Post-Quantum Federated IoT Security: A Survey with QoE Perspectives

Singamaneni Krishnapriya[1], Prof. (Dr.) S. K. Singh[2]

[1] Research Fellow, Lincoln Univerity College,47301,Petaling Jaya, Selangor Darul Ehsan, Malaysia. ;

[2] Professor & Director, Amity Institute of Information Technology, Amity University Uttar Pradesh, Lucknow Campus.;

Email ID : singmanenikrishnpriya@gmail.com

Abstract: The intensely growing Internet of Things (IoT) has brought up critical issues regarding security, privacy, scalability and Quality of Experience (QoE). Current measures to be used, including deep learning-based intrusion detection, blockchain-based security, and federated learning are independent of each other and do not offer a cohesive structure, resulting in fragmented and inefficient protection systems. The paper provides an extensive overview of the IoT security strategies through the analysis and synthesis of intrusion detection systems, blockchain technologies, federated learning models and QoE optimization methods. The paper is a systematic review of current developments providing insights into the main research gaps such as the need to integrate it, the absence of support of post-quantum cryptography, insufficient privacy assurances in federated learning, and a deficiency of connections between security and QoE. The results point to the idea that the existing models are not scalable, do not have a real-time level of flexibility, and can be targeted by future quantum threats. The survey identifies the necessity of integrated, post-quantum, federated and QoE intelligent IoT security. The results of this paper can be used in the design of safe and user-friendly IoT systems in smart cities, healthcare, and future 5G/6G communication infrastructure.

Keywords: IoT Security; Intrusion Detection Systems; Federated Learning; Blockchain; Post-Quantum Cryptography; Quality of Experience (QoE).

Introduction

The fast gained Internet of Things (IoT) has transformed different areas (smart city, health care, robotization of industries, and intelligent transportation) [1]. IoT makes it easy to exchange data in real-time and make smart decisions by allowing the seamless connectivity between heterogeneous devices [1]. Nevertheless, such a fast development has also brought serious security, privacy, and scalability challenges as well as Quality of Experience (QoE) [2].

The customary IoT security systems tend to be disjointed and deal with single facets in the form of intrusion detection, encryption, or network optimization [3]. The intrusion detection systems (IDS) based on deep learning have proven to be very accurate to detect cyber threats [4] whereas blockchain technology provides decentralized trust and data integrity [5]. Likewise, federated learning (FL) has also become a potential solution to privacy-preserving training of models without sharing raw data [6]. Although these enhancements have been made, the available solutions are not integrated, scalable, and efficient security frameworks [7].

Moreover, the advent of quantum computing is a major threat to traditional cryptographic methods of IoT systems [8]. The majority of the available blockchain and security systems do not have post-quantum resistance, thus leaving IoT systems vulnerable to future attacks [9]. Besides this, the existing models

tend to ignore the collaboration between QoE and security systems, which leads to the appearance of security systems that are not user-friendly [10].

Thus, the main issue that has been identified in this survey is the absence of a coherent, post-quantum, federated, and QoE-conscious IoT security system that combines intrusion detection, blockchain-based trust, and privacy-preserving learning. The purpose of this paper is to comprehensively review the current strategies, outline some of the main research gaps, and point to the perspectives of the future development of secure, scalable, and user-centric IoT ecosystems in the context of next-generation 5G/6G networks.

2. Related Work

Deep Learning-based IDS

Intrusion Detection Systems (IDS) based on deep learning have become a popular method of detecting intrusions in networks with an IoT environment because they can identify anomalies using complex traffic patterns automatically [11]–[13]. Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM), and hybrid networks have been proven to be highly accurate in detecting certain datasets, including NSL-KDD and IoT-TON [11], [12]. Nevertheless, these methods are usually centralized and need large amounts of labeled data, which do not fit better into distributed IoT systems [12]. Also, they are not flexible to changing threats and fail to include privacy-saving mechanisms [13].

Blockchain-based IoT Security

The blockchain technology offers an unmanaged and impeccable system of securing IoT networks through integrity of data, authentication, and management of trust [14]–[16]. Smart contracts can be used to automatically enforce security policies, and distributed ledgers can be used to eliminate single points of failure [14]. Regardless of these benefits, blockchain-based solutions involve a considerable amount of overhead and latency that cannot be used on resource-constrained IoT devices [15]. In addition, the vast majority of current blockchain systems are not post-quantum resistant, which poses a question of the security in the long-term [16].

Federated Learning in IoT

Federated Learning (FL) supports training massive models of individual IoT devices that collaboratively train models without any physical exchanges of raw data hence privacy and alleviating communication overheads [17], [18]. FL-based IDS structures have been demonstrated to be successful in decentralized systems allowing local model updates and global aggregation [17]. Nevertheless, the current FL models are susceptible to the poisoning attacks, have no safe aggregation methods, and are frequently incompatible with other security tiers, including blockchain [18], [19]. Also, FL methods do not pay much attention to QoE measurements in model optimization [19].

QoE Optimization Models

Quality of Experience (QoE) optimization aims at maximizing user satisfaction using network performance indicators like latency, throughput and stability [20]–[22]. Prediction and optimization of QoE in IoT-enabled applications such as video streaming and smart healthcare have been predicted and optimized in machine learning and deep learning techniques [20], [21]. Nevertheless, the models are generally formulated without reference to security frameworks and are not included in the cyber threats or privacy risk [21]. This culminates into the absence of combined solutions that can optimize both QoE and security of IoT systems [22].

Table 1. Comparative analysis of recent IoT security approaches based on IDS, blockchain, federated learning, and QoE optimization

Approach / Work	Technique Used	Security	Privacy	QoE	PQC Support	Key Limitation
[11] (2021) DL-based IDS	CNN, LSTM	High	Low	No	No	Centralized, labeled data
[12] (2022) Hybrid DL-IDS	CNN + LSTM	High	Low	No	No	High computation
[13] (2023) Attention IDS	CNN + Attention	High	Low	No	No	Limited adaptability
[14] (2021) Blockchain IoT	Smart Contracts	Medium	Medium	No	No	Latency overhead
[15] (2022) Lightweight Blockchain	Optimized Ledger	Medium	Medium	No	No	Scalability issues
[16] (2023) Blockchain + Edge	Edge-enabled Blockchain	Medium	Medium	No	No	Not PQC-ready
[17] (2021) FL-based IDS	Federated Learning	Medium	High	No	No	Poisoning attacks
[18] (2022) Secure FL	Secure Aggregation	Medium	High	No	No	Communication overhead
[19] (2024) FL + Blockchain	Hybrid Framework	High	High	No	No	Complex integration
[20] (2021) QoE ML Model	ML Prediction	Low	No	High	No	No security
[21] (2023) QoE DL Model	Deep Learning QoE	Low	No	High	No	Ignores threats
[22] (2024) QoE Edge AI	Edge-based QoE	Low	No	High	No	Not privacy-aware

Key Contributions

This survey paper helps to fill the gap in the existing body of knowledge that offers a detailed and combined examination of IoT security mechanisms and the emphasis on emerging technologies. In contrast to conventional studies, which discuss the elements of security separately, this paper performs a systematic survey and comparison of intrusion detection systems (IDS), blockchain-based security, federated learning (FL) and Quality of Experience (QoE) optimization in one perspective.The key contributions of this paper are summarized as follows:

- Comprehensive Review: Provides a systematic survey of the recent developments in deep learning-based IDS, blockchain security architecture, federated learning model, and QoE optimization methods in the IoT setup.
- Comparative Analysis: A comparative analysis of current methods is presented in terms of such parameters as security, privacy, scalability, and QoE with their advantages and disadvantages.
- Unified Perspective: Disputes the importance of a single IoT security framework that is integrative of an AI-driven intrusion detection system, decentralized blockchain trust, and federated learning that preserves privacy.
- Future Research Directions: Suggests conducting post-quantum, QoE-conscious and scalable IoT security solutions and frameworks on next-generation 5G/6G settings.

Survey Methodology and Analysis

Methodology

The literature review is conducted by obtaining research articles in reputed databases of IEEE Xplore, SpringerLink, ScienceDirect and ACM Digital Library. The selection criteria will be recent publications (mainly 20152025), relevance to the field in IoT security, and the presence of such techniques as deep learning-based intrusion detection, blockchain security, federated learning and QoE optimization. The gathered literature is divided according to the main way of approach and area of application.

Analysis of Existing Approaches

The literature under review is discussed in terms of some fundamental parameters such as security effectiveness, privacy preservation, scalability, latency, and Quality of Experience (QoE). Detection accuracy of deep learning-based IDS methods is high, but the methods have centralized processing and scalability problems. Decentralized trust is given by the blockchain-based solutions, but they come with computational overhead and latency. Federated learning models guarantee privacy, but they are weak to the adversarial attack and in most cases, they are not compatible with blockchain mechanisms

Discussions

The review of the current IoT security solutions has denoted that the solutions that are offered are, to a large extent, disjointed as they focus on intrusion detection, blockchain-based trust, federated learning, and QoE optimization individually, but not as a system. Although the deep learning-based models of IDS have a high detection rate, they are centralized and, hence, cannot scale up in distributed IoT systems. Blockchain solutions enhance trust and data integrity, but have latency and computation overhead, and are inappropriate in resource-constrained devices. Federated learning provides privacy protection, but it does not have effective security measures against adversarial attacks and is not often combined with blockchain systems. Based on these observations, there is a strong necessity to have a common architecture that takes into consideration security, privacy and QoE without compromising upon scalability and real-time execution.

Conclusions

The survey is a response to the problem of poor system fragmentation with IoT security solutions where intrusion detection, blockchain, federated learning, and QoE optimization are created separately, and a more unified, scalable, and post-quantum-resilient system is needed. The systematic literature review of the recent researches shows that deep learning-based IDS is highly accurate, blockchain is trusted but introduces latency, and federated learning does not violate privacy, whereas QoE models are frequently independent of security measures. Moreover, the majority of the current solutions lack the inclusion of

post-quantum cryptography, which renders them vulnerable to potential future threatsThe future study should be aimed at creating a unified IoT security architecture to integrate these technologies with QoE awareness and post-quantum resilience to deploy efficiently in the next-generation 5G/6G architecture.

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