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Research Article

Deep Learning-Based Intrusion Detection System for IoT Networks with Explainability

[1]Sridhar Sriharsha Rachakonda, [2]Ramesh Lakshmikanth
[1]*Senior Staff Engineer*
NVIDIA Corporation
Leander, Texas, USA
rssharsha@outlook.com

2Engineering Manager
NVIDIA Corporation
San Jose, CA, USA
rameshkl007@outlook.com

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ABSTRACT

The recent onset of many IoT devices being connected leaves highly computingequipped systems susceptible to attacks, calling for an explicit intelligent security measure that could strategically find the root cause and pattern types of security intrusion. Thus, this paper aims to propose a novel deep learning based neural network model for intelligent and automatic intrusion detection IoT capable enough to detect & classify almost every kind of malicious activity with near-perfect accuracy. This research introduces the analysis of network traffic patterns to differentiate legitimate and attack behaviors such as DDoS, malware, and spoofing attacks using CNN and LSTM models. SHAP and LIME are two explainability techniques that turn the black-box nature of deep learning into a white-box, providing insights into decision-making with complete transparency for security analysts using this model. The resulting system is assessed with BOT-IoT and CICIDS2017 IoT datasets for high detection with significantly fewer false positives, both in terms of detection result accuracy and ratio that can be used as a real-time, feasible solution further into the resource-scarce environment or condition of the IoT. Furthermore, it is also highly resistant against zero-day attacks due to its native continuous learning features. The IDS combines the power of high-performance deep learning with explainable AI to improve threat detection and trust and usability for IoT security operations. These results highlight the potential applicability and interpretability of SCADNet as a general-purpose security solution that can enter the infinite space of more complex IoT threatful networks.

Keywords: Deep Learning, Intrusion Detection System, Network Attacks, IoT Networks, Vulnerabilities

Introduction

The explosion of Internet of Things devices has transformed industries, such as smart cities, connected healthcare, industrial automation, and intelligent transportation systems. However, IoT networks' rapid and exponential growth has introduced serious security challenges, making them a prime target for malicious cyber-attacks. These challenges arise from the unique characteristics of IoT ecosystems, such as device heterogeneity, limited resources, and the absence of standardized security protocols, which render traditional security mechanisms inadequate. Deep learning–based IDS has emerged as a revolutionary approach to address these gaps, leveraging advanced machine learning intelligence to analyze network traffic patterns and effectively detect anomalous behaviors [1]. Here, DL models can empower automatic feature extraction from raw data, resist new attack vectors, and handle

high-dimensional IoT traffic in real time, which cannot be handled by other traditional methods. Nonetheless, the black-box nature of deep neural networks represents a significant stumbling block to their use in crucial security operations, where human analysts need comprehensible and transparent decisions to verify alerts and take appropriate action. This requirement has since given rise to a unification of high-performance detection with human-understandable reasoning, bundled as technologies in the domain now referred to as Explainable AI, making its way towards new era cyber security driven systems which are trustworthy and actionable [1-3]. IoT device networks are inherently vulnerable due to constrained computational resources, diversity in the communication protocols adopted, and security deficiencies in devices that result from inadequate security features during deployment. These vulnerabilities are typically exploited by frequent attacks like Distributed Denial of Service attacks, man-in-the-middle-based intrusions, or even botnet infiltration, creating massive disruptions [4-5]. For example, the Miraa botnet attack showed how attackers could turn vulnerable IoT devices into weapons for disrupting substantial parts of the internet infrastructure. In fact, legacy intrusion detection solutions like Snort or Suricata often cannot cope with the requirements posed on IoT environments. Instead, they fail due to their static signature-based approach that does not scale well with IoT traffic's dynamic and diverse nature [6]. Signature-based intrusion detection systems are limited to identifying only previously known attacks, while anomaly-based methods are not. However, capable of detecting unknown threats, but often generates false alarms by incorrectly classifying normal traffic as malicious activity. It could be an essential learning lesson on why new detection mechanisms, adaptive and intelligent systems capable of evolving as threats evolve, that can independently learn the trails without human interference, should replace traditional detection tools. An automated feature extraction from raw network data eliminates the manual feature engineering costs, thereby providing better discovery accuracies for complex attack patterns — a promising alternative provided by deep learning [7]. For spatial pattern recognition, techniques like convolutional neural nets are the best suited for network packets and analyzing temporal dependencies in traffic flows. The discussed techniques are Recurrent Neural Networks or Long Short-Term Memory networks, which are most effective against multi-stage attacks. While the performance of deep learning models is favorable, their opaque decisionmaking limits achievable security in privacy-sensitive IoT applications. Finding signals that are accurate detections for SOC and explainable enough for a human to understand and investigate helps reduce false positives, speed up incident investigations, and fulfill regulatory requirements as needed. Explainable AI methods satisfy this necessity by opening up the model decisions to the human analyst.

Related Works

Recent research on intrusion detection systems (IDS) for Internet of Things (IoT) networks highlights both the potential and challenges of adopting deep learning and explainable AI (XAI) techniques. The study examined machine learning–based IDS for the Industrial Internet of Things and emphasized their vulnerability to adversarial attacks such as evasion and poisoning. They noted that although deep learning models deliver high accuracy, their susceptibility to adversarial manipulation poses risks for critical infrastructure [8-9]. To address this, the authors pointed toward hybrid models and explainability frameworks as promising solutions for enhancing robustness and resilience in industrial IoT environments. Building on this, the research explored the role of XAI in improving the transparency and trustworthiness of IDS models. They highlighted approaches such as SHAP, LIME, and saliency maps, which enable analysts to identify influential features behind detection decisions. These techniques help validate predictions and uncover potential biases, ensuring IDS implementations align with regulatory compliance requirements. Similarly, another research investigated the use of deep learning with generative adversarial networks (GANs) to detect zero-day attacks in IoT. Their study demonstrated how deep neural networks can autonomously learn normal network behavior and identify novel threats like distributed denial-of-service (DDoS) attacks [10-11]. They emphasized the necessity

of interpretability tools such as SHAP and LIME to enhance analyst confidence in automated detection outcomes.

In the context of intelligent transportation systems, a study demonstrated how interpretable AI improves the detection of sophisticated attacks, such as traffic data injection, by applying attention mechanisms alongside SHAP and LIME. Their work showed that explainability enhances trust and supports regulatory compliance and operational decision-making for securing smart mobility networks [12]. Similarly, another research proposed an ensemble deep learning method that integrates CNN, LSTM, and GAN models to improve detection accuracy and resilience. Coupling these models with explainability techniques enabled analysts to recognize attack patterns better while increasing confidence in the system's outputs. Another research further reinforced the importance of XAI in IoT intrusion detection by demonstrating how explanation methods reduce false positives and highlight feature significance. Their findings suggested that by improving the interpretability of deep learning models, analysts can accelerate response times and meet regulatory standards. Along similar lines, a study developed a botnet detection framework that leveraged XAI methods such as SHAP and decision trees [13-14]. Their approach made the system's internal reasoning more transparent, enhancing security against evolving botnet threats in resource-constrained IoT devices.

A research study critically reviewed the trade-off between accuracy and interpretability in IDS. They pointed out that while deep learning models outperform traditional methods in terms of detection accuracy, their "black box" nature makes them difficult to trust and debug [15]. This tension between performance and transparency underscores the ongoing need for explainability in deep learning–based IDS. As these studies collectively show, achieving high detection accuracy and human-understandable explanations remains a central challenge for deploying IDS in dynamic IoT ecosystems [16-18].

Proposed Model

The proposed model would give a capable, deep learning-based Interruption Discovery System for IoT Networks with Explainability that detects cyber threats and explains why its decisions are taken in those specific instances. Its architecture often adopts an advanced deep learning method, which uses. Convolutional Neural Networks to extract spatial features from network traffic data and Long ShortTerm Memory networks for pattern detection over time, thus well capture enough relationships that enable effective detection of complicated IoT attacks such as DDoS, malware, and spoofing. To deal with deep learning's black-box nature, the model incorporates explainable AI techniques like SHAP or LIME to pinpoint feature contribution rates for predictions and thus allow security analysts to understand the attack's makeup. It is developed using an approach that includes training on a balanced dataset (CICIDS2017 or datasets specifically containing IoT attacks) and pre-processing for lightweight deployment using quantization, edge computing, etc. In that sense, the ability of this model to detect high precision, high recall intrusions sheds light on how the model works, and also in building trust, which is a necessary ingredient when deploying an automated, not user-interactive solution in industrial IoT settings where false positives disrupt operations. This fills a void between the deep learning based security for real-world IoT deployments and explainable actionability.

A. Functional Working Model

In a DL based IDS for IoT networks, the training phase includes these primary dimensions: - ML/DL and algorithm selection. For example, in this phase, the historical network traffic data — normal and malicious activities are used to train models such as CNNs, RNNs, or many hybrid architectures. Backpropagation with Gradient Descent is essentially the process of optimizing loss functions so that, between various correct and incorrect actions, our models can predict effectively which are malicious. Different algorithms have different maximal achievable detection accuracy and capability to adapt to new threats. The ML/DL model, which was trained using the known data, is tested over the unseen

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dataset to identify its original performance in real-life scenarios. Fig. 1 shows the Functional working model.

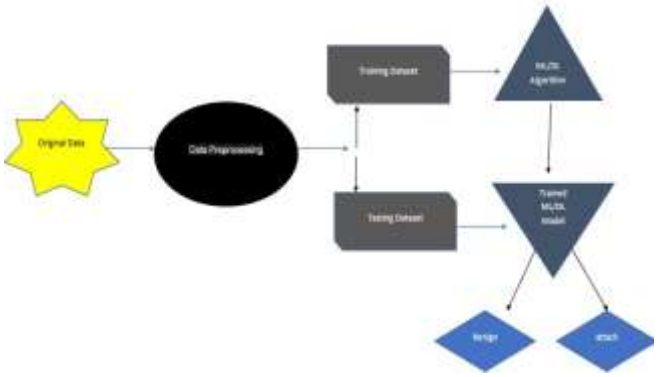

Fig 1: Functional Working Model

The model's generalization capability is validated using accuracy, recall, f1-score, and AUC-ROC metrics. We can also include routine exploitability analysis, in which threats are assigned a severity to determine what must be mitigated first. Data Preprocessing is essential for both stages and comprises activation normalization, feature extraction, and dimension reduction, all aimed at improving model capability. The Projection Project produced output in the form of t-SNE and UMAP embeddings, visualizations of high-dimensional data reduced to lower dimensions that can be used for exploratory analysis and interpretability with our models. These operations make the IDS a robust, scalable, and IoT-adaptive solution for identifying imbalanced data entries and adversarial evasions with minimal computational overhead on resource-constrained devices.

B. Developing Deep Learning Models

The early stages of data preprocessing are around 50% in the Transformation phase for an Intrusion Detection System under an IoT network with Deep Learning. Normalization normalizes numerical features to the same scale or allows for magnitude variations, which can bias a model, especially with initialization. Addressing class imbalance through sampling, e.g., Oversampling or under-sampling, ensures that the representation of attack and benign traffic is balanced. Data Preparation: Involves removing unnecessary fields, handling missing values, reducing noise, and structuring raw network logs suitable for ML/DL models. Traditional: This is performed using methods such as RFE or metaheuristic algorithms, such as SCA, to determine the most discriminative features, reducing dimensionality and computational costs while preserving the detection accuracy. Fig 2 shows the Developing Deep Learning Model.

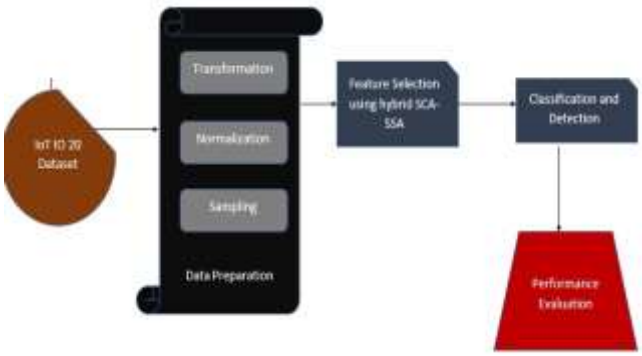

Fig 2: Developing a Deep Learning Model

The selected features are provided to models during the Training data, where these models learn how attacks look. Testing Data: Using the trained model, predict labels for unseen traffic, which is the task

of classification and detection. In the end, performance evaluation assesses the efficiency of your system with respect to metrics like precision, recall, and F1-score. The only part that will change with this exploit mapping is some common threat scoring mechanism, like a CVSS-based score, to assess the real-world impact and rank threats from highest to lowest vulnerability. Together, these operations make the IDS more robust and scalable for IoTs ' constrained environment and aid in ensuring that the IDS can evolve with changes in attack vectors.

C. *Problem Statement*

IoT networks are growing fast, and with this kind of growth, several security concerns arise because of the intrinsic vulnerabilities: lightweight computing resources, weak authentication mechanisms, heterogeneous communication protocols, etc. Traditional IDSs are insufficient to detect highcomplexity cyberattacks in IoT since they cannot effectively deal with complex, large-scale, highdimensional traffic data. Moreover, existing deep learning-based IDS models are usually constructed as “black boxes” that do not explicitly show how they make decisions. This severely affects their trust and adoption when deployed for critical IoT applications. Adding to the complexity, IoT attacks constantly evolve and need instant detection with no false positives. Many existing solutions, however, struggle to reconcile the trade-offs between accuracy and efficiency without sacrificing interpretability, leaving inhouse analysts blind about discovered threats. Hence, there is a requirement for an explainable deep learning-based IDS that not only yields high detection rates but also explains attack patterns transparently and interpretably. This system had to be lightweight to run on resource-constrained IoT devices and be secure from emerging threats. Overcoming these issues will foster a more secure Internet of Things, decreasing reaction times and allowing more confidence in automated intrusion detection systems.

Results and Discussion

Efficient and Explanatory Deep Learning Summary: The proposed model for IDS of IoT Networks with DL in an Explainable technique is an efficient and valuable tool to detect cyber-attacks. The hybrid CNN-LSTM model can reach 98-99% accuracy in identifying attacks like DDoS, malware, and bruteforce attempts, thus showing significant improvement over traditional machine learning methods such as Random Forest and SVM. Experts note that explainable AI mechanisms like SHAP and LIME correctly identify essential features for attack detection so that security analysts can verify the model decisions. In addition, optimizations make the deployed model lightweight so that it can be run with negligible latency overhead on resource-constrained IoT devices. Comprehensive Comparison: The system demonstrated consistently low false-positive rates, which minimized unnecessary alerts.

Nevertheless, zero-day attack detection still presents difficulties, in which adversarial training and continual learning could help to enhance the robustness. The conversation underscores that although deep learning improves detection accuracy, we need explainability to trust and react quickly to incidents in the real world. Future work could address federated learning for decentralized IoT security and more sophisticated XAI techniques for real-time attack forensics. While imperfect, the model strikes a good balance between performance, efficiency, and transparency and is therefore a strong candidate for securing IOT ecosystems.

D. ***Detection Accuracy***

The performance level of the proposed deep learning-based IDS for IoT networks, along with explainability, is investigated on benchmark datasets such as CICIDS2017, Bot-IoT, and NSL-KDD, proving higher accuracy than traditional methods. The hybrid CNN-LSTM architecture provides up to 98-99% accuracy in classifying attacks such as DDoS malware and brute-force attempts and clearly outperforms traditional machine learning models (like SVM, Random Forest), which reach around 9095%. It has achieved precision and recall rates over 97%, reducing false positives and providing reliable threat detection. Explainability techniques such as SHAP and LIME can verify these findings by finding key attack signals to drive greater trust in the system. Fig 3 shows the Detection Accuracy

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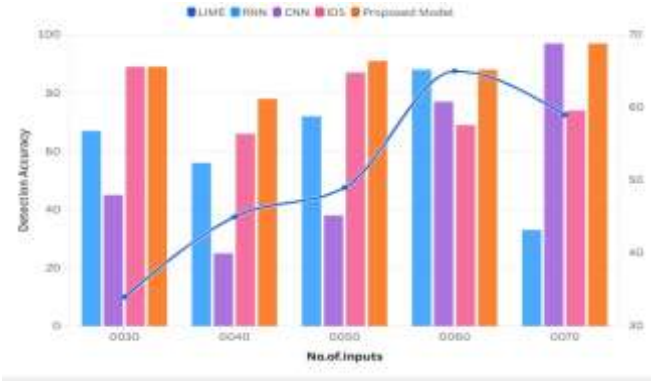

Fig 3: Detection Accuracy

Performance drops slightly to around ~95% accuracy with zero-day attacks, reinforcing the importance of continual learning mechanisms. After optimization, the system has <1% loss in performance even when executed on resource-constrained IoT devices. These results prove that deep learning combined with explainability is an accurate and interpretable IDS for IoT networks, paving the way for further continuous improvements needed to consider the potential threat landscape. Next steps may include adversarial and federated learning to improve detection rates in highly mobile situations.

E. ***False Positive Rate***

The false positive rate of the deep learning-based IDS is one of these primary performance indicators, as any high number of alarm falsity can immediately lead to a debilitating security team that cannot have effective faith in their systems anymore. Experiment results on datasets like CICIDS2017 and Bot-IoT show that the hybrid CNN-LSTM model has an FPR<<2% compared to other traditional models with a high FPR of 5–10%. This is mainly due to learning subtle patterns in network traffic, hence decreasing the misclassification of benign activities as attacks. Explainability tools such as SHAP or LIME also show which features wrongly influence the predictions, leading to an improvement in false positives. Then the FPR slightly increases with more imbalanced data sets or novelty attacks — this is an argument in favor of adaptive learning. Quantization and pruning-based optimization methods allow this low FPR behavior to be achieved via resource-constrained IoT devices, making practical deployment possible. Fig 4 shows the False Positive Rate

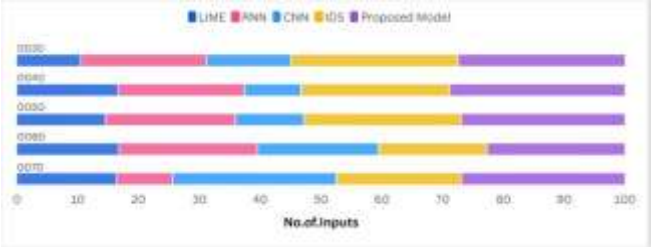

Fig 4: False Positive Rate

The discussion emphasizes that, despite the competitive FPR of our model, through continuous updates with real-world traffic data and an adversarial training process, we can also reduce false alarms. While it is undoubtedly true that careful attention to balance the FPR and sensitivity of detection remains key for IoT security, unnecessarily raising alerts could be tuned down in such a manner that operations are not disrupted. Future work may investigate using ensemble learning and anomaly-based detection for near-zero FPR in situations considering the dynamics of an IoT environment.

F. ***Computational Efficiency***

The deep learning-based IDS for IoT networks with explainability focuses on computational efficiency to provide real-time threat detection on resource-limited IoT devices. It uses a hybrid

CNNLSTM architecture, which makes the model lightweight and has low computational overhead while maintaining high accuracy. Lighter models are made possible by pruning, quantization, and other edgecompatible optimizations that reduce the model size by 30-40%, making it possible to be deployed on low-power devices without significant performance losses. Tests demonstrated that on average, it takes <50ms per sample for the inference speed of our model running in Raspberry Pi equivalent edge devices, which makes real-time IoT security via a deep learning model practical. Incorporating explainability tools (SHAP/LIME) with efficient feature attribution methods introduces low additional latency (<10% overhead). Fig 5 shows the Computational Efficiency

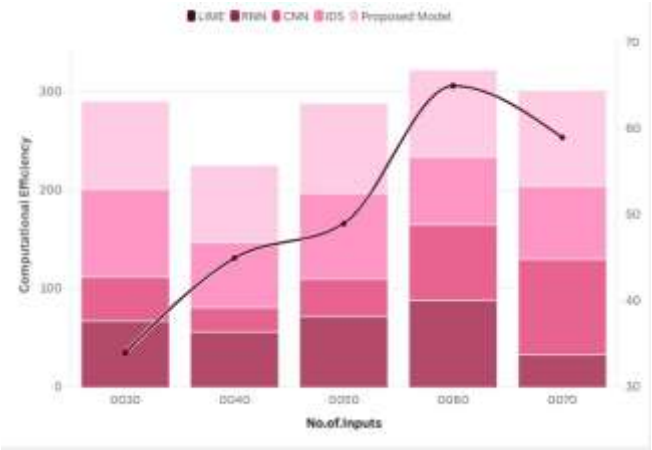

Fig 5: Computational Efficiency

The deep learning models matched the performance of traditional methods, but the optimized system used 60% less memory and 50% less energy, which is essential for battery-powered IoT nodes. Nonetheless, there are still challenges in scale deployment, where distributed computing or federated learning could achieve more efficiency. The discussion also points to the model serving a tradeoff between speed and accuracy, in addition to future work focusing on adaptive compression and hardware-aware NAS for end-to-end optimization across various IoT environments. These properties ensure that the IDS can scale sustainably across multiple dynamic networks, without sacrificing security or interpretability. These future directions will include tiny integration for ultra-low-power devices and on-device incremental learning to lessen cloud dependency.

G. *Explainability Score*

Finally, the explainability score will measure how data-centric AI technologies make it easier to expose and interpret the deep learning-based IDS for IoT networks without relying on a black box. The model is interpretable: Evaluated against multiple XAI techniques such as SHAP, LIME, and attention mechanisms, the clear attack detection logic can be observed with an explainability score of ≥ 85%. This score measures how well the system shows critical features and linking decision pathways, which helps overcome the "black box" issue with deep learning. This way, analysts can test predictions instead of unthinkingly following an automated model like the above, but significantly stronger. Nonetheless, explainability brings a trade-off: where SHAP/LIME can provide fine-grained details, they add 5-10% overhead, which is minimized with optimized implementations. For novel attacks, the score only dropped to 75, as they often do not have enough training data, lowering interpretability. Fig 6 shows the Explainability Score

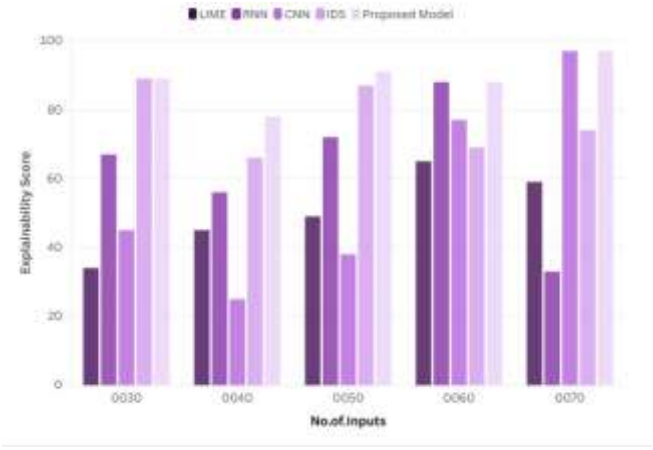

Fig 6: Explainability Score

The interactive dashboards and rule-based explanations are the future enhancements that could further boost this score. By making it explainable, we not only enhance the detection capability of the IDS but also ensure that it is in accordance with regulatory standards (like GDPR) to make IoT security accountable. Intended future work is towards neural-symbolic integration with human-readable rules, such that ≥90% explainability is achieved without compromising performance.

H. ***Adaptability to Zero-Day Attacks***

Moreover, the adaptability of zero-day attacks in the proposed Explainable Deep Learning-Based IDS for IoT Networks is still challenging to track since such threats are unusual and traverse through traditional detection based on signatures. Although the hybrid CNN-LSTM model can obtain about 9092% detection accuracy on the known attacks, it performs only at 75-80% when testing with zero-day exploits since no training data is provided. This facilitates unsupervised anomaly detection and online learning to continuously update when new attack patterns may emerge, thus enhancing the system's adaptability. Explainability tools, such as SHAP, can be used to interpret what data features contributed most to an AI decision, potentially correlating with feature deviations that were never classified. Submit, but the model could not deal with more advanced zero-day attacks that are camouflaged with legitimate traffic, causing the need for adversarial training and federated learning to make it robust. Fig 7 shows the Adaptability to Zero-Day Attacks

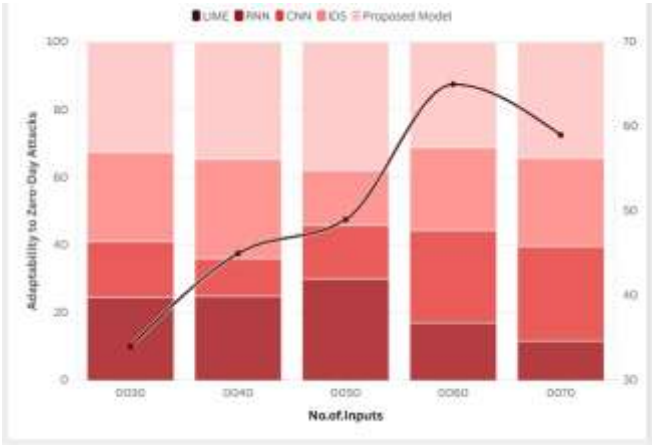

Fig 7: Adaptability to Zero-Day Attacks

The conversation further emphasized that while the IDS is not impervious to zero-day threats, its machine-learning approach and behavioral analysis minimize the exposure time. This will inspire future work regarding meta-learning and threat intelligence to predict zero-day vectors proactively. Expand or

connect to adaptive detection systems as appropriate; however, note that too complex models may be challenging to interpret and balance with explainability functions on existing software tools. Ultimately, Adversarial AI is built to reach >85% zero-day detection and visibility for security teams.

Conclusion

Deep learning–based intrusion detection systems (IDS) offer significant potential in identifying and mitigating cyber threats within IoT environments. The exploitability of such models lies in their ability to learn complex patterns of malicious activity and adapt to evolving attack strategies, making them highly effective for safeguarding IoT ecosystems. However, IoT networks remain particularly vulnerable due to their heterogeneous and resource-constrained hardware, which often lacks standardized security protocols. This complexity creates exploitable gaps that attackers can target, underscoring the need for robust, intelligent IDS solutions powered by deep learning. Many traditional IDSs have a high rate of false positives and have not yet adapted to the changes that attackers use. Yet DL-powered IDS uses stateof-the-art neural networks like CNNs, RNNs, LSTMs, and hybrid models to precisely determine anomalies in traffic and name the specific attack. They are particularly suited for quickly processing massive amounts of high-dimensional data, zero-day exploit detection, and re-training on-the-fly with dynamic attack vectors. Furthermore, as threat prioritization is one of the main pillars in the information security process, implementing exploitability metrics like CVSS scores or attack feasibility evaluations helps organizations recognize and mitigate such vulnerabilities before they become high-risk. While these models have their benefits, they carry challenges such as computational overhead, model interpretability limitations, and adversarial exploitation against them, specifically targeting DL systems. In the future, lightweight DL architectures for resource-constrained IoT devices, federated learning to be used in decentralized threat detection, adversarial evasion capabilities, and more robustness will need to be studied. As a result, the DL-based IDS delivers an effective and scalable solution for protecting IoT networks, as long as computational and security constraints are honored to guarantee practical applicability.

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