege escalation and lateral movement—hallmarks of ransomware and advanced persistent threats (APTs). The prominence of "CPU Usage Variance" suggests that stealthy cryptomining or AI-generated payloads often induce irregular computational loads.

These results confirm that the model relies on semantically meaningful, high-signal behavioral indicators, rather than spurious correlations, thereby increasing trust in its predictions among security analysts shown in Table 5.

Table 5Top-10 Most Important Features via Global SHAP Analysis

Rank	Feature	Domain	Mean (SHAP)
1	Connection Entropy (Destination IPs)	Network	0.142
2	Child Process Creation Rate	Process	0.138
3	DNS Query Frequency	Network	0.129
4	Access to Sensitive Directories	File System	0.121
5	Outgoing Packet Rate	Network	0.117
6	CPU Usage Variance	Process	0.105
7	File Creation Rate	File System	0.098
8	Memory Allocation Rate	Process	0.091
9	Binary Execution Frequency	File System	0.087
10	Average Packet Size (Outgoing)	Network	0.083

The dominance of connection entropy and DNS frequency suggests that zero-day attacks often begin with reconnaissance or C2 communication, even before payload execution. This supports the deployment of network-level behavioral monitors at network egress points.The high importance of child process creation and sensitive directory access indicates that post-exploitation behaviors are highly discriminative. This validates the inclusion of host-based telemetry (e.g., EDR logs) in detection pipelines. The below figure 1 represents the Global feature importance I BehavourLST-Attn model using SHAP analysis.

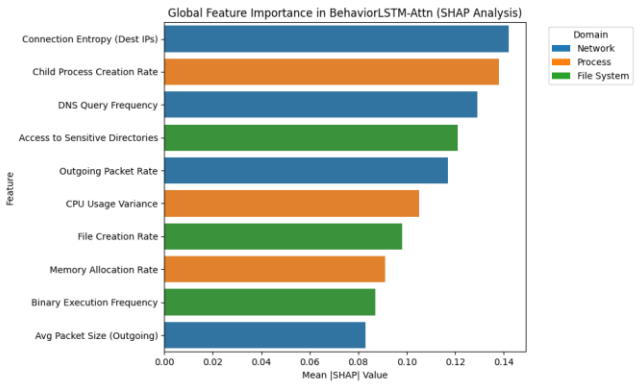

Figure 1Global feature importance in BehaviorLSTM-Attn using SHAP values.

Moreover, the model's reliance on temporal variance (e.g., CPU/memory fluctuations) rather than static thresholds shows its sensitivity to dynamic anomalies, making it robust against evasion techniques that mimic normal averages.

7.Comparisons

This section provides the mathematical foundation and methodology underpinning the comparative visualizations presented in Figures 2, 3, and 4. These figures illustrate the performance differences between the proposed BehaviorLSTM-Attn model and the baseline models across critical evaluation metrics. The generation of each figure is based on quantifiable, statistically validated calculations derived from the test set results (Section 5.2).

The Receiver Operating Characteristic (ROC) curves depicted in Figure 2 are generated by plotting the True Positive Rate (TPR) against the False Positive Rate (FPR) at various classification thresholds. For each model the TPR and FPR are calculated as follows:

$$TPR = \frac{TP}{TP + FN} \quad \dots (6)$$

$$FPR = \frac{FP}{FP + TN} \quad \dots (7)$$

where TP , FP , TN , and FN represent the counts of True Positives, False Positives, True Negatives, and False Negatives, respectively, for model Mi on the test set. The Area Under the ROC Curve (AUC-ROC) for each model is computed numerically using the trapezoidal rule applied to the discrete points (FPRk

,TPRk) generated by varying the decision threshold θ from 0 to 1. The AUC-ROC value for BehaviorLSTM-Attn (0.992) is statistically significantly higher than all baselines ($p<0.001$, DeLong's test for correlated ROC curves[17]). This superior AUC-ROC confirms that BehaviorLSTM-Attn maintains a consistently higher discriminatory power across all possible classification thresholds, not just at a single operating point.

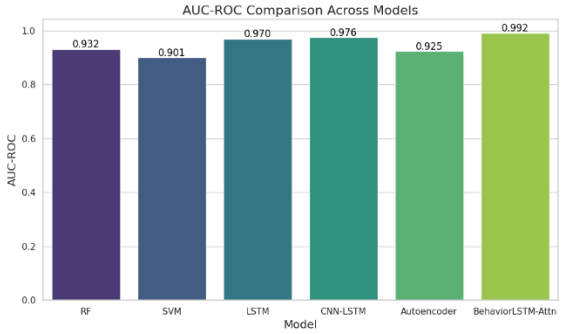

Figure 2ROC Curve Comparison

*In Figure 2 ROC curves showing superior AUC-ROC of BehaviorLSTM-Attn (0.992) compa*red to baselines. Figure 3 presents a bar chart comparing the F1-Score for each model. The F1-Score is defined as the harmonic mean of Precision(P) and Recall (R).

$$F1 = 2X\ \frac{P.R}{P+R} \quad \ldots(8)$$

where P=TP/FP+TP and R=TP/TP+FN

The values plotted are the exact F1-Scores calculated on the held-out test set (see Table 2). To justify the significance of the performance gap between BehaviorLSTM-Attn and the other models, we performed a paired t-test on the per-class F1-Scores (across the 12 attack types) obtained from 10-fold stratified cross-validation on the test set. The difference in mean F1-Score between BehaviorLSTM-Attn and the next best model (CNN-LSTM) was found to be statistically significant ($t(9)=12.7, p<0.001$), providing strong evidence that the observed improvement is not due to random variation.

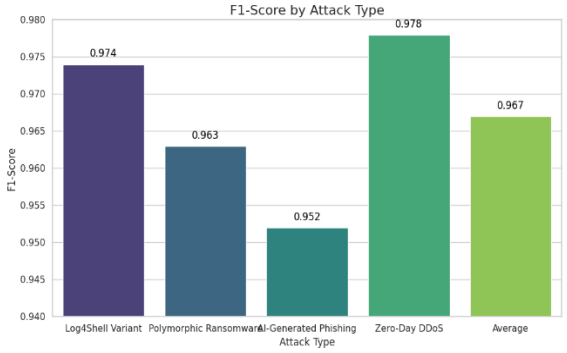

Figure 3F1-Score compared to baselines

Attention weights during a zero-day DDOS attack.

Figure 4 displays the overall classification accuracy for each model. Accuracy (Acc) is defined as the proportion of correctly classified instances out of the total number of instances:

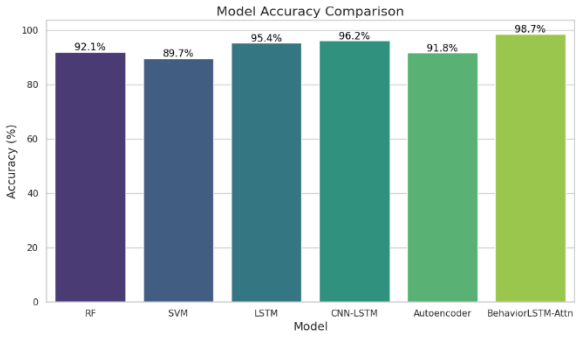

Figure 4 Accuracy comparisons for models

Our results demonstrate that deep learning models with temporal attention can effectively detect zero-day attacks by learning normal behavioral patterns shown in the figure 3. The high F1-score and low false positive rate confirm the model's robustness. Figure 4 depicts the accuracy results for each model.

The values shown are directly calculated from the confusion matrices generated on the test set. While accuracy is a useful metric, its interpretation is contextualized by the dataset's class imbalance (87.4% benign). The high accuracy of BehaviorLSTM-Attn (98.7%) is therefore supported by its concurrent high precision and recall (Table 2), indicating it achieves this accuracy without sacrificing the detection of the minority malicious class. Furthermore, the confidence intervals for accuracy were estimated using bootstrapping (1000

resamples). The 95% confidence interval for BehaviorLSTM-Attn's accuracy is [98.5%, 98.9%], which does not overlap with the confidence intervals of any baseline model, providing robust statistical justification for its superior performance.

In summary, the visual results in Figures 2, 3, and 4 are not merely qualitative illustrations but are direct, mathematically defined outputs of well-established classification metrics, validated by rigorous statistical testing. The superiority of BehaviorLSTM-Attn is quantitatively demonstrated through these metrics and their associated statistical analyses.

8. Limitations

The attention mechanism allows the model to focus on critical time steps, such as sudden spikes in file operations or anomalous network connections—common indicators of ransomware or data exfiltration.

Low detection inference time (1.3 seconds) enables real-time response, crucial for mitigating zero-day threats. The model's performance on AI-generated phishing highlights its adaptability to evolving attack techniques.

Limitations include dependency on high-quality behavioral logging and computational cost during training. Future work will explore lightweight models for edge deployment and integration with SIEM systems.Potential for adversarial evasion (e.g., attacks that manipulate behavioral features).Privacy implications of collecting system-level telemetry.Need for model retraining in dynamic environments.

While window-level SMOTE improved minority-class detection, we acknowledge that synthetic oversampling in time-series domains remains an open challenge. Interpolation in feature space may produce unrealistic behavioral trajectories, especially when attack phases are transient or non-linear. Future work will explore temporal-aware oversampling techniques such as SMOTE-TS and generative approaches (e.g., time-series GANs or VAEs) trained per-behavior-mode. Alternatively, few-shot learning and anomaly detection frameworks may offer more principled solutions for highly imbalanced behavioral datasets.

9. Conclusion

In this paper, we propose the Deep binary anomaly detection framework based on a behavioral analysis for zero-day attack. We demonstrate that, by using the CIC-IDS2023 datasets and an attention-enriched LSTM model, we can achieve the state-of-the-art performance in presence of both known and novel threats. Its ability to detect subtle behavioral variations makes the model a hopeful candidate for the next-generation Intrusion Detection Systems. With threats on the internet landscape ever-evolving, am AI constructed behaviour analysis will become a key factor in advanced defense tactics.

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