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Aims and Scope

International Journal of Cyberspace Security (IJCS) is an international, peer-reviewed academic journal dedicated to advancing research on the security, resilience, and trustworthiness of cyberspace. The journal provides a scholarly platform for theoretical, technical, and applied studies addressing security challenges across digital infrastructures, information systems, and interconnected cyber–physical environments.

The journal focuses on cyberspace as an integrated system, encompassing networks, platforms, data, devices, and human interactions. It aims to promote innovative research that enhances the protection of digital assets, ensures secure operations, and supports the governance of complex cyber environments in an increasingly connected world.

Topics of interest include, but are not limited to:

Cyberspace Security Technologies: Network and systems security; Cryptography and secure communication; Malware analysis, intrusion detection, and prevention; Cloud, edge, and distributed systems security

Data, Privacy, and Trust: Data security and privacy-preserving technologies; Identity management, authentication, and access control; Trust models and secure data sharing

Cyber–Physical and Critical Infrastructure Security: Cyber–physical systems security; Industrial control systems and critical infrastructure protection; Internet of Things (IoT) and smart infrastructure security

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Volume 1 | Issue 1 | December 2025 | Page 1-63

Contents

ARTICLE

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Article

IoT Security Vulnerabilities: A Systematic Analysis of Risk Vectors and Multi-Layered Mitigation Strategies

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ABSTRACT
The rapid proliferation of Internet of Things (IoT) devices has transformed critical infrastructure, smart cities, and personal lifestyles, while simultaneously expanding the cyber threat landscape. This study conducts a systematic analysis of IoT security vulnerabilities across four core layers—physical, communication, firmware, and application-service—identifying key risk vectors such as weak authentication, insecure communication protocols, and supply chain flaws. Through evaluating 120 peer-reviewed studies and real-world incident data from 2022 to 2025, the research assesses the effectiveness of existing mitigation measures, including AI-driven intrusion detection, lightweight encryption, and blockchain-based identity authentication. A multi-layered mitigation framework integrating technical safeguards, regulatory compliance, and industry collaboration is proposed to address the unique constraints of resource-constrained IoT devices. The findings highlight the urgency of standardized security frameworks and adaptive defense mechanisms, providing actionable insights for researchers, IoT manufacturers, and policymakers. This study contributes to the advancement of IoT security resilience by bridging the gap between theoretical research and practical implementation.

Keywords: IoT security; Vulnerability analysis; Risk vectors; Multi-layered mitigation; Lightweight encryption; Blockchain authentication

1. Introduction

The Internet of Things (IoT) has evolved into a foundational component of the global digital infrastructure, with projections indicating over 210 billion connected devices worldwide by 2025. These devices permeate diverse sectors, including healthcare, energy, transportation, and smart homes, enabling unprecedented levels of automation, data-driven decision-making, and operational efficiency. However, the exponential growth of IoT ecosystems has been accompanied by a surge in security breaches, as malicious actors exploit inherent vulnerabilities to launch attacks ranging from botnet recruitment and data theft to large-scale distributed denial-of-service (DDoS) attacks and critical infrastructure disruptions. High-profile incidents such as the 2023 Mirai variant botnet attack on European smart grid systems and the 2024 healthcare IoT data breach affecting 500,000 patients underscore the severe consequences of inadequate IoT security—encompassing financial losses, privacy violations, and threats to public safety.

Traditional cybersecurity approaches, designed for resource-rich computing environments, are often incompatible with IoT devices, which are typically characterized by limited processing power, memory, and energy resources. This mismatch has created a critical security gap: many IoT devices lack robust encryption, real-time intrusion detection capabilities, and automated security update mechanisms, making them easy targets for adversaries. Furthermore, the fragmented nature of the IoT industry, coupled with inconsistent regulatory standards across regions, has hindered the adoption of uniform security practices. While recent research has focused on individual mitigation technologies, there remains a dearth of systematic analyses that integrate vulnerability identification, existing solution evaluation, and comprehensive framework development tailored to the multi-layered nature of IoT ecosystems.

This study addresses these gaps through three primary objectives: (1) systematically identify and categorize IoT security vulnerabilities across physical, communication, firmware, and application-service layers; (2) evaluate the effectiveness and limitations of current mitigation technologies, including AI-driven detection, lightweight encryption, and blockchain-based authentication; (3) propose a holistic multi-layered mitigation framework that balances technical feasibility, regulatory compliance, and industry collaboration. The significance of this research lies in its comprehensive scope—bridging theoretical insights with real-world incident data—and its focus on actionable solutions that account for the resource constraints of IoT devices. By addressing these critical issues, this study aims to inform IoT manufacturers, cybersecurity practitioners, and policymakers in enhancing the resilience of global IoT ecosystems.

The remainder of this paper is structured as follows: Section 2 reviews the existing literature on IoT security vulnerabilities and mitigation strategies, identifying key research gaps. Section 3 presents the methodology employed in this systematic analysis, including data collection and evaluation criteria. Section 4 analyzes the multi-layered IoT security vulnerabilities and associated risk vectors, supported by real-world case studies. Section 5 evaluates current mitigation technologies and their practical limitations. Section 6 proposes the multi-layered mitigation framework and discusses its implementation pathways. Section 7 presents the conclusions and future research directions.

2. Literature Review

The past decade has witnessed a growing body of research on IoT security, reflecting the escalating threats to interconnected devices and ecosystems. This section reviews key studies published between 2022 and 2025, focusing on IoT vulnerability classification, mitigation technologies, and regulatory frameworks, while identifying gaps in the existing literature.

Early research on IoT security primarily focused on individual vulnerability types, with limited attention to the multi-layered nature of IoT ecosystems. However, recent studies have adopted a more holistic approach to vulnerability classification. For instance, Zhang et al. (2023) proposed a layered framework for IoT attack surfaces, dividing vulnerabilities into physical, communication, firmware, and application layers. Their research highlighted that physical layer attacks—such as chip tampering and sensor interference—are often overlooked despite their potential to compromise device integrity. Similarly, a systematic review by Singh et al. (2024) analyzed 82 peer-reviewed studies and identified weak authentication, insecure communication protocols, and firmware vulnerabilities as the most prevalent risk vectors, accounting for over 60% of IoT security breaches.

Research on mitigation technologies has focused on three primary areas: AI-driven threat detection, lightweight encryption, and blockchain-based authentication. Regarding AI-driven solutions, Lee et al. (2023) developed a deep learning-based intrusion detection system (IDS) tailored for resource-constrained IoT devices, achieving a detection rate of 92% for DDoS attacks and malware propagation. However, their study noted that adversarial AI techniques—such as data poisoning and model evasion—pose significant risks to the reliability of AI-driven IDS. In the realm of lightweight encryption, Wang et al. (2024) proposed a modified AES algorithm optimized for low-power IoT devices, reducing computational overhead by 35%

compared to standard AES implementations. While this advancement addresses resource constraints, the study acknowledged that lightweight encryption algorithms often trade off security strength for efficiency, creating potential vulnerabilities.

Blockchain technology has emerged as a promising solution for IoT identity authentication and data integrity. A study by Hassan et al. (2025) developed a blockchain-based decentralized authentication framework for smart home IoT devices, eliminating the reliance on vulnerable centralized servers. Their experimental results demonstrated that the framework reduces authentication latency by 28% and enhances resistance to man-in-the-middle attacks. However, the scalability of blockchain solutions remains a challenge, with transaction throughput limitations hindering their applicability to large-scale IoT ecosystems.

In terms of regulatory frameworks, research has highlighted the fragmentation of global IoT security standards. The European Union's ETSI EN 303 645 standard (2022) mandates specific security requirements for consumer IoT devices, such as secure default passwords and regular firmware updates. In contrast, the United States' IoT Cybersecurity Improvement Act (2020) focuses primarily on federal government-owned devices, with limited applicability to the private sector. A study by European Commission (2024) found that this regulatory fragmentation increases compliance costs for multinational IoT manufacturers and creates security disparities across regions. Despite these insights, existing research has not fully integrated regulatory considerations into technical mitigation frameworks, nor has it adequately addressed the challenges of implementing standardized security practices in resource-constrained environments.

Several critical research gaps remain. First, most studies focus on individual mitigation technologies rather than integrating them into a cohesive framework that addresses vulnerabilities across all IoT layers. Second, there is a lack of empirical research on the long-term effectiveness of mitigation strategies in real-world IoT deployments. Third, the interplay between regulatory compliance and technical feasibility—particularly for small and medium-sized IoT manufacturers—has not been sufficiently explored. This study addresses these gaps by conducting a systematic analysis of multi-layered vulnerabilities and proposing an integrated mitigation framework that balances technical, regulatory, and industry perspectives.

3. Methodology

This study employs a systematic analysis approach, adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, to ensure rigor, transparency, and reproducibility. The methodology encompasses three core phases: data collection, vulnerability classification, and mitigation technology evaluation.

3.1 Data Collection

Two primary data sources were utilized in this study: peer-reviewed academic literature and real-world IoT security incident reports. For the academic literature, a systematic search was conducted across four major databases—IEEE Xplore, ACM Digital Library, Web of Science, and MDPI—using the following keywords: "IoT security vulnerabilities", "IoT attack vectors", "lightweight encryption IoT", "AI intrusion detection IoT", and "blockchain IoT authentication". The search was restricted to studies published between 2022 and 2025, resulting in an initial pool of 320 articles. These articles were then screened based on predefined inclusion criteria: (1) focus on IoT devices or ecosystems; (2) address security vulnerabilities or mitigation technologies; (3) include empirical data or experimental results; (4) published in English. After removing duplicates and non-relevant studies, 120 articles were selected for detailed analysis.

For real-world incident data, information was collected from authoritative sources, including the European Union Agency for Cybersecurity (ENISA), the U.S. Cybersecurity and Infrastructure Security Agency (CISA), and the IoT Security Foundation (IoTSF). Incidents were included if they occurred between 2022 and 2025, involved confirmed IoT vulnerabilities, and had publicly available details on attack vectors, impacts, and mitigation attempts. A total of 45 significant incidents were analyzed, spanning sectors such as healthcare, energy, smart cities, and consumer electronics.

3.2 Vulnerability Classification

The identified vulnerabilities were classified into four layers based on the IoT ecosystem architecture: physical, communication, firmware, and application-service. This classification framework was selected due to its alignment with the hardware and software structure of IoT devices, enabling a comprehensive analysis of attack surfaces. Each vulnerability was further categorized by its associated risk vector (e.g., weak authentication, sensor interference, protocol exploitation) and impact severity (low, medium, high) based on the criteria defined by ENISA (2023): low impact (limited data exposure, no operational disruption), medium impact (significant data exposure, temporary operational disruption), high impact (critical data theft, long-term operational disruption, threat to public safety).

3.3 Mitigation Technology Evaluation

Current mitigation technologies were evaluated against three key criteria: (1) effectiveness in addressing specific vulnerabilities; (2) compatibility with resource-constrained IoT devices (e.g., low computational overhead, energy efficiency); (3) practical feasibility of implementation (e.g., cost, scalability, regulatory compliance). Data on technology effectiveness was extracted from the peer-reviewed literature, including experimental results on detection rates (for IDS), encryption strength (for lightweight algorithms), and authentication success rates (for blockchain solutions). Compatibility and feasibility data were derived from both academic studies and industry reports, including cost analyses and case studies of real-world implementations.

4. Multi-Layered IoT Security Vulnerabilities and Risk Vectors

This section analyzes the identified IoT security vulnerabilities across physical, communication, firmware, and application-service layers, detailing their associated risk vectors, real-world impacts, and prevalence based on the systematic data collection.

4.1 Physical Layer Vulnerabilities

The physical layer encompasses IoT device hardware components, including sensors, microcontrollers, interfaces (e.g., USB, GPIO), and power supplies. Vulnerabilities at this layer are often overlooked due to the perception that physical access is required, yet they pose significant risks in scenarios where devices are deployed in public or unmonitored environments (e.g., smart city sensors, industrial IoT devices).

Key risk vectors in the physical layer include chip tampering, sensor interference, and physical DoS attacks. Chip tampering involves modifying or replacing integrated circuits (ICs) to or bypass security controls. For example, a 2023 incident involved attackers tampering with industrial IoT sensors in a European manufacturing plant, leading to incorrect temperature readings and production losses of over €2 million (ENISA, 2023). Sensor interference—such as laser irradiation of light sensors or radio frequency (RF) jamming of motion detectors—can disrupt device functionality or generate false data. A notable case in 2024 saw attackers using RF jamming to disable smart home security sensors, enabling unauthorized access to residential properties (CISA, 2024). Physical DoS attacks, such as sleep deprivation attacks that drain device batteries, are particularly effective against battery-powered IoT devices, such as wearables and environmental monitors.

According to the systematic analysis, physical layer vulnerabilities account for approximately 15% of all IoT security breaches, with high-impact incidents primarily occurring in industrial and critical infrastructure sectors. The primary challenge in mitigating these vulnerabilities is the lack of cost-effective hardware-level security measures, as most IoT manufacturers prioritize low production costs over physical security.

4.2 Communication Layer Vulnerabilities

The communication layer facilitates data transmission between IoT devices, gateways, and cloud servers, utilizing both wireless (e.g., Wi-Fi, Bluetooth, ZigBee, LoRa) and wired protocols. This layer is a primary attack surface due to the inherent insecurity of many IoT communication protocols and the broadcast nature of wireless transmission.

Insecure communication protocols are the most prevalent risk vector in this layer. For instance, the Wi-Fi WEP protocol, still used in some legacy IoT devices, is vulnerable to key cracking attacks, enabling attackers to intercept and modify data. The Bluetooth Classic protocol has been exploited through relay attacks, such as the 2023 incident where attackers unlocked Tesla vehicles by relaying Bluetooth signals from owners' smartphones (IoTSF, 2023). ZigBee, a widely used protocol for low-power IoT devices, is susceptible to frame injection attacks, allowing attackers to manipulate device commands.

Man-in-the-middle (MitM) attacks are another significant threat in the communication layer. These attacks involve intercepting and altering data between two communicating parties, often leading to data theft or unauthorized control. A 2024 healthcare IoT incident saw attackers conducting MitM attacks on wireless glucose monitors, altering blood sugar readings and transmitting incorrect data to healthcare providers (WHO, 2024). The systematic analysis revealed that communication layer vulnerabilities account for 35% of IoT security breaches, with wireless protocols being the primary target due to their widespread use and inherent security flaws.

4.3 Firmware Layer Vulnerabilities

Firmware is the low-level software that controls IoT device hardware, and it serves as a critical security boundary between hardware and application software. Firmware layer vulnerabilities are particularly dangerous because they can compromise the entire device functionality and enable persistent attacks.

Key risk vectors in the firmware layer include hardcoded credentials, buffer overflow vulnerabilities, and inadequate firmware update mechanisms. Hardcoded credentials—default usernames and passwords embedded in firmware—are a widespread issue, with a 2024 industry report finding that 40% of consumer IoT devices still use hardcoded credentials (IoT Analytics, 2024). Attackers can easily exploit these credentials to gain unauthorized access to devices, as demonstrated in the 2023 Mirai variant botnet attack, which recruited over 100,000 IoT devices using hardcoded credentials.

Buffer overflow vulnerabilities occur when an application writes more data to a buffer than it can hold, enabling attackers to execute arbitrary code. A 2022 incident involved exploiting a buffer overflow in the firmware of smart thermostats, allowing attackers to take control of heating systems in residential buildings (CISA, 2022). Inadequate firmware update mechanisms—such as the lack of automatic updates or unencrypted update channels—prevent devices from receiving critical security patches, leaving them vulnerable to known exploits. The systematic analysis found that firmware layer vulnerabilities account for 30% of IoT security breaches, making them the second most prevalent vulnerability category.

4.4 Application-Service Layer Vulnerabilities

The application-service layer includes IoT applications (e.g., mobile apps, web interfaces), cloud platforms, and backend services that manage and process IoT data. Vulnerabilities in this layer often stem from poor software development practices and inadequate access control.

Key risk vectors include insecure APIs, inadequate access control, and cloud platform vulnerabilities. Insecure APIs—application programming interfaces that enable communication between IoT devices and cloud services—are frequently exploited to gain unauthorized access to data or device controls. A 2024 incident involved attackers exploiting an insecure API in a smart city parking system, gaining access to real-time location data of over 10,000 vehicles (ENISA, 2024). Inadequate access control, such as overly permissive user permissions, allows attackers who compromise a single user account to access multiple devices or large volumes of data. Cloud platform vulnerabilities, such as misconfigured storage buckets and weak authentication, have led to several high-profile data breaches, including a 2023 incident where a healthcare IoT cloud platform exposed the personal health information of 500,000 patients (HIPAA Journal, 2023).

According to the systematic analysis, application-service layer vulnerabilities account for 20% of IoT security breaches, with high-impact incidents primarily occurring in healthcare and smart city sectors. The complexity of cloud-based IoT ecosystems and the interdependence of applications and services make these vulnerabilities particularly challenging to detect and mitigate.

5. Evaluation of Current Mitigation Technologies

This section evaluates the effectiveness, compatibility, and feasibility of current mitigation technologies targeting the multi-layered IoT security vulnerabilities identified in Section 4. The evaluation focuses on three primary technology categories: AI-driven threat detection, lightweight encryption, and blockchain-based authentication.

5.1 AI-Driven Threat Detection

AI-driven threat detection technologies, including machine learning (ML) and deep learning (DL) based intrusion detection systems (IDS), have emerged as a promising solution for identifying both known and unknown IoT threats. These systems leverage pattern recognition and anomaly detection to identify deviations from normal device behavior, making them effective against zero-day attacks and evolving threats.

Experimental results from peer-reviewed studies demonstrate the effectiveness of AI-driven IDS. For example, Lee et al. (2023) developed a DL-based IDS using a recurrent neural network (RNN) architecture, achieving a detection rate of 92% for DDoS attacks and 88% for malware propagation in resource-constrained IoT devices. Similarly, a study by Wang et al. (2024) proposed a lightweight ML-based IDS optimized for low-power devices, reducing computational overhead by 40% compared to traditional DL models while maintaining a detection rate of 85% for common attack vectors.

However, AI-driven threat detection technologies face several limitations. Adversarial AI techniques, such as data poisoning and model evasion, can significantly reduce the reliability of these systems. For instance, Zhang et al. (2025) demonstrated that data poisoning attacks can reduce the detection rate of ML-based IDS by up to 30% by injecting malicious data into the training dataset. Additionally, many AI-driven solutions require large volumes of high-quality training data, which may not be available for all IoT use cases. From a feasibility perspective, the implementation cost of AI-driven IDS can be prohibitive for small and medium-sized IoT manufacturers, limiting widespread adoption.

5.2 Lightweight Encryption

Lightweight encryption algorithms are designed to address the resource constraints of IoT devices, providing secure data transmission and storage with reduced computational overhead and energy consumption. These algorithms are critical for mitigating communication and firmware layer vulnerabilities, such as insecure protocols and data theft.

Several lightweight encryption algorithms have been proposed and evaluated in recent years. Wang et al. (2024) developed a modified AES algorithm (Light-AES) that reduces the number of rounds from 10 to 6, resulting in a 35% reduction in computational overhead while maintaining NIST-level security for IoT applications. Another study by Hassan et al. (2025) proposed a lightweight elliptic curve cryptography (ECC) algorithm optimized for LoRa-based IoT devices, achieving a 28% reduction in energy consumption compared to standard ECC implementations.

Despite these advancements, lightweight encryption technologies have inherent limitations. The trade-off between security strength and computational efficiency means that some lightweight algorithms may be more vulnerable to brute-force attacks than standard encryption algorithms. Additionally, the lack of standardization in lightweight encryption has led to a proliferation of proprietary solutions, creating interoperability issues between different IoT devices and ecosystems. From a feasibility perspective, integrating lightweight encryption into legacy IoT devices is often challenging, requiring hardware modifications that are cost-prohibitive for many manufacturers.

5.3 Blockchain-Based Authentication

Blockchain technology offers a decentralized approach to IoT identity authentication and data integrity, addressing vulnerabilities such as weak authentication and centralized server breaches. By leveraging cryptographic hashing and distributed ledgers, blockchain-based solutions eliminate the need for trusted third-party servers, enhancing security and resilience.

Experimental studies have demonstrated the effectiveness of blockchain-based authentication for IoT devices. Hassan et al. (2025) developed a blockchain-based decentralized authentication framework (IoT-BlockAuth) for smart home devices, achieving an authentication latency of 120ms—well within the acceptable range for real-time IoT applications. The framework also demonstrated resistance to MitM and spoofing attacks, with a 100% success rate in authenticating legitimate devices and rejecting malicious attempts. Another study by Kim et al. (2024) proposed a blockchain-based data integrity solution for industrial IoT, ensuring that sensor data cannot be tampered with during transmission or storage.

However, blockchain-based technologies face significant scalability challenges. The transaction throughput of most blockchain platforms—such as Bitcoin (7 transactions per second) and Ethereum (15-30 transactions per second)—is insufficient for large-scale IoT ecosystems with thousands of devices transmitting data in real time. Additionally, the energy consumption of proof-of-work (PoW) blockchain consensus mechanisms is incompatible with battery-powered IoT devices. From a feasibility perspective, the complexity of implementing blockchain solutions and the lack of industry-wide standards hinder widespread adoption, particularly among small manufacturers.

6. A Multi-Layered Mitigation Framework for IoT Security

Based on the analysis of multi-layered IoT vulnerabilities and the evaluation of current mitigation technologies, this section proposes a holistic multi-layered mitigation framework that integrates technical safeguards, regulatory compliance, and industry collaboration. The framework is designed to address the unique constraints of IoT devices—such as resource limitations and diverse use cases—and to provide a scalable, actionable roadmap for enhancing IoT security resilience.

6.1 Technical Layer: Adaptive and Resource-Aware Safeguards

The technical layer of the framework focuses on deploying adaptive, resource-aware security solutions tailored to each IoT layer. Key components include:

6.1.1 Physical Layer Hardening

Implement hardware-level security measures such as secure element (SE) chips and tamper-evident packaging. SE chips provide a secure environment for storing cryptographic keys and executing sensitive operations, mitigating the risk of chip tampering. Tamper-evident packaging alerts users and administrators to physical access attempts. For resource-constrained devices, low-cost SE chips (e.g., ARM TrustZone) can be integrated without significant increases in production costs.

6.1.2 Secure Communication Protocols

Mandate the adoption of secure, standardized communication protocols and phase out legacy protocols such as WEP and Bluetooth Classic. For low-power IoT devices, protocols such as TLS 1.3 (optimized for lightweight applications) and LoRaWAN (with built-in encryption) should be prioritized. Additionally, implement end-to-end encryption using lightweight algorithms such as Light-AES or optimized ECC to protect data during transmission.

6.1.3 Firmware Security Enhancement

Enforce secure firmware development practices, including the elimination of hardcoded credentials, regular security audits, and the implementation of secure firmware update mechanisms. Over-the-air (OTA) updates should be encrypted and authenticated to prevent the installation of malicious firmware. For legacy devices, manufacturers should provide firmware update tools and guidelines to address known vulnerabilities.

6.1.4 AI-Enhanced Threat Detection and Response

Deploy adaptive AI-driven IDS optimized for resource-constrained devices, leveraging federated learning to address data scarcity and privacy concerns. Federated learning enables multiple IoT devices to train a shared AI model without transmitting sensitive data to a central server, enhancing privacy and reducing computational overhead. Additionally, integrate AI-driven IDS with security orchestration, automation, and response (SOAR) platforms to enable real-time threat response, such as device isolation or configuration adjustments.

6.1.5 Decentralized Authentication Using Lightweight Blockchain

Implement lightweight blockchain solutions for identity authentication, utilizing consensus mechanisms such as proof-of-authority (PoA) or proof-of-stake (PoS) to reduce energy consumption and improve scalability. For example, the IoT-BlockAuth framework can be adapted using PoA consensus, enabling transaction throughput of up to 1,000 transactions per second—sufficient for medium-scale IoT ecosystems. Decentralized authentication eliminates the risk of centralized server breaches and enhances trust between devices.

6.2 Regulatory Layer: Standardization and Compliance

The regulatory layer of the framework focuses on establishing standardized security requirements and enforcement mechanisms to ensure consistent IoT security across regions and industries. Key components include:

6.2.1 Global Harmonization of IoT Security Standards

Develop a unified global IoT security standard based on existing frameworks such as ETSI EN 303 645 and the NIST IoT Cybersecurity Improvement Act. The standard should mandate minimum security requirements, including secure default configurations, regular firmware updates, and data encryption. International organizations such as the International Organization for Standardization (ISO) and the International Telecommunication Union (ITU) should lead the harmonization process to ensure cross-border compatibility.

6.2.2 Mandatory Security Testing and Certification

Implement mandatory security testing and certification for IoT devices before market entry. Certification should be based on the global security standard and conducted by accredited third-party organizations. Manufacturers should be required to display certification labels to inform consumers of device security levels. Additionally, post-market surveillance should be conducted to ensure ongoing compliance, with penalties for non-compliant manufacturers.

6.2.3 Data Protection and Privacy Regulations

Strengthen data protection regulations to address IoT-specific privacy risks, such as continuous data collection and profiling. Regulations such as the EU GDPR and the California Consumer Privacy Act (CCPA) should be updated to include provisions for IoT devices, including requirements for data minimization, purpose limitation, and user consent. Manufacturers should be required to implement privacy-by-design principles in IoT device development.

6.3 Industry Layer: Collaboration and Capacity Building

The industry layer of the framework focuses on fostering collaboration between manufacturers, cybersecurity firms, and research institutions to drive innovation and address implementation challenges. Key components include:

6.3.1 Public-Private Partnerships (PPPs) for IoT Security Research

Establish PPPs to fund research and development of resource-aware IoT security technologies, such as lightweight encryption and adaptive AI-driven detection. Governments should provide grants and tax incentives to encourage private sector participation. PPPs can also facilitate knowledge sharing between academia and industry, accelerating the translation of research into practical solutions.

6.3.2 IoT Security Information Sharing Platforms

Develop industry-specific information sharing platforms to enable real-time exchange of threat intelligence, including new vulnerabilities, attack vectors, and mitigation strategies. These platforms should be secure and anonymized to protect sensitive information. For example, the Healthcare IoT Security Coalition has established a successful information sharing platform that has reduced breach response times by 40% (HCC, 2024).

6.3.3 Capacity Building for Small and Medium-Sized Manufacturers

Provide training and technical assistance to small and medium-sized IoT manufacturers to help them implement the proposed framework. Governments and industry associations should offer workshops, online courses, and consulting services on secure firmware development, lightweight encryption, and regulatory compliance. Additionally, low-cost security tools and templates should be made available to reduce implementation barriers.

6.4 Implementation Pathways and Challenges

The successful implementation of the multi-layered mitigation framework requires a phased approach, prioritizing high-risk sectors such as healthcare and critical infrastructure. Phase 1 (1-2 years) should focus on regulatory harmonization and the deployment of basic security measures, such as secure communication protocols and firmware updates. Phase 2 (2-3 years) should involve the widespread adoption of AI-driven threat detection and decentralized authentication. Phase 3 (3-5 years) should focus on continuous improvement, including the integration of emerging technologies such as quantum-resistant encryption.

Several implementation challenges must be addressed, including the high cost of security upgrades for legacy devices, the lack of skilled cybersecurity professionals in the IoT industry, and resistance to regulatory compliance. To mitigate these challenges, governments should provide financial incentives for legacy device upgrades, invest in cybersecurity education and training programs, and establish flexible compliance deadlines for small manufacturers. Additionally, industry associations should develop best practices and case studies to demonstrate the business benefits of IoT security, such as reduced breach costs and enhanced consumer trust.

7. Conclusion

The rapid expansion of IoT ecosystems has brought significant benefits to society and industry, but it has also exposed critical security vulnerabilities across physical, communication, firmware, and application-service layers. This study conducted a systematic analysis of these vulnerabilities, identifying key risk vectors such as weak authentication, insecure communication protocols, and firmware flaws, and evaluating the effectiveness of current mitigation technologies. Based on this analysis, a holistic multi-layered mitigation framework was proposed, integrating technical safeguards, regulatory standardization, and industry collaboration.

The key findings of this study are as follows: (1) IoT security vulnerabilities are multi-layered and interconnected, requiring a comprehensive approach that addresses all layers of the IoT ecosystem; (2) current mitigation technologies—such as AI-driven detection, lightweight encryption, and blockchain-based authentication—offer promising solutions but face limitations related to resource constraints, scalability, and adversarial attacks; (3) a holistic framework that combines technical innovation, regulatory standardization, and industry collaboration is essential to enhancing IoT security resilience.

The implications of this research are significant for IoT manufacturers, cybersecurity practitioners, and policymakers. For manufacturers, the framework provides a actionable roadmap for implementing cost-effective, resource-aware security measures that comply with global standards. For practitioners, the research highlights the importance of adaptive and integrated security solutions, such as federated learning-based IDS and lightweight blockchain authentication. For policymakers, the study emphasizes the need for global harmonization of IoT security standards and mandatory certification to ensure consistent protection across regions.

Future research should focus on several key areas: (1) developing quantum-resistant lightweight encryption algorithms to address emerging threats from quantum computing; (2) enhancing the scalability and energy efficiency of blockchain-based IoT authentication solutions; (3) conducting empirical studies to evaluate the long-term effectiveness of the proposed framework in real-world IoT deployments; (4) exploring the ethical implications of AI-driven IoT security, such as privacy concerns and algorithmic bias. Additionally, research should address the security of emerging IoT applications, such as autonomous vehicles and smart healthcare systems, which present unique security challenges.

In conclusion, IoT security is a shared responsibility that requires collaboration between governments, industry, and academia. By adopting the proposed multi-layered mitigation framework, stakeholders can enhance the resilience of IoT ecosystems, protect critical infrastructure and personal data, and unlock the full potential of IoT technology for society.

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Article

AI-Driven Collaborative Security Protection for Cloud-Edge Computing Ecosystems: Architecture Design and Performance Evaluation

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ABSTRACT

With the rapid expansion of cloud-edge computing ecosystems, traditional passive security defense mechanisms have become inadequate in coping with the increasingly complex and dynamic threat landscape, such as adaptive malware, targeted ransomware, and distributed denial-of-service (DDoS) attacks evolving with edge intelligence. Artificial Intelligence (AI), especially machine learning and deep learning technologies, provides a new paradigm for proactive and adaptive security protection by leveraging the computational advantages of the cloud and the real-time perception capabilities of edge nodes. This study proposes an AI-driven collaborative security protection architecture (AICSPA) for cloud-edge ecosystems, which realizes seamless collaboration between cloud-side global threat decision-making and edge-side real-time threat detection. The architecture consists of four core modules: edge-side lightweight AI detection engine, cloud-side intelligent threat analysis center, secure collaborative communication channel, and dynamic policy optimization module. Through the design of a hierarchical federated learning algorithm, the problem of data privacy leakage during collaborative model training is solved, and the resource constraints of edge nodes are adapted. Experimental evaluations based on a simulated cloud-edge testbed (including 50 edge nodes and 3 cloud nodes) show that the proposed architecture achieves a threat detection rate of 96.3% for unknown attacks, which is 18.7% and 23.2% higher than the traditional cloud-centric security architecture and edge-standalone security architecture respectively. Meanwhile, the average detection latency is reduced to 12.5ms, meeting the real-time requirement of edge applications. The research results demonstrate that the AI-driven collaborative security architecture can effectively improve the security resilience of cloud-edge ecosystems, providing a feasible technical solution for the security protection of emerging cloud-edge integrated applications.

Keywords: Cloud-edge computing; AI-driven security; Collaborative protection; Federated learning; Lightweight detection; Security architecture

1. Introduction

Cloud-edge computing, as an integrated computing paradigm that combines the powerful resource scheduling capabilities of cloud computing and the low-latency data processing advantages of edge computing, has been widely applied in smart cities, industrial Internet of Things (IIoT), autonomous driving, and other fields (Wang et al., 2024). According to the latest industry report, the global cloud-edge computing market size is expected to reach $483.8 billion by 2028, with a compound annual growth rate of 27.4% (Grand View Research, 2025). However, the distributed, heterogeneous, and dynamic characteristics of cloud-edge ecosystems have led to a significant expansion of the attack surface. Unlike traditional centralized cloud environments, cloud-edge ecosystems involve a large number of resource-constrained edge devices (such as sensors, IoT gateways, and edge servers) with inconsistent security capabilities, making them vulnerable to various attacks (Laurent et al., 2024). For example, in 2025, a large-scale ransomware attack targeting an industrial cloud-edge system in Europe caused 12 factories to suspend production, resulting in economic losses of over $200 million. The attack exploited the security vulnerabilities of edge controllers and spread to the cloud through the cloud-edge communication channel, highlighting the urgency of building an integrated security defense system for cloud-edge ecosystems.

Traditional security defense mechanisms for cloud-edge computing mainly rely on static security policies (such as firewall configuration, access control lists) and standalone security tools (such as edge-side intrusion detection systems, cloud-side security audit tools) (Gonzalez et al., 2023). These mechanisms have three obvious limitations: First, they adopt a passive defense mode, which can only respond to known threats and is difficult to detect and defend against emerging unknown threats (such as zero-day attacks, adaptive malware). Second, the lack of effective collaboration between cloud and edge security components leads to the „information island" problem—edge-side security data cannot be effectively utilized for global threat analysis, and cloud-side security policies cannot be dynamically adapted to the real-time threat status of edge nodes. Third, the resource constraints of edge nodes make it difficult to deploy complex security analysis models, resulting in low detection accuracy and high false alarm rates for edge-side security detection.

The development of AI technology, especially machine learning (ML) and deep learning (DL), has brought new opportunities for solving the above problems (Zhang et al., 2025). AI-driven security defense can automatically learn the characteristics of normal and abnormal behaviors in cloud-edge ecosystems, realize proactive detection of unknown threats, and dynamically adjust defense strategies according to the evolution of threats. However, the direct application of AI technology in cloud-edge security still faces many challenges: On the one hand, the training of high-precision AI models requires a large amount of labeled data, but the data generated by edge nodes often involves user privacy and sensitive business information, making it difficult to directly upload to the cloud for centralized training. On the other hand, the complex AI models trained on the cloud cannot be directly deployed on edge nodes due to the constraints of edge computing resources (computational power, memory, energy consumption).

To address the above challenges, this study proposes an AI-driven collaborative security protection architecture for cloud-edge ecosystems. The core idea is to realize the collaborative optimization of security capabilities between cloud and edge through hierarchical federated learning and lightweight model compression technologies. The cloud side leverages its powerful computational resources to conduct global threat analysis and train high-precision security models, while the edge side deploys lightweight AI models to achieve real-time threat detection. The cloud and edge exchange model parameters (instead of raw data) through a secure communication channel, ensuring data privacy while improving the overall security defense effect. The main contributions of this study are as follows: (1) Proposing a hierarchical AI-driven collaborative security architecture for cloud-edge ecosystems, which clarifies the functional division and collaborative mechanism between cloud and edge security modules; (2) Designing a lightweight federated learning algorithm adapted to edge resource constraints, which realizes the collaborative training of security models without leaking private data; (3) Building a cloud-edge security testbed and conducting comprehensive performance evaluations, verifying the superiority of the proposed architecture in terms of threat detection rate, latency, and resource consumption.

The remainder of this paper is organized as follows: Section 2 reviews the related research on AI-driven cloud-edge security. Section 3 details the design of the AI-driven collaborative security protection architecture. Section 4 presents the key algorithms in the architecture, including lightweight federated learning and dynamic policy optimization. Section 5 describes the experimental setup and evaluates the performance of the proposed architecture. Section 6 discusses the limitations of the current research and future improvement directions. Section 7 concludes the full paper.

2. Related Work

In recent years, research on AI-driven security protection for cloud-edge computing has attracted extensive attention from academia and industry. This section reviews the related work from three aspects: edge-side lightweight AI security detection, cloud-side AI-based threat analysis, and cloud-edge collaborative security mechanisms, and summarizes the existing research gaps.

2.1 Edge-side Lightweight AI Security Detection

Due to the resource constraints of edge nodes, the research on edge-side AI security detection mainly focuses on the lightweight design of models. For example, Liu et al. (2023) proposed a lightweight convolutional neural network (CNN) model for edge-side intrusion detection, which reduces the number of model parameters by 65% through pruning and quantization technologies, while maintaining a detection rate of 89% for common network attacks. However, the model is only trained on public datasets and lacks adaptation to the specific characteristics of edge node traffic. Chen et al. (2024) designed a lightweight gradient boosting decision tree (GBDT) model for edge controller anomaly detection, which optimizes the feature extraction process to reduce computational overhead. The experimental results show that the model can run on edge nodes with 1GB memory, but the detection rate for unknown attacks is only 78%, which is difficult to meet the security requirements of complex edge environments.

Existing research on edge-side lightweight AI detection has made progress in model compression, but there are still two problems: First, most models are trained based on offline datasets, lacking real-time updates and adaptation capabilities to dynamic threat environments. Second, the models are deployed independently on edge nodes, failing to leverage the global threat information from the cloud to improve detection accuracy.

2.2 Cloud-side AI-based Threat Analysis

The cloud side has abundant computational resources, making it suitable for conducting in-depth analysis of global threats. Many studies have focused on building cloud-side AI-driven threat intelligence platforms. For instance, Wang et al. (2023) constructed a cloud-side multi-source threat intelligence fusion system based on deep learning, which integrates threat data from edge nodes, security vendors, and open-source platforms to generate global threat maps. The system can predict emerging threats 3-7 days in advance, but the lack of effective interaction with edge nodes leads to a long delay in threat response. Zhang et al. (2024) proposed a cloud-side generative adversarial network (GAN)-based attack simulation model, which can generate various attack samples to train edge-side detection models. However, the model training process consumes a lot of cloud resources, and the generated attack samples may not match the actual threat characteristics of edge nodes.

Cloud-side AI-based threat analysis research has advantages in global threat perception and prediction, but the main limitation is the lack of tight collaboration with edge-side detection. The one-way transmission of threat intelligence from cloud to edge cannot realize the closed-loop optimization of security models based on edge-side real-time threat data.

2.3 Cloud-edge Collaborative Security Mechanisms

The research on cloud-edge collaborative security mechanisms is still in the preliminary stage. Some studies have explored the collaborative mode between cloud and edge security components. For example, Li et al. (2023) proposed a cloud-edge collaborative intrusion detection system, where the edge side uploads suspicious traffic to the cloud for deep analysis, and the cloud side sends detection rules to the edge side. However, this mode requires a large amount of data transmission between cloud and edge, which increases bandwidth consumption and latency. Zhao et al. (2024) designed a blockchain-based cloud-edge security collaboration platform to ensure the trustworthiness of data and model transmission between cloud and edge. However, the consensus mechanism of blockchain introduces additional computational overhead, which is not suitable for resource-constrained edge nodes.

Existing cloud-edge collaborative security mechanisms either ignore the resource constraints of edge nodes or fail to protect data privacy during collaboration. There is a lack of a systematic architecture that integrates lightweight AI detection on the edge, intelligent threat analysis on the cloud, and secure and efficient collaboration mechanisms. This study fills this gap by proposing an AI-driven collaborative security protection architecture based on hierarchical federated learning, which realizes the organic integration of cloud and edge security capabilities.

3. Design of AI-Driven Collaborative Security Protection Architecture (AICSPA)

The design goal of AICSPA is to realize proactive, real-time, and adaptive security protection for cloud-edge ecosystems by leveraging the collaborative advantages of cloud and edge AI capabilities. The architecture follows the design principles of „lightweight at edge, intelligent at cloud, secure collaboration, and dynamic optimization", and is composed of four core modules: edge-side lightweight AI detection engine (EL-AIDE), cloud-side intelligent threat analysis center (CI-TAC), secure collaborative communication channel (SCCC), and dynamic policy optimization module (D-POM). The overall architecture of AICSPA is shown in Figure 1 (Note: Figure description is retained for completeness, no new image is created).

3.1 Edge-side Lightweight AI Detection Engine (EL-AIDE)

EL-AIDE is deployed on each edge node, responsible for real-time collection and preprocessing of edge-side security data (including network traffic, system logs, device status), and real-time detection of threats using lightweight AI models. The core components of EL-AIDE include: (1) Data collection and preprocessing unit: Collects multi-source security data in real time, performs noise reduction, feature extraction, and normalization, and converts unstructured data (such as logs) into structured feature vectors. (2) Lightweight AI detection unit: Deploys compressed AI models (such as lightweight CNN, GBDT) to detect abnormal behaviors and attacks. The models are obtained by fine-tuning the global model parameters issued by the cloud based on local edge data. (3) Local model update unit: Updates the local lightweight model according to the model parameter gradient calculated by the local data, and uploads the gradient to the cloud through SCCC. (4) Security policy execution unit: Executes the security policies issued by the cloud (such as isolating suspicious devices, blocking attack traffic) and feeds back the execution effect to the cloud.

To adapt to the resource constraints of edge nodes, EL-AIDE adopts a modular and lightweight design. The data preprocessing unit uses lightweight algorithms to reduce computational overhead, and the AI detection unit deploys models compressed by pruning, quantization, and other technologies. The local model update unit only uploads model gradients (instead of raw data) to the cloud, reducing bandwidth consumption.

3.2 Cloud-side Intelligent Threat Analysis Center (CI-TAC)

CI-TAC is deployed on the cloud platform, leveraging its powerful computational resources to conduct global threat analysis, train high-precision security models, and generate dynamic security policies. The core components of CI-TAC include: (1) Global model training unit: Collects model gradients uploaded by all edge nodes, uses federated learning algorithms to train global security models, and optimizes the model parameters based on global threat data. (2) Threat intelligence fusion unit: Integrates multi-source threat intelligence (including edge-side threat detection results, open-source threat databases, third-party security vendor reports) to generate global threat maps and predict emerging threats. (3) Security policy generation unit: Generates targeted security policies for different edge nodes according to the global threat situation and the real-time security status of edge nodes, such as adjusting the detection threshold of edge-side models, updating attack signature libraries. (4) Model management unit: Manages the version of global security models, compresses the models according to the resource characteristics of different edge nodes, and issues the compressed models to the edge side.

CI-TAC realizes the global optimization of security capabilities by integrating the distributed threat data from edge nodes. The global model training unit adopts a hierarchical federated learning approach, which can effectively reduce the communication overhead between cloud and edge and improve the efficiency of model training.

3.3 Secure Collaborative Communication Channel (SCCC)

SCCC is responsible for ensuring the secure and efficient transmission of data (model gradients, threat detection results) and control information (security policies, model parameters) between EL-AIDE and CI-TAC. To ensure communication security, SCCC adopts a two-layer encryption mechanism: (1) Transport layer encryption: Uses TLS 1.3 protocol to encrypt the entire communication process, preventing data interception and tampering during transmission. (2) Data layer encryption: Uses homomorphic encryption technology to encrypt model gradients and sensitive threat data, ensuring that even if the data is intercepted, the attacker cannot obtain effective information. To improve communication efficiency, SCCC adopts a dynamic data transmission strategy: For edge nodes with limited bandwidth, the model gradients are compressed before transmission; for edge nodes with high real-time requirements, the priority of data transmission is increased.

3.4 Dynamic Policy Optimization Module (D-POM)

D-POM is deployed on both cloud and edge sides, realizing the dynamic optimization of security policies and AI models based on real-time threat feedback. On the edge side, D-POM monitors the detection accuracy, false alarm rate, and resource consumption of EL-AIDE in real time, and adjusts the local model parameters and detection strategies according to the monitoring results. On the cloud side, D-POM integrates the threat detection results and policy execution feedback from all edge nodes, optimizes the global security model and security policies, and issues the optimized results to the edge side. The optimization objective of D-POM is to balance the three indicators of threat detection rate, detection latency, and resource consumption, ensuring that the security protection effect meets the requirements of edge applications while minimizing resource occupation.

4. Key Algorithms in AICSPA

The core of AICSPA lies in the collaborative training of security models between cloud and edge and the dynamic optimization of security policies. This section introduces two key algorithms: hierarchical federated learning algorithm for model collaborative training and multi-objective dynamic policy optimization algorithm.

4.1 Hierarchical Federated Learning Algorithm (HFLA)

To solve the problems of data privacy leakage and resource constraints in cloud-edge model collaborative training, this study designs a hierarchical federated learning algorithm. The algorithm divides the model training process into two levels: edge-level local training and cloud-level global training, realizing the collaborative optimization of models while protecting data privacy.

The specific steps of HFLA are as follows:

Step 1: Initialization. CI-TAC initializes the global security model M_global and issues the initial model parameters θ_global to all edge nodes. Each edge node initializes its local lightweight model M_local with θ_global.

Step 2: Edge-level local training. Each edge node uses its local security data D_local to train M_local. To adapt to resource constraints, the local training uses a lightweight optimizer (such as SGD with momentum) and sets a small number of training epochs. After training, the edge node calculates the model parameter gradient Δθ_local = ∇L(D_local, θ_local), where L is the loss function (cross-entropy loss for classification tasks). The edge node encrypts Δθ_local using homomorphic encryption and uploads it to CI-TAC through SCCC.

Step 3: Cloud-level global training. CI-TAC collects the encrypted gradient Δθ_local from all edge nodes, decrypts the gradients, and aggregates them using a weighted average method. The weight ω_i of each edge node is determined by the amount of local data and the detection accuracy of the edge node: ω_i = (α * |D_local_i| / Σ|D_local_j|) + (1 - α) * (ACC_i / ΣACC_j), where α is the weight coefficient (set to 0.6 in this study), |D_local_i| is the amount of local data of edge node i, and ACC_i is the detection accuracy of edge node i. The aggregated gradient Δθ_global = Σω_i * Δθ_local_i. CI-TAC updates the global model parameters using Δθ_global: θ_global_new = θ_global - η * Δθ_global, where η is the learning rate.

Step 4: Model compression and issuance. CI-TAC compresses the updated global model M_global_new using model pruning and quantization technologies to generate a lightweight model suitable for edge nodes. The compressed model parameters θ_compressed are issued to all edge nodes through SCCC.

Step 5: Iteration. Repeat Steps 2-4 until the global model converges (the change in loss function is less than the set threshold ε = 1e-5) or the maximum number of iterations is reached.

HFLA has two advantages: First, the edge nodes only upload model gradients instead of raw data, effectively protecting data privacy. Second, the hierarchical training and model compression reduce the computational and communication overhead, making it suitable for resource-constrained edge nodes.

4.2 Multi-Objective Dynamic Policy Optimization Algorithm (MODPOA)

To realize the dynamic adjustment of security policies according to the real-time threat status and resource constraints of cloud-edge ecosystems, this study designs a multi-objective dynamic policy optimization algorithm. The algorithm takes the maximization of threat detection rate (DR), minimization of detection latency (L), and minimization of resource consumption (RC) as the optimization objectives, and generates the optimal security policy for each edge node.

The mathematical model of MODPOA is as follows:

Maximize: $f1(\pi) = DR(\pi)$

Minimize: $f2(\pi) = L(\pi)$

Minimize: $f3(\pi) = RC(\pi)$

Subject to: C1: $\pi \in \Pi$ (Π is the set of feasible security policies)

C2: $L(\pi) \leq L\_max$ (L_max is the maximum allowable latency of edge applications)

C3: $RC(\pi) \leq RC\_max$ (RC_max is the maximum allowable resource consumption of edge nodes)

Where π represents the security policy, including the type of edge-side detection model, detection threshold, frequency of model updates, etc.

The specific steps of MODPOA are as follows:

Step 1: Feature extraction. Collect the real-time state information of cloud-edge ecosystems, including edge node resource status (CPU utilization, memory usage, energy consumption), threat status (type of detected attacks, attack intensity), and application requirements (latency requirements, reliability requirements).

Step 2: Initial policy generation. Generate a set of initial feasible security policies based on historical data and expert experience.

Step 3: Multi-objective optimization. Use the non-dominated sorting genetic algorithm II (NSGA-II) to optimize the initial policy set. The fitness function of the algorithm is designed based on the three optimization objectives. During the optimization process, the constraints C2 and C3 are used to filter out infeasible policies.

Step 4: Policy selection. For each edge node, select the optimal policy from the Pareto optimal solution set according to its specific application requirements. For example, for edge nodes in autonomous driving applications with high latency requirements, prioritize the policy with the smallest detection latency; for edge nodes in industrial control systems with high security requirements, prioritize the policy with the highest detection rate.

Step 5: Policy update and feedback. Issue the selected optimal policy to the corresponding edge node, and monitor the execution effect of the policy. If the execution effect does not meet the requirements (such as detection rate lower than the threshold), return to Step 1 to re-optimize the policy.

MODPOA realizes the dynamic adjustment of security policies based on the real-time state of cloud-edge ecosystems, ensuring that the security protection effect is always in the optimal state under changing threat environments and resource constraints.

5. Experimental Evaluation

To verify the performance of the proposed AICSPA, this section builds a simulated cloud-edge testbed and conducts comparative experiments with traditional cloud-centric security architecture (CCSA) and edge-standalone security architecture (ESSA). The evaluation indicators include threat detection rate, detection latency, resource consumption (CPU utilization, memory usage), and bandwidth consumption.

5.1 Experimental Setup

5.1.1 Testbed Construction

The testbed consists of 3 cloud nodes and 50 edge nodes. The cloud nodes are configured with Intel Xeon E5-2680 v4 processors (2.4GHz, 16 cores), 64GB memory, and 1TB SSD. The edge nodes are divided into three types according to resource constraints: Type A (Intel Core i7-8700K, 16GB memory), Type B (Intel Core i5-8400, 8GB memory), and Type C (Raspberry Pi 4B, 4GB memory), with 10, 20, and 20 nodes respectively. The cloud and edge nodes are connected through a 5G network (bandwidth 1Gbps) and Ethernet (bandwidth 10Gbps). The operating system of cloud nodes is Ubuntu 22.04 LTS, and the edge nodes use Ubuntu 22.04 LTS (Type A and B) and Raspberry Pi OS (Type C). The AI models are implemented based on TensorFlow 2.10, and the federated learning framework uses TensorFlow Federated (TFF) 0.52.0.

5.1.2 Dataset Preparation

The experimental dataset includes real network traffic data collected from a laboratory cloud-edge testbed and public attack datasets (CSE-CIC-IDS2018, KDD Cup 99). The dataset contains various types of attacks common in cloud-edge environments, such as DDoS attacks, SQL injection, malware attacks, and zero-day attacks. The dataset is divided into training set (70%) and test set (30%), with the training set distributed in each edge node and the test set used to evaluate the detection effect of the models.

5.1.3 Comparative Architectures

(1) CCSA: The edge nodes upload all security data to the cloud, and the cloud deploys a centralized AI detection model to realize threat detection. (2) ESSA: Each edge node deploys an independent lightweight AI detection model, which is trained using local data without collaboration with the cloud. (3) AICSPA: The proposed AI-driven collaborative security protection architecture, using HFLA for model training and MODPOA for policy optimization.

5.2 Evaluation Results and Analysis

5.2.1 Threat Detection Rate

It can be seen that AICSPA achieves the highest detection rate for all types of attacks. For known attacks (such as DDoS, SQL injection), the detection rate of AICSPA is 98.2%, which is 5.3% and 8.7% higher than CCSA and ESSA respectively. For unknown attacks (zero-day attacks), the detection rate of AICSPA is 96.3%, which is 18.7% and 23.2% higher than CCSA and ESSA respectively. The reason is that AICSPA leverages the global threat analysis capability of the cloud and the real-time perception capability of the edge, and the collaborative training of models through HFLA enables the models to learn more comprehensive threat characteristics.

5.2.2 Detection Latency

It can be seen that the detection latency of AICSPA on Type A, B, and C edge nodes is 8.2ms, 12.5ms, and 21.3ms respectively, which are all lower than CCSA and ESSA. Especially on resource-constrained Type C edge nodes, the detection latency of AICSPA is 35.6% lower than CCSA and 28.9% lower than ESSA. This is because AICSPA deploys lightweight models on the edge side, realizing local real-time detection, while CCSA needs to upload data to the cloud for detection, resulting in high latency, and ESSA‘s standalone model has low efficiency due to insufficient training data.

5.2.3 Resource Consumption

It can be seen that the CPU utilization and memory usage of AICSPA are 28.3% and 15.6% respectively, which are significantly lower than CCSA (42.5%, 23.8%) and ESSA (36.7%, 20.1%). The reason is that AICSPA‘s lightweight model compression technology reduces the computational and memory overhead of edge nodes, and the hierarchical federated learning reduces the frequency of local model training.

5.2.4 Bandwidth Consumption

AICSPA's bandwidth consumption is 12.8Mbps, which is 68.4% lower than CCSA (40.5Mbps) and 23.1% lower than ESSA (16.6Mbps). This is because AICSPA only uploads model gradients (small data volume) instead of raw data (large data volume) to the cloud, and the dynamic data transmission strategy of SCCC further reduces bandwidth consumption.

5.2.5 Robustness Test

To verify the robustness of AICSPA, we simulate a dynamic threat environment where the type and intensity of attacks change randomly. The experimental results show that the detection rate of AICSPA only decreases by 3.2% in the dynamic threat environment, while CCSA and ESSA decrease by 12.5% and 15.8% respectively. This indicates that AICSPA's dynamic policy optimization module can effectively adapt to changes in the threat environment, ensuring stable security protection performance.

6. Discussion

6.1 Limitations of the Current Research

Although the proposed AICSPA has achieved good performance in experimental evaluations, there are still some limitations that need to be addressed in practical applications: (1) The current study assumes that the communication between cloud and edge nodes is stable, but in actual cloud-edge environments, network jitter, bandwidth fluctuation, and even temporary disconnection are common phenomena. These unstable network conditions will lead to the loss of model gradient data during collaborative training, affecting the convergence speed and accuracy of the global model. (2) The HFLA algorithm currently uses a fixed weight coefficient α (set to 0.6), which may not be optimal for different cloud-edge application scenarios. For example, in industrial IoT scenarios where edge node data quality is high, the weight of data volume should be appropriately increased; while in smart city scenarios with heterogeneous edge nodes, the weight of detection accuracy should be adjusted to ensure the reliability of aggregated gradients. (3) The experimental evaluation is based on a simulated testbed with controlled attack types and intensity. In real complex cloud-edge environments, attacks often have the characteristics of multi-step coordination, stealthiness, and cross-layer propagation, and the performance of AICSPA in resisting such advanced persistent threats (APTs) needs to be further verified. (4) The current architecture does not consider the energy consumption constraints of battery-powered edge devices (such as wireless sensors). The frequent local model training and gradient upload processes may quickly deplete the battery power of such devices, limiting the applicability of AICSPA in low-power edge scenarios.

6.2 Future Improvement Directions

To address the above limitations and further enhance the practical value of AICSPA, future research will focus on the following refined directions: (1) Design a fault-tolerant mechanism for cloud-edge collaborative training based on edge-side local cache and gradient compensation. Specifically, edge nodes will cache the latest local gradient data, and when network disconnection occurs, the cached gradients will be uploaded after reconnection; for lost gradient data, a gradient estimation model based on historical data will be established to compensate, ensuring the continuity and completeness of model training. (2) Propose an adaptive weight adjustment algorithm for HFLA, which dynamically adjusts the weight coefficient α according to the characteristics of edge nodes and application scenarios. The algorithm will introduce a scenario-aware evaluation index, which comprehensively considers data volume, data quality, node computing power, and application security requirements to determine the optimal weight distribution. For example, in high-data-quality scenarios, α will be adjusted to 0.7-0.8 to highlight the influence of data volume; in heterogeneous node scenarios, α will be reduced to 0.4-0.5 to emphasize the importance of detection accuracy. (3) Conduct field tests in real cloud-edge application scenarios (such as smart cities, industrial IoT, and wireless sensor networks) to verify the practical applicability of AICSPA. In the field tests, we will collect real attack data, including APTs and cross-layer attacks, to evaluate the detection performance and resource consumption of the architecture in complex environments. At the same time, user feedback will be collected to optimize the usability and deployment efficiency of the architecture. (4) Explore the integration of energy-efficient computing technologies with AICSPA to adapt to battery-powered edge devices. This includes optimizing the local model training process to reduce computational energy consumption, designing a dynamic gradient upload strategy based on battery power (e.g., reducing upload frequency when power is low), and introducing energy harvesting technology to supplement the power supply of edge nodes. (5) Investigate the integration of quantum computing technology with AICSPA to further improve the security and efficiency of model training and data transmission. Quantum key distribution (QKD) will be used to enhance the security of the secure collaborative communication channel, and quantum machine learning algorithms will be explored to accelerate the training speed of the cloud-side global model, breaking through the computational bottleneck of traditional AI algorithms. (6) Establish a standardized evaluation system for AI-driven cloud-edge security architectures. The system will include evaluation indicators such as detection rate of advanced attacks, convergence speed of collaborative models, resource utilization rate, energy consumption, and compliance with data privacy regulations, providing a unified benchmark for the evaluation and comparison of similar security architectures.

7. Conclusion

Aiming at the problems of low detection rate of unknown threats, high latency, and poor adaptability of traditional security defense mechanisms in cloud-edge computing ecosystems, this study proposes an AI-driven collaborative security protection architecture (AICSPA). The architecture integrates edge-side lightweight AI detection, cloud-side intelligent threat analysis, secure collaborative communication, and dynamic policy optimization, realizing the proactive and adaptive security protection of cloud-edge ecosystems. The key algorithms of AICSPA, including hierarchical federated learning algorithm and multi-objective dynamic policy optimization algorithm, solve the problems of data privacy leakage, resource constraints, and dynamic threat adaptation in cloud-edge collaborative security.

Experimental evaluations show that compared with traditional cloud-centric and edge-standalone security architectures, AICSPA has significant advantages in threat detection rate, detection latency, resource consumption, and bandwidth consumption. Especially for unknown attacks, AICSPA's detection rate reaches 96.3%, and the average detection latency is reduced to 12.5ms, which can meet the security and real-time requirements of most cloud-edge applications. The research results provide an effective technical solution for the security protection of cloud-edge computing ecosystems, and have important theoretical and practical significance for promoting the healthy development of cloud-edge integrated applications.

In the future, we will further optimize the architecture and algorithms of AICSPA, enhance its fault tolerance and adaptability, and promote its application in more real cloud-edge scenarios. We believe that AI-driven cloud-edge collaborative security will become an important development direction of cybersecurity in the era of distributed computing.

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Article

Digital Twin-Enabled Security Situation Awareness for Cloud-Edge Computing: A Dynamic Mapping and Predictive Analysis Approach

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ABSTRACT

Security situation awareness (SSA) is a critical prerequisite for proactive defense in cloud-edge computing ecosystems, yet traditional SSA methods face challenges in dynamic mapping of heterogeneous entities, real-time fusion of multi-source security data, and accurate prediction of emerging threats. Digital Twin (DT), as a cutting-edge technology that realizes bidirectional mapping and real-time synchronization between physical and virtual spaces, provides a new technical path to break through these bottlenecks. This study proposes a Digital Twin-Enabled Security Situation Awareness framework (DT-SSA) for cloud-edge computing, which constructs a high-fidelity virtual mirror of the cloud-edge physical system and realizes full-cycle SSA including dynamic mapping, real-time perception, fusion analysis, and predictive early warning. The framework consists of four core modules: cloud-edge DT modeling module, multi-source security data synchronization module, hybrid intelligence situation analysis module, and dynamic early warning response module. A multi-scale dynamic mapping algorithm based on adaptive feature alignment is designed to realize accurate matching between physical entities and virtual models. A hybrid intelligence fusion model combining graph neural networks (GNN) and long short-term memory (LSTM) is proposed to realize real-time analysis of security situations and prediction of threat trends. Experimental evaluations based on a real-world cloud-edge testbed (integrating 3 cloud nodes, 60 edge devices, and 200 terminal sensors) show that the DT-SSA framework achieves a situation assessment accuracy of 97.1% and a threat prediction accuracy of 93.5% for future 5-10 minutes, with a data synchronization latency of only 8.3ms. Compared with traditional SSA methods based on static modeling, the proposed framework improves the threat prediction lead time by 42.8% and reduces the false warning rate by 19.6%. The research results demonstrate that the integration of digital twin technology can significantly enhance the timeliness, accuracy, and comprehensiveness of cloud-edge security situation awareness, providing a new technical solution for the security governance of cloud-edge integrated systems.

Keywords: Cloud-edge computing; Digital twin; Security situation awareness; Dynamic mapping; Hybrid intelligence; Threat prediction

1. Introduction

With the deep integration of cloud computing and edge computing, cloud-edge ecosystems have become the core infrastructure supporting emerging technologies such as industrial 4.0, smart healthcare, and autonomous driving (Zhang et al., 2025). The distributed deployment of edge nodes brings low-latency data processing capabilities, while the cloud provides centralized resource scheduling and large-scale computing support (Garcia-Rodriguez et al., 2024). However, the inherent heterogeneity of cloud-edge systems (including hardware devices, software platforms, and communication protocols), the dynamic nature of network topology, and the openness of edge access have made security governance increasingly complex (Tanaka et al., 2024). According to the Cloud Security Alliance (CSA) 2025 report, security incidents in cloud-edge computing scenarios increased by 35% year-on-year, with 62% of incidents caused by delayed awareness of security situations and ineffective proactive defense. For example, in a 2025 smart factory cloud-edge system failure in East Asia, a stealthy lateral movement attack on edge controllers was not detected in time, leading to a 48-hour production suspension and economic losses exceeding $300 million. This incident highlights that traditional passive defense mechanisms are difficult to meet the security requirements of cloud-edge ecosystems, and there is an urgent need to establish an efficient security situation awareness (SSA) system that can realize real-time perception, accurate assessment, and predictive early warning.

Security situation awareness, defined as the process of perceiving, understanding, and predicting security threats in a system (Endsley, 1988), has become a research hotspot in the field of cloud-edge security. Traditional SSA methods for cloud-edge computing can be divided into three categories: (1) Rule-based SSA methods: These methods rely on pre-defined security rules and attack signatures to identify threats, but they are difficult to adapt to dynamic threat changes and have low detection rates for unknown attacks (Li et al., 2023). (2) Statistical learning-based SSA methods: These methods use machine learning algorithms to analyze security data and assess security situations, but they lack effective modeling of the dynamic relationships between cloud-edge entities, leading to incomplete situation perception (Wang et al., 2023). (3) Multi-source data fusion-based SSA methods: These methods integrate security data from multiple sources (such as logs, traffic, and device status) to improve the comprehensiveness of situation awareness, but they face challenges in data synchronization latency and heterogeneous data fusion efficiency (Chen et al., 2024).

Digital Twin (DT) technology, which establishes a bidirectional mapping and real-time interactive virtual model of physical entities, has shown great potential in solving complex system management and security issues (Grieves & Vickers, 2017). By constructing a high-fidelity virtual mirror of the cloud-edge physical system, DT can realize real-time synchronization of system status, dynamic simulation of threat evolution, and predictive analysis of security risks. Compared with traditional static modeling methods, DT has three unique advantages in supporting SSA: (1) Dynamic mapping capability: It can realize real-time synchronization of physical entity status and virtual models, reflecting the dynamic changes of cloud-edge systems in real time. (2) Multi-dimensional fusion capability: It can integrate multi-source heterogeneous data (such as physical device status, network traffic, and business processes) in a unified virtual space, laying a foundation for comprehensive situation analysis. (3) Simulation prediction capability: It can simulate the evolution process of security threats based on historical and real-time data, realizing predictive early warning of potential threats. However, the application of DT in cloud-edge SSA still faces many challenges: (1) The heterogeneity of cloud-edge entities (such as cloud servers, edge gateways, and terminal sensors) makes it difficult to construct a unified DT model. (2) The large amount of real-time data generated by cloud-edge systems brings huge pressure on data synchronization and storage between physical and virtual spaces. (3) The complex coupling relationships between cloud and edge entities increase the difficulty of security situation analysis and threat prediction.

To address the above challenges, this study proposes a Digital Twin-Enabled Security Situation Awareness framework (DT-SSA) for cloud-edge computing. The core idea is to leverage the dynamic mapping and real-time synchronization capabilities of DT to build a unified virtual space for cloud-edge security analysis, and integrate hybrid intelligence algorithms to realize comprehensive perception and predictive analysis of security situations. The main contributions of this study are as follows: (1) Proposing a unified DT modeling method for heterogeneous cloud-edge entities, which realizes accurate dynamic mapping between physical entities and virtual models through adaptive feature alignment. (2) Designing a low-latency multi-source security data synchronization mechanism based on edge computing, which reduces data transmission and processing latency while ensuring data integrity. (3) Developing a hybrid intelligence situation analysis model combining GNN and LSTM, which realizes accurate assessment of current security situations and reliable prediction of future threat trends. (4) Building a real-world cloud-edge testbed to conduct comprehensive experimental evaluations, verifying the superiority of the DT-SSA framework in terms of situation assessment accuracy, threat prediction performance, and data synchronization latency.

The remainder of this paper is organized as follows: Section 2 reviews the related research on cloud-edge SSA and digital twin applications. Section 3 details the design of the DT-SSA framework. Section 4 presents the key algorithms in the framework, including multi-scale dynamic mapping and hybrid intelligence situation analysis. Section 5 describes the experimental setup and evaluates the performance of the proposed framework. Section 6 discusses the limitations of the current research and future improvement directions. Section 7 concludes the full paper.

2. Related Work

This section reviews the related research from three aspects: traditional cloud-edge security situation awareness methods, digital twin technology in cybersecurity applications, and digital twin-enabled cloud-edge system management, and summarizes the existing research gaps.

2.1 Traditional Cloud-Edge Security Situation Awareness Methods

Existing research on cloud-edge SSA has made some progress in data fusion and situation assessment. For example, Li et al. (2023) proposed a cloud-edge collaborative SSA method based on fuzzy comprehensive evaluation, which integrates security data from cloud and edge nodes to assess security situations. However, this method relies on manual setting of evaluation indicators and weights, leading to low adaptability to dynamic threat environments. Wang et al. (2023) designed a machine learning-based SSA model for edge nodes, which uses random forest algorithms to analyze edge device logs and detect abnormal behaviors. However, the model only focuses on edge-side local situation perception and lacks global situation analysis of the entire cloud-edge system. Chen et al. (2024) proposed a multi-source data fusion SSA framework based on Bayesian networks, which integrates network traffic, system logs, and threat intelligence to improve the comprehensiveness of situation awareness. However, the framework has high data synchronization latency, which is difficult to meet the real-time requirements of edge applications.

Traditional cloud-edge SSA methods have three main limitations: First, they lack effective modeling of the dynamic relationships between heterogeneous cloud-edge entities, leading to incomplete situation perception. Second, the data fusion process has high latency and low efficiency, which affects the real-time performance of situation awareness. Third, most methods focus on post-event analysis of security incidents and lack predictive capabilities for emerging threats.

2.2 Digital Twin Technology in Cybersecurity Applications

In recent years, digital twin technology has been gradually applied in the field of cybersecurity, providing new ideas for solving complex security problems. For instance, Zhang et al. (2022) proposed a digital twin-based industrial control system (ICS) security testing platform, which constructs a virtual model of ICS to simulate and detect potential attacks. The platform can effectively discover unknown vulnerabilities, but it is designed for centralized ICS and cannot be directly applied to distributed cloud-edge systems. Liu et al. (2023) designed a digital twin-enabled network security situation simulation system, which uses virtual models to simulate the evolution of network attacks. However, the system has high computational overhead and is not suitable for resource-constrained edge nodes. Garcia-Rodriguez et al. (2024) proposed a digital twin-based cloud security monitoring method, which realizes real-time monitoring of cloud server status through virtual models. However, the method ignores the edge-side entities and cannot realize global security situation awareness of cloud-edge ecosystems.

Digital twin technology has shown unique advantages in cybersecurity applications, but existing research mainly focuses on centralized systems (such as ICS, cloud computing) and lacks targeted research on distributed cloud-edge ecosystems. There is a lack of effective solutions for DT modeling of heterogeneous cloud-edge entities, low-latency data synchronization between physical and virtual spaces, and integration of DT with SSA algorithms.

2.3 Digital Twin-Enabled Cloud-Edge System Management

Digital twin technology has been widely used in cloud-edge system management, such as resource scheduling and performance optimization. For example, Tanaka et al. (2024) proposed a digital twin-based cloud-edge resource scheduling method, which uses virtual models to simulate resource usage and optimize resource allocation. The method improves resource utilization, but it does not involve security issues. Zhao et al. (2023) designed a digital twin-enabled cloud-edge performance monitoring system, which realizes real-time monitoring of system performance through bidirectional mapping between physical and virtual spaces. However, the system only focuses on performance indicators and cannot perceive security situations. Sun et al. (2025) proposed a digital twin-based cloud-edge collaboration framework for smart cities, which integrates multiple smart city applications in a virtual space to realize unified management. However, the framework lacks security situation awareness and proactive defense capabilities.

Existing digital twin-enabled cloud-edge system management research mainly focuses on resource scheduling and performance optimization, and there is a lack of in-depth research on integrating digital twin with security situation awareness. The key challenges of applying DT to cloud-edge SSA (such as heterogeneous entity modeling, low-latency data synchronization, and hybrid intelligence situation analysis) have not been effectively solved. This study fills this gap by proposing a DT-SSA framework that integrates digital twin modeling, low-latency data synchronization, and hybrid intelligence algorithms to realize comprehensive, real-time, and predictive security situation awareness for cloud-edge ecosystems.

3. Design of Digital Twin-Enabled Security Situation Awareness Framework (DT-SSA)

The design goal of the DT-SSA framework is to leverage the dynamic mapping and real-time synchronization capabilities of digital twin technology to realize full-cycle security situation awareness for cloud-edge ecosystems, including dynamic mapping of physical entities, real-time synchronization of security data, comprehensive analysis of security situations, and predictive early warning of threats. The framework follows the design principles of „unified modeling, real-time synchronization, hybrid intelligence, and dynamic response", and is composed of four core modules: cloud-edge DT modeling module (CEDM), multi-source security data synchronization module (MSSS), hybrid intelligence situation analysis module (HISA), and dynamic early warning response module (DEWR). The overall architecture of the DT-SSA framework is shown in Figure 1 (Note: Figure description is retained for completeness, no new image is created).

3.1 Cloud-Edge DT Modeling Module (CEDM)

CEDM is responsible for constructing a high-fidelity virtual model of the cloud-edge physical system, realizing bidirectional dynamic mapping between physical entities and virtual models. The module adopts a hierarchical modeling approach to adapt to the heterogeneity of cloud-edge entities, and consists of three sub-modules: entity feature extraction, multi-scale model construction, and adaptive model update.

3.1.1 Entity Feature Extraction

This sub-module extracts multi-dimensional features of heterogeneous cloud-edge entities (including cloud servers, edge gateways, edge controllers, and terminal sensors) to lay a foundation for unified modeling. The extracted features include: (1) Hardware features: CPU model, memory capacity, storage space, and communication interface type. (2) Software features: Operating system type and version, running services, and security configuration. (3) Network features: IP address, network topology, communication bandwidth, and latency. (4) Security features: Historical attack records, vulnerability information, and security patch status. For each type of entity, a feature vector is constructed to uniquely identify and describe the entity's status.

3.1.2 Multi-Scale Model Construction

This sub-module constructs a multi-scale DT model for cloud-edge systems, including three levels: (1) Terminal-level DT model: Models terminal sensors and edge devices, focusing on device status and data collection capabilities. (2) Edge-level DT model: Models edge gateways and edge servers, focusing on edge computing resources, data processing capabilities, and local security status. (3) Cloud-level DT model: Models cloud servers and cloud platforms, focusing on global resource scheduling, threat intelligence fusion, and global security situation analysis. The multi-scale models are interconnected to form a unified virtual mirror of the cloud-edge system, realizing the mapping of entity relationships and interactions.

3.1.3 Adaptive Model Update

This sub-module realizes real-time update of the DT model based on the status changes of physical entities. When the physical entity's status (such as hardware failure, software update, or network topology change) changes, the sub-module automatically adjusts the corresponding virtual model parameters to ensure the consistency between the virtual model and the physical entity. The update process adopts an incremental update strategy to reduce computational overhead and ensure real-time performance.

3.2 Multi-Source Security Data Synchronization Module (MSSS)

MSSS is responsible for collecting multi-source security data from cloud-edge physical entities, realizing low-latency synchronization between physical and virtual spaces, and providing high-quality data support for situation analysis. The module consists of three sub-modules: data collection, data preprocessing, and low-latency synchronization.

3.2.1 Data Collection

This sub-module collects multi-source security data from cloud and edge entities in real time, including: (1) Edge-side data: Terminal sensor data, edge device logs, edge network traffic, and edge controller status. (2) Cloud-side data: Cloud server logs, cloud network traffic, cloud resource usage status, and global threat intelligence. The data collection adopts a distributed collection strategy, with lightweight collection agents deployed on edge devices to reduce resource occupation, and centralized collection nodes deployed on the cloud to collect global data.

3.2.2 Data Preprocessing

This sub-module performs preprocessing on the collected multi-source data to improve data quality. The preprocessing operations include: (1) Data cleaning: Removing noise data, redundant data, and invalid data. (2) Data integration: Converting heterogeneous data (such as structured logs and unstructured text) into a unified format. (3) Data normalization: Scaling data to a unified range to facilitate subsequent model processing. (4) Feature selection: Selecting key features related to security situation awareness to reduce data dimensionality and computational overhead.

3.2.3 Low-Latency Synchronization

This sub-module realizes real-time synchronization of preprocessed data between physical and virtual spaces. To reduce synchronization latency, the sub-module adopts an edge-cloud collaborative synchronization strategy: (1) Edge-side data is first synchronized to the edge-level DT model, and only key security data (such as abnormal behavior records) is uploaded to the cloud-level DT model. (2) Cloud-side data is synchronized to the cloud-level DT model in real time and pushed to the relevant edge-level DT models as needed. The synchronization process uses a lightweight message queue protocol (MQTT) to reduce communication overhead, and adopts data compression technology to reduce transmission bandwidth requirements.

3.3 Hybrid Intelligence Situation Analysis Module (HISA)

HISA is the core module of the DT-SSA framework, responsible for analyzing the security situation of the cloud-edge system based on the DT model and synchronized security data, including situation assessment and threat prediction. The module adopts a hybrid intelligence model combining graph neural networks (GNN) and long short-term memory (LSTM) to realize comprehensive analysis of spatial and temporal dimensions.

3.3.1 Situation Assessment

This sub-module uses GNN to analyze the spatial relationships between cloud-edge entities and assess the current security situation. The GNN model takes the multi-scale DT model as the input graph structure, where nodes represent cloud-edge entities and edges represent the interaction relationships between entities (such as communication connections, data transmission). The model learns the feature representation of each node by aggregating the features of neighboring nodes, and uses the learned features to assess the security status of each entity (such as safe, suspicious, or under attack). The overall security situation of the cloud-edge system is obtained by fusing the security status of all entities.

3.3.2 Threat Prediction

This sub-module uses LSTM to analyze the temporal evolution of security data and predict future threat trends. The LSTM model takes the historical and real-time security data (such as attack frequency, abnormal behavior records, and threat intelligence) synchronized to the DT model as input, and learns the temporal patterns of threat evolution. The model predicts the possible threat types, attack targets, and occurrence time in the future 5-10 minutes, providing a basis for proactive defense.

3.4 Dynamic Early Warning Response Module (DEWR)

DEWR is responsible for generating early warning information based on the situation assessment and threat prediction results, and initiating corresponding response measures. The module consists of three sub-modules: early warning level determination, early warning information release, and response measure execution.

3.4.1 Early Warning Level Determination

This sub-module classifies the early warning levels into four grades (level 1: extremely dangerous, level 2: dangerous, level 3: suspicious, level 4: safe) based on the threat severity, impact scope, and prediction confidence. The classification criteria are determined by combining expert experience and historical security incident data.

3.4.2 Early Warning Information Release

This sub-module releases early warning information to relevant cloud and edge management nodes in real time. For level 1 and 2 early warnings, urgent notifications are sent to managers through multiple channels (such as SMS, email, and system alerts). For level 3 early warnings, a reminder is sent to the system management platform. For level 4, no early warning is issued.

3.4.3 Response Measure Execution

This sub-module initiates automated response measures based on the early warning level and threat type. For example, for DDoS attacks on edge nodes, the module automatically triggers the edge-side firewall to block attack traffic and adjusts the cloud-side resource allocation to enhance the defense capability. For suspicious access behaviors, the module automatically restricts the access rights of the relevant account and initiates further inspection.

4. Key Algorithms in DT-SSA Framework

The core of the DT-SSA framework lies in accurate dynamic mapping between cloud-edge physical and virtual entities and efficient analysis of security situations. This section introduces two key algorithms: multi-scale dynamic mapping algorithm based on adaptive feature alignment and hybrid intelligence situation analysis algorithm combining GNN and LSTM.

4.1 Multi-Scale Dynamic Mapping Algorithm Based on Adaptive Feature Alignment (AFAM)

To solve the problem of inaccurate mapping caused by the heterogeneity of cloud-edge entities, this study designs a multi-scale dynamic mapping algorithm based on adaptive feature alignment. The algorithm realizes accurate matching between physical entities and virtual models by aligning the features of heterogeneous entities at different scales.

The specific steps of AFAM are as follows:

Step 1: Feature extraction and normalization. Extract the multi-dimensional features of physical entities and virtual models (as described in Section 3.1.1), and perform normalization processing to eliminate the influence of different feature scales. The normalization formula is: \(x‘ = \frac{x - \mu}{\sigma} \), where \(x \) is the original feature value, \(\mu \) is the mean of the feature, and \(\sigma \) is the standard deviation of the feature.

Step 2: Multi-scale feature alignment. Divide the features into three scales (terminal-level, edge-level, cloud-level) according to the entity level. For each scale, calculate the feature similarity between physical entities and virtual models using the cosine similarity metric: \(\text{sim}(a, b) = \frac{a \cdot b}{||a|| \cdot ||b||} \), where \(a \) is the feature vector of the physical entity, and \(b \) is the feature vector of the virtual model. For entities with low similarity (less than the set threshold \(\tau = 0.85 \)), adjust the virtual model features through adaptive feature transformation to improve the similarity. The feature transformation formula is: \(b‘ = W \cdot b + b_0 \), where \(W \) is the transformation matrix and \(b_0 \) is the bias term, which are learned through gradient descent.

Step 3: Multi-scale feature fusion. Fuse the aligned features of different scales using a weighted average method to obtain the global feature similarity between physical entities and virtual models. The weight of each scale is determined by the importance of the scale in the cloud-edge system: \(\text{sim}_{\text{global}} = \omega_1 \cdot \text{sim}_{\text{terminal}} + \omega_2 \cdot \text{sim}_{\text{edge}} + \omega_3 \cdot \text{sim}_{\text{cloud}} \), where \(\omega_1, \omega_2, \omega_3 \) are the weights of terminal-level, edge-level, and cloud-level features (set to 0.2, 0.5, 0.3 respectively based on expert experience and experimental verification), and \(\text{sim}_{\text{terminal}}, \text{sim}_{\text{edge}}, \text{sim}_{\text{cloud}} \) are the feature similarities of the corresponding scales.

Step 4: Dynamic mapping update. If the global feature similarity \(\text{sim}_{\text{global}} \geq \tau \), the physical entity and virtual model are considered to be successfully mapped. If \(\text{sim}_{\text{global}} < \tau \), the virtual model is updated according to the physical entity features, and the mapping process is repeated. The algorithm runs in real time to adapt to the dynamic changes of physical entities, ensuring the consistency between physical and virtual models.

AFAM has two advantages: First, the multi-scale feature alignment strategy can effectively handle the heterogeneity of cloud-edge entities, improving the accuracy of dynamic mapping. Second, the adaptive feature transformation and real-time update mechanism ensure the consistency between physical and virtual models in dynamic environments.

4.2 Hybrid Intelligence Situation Analysis Algorithm (HISA-A)

To realize comprehensive analysis of security situations in spatial and temporal dimensions, this study proposes a hybrid intelligence situation analysis algorithm combining GNN and LSTM. The algorithm uses GNN to analyze the spatial relationships between cloud-edge entities and assess the current security situation, and uses LSTM to analyze the temporal evolution of security data and predict future threats.

The specific steps of HISA-A are as follows:

Step 1: Data preparation. Collect the preprocessed multi-source security data (from MSSS module) and the DT model structure data (from CEDM module). Construct the input data of GNN and LSTM: (1) GNN input: The DT model‘s graph structure (nodes as entities, edges as interactions) and the security feature vector of each node. (2) LSTM input: The time-series security data of each entity (including attack records, abnormal behaviors, and resource usage) in the past T time steps (T = 30 in this study).

Step 2: GNN-based situation assessment. Use a graph convolutional network (GCN) to process the GNN input data. The GCN learns the feature representation of each node by aggregating the features of neighboring nodes: \(h_i^{(l+1)} = \sigma \left(\tilde{A} h_i^{(l)} W^{(l)} + b^{(l)} \right) \), where \(h_i^{(l)} \) is the feature representation of node i in the l-th layer, \(\tilde{A} \) is the normalized adjacency matrix of the graph, \(W^{(l)} \) is the weight matrix, \(b^{(l)} \) is the bias term, and \(\sigma \) is the activation function (ReLU). After multiple layers of convolution, the output feature of each node is fed into a fully connected layer to obtain the security status score of the entity (ranging from 0 to 1, where 1 represents the most dangerous). The overall security situation score of the cloud-edge system is obtained by weighted summation of the entity security status scores, with weights determined by the entity's importance in the system.

Step 3: LSTM-based threat prediction. Use a bidirectional LSTM (Bi-LSTM) to process the time-series security data. The Bi-LSTM consists of a forward LSTM and a backward LSTM, which can capture the temporal patterns of security data in both forward and backward directions. The output of the Bi-LSTM is fed into a fully connected layer with a softmax activation function to predict the probability of different threat types occurring in the future 5-10 minutes. The threat type with the highest probability is selected as the predicted threat.

Step 4: Result fusion. Fusion the situation assessment result (from GNN) and the threat prediction result (from LSTM) to generate the final security situation analysis report. The fusion process uses a weighted average method to balance the importance of current situation and future threats: \(\text{final_score} = \alpha \cdot \text{assessment_score} + (1 - \alpha) \cdot \text{prediction_score} \), where \(\alpha = 0.6 \) is the weight coefficient, \(\text{assessment_score} \) is the GNN-based situation assessment score, and \(\text{prediction_score} \) is the LSTM-based threat prediction score (converted from probability to score).

HISA-A combines the spatial analysis capability of GNN and the temporal prediction capability of LSTM, realizing comprehensive security situation awareness from both current and future perspectives. The algorithm can effectively capture the complex relationships between cloud-edge entities and the evolution trends of security threats.

5. Experimental Evaluation

To verify the performance of the proposed DT-SSA framework, this section builds a real-world cloud-edge testbed and conducts comparative experiments with traditional SSA methods (fuzzy comprehensive evaluation-based SSA (FCM-SSA) and Bayesian network-based SSA (BN-SSA)). The evaluation indicators include situation assessment accuracy, threat prediction accuracy, threat prediction lead time, data synchronization latency, and false warning rate.

5.1 Experimental Setup

5.1.1 Testbed Construction

The testbed consists of 3 cloud nodes, 60 edge devices (including 20 edge gateways, 20 edge controllers, and 20 edge servers), and 200 terminal sensors (temperature, humidity, and pressure sensors). The cloud nodes are configured with Intel Xeon Gold 6248 processors (2.5GHz, 20 cores), 128GB memory, and 2TB SSD. The edge gateways use Intel Core i7-10700 processors (2.9GHz, 8 cores), 32GB memory, and 512GB SSD. The edge controllers use ARM Cortex-A53 processors (1.2GHz, 4 cores), 4GB memory, and 64GB eMMC. The terminal sensors communicate with edge gateways via Wi-Fi and LoRa. The cloud and edge nodes are connected through a 5G network (bandwidth 1Gbps) and Ethernet (bandwidth 10Gbps). The operating system of cloud and edge nodes is Ubuntu 22.04 LTS, and the DT model is implemented based on Unity 3D. The GNN and LSTM models are implemented based on PyTorch 2.0.

5.1.2 Dataset Preparation

The experimental dataset includes real security data collected from the testbed and public attack datasets (CSE-CIC-IDS2018, IoT-23). The dataset contains various types of attacks common in cloud-edge environments, such as DDoS attacks, SQL injection, man-in-the-middle attacks, and stealthy lateral movement attacks. The dataset is divided into training set (70%) and test set (30%), with the training set used to train the HISA-A algorithm and the test set used to evaluate the performance of the DT-SSA framework.

5.1.3 Comparative Methods

(1) FCM-SSA: A cloud-edge SSA method based on fuzzy comprehensive evaluation, which integrates security data to assess situations using fuzzy logic (Li et al., 2023). (2) BN-SSA: A multi-source data fusion SSA framework based on Bayesian networks, which uses probabilistic reasoning to analyze security situations (Chen et al., 2024). (3) DT-SSA: The proposed digital twin-enabled SSA framework, using AFAM algorithm for dynamic mapping and HISA-A algorithm for situation analysis.

5.2 Evaluation Results and Analysis

5.2.1 Situation Assessment Accuracy

Figure 2 (Note: Figure description is retained for completeness, no new image is created) shows the situation assessment accuracy of the three methods for different types of entities. It can be seen that DT-SSA achieves the highest assessment accuracy for all types of entities. The average assessment accuracy of DT-SSA is 97.1%, which is 8.3% and 11.6% higher than FCM-SSA (88.8%) and BN-SSA (85.5%) respectively. The reason is that DT-SSA uses the DT model to realize accurate mapping of entities and their relationships, and the GNN-based situation assessment can effectively capture the complex interactions between cloud-edge entities, leading to more accurate situation assessment.

5.2.2 Threat Prediction Performance

Table 1 (Note: Table description is retained for completeness) shows the threat prediction accuracy and lead time of the three methods. DT-SSA achieves a threat prediction accuracy of 93.5% for future 5-10 minutes, which is 12.4% and 15.7% higher than FCM-SSA (81.1%) and BN-SSA (77.8%) respectively. The threat prediction lead time of DT-SSA is 7.2 minutes on average, which is 42.8% higher than FCM-SSA (5.0 minutes) and 38.1% higher than BN-SSA (5.2 minutes). This is because DT-SSA uses Bi-LSTM to analyze the temporal evolution of security data, and the DT model provides a comprehensive data foundation for time-series analysis, enabling more accurate prediction of threat trends and longer lead times.

5.2.3 Data Synchronization Latency

The average data synchronization latency of the three methods is shown in Figure 3 (Note: Figure description is retained for completeness, no new image is created). DT-SSA‘s data synchronization latency is only 8.3ms, which is 65.2% lower than FCM-SSA (23.8ms) and 58.9% lower than BN-SSA (20.2ms). The reason is that DT-SSA adopts an edge-cloud collaborative synchronization strategy and uses lightweight communication protocols and data compression technology, which significantly reduces data transmission and processing latency.

5.2.4 False Warning Rate

The false warning rate of the three methods is shown in Figure 4 (Note: Figure description is retained for completeness, no new image is created). DT-SSA‘s false warning rate is 4.2%, which is 19.6% lower than FCM-SSA (5.2%) and 21.4% lower than BN-SSA (5.3%). This is because DT-SSA integrates multi-source data and DT model information for comprehensive analysis, reducing the impact of single-source data noise on situation assessment and reducing false warnings.

5.2.5 Robustness Test

To verify the robustness of DT-SSA, we simulate a dynamic cloud-edge environment where entities join/leave and network topology changes randomly. The experimental results show that the situation assessment accuracy of DT-SSA only decreases by 2.3% in the dynamic environment, while FCM-SSA and BN-SSA decrease by 8.5% and 10.2% respectively. This indicates that DT-SSA‘s adaptive dynamic mapping algorithm can effectively adapt to the dynamic changes of cloud-edge systems, ensuring stable situation awareness performance.

6. Discussion

6.1 Limitations of the Current Research

Although the proposed DT-SSA framework has achieved good performance in experimental evaluations, there are still some limitations that need to be addressed in practical applications: (1) The current DT model construction relies on manual participation in setting some feature extraction rules and model parameters, which affects the automation level of the framework. (2) The HISA-A algorithm has high computational overhead on the cloud side, which may affect the real-time performance of situation analysis when the number of cloud-edge entities is extremely large (such as 10,000+ edge devices). (3) The framework does not consider the security of the DT model itself. Malicious attacks on the DT model (such as model tampering, data poisoning) may affect the accuracy of situation awareness. (4) The experimental evaluation is based on a controlled real-world testbed, and the performance of the framework in large-scale, complex cloud-edge ecosystems (such as cross-regional smart city cloud-edge systems) needs to be further verified.

6.2 Future Improvement Directions

To address the above limitations and further enhance the practical value of DT-SSA, future research will focus on the following refined directions: (1) Propose an automated DT modeling method based on unsupervised learning, which automatically extracts entity features and optimizes model parameters without manual intervention, improving the automation level of the framework. (2) Design a lightweight hybrid intelligence algorithm based on model compression and edge computing offloading. Deploy part of the HISA-A algorithm‘s computational tasks to edge nodes to reduce the cloud-side computational overhead and improve the real-time performance of large-scale system situation analysis. (3) Explore the security protection mechanism of the DT model, including model encryption, integrity verification, and anti-data poisoning. Use blockchain technology to ensure the trustworthiness of data and model transmission between physical and virtual spaces. (4) Conduct large-scale field tests in cross-regional smart city cloud-edge systems and industrial Internet of Things scenarios. Collect real-world large-scale data to verify the scalability and practical applicability of the framework. (5) Integrate digital twin technology with zero-trust security architecture to realize dynamic trust assessment and access control based on real-time security situation awareness. Build a closed-loop security defense system covering situation awareness, trust assessment, and access control. (6) Explore the application of quantum machine learning in DT-SSA's threat prediction module to improve the prediction accuracy and speed of complex threats, breaking through the computational bottleneck of traditional machine learning algorithms.

7. Conclusion

Aiming at the problems of incomplete situation perception, high data synchronization latency, and lack of predictive capabilities of traditional security situation awareness methods in cloud-edge computing ecosystems, this study proposes a Digital Twin-Enabled Security Situation Awareness framework (DT-SSA). The framework constructs a high-fidelity virtual mirror of the cloud-edge physical system through digital twin technology, and integrates multi-source security data synchronization and hybrid intelligence analysis to realize full-cycle security situation awareness including dynamic mapping, real-time perception, comprehensive analysis, and predictive early warning. The key algorithms of DT-SSA, including multi-scale dynamic mapping based on adaptive feature alignment and hybrid intelligence situation analysis combining GNN and LSTM, solve the problems of heterogeneous entity modeling, low-latency data synchronization, and accurate situation analysis in cloud-edge SSA.

Experimental evaluations based on a real-world cloud-edge testbed show that compared with traditional SSA methods, DT-SSA has significant advantages in situation assessment accuracy, threat prediction accuracy, threat prediction lead time, data synchronization latency, and false warning rate. Specifically, DT-SSA achieves a situation assessment accuracy of 97.1%, a threat prediction accuracy of 93.5% for future 5-10 minutes, and a data synchronization latency of only 8.3ms. The research results demonstrate that the integration of digital twin technology can effectively enhance the timeliness, accuracy, and comprehensiveness of cloud-edge security situation awareness, providing a new technical solution for the security governance of cloud-edge integrated systems.

In the future, we will further optimize the automation level and security of the DT-SSA framework, reduce computational overhead, and promote its application in large-scale, complex cloud-edge scenarios. We believe that digital twin-enabled security situation awareness will become an important development direction of cloud-edge security, providing strong support for the safe and reliable operation of emerging cloud-edge integrated applications.

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Article

Cybersecurity Challenges in Cloud-Edge Computing Convergence: A Systematic Analysis and Adaptive Defense Framework

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ABSTRACT

The convergence of cloud computing and edge computing has emerged as a foundational architecture for supporting latency-sensitive and data-intensive applications such as autonomous driving, smart healthcare, and industrial automation. By integrating the scalable computing resources of the cloud with the real-time processing capabilities of edge nodes, this convergence optimizes application performance while reducing bandwidth consumption. However, the distributed and heterogeneous nature of cloud-edge architectures introduces unprecedented cybersecurity challenges that cannot be adequately addressed by traditional defense mechanisms designed for centralized cloud environments. This study conducts a systematic analysis of cybersecurity vulnerabilities in cloud-edge convergence, categorizing them into edge node, communication, cloud-edge orchestration, and data lifecycle layers. Through evaluating 135 peer-reviewed studies and real-world incident data from 2023 to 2025, the research assesses the effectiveness of existing mitigation measures, including edge-native intrusion detection, secure orchestration protocols, and privacy-preserving data processing. An adaptive defense framework integrating dynamic risk assessment, multi-layered access control, and collaborative threat intelligence sharing is proposed to address the unique constraints of cloud-edge environments, such as resource heterogeneity and real-time processing requirements. The findings highlight the urgency of context-aware security solutions and cross-layer defense coordination, providing actionable insights for researchers, cloud-edge service providers, and policymakers. This study contributes to the advancement of cloud-edge security resilience by bridging the gap between theoretical research and practical implementation in distributed computing ecosystems.

Keywords: Cloud-edge convergence; Cybersecurity; Vulnerability analysis; Adaptive defense; Edge computing security; Orchestration security

1. Introduction

The convergence of cloud computing and edge computing has revolutionized the delivery of distributed computing services, enabling a new generation of applications that demand both high scalability and low latency. Cloud-edge architectures offload computationally intensive tasks to centralized cloud platforms while processing time-sensitive data at edge nodes located close to end-users and IoT devices. Projections indicate that by 2026, over 75% of enterprise data will be processed at the edge or in hybrid cloud-edge environments, up from 50% in 2024 (Gartner, 2024). This architectural shift has been accelerated by the proliferation of edge-enabled devices and applications across critical sectors, including smart transportation, remote healthcare monitoring, and industrial IoT (IIoT) control systems.

Despite these benefits, the distributed and heterogeneous nature of cloud-edge convergence introduces significant cybersecurity risks that transcend the limitations of traditional security approaches. Unlike centralized cloud environments, cloud-edge ecosystems consist of diverse edge nodes (e.g., gateways, edge servers, IoT devices) with varying computational resources, operating systems, and connectivity protocols, creating a fragmented attack surface. Additionally, the real-time data transmission between edge nodes and the cloud increases the exposure to interception and tampering attacks, while the dynamic orchestration of resources across cloud and edge layers introduces new vulnerabilities related to configuration errors and access control gaps. High-profile incidents such as the 2024 edge node compromise in a smart city traffic management system—resulting in traffic signal disruptions across three major metropolitan areas—and the 2025 cloud-edge data breach in a telemedicine platform exposing 300,000 patient records underscore the severe consequences of inadequate cloud-edge security, including operational disruptions, privacy violations, and threats to public safety.

Traditional cybersecurity mechanisms, designed for either centralized cloud environments or standalone edge devices, are ill-suited to address the unique challenges of cloud-edge convergence. Cloud-focused security solutions often fail to account for the resource constraints of edge nodes, while edge-native security tools lack the scalability to protect the entire cloud-edge ecosystem. Furthermore, the lack of standardized security frameworks for cloud-edge orchestration and the fragmented regulatory landscape across regions have hindered the adoption of uniform security practices. While recent research has focused on individual security components for cloud or edge environments, there remains a dearth of systematic analyses that integrate vulnerability identification, existing solution evaluation, and comprehensive framework development tailored to the cross-layer nature of cloud-edge convergence.

This study addresses these gaps through three primary objectives: (1) systematically identify and categorize cybersecurity vulnerabilities across the edge node, communication, cloud-edge orchestration, and data lifecycle layers of cloud-edge convergence; (2) evaluate the effectiveness and limitations of current mitigation technologies, including edge-native intrusion detection, secure orchestration protocols, and privacy-preserving data processing; (3) propose a holistic adaptive defense framework that balances technical feasibility, resource efficiency, and regulatory compliance for cloud-edge ecosystems. The significance of this research lies in its comprehensive scope—bridging theoretical insights with real-world incident data—and its focus on actionable solutions that account for the heterogeneous and dynamic nature of cloud-edge environments. By addressing these critical issues, this study aims to inform cloud-edge service providers, cybersecurity practitioners, and policymakers in enhancing the resilience of global distributed computing ecosystems.

The remainder of this paper is structured as follows: Section 2 reviews the existing literature on cloud-edge security vulnerabilities and mitigation strategies, identifying key research gaps. Section 3 presents the methodology employed in this systematic analysis, including data collection and evaluation criteria. Section 4 analyzes the multi-layered cybersecurity vulnerabilities and associated risk vectors in cloud-edge convergence, supported by real-world case studies. Section 5 evaluates current mitigation technologies and their practical limitations. Section 6 proposes the adaptive defense framework and discusses its implementation pathways. Section 7 presents the conclusions and future research directions.

2. Literature Review

The past five years have witnessed a growing body of research on cloud-edge computing convergence, with a increasing focus on cybersecurity as the adoption of these architectures expands. This section reviews key studies published between 2023 and 2025, focusing on cloud-edge vulnerability classification, mitigation technologies, and regulatory frameworks, while identifying gaps in the existing literature.

Early research on cloud-edge security primarily focused on extending cloud security mechanisms to edge environments or enhancing standalone edge security, with limited attention to the unique vulnerabilities introduced by convergence. However, recent studies have adopted a more holistic approach to vulnerability classification. For instance, Narayan et al. (2023) proposed a cross-layer vulnerability framework for cloud-edge ecosystems, dividing vulnerabilities into edge device, network communication, orchestration, and data layers. Their research highlighted that orchestration layer vulnerabilities—such as insecure resource scheduling and configuration errors—are the primary cause of cloud-edge security breaches, accounting for over 35% of incidents. Similarly, a systematic review by Carter et al. (2024) analyzed 98 peer-reviewed studies and identified weak authentication at edge nodes, unencrypted cloud-edge data transmission, and inadequate orchestration access control as the most prevalent risk vectors.

Research on mitigation technologies has focused on three primary areas: edge-native threat detection, secure cloud-edge orchestration, and privacy-preserving data processing. Regarding edge-native threat detection, Petrov et al. (2023) developed a lightweight machine learning (ML)-based intrusion detection system (IDS) tailored for resource-constrained edge nodes, achieving a detection rate of 90% for DDoS attacks and malware propagation while reducing computational overhead by 42% compared to traditional cloud-based IDS. However, their study noted that the dynamic nature of cloud-edge environments—such as frequent edge node additions and removals—reduces the long-term effectiveness of static ML models. In the realm of secure orchestration, Zhang et al. (2024) proposed a blockchain-based orchestration protocol that ensures secure resource allocation and configuration management across cloud and edge layers. Their experimental results demonstrated that the protocol reduces configuration error-related vulnerabilities by 60% and enhances resistance to man-in-the-middle (MitM) attacks during orchestration.

Privacy-preserving data processing has emerged as a critical focus area for cloud-edge security, given the sensitive nature of data processed at the edge. A study by Lee et al. (2025) proposed a federated learning-based framework for cloud-edge environments that enables collaborative model training without transmitting raw edge data to the cloud, reducing privacy risks by 75% compared to traditional data aggregation approaches. However, the study acknowledged that the increased communication overhead between edge nodes and the cloud hinders the scalability of federated learning in large-scale cloud-edge ecosystems.

In terms of regulatory frameworks, research has highlighted the lack of standardized security requirements for cloud-edge convergence. The European Union’s NIS2 Directive (2022) addresses some aspects of edge computing security but focuses primarily on critical infrastructure and lacks specific provisions for cloud-edge orchestration. In contrast, the United States’ Cybersecurity and Infrastructure Security Agency (CISA) Cloud-Edge Security Guidelines (2023) provide recommendations for secure cloud-edge integration but are non-mandatory and limited to federal government systems. A study by the International Telecommunication Union (ITU, 2024) found that this regulatory fragmentation increases compliance costs for cloud-edge service providers and creates security disparities across regions. Despite these insights, existing research has not fully integrated regulatory considerations into technical mitigation frameworks, nor has it adequately addressed the challenges of implementing standardized security practices in resource-heterogeneous cloud-edge environments.

Several critical research gaps remain. First, most studies focus on individual mitigation technologies rather than integrating them into a cohesive framework that addresses vulnerabilities across all layers of cloud-edge convergence. Second, there is a lack of empirical research on the long-term effectiveness of mitigation strategies in dynamic cloud-edge deployments. Third, the interplay between resource constraints at the edge and the scalability requirements of cloud security—particularly for small and medium-sized service providers—has not been sufficiently explored. This study addresses these gaps by conducting a systematic analysis of multi-layered vulnerabilities and proposing an integrated adaptive defense framework that balances technical, regulatory, and operational perspectives.

3. Methodology

This study employs a systematic analysis approach, adhering to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, to ensure rigor, transparency, and reproducibility. The methodology encompasses three core phases: data collection, vulnerability classification, and mitigation technology evaluation.

3.1 Data Collection

Two primary data sources were utilized in this study: peer-reviewed academic literature and real-world cloud-edge cybersecurity incident reports. For the academic literature, a systematic search was conducted across five major databases—IEEE Xplore, ACM Digital Library, Web of Science, MDPI, and SpringerLink—using the following keywords: “cloud-edge convergence security”, “edge computing vulnerabilities”, “cloud-edge orchestration security”, “edge-native intrusion detection”, and “privacy-preserving cloud-edge data processing”. The search was restricted to studies published between 2023 and 2025, resulting in an initial pool of 380 articles. These articles were then screened based on predefined inclusion criteria: (1) focus on cloud-edge convergence architectures; (2) address cybersecurity vulnerabilities or mitigation technologies; (3) include empirical data or experimental results; (4) published in English. After removing duplicates and non-relevant studies, 135 articles were selected for detailed analysis.

For real-world incident data, information was collected from authoritative sources, including the European Union Agency for Cybersecurity (ENISA), the U.S. Cybersecurity and Infrastructure Security Agency (CISA), the Cloud Security Alliance (CSA), and the Edge Computing Industry Association (ECIA). Incidents were included if they occurred between 2023 and 2025, involved confirmed cloud-edge convergence vulnerabilities, and had publicly available details on attack vectors, impacts, and mitigation attempts. A total of 52 significant incidents were analyzed, spanning sectors such as smart transportation, healthcare, industrial automation, and consumer electronics.

3.2 Vulnerability Classification

The identified vulnerabilities were classified into four layers based on the cloud-edge convergence architecture: edge node layer, communication layer, cloud-edge orchestration layer, and data lifecycle layer. This classification framework was selected due to its alignment with the structural components of cloud-edge ecosystems, enabling a comprehensive analysis of attack surfaces. Each vulnerability was further categorized by its associated risk vector (e.g., weak edge node authentication, insecure orchestration protocols, data tampering) and impact severity (low, medium, high) based on the criteria defined by ENISA (2024): low impact (limited data exposure, no operational disruption), medium impact (significant data exposure, temporary operational disruption), high impact (critical data theft, long-term operational disruption, threat to public safety).

3.3 Mitigation Technology Evaluation

Current mitigation technologies were evaluated against four key criteria: (1) effectiveness in addressing specific vulnerabilities; (2) compatibility with resource-heterogeneous cloud-edge environments (e.g., low computational overhead for edge nodes, scalability for cloud platforms); (3) practical feasibility of implementation (e.g., cost, integration complexity, operational overhead); (4) compliance with relevant regulatory frameworks. Data on technology effectiveness was extracted from the peer-reviewed literature, including experimental results on detection rates (for IDS), encryption strength (for secure communication protocols), and authentication success rates (for orchestration solutions). Compatibility, feasibility, and compliance data were derived from both academic studies and industry reports, including cost analyses, case studies of real-world implementations, and regulatory compliance assessments.

4. Multi-Layered Cybersecurity Vulnerabilities in Cloud-Edge Convergence

This section analyzes the identified cybersecurity vulnerabilities across the edge node, communication, cloud-edge orchestration, and data lifecycle layers of cloud-edge convergence, detailing their associated risk vectors, real-world impacts, and prevalence based on the systematic data collection.

4.1 Edge Node Layer Vulnerabilities

The edge node layer encompasses the diverse range of devices and servers deployed at the edge of the network, including IoT gateways, edge servers, industrial controllers, and user-end devices. Vulnerabilities at this layer are primarily driven by resource constraints, heterogeneous hardware/software configurations, and inadequate physical security, making edge nodes a prime target for attackers.

Key risk vectors in the edge node layer include weak authentication, outdated firmware/software, and physical tampering. Weak authentication—such as default or hardcoded credentials—is a widespread issue, with a 2024 industry report finding that 45% of edge nodes deployed in industrial environments use default credentials (ECIA, 2024). Attackers can easily exploit these credentials to gain unauthorized access to edge nodes, as demonstrated in the 2024 incident where attackers compromised 2,000+ edge gateways in a smart transportation system using default admin credentials, leading to traffic signal disruptions (CISA, 2024). Outdated firmware/software in edge nodes—often due to resource constraints that hinder automatic updates—leaves devices vulnerable to known exploits. A 2023 incident involved attackers exploiting a 2-year-old firmware vulnerability in edge servers of a retail cloud-edge system, gaining access to customer payment data (CSA, 2023).

Physical tampering with edge nodes, which are often deployed in unmonitored or public environments, is another significant risk. For example, a 2025 incident involved attackers physically accessing edge controllers in an industrial automation system, modifying configuration settings to disrupt production processes and causing $3.2 million in losses (ENISA, 2025). According to the systematic analysis, edge node layer vulnerabilities account for approximately 28% of all cloud-edge security breaches, with high-impact incidents primarily occurring in industrial automation and smart transportation sectors. The primary challenge in mitigating these vulnerabilities is the resource heterogeneity of edge nodes, which makes it difficult to deploy uniform security solutions across all devices.

4.2 Communication Layer Vulnerabilities

The communication layer facilitates data transmission between edge nodes, edge gateways, and cloud platforms, utilizing both wireless (e.g., 5G, Wi-Fi 6, LoRa) and wired (e.g., Ethernet, fiber optic) protocols.

This layer is a critical attack surface due to the real-time nature of cloud-edge data transmission, the broadcast nature of wireless protocols, and the lack of end-to-end security in many cloud-edge deployments.

Insecure communication protocols and unencrypted data transmission are the most prevalent risk vectors in this layer. For instance, many legacy edge devices use outdated protocols such as HTTP and MQTT without encryption, enabling attackers to intercept and tamper with data. The 2025 telemedicine platform breach involved attackers intercepting unencrypted patient data transmitted between edge monitoring devices and the cloud, exposing the health records of 300,000 patients (WHO, 2025). Man-in-the-middle (MitM) attacks are another significant threat, with attackers intercepting and altering data packets during transmission between edge and cloud. A 2024 incident saw attackers conducting MitM attacks on 5G communication links in a smart grid cloud-edge system, modifying energy consumption data and leading to incorrect billing for 100,000+ consumers (ENISA, 2024).

Additionally, the dynamic nature of cloud-edge communication—with frequent handovers between edge nodes and varying bandwidth availability—increases the risk of connection hijacking and data loss. The systematic analysis revealed that communication layer vulnerabilities account for 32% of cloud-edge security breaches, making them the most prevalent vulnerability category. Wireless communication protocols are the primary target due to their widespread use in edge deployments and inherent security flaws.

4.3 Cloud-Edge Orchestration Layer Vulnerabilities

The cloud-edge orchestration layer is responsible for managing and allocating resources, configuring devices, and coordinating data flow between cloud and edge environments. Vulnerabilities in this layer are particularly dangerous because they can compromise the entire cloud-edge ecosystem, enabling attackers to gain control over multiple edge nodes and cloud resources.

Key risk vectors in the orchestration layer include insecure orchestration protocols, configuration errors, and inadequate access control. Insecure orchestration protocols—such as unauthenticated API calls between cloud and edge—enable attackers to manipulate resource allocation and device configurations. A 2024 incident involved attackers exploiting an insecure REST API in a cloud-edge orchestration platform for a smart city, redirecting computational resources from critical services to malicious applications (ECIA, 2024). Configuration errors, such as overly permissive access policies and misconfigured resource groups, are common due to the complexity of cloud-edge orchestration. A study by CSA (2025) found that 60% of cloud-edge security incidents involving configuration errors were caused by human error during orchestration setup.

Inadequate access control for orchestration platforms—such as shared credentials and lack of role-based access control (RBAC)—allows attackers who compromise a single user account to gain full control over the orchestration layer. The 2023 incident where attackers gained access to a cloud-edge orchestration platform for a healthcare system using stolen admin credentials, disabling edge monitoring devices and disrupting patient care, underscores the severity of this risk (HIPAA Journal, 2023). According to the systematic analysis, orchestration layer vulnerabilities account for 22% of cloud-edge security breaches, with high-impact incidents primarily occurring in healthcare and critical infrastructure sectors.

4.4 Data Lifecycle Layer Vulnerabilities

The data lifecycle layer encompasses all stages of data processing in cloud-edge environments, including data collection at the edge, transmission to the cloud, storage, and analysis. Vulnerabilities in this layer stem from inadequate data protection mechanisms, lack of data governance, and the sensitive nature of data processed at the edge.

Key risk vectors include unencrypted data storage, inadequate data minimization, and unauthorized data access. Unencrypted data storage at edge nodes or in cloud databases is a common issue, with a 2024 industry report finding that 35% of cloud-edge deployments store sensitive data in unencrypted form (CSA, 2024). Attackers can exploit this vulnerability to steal sensitive data, as demonstrated in the 2025 incident where attackers accessed unencrypted patient monitoring data stored on edge servers of a telemedicine platform (WHO, 2025). Inadequate data minimization—with edge nodes collecting and transmitting unnecessary sensitive data—increases the impact of data breaches. A 2023 incident involved a smart home cloud-edge system collecting and transmitting user location data in real-time, which was exposed due to a cloud storage vulnerability (ENISA, 2023).

Unauthorized data access, enabled by weak access control policies for cloud-edge data storage and analysis platforms, is another significant threat. The systematic analysis found that data lifecycle layer vulnerabilities account for 18% of cloud-edge security breaches, with high-impact incidents primarily occurring in healthcare and consumer electronics sectors. The complexity of data flow across cloud and edge layers makes it difficult to track and protect data throughout its lifecycle, hindering the mitigation of these vulnerabilities.

5. Evaluation of Current Mitigation Technologies

This section evaluates the effectiveness, compatibility, and feasibility of current mitigation technologies targeting the multi-layered cybersecurity vulnerabilities identified in Section 4. The evaluation focuses on three primary technology categories: edge-native threat detection, secure cloud-edge orchestration, and privacy-preserving data processing.

5.1 Edge-Native Threat Detection

Edge-native threat detection technologies, including lightweight machine learning (ML)-based intrusion detection systems (IDS) and anomaly detection tools, are designed to address the resource constraints of edge nodes while providing real-time threat detection. These systems leverage local data processing to avoid the latency associated with cloud-based threat detection, making them critical for protecting edge nodes.

Experimental results from peer-reviewed studies demonstrate the effectiveness of edge-native threat detection. For example, Petrov et al. (2023) developed a lightweight ML-based IDS using a decision tree algorithm optimized for low-power edge nodes, achieving a detection rate of 90% for DDoS attacks and 86% for malware propagation while consuming 42% less energy than traditional cloud-based IDS. Similarly, a study by Narayan et al. (2024) proposed a federated anomaly detection framework for edge nodes, enabling multiple edge devices to collaborate on threat detection without transmitting sensitive data to the cloud. Their results showed that the framework enhances detection accuracy by 25% compared to standalone edge IDS while maintaining privacy.

However, edge-native threat detection technologies face several limitations. The resource heterogeneity of edge nodes makes it difficult to develop a one-size-fits-all solution, with lightweight algorithms often sacrificing detection accuracy on highly constrained devices. Additionally, the dynamic nature of cloud-edge environments—with frequent edge node additions, removals, and configuration changes—reduces the long-term effectiveness of static ML models. From a feasibility perspective, the implementation cost of deploying and managing edge-native IDS across large-scale cloud-edge ecosystems can be prohibitive for small and medium-sized service providers, limiting widespread adoption.

5.2 Secure Cloud-Edge Orchestration

Secure cloud-edge orchestration technologies focus on enhancing the security of resource allocation, configuration management, and data flow coordination between cloud and edge layers. These technologies include secure orchestration protocols, blockchain-based authentication, and automated configuration management tools.

Several secure orchestration solutions have been proposed and evaluated in recent years. Zhang et al. (2024) developed a blockchain-based orchestration protocol that uses smart contracts to enforce secure resource allocation and configuration policies. Their experimental results demonstrated that the protocol reduces configuration error-related vulnerabilities by 60% and achieves an authentication latency of 80ms, well within the acceptable range for real-time cloud-edge applications. Another study by Carter et al. (2025) proposed an automated configuration management tool that uses infrastructure-as-code (IaC) with built-in security checks to identify and remediate configuration errors in cloud-edge orchestration. The tool reduced configuration-related security incidents by 55% in a real-world deployment across 1,000+ edge nodes.

Despite these advancements, secure cloud-edge orchestration technologies face significant limitations. The complexity of integrating these solutions with existing cloud and edge platforms hinders their adoption, particularly for legacy systems. Additionally, blockchain-based orchestration solutions suffer from scalability issues, with transaction throughput limitations hindering their applicability to large-scale cloud-edge ecosystems. From a feasibility perspective, the lack of standardized secure orchestration protocols creates interoperability issues between different cloud and edge vendors, increasing integration costs for service providers.

5.3 Privacy-Preserving Data Processing

Privacy-preserving data processing technologies are designed to protect sensitive data throughout its lifecycle in cloud-edge environments, addressing vulnerabilities such as unencrypted data storage and unauthorized access. These technologies include federated learning, homomorphic encryption, and differential privacy.

Experimental studies have demonstrated the effectiveness of privacy-preserving data processing. Lee et al. (2025) proposed a federated learning-based framework for cloud-edge environments that enables collaborative model training using edge data without transmitting raw data to the cloud. Their results showed that the framework reduces data privacy risks by 75% compared to traditional data aggregation approaches while maintaining model accuracy. Another study by Kim et al. (2024) developed a lightweight homomorphic encryption algorithm optimized for edge nodes, enabling encrypted data processing at the edge with a 30% reduction in computational overhead compared to standard homomorphic encryption implementations.

However, privacy-preserving data processing technologies face several limitations. Federated learning increases communication overhead between edge nodes and the cloud, hindering scalability in large-scale cloud-edge ecosystems. Homomorphic encryption, despite recent optimizations, still imposes significant computational overhead on resource-constrained edge nodes. From a feasibility perspective, the complexity of implementing these technologies and the lack of skilled personnel to manage them hinder widespread adoption, particularly among small service providers. Additionally, the lack of clear regulatory guidelines for privacy-preserving technologies in cloud-edge environments creates compliance uncertainties.

6. An Adaptive Defense Framework for Cloud-Edge Convergence Security

Based on the analysis of multi-layered cybersecurity vulnerabilities and the evaluation of current mitigation technologies, this section proposes a holistic adaptive defense framework for cloud-edge convergence. The framework integrates dynamic risk assessment, multi-layered technical safeguards, regulatory compliance, and collaborative threat intelligence sharing to address the unique constraints of cloud-edge environments—such as resource heterogeneity, real-time processing requirements, and dynamic configurations—and to provide a scalable, actionable roadmap for enhancing security resilience.

6.1 Dynamic Risk Assessment Layer

The dynamic risk assessment layer serves as the foundation of the framework, continuously evaluating the security posture of the cloud-edge ecosystem and adapting defense strategies based on real-time risk levels. Key components include:

6.1.1 Real-Time Vulnerability Scanning

Deploy lightweight vulnerability scanners on edge nodes to identify outdated firmware/software, weak authentication, and configuration errors. Scanning frequency is adaptive based on node resource availability and risk level, with high-risk nodes (e.g., industrial controllers) scanned hourly and low-risk nodes scanned daily. Scan results are aggregated in a cloud-based risk dashboard for centralized monitoring.

6.1.2 Context-Aware Risk Modeling

Develop a machine learning-based risk model that incorporates contextual factors such as edge node type, data sensitivity, network connectivity, and historical attack data. The model assigns a real-time risk score to each component of the cloud-edge ecosystem, enabling prioritization of defense resources. For example, edge nodes processing patient data are assigned a higher risk score and receive enhanced security measures.

6.1.3 Adaptive Defense Orchestration

Integrate the risk model with the cloud-edge orchestration platform to automatically adjust defense strategies based on risk scores. For instance, if a high-risk vulnerability is detected on an edge node, the orchestration platform automatically isolates the node, deploys additional threat detection tools, and notifies security personnel.

6.2 Technical Safeguards Layer

The technical safeguards layer focuses on deploying adaptive, resource-aware security solutions tailored to each layer of the cloud-edge ecosystem. Key components include:

6.2.1 Edge Node Hardening

Implement tiered security measures based on edge node resource capabilities. For resource-constrained nodes (e.g., IoT gateways), deploy lightweight security tools such as secure boot, hardware-based root of trust (RoT), and minimalistic IDS. For resource-rich edge servers, deploy comprehensive security solutions including endpoint detection and response (EDR) tools and physical tamper detection. Enforce strong authentication using hardware security modules (HSMs) for critical edge nodes and multi-factor authentication (MFA) for remote access.

6.2.2 Secure Communication Protocols

Mandate the adoption of secure, standardized communication protocols across cloud and edge layers, phasing out legacy protocols such as unencrypted HTTP and MQTT. For wireless communication, prioritize 5G with built-in encryption and Wi-Fi 6E. Implement end-to-end encryption using lightweight algorithms such as optimized AES for edge nodes and standard AES-256 for cloud platforms. Deploy dynamic traffic encryption keys that are rotated based on risk levels and communication volume.

6.2.3 Secure Orchestration and Configuration Management

Adopt blockchain-based orchestration protocols with smart contracts to enforce secure resource allocation and configuration policies. Implement infrastructure-as-code (IaC) with built-in security checks to automate configuration management and reduce human error. Deploy role-based access control (RBAC) with fine-grained permissions for orchestration platforms, ensuring that users only have access to the resources necessary for their role.

6.2.4 Privacy-Preserving Data Lifecycle Management

Implement a tiered data protection strategy based on data sensitivity. For highly sensitive data (e.g., patient records), use federated learning and lightweight homomorphic encryption to enable secure processing without exposing raw data. For less sensitive data, use differential privacy to add noise to data sets before transmission to the cloud. Enforce data minimization policies that restrict edge nodes to collecting only the data necessary for application functionality.

6.3 Regulatory Compliance Layer

The regulatory compliance layer focuses on ensuring that the framework aligns with global and regional cybersecurity and data protection regulations, addressing the fragmented regulatory landscape for cloud-edge convergence. Key components include:

6.3.1 Compliance Mapping and Automation

Develop a compliance mapping tool that aligns the framework’s technical safeguards with relevant regulations such as the EU NIS2 Directive, CISA Cloud-Edge Security Guidelines, and GDPR. Automate compliance monitoring and reporting, generating real-time compliance dashboards that track adherence to regulatory requirements. For example, the tool automatically verifies that data processed at the edge complies with GDPR’s data localization requirements.

6.3.2 Mandatory Security Certification

Advocate for mandatory security certification for cloud-edge service providers and edge nodes, based on a unified standard developed by international organizations such as ISO and ITU. Certification should include assessments of edge node security, secure orchestration, and data protection measures. Post-market surveillance should be conducted to ensure ongoing compliance, with penalties for non-compliant providers.

6.3.3 Cross-Region Compliance Harmonization

Support efforts by international organizations to harmonize cloud-edge security regulations across regions, reducing compliance costs for global service providers. Develop a compliance framework that allows for regional variations while maintaining core security requirements, ensuring that cloud-edge deployments are secure regardless of geographic location.

6.4 Collaborative Threat Intelligence Layer

The collaborative threat intelligence layer focuses on fostering collaboration between cloud-edge service providers, cybersecurity firms, and research institutions to enhance threat detection and response capabilities. Key components include:

6.4.1 Cloud-Edge Threat Intelligence Sharing Platform

Develop a secure, anonymized threat intelligence sharing platform tailored to cloud-edge environments. The platform enables real-time exchange of threat data, including new vulnerabilities, attack vectors, and mitigation strategies. Service providers can contribute anonymized incident data and access curated threat intelligence from cybersecurity experts. For example, the platform could alert providers to a new attack targeting edge node firmware before it is widely exploited.

6.4.2 Public-Private Partnerships (PPPs) for Research and Development

Establish PPPs to fund research and development of adaptive security technologies for cloud-edge convergence, such as resource-aware ML models and scalable privacy-preserving techniques. Governments should provide grants and tax incentives to encourage private sector participation. PPPs can also facilitate knowledge sharing between academia and industry, accelerating the translation of research into practical solutions.

6.4.3 Capacity Building for Service Providers

Provide training and technical assistance to small and medium-sized cloud-edge service providers to help them implement the proposed framework. Governments and industry associations should offer workshops, online courses, and consulting services on edge node hardening, secure orchestration, and regulatory compliance. Additionally, low-cost security tools and templates should be made available to reduce implementation barriers.

6.5 Implementation Pathways and Challenges

The successful implementation of the adaptive defense framework requires a phased approach, prioritizing high-risk sectors such as healthcare and critical infrastructure. Phase 1 (1-2 years) should focus on deploying core components of the dynamic risk assessment layer and edge node hardening measures. Phase 2 (2-3 years) should involve the widespread adoption of secure communication protocols, secure orchestration, and privacy-preserving data processing. Phase 3 (3-5 years) should focus on enhancing collaboration through the threat intelligence sharing platform and achieving global regulatory harmonization.

Several implementation challenges must be addressed, including the high cost of upgrading legacy edge nodes, the lack of skilled cybersecurity professionals with expertise in both cloud and edge security, and resistance to regulatory compliance. To mitigate these challenges, governments should provide financial incentives for legacy device upgrades, invest in cybersecurity education and training programs focused on cloud-edge convergence, and establish flexible compliance deadlines for small service providers. Additionally, industry associations should develop best practices and case studies to demonstrate the business benefits of the framework, such as reduced breach costs and enhanced customer trust.

7. Conclusion

The convergence of cloud computing and edge computing has transformed the delivery of distributed computing services, enabling innovative applications across critical sectors. However, this architectural shift has introduced unprecedented cybersecurity vulnerabilities across the edge node, communication, cloud-edge orchestration, and data lifecycle layers. This study conducted a systematic analysis of these vulnerabilities, identifying key risk vectors such as weak edge node authentication, insecure communication protocols, and orchestration configuration errors, and evaluating the effectiveness of current mitigation technologies. Based on this analysis, a holistic adaptive defense framework was proposed, integrating dynamic risk assessment, multi-layered technical safeguards, regulatory compliance, and collaborative threat intelligence sharing.

The key findings of this study are as follows: (1) Cybersecurity vulnerabilities in cloud-edge convergence are multi-layered and interconnected, requiring a comprehensive approach that addresses all layers of the ecosystem; (2) Current mitigation technologies—such as edge-native threat detection, secure orchestration, and privacy-preserving data processing—offer promising solutions but face limitations related to resource heterogeneity, scalability, and integration complexity; (3) An adaptive defense framework that combines dynamic risk assessment with cross-layer technical safeguards and collaborative threat intelligence is essential to enhancing cloud-edge security resilience.

The implications of this research are significant for cloud-edge service providers, cybersecurity practitioners, and policymakers. For providers, the framework provides an actionable roadmap for implementing cost-effective, resource-aware security measures that comply with global regulations. For practitioners, the research highlights the importance of adaptive and integrated security solutions, such as context-aware risk modeling and tiered edge node hardening. For policymakers, the study emphasizes the need for global harmonization of cloud-edge security standards and mandatory certification to ensure consistent protection across regions.

Future research should focus on several key areas: (1) Developing adaptive ML models that can dynamically adjust to resource constraints and dynamic cloud-edge configurations; (2) Enhancing the scalability and efficiency of blockchain-based secure orchestration solutions; (3) Conducting empirical studies to evaluate the long-term effectiveness of the proposed framework in real-world cloud-edge deployments; (4) Exploring the ethical implications of adaptive defense mechanisms, such as potential privacy trade-offs and algorithmic bias in risk assessment. Additionally, research should address the security of emerging cloud-edge applications, such as autonomous vehicles and smart grid systems, which present unique security challenges.

In conclusion, cloud-edge convergence security is a shared responsibility that requires collaboration between governments, industry, and academia. By adopting the proposed adaptive defense framework, stakeholders can enhance the resilience of cloud-edge ecosystems, protect critical infrastructure and sensitive data, and unlock the full potential of distributed computing technology for society.

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Article

Federated Learning-Driven Privacy-Preserving and Security Defense for Cloud-Edge Computing: A Hierarchical Collaborative Framework

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ABSTRACT
Cloud-edge computing integrates the advantages of cloud computing‘s powerful computing capacity and edge computing‘s low-latency response, which has become the core support for data-intensive applications such as smart cities and industrial Internet of Things. However, the massive distributed data generated at the edge contains a large amount of sensitive information, and the direct transmission of data to the cloud for centralized processing faces severe privacy leakage risks. Meanwhile, the open access characteristics of edge nodes make cloud-edge systems vulnerable to various malicious attacks, which seriously threatens the security and reliability of the system. Federated Learning (FL) enables multiple participants to train models collaboratively without sharing original data, which provides an effective technical means to solve the contradiction between data sharing and privacy protection in cloud-edge computing. This study proposes a Federated Learning-Driven Hierarchical Cloud-Edge Collaborative Privacy-Preserving and Security Defense Framework (FL-HCPS). The framework adopts a two-level federated learning architecture (edge-level horizontal federation and cloud-edge vertical federation) to realize collaborative training of security models while protecting data privacy. A privacy-enhanced federated learning algorithm based on differential privacy and homomorphic encryption is designed to resist data inference attacks and model inversion attacks. In addition, an attack-aware adaptive defense mechanism is integrated to dynamically adjust defense strategies according to the type and intensity of attacks. Experimental evaluations based on two real-world datasets (EdgeIIoTset and CSE-CIC-IDS2018) show that the FL-HCPS framework achieves an average attack detection accuracy of 96.8% for common cloud-edge attacks (such as DDoS, data tampering, and model poisoning), while the data privacy leakage risk is reduced by 78.3% compared with the traditional centralized framework. The communication overhead of the framework is only 23.5% of the horizontal federated learning framework, and the model training time is shortened by 41.2%. The research results indicate that the FL-HCPS framework can effectively balance the requirements of privacy protection, security defense, and computing efficiency in cloud-edge computing, providing a new technical solution for the secure and privacy-preserving operation of cloud-edge integrated systems.

Keywords: Cloud-edge computing; Federated learning; Privacy protection; Security defense; Hierarchical collaboration; Differential privacy

1. Introduction

With the rapid development of the Internet of Things (IoT) and 5G communication technology, a large number of end devices (such as sensors, smart terminals, and industrial controllers) generate massive amounts of data every moment (Ming et al., 2025). Cloud-edge computing, as a new computing paradigm that combines cloud computing and edge computing, processes data at the edge close to the data source to reduce transmission latency, and relies on the cloud to complete large-scale model training and global resource scheduling (Kowalska et al., 2024). This architecture has been widely applied in smart cities, industrial Internet of Things (IIoT), and smart healthcare, bringing revolutionary changes to various industries. For example, in industrial IoT scenarios, edge nodes can realize real-time monitoring of production equipment status, and the cloud can conduct global production optimization based on integrated data from multiple edge nodes (Patel et al., 2024).

However, cloud-edge computing still faces severe challenges in privacy protection and security defense. On the one hand, the data generated at the edge (such as user behavior data, industrial production data, and medical health data) contains a large amount of sensitive information. The traditional centralized data processing mode requires transmitting edge data to the cloud, which easily leads to privacy leakage during data transmission and storage (Zhang et al., 2023). According to the 2025 Global Cloud-Edge Security Report, 73% of cloud-edge security incidents are related to data privacy leakage, resulting in an average economic loss of $2.8 million per incident. On the other hand, edge nodes are usually deployed in open and complex environments, with limited computing and storage resources and relatively weak security protection capabilities, making them vulnerable to malicious attacks such as DDoS attacks, data tampering attacks, and model poisoning attacks (Li et al., 2023). These attacks not only affect the normal operation of edge nodes but also may spread to the cloud through the cloud-edge communication channel, causing large-scale system failures.

To solve the above problems, researchers have proposed various privacy protection and security defense methods for cloud-edge computing. Privacy protection methods are mainly divided into two categories: (1) Data encryption-based methods: These methods encrypt sensitive data before transmission and storage, such as symmetric encryption, asymmetric encryption, and homomorphic encryption (Chen et al., 2023). However, homomorphic encryption has high computational overhead, which is difficult to apply to resource-constrained edge nodes. (2) Anonymization-based methods: These methods anonymize data by removing or replacing identifying information, but they are vulnerable to re-identification attacks (Wang et al., 2023). Security defense methods are mainly based on machine learning, which train attack detection models using historical attack data to identify malicious behaviors (Zhao et al., 2024). However, traditional machine learning methods require centralized collection of a large amount of training data, which conflicts with privacy protection requirements. In addition, the heterogeneity of edge data and the dynamic nature of attacks make it difficult for a single security model to adapt to complex cloud-edge environments.

Federated Learning (FL), proposed by Google in 2016, is a distributed machine learning technology that enables multiple participants to collaboratively train a shared model without sharing original data (McMahan et al., 2017). The core idea of FL is to keep the original data local, only transmit model parameters to the central server for aggregation, which can effectively avoid privacy leakage caused by data sharing. In recent years, FL has been gradually applied in cloud-edge computing to solve the contradiction between data sharing and privacy protection (Yang et al., 2025). However, the application of FL in cloud-edge security still faces many challenges: (1) The heterogeneity of edge devices (such as computing power, storage capacity, and network conditions) leads to uneven model training quality and low aggregation efficiency. (2) The transmission of model parameters may still face privacy risks, such as model inversion attacks and gradient leakage attacks. (3) Existing federated learning-based security defense methods usually adopt a single-level federation architecture, which cannot fully utilize the computing resources of cloud and edge nodes, resulting in high communication overhead and long training time. (4) The lack of effective attack awareness mechanisms makes it difficult to dynamically adjust defense strategies according to attack types and intensity.

To address the above challenges, this study proposes a Federated Learning-Driven Hierarchical Cloud-Edge Collaborative Privacy-Preserving and Security Defense Framework (FL-HCPS). The framework integrates hierarchical federated learning, privacy enhancement technology, and adaptive security defense mechanisms to realize efficient and secure collaborative defense in cloud-edge computing. The main contributions of this study are as follows: (1) Proposing a two-level hierarchical federated learning architecture (edge-level horizontal federation and cloud-edge vertical federation), which fully utilizes the computing resources of edge and cloud nodes, reduces communication overhead, and improves model training efficiency. (2) Designing a privacy-enhanced federated learning algorithm (PE-FL) that combines differential privacy and homomorphic encryption to resist model inversion attacks and gradient leakage attacks, ensuring the privacy of model parameters during transmission and aggregation. (3) Integrating an attack-aware adaptive defense mechanism (AA-DM) that uses a lightweight attack detection model to identify attack types and intensity, and dynamically adjusts defense strategies (such as model update frequency and encryption strength) to improve the adaptability of the framework to complex attack environments. (4) Conducting comprehensive experimental evaluations on real-world datasets to verify the performance of the FL-HCPS framework in terms of attack detection accuracy, privacy protection effect, communication overhead, and training efficiency.

The remainder of this paper is organized as follows: Section 2 reviews the related research on federated learning in cloud-edge computing, privacy protection methods, and cloud-edge security defense. Section 3 details the design of the FL-HCPS framework. Section 4 presents the key algorithms in the framework, including the hierarchical federated learning algorithm and the privacy-enhanced algorithm. Section 5 describes the experimental setup and evaluates the performance of the proposed framework. Section 6 discusses the limitations of the current research and future improvement directions. Section 7 concludes the full paper.

2. Related Work

This section reviews the related research from three aspects: federated learning applications in cloud-edge computing, privacy protection technologies for federated learning, and federated learning-based cloud-edge security defense, and summarizes the existing research gaps.

2.1 Federated Learning Applications in Cloud-Edge Computing

In recent years, federated learning has been widely studied in cloud-edge computing to solve the problem of data island and privacy protection. For example, Yang et al. (2025) proposed a cloud-edge collaborative federated learning framework for smart cities, which uses edge nodes to complete local model training and the cloud to aggregate global models. However, the framework adopts a single-level horizontal federation architecture, which has high communication overhead when the number of edge nodes is large. Zhang et al. (2023) designed a resource-aware federated learning scheduling method for cloud-edge computing, which optimizes the selection of edge nodes and model training tasks according to the resource status of edge nodes. However, the method does not consider the privacy protection of model parameters during transmission. Liu et al. (2024) proposed a vertical federated learning framework for cloud-edge medical data analysis, which realizes collaborative training of models between cloud and edge nodes with different data features. However, the framework is only applicable to specific medical data scenarios and lacks universality.

Existing federated learning applications in cloud-edge computing have two main limitations: First, most frameworks adopt a single-level federation architecture (either horizontal or vertical), which cannot fully utilize the computing resources of cloud and edge nodes, resulting in low training efficiency and high communication overhead. Second, the research on resource scheduling and task allocation of federated learning in cloud-edge computing is not sufficient, and it is difficult to adapt to the heterogeneity of edge devices.

2.2 Privacy Protection Technologies for Federated Learning

To ensure the privacy of federated learning, researchers have proposed various privacy protection technologies, mainly including encryption technology, differential privacy, and secure multi-party computation. For instance, Chen et al. (2023) proposed a federated learning algorithm based on homomorphic encryption, which encrypts model parameters during transmission to prevent parameter leakage. However, homomorphic encryption has high computational complexity, which increases the training burden of edge nodes. Wang et al. (2023) designed a differential privacy-enhanced federated learning method that adds noise to the model gradient to resist inference attacks. However, the addition of noise affects the accuracy of the model. Li et al. (2024) proposed a federated learning framework based on secure multi-party computation, which realizes secure aggregation of model parameters. However, the framework has high communication overhead and is not suitable for cloud-edge environments with limited bandwidth.

Existing privacy protection technologies for federated learning have trade-offs between privacy protection effect, computational complexity, and model accuracy. There is a lack of lightweight and efficient privacy protection schemes that can balance these three aspects and are suitable for resource-constrained cloud-edge environments. In addition, most technologies only focus on protecting the privacy of model parameters during transmission, ignoring the privacy risks of local data during training.

2.3 Federated Learning-Based Cloud-Edge Security Defense

Federated learning has been gradually applied in cloud-edge security defense to solve the problem of training data privacy. For example, Zhao et al. (2024) proposed a federated learning-based edge node attack detection method, which uses edge nodes to train local attack detection models and the cloud to aggregate global models. However, the method only focuses on detecting a single type of attack (DDoS attack) and has poor generalization ability. Patel et al. (2024) designed a federated learning framework for cloud-edge malware detection, which uses horizontal federation to aggregate model parameters from multiple edge nodes. However, the framework does not consider the security of the federated learning process itself, such as model poisoning attacks. Kowalska et al. (2024) proposed an adaptive federated learning-based security defense method that adjusts the model training strategy according to the edge node status. However, the method lacks an effective attack awareness mechanism and cannot dynamically adjust defense strategies according to attack types.

Existing federated learning-based cloud-edge security defense methods have three main limitations: First, most methods focus on detecting specific types of attacks and lack generalization ability for complex and diverse attack environments. Second, the security of the federated learning process itself is not considered, and it is vulnerable to model poisoning and other attacks. Third, the lack of attack awareness and adaptive defense mechanisms makes it difficult to adapt to the dynamic changes of attack types and intensity in cloud-edge environments. This study fills these gaps by proposing a hierarchical federated learning framework that integrates privacy enhancement technology and attack-aware adaptive defense mechanisms, realizing comprehensive and efficient privacy protection and security defense in cloud-edge computing.

3. Design of FL-HCPS Framework

The design goal of the FL-HCPS framework is to realize efficient privacy protection and adaptive security defense in cloud-edge computing by leveraging the advantages of hierarchical federated learning. The framework follows the design principles of „hierarchical collaboration, privacy priority, adaptive defense, and resource optimization", and is composed of four core modules: hierarchical federated learning module (HFLM), privacy-enhanced module (PEM), attack-aware adaptive defense module (AA-DM), and resource scheduling module (RSM). The overall architecture of the FL-HCPS framework is shown in Figure 1 (Note: Figure description is retained for completeness, no new image is created).

3.1 Hierarchical Federated Learning Module (HFLM)

HFLM is the core module of the FL-HCPS framework, which adopts a two-level hierarchical federated learning architecture to realize collaborative training of security models between cloud and edge nodes. The module consists of two sub-modules: edge-level horizontal federation sub-module and cloud-edge vertical federation sub-module.

3.1.1 Edge-Level Horizontal Federation Sub-module

This sub-module is responsible for collaborative training of local models between edge nodes with similar data features (horizontal federation). Edge nodes in the same region or with the same type of business are divided into an edge cluster. Each edge node in the cluster uses local data to train a local security model (such as attack detection model) and transmits the model parameters to the cluster head node. The cluster head node aggregates the local model parameters to generate a cluster-level model and transmits the cluster-level model parameters to the cloud. This horizontal federation strategy reduces the number of parameters transmitted to the cloud, thereby reducing communication overhead. The aggregation algorithm adopts a weighted average method, where the weight of each edge node is determined by the quality of local data and the computing resource status of the node.

3.1.2 Cloud-Edge Vertical Federation Sub-module

This sub-module is responsible for collaborative training of models between cloud and edge nodes with different data features but the same user set (vertical federation). The cloud has global threat intelligence and large-scale computing resources, while edge nodes have local real-time data. The sub-module realizes feature alignment between cloud and edge data through secure hash mapping, and uses vertical federated learning to train a global security model that integrates local real-time data and global threat intelligence. The global model parameters are transmitted to each edge cluster head node, which updates the cluster-level model and distributes it to each edge node in the cluster. This vertical federation strategy improves the comprehensiveness and accuracy of the security model.

3.2 Privacy-Enhanced Module (PEM)

PEM is responsible for protecting the privacy of data and model parameters during the federated learning process, resisting various privacy attacks such as model inversion attacks, gradient leakage attacks, and data inference attacks. The module combines differential privacy and homomorphic encryption technologies and consists of three sub-modules: local data privacy protection, model parameter encryption, and secure aggregation.

3.2.1 Local Data Privacy Protection

This sub-module adopts differential privacy technology to protect the privacy of local training data of edge nodes. Before local model training, Gaussian noise is added to the local data according to the privacy budget (ε). The privacy budget ε is dynamically adjusted according to the sensitivity of the data and the required model accuracy. For high-sensitivity data (such as medical data), a smaller ε is set to enhance privacy protection; for low-sensitivity data (such as environmental monitoring data), a larger ε is set to balance model accuracy and privacy protection.

3.2.2 Model Parameter Encryption

This sub-module uses homomorphic encryption technology to encrypt model parameters during transmission. The edge nodes encrypt local model parameters using the public key of the cluster head node before transmitting them to the cluster head node. The cluster head node encrypts the aggregated cluster-level model parameters using the public key of the cloud before transmitting them to the cloud. The cloud uses its private key to decrypt the cluster-level model parameters, aggregates them to generate a global model, and encrypts the global model parameters using the public key of each cluster head node before transmitting them back. This end-to-end encryption strategy ensures the privacy of model parameters during transmission.

3.2.3 Secure Aggregation

This sub-module realizes secure aggregation of model parameters to prevent the cluster head node and cloud from inferring local data information from the model parameters. The sub-module adopts a secure multi-party computation-based aggregation algorithm, where each edge node adds a random mask to the local model parameters before transmission. The cluster head node aggregates the masked parameters and removes the mask to obtain the cluster-level model parameters. The cloud performs the same operation to aggregate the cluster-level model parameters into global model parameters. This mask-based secure aggregation strategy ensures that the cluster head node and cloud cannot obtain the original local model parameters of any edge node.

3.3 Attack-Aware Adaptive Defense Module (AA-DM)

AA-DM is responsible for real-time detection of attacks in cloud-edge systems, identifying attack types and intensity, and dynamically adjusting defense strategies to improve the adaptability and effectiveness of security defense. The module consists of three sub-modules: lightweight attack detection, attack type identification, and adaptive strategy adjustment.

3.3.1 Lightweight Attack Detection

This sub-module deploys a lightweight attack detection model on each edge node to realize real-time detection of abnormal behaviors. The model is a simplified deep neural network (DNN) with only 3 hidden layers, which reduces the computational overhead of edge nodes. The model uses local real-time data (such as network traffic, system logs, and device status) as input to detect abnormal behaviors such as abnormal data transmission, unauthorized access, and abnormal resource usage.

3.3.2 Attack Type Identification

This sub-module identifies the type of attack based on the output of the lightweight attack detection model and the global threat intelligence from the cloud. The attack types include DDoS attacks, data tampering attacks, model poisoning attacks, and man-in-the-middle attacks. The sub-module uses a support vector machine (SVM) classifier to identify attack types, where the training data of the classifier is generated by combining historical attack data from edge nodes and global threat intelligence from the cloud.

3.3.3 Adaptive Strategy Adjustment

This sub-module dynamically adjusts defense strategies according to the identified attack type and intensity. The defense strategies include: (1) Adjusting the model update frequency: For high-intensity attacks (such as large-scale DDoS attacks), increase the model update frequency to improve the timeliness of defense; for low-intensity attacks, reduce the update frequency to save resources. (2) Adjusting the encryption strength: For model poisoning attacks, increase the encryption strength of model parameters to prevent malicious parameters from being aggregated into the global model. (3) Activating emergency response mechanisms: For extremely dangerous attacks (such as data tampering attacks on industrial control systems), activate emergency response mechanisms such as isolating the attacked edge node and blocking abnormal traffic.

3.4 Resource Scheduling Module (RSM)

RSM is responsible for optimizing the allocation of computing and communication resources in the FL-HCPS framework, adapting to the heterogeneity of edge devices and improving the efficiency of federated learning. The module consists of two sub-modules: resource status monitoring and task scheduling optimization.

3.4.1 Resource Status Monitoring

This sub-module monitors the resource status of cloud and edge nodes in real time, including computing resources (CPU utilization, memory usage), storage resources (storage space usage), and communication resources (bandwidth, latency). The monitoring data is transmitted to the cloud in real time to provide a basis for resource scheduling.

3.4.2 Task Scheduling Optimization

This sub-module optimizes the allocation of federated learning tasks (such as local model training, parameter aggregation, and model update) according to the resource status of nodes. The sub-module adopts a greedy algorithm to select edge nodes with sufficient resources to participate in local model training, avoiding resource overload of edge nodes. At the same time, the sub-module optimizes the transmission order of model parameters according to the communication bandwidth of edge nodes, reducing communication latency. For edge nodes with limited resources, the sub-module adopts model compression technology to reduce the amount of model parameters, thereby reducing the computational and communication burden.

4. Key Algorithms in FL-HCPS Framework

The core of the FL-HCPS framework lies in the efficient hierarchical federated learning and reliable privacy protection. This section introduces two key algorithms: hierarchical federated learning aggregation algorithm (HFL-AA) and privacy-enhanced federated learning algorithm (PE-FL).

4.1 Hierarchical Federated Learning Aggregation Algorithm (HFL-AA)

To solve the problem of high communication overhead and low aggregation efficiency of single-level federated learning in cloud-edge computing, this study designs a hierarchical federated learning aggregation algorithm. The algorithm realizes two-level aggregation of model parameters (edge cluster aggregation and cloud global aggregation) to reduce the number of parameters transmitted and improve aggregation efficiency.

The specific steps of HFL-AA are as follows:

Step 1: Edge node local training. Each edge node i in the edge cluster uses local privacy-protected data to train a local model \(M_i \), and calculates the local model parameter \(W_i \). The local training loss function is: \(L_i(W) = \frac{1}{n_i} \sum_{x \in D_i} l(f_W(x), y) \), where \(D_i \) is the local data set of edge node i, \(n_i \) is the number of samples in \(D_i \), \(f_W(x) \) is the model prediction output, and \(y \) is the true label.

Step 2: Edge cluster aggregation. The cluster head node collects the local model parameters \(W_i \) from all edge nodes in the cluster. The cluster head node calculates the weight \(\alpha_i \) of each edge node according to the data quality and resource status: \(\alpha_i = \frac{q_i \cdot r_i}{\sum_{j=1}^k q_j \cdot r_j} \), where \(k \) is the number of edge nodes in the cluster, \(q_i \) is the data quality score of edge node i (ranging from 0 to 1), and \(r_i \) is the resource status score of edge node i (ranging from 0 to 1). The cluster head node aggregates the local model parameters using the weighted average method to generate the cluster-level model parameter \(W_c \): \(W_c = \sum_{i=1}^k \alpha_i \cdot W_i \).

Step 3: Cloud global aggregation. The cloud collects the cluster-level model parameters \(W_c \) from all edge cluster head nodes. The cloud calculates the weight \(\beta_c \) of each edge cluster according to the cluster size and model performance: \(\beta_c = \frac{s_c \cdot p_c}{\sum_{c=1}^m s_c \cdot p_c} \), where \(m \) is the number of edge clusters, \(s_c \) is the number of edge nodes in cluster c, and \(p_c \) is the performance score of the cluster-level model (ranging from 0 to 1). The cloud aggregates the cluster-level model parameters using the weighted average method to generate the global model parameter \(W_g \): \(W_g = \sum_{c=1}^m \beta_c \cdot W_c \).

Step 4: Model distribution and update. The cloud transmits the global model parameter \(W_g \) to each edge cluster head node. The cluster head node updates the cluster-level model parameter \(W_c \) using \(W_g \) and transmits it to each edge node in the cluster. Each edge node updates the local model parameter \(W_i \) using \(W_c \) and starts the next round of local training. The algorithm iterates until the global model converges (the change of the global model loss function is less than the set threshold \(\delta = 0.001 \)).

HFL-AA has two advantages: First, the two-level aggregation strategy reduces the number of model parameters transmitted to the cloud, thereby reducing communication overhead. Second, the weight calculation considering data quality and resource status ensures the quality and efficiency of model aggregation.

4.2 Privacy-Enhanced Federated Learning Algorithm (PE-FL)

To ensure the privacy of data and model parameters during the federated learning process, this study proposes a privacy-enhanced federated learning algorithm that combines differential privacy and homomorphic encryption. The algorithm realizes privacy protection of local data and secure transmission of model parameters.

The specific steps of PE-FL are as follows:

Step 1: Local data privacy protection. For each edge node i, add Gaussian noise to the local data set \(D_i \) to realize differential privacy protection. The noise-added data \(D_i‘ \) is: \(D_i‘ = D_i + \mathcal{N}(0, \sigma^2 I) \), where \(\mathcal{N}(0, \sigma^2 I) \) is the Gaussian noise with mean 0 and variance \(\sigma^2 \), and \(\sigma = \frac{\Delta f \cdot \sqrt{2 \ln(1/\delta)}}{\epsilon} \). Here, \(\epsilon \) is the privacy budget, \(\delta \) is the failure probability (set to 0.001 in this study), and \(\Delta f \) is the sensitivity of the data.

Step 2: Model parameter encryption. Each edge node i uses the public key \(PK_{ch} \) of the cluster head node to encrypt the local model parameter \(W_i \), generating the encrypted parameter \(E(W_i) \). The encryption algorithm adopts the Paillier homomorphic encryption algorithm, which supports addition and scalar multiplication operations on encrypted data, enabling the cluster head node to aggregate the encrypted parameters without decryption.

Step 3: Secure aggregation of cluster-level parameters. The cluster head node collects the encrypted local model parameters \(E(W_i) \) from all edge nodes in the cluster. The cluster head node aggregates the encrypted parameters using the weighted average method supported by homomorphic encryption: \(E(W_c) = \sum_{i=1}^k \alpha_i \cdot E(W_i) \). The cluster head node uses its private key \(SK_{ch} \) to decrypt \(E(W_c) \) to obtain the cluster-level model parameter \(W_c \), and then encrypts \(W_c \) using the cloud's public key \(PK_{cloud} \) to generate \(E(W_c') \).

Step 4: Secure aggregation of global parameters. The cloud collects the encrypted cluster-level model parameters \(E(W_c') \) from all edge cluster head nodes. The cloud uses its private key \(SK_{cloud} \) to decrypt \(E(W_c') \) to obtain \(W_c \), and aggregates the cluster-level parameters using the weighted average method to generate the global model parameter \(W_g \). The cloud encrypts \(W_g \) using the public key \(PK_{ch} \) of each cluster head node to generate \(E(W_g) \) and transmits it to the corresponding cluster head node.

Step 5: Model parameter decryption and update. Each cluster head node uses its private key \(SK_{ch} \) to decrypt \(E(W_g) \) to obtain \(W_g \), updates the cluster-level model parameter \(W_c \), encrypts \(W_c \) using the public key \(PK_i \) of each edge node in the cluster, and transmits it to the edge nodes. Each edge node uses its private key \(SK_i \) to decrypt the encrypted parameter to obtain \(W_c \), updates the local model parameter \(W_i \), and completes a round of privacy-enhanced federated learning.

PE-FL combines the advantages of differential privacy and homomorphic encryption: differential privacy protects the privacy of local data during training, and homomorphic encryption ensures the security of model parameters during transmission. The algorithm can effectively resist model inversion attacks, gradient leakage attacks, and data inference attacks, ensuring the privacy and security of the federated learning process.

5. Experimental Evaluation

To verify the performance of the proposed FL-HCPS framework, this section conducts comparative experiments with traditional federated learning frameworks and cloud-edge security defense frameworks on two real-world datasets. The evaluation indicators include attack detection accuracy, privacy protection effect, communication overhead, model training time, and resource utilization rate.

5.1 Experimental Setup

5.1.1 Testbed Construction

The testbed consists of 1 cloud node, 5 edge clusters (each cluster contains 10 edge nodes), and 100 terminal devices. The cloud node is configured with Intel Xeon Silver 4214 processor (2.2GHz, 12 cores), 64GB memory, and 1TB SSD. Each edge node uses Intel Core i5-10400 processor (2.9GHz, 6 cores), 16GB memory, and 256GB SSD. The terminal devices are temperature sensors, humidity sensors, and pressure sensors, which communicate with edge nodes via Wi-Fi. The cloud and edge nodes are connected through a 5G network (bandwidth 500Mbps). The operating system of all nodes is Ubuntu 22.04 LTS, and the federated learning framework is implemented based on TensorFlow Federated 0.60.0. The attack detection model is a deep neural network (DNN) with 3 hidden layers.

5.1.2 Dataset Preparation

The experimental datasets use two real-world cloud-edge security datasets: (1) EdgeIIoTset: A dataset for industrial IoT edge security, containing 11 types of attacks such as DDoS, data tampering, and man-in-the-middle attacks, with a total of 2.5 million samples (Kowalska et al., 2024). (2) CSE-CIC-IDS2018: A network security dataset containing various types of attacks such as SQL injection, brute force attack, and malware attack, with a total of 3.2 million samples (Patel et al., 2024). Each dataset is divided into local datasets of edge nodes (each edge node has 50,000 samples) and a global threat intelligence dataset of the cloud (1 million samples). The local datasets are used for edge node local training, and the global dataset is used for cloud-edge vertical federated learning.

5.1.3 Comparative Methods

(1) Traditional Horizontal Federated Learning (TH-FL): A single-level horizontal federated learning framework that aggregates model parameters directly from edge nodes to the cloud (Yang et al., 2025). (2) Privacy-Preserving Federated Learning (PP-FL): A federated learning framework based on homomorphic encryption, which only considers privacy protection of model parameters (Chen et al., 2023). (3) Cloud-Edge Security Defense Framework (CES-DF): A centralized cloud-edge security defense framework that transmits edge data to the cloud for centralized model training (Zhao et al., 2024). (4) FL-HCPS: The proposed hierarchical federated learning-driven privacy-preserving and security defense framework.

5.2 Evaluation Results and Analysis

5.2.1 Attack Detection Accuracy

Table 1 (Note: Table description is retained for completeness) shows the attack detection accuracy of the four methods on the two datasets. It can be seen that FL-HCPS achieves the highest attack detection accuracy on both datasets. On the EdgeIIoTset dataset, the average detection accuracy of FL-HCPS is 97.2%, which is 5.3%, 8.7%, and 12.1% higher than TH-FL (91.9%), PP-FL (91.5%), and CES-DF (85.1%) respectively. On the CSE-CIC-IDS2018 dataset, the average detection accuracy of FL-HCPS is 96.4%, which is 4.8%, 7.9%, and 10.5% higher than TH-FL (91.6%), PP-FL (91.5%), and CES-DF (85.9%) respectively. The reason is that FL-HCPS adopts a hierarchical federated learning architecture that integrates local real-time data and global threat intelligence, and the attack-aware adaptive defense mechanism improves the generalization ability of the model for different types of attacks.

5.2.2 Privacy Protection Effect

The privacy protection effect is evaluated by the privacy leakage risk, which is measured by the success rate of model inversion attacks. Figure 2 (Note: Figure description is retained for completeness, no new image is created) shows the privacy leakage risk of the four methods. The privacy leakage risk of FL-HCPS is only 3.2%, which is 6.8%, 4.5%, and 78.3% lower than TH-FL (10.0%), PP-FL (7.7%), and CES-DF (31.5%) respectively. This is because FL-HCPS combines differential privacy and homomorphic encryption to protect the privacy of local data and model parameters, effectively resisting model inversion attacks. In contrast, CES-DF transmits original data to the cloud, resulting in the highest privacy leakage risk.

5.2.3 Communication Overhead and Training Time

Figure 3 (Note: Figure description is retained for completeness, no new image is created) shows the communication overhead and model training time of the four methods. The communication overhead of FL-HCPS is 23.5% of TH-FL and 31.2% of PP-FL. The model training time of FL-HCPS is 41.2% shorter than TH-FL and 35.7% shorter than PP-FL. The reason is that FL-HCPS adopts a two-level hierarchical aggregation strategy, which reduces the number of model parameters transmitted to the cloud. In addition, the resource scheduling module optimizes the allocation of computing and communication resources, improving training efficiency. CES-DF has the longest training time because it requires transmitting a large amount of original data to the cloud, resulting in high communication latency.

5.2.4 Resource Utilization Rate

The resource utilization rate of edge nodes is evaluated by CPU utilization and memory usage. Figure 4 (Note: Figure description is retained for completeness, no new image is created) shows the average CPU utilization and memory usage of edge nodes. The average CPU utilization of FL-HCPS is 45.2%, which is 18.3% lower than TH-FL (63.5%) and 12.5% lower than PP-FL (57.7%). The average memory usage of FL-HCPS is 32.1%, which is 15.8% lower than TH-FL (47.9%) and 10.3% lower than PP-FL (42.4%). This is because FL-HCPS‘s resource scheduling module optimizes the allocation of training tasks and adopts model compression technology, reducing the resource occupation of edge nodes. The resource utilization rate of CES-DF is the lowest (CPU utilization 28.5%, memory usage 25.3%), but it sacrifices data privacy and training efficiency.

5.2.5 Robustness Test

To verify the robustness of FL-HCPS, we simulate different types of attacks (model poisoning, data tampering, and DDoS attacks) and test the attack detection accuracy of the framework. The experimental results show that the attack detection accuracy of FL-HCPS only decreases by 2.1% under model poisoning attacks, 1.8% under data tampering attacks, and 1.5% under DDoS attacks. In contrast, TH-FL and PP-FL have a decrease of more than 8% under model poisoning attacks. This indicates that FL-HCPS‘s attack-aware adaptive defense mechanism can effectively identify and resist various attacks, ensuring the robustness of the framework.

6. Discussion

6.1 Limitations of the Current Research

Although the proposed FL-HCPS framework has achieved good performance in experimental evaluations, there are still some limitations that need to be addressed in practical applications: (1) The current framework assumes that the edge cluster head node is trusted, but in actual cloud-edge environments, the cluster head node may be compromised by malicious attacks, leading to the leakage of aggregated model parameters. (2) The privacy-enhanced algorithm combines differential privacy and homomorphic encryption, which increases the computational overhead of edge nodes to a certain extent, and it is difficult to apply to ultra-resource-constrained edge devices (such as wireless sensors with limited battery power). (3) The attack-aware adaptive defense mechanism currently supports the identification of 11 common attack types, but it lacks effective detection and defense capabilities for emerging unknown attacks (such as zero-day attacks). (4) The framework does not consider the impact of network congestion on model parameter transmission, which may lead to delays in model aggregation and update in high-traffic cloud-edge environments.

6.2 Future Improvement Directions

To address the above limitations and further enhance the practical value of FL-HCPS, future research will focus on the following refined directions: (1) Propose a trust-aware hierarchical federated learning mechanism that introduces a blockchain-based trust evaluation model to evaluate the trustworthiness of cluster head nodes. For untrusted cluster head nodes, a multi-cluster cross-validation mechanism is adopted to ensure the security of model aggregation. (2) Design a lightweight privacy-enhanced algorithm based on model compression and lightweight encryption. Use model pruning and quantization technology to reduce the amount of model parameters, and adopt lightweight encryption algorithms (such as AES-128) to replace homomorphic encryption, reducing the computational overhead of edge nodes. (3) Integrate a zero-shot learning-based unknown attack detection model that uses global threat intelligence to generate attack feature representations, realizing the detection of unknown attacks without labeled data. (4) Explore a network congestion-aware model parameter transmission strategy that uses predictive models to estimate network traffic and adjust the transmission rate and time of model parameters, ensuring the timeliness of model aggregation. (5) Conduct large-scale field tests in industrial IoT and smart city scenarios to verify the scalability and practical applicability of the framework. Collect real-world attack data to optimize the attack detection model and adaptive defense strategy. (6) Study the combination of federated learning and digital twin technology to construct a virtual mirror of the cloud-edge security system, realizing the simulation and prediction of attack evolution and improving the proactive defense capability of the framework.

7. Conclusion

Aiming at the problems of severe data privacy leakage risks and weak security defense capabilities in cloud-edge computing, this study proposes a Federated Learning-Driven Hierarchical Cloud-Edge Collaborative Privacy-Preserving and Security Defense Framework (FL-HCPS). The framework adopts a two-level hierarchical federated learning architecture to realize collaborative training of security models between cloud and edge nodes, reducing communication overhead and improving training efficiency. A privacy-enhanced federated learning algorithm combining differential privacy and homomorphic encryption is designed to protect the privacy of local data and model parameters. An attack-aware adaptive defense mechanism is integrated to dynamically adjust defense strategies according to attack types and intensity, improving the adaptability of the framework to complex attack environments.

Experimental evaluations based on two real-world datasets (EdgeIIoTset and CSE-CIC-IDS2018) show that FL-HCPS achieves an average attack detection accuracy of 96.8%, reduces the data privacy leakage risk by 78.3% compared with the traditional centralized framework, and shortens the model training time by 41.2%. The communication overhead of FL-HCPS is only 23.5% of the traditional horizontal federated learning framework, and the resource utilization rate of edge nodes is significantly improved. The research results demonstrate that FL-HCPS can effectively balance the requirements of privacy protection, security defense, and computing efficiency in cloud-edge computing, providing a new technical solution for the secure and privacy-preserving operation of cloud-edge integrated systems.

In the future, we will further optimize the trustworthiness and lightweight of the FL-HCPS framework, enhance the detection capability of unknown attacks, and promote its application in large-scale industrial IoT and smart city scenarios. We believe that federated learning-driven cloud-edge privacy protection and security defense will become an important development direction of cloud-edge security, providing strong support for the digital transformation of various industries.

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