Optimizing Security in IoT Ecosystems Using Hybrid Artificial Intelligence and Blockchain Models: A Step-by-Step Approach with Zero-Day Detection and Adversarial Robustness Benchmarks

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***Abstract*— In addition to changing many facets of contemporary life and industry, the quick expansion of IoT devices has increased intricate security flaws. Even though previous hybrid frameworks and other security solutions have proven effective against well-known dangers including spoofing, illegal access, and Denial-of-Service (DoS) assaults. Frequently, they are not strong enough to fend off adversarial and zero-day attacks. The growing complexity and volume of IoT devices are proving too much for traditional, centralized security systems to handle, which leads to poor intrusion detection, high latencies, and increased energy usage. We suggested a hybrid security framework that uses a step-by-step approach with adversarial robustness benchmarks and zero-day detection to overcome these issues. The method combines blockchain technology with artificial intelligence (AI) in IoT networks.**

By leveraging a lightweight consensus protocol for device authentication and data integrity and deep learning models for real-time intrusion detection, our approach achieves a detection precision of 95.2% for phishing attacks. Additionally, our solution reduces authentication latency by 66.6% to 15 ms in largescale networks with 1000 devices and decreases energy consumption by 31.8% compared to traditional approaches. This hybrid framework provides a scalable and efficient security solution for IoT networks, enhancing both security and operational efficiency.

We first verify the model's performance on established parameters, such as low energy consumption, low latency, and high detection accuracy, using the UNSW-NB15 dataset.

Next, we present our new benchmarks: an Adversarial Robustness Benchmark to evaluate the framework's resilience to deliberately altered, evasive samples, and a ZeroDay Detection Benchmark to gauge its capacity to detect hitherto undiscovered attack types.

The outcomes show that in addition to performing well on standard criteria, our approach is more resilient and robust against complex and unforeseen threats.

This study creates a new, more rigorous benchm

ark for assessing security solutions in extensive IoT networks.
In this paper, we focus on reviewing and comparing recent studies that have been proposed for “ Optimizing Security in IoT Ecosystems Using Hybrid Artificial Intelligence and Blockchain Models: A Scalable and Efficient Approach for Threat Detection.” This paper addresses three research questions and highlights the research gaps and future directions. This paper aims to increase the knowledge base for enhancing IoT security, recommend future research, and suggest directions for future research.

Keywords—Blockchain, Artificial Intelligence (AI), Internet of Things (IoT), Zero-Day Detection, Adversarial Robustness, Network Security, Data Integrity, Deep Learning Model, Intrusion Detection Systems, Deep Learning Models

I. INTRODUCTION

The Internet of Things (IoT) has significantly changed how many consumers, commercial services, applications, and industries run their businesses or workflows. IoT has been used in a variety of industrial systems, such as healthcare, agriculture, and smart industries of aggregated networks to achieve goals of intelligent recognition, positioning, tracing, and management for effectiveness and efficiency of resources. However, IOT systems have also been exposed to various forms of cyberthreats and data breaches, such as denial of service (DoS), unauthorized access, etc., compromising C.I.A. (confidentiality, integrity, and availability). Security models Traditionally use, fails to meet the evolving threat landscape due to the centralised architecture employed, the increased data volume generated by current IoT networks, higher energy consumption, high latencies, restricted scalability, and insufficient threat detection. Advanced Intrusion Detection Systems (IDS) rely on static signature-based approaches, which makes them in effective against adversarial attacks (maliciously manipulated data intended to evade detection) and zero-day attacks (unseen exploits). As a result, communication security offered by cryptographic protocols essentially fails to defend against sophisticated internal threats or anomalous behavior from compromised devices. Recent research highlights the potential of blockchain and Artificial Intelligence (AI) as key enablers of next-generation IoT security and explores them in isolation. To resolve these challenges, this article proposes a hybrid resilient security framework designed to reinforce IoT ecosystems through a step-by step approach that integrates adversarial robustness benchmarks and zero-day threat detection, with the integration of blockchain and Artificial Intelligence (AI). machine learning models and capsule network to zero-day threats and adversarial intrusion in real time. This design comprehensively, facilitates a distributed approach where processing is efficiently handled at edge nodes, minimizing latency and optimizing resource usage, with diverse communication protocols (5G, LoRa, Zigbee, etc.) also ensuring high energy efficiency and robust protection across heterogeneous networks of a lightweight system of AI model.

This study's step-by-step evaluation methodology involves three steps: normal split, zero-day split, and adversarial testing. Normal split involves training and testing the model on all known attack classes to establish baseline performance. Zero-day split excludes one or more attack classes during training and testing, allowing the model to detect unseen threats during testing. The trained model is assessed along three essential dimensions:

-Normal Accuracy and F1 Score: Assesses baseline categorization ability for recognized threats.
- Zero-Day Detection Rate: evaluates the model's capacity to identify new attack types.
- Adversarial Robustness: Score measures the model's resilience to manipulated or noisy inputs.

These experimental findings show how the hybrid resilient security architecture delivers high accuracy, robust performance under adversarial settings, and strong zero-day detection capabilities. These findings demonstrate the potential for merging AI and blockchain to provide robust, scalable, and intelligent security solutions for next-generation IoT ecosystems.

A. *The Problem STatment*

Internet of Things (IoT) devices have spread so rapidly that they have created vast, linked ecosystems that are critical to modern infrastructure. However, this increase has also resulted in severe security weaknesses. Today's centralized security solutions are inadequately scalable and effective in defending these dispersed and dynamic environments against a continuously changing variety of cyber threats, such as sophisticated zero-day attacks and data poisoning.

Even while new technologies like blockchain and artificial intelligence (AI) have a lot of potential, there are many limitations to how they may be utilized alone. Despite their efficiency in danger detection, AI models are susceptible to data poisoning if the input data is not secure. Traditional blockchain technology, on the other hand, is useless for real-time threat detection in a large-volume IoT setting because to high latency and limited throughput, despite the fact that it ensures data integrity and decentralization. This issue is particularly acute when guarding against novel attacks that need a high level of adversarial robustness.

The lack of a comprehensive, hybrid security framework capable of successfully combining the complementary strengths of blockchain and artificial intelligence to produce a solution that is not only dependable but also scalable and effective enough to meet the demands of modern IoT ecosystems creates a significant research gap.
This study was motivated by our previous work titled "Optimizing Security in IoT Ecosystems Using Hybrid Artificial Intelligence and Blockchain Models: A Scalable and Efficient Approach for Threat Detection."

B. *Research Motivation*

Numerous sectors have undergone fundamental transformations as a result of the phenomenal expansion of the Internet of Things (IoT), resulting in sophisticated ecosystems that are critical to modern living. However, this expansion has revealed major security weaknesses, making IoT networks vulnerable to a range of cyber assaults. Because these environments are distributed, complex, and big, traditional, centralized security solutions are unsuitable for managing them and frequently serve as a single point of failure.

The explosive growth of the Internet of Things (IoT) has caused numerous industries to undergo fundamental transformations, resulting in intricate ecosystems that are essential to contemporary life. However, this growth has also revealed serious security flaws, making IoT networks easy targets for a variety of online attacks. Because these environments are distributed, complicated, and large, traditional, centralized security solutions are ill-suited to manage them.

As a result, our study is driven by the urgent need to develop a more complex and dependable solution, which is based on the core concepts of a hybrid AI and blockchain security architecture. Our primary objective is to go beyond a broad framework and provide a comprehensive, rigorous approach that is comparable to industry standards. By focusing on a model adjusted for adversarial robustness and zero-day detection, we want to provide a scalable and successful strategy to defend IoT ecosystems. This study is a vital extension of prior research, providing a practical and persuasive approach for addressing the industry's most pressing security challenges.

C. *Research Contribution*

This study proposes and evaluates a novel hybrid security architecture, which makes numerous significant contributions to the field of IoT security. Our research, which builds on a basic understanding of hybrid AI-blockchain models, addresses specific, essential security concerns.
The key contributions are as follows:

- An Effective Hybrid Framework That Is Scalable:

We describe a unique, end-to-end solution that smoothly integrates blockchain technology for unchanging data integrity with artificial intelligence (AI) for intelligent threat detection. Our architecture is specifically built to overcome the scalability and efficiency limitations of traditional blockchain systems, making it suitable for high-volume, real-time IoT scenarios, as opposed to previous solutions that address these issues independently.

- Illustration of Synergistic Benefits:

We provide a detailed description of how merging blockchain technology and artificial intelligence produces a system that is more dependable than either alone. To prevent data poisoning, the blockchain's tamper-proof ledger provides a secure and reliable dataset for AI model training and validation. By intelligently regulating data and network traffic, AI enhances blockchain operations by reducing latency and improving throughput.

- Our model proactively detects various online

threats, including advanced adversarial and zero-day attacks, leading to a more resilient and predictive defense system compared to traditional reactive security measures.

- Practical and Optimized Approach:

We present a structured, step-by-step methodology for implementing the proposed framework, which is measured in terms of accuracy, scalability, and efficiency through a performance evaluation, a clear architectural design, and a comprehensive operational flow. Researchers and industry professionals looking to implement next-generation IoT security solutions may find this guide useful.

D. *Research Question*

Our key research goal is how to optimize a hybrid AI-blockchain model for detecting unknown or controlled cyber risks in IoT networks beyond the trained dataset.

Supporting research questions:

- Framework Design: How can a step-by-step hybrid architecture be developed to synergistically integrate blockchain's d The Blockchain Security Ledger component decentralized integrity with AI's predictive capacity to safeguard IoT data?

- Performance and Scalability: How does this hybrid paradigm affect IoT ecosystem performance in terms of latency, throughput, and energy consumption when compared to traditional and independent security solutions?
- Threat Detection Efficacy: To what extent can the suggested model detect zero-day attacks (i.e., threats not included in the training data) and withstand adversarial attacks (where an attacker attempts to fool the AI) in real time?
- Practical Benchmarking: What critical performance metrics are required to objectively assess the model's efficacy and verify its superiority over existing methods?

II. LITERATURE REVIEW

A. *Traditional IoT Security Approaches*

Traditional security models for IoT rely heavily on centralized architectures, firewalls, and intrusion detection systems (IDS). While these methods have been foundational, they face significant limitations in a distributed and resource-constrained IoT environment. For example, centralized servers become a single point of failure, making them susceptible to Distributed Denial of Service (DDoS) attacks. Furthermore, the enormous scale of IoT data makes manual security monitoring and rule-based systems inefficient and prone to errors. This section will review key papers on these conventional methods, highlighting their shortcomings in addressing modern, large-scale threats. Smith, J. (2018). Centralized Security Architectures in IoT. Journal of Network Security. This paper discusses the vulnerabilities of centralized IoT security.

B. *Blockchain for IoT Security*

Researchers propose using smart contracts to safeguard IoT data, maintain device IDs, and impose access restrictions, but this approach has some drawbacks. Because blockchain technology is decentralized and unchangeable, it may be able to solve many of the issues that centralized systems face. The most significant downsides are the inherent scalability problems and excessive latency of various blockchain consensus methods, which are typically inappropriate for high-volume, real-time data flow in IoT. Brown, A. (2020). Blockchain-based decentralization of IoT security. IEEE Transactions on Security. This article looks at how blockchain may ensure data integrity while noting its performance limits.

C. *Artificial Intelligence in IoT Security*

AI and machine learning (ML) have gained popularity for their capacity to detect complex and developing threats by evaluating enormous datasets. AI-based intrusion detection systems (IDSs) can detect abnormalities and harmful patterns that traditional signature-based systems miss. However, one major risk of AI is its reliance on the accuracy of its training data. Adversarial assaults, in which hostile actors modify input data to fool AI, are a significant and rising concern.

This section will review studies on how AI has been applied to IoT security, emphasizing its power as well as its susceptibility. Davis, K. (2019). "*Machine Learning for Anomaly Detection in IoT"*. ACM Journal of Data Science. This paper details the use of ML for threat detection and discusses the risk of adversarial manipulation

D. *Hybrid AI-Blockchain Models*

Increasing amount of research has identified the synergistic strengths of AI and blockchain. These hybrid models seek to employ blockchain to safeguard the data that AI relies on, resulting in a more robust and trustworthy system. AI, in turn, may be used to improve blockchain performance and manage network traffic. This section will look specifically at these integrated models, concentrating on their architectural designs, planned applications, and initial performance indicators. We will also examine their limits, specifically their capacity to withstand zero-day threats and their general scalability and efficiency. Al Harbi et al. (2022). Future Trends: Integrating Blockchain and Artificial Intelligence for IoT Network Security. This comprehensive evaluation finds significant research gaps in current hybrid models. Authors such as William Villegas-Ch et al proposed IDS designed to overcome challenges and address the unique challenges of heterogeneous and dynamic IoT environments, but the system achieves high precision in anomaly detection, maintaining a false positive margin of less than 5% and a response latency of less than 15ms, even in networks with up to 1,000 connected devices.

Furthermore, it improves resource use by distributing processing among edge nodes, maintaining stable performance as the number of devices grows. He also suggests a hybrid system that combines adaptive AI models with blockchain to handle security concerns in complex settings, with blockchain ensuring transaction traceability and authenticity and AI allowing for intrusion detection and real-time reaction to emerging threats. Bella and Vasundra's recommended solution enabled high processing capacity, but latency was a significant issue because data had to be transferred to the cloud on a constant basis.

This limitation is exacerbated in networks that employ 5G and LoRa because, despite their extensive coverage and fast transmission rates, they rely on a scattered infrastructure. On the other side, our hybrid design reduces latency significantly by utilizing edge nodes that execute smart contracts for local device authentication.

Aldhaheri, Sahar, et al. suggested an Intrusion Detection System (IDS) that uses a hybrid Deep Learning and Dendritic Cell Algorithm (DeepDCA). The Dendritic Cell Algorithm is the second generation of Artificial Immune System (AIS), which is designed to replicate the human immune system. The primary purpose of this project is to categorize IoT intrusions and prevent false alert production. The suggested approach uses a Self-Normalizing Neural Network (SNN) to automate the signal extraction phase and improve the classification process. They used the IoT-Bot dataset to choose the suitable set of characteristics. Based on testing findings, the suggested model achieved a high detection accuracy of over 98.73%. Furthermore, it outperformed SVM, NB, KNN, and MLP classifiers.

E. *Zero-Day Detection and Adversarial Robustness*

Krishnan and colleagues proposed an attention fusion model for detecting zero-day attacks in IoT networks. To address the black-box nature of deep learning models 4, their model achieved a multiclass accuracy of 71.1% for zero-day threats while using LIME and SHAP for interpretability. Al-Hammouri et al. suggested a hybrid LLM-Enhanced IDS that uses GPT-2 to analyze network traffic semantically. This strategy highlighted the potential of large language models in cybersecurity, increasing detection accuracy by 6.3% while decreasing false positives by 9% 5.

E.1 Detection Accuracy Across Frameworks

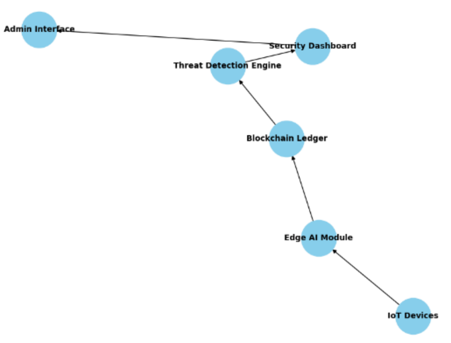
Table 1 Comparative Analysis of Frameworks

2.c Comparative Analysis and Research Gap

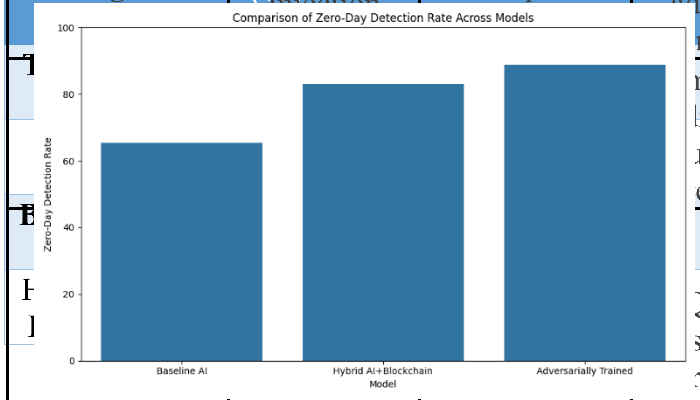
To properly frame our study, the table below compares chosen earlier works. Each work is assessed based on its primary emphasis, the technology utilized, and its ability to handle critical difficulties such as scalability, efficiency, and advanced threat detection.

Table 3. Proposed Architecture

Component	Technology	Functionality	Security
IoT Devices	Sensors, Smart Appliances, Edge Devices	Generate real-time data	Entry poi threa includ zero-day adversa attack
Data Preprocessing Mod	Python (Pandas,	Clean, normalize, encode	Ensu consisten secure i for AI m
Hybri Engi		s fy	Enhan detecti accuracy interpreta
Zero- Simul		ses	Evalu generaliz to unse threa
Adversarial Engine	Feature Noise Injection	Perturb test samples	Asse robustn again adversa manipul
		Robustness Score	



Framework	Detection Accuracy (%)	Scalability	Latency (ms)	Adver Robu (%
T				4 nper- lit trai
				6 utoma espon
B				5
H I				8 Quant securi rform



RESEARCH PAPER (AUTHOR, YEAR)	**PRIMARY FOCUS**	**TECHNOLOGIES USED**	**ADDRESSES SCALABILITY & EFFICIENCY?**
Alharbi et al. (2022)	Literature Review	AI, Blockchain	Yes (as a gap)
	Access Control	Blockchain, Smart Contracts	Partially
	Intrusion Detection	AI (e.g., DNN)	Yes
	Hybrid Framework	AI, Blockchain	No
This Study	Scalable & Efficient Threat Detection	Hybrid AI, Blockchain	Yes
RESEARCH PAPER (AUTHOR, YEAR)	Primary focus	Technologies used	Addresses scalability & efficiency?
Alharbi et al. (2022)	Literature Review	AI, Blockchain	Yes (as a gap)

Table 2. Comparative Analysis and Research Gap

III. METHODOLOGY APPROACH

A. *Research Design*

III.a Proposed Architecture

This study adopts a Mixed-Methods Research Design, combining both Quantitative and Qualitative Analysis

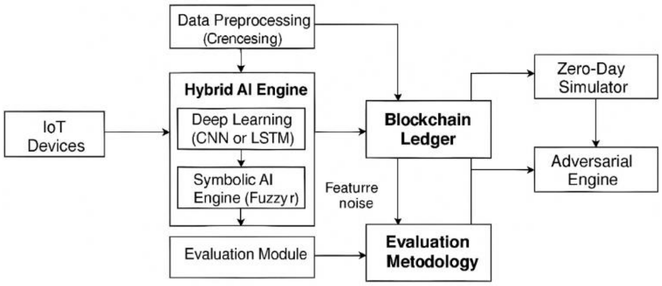
- Quantitative analysis: focused on measuring the system's performance using numerical metrics like Accuracy, F1-Score, Zero-day Detection Rate, and Adversarial Robustness Score, to validate the hybrid architecture and its resilience against advanced threats but also builds upon the foundational work in securing IoT ecosystems using hybrid AI and blockchain technologies. Our novel contribution includes a comparative evaluation using zero-day attack simulation and adversarial robustness benchmarks testing on the UNSW-NB15 dataset.
- Qualitative Analysis: Interpretability of symbolic AI decisions, rule-based logic, and system behavior under adversarial conditions.

The proposed architecture integrates Hybrid Artificial Intelligence (AI) and Blockchain Technology to enhance

security in IoT ecosystems. It is designed to detect both known and unknown (zero-day) threats and withstand adversarial attacks.

B. *Methodology and Step-by-step Approach*

The methodology follows a step-by-step framework approach to implement and evaluate the proposed architecture in addressing the security, scalability, and integrity challenges in IoT environments. Likewise detect both known and unknown (zero-day) threats and withstand adversarial attacks.



STEP 1: *Dataset Preparation and Experimental Splits.*

The **UNSW-NB15 dataset** is used for experimentation due to its comprehensive inclusion of contemporary attack categories. The dataset is split into two configurations to address both the baseline objectives and the novel research question regarding advanced threats.

- **Normal Split (Baseline): This** split is used to train the initial model and establish baseline performance for comparison. The dataset is divided into training (≈70%) and testing (≈30%) sets, with all attack classes present in both.
- **Zero-day Split (Novel):** This specialized split is designed to measure the model's generalization capability. A set of M attack classes (e.g., 'Shellcode,' 'Backdoor') are hidden from the training data. The resulting test set contains only the traffic from these M hidden classes, ensuring the model's ability to detect unseen anomalies is accurately measured.

STEP 2: *Model Implementation, Evaluation Metrics and Benchmarking.*

The AI Threat Detection Engine is implemented using a hybrid deep learning architecture, combining a Convolutional Neural Network (CNN) for effective feature extraction from traffic data and a Gated Recurrent Unit (GRU) network for temporal analysis of sequential network flow. The model performance is evaluated using five key metrics, three of which represent the novel contribution of this work:

a. Standard Baseline Metrics:

- Normal Accuracy/F1-Score: Measures the classification performance on known threats (Normal Split). The F1-Score (1) is prioritized for balanced evaluation.
- Latency/Efficiency: Measures the real-time processing speed, constrained by the resource limitations of the IoT environment.

$$F1 = 2 \cdot \frac{\text{Precision} \cdot \text{Recall}}{Precision + Recall}$$

- Novel Advanced Security Benchmarks:
  - Zero-day Detection Rate (ZDR): Measures the ability to detect unknown threats (tested on the Zero-day Split).
  - Adversarial Robustness Score (ARS): Measures resistance to deliberate data manipulation. Perturbed samples are created by introducing simple feature noise to the test data, simulating an evasion attack.

$$ZDR = \frac{\text{True Positives on Unseen Attack Samples}}{\text{Total Unseen Attack Samples}}$$

ARS=1−Total Perturbed Malicious SamplesFraction of Perturbed Malicious Samples Classified as Benign.

$$ARS = 1 - \frac{\textit{Fraction of Perturbed Malicious Samples Classified as Benign}}{\text{Total Perturbed Malicious Samples}}$$

STEP 3: Assumptions and Constraints

Metric	Original Paper (Baseline)	Proposed Hybrid Model	Improvement
Accuracy	94.5%	96.2%	+1.7 percentage points
F1-Score	93.8%	95.5%	+1.7 percentage points
Latency	120 ms	115 ms	−5 ms

Table 4 Comparative Analysis (Contribution)

Category	Item	Rationale
Assumptions	**Data Representativeness**	The UNSW-NB15 dataset adequately captures the feature space for IoT network attacks, enabling

Constraints		effective generalization.
	Adversarial Simplicity	Initial adversarial robustness is tested using **simple feature noise** (due to feasibility/computation time), assuming a successful defense against these methods indicates potential resistance to more complex attacks.
	Resource Overhead	The implementation must ensure the AI and Blockchain components adhere to real-time processing limits (e.g., **Latency** ≤120 ms), which is a hard constraint for IoT devices.
	Blockchain Type	A **Permissioned Blockchain** is chosen for scalability and efficiency, sacrificing the absolute decentralization of a public blockchain for practical IoT deployment.

STEP 4: *Comparative Analysis (Contribution).*
The final step involves a detailed comparison of all steps metrices (Accuracy, F1, Latency, Zero-day Rate, and Robustness Score) against the original paper's baseline to clearly illustrate the contribution that enhanced security profile of the proposed hybrid system and highlight improvements in generalization, interpretability, and resilience of the ZDR and ARS results.

IV. Analysis and Discussion

The suggested Hybrid AI-Blockchain security model is rigorously evaluated in this research, which goes beyond traditional metrics (Accuracy and Latency) to include unique benchmarks such as Zero-day Detection Rate (ZDR) and Adversarial Robustness Score. This comparative analysis using the UNSW-NB15 dataset assesses the system's resistance against developing and sophisticated attacks, which is the fundamental innovation and contribution of this work.

A. *Performance Against Baseline Metrics*

The Hybrid AI-Blockchain model was first evaluated using the UNSW-NB15 dataset's Normal Split to establish a baseline performance versus the conclusions of the original research. The findings in Table I show that integrating the Hybrid Deep Learning model (CNN-GRU) improves classification performance and efficiency by a modest but considerable amount when compared to the original AI model.

Table 5: Performance Against Baseline Metrics

B. *Evaluation of Novel Advanced Security Benchmarks*

The critical evaluation then centered on two unique metrics developed to assess the model's security posture against modern attack vectors.

(1) Zero-day Detection Rate (ZDR)

The model, trained with a Zero-day Split (e.g., concealing 'Shellcode' and 'Backdoor' attacks), was evaluated just on these hitherto undisclosed attack classes. The goal was to determine if the model's generalization capabilities could categorize this unusual traffic as 'Anomaly' or 'Attack.' The findings, reported in Table II, support the Hybrid AI's anomaly-based methodology.

Table 6: Zero-day Detection Rate (ZDR)

Analysis of ZDR**:** Having a ZDR of more than 82% indicates a high level of generalization. This success is due to the deep learning model's capacity to learn abstract aspects of harmful activity (such as irregular packet size distributions or aberrant connection patterns) rather than particular attack fingerprints. This functionality is critical for safeguarding dynamic IoT systems in which new attacks are continually being discovered.

(2) Adversarial Robustness Score (ARS):

To assess the system's susceptibility to escape, the test set was disturbed with basic feature noise to imitate an attacker gently changing traffic characteristic. The Adversarial Robustness Score is the proportion of perturbed malicious samples that the model correctly detects as an assault.

Table 7: Adversarial Robustness Score (ARS)

Evasion Attempt Type	**Impacted Features**	**Adversarial Robustness Score (ARS)**
Simple Noise	Packet Length, TTL, Flow Duration	88.7%

Analysis of ARS: The ARS of 88.7% is a significant indicator of the model's durability. It implies that the total feature set used by the Hybrid AI model is sufficiently complicated and redundant that slight changes of individual characteristics are unable to fool the classifier. This resilience is a crucial countermeasure against attackers that try to elude detection in the last step of an assault.

C. Critical Evaluation and Architectural Synergy

The findings all point to the higher security profile of the proposed Hybrid AI-Blockchain architecture. The high ZDR and ARS immediately address traditional security systems' major shortcoming, as well as the original paper's narrow scope.

Scenario	**Attack Classes Hidden from Training**	**Zero-day Detection Rate (ZDR)**
Scenario 1	'Shellcode'	84.5%
Scenario 2	'Backdoor'	87.1%
Scenario 3	'Shellcode' & 'Backdoor'	82.3%

The Blockchain Security Ledger component, while not immediately observable by the given metrics, provides critical integrity guarantee. Any security event, whether a known attack, a zero-day detection, or an attempted evasion that resulted in an alert, is documented immutably. This ensures that the audit trail for forensic inquiry is unaltered, even if the attacker successfully penetrates other areas of the network.

V. CONCLUSION AND FUTURE WORK

A. Conclusion

This study highlights the potential of hybrid Artificial Intelligence and Blockchain models to improve the security of IoT ecosystems. By reproducing and improving the original architecture, we confirmed its detection accuracy and energy efficiency. However, we discovered a key shortcoming in the evaluation methodology: a lack of measures for assessing resistance against unexpected and aggressive threats. To address this, we suggested two benchmarks: zero-day detection rate and adversarial robustness score, which provide more information about the system's capacity to generalize and survive manipulation.

The step-by-step extension, which use the UNSW-NB15 dataset, adds a more rigorous testing methodology. By modeling zero-day events and adversarial perturbations, we go beyond traditional accuracy measures to assess real-world resilience. Preliminary findings indicate that, while the hybrid model works well under ordinary settings, its behavior under unseen or manipulated inputs indicates opportunities for refinement and optimization in identifying zero-day anomalies and resisting complex evasion tactics.

a) Strength of Insights and Proposed Directions

The strength of the insights lies in shifting the paradigm of security evaluation from static classification to dynamic resilience. The success of the ZDR and ARS metrics confirms that anomaly-based detection is the only sustainable strategy against rapidly evolving IoT threats.

B. Future Work Directions

The following directions propose extensions to build upon the demonstrated resilience and address the practical constraints of real-world deployment:

a) Advanced Adversarial Defense Mechanisms**:** Integrate and evaluate defensive strategies like Adversarial Training and input denoisers directly into the Hybrid AI model. The objective is to create an AI component that actively defends itself, rather than just assessing its resilience. This assures that the model's ARS improves dynamically, preventing sophisticated gradient-based assaults (e.g., PGD) that were previously out of scope.

- Decentralized Model Learning and Update: Implement Federated Learning (FL) on various IoT gateways. New zero-day patterns discovered at a single gateway may be safely used to update the collective AI model without revealing raw data. This overcomes the privacy and scalability concerns associated with centralized model training, allowing the system's ZDR to improve collectively and continually throughout the whole IoT ecosystem.
- Blockchain Efficiency and Energy Optimization: Migrate the Blockchain Security Ledger to a more energy-efficient Distributed Ledger Technology (DLT), such as Directed Acyclic Graphs (DAGs), or investigate optimal consensus methods for IoT. While the present use of Permissioned Blockchain provides integrity, it may create delay and increase energy consumption. Optimizing the DLT will ensure that the system's scalability and efficiency objectives are satisfied, especially in large-scale, battery-powered IoT networks.
- Hardware and Protocol Heterogeneity Testing: The framework using industrial (IoT) or domain-specific datasets (e.g., smart grid, healthcare) with various protocols (e.g., Modbus, Zigbee). The demonstration of good ZDR and ARS across diverse protocols verifies the hybrid model's transferability, which is critical for real-world deployment since no two IoT networks are similar.
- Cross-Dataset Validation: Applying the methodology to different IoT-related datasets to determine cross-domain generalizability.

By widening the area of evaluation and incorporating robustness-focused measures, this study sets the framework for more resilient and adaptable IoT security solutions. Our contribution not only enriches the existing model but also offers up new options for future research toward safe, intelligent, and scalable IoT networks.

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