Annual Methodological Archive Research Review
http://amresearchreview.com/index.php/Journal/about
Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189

http://amresearchreview.com/index.php/Journal/about

An Enhanced 6G-Enabled IoT Network Security Framework Using Edge AI and Machine Learning

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ABSTRACT

The 6G wireless network can combine with the Internet of Things (IoT) to enable terahertz (THz) communication, reconfigurable intelligent surfaces (RIS), network slicing, and AI-native radio access networks (RANs), which would connect trillions of heterogeneous resource-constrained devices. Such enormous size, coupled with the demands of ultra-low latency and mass connectivity, significantly increases the attack surface that IoT ecosystems face today, and makes it difficult to meet the latency, bandwidth, and privacy demands of 6G. This study provides a comprehensive discussion of the current state of security research in Edge Artificial Intelligence and Machine Learning approaches to securing 6G-enabled IoT networks, and is explicitly contextualized with respect to previous surveys of 6G-IoT security, while uniquely

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Online ISSN 3007-3197
Print ISSN 3007-3189

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focusing on introducing the reader to the field of Edge AI and ML 6G-IoT security. We review recent works dealing with federated learning-based intrusion detection, deep and hybrid learning architectures, deep reinforcement learning for adaptive defense, TinyML for extreme-edge inference, explainable AI for auditability, and blockchain-assisted zero trust access control. On top of the identified gaps, we present an Enhanced 6G-IoT Security Framework, consisting of a closed-loop, federated detection-and-response workflow that incorporates a five-layer architecture, namely the perception, edge-AI, 6G network, cloud-intelligence, and application layers. Comparative tables represent techniques, threat taxonomies, and design trade-offs, as well as architecture. The study ends by highlighting many open challenges, such as the lack of 6G-IoT representative datasets, adversarial robustness, energy-latency-accuracy tradeoffs at the extreme edge, as well as the need for quantum-safe secure information, models with explainability, and sustainable secure information. The study provides a basic research roadmap for developing more trustworthy 6G-IoT systems in the future.

Keywords—6G Networks; Internet of Things; Edge AI; Machine Learning; Federated Learning; Network Security; Intrusion Detection; Zero-Trust Architecture

I. Introduction

Conventional fifth-generation (5G) networks are already facing structural constraints under the pressure of emerging applications in the Internet of Everything (IoE) including autonomous driving, immersive extended reality (XR) and large-scale digital twins [1]. The design of 6th-generation (6G) networks has been pushed to overcome these limits by adopting the use of the terahertz (THz) spectrum, reconfigurable intelligent surfaces (RIS), AI-native radio access networks, space-air-ground integration and network slicing which enables to provide sub-millisecond latency and order of magnitude more connection density than 5G [2]. At the same time, the Internet of Things (IoT) is expected to include tens of billions of devices that vary widely in type, power and size, ranging from smart health applications to Industry 5.0, intelligent transportation systems, and smart cities [3].

The convergence of these two, hence 6G-IoT in the world of 6G magnifies both the opportunity and the risk. On the one hand, AI-native connectivity allows to provide real-time, context-aware services while on the other hand, the size, diversity and mobility of connected devices drastically increases the attack surface which can be exploited to compromise the device, the network or even target increasingly sophisticated attack that exploits the machine learning models embedded in the device itself and the network itself, such as the adversarial perturbations, data poisoning or the model-inversion attack [4,5]. In a traditional cloud-based security system, where data is sent to centralized security servers for processing, there are limitations on

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latency and privacy for 6G and there is a single point of failure that is ill-equipped for the vast number of huge IoT deployments [6-8].

$$s(t) = (x * w)(t) = \sum_{a=-\infty}^{\infty} x(a)w(t - a) \quad \text{Eq (1)}$$

W stands for the kernel filter, x stands for the input signal, t stands for time and s is the output signal. The convolution process with two-dimensional input data is described by Equation (2).

$$S(i,j) = (I * K)(i,j) = \sum_m a \sum_n I(i,j) * K(i-m, j-n) \quad \text{Eq (2)}$$

The variables iii and jjj are the spatial position in the output matrix following the convolution operation. In this process, the center of the filter is matched with the corresponding image area, so as to achieve the best feature extraction effect. Moreover, the proposed framework uses the cross-entropy loss as the optimization objective, which is shown in Equation (3).

$$S(i,j) = (I * K)(i,j) = \sum_m a \sum_n I(i + m, j + n) * K(m,n) \quad \text{Eq (3)}$$

To overcome these requirements, Edge Artificial Intelligence (Edge AI) has become an attractive paradigm that places the data closer to the system where it is used and, to a greater extent, where it is learned [9-11]. To retain privacy and mitigate the communication overhead, federated learning enables distributed IoT and edge nodes to jointly train a federated model with minimal sharing of raw data with a central server [12-14]. For inference on devices with a small memory footprint, such as microcontrollers, complementary techniques like TinyML [15] can be used, and deep reinforcement learning is suitable for self-optimizing defense policies for dynamic 6G scenarios [16, 17]. Explainable AI and blockchain-based zero-trust mechanisms also provide solutions to the issues of trust, auditability and identity management in fully autonomous AI-powered security pipelines [18-21].

ReLu

$$f(x) = \begin{cases} 0, x < 0 \\ x, x \geq 0 \end{cases}, f(x)' = \begin{cases} 0, x < 0 \\ x, x \geq 0 \end{cases} \quad \text{Eq (4)}$$

Although a collection of isolated and distinct works have emerged, there is still no single framework in the literature that systematically charts the 6G-IoT threat landscape along key aspects of the deployment of Edge AI and ML technologies, namely device, network, and AI-model layers; The prevailing Edge AI and ML paradigms for relevant aspects of limited IoT resource availability such as latency, communication overhead, privacy, robustness, and energy; and proposes an integrated, closed-loop architecture that operationalizes these approaches within the 6G-IoT security pipeline [22-25]. This paper fills that deficiency. The major contributions are the following:

Online ISSN 3007-3197
Print ISSN 3007-3189

we present a structured overview of 6G-enabling technologies and discuss the implications it has for 6G-IoT security, and propose a layer-wise taxonomy of 6G-IoT security threats, covering the perception layer, network layer and AI-model layer [26]. Recent study of highly cited journal papers (2020-2026) related to federated learning, deep and hybrid learning, deep reinforcement learning, TinyML, explainable AI and blockchain-based Zero Trust IoT and 6G security mechanisms [27].

We proposed an Enhanced 6G-IoT Security Framework to combine these techniques into a 5-layer architecture and a closed loop detection-response workflow mechanism based on 6GIoT use-case scenarios and provide the original architecture and workflow diagrams. Comparative tables summarizing threats, typical techniques and design trade-offs are provided and open research challenges and future directions for trustworthy 6G-IoT security are outlined.

A. Review Methodology

The wide range of the topic searched a more selective process is carried out for the review; a strictly systematic search process is not performed. The literature was collected using an IEEE Xplore, ACM Digital Library, ScienceDirect, and SpringerLink searches based on a set of combinations for the keywords 6G, Internet of Things, edge AI, federated learning, TinyML, deep reinforcement learning, explainable AI, zero trust, and intrusion detection. Only peer-reviewed journal articles and preprinted conference papers from between 2019-2026 were eligible for coverage, and emphasis was given to the presenters from 2023-2026, typically assumed to be “6G”-related, and making it closer to the conference schedule four years later. Preprints and non-English papers were ignored; papers published in both the conference and the journal were ignored if the conference was superseded by the journal a year later. Following this, the remaining part of this review is organized around the six families of techniques for Edge AI and ML introduced in Section IV, and the threat taxonomy developed in Section III.The resulting 41 primary sources were summarized in the Reference list and kept organized around these 6 families of techniques for Edge AI and ML and the taxonomy of threats developed in Section III.

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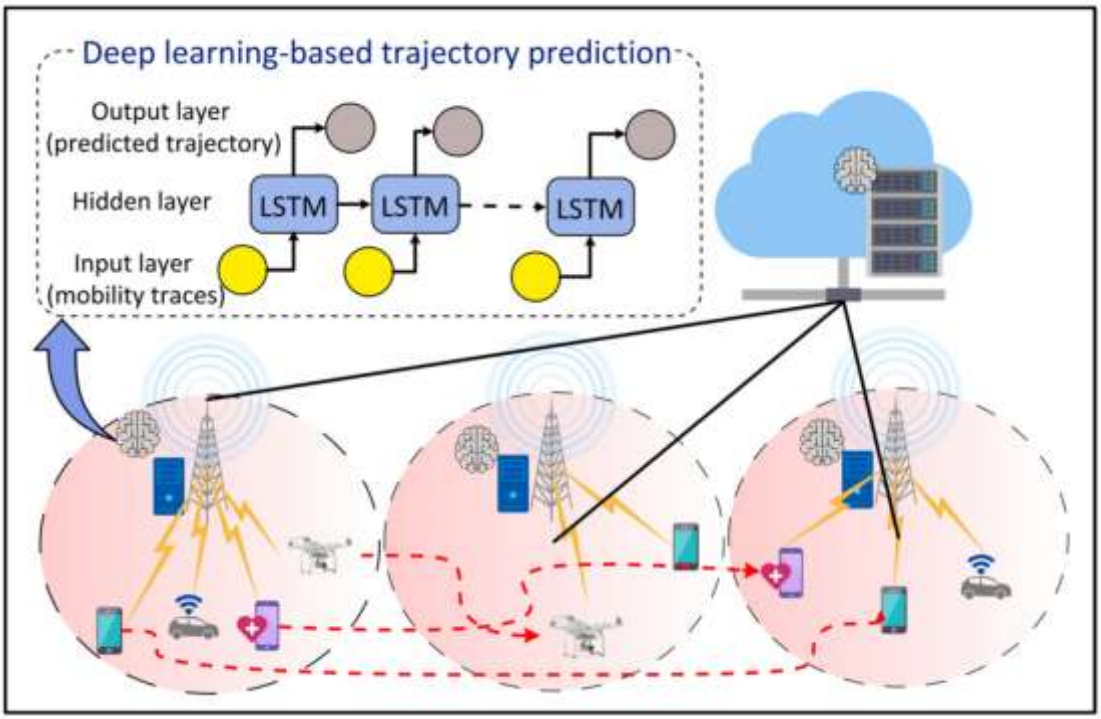

Fig. 1 (a). Generic Intelligent network architecture based on DL [28]

B. Positioning Relative to Existing Surveys

While several surveys in existence cover portions of the 6G-IoT security space, they fall short of integrating a threat taxonomy and taxonomy of multiple paradigms of Edge AI and ML with a concrete and integrated defense architecture. To put this review in perspective of five representative prior reviews, see Table I.

TABLE I POSITIONING OF THIS REVIEW RELATIVE TO REPRESENTATIVE EXISTING SURVEYS

Primary Scope	6G-Specific Focus	Threat-Taxonomy Scope	Integrated Framework Proposed
Edge-learning vulnerabilities, datasets, and defenses for 6G-enabled IoT [29-31]	Yes	Device/network/model, vulnerability-centric	No
XAI techniques for 5G/6G security and slicing decisions [32]	Partial (5G/6G)	XAI-centric, not a full threat taxonomy	No
Systematic review of federated-learning-based	No (general	Algorithm-centric, not	No

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intrusion detection [33,34]	IoT)	layer-wise	
ML-based IoT security solutions and open challenges [35-38]	No (pre-6G)	Broad ML-security survey, not 6G-specific	No
TinyML techniques for extreme-edge intelligence [39-42]	No	Not security-threat-taxonomy focused	No
FL, deep/hybrid learning, DRL, TinyML, XAI, and blockchain zero-trust for 6G-IoT security [43-45]	Yes	Device, network, AI-model, and cross-layer trust	Yes — five-layer architecture with closed-loop workflow

Previously carried out surveys often focus on one of the three main families of techniques: XAI [46, 47], federated learning or TinyML browsers; or they are more limited to only the challenge of vulnerabilities and data, but ignore the nature of 6G-IoT threats and a thorough comparative study of potential defense paradigms [48-50].

Sigmoid

$$f(x) = \frac{1}{1+e^{-2}}, f'(x) = f(x)(1 - f(x)) \quad \text{Eq (5)}$$

Tanh:

$$\tan h\,(x) = \frac{2}{1+e^{-2x}} - 1, f'(x) = 1f(x)^2 \quad \text{Eq (6)}$$

As shown in Table I, most of the surveys covered in the literature have limited scope to a particular technique family, or adopted an approach that predates the advent of 6G threats completely. This review is unique in bringing together a taxonomy of threats that cross the device, network and AI and ML, as well as a synthesis of six Edge AI and ML paradigms, along with an original threat framework that spans five layers and features a closed loop cyclic [51-55].

Clipped ReLU:

$$f(x) = \begin{cases} 0, x < 0 \\ x0 \leq x < \text{ceiling} \\ ceiling, \geq \text{ceiling} \end{cases} \quad \text{Eq (7)}$$

Leaky ReLU:

$$f(x) = \begin{cases} 0, x < 0 \\ scale * x, x < 0 \end{cases} \quad \text{Eq (8)}$$

The rest of this paper is structured in the following way. In Section II, the 6G-IoT convergence and enabling technologies are described. In Section III, we discuss a taxonomy of the 6G-IoT security threat landscape. In Section IV, edge artificial

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intelligence and machine learning (ML) solutions are discussed for 6G-IoT security. The proposed improved framework is presented in Section V. A comparative analysis and discussion among the selected contentious policies are provided in Section VI. Open challenges and future research are described in section VII while section VIII concludes the paper.

$$S_i^{(b,t)} = \sum_{z=1}^{E} p_{iz}^{(b)} J_z^{(b-1,t)} + \sum_{i'}^{y} x_{ii'}^{(b)} J_{i'}^{(b,t-1)} \qquad \text{Eq (9)}$$

II. 6G-IoT Convergence: Architecture and Enabling Technologies

The envisioned 6G networks support THz-band communication, massive and holographic MIMO, RIS-assisted propagation control and pervasive AI embedded in RAN and core network functions to achieve the peak data rate of > 100Gbps and the air-interface latency of < 0.1ms, the ultra-high connection density of up to 107devices/km² [56-59].

$$S_h = 60° \begin{cases} 0 + \frac{(\beta_g - \beta_b)}{(m_x - m_n)}, if m_x = \beta_r \\ 2 + \frac{(\beta_b - \beta_r)}{(m_x - m_n)}, if m_x = \beta_g \\ 4 + \frac{(\beta_r - \beta_g)}{(m_x - m_n)}, if m_x = \beta_b \end{cases} \qquad \text{Eq (10)}$$

Software-defined networking and network function virtualization (SDN/NFV) enables operators to create separate virtual networks designed to suit diverse IoT applications, including ultra-reliable and low-latency networks for industrial control to massive machine-type communication (MMC) for environmental sensing [60-62].

$$o_t = \sigma(W_o x_t + W_o h_{t-1} + b_o) \qquad \text{Eq (11)}$$

The IoT ecosystem point of view, these are three structural changes. The perception layer of the system gets much more diverse and includes from ultra-low-power sensors to autonomous vehicles to unmanned aerial vehicles with different compute, power, and mobility requirements. Secondly, the wider network layer itself becomes programmable and is AI-native, with slicing, RIS, and SDN/NFV adding to the attack surface if not secured in addition to being enablers for service differentiation [63-64].

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Online ISSN 3007-3197
Print ISSN 3007-3189
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$$y = f\left(\sum_{k=1}^{K} h^k * w^k + c^k\right)$$ Eq (13)

Third, intelligence gets distributed, in the sense that the intelligence of 6G-IoT is more and more cascaded over the different hierarchies of device, edge and fog, and cloud levels, so that systems increasingly move closer and closer to the Edge AI paradigm introduced in Section IV.

TABLE II KEY 6G-ENABLING TECHNOLOGIES AND THEIR IMPLICATIONS FOR IoT SECURITY

Enabling Technology	Role in 6G-IoT	Security Implication
THz Communication & Massive MIMO	Ultra-high-bandwidth, low-latency links for dense IoT deployments	New physical-layer eavesdropping and jamming surfaces; short-range links reduce but do not eliminate interception risk [65-67]
Reconfigurable Intelligent Surfaces (RIS)	Programmable radio environment for coverage and energy efficiency	RIS misconfiguration or spoofing can be exploited to redirect or intercept signals [68-69]
Network Slicing / SDN-NFV	Isolated virtual networks per IoT application class	Slice isolation failures and controller compromise can cascade across tenants [70], [71]
AI-Native RAN / Edge Intelligence	In-network learning and adaptive resource orchestration	Introduces AI-specific attack vectors: poisoning, evasion, and model extraction [72-75]
Space-Air-Ground Integrated Networks	Extends connectivity to remote/mobile IoT (UAV, satellite)	Heterogeneous trust domains complicate authentication and key management [76-79]
Digital Twin Integration	Real-time virtual replica for monitoring and simulation	Synchronization channel and twin-data integrity become new targets [80]

III. Security Threat Landscape in 6G-Enabled IoT

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Volume 4, Issue 1 (2026)

Online ISSN 3007-3197
Print ISSN 3007-3189
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Securing 6G-IoT systems necessitates a holistic approach to understanding and mitigating threats across multiple layers, including those from the physical aspect, the network as it essentially becomes an AI-based fabric, and the machine learning models that are increasingly shaping network decisions. We categorize the threat landscape into three layers similar to previous surveys of vulnerabilities occurring in 6G-IoT [81-83].

$$\mathrm{TDI} = \sqrt{(\Delta C)^2 + (\Delta \sigma)^2} \qquad \text{Eq (14)}$$

A. Device / Perception-Layer Threats

Resource-constrained IoT endpoints can be physically captured and firmware can be tampered, lightweight primitive cryptography attacks can be launched, and physically unclonable function identities can be stolen. However, the botnet recruitment of poorly secured consumer and industrial devices is still a prevalent attack surface for large-scale distributed denial of service (DDoS) attacks [84-87].

$$\mathrm{MCC} = \frac{\mathrm{TP} * \mathrm{TN} - \mathrm{FP} * \mathrm{FN})}{\sqrt{((\mathrm{TP} + \mathrm{FP}) * (\mathrm{TP} + \mathrm{FN}) * (\mathrm{TN} + \mathrm{FP}) * (\mathrm{TN} + \mathrm{FN}))}} \qquad \text{Eq (15)}$$

B. Network-Layer Threats

The programmability features of 6G also trigger some known and new threat vectors in the network layer, including volumetric and protocol-level DDoS attacks, man-in-the-middle interception, Sybil and Byzantine behavior in distributed consensus or federated aggregation, RIS- and beam-based eavesdropping, and jamming of THz links [88-91].

$$f_t = \mu + \rho \mathrm{GEGR}_{it-1} + \vartheta^{+} \mathrm{EU}^{+}_{it-1} \qquad \text{Eq (16)}$$

Faults or malicious traffic can spread between formerly-isolated networks and tenants from network-slice isolation breaches and compromise of SDN controllers [92, 93].

$$C_t = \vartheta^{-} \mathrm{EU}^{-}_{it-1} + \emptyset^{+} \mathrm{FD}^{+}_{it-1} + \vartheta^{+} \mathrm{EU}^{+}_{it-1} \qquad \text{Eq (17)}$$

C. AI-Model-Layer Threats

The increasing role of embedded models of ML and DL in security for 6G-IoT, the models themselves are becoming targets to be attacked [94-96]. Multiple types of attacks can be distinguished by their taxonomy; in this project at least eight from the following will be taken into account: backdoor attacks, attacks with adversarial examples, combined and blended attacks, data-poisoning attacks, Sybil attacks against federated aggregation, Byzantine attacks, membership and inference attacks that leak private training data, and dropping availability attacks, which degrade collaborative learning [97].

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Online ISSN 3007-3197
Print ISSN 3007-3189

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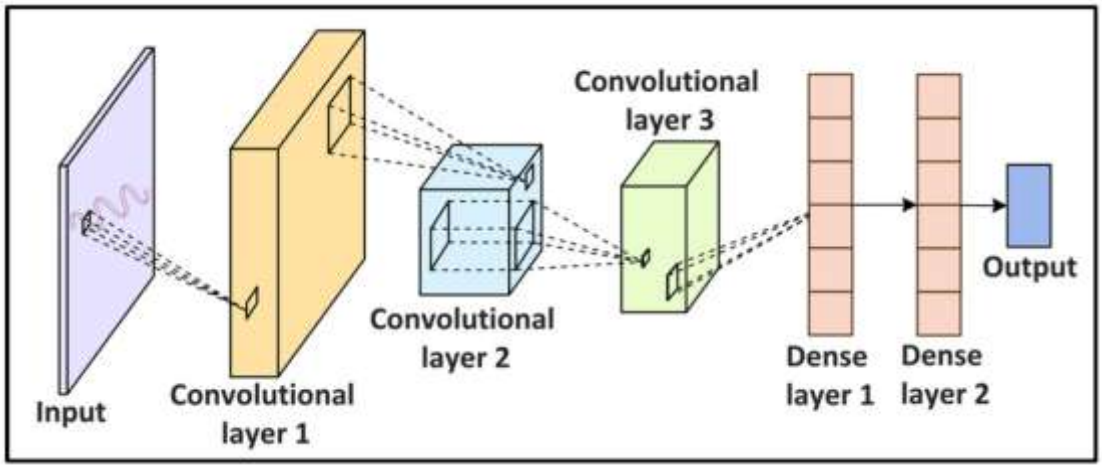

Fig. 1 (b). Generic Intelligent network architecture for enhanced 6G-IoT security using Convolutional Neural Network (CNN) [98].

$$I_t = \omega^{+} TI^{+}_{it-1} + \omega^{-} TI^{-}_{it-1} \qquad \text{Eq (18)}$$

Another, less studied, category of AI-native 6G network control threat identified is reward-poisoning attacks on reinforcement learning agents serving as network controllers [99].

$$\Delta f_{t_i} = \sum_{j=1}^{n-1} \alpha j \, \Delta GERG_{it-1} + \sum_{j=0}^{n2} (\pi^{j+} \Delta EU^{+}_{it-j} \qquad \text{Eq (19)}$$

TABLE III TAXONOMY OF SECURITY THREATS IN 6G-ENABLED IoT NETWORKS

Layer	***Representative Threats***	***Primary Impact***
Perception / Device	Physical capture, firmware tampering, side-channel attacks, PUF spoofing, botnet recruitment	Loss of device integrity; entry point for large-scale botnets [100, 101]]
Network / Connectivity	DDoS, MITM, jamming, RIS/beam eavesdropping, slice-isolation breach, SDN controller compromise	Service disruption, data interception, cross-tenant contamination [102], [103]
AI / ML Model	Data poisoning, backdoor attacks, adversarial examples, Sybil/Byzantine FL attacks, membership inference, reward poisoning (DRL)	Corrupted detection models, privacy leakage, unsafe autonomous decisions [104], [105]
Cross-Layer / Trust	Identity spoofing, unauthorized lateral	Erosion of end-to-end trust across heterogeneous

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http://amresearchreview.com/index.php/Journal/about
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Online ISSN 3007-3197
Print ISSN 3007-3189
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movement, weak zero-trust enforcement	domains [106], [107]

IV. Edge AI and Machine Learning for 6G-IoT Security

This section introduces some essential techniques of edge AI and machine learning to solve the security problems of 6G-IoT. It emphasizes key challenges and opportunities arising from intelligent, distributed, and adaptive learning techniques for improving threat detection, intrusion detection, anomaly identification, privacy protection and secure resource management. Specific focus is dedicated to Federated Learning, Deep Learning [108], Hybrid ML models [109], Deep Reinforcement Learning [110], TinyML [111] and Explainable AI [112]. These enable security intelligence to act near IoT devices and near the network edges, solving latency issues, scalability concerns, enabling real-time security decisions, and mitigating privacy and resource challenges.

$$\Delta f_{t_1} = \sum_{j=0}^{n3} (\tau^{j+} \Delta FD^{+}_{it-j} + \tau^{-}_{j} \Delta FD^{-}_{it-j}) \qquad \text{Eq (20)}$$

A. Federated Learning-Based Intrusion Detection

Federated Learning, nodes can collaboratively train the ID models with only the exchange of ID model parameters, as compared to sending raw traffic data, thereby meeting the privacy and bandwidth requirement of centralized approaches [25]. Semi-supervised Federated schemes alleviate the labeling efforts on the edge devices while preserving detection accuracy in non-independent and identically disrupted environments [26].

$$\Delta f_{t_2} = \sum_{j=0}^{n3} (\tau^{j+} \Delta FD^{+}_{it-j} + \tau^{-}_{j} \Delta FD^{-}_{it-j}) \qquad \text{Eq (21)}$$

Improved robustness to statistical heterogeneity in large-scale, heterogeneous IoT deployments due to clustering-based and hierarchical Federated Learning architectures which group together devices sharing similar traffic characteristics before aggregation. In industrial IoT environments with devices' nature of diversity and uneven connectivity & computing resources, the latency and energy cost of aggregation are minimized under asynchronous and delay-aware variants of Federated Learning [27]. In recent years, systematic reviews validate Federated Learning based intrusion detection as one of the most prolific research approaches in the field of IoT security, and list open problems like secure aggregation protocols and the vulnerability to poisoning.

$$\Delta f_{t_2} = \sum_{j=0}^{n4} (\sigma^{j+} \Delta TI + \sigma^{-}_{j} \Delta TI^{-}_{it-j}) + \varepsilon_{it} \qquad \text{Eq (22)}$$

B. Deep and Hybrid Learning Architectures

Federated Learning distributed-training dimension, there are also underlying models' architectures, and their selection significantly impacts both detection accuracy and the

Online ISSN 3007-3197
Print ISSN 3007-3189

computational overhead [28]. Industrial and consumer IoT intrusion detection has been explored in different approaches to enable the use of spatial, temporal and topological network traffic structure via convolutional neural network–long short-term memory CNN-LSTM hybrids; autoencoders as well as graph neural networks. Measures taken to design specific and efficient local models turn out to achieve comparable centralized detection accuracy while meeting tight latency requirements in a federated deep-learning framework for an industrial cyber-physical system [29]. Examples of such types of frameworks are zero-day botnet detection systems that use federated deep learning combined with deep learning at the edge of the deployment network, showing the applicability of this class of solutions to unknown attack signatures [30].

C. Deep Reinforcement Learning for Adaptive Defense

AI-native 6G radio access networks and slicing, deep reinforcement learning (DRL) provides a means for the network controller to discover customizable defense and resource-allocation policies through interaction with the environment, a crucial capability [31]. Explanation-based DRL methods also seek to ensure that the slicing and defense decisions are explainable to network operators to mitigate the issue of trust concern in fully autonomous control loops [32]. DRL-based controllers, however, add their respective attack surface, one of which concerns reward-poisoning attacks, which incrementally push the policy learned by the agent towards unsafe policies; this is a topic which, in comparison to threats in supervised learning, has been relatively under-effected.

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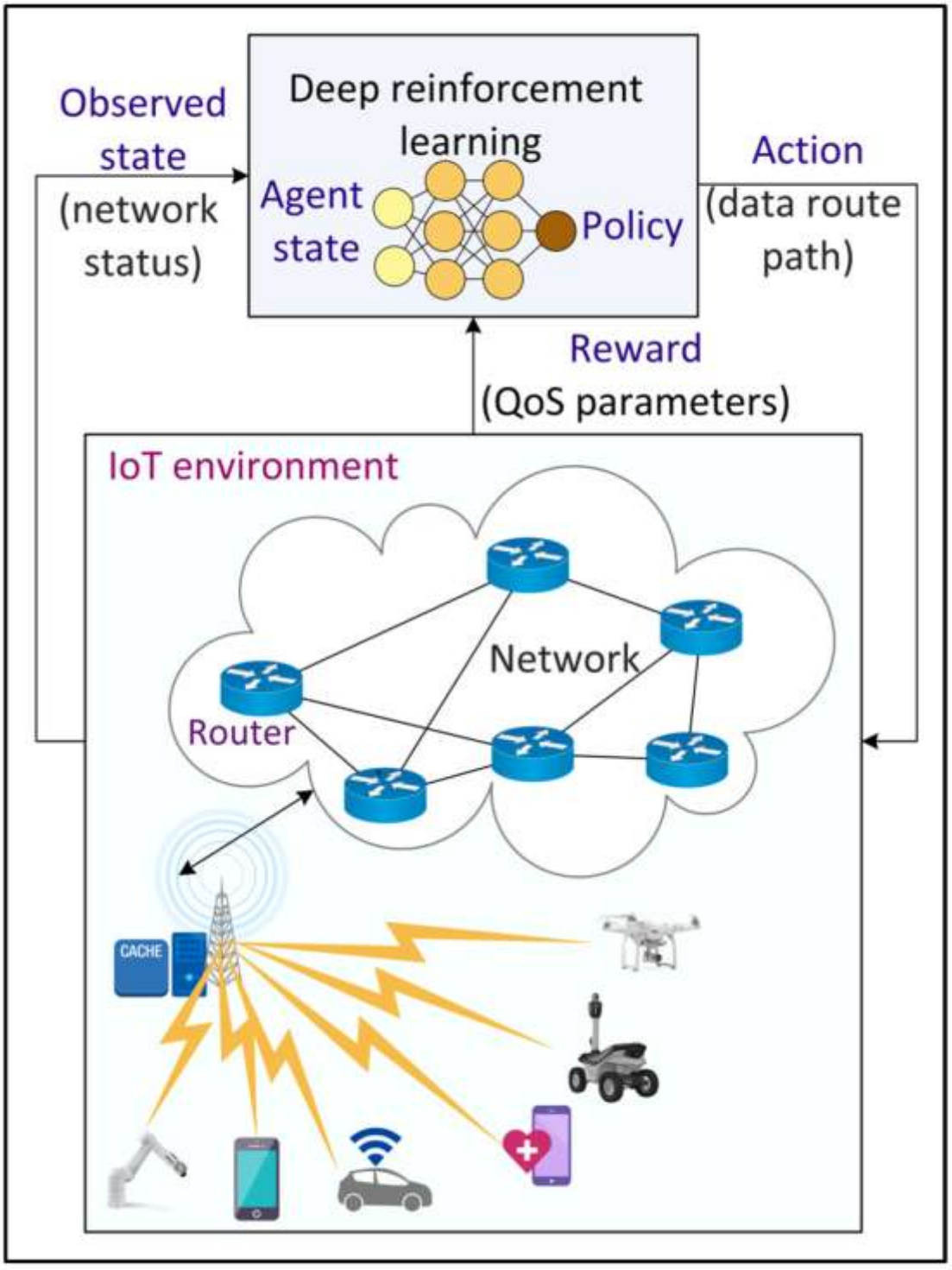

Fig. 1 (c). Generic Deep Reinforcement Learning Architecture for enhanced 6G-IoT security

D. TinyML and Extreme-Edge Inference

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TinyML is the compression of ML and DL inference, and increasingly incremental on-device training, that runs efficiently in the kilobytes to megabytes of memory available to most IoT use cases implemented in microcontroller-class devices with methods like quantization, pruning, knowledge distillation, and sparse versus reconfigurable accelerators. Recent work has shown examples for real-time anomaly detection for predictive maintenance and consumer internet-of-things protection leveraging TinyML with good accuracy-to-footprint trade-offs as well as variants of transformer-based and incremental-learning algorithms that are adapted for the extreme edge [33]. With this in mind, TinyML is increasingly integrated with federated learning also known as "TinyFL" to provide constant and private model optimization directly at the clamp of the limited resources in 6G-IoT endpoints, especially battery-powered ones.

E. Explainable AI for Trust and Auditability

Network operations and network security tasks are handed over to more and more autonomous ML and DL models, and explainability becomes a must for operators to be trusted, to meet regulatory requirements, and to react appropriately when incidents occur. Recent surveys list XAI techniques for 5G/6G security and network-slicing decisions and point to the nature of a tradeoff between model complexity and interpretability as a key open question for AI-native 6G [34]. Seeding XAI in the security pipeline allows human threat analysts to validate the automated threat classification before taking costly action to fix it.

F. Blockchain-Assisted Zero-Trust Access Control

The continuous verification of every device, user and service, irrespective of network location, is increasingly being suggested as the backbone for identity and access-control for the 6G-IoT [35]. Distributed ledgers are useful for distributed trust without a single point of failure: They are blockchain-based recording of the numbers of authentication events and logging of the provenance of model-updates, as exploited in spectrum-access security, vehicular handover authentication [36] and consumer-IoT identity management. Some approaches on how to embed ZTA directly into the federated-learning client-admission process have also been suggested to prevent slow-poisoning attacks against federated models [37].

TABLE IV COMPARATIVE SUMMARY OF REPRESENTATIVE EDGE AI/ML TECHNIQUES FOR 6G-IoT SECURITY

Techniques	Primary Strength	Key Limitation
Federated Learning (FL)	Privacy-preserving and distributed; scales across	Vulnerable to poisoning and Sybil attacks;

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Online ISSN 3007-3197
Print ISSN 3007-3189
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IDS [3], [4], [5], [7], [9]	heterogeneous devices	aggregation communication overhead
Deep / Hybrid Learning (CNN-LSTM, GNN, Autoencoder) [8], [10], [22]	High detection accuracy for complex, high-dimensional traffic	Computationally intensive; limited native interpretability
Deep Reinforcement Learning (DRL) [18], [19], [28]	Adaptive, self-optimizing policies for dynamic 6G environments	Sample inefficiency; susceptible to reward-poisoning attacks
TinyML / Extreme-Edge Inference [23], [24], [25], [26], [27]	Minimal memory and energy footprint; enables real-time on-device detection	Constrained model capacity; accuracy–footprint trade-off
Explainable AI (XAI) [2], [30]	Improves operator trust, auditability, and regulatory compliance	Explanation fidelity vs. model complexity trade-off
Blockchain-Assisted Zero-Trust [20], [21], [29], [31], [32]	Decentralized, tamper-resistant identity and provenance management	Ledger latency and energy costs may conflict with 6G URLLC targets

V. Proposed Enhanced Framework

To address limitations listed above, notably the absence of a unified framework that accommodates privacy-preserving distributed learning, defense under extreme conditions at the edge, extreme-edge inference and auditable trust within an integrated framework, we propose an Enhanced 6G-IoT security framework, which is a proposed five-layer architecture with a closed detection-response feedback loop.

A. Layered Architecture

The proposed solution architecture is shown in Fig.1. Perception and Device Layer consists of sensors, wearables, industrial IoT nodes and mobile units secured using light-weight cryptography and PUF-based authentication. The Edge AI and Fog Security Layer enables most security decisions without round-trip to the cloud by providing on-device or TinyML inference, a federated-learning aggregator, lightweight hybrid models such as CNN-LSTM and autoencoders, and an edge trust, anomaly scoring module. The 6G Network Connectivity Layer features network

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slicing, SDN/NFV based isolation, physical-layer security (THz + RIS), zero-trust access control, and blockchain-based identity & ledger services [38]. On the edge, the Cloud Core Intelligence Layer merges local model updates to a global model, deploys heavier deep and reinforcement-learning engines, stores heavier threat-intelligence feeds, stores digital-twin state, and applies XAI-based auditing prior to decisions being forwarded back to the edge. Lastly, the Application Layer bridges those security services to verticals like smart healthcare, Industry 5.0, smart grid intelligent transportation and smart cities.

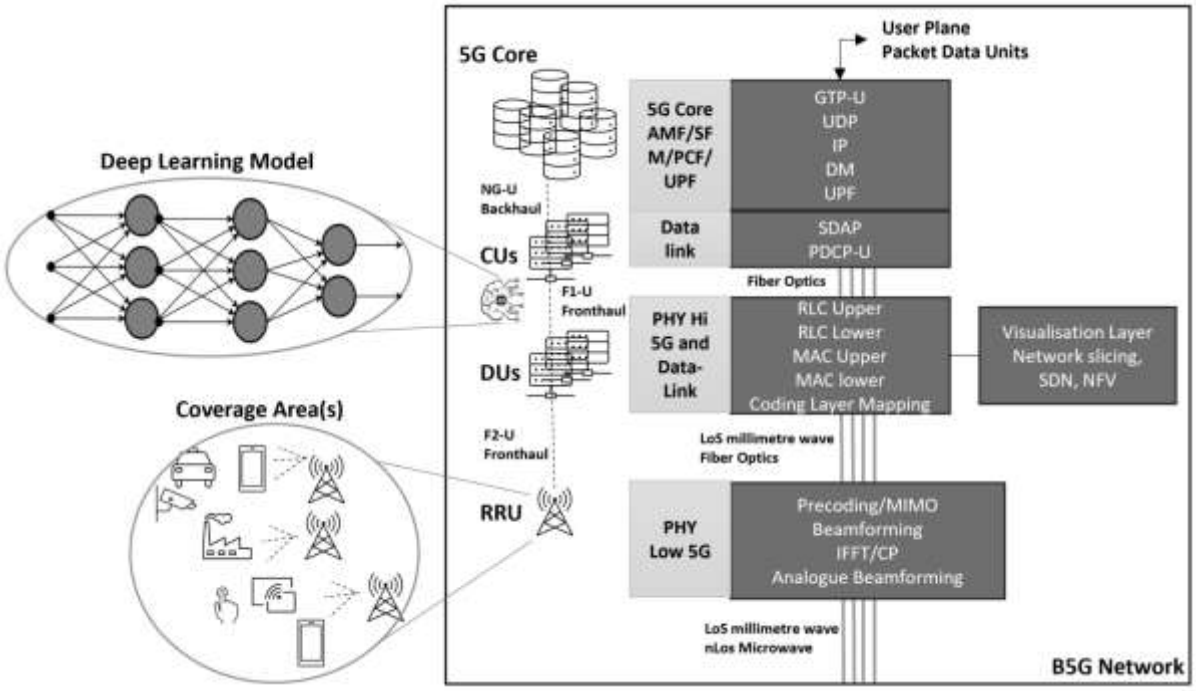

Fig. 1 (d). Intelligent network Layered architecture for enhanced 6G-IoT security framework with Edge AI/ML integration.

B. Closed-Loop Detection-Response Workflow

The workflow of the operation is shown in figure 2. Preprocessing occurs at the edge (normalization, feature selection) and on-device anomaly/intrusion scoring is done by a lightweight model. IoT device traffic and 6G traffic data are processed at the edge (normalization and feature selection) first and then processed at the device level using a light-weighted local model. There is a threshold distinction between benign traffic (which is passively monitored) and suspicious traffic (which initiates the transmission of model-updates in a privacy-preserving manner). Updates undergo zero-trust verification and get recorded on a blockchain ledger before being sent along a 6G slice- or RIS-secured link. The essence of updates is to first combine the information into a refined global model, and then validate the updated threat classification along with generating human-interpretable alerts in advance to any action taken by an

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automated response that would involve isolating a device, reconfiguring a network or updating a security policy. A closed loop for continuous adaptation to new threats is then closed at the edge nodes with refined global model [39].

C. Design Rationale

This framework is built on four principles that have been extracted from sections III and IV. First, privacy-by-architecture: data is always at the device edge tier, as with FL-based systems. Second, latency-aware tiering: most decisions are made locally and only aggregated; more complicated analytics and audit are made with cloud's participation; the cloud-based IDS lacks a cost of round trip - time penalty. Third, verifiable trust: The zero-trust authentication and blockchain logging polices both explicitly and implicitly reject models updates or devices, addressing the concerns in Table III towards Sybil attack, Byzantine attack and identity spoofing attack. Fourth, human-valid autonomy: XAI validation capable before automation responses are taken: latency advantages of automation vs accountability requirements growingly placing on AI-driven network security [40].

It is important to reiterate that the proposed framework is more of a conceptual, literature-based reference model, not an empirically proven system: Its layers and workflow are amalgamation of design patterns and experiences based on the literature consulted for reports of best practice, not a new system implementation. The framework would need to be validated in a real testbed simulation environment reproducing realistic wireless IoT traffic and representative THz/RIS-assisted 6G links in the future, as well as evaluation of the detection-capability, overhead, privacy, deplorability and robustness criteria in Table V under adversarial conditions like poisoning and reward manipulation, at least in terms of a testbed or simulation environment of the successful system that includes both THz/RIS-assisted 6G wireless links and representative IoT traffic in the future, deployment of the federated aggregation, TinyML inference, and XAI-auditing modules on the previously mentioned heterogeneous edge hardware, and evaluations of all the previously mentioned criteria of detection-capability, overhead, privacy, deplorability and robustness under adversarial circumstances such as poisoning and reward manipulation. We acknowledge this end-to-end implementation and benchmarking project as one of the main areas for future work.

VI. Comparative Analysis and Discussion

The trends highlighted in the qualitative comparisons of the different technique family groups in the reviewed literature are in Table V to show the potential application feasibility of the various 6G-IoT techniques in latency sensitive resource-constrained deployments. The ratings are only general patterns, as there are lots of variations in the experimental settings, data sets and the hardware in the cited works.

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TABLE V QUALITATIVE TRADE-OFF COMPARISON OF EDGE AI/ML PARADIGMS FOR 6G-IoT SECURITY

Paradigm	**Detection Capability**	**Comm. Overhead**	**Privacy Preservation**	**Edge Deplorability**	**Adversarial Robustness**
Centralized Deep Learning	High	High	Low	Low	Low–Medium
Federated Learning	Medium–High	Medium	High	Medium–High	Medium (vulnerable to poisoning)
TinyML / Extreme Edge	Medium	Low	High	High	Medium
Deep Reinforcement Learning	High (adaptive)	Medium	Medium	Medium	Low (reward poisoning)
XAI-Augmented Pipelines	High (with audit)	Medium	Medium–High	Medium	Medium–High
Blockchain-Assisted Zero-Trust	N/A (access control)	Medium–High	High	Medium	High (identity layer)

This comparison finds a key divide in the design of 6G-IoT security: methods capable of achieving the greatest detection accuracy centralized deep learning, DRL are associated with the highest computational overhead communication load, or the most restricted privacy protection, while those that are suitable for edge deployment TinyML trade detection capability for being less effective. This inspires the proposed hybrid tiered approach outlined in the proposed framework Section V: lightweight local models are used for handling the bulk of the traffic, whereas heavier and more precise models are used only as needed, down the federated path of updates, in the cloud tier. The analysis also reveals that each technique family discussed on their own is insufficient to solve adversarial robustness; all these techniques need to be

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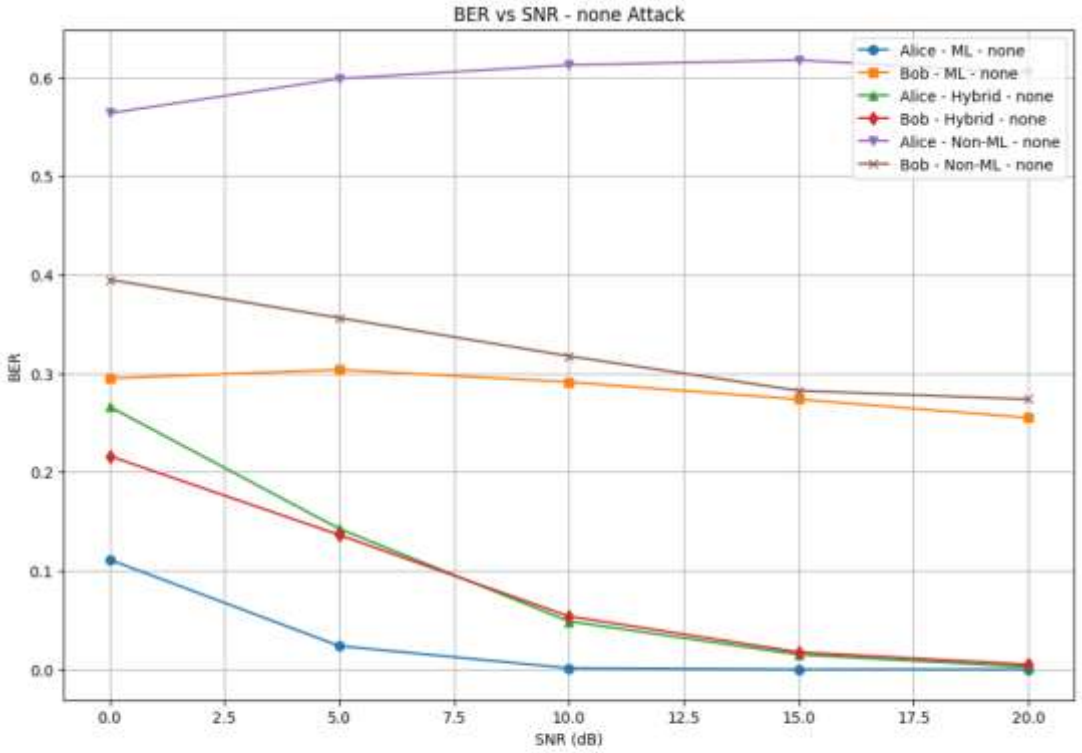
complemented by one another, where federated aggregation safeguards, blockchain-based provenance and XAI-based auditing are complementary layers of security [41].



(a) No attack.

Fig. 2 (a). Intelligent network Evaluation when No Attack using Model Accuracy with different approaches of non-ML, ML and hybrid model

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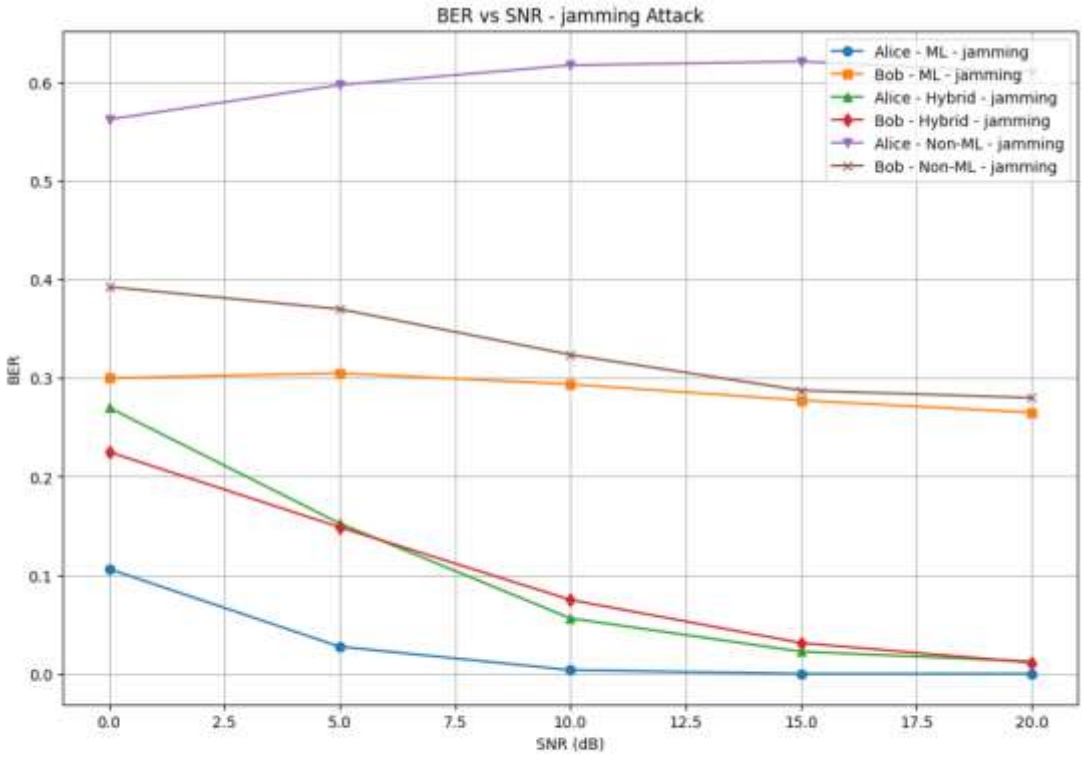

(b) Jamming attack.

Fig. 2 (b). Intelligent network Evaluation when Jamming Attack using Model Accuracy with different approaches of non-ML, ML and hybrid model

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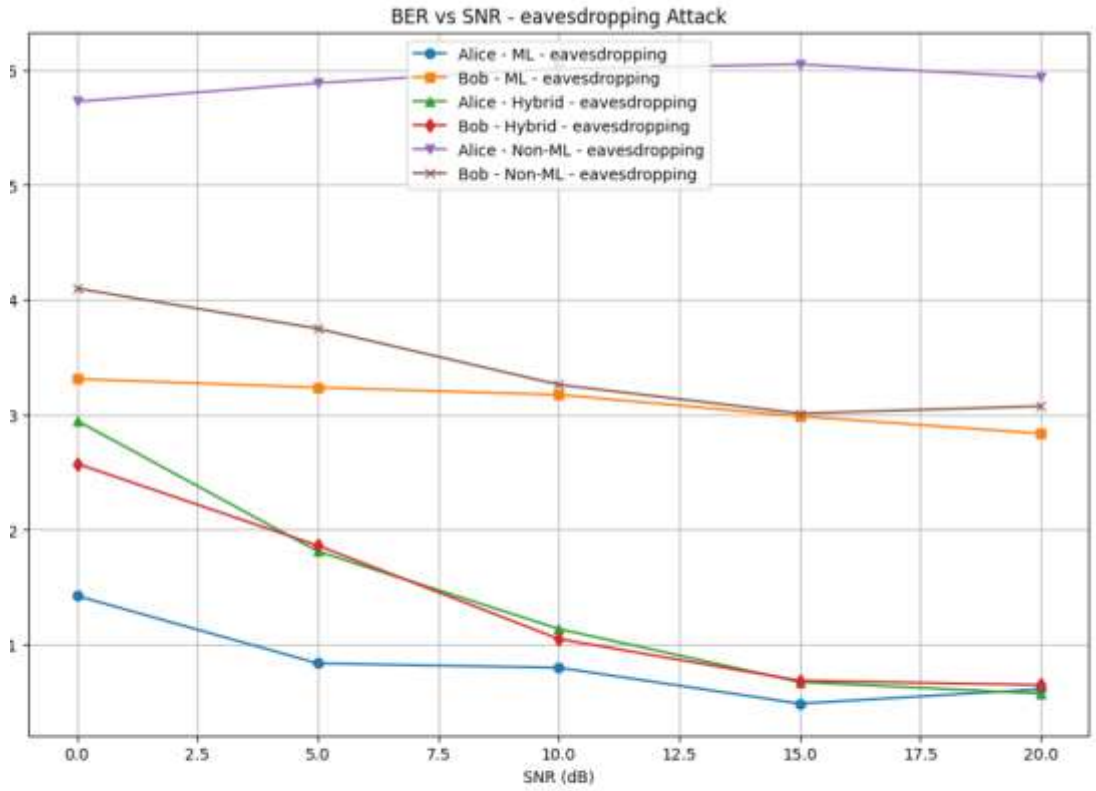

(c) Eavesdropping.

Fig. 2 (c). Intelligent network Evaluation when Eavesdropping using Model Accuracy with different approaches of non-ML, ML and hybrid model

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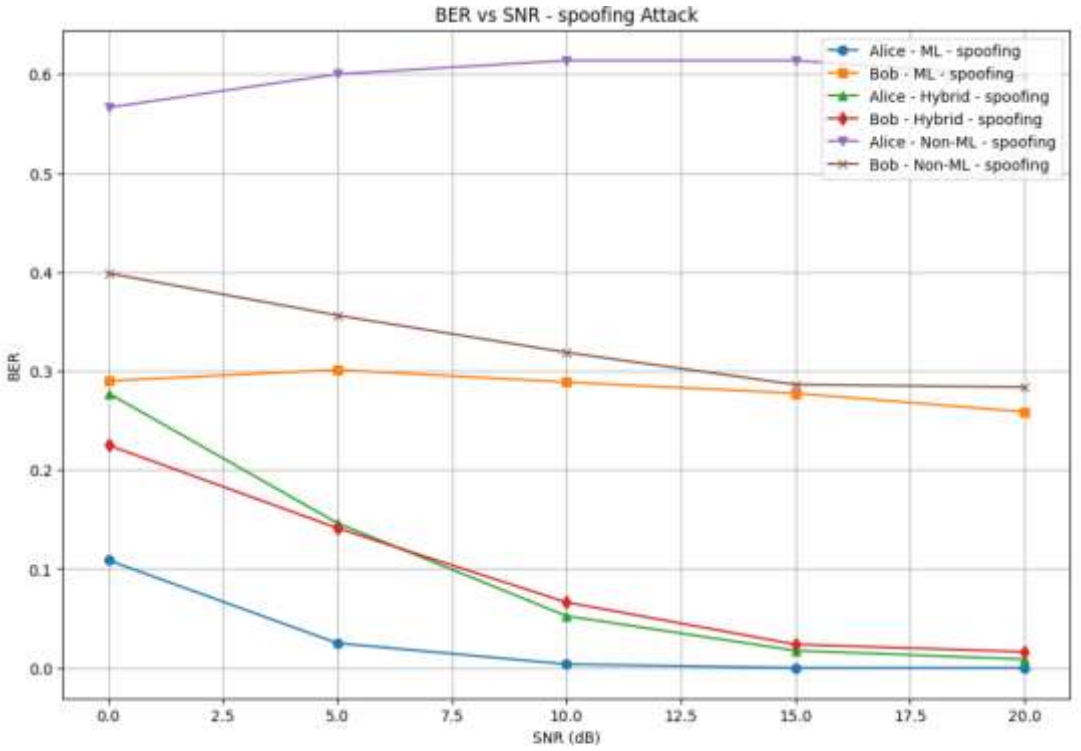

(d) Spoofing.

Fig. 2 (d). Intelligent network Evaluation when Spoofing using Model Accuracy with different approaches of non-ML, ML and hybrid model

VII. Open Challenges and Future Research Directions

Although significant strides have been made, there are still several open challenges that need to be resolved before the deployment of security frameworks based on Edge AI ML can be assured at a 6G scale.

1. Lack of 6G-representative datasets: Solely, most publicly-available intrusion-detection datasets are outdated and fail to represent traffic patterns of the more recent 6G like THz links, RIS-assisted routing, network slicing, which means that the external validation of reported detection accuracies is questionable.
2. Adversarial and poisoning robustness: Federated and Reinforcement Learning pipelines still lack the ability to be robust both against Sybil attacks, Byzantine attacks, and against reward poisoning; robust aggregation and anomaly-aware client selection is still maturing.

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3. Optimizing between detection fidelity and judicious memory, compute and battery usage regimes is a trade-off at the extreme
4. Transforming the production of explanations to be understandable to humans in real time for the high volume of 6G traffic – with minimal impact on the required latency remains an engineering challenge.
5. Lightweight post-quantum cryptography and resource limited perception layer devices: When quantum computing comes into reality, lightweight post-quantum cryptography needs to balance the resource limited perception - layer devices with the low latency requirements of the 6G systems.
6. Cross-domain and cross-operator trust: zero-trust principles need to be expanded to interoperate across multiple domain and multi-operator network slicing, and in space-air-ground integration.
7. Sustainability of AI security: The high energy consumption required for ongoing federated training, blockchain consensus and cloud-based monitoring by billions of devices is a concern for sustainability, which needs to be addressed by considering the system design to be Green-AI capable.
8. A potential extension of the combination of the proposed framework and digital twins would be for the use of digital twins in real-time whilst in practice, it would enable a change from reactive to proactive threat mitigation, but the synchronization-channel integrity would present as a new attack surface and need protection.

VIII. Conclusion

The study presents the different approaches to secure 6G-enabled IoT networking using Edge AI and machine learning. We explored the enabling technologies and structure of 6G-IoT convergence, made a layer-wise taxonomy of different threats from device-, network- and AI-model-levels, and critically integrated recent work in federated learning, deep learning, hybrid learning, deep reinforcement learning, TinyML, Explainable AI, and blockchain in zero-trust approach. Based on the received gaps, we designed an Enhanced 6G-IoT Security Framework, which unified the identified techniques within a security framework comprising five layers and a closed loop detection-response workflow while not involving personal privacy. The comparative analysis showed that none of the technique families is simultaneously optimal for detection accuracy, communication overhead, privacy, deploy ability at the edge, or adversarial robustness, supporting the need for hybrid, multi-tiered systems like the system presented here. Future studies should focus on developing the benchmark datasets for characterizing 6G-IoT networks and developing reliable

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Print ISSN 3007-3189

aggregation mechanisms that are designed against poisoning and reward-manipulation attacks, as well as on latency-aware explainability approaches and on quantum-safe designs that thrive in the exponential network expansion that the promises of 6G-IoT bring.

DECLARATIONS

Acknowledgement: We appreciate the generous support from all the contributor to the research and their different affiliations.
Funding: No funding body in the public, private, or nonprofit sectors provided a particular grant for this research.
Availability of data and material: In the approach, the data sources for the variables are stated.
Authors' contributions: Each author participated equally in the creation of this work.
Conflicts of Interest: The authors declare no conflict of interest.
Consent to Participate: Yes
Consent for publication and Ethical approval: Because this study does not include human or animal data, ethical approval is not required for publication. All authors have given their consent.

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