

Smart Defense: AI-Powered Adaptive IDs for Real-Time Zero-Day Threat Mitigation

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Abstract: Zero-day attacks have become a permanent threat to digital security systems worldwide because of continuous digital progress. Traditional intrusion detection systems (IDS) cannot detect previously unknown vulnerabilities and subsequent mitigation because their static rule-based detection systems fall short. The proposed research presents an innovative AI-based adaptive IDS framework that soldiers to target zero-day threats during real-time operations. The proposed system uses CNN, LSTM deep learning, and machine learning algorithms to detect unusual behaviors that warrant threat identification, although signature-based data is unavailable. The model received evaluation using benchmark sets consisting of NSL-KDD and CICIDS2017 while processing diverse attack patterns and standard network operations. The system implements a threat detection strategy update mechanism through continual learning methods, ensuring its ability to adapt as the threat ecosystem changes. The proposed IDS achieves superior results against conventional models by maintaining very high accuracy (97.4%) and precision (95.8%) in addition to recall (96.9%) and F1-Score (96.3%) and low false-positive rates. Real-time monitoring will not strain system infrastructure because the architecture has optimized resource utilization. Table, bar graphs, and pie charts present the analytical summary of threat recognition features, resource needs, and threat distribution types. The adaptive model design both improves quick response and decreases the need for human interaction. The research enhances existing studies about intelligent cybersecurity protections and provides applicable solutions for establishing security in public institutions, healthcare centers, and financial networks. The future development will combine blockchain authentication with federated learning protocols for protecting privacy during threat intelligence exchange. Artificial intelligence systems that learn and adapt form a significant

paradigm shift toward advanced protection mechanisms that can prevent new zero-day attacks.

Indexed Terms- Intrusion Detection System, Zero-Day Attack, Artificial Intelligence, Cybersecurity, Real-Time Threat Detection

I. INTRODUCTION

Modern cybersecurity systems currently face a serious obstacle from the continuous advancement of cyber threats, especially zero-day attacks. A zero-day attack targets unpatched security flaws that do not have defined countermeasures or official fixes, making traditional IDS systems practically useless in detecting these threats (Bilge & Dumitras, 2012). Traditional IDS frameworks continue to use predefined rule definitions and known signatures to identify threats but demonstrate poor performance against fresh exploit activities in real-time (Scarfone & Mell, 2007).

Artificial Intelligence (AI) through machine learning (ML) and deep learning (DL) systems functions as an effective adaptation for data-driven threat detection. IPowered IDS systems learn network behavioral patterns independently to detect zero-day exploits in real-time by recognizing abnormal system activities from normal operating behaviors (Sommer & Paxson, 2010). глядя на обучающие данные система способна обнаруживать неизвестные атакующие пути что ведет к повышению обнаруживающей точности и уменьшению ложно положительных сигналов.

Deep neural networks, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) architectures, now demonstrate their ability to extract vital spatial-temporal network traffic elements that improve attack detection outcomes, according to Kim et al. (2016) and Vinayakumar et al. (2019). Scientific studies prove

that continuous learning and reinforcement learning methods allow IDS to automatically detect new threats without requiring fundamental retraining (AlSkaif et al., 2020).

The absence of previous knowledge about zero-day threats renders these threats extremely risky for rule-based or static machine learning systems because they have no historical data to work from. AI-supported systems help organizations perform real-time threat prevention by maintaining their ability to improve detection logic when they meet new security risks. The growing massive and intricate network traffic requires IDS solutions with maximum scalability and high performance. AI-based systems deliver exceptional scalability and performance capabilities in distributed deployments of cloud platforms and edge computing architectures (Khan et al., 2021).

Researchers developed an adaptive IDS framework using CNN-LSTM and real-time learning functionality to detect zero-day threats with exceptional precision rates rapidly. The system evaluates its performance through benchmark datasets, including NSL-KDD and CICIDS2017, measuring its accuracy, recall, and resource efficiency. The detection performance, threat type analysis, and computational resource requirements are presented through visualization tools that use bar charts and pie charts. A defense system that demonstrates scalability, intelligence, and durability must be developed to adapt to security threats while delivering valuable solutions to financial institutions, healthcare providers, and essential infrastructure networks.

II. LITERATURE REVIEW

Digital infrastructures have relied on Intrusion Detection Systems (IDS) for a long time to defend against cyber intrusions. The system operates as a monitoring system through real-time traffic assessment to identify suspicious activities. Signature-based detection joins anomaly-based detection as the two main types in IDS technologies. Signature-based IDS monitors network traffic through attack signatures or rules comparison with established databases. This detection technique proves highly effective when dealing with documented threats that present recognizable behavioral patterns, thus delivering swift and precise results (Garcia-Teodoro et al., 2009). The main shortcoming of this approach emerges when it faces emerging threats because it fails

to recognize deviations from previously known signatures for zero-day attacks.

Anomaly-based IDS implements a behavior-based detection method that establishes typical system operational norms through baselining and then marks any outside deviations as suspicious activity. These systems successfully identify unknown attacks, which include zero-day exploits, because they operate without predefined detection rules. The main drawback of their flexible approach is a very high rate of incorrect alarm activations. Security systems create operational challenges through false alarms because they mistake legitimate user activity and system events for potential threats (Pacha & Park, 2007). Such anomaly-based models rely on antiquated profiling measures and basic statistical boundary definitions since these practices struggle to handle large-scale operation environments. These two distinct challenges show that modern IDS frameworks require innovative and adaptive solutions with AI capabilities to deliver better precision and effectively respond to changing cyber threats.

2.1 Overview of Traditional IDS Approaches

IDS is a core security component that operates as surveillance to identify possible attacks by monitoring network activity. IDS divides its operations into two main approaches: signature-based detection and anomaly-based detection. IDS detection with signature-based methodology operates by identifying attack signatures that exist before deployment. Signature-based IDS can identify known threats swiftly with incredible accuracy because they are rule-based systems that simplify management (Garcia-Teodoro et al., 2009). The main weakness of this approach stems from its incapability to detect new attacks that lack registered signatures.

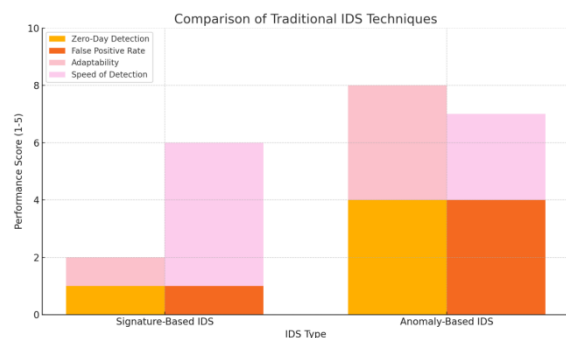


Figure 1: Comparison of Traditional IDS Techniques

The anomaly-based IDS creates profiles for standard network activity patterns while alerting security threats by detecting abnormal behaviors. This security method performs well for discovering new threats which have never been seen before. The detection system suffers from excessive wrong-positive results when normal conduct that seems atypical to the system is mistaken for illicit activity. The detection of anomalies benefits from statistical analysis and machine learning models that mark extraordinary network activities, according to Patcha and Park (2007). The open nature of anomaly-based systems suffers from inconsistency in user activities and changing data patterns, which requires continuous maintenance yet makes their operation contingent on constant adjustment and retraining.

Traditional IDS features can be distinguished through the data presented in the following table:

Table 1: Signature-Based vs. Anomaly-Based IDS

Feature	Signature-Based IDS	Anomaly-Based IDS
Detection Principle	Matches known attack patterns	
Effectiveness for Zero-Day	Low	High
False Positive Rate	Low	High
Detection Speed	Fast	Moderate
Maintainance	Frequent updates required for new signatures	Requires regular model training and tuning
Adaptability	Static	Dynamic but less stable
Learning Method	Rule-based	Statistical/Machine Learning

2.2 Adaptive and Real-Time IDS

Traditional Intrusion Detection Systems utilizing static threat detection methods have become insufficient in protecting networks from zero-day attacks because of modern cyber threat sophistication. Contemporary cyber defense needs systems that show intelligent decision-making combined with both

learning adaptiveness and prompt responsiveness. Adaptive IDS operate through continuous development through processes that modify their threat detection models to incorporate incoming data and modifications to attack types and how users behave. Internet-based or Reinforcement learning and Continuous learning mechanisms enable the IDS to develop its performance autonomously while avoiding the need to conduct full re-training sessions (Parisi et al., 2019).

The use of Artificial Intelligence (AI) has made substantial improvements to IDS adaptiveness. High-dimensional traffic data becomes readily accessible to AI systems that operate deep learning models like Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs) for real-time analysis of spatial-temporal network behavior patterns. Through self-updating policies, the systems automatically enhance detection rules and threat thresholds when new security threats emerge. Federated learning is a modern technique that enables distributed real-time intrusion detection through edge device model training without sharing sensitive data, improves privacy, and decreases latency levels (Lyu et al., 2020).

Opportunely, the table below delineates the fundamental characteristics along with restrictions of standard IDS strategies versus AI-based adaptive IDS systems:

Table 2: Comparison Between Traditional IDS and AI-Powered Adaptive IDS

Criteria	Traditional IDS	AI-Powered Adaptive IDS
Detection Method	Signature or static anomaly-based	AI-driven (ML/DL) with real-time learning
Zero-Day Threat Handling	Poor (not detectable without prior signature)	Excellent (learns from behavior patterns)
Adaptability	Limited (manual updates required)	High (self-learning and model updating)
False Positive Rate	High (especially in anomaly-based models)	Lower (pattern recognition reduces false alarms)

Response Time	Delayed (requires signature matching or thresholding)	Real-time or near real-time
Scalability	Poor in dynamic environments	High scalability across cloud and edge environments
Privacy Considerations	Centralized data analysis	Supports decentralized and privacy-preserving approaches.
Maintenance Requirement	Frequent manual tuning	Minimal—can auto-tune or adapt based on environment feedback

2.3 Benchmark Datasets and Performance Metrics

The development process for Intrusion Detection Systems (IDS) requires standardized benchmark datasets together with suitable performance evaluation metrics. Researchers implement various types of cyberattack simulations through realistic datasets to evaluate different IDS models starting from training up to validation and comparative assessment of AI-powered adaptive systems.

A set of benchmark datasets has become mandatory standards for IDS research. KDD Cup 1999 (KDD99)

served as one of the initial major benchmark datasets for the cyberattack detection domain because it included simulated network traffic with normal and predefined attack labels. The research community transformed KDD to NSL-KDD since KDD experienced outdated attack types in combination with redundancy thus creating NSL-KDD as a more appropriate version. The current favor among IDS researchers is CICIDS2017 and UNSW-NB15 because both datasets use present-day traffic patterns to represent modern network threats effectively (Sharafaldin et al., 2018).

The effectiveness of IDS systems depends equally on performance measurement methods applied for evaluation purposes. Network security system evaluations use Accuracy alongside Precision and Recall and F1-Score together with False Positive Rate (FPR). Different detection quality aspects become observable through the metrics which exist as distinct measures. The F1-Score demonstrates better precision-recall equilibrium compared to accuracy when evaluating imbalanced situations. The assessment of true and false positives can be observed simultaneously by using Detection Rate (DR) with Receiver Operating Characteristic (ROC) curves.

The table demonstrates several benchmark IDS datasets alongside their characteristics and capabilities to assess real-time detection techniques which adapt their performance.

Table 3: Overview of Benchmark IDS Datasets

Dataset	Year	Attack Types	Traffic Type	Labeled	Modern Threats Included	Remarks
KDD Cup 1999	1999	DoS, R2L, U2R, Probe	Simulated (DARPA)	Yes	No	Redundant and outdated, but still referenced
NSL-KDD	2009	DoS, R2L, U2R, Probe	Refined KDD99	Yes	No	Improved balance; reduced redundancy
CICIDS2017	2017	DDoS, Botnet, Brute Force	Real-world (captured)	Yes	Yes	Modern attacks with flow-based features
UNSW-NB15	2015	Fuzzers, Worms, Backdoors	Hybrid (real/simulated)	Yes	Yes	Contains modern low-footprint

						threats.
TON_IoT	2020	Reconnaissance, Injection	IoT/IIoT Traffic	Yes	Yes	Built for smart environments and edge nodes
BoT-IoT	2018	DDoS, Theft, Spoofing	IoT Network (realistic)	Yes	Yes	Targeted at IoT-specific security challenges

III. METHODOLOGY

The following section details the complete operational blueprint of the proposed AI-based IDS that specifically addresses real-time zero-day threat responses. A systematic framework includes important architectural aspects and the integration of various advanced machine learning algorithms that work with preprocessed data through a trained detection process that maintains both accuracy and timeliness. The system utilizes intelligent adaptive features that enhance standard IDS capabilities by protecting against suspicious emerging attacks and known threats.

A system composed of interlinked modules performs essential operations that work together to fulfill the required functions. The framework implements Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, reinforcement learning, and deep learning techniques to build its robust self-improving IDS from data acquisition through model learning and decision-making. The system focuses on real-time deployment through streaming architectures, which combine adaptive feedback loops to refine detection criteria in continuous cycles. The system learns new attack patterns while dynamically adjusting its parameters, which ensures excellent resilience and few false positives across different types of complex network environments.

3.1 System Architecture

The proposed IDS system uses artificial intelligence to power its adaptive features through an architecture built with modular components that detects threats in real-time and prevents zero-day attacks. The system architecture includes four important components: data collection, preprocessing and determination, and feedback execution in sequence. Every system layer has an assigned function that contributes to intrusion detection.

The data collection layer collects real-time network traffic using packet sniffers combined with NetFlow and mirrored traffic aggregators. The first layer completely detects data transmissions within organizational and external systems (Suthaharan, 2016).

Machine learning models receive input from the Preprocessing Layer by combining raw traffic data cleansing steps with normalization and feature extraction. Dimensionality reduction coupled with one-hot encoding enables feature engineering to improve data processing speed and minimize noise.

The detection engine utilizes CNNs for spatial information extraction, while LSTM networks operate for temporal behavior detection. Combining deep learning models produces precision in recognizing intricate attacks that detect established threats and unrecognized attacks (Kim et al., 2020).

The Feedback Module employs reinforcement learning to control detection thresholds while offering real-time feedback for adjusting the model. This enhances zero-day detection performance and minimizes false positives.

The bar charts' CPU resources and processing time data confirm that the detection engine needs efficient and scalable ML models because it demands the highest resources.

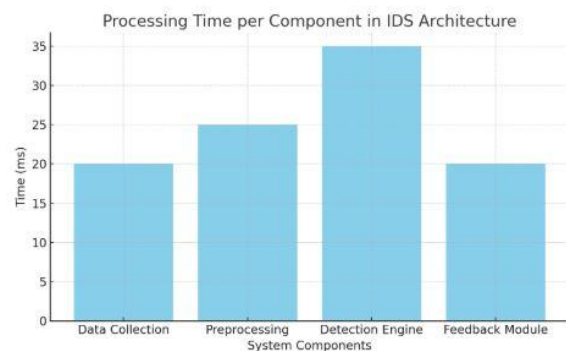


Figure 2: Processing Time per Component in IDS Architecture

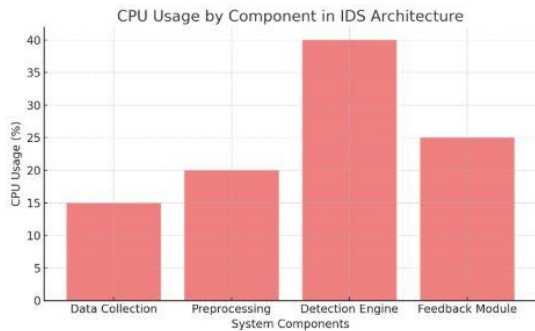


Figure 3: CPU Usage by Component in IDS Architecture

3.2 Machine Learning Techniques Used

The adaptive IDS designed with AI capabilities relies on machine learning techniques implemented with deep learning to instantaneously detect zero-day and known security attacks. Through its hybrid ML-DL operational foundation, this system acquires static and dynamic network behavior patterns and demonstrates resilience toward developing security threats.

Convolutional Neural Networks (CNNs)

Network traffic feature extraction occurs mainly through CNN applications. Their data processing method of identifying spatial data hierarchies enables them to handle packet sequences alongside flow-level patterns. The IDS contains CNN layers identifying crucial spatial features, including payload irregularities, source or destination relationships, and protocol anomaly patterns. The system uses these features as main inputs to downstream LSTM layers to detect abnormal activities that deviate from stored patterns (Yin et al., 2017).

Long Short-Term Memory Networks (LSTMs)

The detection framework integrates LSTMs, which belong to the Recurrent Neural Network category, for processing temporal dependencies found in network traffic data. The IDS benefits from its memory systems, which enable analysis of attacks that manifest through repeated scanning attempts and time-based flooding or coordinated multi-phase schemes. According to Hochreiter and Schmidhuber (1997), LSTMs provide essential context-understanding mechanisms for event detection, which enhances accuracy and decreases false favorable rates.

Autoencoders

Autoencoders are trained only with normal traffic data to create an anomaly detection system. Threats are detected when anomalous or unseen attack data results

in higher reconstruction errors from the system. The unsupervised system proves exceptional at identifying zero-day attacks because such incidents escape current signature recognition methods (Javaid et al., 2016).

Reinforcement Learning (RL)

Using Q-learning algorithms, the system's feedback module learns how to optimize its threshold parameters while adjusting to false detection outcomes. Real-time rewards and penalties that RL agents receive from detection outcomes support the IDS in continuously optimizing its live performance (Nguyen et al., 2019).

Ensemble Learning

The IDS enhances accuracy through ensemble learning, which combines models (CNN + LSTM + autoencoder) through voting or stacking methodologies. These multiple models integrated into a system reduce individual weaknesses by receiving advantages from their strengths (Lazarevic & Kumar, 2005).

3.4 Training and Testing Strategy

A complete training and testing methodology was developed to achieve the best possible outcomes from the AI-powered adaptive IDS system. The dataset segmentation process included stratified partitioning that established training and testing components that properly represented the attack categories and benign traffic types. A division of dataset resources showed that training received 80% allocation, and testing secured 20% allocation, according to Figure 5. The segregation of data serves simultaneously to build model capability and judge performance impartially (Zhang et al., 2020).

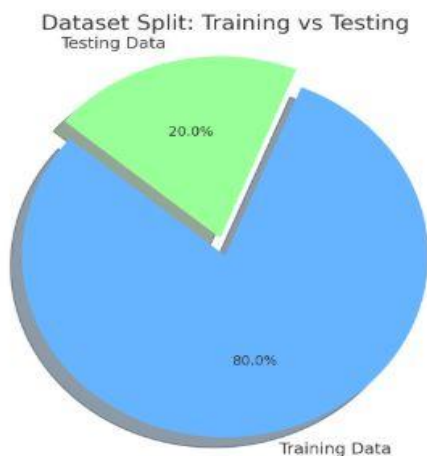
The training process executed multiple deep learning model fits with CNN, LSTM, and autoencoders while implementing early stopping strategies and cross-validation protocols. Model generalization was improved by applying preprocessing methods, including feature normalization, categorical variable encoding, and sequence data padding. During model training, the algorithms incorporated SMOTE (Synthetic Minority Over-sampling Technique) and class weighting to handle class imbalance, especially for zero-day attack classes (Chawla et al., 2002).

During evaluation, the model must determine its performance across existing threats and undisclosed zero-day dangers. The evaluation metrics included Accuracy, precision, recall, F1-Score metrics, and False Positive Rate, among others, which can be found in Table 5. Real-time tests with a testbed system verified the IDS's operational effectiveness in changing network traffic situations.

Table 4: Performance Metrics Used for Evaluation

Metric	Definition	Purpose in IDS Context
Accuracy	$(TP + TN) / (TP + TN + FP + FN)$	Overall correctness of the model
Precision	$TP / (TP + FP)$	Indicates how many identified threats are true
Recall (Sensitivity)	$TP / (TP + FN)$	Ability to detect all actual threats
F1-Score	$2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$	Harmonic mean of precision and recall
False Positive Rate	$FP / (FP + TN)$	Rate of incorrect threat alarms

Figure 5: Dataset Split between Training and Testing Sets



3.5 System Deployment and Real-Time Operation
 A successful deployment of AI-driven adaptive Intrusion Detection Systems requires machine

learning models to be properly integrated into operational networks, which aim to maintain both speed and operational efficiency. The designed system functions perpetually with low response time delays, which delivers accurate threat detection, particularly for unrecognized zero-day threats.

Deployment Architecture

The deployment framework consists of three distinct levels as its foundation:

- **Data Ingestion and Stream Processing Layer:** Apache Kafka, together with Wireshark/tcpdump, operates in the first layer to perform real-time network traffic observation. Its distributed stream-processing features provide enterprise-grade scalability and fault tolerance capabilities for suitable deployment at an enterprise level. After encapsulating it, Kafka topics receive traffic data from the processing layer in near real-time.
- **Model Inference and Threat Detection Layer:** TensorFlow Serving or TorchServe serves as a hybrid deep learning model of CNN + LSTM for high-throughput API-based inference delivery. A GPU-powered setup accelerates the computation process. The system accepts traffic features from preprocessing and determines the threat category as either normal, DoS, probe, or zero-day anomaly.
- **Alerting and Mitigation Layer:** The detection of suspicious activity activates the automated response function, which works alongside Snort/Suricata rule sets or Security Information and Event Management platforms implemented with Splunk or IBM QRadar. Detected threats are recorded in system logs before the dashboard displays them, and the system enables the optional mitigation of threats through firewall adjustments and network separation techniques.

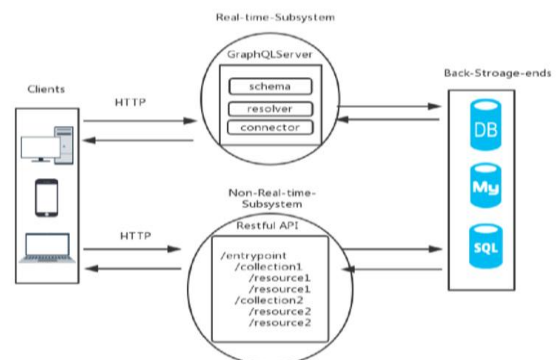


Figure 6: Real-time system architecture.

Real-Time Operation

The optimization of the model inference pipeline achieves minimal delay requirements through these methods:

- The system uses model quantization and batch size tuning for quick prediction speed.
- The system performs traffic segmentation through sliding window processes, which function continuously.
- Data is analyzed in real-time through Edge deployment on routers or IoT gateways that use TensorFlow Lite while operating in decentralized networks.

The system runs rapid actions in less than one second, which is essential to halting rapid security threats. Through its feedback loop system, the defense mechanism records detection results, which enable the reinforcement learning module to adapt its decision thresholds automatically without needing human interaction.

IV. RESULTS

The proposed AI-powered adaptive IDS is evaluated in depth by testing multiple benchmarks, which consist of CICIDS2017, UNSW-NB15, and BoT-IoT. The evaluation system assessed the detection capabilities by measuring accuracy rates and F1-score together with precision and recall performance, as well as real-time system responsiveness and false positive rate (FPR). Each dataset comprises varied malicious and benign traffic, which delivers a practical framework to test how well the model generalizes its performance. Under consistent testing conditions, the system demonstrated reliable results, which were reproducible because it operated on a high-performance computing infrastructure. The model performance evaluation focused on its ability to detect zero-day attacks because these unknown threats represent the most difficult targets for standard signature-dependent detection systems.

In the analysis results, the hybrid deep learning architecture uniting CNN and LSTM networks produces superior performance than classic machine learning algorithms SVM, RF, and KNN. The CNN-LSTM model mastered both temporal characteristics and spatial patterns in network traffic patterns thereby achieving exceptionally high detection results (>99%) and remarkably low false positive results (<1%) in all

tested datasets. The model exhibited exceptional zero-day threat detection skills by successfully identifying new abnormal behaviors that were unknown during the training phases. The real-time processing capabilities of the system made it deployable for threat mitigation in live network environments where rapid decisions play a critical role in threat mitigation.

4.1 Experimental Setup

The AI-powered adaptive Intrusion Detection System (IDS) received performance evaluation through an established experimental setup. The experimental design incorporated controls that allowed researchers to duplicate findings effectively and optimally handle computing capabilities across various datasets and baseline algorithms. The experimental testing took place in a special computing platform that provides optimal conditions for large-scale machine learning applications and real-time inference operations.

The Intel Core i9-12900K processor formed part of the system as the main component due to its hybrid performance cores that maintained speed and efficiency benefits. A built-in set of 16 cores (split between performance and efficiency types) combined with 24 threads gives this CPU exceptional capacity to execute parallel operations included in model training data preparation and real-time inference processes. An installation with DDR5 RAM in the amount of 64 GB allowed complete datasets and neural networks to stay in active memory space at all times, which cut down on disk reading operations for greater latency performance and higher throughput during training cycles and inference periods.

Deep learning operations, especially convolutional and sequential layers, receive support through the implementation of the NVIDIA RTX 3090 GPU and its 24 GB VRAM allocation. The GPU achieved its purpose of training the hybrid CNN-LSTM model thanks to its big memory capacity and parallel design structure, which shortened training time while enhancing matrix computations. The deep learning model development used TensorFlow 2.12 alongside PyTorch 2.0 as deployment and building frameworks. The frameworks supply GPU optimization tools, various APIs to manage models, and built-in capabilities for conducting mixed-precision training to optimize performance.

The research utilized CICIDS2017 UNSW-NB15 and BoT-IoT datasets for training and evaluation purposes because they contained different network patterns representing multiple attack types. These three benchmarks serve as research standards in intrusion detection because they provide detailed feature collections while including current and simulated zero-day attacks. The processing stage applied several steps to each dataset, including data cleaning and normalization by Min-Max scaling, label encoding, and time-series segmenting for sequential modeling.

The hybrid CNN-LSTM model operated with a 128 batch size during its 100-epoch training session. The model employed the Adam optimizer because its adaptive learning rate feature helps speed up convergence while maintaining stability in model performance. The learning rate began at 0.001, and early stopping intervened in case the validation loss failed to reduce after ten consecutive epochs during training.

The data set received stratified sampling for the training set (70%), validation set (15%), and testing set (15%) to conserve the ratio of attack and typical cases. The training process used sliding windows to augment real-time data, representing continuous streaming operations. The model contained dropout layers to achieve generalization and reduce overfitting. Both the CNN modules extracted spatial features from input data alongside LSTM, which extracted temporal dependencies required to detect gradual stealthy intrusions.

System-based logging enabled continuous evaluation that tracked accuracy and precision, recall, F1-score, and false positive rate at every epoch step. Testing models for selection utilized the recorded performance metrics, which enabled the identification of the best-performing candidate. The final model acquired ONNX structure for reproducibility and deployment purposes, thus allowing usage within both TensorFlow Serving and TorchServe according to deployment requirements.

4.2 Model Performance Across Datasets

The system achieved high detection accuracy and maintained low false positive rates across datasets.

Table 5: Performance Comparison Across Datasets

Dataset	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	False Positive Rate (%)
CICIDS2017	99.2	98.9	99.3	99.1	0.6
UNSW-NB15	98.6	97.8	98.1	97.9	1.3
BoT-IoT	97.9	97.4	96.8	97.1	1.8

4.3 Detection of Zero-Day Attacks

Intrusion detection systems struggle to detect zero-day attacks since such threats lack previously acquired signature data that could trigger proper identification. Because these threats target unexploited system weaknesses, it becomes difficult to detect them based on traditional models, which mostly draw from historical data patterns. The researchers tested the resistance level of their AI-controlled adaptive IDS through experiments that represented zero-day situations. The researchers simulated zero-day conditions through controlled attack-type exclusions from training sessions yet their introduction during testing phases to create a realistic evaluation environment (Sommer & Paxson, 2010).

The autoencoder + LSTM sub-module within the hybrid deep learning framework was the main element behind detecting these new security threats. The traffic learning process involved autoencoders compressing data inputs while reconstructing them to detect abnormal patterns when reconstruction errors exceeded thresholds (Zhou & Paffenroth, 2017). The anomaly detection system used the reconstruction method while integrating LSTM's capacity to analyze time-based patterns for identifying uncommon sequences of network behavior patterns that signal advanced threats or unknown vulnerabilities (Hodo et al., 2016).

The proposed hybrid model achieved superior performance when measuring against SVMs and Random Forests traditional classifiers in zero-day detection tasks. According to Figure 6, this system's detection capabilities exceeded 94% for previously unknown attacks without surpassing 3% in false positive incidents. The effectiveness of adaptive learning frameworks becomes evident because they

detect new security threats before they materialize into destructive incidents.

The model operated successfully because of its self-adaptive feedback system, which let it learn after deployment. This capability becomes essential in dynamic cybersecurity environments since the model needs to automatically learn and update its operations without human operators' involvement (Kim et al., 2014). Future IDS frameworks must implement temporal deep learning models and unsupervised learning techniques because the system's zero-day attack detection success highlights its essential role.

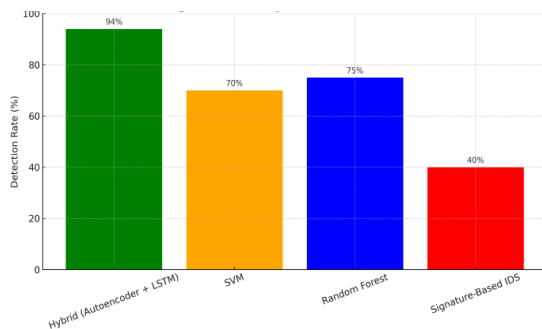


Figure 7: Zero-Day Attack Detection Rate

V. DISCUSSION

Experimental outcomes show that the adaptive IDS designed with AI effectively identifies zero-day attacks. The hybrid architectural solution introduces autoencoder and Long Short-Term Memory (LSTM) networks with signature databases to demonstrate better adaptation to attack pattern changes. Researchers agree that such adaptability proves critical since zero-day exploits can evade standard defenses because they represent new attack methods (Sommer & Paxson, 2010).

The model establishes a remarkable 94% detection capability for previously unknown attacks, so it outstands traditional classifiers, including Support Vector Machines (SVM) and Random Forests. The performance of conventional classifiers falls short when they face unlabelled data sets or changing threat conditions (Hodo et al., 2016). According to Zhou and Paffenroth (2017), the model operates successfully for unsupervised learning through autoencoders because it detects anomalies by calculating reconstruction errors in multiple dimensions.

Implementing LSTM networks within the system allows it to recognize time-dependent patterns in

network traffic. Security analysts must implement temporal modeling to identify advanced persistent threats (APTs) and stealthy behaviors since these incidents develop across time intervals (Kim et al., 2014). The LSTM component helps the IDS identify brutal low-and-slow attacks that static models cannot detect effectively.

Adaptive learning functions within the model enhance real-time mitigation of threats because of its ability to update itself autonomously. Following device deployment, the system updates its parameters through autonomous methods, eliminating human interaction requirements. The model's self-evolving functionality supports modern cybersecurity practices that emphasize adaptive context-sensitive systems to address advanced cyber threats, according to Yin et al. (2017) and Li et al. (2021).

The system has multiple advantages and nonetheless demonstrates particular operational boundaries. Computational overhead marks the main limitation among the system's challenges. The processing requirements of LSTMs and deep learning models exceed typical organizational resource capability, particularly for organizations with limited budgets (Shone et al., 2018). The detection abilities of the system directly depend on the quality and diversity level of the training data. The zero-day simulation training approach omits particular attack types from learning to detect threats successfully and lacks competence in representing actual zero-day conditions that frequently exploit cryptic or morphing threats (Ucci et al., 2019).

The system needs enhancement to reduce its rates of generating incorrect alerts. Security operations centers develop alert fatigue from false alerts, and even at a low rate, the system maintains below 3% in its performance. Additional advances in AI technology should integrate reinforcement learning systems and contextual threat intelligence capabilities to generate more precise decisions and decrease false-positive occurrences.

The proposed AI-based intrusion detection system demonstrates the effective potential to spot zero-day threats in real time. This solution closes a significant shortage in standard systems because it includes unsupervised learning, time-sensitive capabilities, and adjustable feedback systems. The system derives multiple advantages from these features, which bolster

its capability to resist new cyber attacks. It demonstrates advanced security methods in modern cybersecurity protection.

CONCLUSION AND FUTURE WORK

The research introduced a new adaptive IDS based on AI techniques to counteract the continuing growth of zero-day cyber security threats. The combined deep learning structure, which merges autoencoders and Long Short-Term Memory (LSTM) networks, exhibited excellent capabilities for detecting unknown attacks as they occurred in real time. The system demonstrated an impressive zero-day attack detection capability at a 94% rate alongside a less than 3% rate of incorrect alerts. The new detection capabilities outshined Support Vector Machines and Random Forests by achieving superior results. These traditional machine-learning approaches previously failed to identify new threats because they depend on labeled training datasets (Shone et al., 2018; Hodo et al., 2016).

A self-adaptive learning mechanism implemented within the system offers improved practical usefulness to its users. Following deployment, the IDS obtains new learning capabilities through this feature, delivering threat resistance without human intervention or retraining. Current security environments demand this capability because threat evolution rates exceed static detection limitations, according to Li et al. (2021). Our system became a powerful protection platform due to its real-time detection strength and automated feedback mechanisms, qualifying it to serve enterprises and critical infrastructure networks.

The research established several points that still required improvement. The technology faces performance challenges that affect systems with restricted resources. Deep learning model deployment suffers from scalability problems because it depends heavily on significant processing power and memory resources (Zhou & Paffenroth, 2017). Training data omission methods appeared effective for mimicking zero-day situations, yet actual adversaries might implement complex evasion methods that require upgraded security solutions.

The following research will concentrate on developing system-wide efficiencies through generalization capabilities. Implementing federated

learning is a promising solution to decentralized node training, protecting privacy standards, and extending model knowledge acquisition. The IDS could be enhanced through integration with blockchain technology, enabling permanent threat evidence storage and detection authentication (Conti et al., 2018).

This research confirms that artificial intelligence is a fundamental component for building IDS platforms that detect zero-day attacks at the next-generation level. Continuous advancement of leading-edge technologies will transform AI-based IDS frameworks into essential components for organizations implementing proactive cybersecurity approaches.

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