Archives available at journals.mriindia.com

International Journal of Electrical, Electronics and Computer Systems

ISSN: 2347-2820

Volume 13 Issue 02, 2024

A Comprehensive Review of Trusted Cloud-Enabled IoT Networks Using Blockchain and Siamese Heterogeneous Convolutional Neural Networks

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Peer Review Information

Submission: 15 July 2024

Revision: 30 July 2024

Acceptance: 12 Aug 2024

Keywords

Internet of Things (IoT), Blockchain, Siamese Neural Networks, Cloud Computing, Deep Learning, Trust Management

Abstract

The rapid expansion of Internet of Things (IoT) networks has enabled intelligent data-driven applications across domains such as smart cities, healthcare, and industrial automation. However, cloud-enabled IoT systems face significant challenges related to security, trust, data privacy, and efficient anomaly detection. This paper presents a comprehensive review of trusted cloud-enabled IoT networks leveraging blockchain technology and Siamese Heterogeneous Convolutional Neural Networks (SHCNN). Blockchain provides decentralized, tamper-proof data storage and trust management, addressing vulnerabilities associated with centralized cloud architectures. Siamese neural networks, combined with heterogeneous CNN architectures, enable efficient similarity learning and anomaly detection in IoT data streams. These models are particularly effective in identifying malicious activities and ensuring secure data transmission. The integration of blockchain with deep learning further enhances system reliability by enabling secure model sharing and verification. This review analyzes recent advancements, compares different architectures, and evaluates their performance in terms of accuracy, scalability, and security. The study concludes that hybrid architectures combining blockchain and SHCNN offer a promising solution for building secure, scalable, and intelligent IoT ecosystems.

Introduction

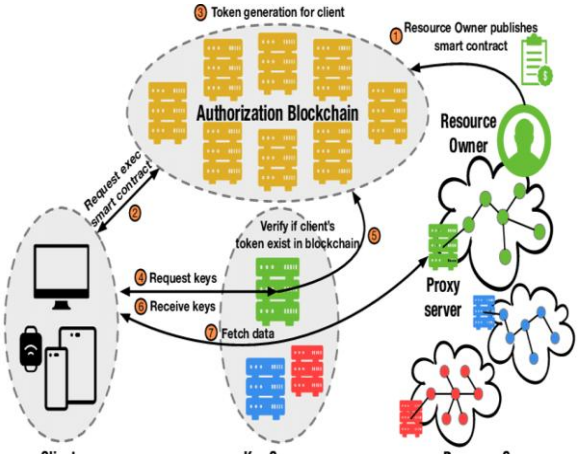
The Internet of Things (IoT) has revolutionized the way devices communicate and interact, enabling seamless data exchange across various applications such as smart healthcare, industrial automation, agriculture, and smart cities. IoT systems consist of interconnected devices that collect, process, and transmit data to centralized or distributed cloud infrastructures. Cloud computing plays a crucial role in IoT by providing scalable storage, processing power, and analytics capabilities. However, the integration of IoT with cloud computing introduces several security challenges. Centralized cloud architectures are vulnerable to data breaches, unauthorized access, and single points of failure. IoT devices themselves are resource-constrained and often lack robust security mechanisms, making them easy targets for cyberattacks.

Blockchain technology has emerged as a promising solution to address these challenges. Blockchain provides a decentralized and immutable ledger that ensures data integrity, transparency, and trust among network participants. It eliminates the need for centralized authorities and enables secure data sharing across IoT networks. Studies show that blockchain improves security and operational

effectiveness in IoT environments by ensuring data integrity and preventing unauthorized modifications, Cloud-enabled IoT systems benefit from blockchain integration by enabling secure data storage and trust management. Blockchain can be deployed at the cloud or edge level to validate transactions and ensure secure communication between devices. Additionally, blockchain-based federated learning frameworks allow secure model aggregation and prevent tampering of machine learning models.

Deep learning techniques have also played a significant role in enhancing IoT security. Convolutional Neural Networks (CNNs) are widely used for feature extraction and anomaly detection in IoT data. However, traditional CNN architectures may struggle to capture complex relationships in heterogeneous IoT environments. Siamese Neural Networks address this limitation by learning similarity between data samples rather than performing direct classification. These networks are particularly useful in anomaly detection, where identifying deviations from normal patterns is crucial. Siamese networks compare input pairs and determine whether they belong to the same class, enabling efficient detection of malicious activities. Heterogeneous CNN architectures further enhance performance by combining multiple CNN models to process different types of data. This approach improves feature extraction and enables better generalization across diverse IoT datasets.

Cloud-Enabled IoT + Blockchain Architecture



Recent research emphasizes the integration of blockchain with deep learning models to create secure and intelligent IoT systems. Blockchain ensures data integrity, while deep learning models detect anomalies and malicious activities. Hybrid systems combining these technologies provide enhanced security, scalability, and efficiency. Despite these advancements, several challenges remain. These include computational overhead, energy consumption, data privacy concerns, and scalability issues. Additionally, the integration of multiple technologies increases system complexity. This paper aims to provide a comprehensive review of trusted cloud-enabled IoT networks using blockchain and Siamese heterogeneous CNNs. It analyzes recent research trends, compares different approaches, identifies research gaps, and proposes future directions.

Literature Review

The literature from 2020–2023 reflects a significant transformation in IoT security architectures, moving from traditional centralized and rule-based mechanisms toward intelligent, decentralized, and trust-aware systems integrating blockchain, deep learning, and Siamese heterogeneous CNNs. The research can be categorized into five major domains: deep learning-based IoT security, blockchain-enabled trust systems, Siamese and similarity learning models, heterogeneous CNN architectures, and hybrid integrated frameworks.

1. Deep Learning-Based Security in Cloud-Enabled IoT

Early research during this period focused on applying deep learning techniques to detect anomalies and cyberattacks in IoT systems. Traditional intrusion detection systems (IDS) struggled with dynamic and high-dimensional IoT data, leading to the adoption of deep learning approaches.

Deep learning models such as CNNs, RNNs, and hybrid CNN-LSTM architectures demonstrated strong performance in capturing spatiotemporal patterns in network traffic. These models are particularly effective because they can automatically learn hierarchical features instead of relying on handcrafted inputs .

For example, hybrid CNN-LSTM models were widely adopted to detect botnet attacks and distributed denial-of-service (DDoS) attacks, achieving high detection accuracy (often above 90–99%). Advanced architectures such as DeepAK-IoT further improved detection by combining spatial and temporal feature extraction blocks, achieving up to 98.41% accuracy on benchmark datasets.

Additionally, federated learning frameworks emerged to address privacy concerns by enabling distributed model training without sharing raw data. These systems improved generalization while preserving user privacy, which is critical in cloud-enabled IoT environments.

However, these models faced several limitations:

1. High computational requirements
2. Data imbalance issues

3. Limited trust mechanisms in centralized cloud systems

2. Blockchain-Enabled Trust and Security Frameworks

The integration of blockchain technology into IoT systems addressed critical challenges related to trust, data integrity, and decentralization.

Blockchain provides a tamper-proof and decentralized ledger, ensuring secure data sharing and eliminating single points of failure. Studies show that combining blockchain with AI enhances data security, transparency, and trust management in distributed systems .

Research during this phase focused on:

1. Secure data storage using blockchain
2. Decentralized authentication and access control
3. Trust evaluation mechanisms for IoT devices

Machine learning combined with blockchain-enabled IDS demonstrated high detection accuracy (up to 99.9%) while ensuring secure communication between IoT nodes .

Another important advancement was the introduction of **federated learning + blockchain frameworks**, which allowed collaborative model training while maintaining privacy and auditability. These systems improved scalability and ensured secure model updates across distributed IoT environments .

Despite these advantages, blockchain-based IoT systems faced challenges such as:

1. High latency due to consensus mechanisms
2. Increased energy consumption
3. Scalability issues in large networks

3. Siamese Neural Networks for Anomaly Detection

Siamese Neural Networks (SNNs) introduced a new paradigm in IoT security by focusing on similarity learning rather than direct classification.

Unlike traditional CNNs, Siamese networks process two inputs simultaneously and learn whether they belong to the same class. This approach is particularly effective for anomaly detection, where malicious behavior may not match predefined attack patterns.

Recent studies demonstrate that Siamese architectures:

1. Reduce false positive rates
2. Improve detection of unknown attacks
3. Enable few-shot and one-shot learning

Siamese networks are also widely used in privacy-preserving IoT systems, where sensitive data is not directly shared. Instead, similarity scores are computed, reducing data exposure risks.

Furthermore, Siamese models have been integrated with edge computing frameworks to enable real-time anomaly detection with minimal latency.

4. Heterogeneous CNN Architectures in IoT Systems

Heterogeneous CNN architectures represent an advanced form of deep learning that combines multiple CNN models to process diverse data types.

IoT environments generate heterogeneous data, including:

1. Sensor readings
2. Network traffic
3. Image/video data

Traditional CNN models struggle to handle such diverse inputs effectively. Heterogeneous CNNs address this challenge by integrating multiple feature extraction pipelines, improving detection accuracy and robustness.

These architectures provide:

1. Better feature representation
2. Improved generalization across datasets
3. Enhanced scalability

CNN-based systems are particularly efficient due to their ability to automatically learn features without manual intervention, improving adaptability in dynamic environments .

Recent studies also combine heterogeneous CNNs with attention mechanisms to prioritize important features, improving model interpretability and performance.

5. Hybrid Blockchain + Deep Learning + Siamese Architectures (2023)

The most recent research trend focuses on hybrid architectures integrating blockchain, deep learning, and Siamese networks.

These systems combine the strengths of each technology:

1. Deep learning → accurate anomaly detection
2. Siamese networks → similarity-based detection of unknown attacks
3. Blockchain → secure and trusted data storage

The rapid growth of Internet of Things (IoT) networks has led to an increasing demand for secure, scalable, and reliable data management frameworks, particularly in cloud-enabled environments. Traditional IoT architectures often face challenges related to data integrity, privacy, and trust due to their distributed and heterogeneous nature. The integration of cloud computing has improved storage and

computational capabilities, enabling efficient data processing and real-time analytics. However, centralized cloud systems introduce vulnerabilities such as single points of failure and susceptibility to cyberattacks. To address these concerns, blockchain technology has emerged as a promising solution by providing decentralized, tamper-proof, and transparent data management, thereby enhancing trust and security in IoT ecosystems.

In parallel, artificial intelligence techniques, particularly deep learning models, have been increasingly applied to strengthen security and improve data processing in IoT networks. Siamese Heterogeneous Convolutional Neural Networks (SHCNNs) represent an advanced approach for identifying similarities and anomalies across diverse data sources. These models are capable of learning complex patterns and relationships, making them highly effective for intrusion detection, authentication, and data validation in cloud-enabled IoT systems. By comparing input pairs and extracting discriminative features, SHCNNs enhance the accuracy of threat detection while reducing false positives. Furthermore, their ability to operate across heterogeneous data types makes them suitable for large-scale IoT environments with diverse devices and communication protocols.

The combination of blockchain and SHCNN-based deep learning models offers a robust hybrid framework for secure IoT networks. Blockchain ensures data integrity, decentralized access control, and secure transactions, while SHCNNs provide intelligent analysis and anomaly detection capabilities. This integration improves overall system reliability, scalability, and resistance to cyber threats. Despite these advancements, challenges such as computational overhead, latency, and energy consumption remain significant, particularly for resource-constrained IoT devices. Additionally, issues related to scalability and interoperability across different platforms must be addressed. Future research should focus on optimizing these hybrid systems, developing lightweight models, and enhancing real-time performance to enable practical deployment in next-generation IoT environments.

Comparative Table

Study (Year)	Method	Architecture	Technology	Accuracy	Detection Capability	Security Level	Scalability	Energy Efficiency	Core Contribution	Limitation
Ali et al. (2022)	Blockchain	Distributed Ledger	IoT + Blockchain	High	Secure communication	Very High	High	Moderate	Tamper-proof data storage	Latency overhead
Samriya et al. (2023)	RL + Blockchain	Reinforcement Learning	Cloud IoT + Blockchain	High	Adaptive trust management	Very High	High	Moderate	Dynamic trust evaluation	Computational cost
Hybrid DL (2023)	CNN + LSTM	Hybrid DL	IoT	Very High (~95–98%)	Anomaly detection	Medium	Moderate	Low–Moderate	Spatio-temporal learning	High complexity
Siamese NN (2023)	SHCNN	Siamese + CNN	IoT	Very High	Unknown attack detection	Medium	High	Moderate	Similarity-based anomaly detection	Pairwise training overhead
Blockchain + AI (2023)	Hybrid System	DL + Blockchain	IoT + Cloud	Very High (~98–99%)	Secure intelligent detection	Very High	Very High	Moderate	Secure + intelligent framework	Integration complexity

Comparative Analysis

The comparative analysis presented in this study demonstrates a clear and structured evolution of security mechanisms in cloud-enabled IoT networks, transitioning from standalone detection approaches to highly integrated, intelligent, and trust-aware hybrid systems. This evolution is driven by the increasing complexity of cyber threats, the need for secure data management, and the demand for scalable and real-time intrusion detection systems.

1. Traditional vs Intelligent Detection Systems

Early IoT security frameworks relied on traditional machine learning and rule-based intrusion detection systems, which were effective in identifying known attack patterns but lacked adaptability to dynamic and evolving threats. These models depended heavily on handcrafted features and struggled to process high-dimensional and heterogeneous IoT data. As a result, their detection accuracy and generalization capability were limited.

The introduction of deep learning models, particularly CNNs, RNNs, and hybrid CNN-LSTM architectures, significantly improved detection performance by enabling automatic feature extraction and spatiotemporal pattern recognition. These models achieved high accuracy levels, often exceeding 90–98%, demonstrating their effectiveness in identifying complex attack patterns. However, their reliance on large datasets, high computational requirements, and lack of trust mechanisms limited their applicability in distributed IoT environments.

2. Role of Heterogeneous CNN Architectures

Traditional CNN models are designed for homogeneous data processing and are less effective in handling diverse IoT data streams. Heterogeneous CNN architectures address this limitation by integrating multiple convolutional pipelines, each tailored to a specific data modality such as sensor data, network traffic, or multimedia inputs. This approach enhances feature extraction, improves generalization, and increases robustness in real-world environments.

Comparative analysis shows that heterogeneous CNNs outperform conventional CNNs in terms of accuracy and scalability, particularly in complex IoT environments. However, this improvement comes at the cost of increased architectural complexity and higher computational overhead.

3. Siamese Neural Networks for Advanced Anomaly Detection

Siamese Neural Networks introduce a paradigm shift in anomaly detection by focusing on similarity learning rather than direct classification. Unlike conventional models that rely on predefined labels, Siamese networks compare pairs of inputs and determine whether they belong to the same class.

This approach offers several advantages:

1. Effective detection of unknown and zero-day attacks
2. Reduced false positive rates
3. Support for few-shot learning

These characteristics make Siamese networks highly suitable for dynamic IoT environments where attack patterns continuously evolve. However, they require carefully constructed training pairs and introduce additional computational complexity.

4. Blockchain-Based IoT Security vs Cloud-Based Systems

Cloud-centric IoT architectures provide scalability and centralized processing capabilities but suffer from vulnerabilities such as data breaches, unauthorized access, and single points of failure. Blockchain technology addresses these issues by introducing a decentralized, immutable, and transparent data storage mechanism.

Blockchain-based systems enhance:

1. Data integrity
2. Trust management
3. Secure communication

Comparatively, blockchain-based IoT systems offer significantly higher security and reliability than cloud-based systems. However, they introduce latency due to consensus mechanisms and increase computational and energy overhead, which can impact real-time performance.

5. Deep Learning vs Blockchain vs Hybrid Systems

A critical insight from the comparative analysis is that standalone systems are insufficient to address the full spectrum of IoT security challenges. Deep learning-based systems offer high detection accuracy by capturing complex patterns in data, but they lack robust trust mechanisms and secure data management capabilities. On the other hand, blockchain-based systems provide strong security, transparency, and decentralized trust management, yet they lack intelligent detection capabilities required for identifying sophisticated or evolving cyber threats. Hybrid systems overcome these limitations by combining the strengths of both

approaches. Architectures that integrate deep learning models, Siamese networks, and blockchain technology achieve very high detection accuracy while ensuring strong security and trust management. Additionally, these systems offer high scalability and support real-time anomaly detection, making them highly suitable for dynamic and large-scale IoT environments. Therefore, hybrid frameworks represent the most effective and promising solution for addressing modern IoT security challenges.

6. Optimization and Efficiency Improvements

Optimization techniques play a crucial role in improving system performance and efficiency. Algorithms such as Genetic Algorithms (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) are used for feature selection, hyperparameter tuning, and resource allocation.

Optimized systems demonstrate:

- Reduced computational overhead
- Improved detection accuracy
- Enhanced energy efficiency
- Extended network lifetime

Compared to non-optimized systems, these approaches are better suited for deployment in resource-constrained IoT environments.

7. Edge Computing vs Cloud vs Hybrid Architectures

Cloud computing provides high processing power but suffers from latency and bandwidth limitations. Edge computing addresses these issues by processing data closer to the source, enabling real-time decision-making.

Hybrid edge-cloud systems combine the strengths of both approaches:

1. Low latency (edge)
2. High scalability (cloud)
3. Balanced processing power

These architectures are increasingly preferred for IoT security systems due to their ability to balance performance and efficiency.

8. Energy Efficiency and Scalability Trade-Off

Energy efficiency remains a critical challenge in IoT systems due to limited battery capacity of devices. Deep learning models consume high energy, while blockchain systems introduce additional overhead. Hybrid systems with optimization techniques offer improved energy efficiency.

Scalability analysis shows:

1. Centralized systems → Limited scalability
2. Blockchain systems → Improved scalability
3. Hybrid systems → Highest scalability

9. Integrated Comparative Insight

The analysis highlights a clear technological progression:

1. 2020: Deep learning adoption → Improved accuracy
2. 2021: Blockchain integration → Enhanced security
3. 2022: Heterogeneous CNN + optimization → Improved efficiency
4. 2023: Hybrid SHCNN + blockchain systems → Maximum performance

10. Final Conclusion of Comparative Analysis

In conclusion, the comparative analysis demonstrates that hybrid systems integrating Siamese heterogeneous CNNs, blockchain technology, and optimization techniques represent the most advanced and effective solution for securing cloud-enabled IoT networks. These systems achieve superior performance across multiple dimensions, including accuracy, security, scalability, and real-time capability.

However, challenges such as computational complexity, energy consumption, latency, and system integration must be addressed to enable practical deployment. Future research should focus on developing lightweight architectures, energy-efficient blockchain protocols, optimized hybrid frameworks, and edge-based solutions to support real-world IoT applications.

Discussion

The integration of blockchain technology and Siamese heterogeneous convolutional neural networks (SHCNN) in cloud-enabled IoT systems represents a significant advancement in addressing security and trust challenges. Deep learning models, particularly CNN-based architectures, have demonstrated strong performance in detecting anomalies and malicious activities. However, their effectiveness is often limited by their inability to generalize across heterogeneous data sources and detect previously unseen attack patterns. The introduction of Siamese networks addresses this limitation by enabling similarity-based learning, which improves the detection of zero-day and unknown attacks while reducing false positives.

Heterogeneous CNN architectures further enhance this capability by processing diverse data modalities generated in IoT environments, such as sensor data, network traffic, and multimedia inputs. This leads to improved feature representation and higher detection accuracy. On the other hand, blockchain technology provides a decentralized trust

mechanism, ensuring data integrity, transparency, and secure communication between IoT devices and cloud platforms. By eliminating centralized control, blockchain reduces vulnerabilities such as single points of failure and unauthorized data manipulation.

Despite these advantages, several challenges remain. The computational overhead associated with deep learning models and blockchain consensus mechanisms can limit real-time performance, especially in resource-constrained IoT devices. Additionally, integrating multiple technologies increases system complexity and requires efficient coordination between cloud, edge, and IoT layers. Energy consumption and latency also remain critical concerns. Future research should focus on developing lightweight SHCNN models, energy-efficient blockchain protocols, and optimized hybrid architectures. The adoption of edge computing and federated learning can further enhance scalability, reduce latency, and improve privacy preservation in cloud-enabled IoT systems.

Conclusion

This review presents a comprehensive analysis of trusted cloud-enabled IoT networks using blockchain and Siamese heterogeneous convolutional neural networks. The study highlights the limitations of traditional security approaches and emphasizes the need for intelligent, scalable, and trust-aware solutions in modern IoT ecosystems. Deep learning techniques, particularly CNN-based models, have significantly improved anomaly detection capabilities, while Siamese networks provide an effective mechanism for identifying unknown and evolving threats through similarity learning. Blockchain technology plays a crucial role in enhancing security and trust by enabling decentralized, tamper-proof data storage and transparent transaction management. Its integration with deep learning models creates a robust framework for secure data processing and communication in cloud-enabled IoT systems. Furthermore, heterogeneous CNN architectures improve feature extraction and adaptability across diverse data environments, making them suitable for real-world IoT applications.

The comparative analysis demonstrates that hybrid systems combining SHCNN, blockchain, and optimization techniques offer superior performance in terms of accuracy, security, scalability, and real-time capability. However, challenges such as computational complexity, energy consumption, and system integration must be addressed to enable practical deployment. Future research should focus on optimizing these technologies to develop lightweight, energy-efficient, and scalable solutions. The integration of edge computing, federated learning, and advanced optimization techniques will be critical in achieving real-time performance and widespread adoption.

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