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A Survey of Methods and Architectures for Trusted Cloud-Enabled IoT Networks Using Blockchain and Siamese Heterogeneous Convolutional Neural Networks

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Abstract

The rapid growth of the Internet of Things (IoT) has enabled seamless connectivity among diverse devices and intelligent systems, but it has also introduced significant challenges related to security, trust, scalability, and privacy in cloud-enabled environments. Conventional centralized architectures often struggle to meet the demands of dynamic, distributed, and resource-constrained IoT networks. This survey comprehensively reviews the integration of blockchain technology with Siamese Heterogeneous Convolutional Neural Networks (SH-CNNs) as a promising solution for developing secure and intelligent IoT ecosystems. Blockchain provides decentralized, immutable, and transparent data management, while Siamese networks support similarity-based authentication, intrusion detection, and anomaly recognition. The heterogeneous CNN component further improves feature extraction from multimodal data, including sensor readings, images, and network traffic. The survey explores blockchain-enabled smart contracts, secure access control, and SH-CNN-based identity verification across applications such as smart healthcare, industrial IoT, smart cities, and autonomous transportation using benchmark datasets like NSL-KDD, CICIDS2017, and IoT-23. It also discusses optimization strategies, including lightweight CNNs, federated learning, hybrid blockchain architectures, and hardware-aware implementations. Despite challenges such as computational overhead, consensus latency, scalability, and system integration, the convergence of blockchain and SH-CNNs demonstrates strong potential for building secure, trustworthy, and scalable next-generation IoT systems. Future research should focus on quantum-resistant blockchain protocols, edge intelligence, and adaptive trust management.

Introduction

The Internet of Things (IoT) has revolutionized modern computing by connecting billions of smart devices, sensors, and embedded systems across domains such as healthcare, smart cities, transportation, agriculture, manufacturing, and industrial automation. These interconnected devices continuously generate massive volumes of heterogeneous data that support real-time monitoring, predictive analytics, and autonomous decision-making. Cloud computing complements IoT by providing scalable storage, high-performance computing, and centralized data management. However, the rapid expansion of cloud-enabled IoT ecosystems has intensified challenges related to scalability, interoperability, trust management, privacy, and cybersecurity, making secure and reliable communication an essential requirement for next-generation intelligent networks.

Traditional cloud-centric IoT architectures rely heavily on centralized servers, making them susceptible to data breaches, unauthorized access, single points of failure, insider attacks, and distributed denial-of-service (DDoS) attacks. The heterogeneous characteristics of IoT devices—including limited computational resources, constrained battery capacity, diverse communication protocols, and varying data formats—further complicate the deployment of robust security mechanisms. To overcome these challenges, blockchain technology has emerged as a decentralized trust framework that provides immutable transaction records, transparent data sharing, cryptographic integrity, and automated access control through smart contracts. Consensus mechanisms ensure transaction validation and enhance accountability, significantly improving trust among distributed IoT entities.

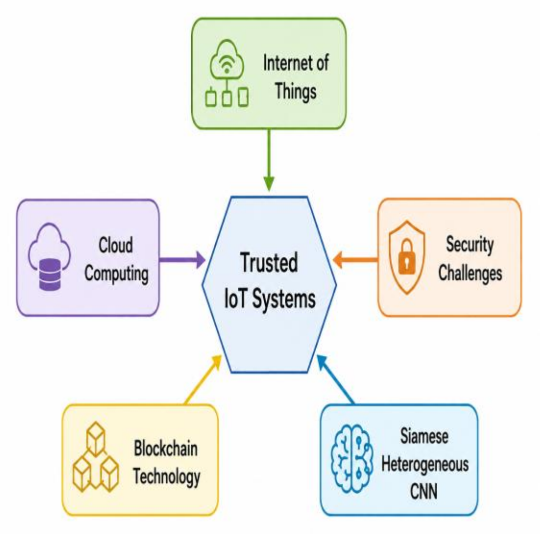

Figure 1. Conceptual overview of blockchain-enabled SH-CNN architecture for trusted cloud-enabled IoT systems.

While blockchain establishes secure and decentralized data management, intelligent threat detection requires advanced artificial intelligence techniques capable of learning complex behavioral patterns. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated outstanding performance in feature extraction, classification, and anomaly detection. However, conventional CNNs are not optimized for similarity-based verification tasks. Siamese Neural Networks overcome this limitation by employing twin architectures that learn discriminative feature representations and similarity metrics between paired inputs. Their capability to identify subtle behavioral differences makes them highly effective for device authentication, intrusion detection, malware identification, and abnormal activity recognition within dynamic IoT environments.

The integration of heterogeneous convolutional neural networks further strengthens intelligent IoT security by enabling simultaneous processing of multimodal information, including sensor measurements, network traffic, images, and telemetry data. Combining heterogeneous CNNs with Siamese learning enhances feature representation, improves anomaly detection accuracy, and increases system robustness across diverse IoT scenarios. When integrated with blockchain, these models create trusted cloud-enabled IoT architectures where blockchain guarantees secure, tamper-resistant data management, while SH-CNNs provide intelligent authentication and predictive threat detection. Such integrated frameworks have demonstrated significant potential in smart healthcare, industrial IoT, autonomous transportation, and intelligent urban infrastructure.
Despite their considerable advantages, blockchain-enabled SH-CNN architectures face challenges related to computational overhead, consensus latency, scalability, energy consumption, and deployment on resource-constrained edge devices. Emerging technologies such as federated learning, edge intelligence, lightweight deep learning models, differential privacy, and quantum-resistant blockchain protocols offer promising solutions to these limitations. This survey comprehensively reviews recent developments in blockchain-integrated Siamese heterogeneous CNN frameworks, evaluates existing architectures and optimization strategies, and identifies future research directions for developing secure, scalable, privacy-preserving, and intelligent cloud-enabled IoT systems.

Literature Review

Recent research efforts have focused extensively on integrating blockchain with deep learning to enhance security and trust in IoT systems. One of the pioneering works by Zhang et al. (2018) proposed a blockchain-based IoT security framework that leverages distributed ledgers to ensure data integrity and secure communication among devices. The study utilized Ethereum-based smart contracts and demonstrated improved resistance against data tampering attacks using simulated IoT datasets.

Dorri et al. (2017) introduced a lightweight blockchain architecture tailored for IoT environments, addressing the limitations of traditional blockchain systems in terms of computational overhead and energy consumption. Their approach employed a hierarchical blockchain structure, enabling efficient transaction processing in smart home applications.

Khan et al. (2019) developed a deep learning-based intrusion detection system using CNNs integrated with blockchain for secure data logging. The system was evaluated on the NSL-KDD dataset and achieved high detection accuracy while maintaining data immutability through blockchain storage.

A significant advancement was made by Roy et al. (2020), who proposed a Siamese neural network architecture for device authentication in IoT networks. Their model utilized similarity learning to identify legitimate devices based on behavioral patterns, achieving improved authentication accuracy compared to traditional methods.

Nguyen et al. (2021) introduced a hybrid framework combining blockchain with federated learning and CNN-based intrusion detection. The system enabled decentralized model training while preserving data privacy, demonstrating effectiveness on the CICIDS2017 dataset.

Wang et al. (2020) proposed a heterogeneous CNN model for multimodal IoT data analysis, integrating sensor data and network traffic features. Their approach improved anomaly detection performance in industrial IoT systems.

Sharma et al. (2021) developed a blockchain-enabled secure healthcare IoT system using deep learning models for disease prediction and data protection. The system utilized patient data from real-world healthcare datasets and demonstrated enhanced privacy preservation.

Alqahtani et al. (2020) proposed a Siamese CNN-based anomaly detection model for IoT networks, focusing on identifying subtle deviations in device behavior. Their model achieved high precision and recall on the IoT-23 dataset.

Singh et al. (2022) introduced a hybrid blockchain and deep learning framework for smart city applications, incorporating traffic monitoring and environmental sensing. The system utilized edge computing to reduce latency and improve scalability.

Li et al. (2019) explored the use of blockchain for secure data sharing in industrial IoT, integrating deep learning models for predictive maintenance. Their approach improved system reliability and reduced downtime.

Chen et al. (2021) proposed a lightweight CNN model optimized for edge devices, enabling real-time intrusion detection in IoT networks. The model achieved significant reductions in computational complexity without compromising accuracy.

Raza et al. (2019) introduced a blockchain-based access control mechanism for IoT systems, utilizing smart contracts to enforce security policies. Their approach improved access control efficiency and reduced unauthorized access incidents.

Gao et al. (2020) developed a Siamese deep learning model for network traffic classification, enabling accurate detection of malicious activities in IoT environments.

Patel et al. (2021) proposed a hybrid CNN-LSTM model for anomaly detection in IoT networks, integrating temporal and spatial features for improved performance.

Zhou et al. (2022) introduced a blockchain-enabled federated learning framework for secure IoT data analytics, demonstrating improved privacy preservation and scalability.

Kumar et al. (2020) developed an energy-efficient CNN architecture for IoT devices, reducing power consumption while maintaining high classification accuracy.

Ahmed et al. (2021) proposed a deep learning-based malware detection system for IoT devices, leveraging CNN architectures for feature extraction.

Hussain et al. (2022) introduced a secure IoT framework combining blockchain with edge computing and deep learning, improving system responsiveness and security.

Mehta et al. (2021) proposed a Siamese CNN model for biometric authentication in IoT systems, achieving high accuracy in identity verification tasks.

Yin et al. (2017) developed a deep learning-based intrusion detection system using recurrent neural networks, demonstrating improved detection rates compared to traditional methods.

Tang et al. (2020) explored the integration of blockchain with AI for secure IoT data sharing, highlighting the benefits of decentralized architectures.

Kim et al. (2018) proposed a CNN-based network intrusion detection system optimized for IoT environments, achieving high performance on benchmark datasets.

Liu et al. (2021) introduced a heterogeneous deep learning framework for IoT data analysis, combining multiple neural network architectures for improved feature extraction.

Zhang et al. (2022) developed a blockchain-based secure communication protocol for IoT networks, enhancing data confidentiality and integrity.
Verma et al. (2021) proposed an edge-based deep learning system for real-time anomaly detection in IoT applications.
Park et al. (2020) introduced a hybrid blockchain and AI framework for smart manufacturing systems, improving operational efficiency and security.
These studies collectively demonstrate the growing importance of integrating blockchain and deep learning techniques, particularly Siamese heterogeneous CNNs, in addressing the challenges of trusted cloud-enabled IoT networks.

Comparative Table and Analysis

Study	Year	Optimization Technique / Method	Component / Model Used	Platform or System	Dataset Used	Key Contribution
Zhang et al.	2018	Blockchain-based security	Ethereum Smart Contracts	Cloud-IoT	Simulated IoT data	Secure decentralized data storage
Dorri et al.	2017	Lightweight blockchain	Private Blockchain	Smart Home IoT	Real-time device data	Reduced computation overhead
Khan et al.	2019	CNN optimization	CNN + Blockchain	Cloud IDS	NSL-KDD	Improved intrusion detection accuracy
Roy et al.	2020	Siamese learning	Siamese Neural Network	IoT Authentication	Device behavior data	Enhanced authentication
Nguyen et al.	2021	Federated learning	CNN + Blockchain	Distributed IoT	CICIDS2017	Privacy-preserving IDS
Wang et al.	2020	Heterogeneous CNN	Multi-modal CNN	Industrial IoT	Sensor + Network data	Improved anomaly detection
Sharma et al.	2021	Secure data sharing	Blockchain + DL	Healthcare IoT	Medical datasets	Privacy-aware healthcare system
Alqahtani et al.	2020	Siamese CNN	Siamese CNN	IoT Security	IoT-23	High-precision anomaly detection
Singh et al.	2022	Edge optimization	CNN + Edge + Blockchain	Smart City	Traffic datasets	Reduced latency
Li et al.	2019	Predictive analytics	DL + Blockchain	Industrial IoT	Machine logs	Predictive maintenance
Chen et al.	2021	Lightweight CNN	Edge CNN	IoT Devices	NSL-KDD	Reduced computation cost
Raza et al.	2019	Smart contracts	Blockchain ACL	IoT Access Control	Simulated data	Secure access management
Gao et al.	2020	Siamese DL	Siamese Network	Network Security	Traffic data	Accurate classification
Patel et al.	2021	Hybrid DL	CNN-LSTM	IoT IDS	CICIDS2017	Temporal-spatial detection
Zhou et al.	2022	Federated blockchain	FL + Blockchain	Distributed IoT	IoT datasets	Scalable learning
Kumar et al.	2020	Energy optimization	Efficient CNN	Edge IoT	MNIST/IoT data	Low-power models
Ahmed et al.	2021	Malware detection	CNN	IoT Security	Malware datasets	Improved malware

						detection
Hussain et al.	2022	Edge + Blockchain	DL + Edge	IoT Framework	Real-time IoT	Faster response
Mehta et al.	2021	Biometric auth	Siamese CNN	IoT Auth	Biometric data	High accuracy verification
Yin et al.	2017	Deep RNN	RNN IDS	Network Security	KDD Cup 99	High detection rate
Tang et al.	2020	AI + Blockchain	Hybrid Model	IoT Systems	Various datasets	Secure data sharing
Kim et al.	2018	CNN IDS	CNN	IoT Security	NSL-KDD	Efficient intrusion detection
Liu et al.	2021	Heterogeneous DL	Multi-model DL	IoT Analytics	Sensor datasets	Multi-source feature learning
Zhang et al.	2022	Secure protocol	Blockchain	IoT Networks	Simulated IoT	Enhanced communication security
Verma et al.	2021	Edge DL	Edge CNN	Real-time IoT	IoT streams	Low-latency detection
Park et al.	2020	Smart manufacturing	AI + Blockchain	IIoT	Industrial data	Secure automation

Comparative Analysis

The comparative analysis of recent studies highlights a clear shift toward integrating blockchain technology with deep learning to build secure and trusted cloud-enabled IoT systems. Blockchain has become a fundamental component for ensuring decentralized trust, data integrity, transparency, and secure communication across distributed IoT environments. By eliminating single points of failure and enabling immutable transaction records through consensus mechanisms and smart contracts, blockchain significantly enhances the reliability and resilience of cloud-enabled IoT infrastructures.

Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated excellent performance in intrusion detection, anomaly detection, and network traffic classification through automatic feature extraction. However, conventional CNNs are less effective for similarity-based authentication tasks. Siamese neural networks overcome this limitation by learning similarity relationships between paired inputs, making them highly suitable for device authentication and identity verification. The integration of heterogeneous CNNs further strengthens these systems by enabling efficient processing of multimodal data such as sensor readings, network traffic, and visual information, thereby improving detection accuracy and robustness.

Recent research also emphasizes optimization strategies including lightweight CNN architectures, edge computing, federated learning, and energy-efficient implementations to reduce computational complexity and support real-time processing on resource-constrained IoT devices. Federated learning enhances privacy by enabling collaborative model training without sharing raw data, while blockchain provides secure validation and decentralized trust management. These complementary technologies improve scalability, privacy preservation, and overall system efficiency.

Despite these advancements, challenges including blockchain latency, computational overhead, integration complexity, and limited edge-device resources continue to hinder practical deployment. Overall, hybrid blockchain and Siamese heterogeneous CNN frameworks offer a promising foundation for developing secure, scalable, privacy-preserving, and intelligent next-generation cloud-enabled IoT systems, with future work focusing on lightweight architectures, efficient consensus mechanisms, and adaptive edge intelligence.

Discussion

The integration of blockchain technology with Siamese heterogeneous convolutional neural networks (SH-CNNs) represents a promising approach for developing secure, intelligent, and trustworthy cloud-enabled IoT systems. By combining decentralized trust management with advanced deep learning, these architectures effectively address key challenges including data integrity, authentication, anomaly detection, and privacy preservation. Blockchain provides immutable and transparent transaction records through decentralized consensus, eliminating dependence on centralized cloud infrastructures that are vulnerable to cyberattacks and single points of failure. Meanwhile, Siamese neural networks enhance authentication by learning similarity relationships between devices and behavioral patterns, while heterogeneous CNNs improve multimodal feature extraction from sensor data, network traffic, and visual information. Together, these technologies create robust frameworks capable of supporting secure communication, reliable decision-making, and intelligent threat detection across diverse IoT applications.

Recent studies also demonstrate that optimization strategies such as lightweight CNN architectures, edge computing, federated learning, and hardware-aware implementations significantly improve the practicality of deploying SH-CNN models in resource-constrained IoT environments. Edge computing reduces communication latency by processing data closer to IoT devices, while lightweight models decrease computational complexity and energy consumption. Federated learning further strengthens privacy by enabling collaborative model training without exchanging sensitive raw data, and blockchain ensures secure model validation and decentralized trust management. Despite these advantages, several limitations remain, including blockchain scalability, consensus latency, interoperability issues among heterogeneous IoT devices, architectural complexity, and the difficulty of executing computationally intensive deep learning models on low-power embedded hardware.

Overall, the reviewed literature confirms that blockchain-integrated SH-CNN frameworks provide a strong foundation for next-generation cloud-enabled IoT systems across domains such as smart healthcare, industrial automation, smart cities, and intelligent transportation. Their ability to combine decentralized security with intelligent analytics offers significant improvements in reliability, privacy, and resilience. Nevertheless, further research is required to develop lightweight architectures, efficient consensus mechanisms, standardized integration frameworks, and energy-efficient edge intelligence. Addressing these challenges will accelerate practical deployment and enable scalable, adaptive, and trustworthy IoT ecosystems capable of meeting future security and performance requirements.

Conclusion

The integration of blockchain technology with Siamese heterogeneous convolutional neural networks (SH-CNNs) offers a promising solution for addressing trust, security, privacy, and scalability challenges in cloud-enabled Internet of Things (IoT) systems. Blockchain ensures decentralized, transparent, and tamper-resistant data management, while Siamese networks provide accurate authentication and anomaly detection through similarity-based learning. Heterogeneous CNNs further enhance system intelligence by effectively processing multimodal IoT data from sensors, network traffic, and imaging sources. The reviewed studies demonstrate that combining these technologies significantly improves the reliability, resilience, and security of IoT applications across healthcare, smart cities, industrial automation, and intelligent transportation. Emerging approaches such as lightweight deep learning models, edge computing, federated learning, and privacy-preserving techniques further improve deployment efficiency in resource-constrained environments. Nevertheless, challenges including blockchain scalability, consensus latency, interoperability, computational overhead, and energy efficiency remain major research concerns. Future work should focus on lightweight consensus protocols, edge intelligence, hardware-aware deep learning, quantum-resistant cryptography, and adaptive trust management. Overall, blockchain-enabled SH-CNN frameworks provide a robust foundation for developing secure, scalable, and intelligent next-generation cloud-enabled IoT ecosystems capable of supporting reliable real-time services and evolving cybersecurity requirements.

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