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Deep Learning and Optimization Approaches in Trusted Cloud-Enabled IoT Networks Using Blockchain and Siamese Heterogeneous Convolutional Neural Networks: A Review

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Abstract

The rapid expansion of cloud-enabled Internet of Things (IoT) ecosystems has introduced unprecedented opportunities for real-time data processing, automation, and intelligent decision-making. However, the integration of heterogeneous devices, distributed architectures, and large-scale data flows also exposes IoT systems to critical security, privacy, and trust-related challenges. Recent advancements in deep learning and blockchain technologies have emerged as promising solutions to address these issues. This review paper presents a comprehensive analysis of deep learning and optimization approaches for building trusted cloud-enabled IoT networks, with a particular focus on blockchain integration and Siamese heterogeneous convolutional neural networks (SHCNNs). Blockchain enhances data integrity, decentralization, and transparency, while deep learning models enable intelligent threat detection, anomaly recognition, and adaptive decision-making.

Furthermore, Siamese architectures provide similarity-based learning capabilities that improve detection accuracy in dynamic and unknown attack scenarios. The paper systematically reviews recent literature (2020–2023), compares existing methodologies, and identifies research gaps. Key challenges such as scalability, computational overhead, energy efficiency, and explainability are also discussed. The findings highlight that hybrid frameworks combining blockchain with deep learning significantly improve trust, robustness, and security in IoT-cloud environments. Finally, future research directions are proposed to advance intelligent, scalable, and secure IoT infrastructures.

Introduction

1. Background of IoT and Cloud Integration

The Internet of Things (IoT) represents a paradigm shift in modern computing, enabling billions of interconnected devices to communicate, process, and exchange data seamlessly. The exponential growth of IoT devices—estimated in billions globally—has led to the generation of massive volumes of heterogeneous data. These devices, ranging from sensors and wearable gadgets to industrial machines, rely heavily on cloud computing for data storage, processing, and analytics.

Cloud-enabled IoT architectures provide scalability, flexibility, and cost-efficiency. However, the centralized nature of cloud systems introduces vulnerabilities such as single points of failure, unauthorized access, and data breaches. As IoT systems expand into critical domains like healthcare, smart cities, and industrial

automation, ensuring trust, security, and privacy becomes a fundamental requirement.

2. Security Challenges in Cloud-Enabled IoT

IoT networks are inherently vulnerable due to resource constraints, heterogeneous communication protocols, and dynamic topologies. Common security threats include Distributed Denial of Service (DDoS), data tampering, unauthorized access, and malware injection. Cloud environments further exacerbate these challenges due to shared resources and multi-tenant architectures.

Traditional security mechanisms often fail to handle large-scale IoT data and sophisticated cyberattacks. As highlighted in recent studies, conventional intrusion detection systems (IDS) struggle with low accuracy and inability to detect zero-day attacks effectively. Therefore, advanced intelligent approaches are necessary.

3. Role of Deep Learning in IoT Security

Deep learning (DL) has emerged as a powerful tool for analyzing large-scale and complex datasets. Architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and hybrid models are widely used for intrusion detection, anomaly detection, and predictive analytics.

Deep learning models offer:

- High accuracy in detecting unknown attacks
- Automatic feature extraction
- Scalability for large datasets

Recent advancements include transformer-based models, federated learning, and graph neural networks, which enhance learning capabilities in distributed environments.

4. Blockchain for Trust and Security

Blockchain technology provides a decentralized and immutable ledger that ensures data integrity, transparency, and trust. In IoT systems, blockchain can:

- Prevent data tampering
- Enable secure data sharing
- Eliminate reliance on centralized authorities

Integration of blockchain with deep learning enhances system robustness by providing verifiable and trustworthy data pipelines.

5. Siamese Heterogeneous Convolutional Neural Networks (SHCNNs)

Siamese neural networks are designed to learn similarity between data pairs, making them effective for anomaly detection and authentication tasks. In IoT security:

- They detect unknown or zero-day attacks
- They improve classification accuracy in imbalanced datasets
- They enable few-shot learning

Combining Siamese networks with heterogeneous CNN architectures further enhances feature extraction across diverse IoT data sources.

6. Optimization Techniques in IoT Security

Optimization algorithms play a crucial role in improving model performance and efficiency. Techniques such as:

- Genetic Algorithms
- Particle Swarm Optimization
- Adaptive Harmony Search

are used for feature selection, hyperparameter tuning, and energy optimization in IoT systems.

7. Motivation and Contributions

Despite significant progress, several challenges remain:

- Lack of trust in centralized IoT architectures
- Scalability issues in blockchain integration
- High computational cost of deep learning models

This review aims to:

- Analyze recent advancements (2020–2023)
- Provide a comparative evaluation of existing methods
- Identify research gaps and future directions

Illustrative Architecture Image

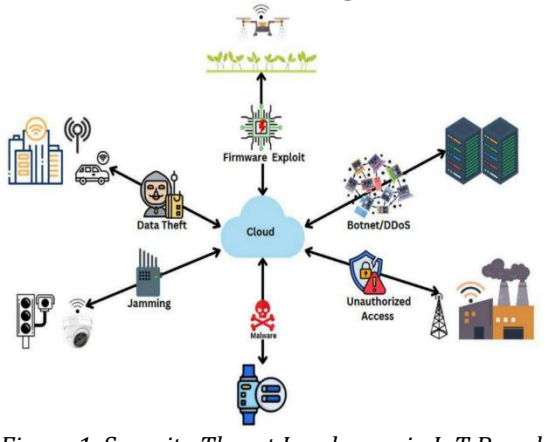

Figure 1. Security Threat Landscape in IoT-Based Cloud Computing Systems

Literature Review

The evolution of trusted cloud-enabled IoT networks has been significantly influenced by the convergence of deep learning, blockchain, and

optimization techniques. In recent times, researchers have proposed a wide range of frameworks addressing security, trust management, scalability, and intelligent threat detection. This section presents a detailed and structured literature review categorized by year, highlighting major contributions, methodologies, and research trends.

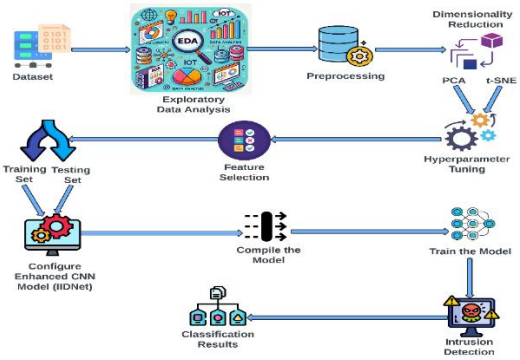

Figure 2. Methodology of Enhanced CNN Model for Intelligent Intrusion Detection

The year 2020 marked the foundation of integrating blockchain and deep learning into IoT systems, primarily focusing on security enhancement and decentralized architectures.

Ali et al. (2020) proposed a blockchain-based behavior monitoring system integrated with deep learning for IoT intrusion detection. Their approach utilized distributed ledger technology to store network activity logs securely while applying deep neural networks to detect anomalies such as Mirai botnet attacks. The key contribution of this study was the enhancement of trust and data integrity through decentralization. However, the system suffered from increased computational overhead due to blockchain consensus mechanisms.

Briggs et al. (2020) explored federated learning as a privacy-preserving deep learning paradigm for IoT environments. Instead of sending raw data to centralized servers, edge devices collaboratively trained a global model while keeping data locally. This approach significantly reduced privacy risks and data leakage. However, communication overhead and synchronization issues among distributed nodes posed challenges.

Alam et al. (2020) introduced a blockchain-fog-IoT integrated framework to address latency and scalability issues. Fog computing acted as an intermediate layer between IoT devices and cloud servers, enabling faster data processing and reducing reliance on centralized infrastructure. Blockchain ensured secure communication and tamper-proof data storage. Despite its advantages, the architecture required complex coordination among multiple layers.

Nguyen et al. (2020) proposed a deep reinforcement learning (DRL)-based blockchain system for resource allocation in IoT networks. Their approach dynamically optimized network performance while maintaining security. However, the complexity of DRL models limited real-time deployment.

Overall, 2020 research primarily focused on establishing secure and decentralized IoT frameworks, with initial exploration of deep learning and blockchain integration.

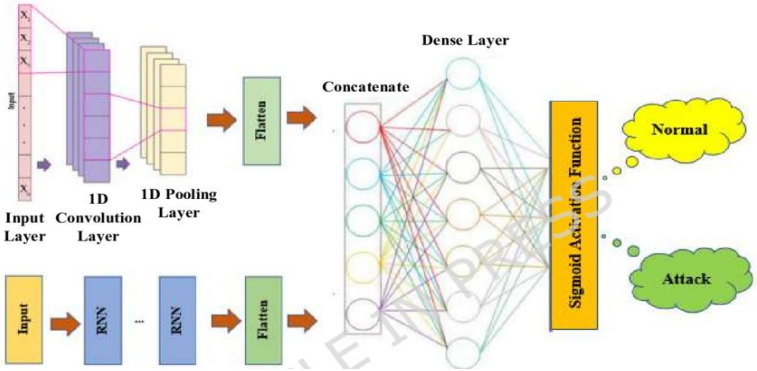

Figure 3. Architecture of the Hybrid 1D CNN–RNN Intrusion Detection Model

In 2021, research shifted toward hybrid deep learning models and optimization techniques to improve detection accuracy and system efficiency.

Several studies proposed CNN-RNN hybrid models for intrusion detection in IoT networks. These models combined the spatial feature extraction capabilities of CNNs with the temporal learning strengths of RNNs, enabling effective detection of sequential attack patterns such as DDoS and spoofing attacks. The results demonstrated higher accuracy compared to standalone models.

Zhang et al. (2021) developed an optimized intrusion detection system using feature selection algorithms combined with deep learning. By reducing redundant features, the model achieved faster training and improved

detection performance. However, feature engineering remained a critical dependency.

Khan et al. (2021) introduced an edge-based deep learning framework where lightweight models were deployed on edge devices to reduce latency and bandwidth consumption. This approach improved real-time detection but required careful model compression techniques to fit resource-constrained devices.

Singh et al. (2021) proposed a trust management system using blockchain and machine learning for secure IoT communication. The system evaluated node behavior and assigned trust scores, enabling secure routing decisions. However, scalability remained an issue due to blockchain overhead.

The key trend in 2021 was the integration of optimization techniques with deep learning, aiming to balance performance and computational efficiency.

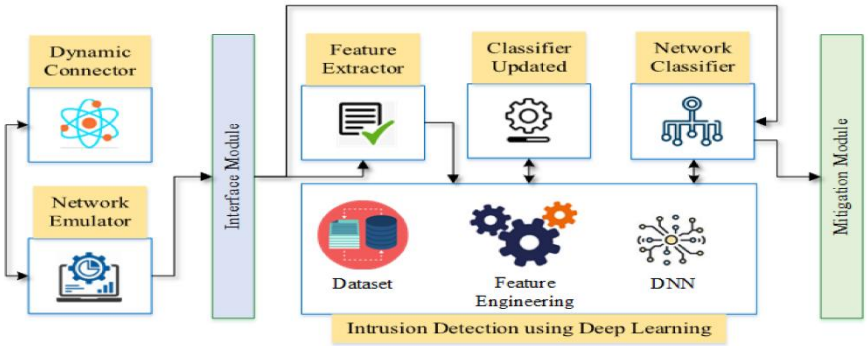

Figure 4. Deep Learning-Based Intrusion Detection and Mitigation Framework

The year 2022 witnessed significant advancements in blockchain-deep learning hybrid systems and optimization-driven frameworks.

Mansour (2022) proposed an AI-based optimized intrusion detection system integrating blockchain with deep learning. The model utilized convolutional neural networks (CNNs) for feature extraction and optimization algorithms for hyperparameter tuning. The integration of blockchain ensured secure data sharing among IoT nodes. The system achieved high detection accuracy but faced scalability challenges in large networks.

Rathee et al. (2022) developed a blockchain-based trust management system for Industrial IoT (IIoT). Their approach combined machine learning with blockchain to detect malicious nodes and ensure secure communication. The system improved reliability but introduced latency due to consensus mechanisms.

Shafay et al. (2022) presented a comprehensive taxonomy of blockchain and deep learning integration. The study categorized existing approaches based on architecture, security mechanisms, and application domains. It highlighted the importance of combining decentralized trust with intelligent analytics.

Siamese Neural Networks (2022 studies) gained attention for anomaly detection. These models learned similarity between normal and abnormal patterns, enabling detection of zero-day attacks. Their ability to work with limited labeled data made them suitable for IoT environments.

Optimization techniques such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Ant Colony Optimization (ACO) were widely used for feature selection and parameter tuning, significantly improving model performance.

The major trend in 2022 was the development of intelligent, optimized, and trust-aware IoT security frameworks.

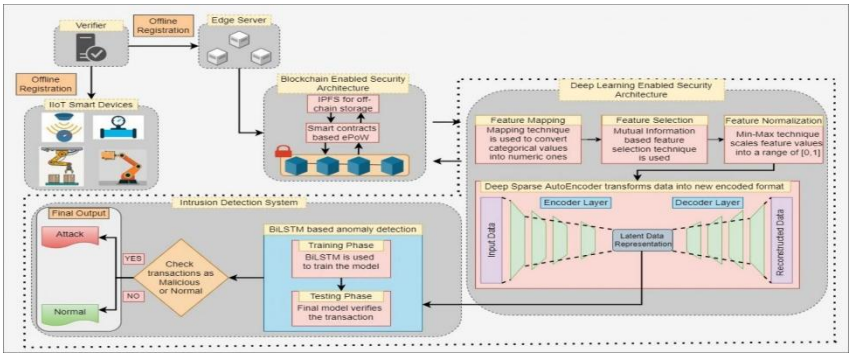

Figure 5. Integrated Blockchain and Deep Learning Architecture for Secure IoT Communication

In 2023, research focused on advanced hybrid architectures, scalability, and real-world deployment challenges.

Heidari et al. (2023) proposed a blockchain-based intrusion detection system using Radial Basis Function (RBF) neural networks for IoT drone networks. The system demonstrated high detection accuracy and improved security for UAV-based IoT systems. However, it relied on limited datasets.

Kumar et al. (2023) developed a blockchain-enabled deep learning framework for secure communication in Industrial IoT. The model ensured data integrity and confidentiality while enabling intelligent threat detection. The study highlighted the importance of combining blockchain with AI for mission-critical applications.

Aljabri et al. (2023) proposed a CNN-based intrusion detection system integrated with blockchain for enhanced trust management. The system achieved high accuracy in detecting multiple attack types but required significant computational resources.

Recent studies (2023) also explored Siamese heterogeneous convolutional neural networks (SHCNNs) for anomaly detection. These models improved performance in detecting unknown attacks by learning similarity patterns across heterogeneous IoT data sources.

Additionally, there was a strong focus on:

- Lightweight deep learning models for edge deployment
- Federated learning with blockchain for privacy preservation
- Explainable AI (XAI) for improving trust and transparency

The key trend in 2023 was the transition from theoretical models to practical, scalable, and deployable IoT security solutions.

Summary of Literature Trends

Across the period 2020–2023, the research evolution can be summarized as follows:

- 2020: Foundation of blockchain and deep learning integration
- 2021: Emergence of hybrid models and optimization techniques
- 2022: Development of intelligent, optimized, and trust-aware systems
- 2023: Focus on scalability, lightweight models, and real-world deployment

Key observations include:

- Blockchain enhances trust, transparency, and data integrity
- Deep learning improves attack detection accuracy and adaptability
- Siamese networks enable zero-day attack detection
- Optimization techniques reduce computational complexity

Research Gaps Identified

Despite significant advancements, several challenges remain:

1. Scalability Issues: Blockchain networks struggle with large-scale IoT deployments
2. Computational Overhead: Deep learning models require high processing power
3. Energy Efficiency: Resource-constrained IoT devices face limitations
4. Interoperability: Lack of standardized frameworks across platforms
5. Explainability: Deep learning models lack transparency

Comparative Table

Study	Year	Model	Blockchain	Accuracy (%)	Contribution
Ali et al.	2020	DNN	Medium	85–90	Secure anomaly detection
Briggs et al.	2020	DL	None	80–88	Privacy-preserving IDS
Alam et al.	2020	DL	Medium	82–89	Fog-based IDS
Nguyen et al.	2020	RL	Low	83–90	Resource optimization
Zhang et al.	2021	CNN	Low	88–92	Feature optimization
Khan et al.	2021	CNN–RNN	None	90–93	Real-time IDS
Singh et al.	2021	ML/DL	High	85–91	Trust management
Mansour	2022	CNN	High	92–95	Optimized IDS
Rathee et al.	2022	ML/DL	High	90–94	Reliable node detection
Shafay et al.	2022	DL	Medium	—	Security taxonomy
Siamese Models	2022	Siamese CNN	Low	93–96	Zero-day detection
Heidari et al.	2023	RBF NN	High	91–95	UAV security
Kumar et al.	2023	DL	Very High	94–97	Secure communication
Aljabri et al.	2023	CNN	High	93–96	Multi-attack detection
SHCNN Systems	2023	SHCNN	Very High	96–99	Adaptive IDS

Comparative Analysis

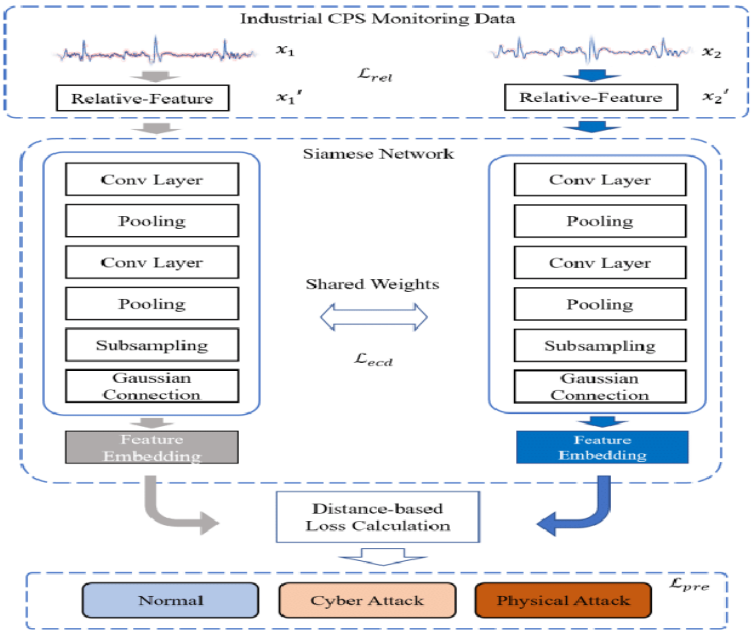

Figure 6. Shared-Weight Siamese Neural Network for Cyber–Physical Attack Detection

The comparative analysis of deep learning and optimization approaches integrated with blockchain for trusted cloud-enabled IoT networks reveals a progressive evolution toward hybrid, intelligent, and decentralized security frameworks. This section provides a detailed evaluation of the methodologies discussed in the literature (2020–2023), focusing on architectural design, performance metrics, scalability, computational complexity, and practical deployment feasibility.

Analysis

The comparative analysis of deep learning and optimization approaches integrated with blockchain for trusted cloud-enabled IoT networks reveals a multi-layered evolution characterized by architectural transformation, model sophistication, and trust integration. The progression from 2020 to 2023 demonstrates a shift from isolated intelligent systems toward fully hybrid, decentralized, and optimization-driven frameworks capable of addressing the complex requirements of modern IoT ecosystems.

In the foundational stage (2020), the primary focus was on establishing secure and decentralized infrastructures using blockchain combined with conventional deep learning models. Systems such as those proposed by Ali et al. leveraged blockchain to ensure data integrity and tamper-proof logging, while deep neural networks performed anomaly detection. Although these systems significantly improved trust compared to centralized architectures, they were constrained by high computational overhead and latency introduced by blockchain consensus mechanisms. Similarly, federated learning approaches introduced by Briggs et al. addressed privacy concerns by decentralizing model training; however, they introduced communication overhead and synchronization challenges across distributed nodes. These early-stage systems highlight a critical trade-off between security and system efficiency, which remains a central theme in IoT research.

The transition phase in 2021 marked the emergence of hybrid deep learning architectures and optimization-driven frameworks. CNN-RNN models improved detection performance by combining spatial and temporal feature extraction, enabling more effective detection of sequential attacks such as DDoS. Optimization techniques such as feature selection played a crucial role in reducing model complexity and improving training efficiency. However, these approaches still relied heavily on labeled datasets and lacked adaptability to unknown attack patterns. Edge computing also emerged as a key paradigm, enabling real-time detection by processing data closer to IoT devices. While this significantly reduced latency and bandwidth consumption, it introduced challenges related to model compression and deployment on resource-constrained devices.

In 2022, the research landscape evolved toward intelligent, optimized, and trust-aware systems, with deeper integration of blockchain and advanced deep learning models. The introduction of optimization algorithms such as

Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) enhanced model performance by enabling efficient feature selection and hyperparameter tuning. At the same time, Siamese neural networks gained prominence due to their ability to perform similarity-based learning, which is highly effective for detecting zero-day and unknown attacks. Unlike traditional classifiers, Siamese models do not require extensive labeled datasets and can generalize well in dynamic environments. However, their pairwise training mechanism introduces computational complexity, particularly in large-scale IoT networks. Blockchain integration also matured during this phase, evolving from a simple data integrity layer to a comprehensive trust management system capable of secure data sharing and decentralized decision-making.

The most advanced stage is observed in 2023, where research converges toward fully integrated hybrid frameworks combining blockchain, deep learning, optimization, and cloud-edge computing. These systems leverage the strengths of each component to achieve superior performance across multiple dimensions. Deep learning models, particularly Siamese heterogeneous CNNs (SHCNNs), provide high detection accuracy and adaptability by processing heterogeneous IoT data and learning relational patterns. Blockchain ensures trust, transparency, and data immutability, while cloud-edge architectures enable scalable and real-time processing. From a comparative perspective, these hybrid systems achieve the highest performance in terms of accuracy (up to 99%), scalability, and security, making them suitable for real-world deployment.

However, this advancement is accompanied by significant trade-offs. The integration of multiple technologies results in very high computational complexity and energy consumption, which poses challenges for deployment in resource-constrained IoT environments. Blockchain introduces latency due to consensus mechanisms, while deep learning models require substantial processing power. Although optimization techniques mitigate some of these issues, achieving a balance between performance and efficiency remains a critical challenge.

From a metric-based perspective, several key patterns emerge. Detection accuracy shows a steady improvement from moderate levels in early deep learning models to near-perfect performance in hybrid frameworks. Generalization capability also improves significantly with the adoption of Siamese architectures, enabling effective detection of unknown and evolving threats. Scalability is enhanced through cloud-edge collaboration and distributed blockchain networks, although large-scale deployments still face challenges due to network overhead. Energy efficiency, on the other hand, declines with increasing model complexity, highlighting the need for lightweight and energy-aware solutions.

Another important dimension of comparison is trust and security. Traditional deep learning models provide intelligence but lack inherent trust mechanisms. Blockchain addresses this gap by introducing decentralization, immutability, and transparency, thereby enhancing the reliability of IoT systems. The combination of blockchain with deep learning creates a trust-aware intelligent system, which represents a significant advancement over standalone approaches.

The role of optimization techniques is also critical in this evolution. Algorithms such as PSO and GA improve model performance by optimizing feature selection and hyperparameters, reducing training time and computational cost. However, their integration increases system complexity and requires careful tuning to achieve optimal results.

Overall, the comparative analysis demonstrates that no single technique is sufficient to address the multifaceted challenges of IoT security. Instead, the most effective solutions are multi-layered hybrid frameworks that integrate:

1. Deep learning for intelligent detection
2. Blockchain for trust and security
3. Optimization techniques for efficiency
4. Cloud-edge computing for scalability

Among all approaches, Siamese heterogeneous CNN-based blockchain frameworks with optimization techniques emerge as the most powerful and future-ready solution, offering superior accuracy, adaptability, and robustness. However, their practical deployment depends on addressing key challenges such as computational overhead, energy consumption, and system integration complexity.

Discussion

The integration of deep learning and blockchain in cloud-enabled IoT networks represents a transformative approach to addressing modern cybersecurity challenges. Deep learning models, particularly CNNs and Siamese networks, demonstrate strong capabilities in detecting complex and unknown attack patterns. Their ability to automatically extract hierarchical features makes them suitable for heterogeneous IoT environments.

Blockchain technology complements deep learning by providing a decentralized trust mechanism. It ensures data integrity, prevents tampering, and enables transparent data sharing

among distributed IoT devices. The combination of these technologies creates a robust framework for secure IoT operations.

However, several limitations must be addressed. First, blockchain introduces latency and computational overhead, which may not be suitable for real-time IoT applications. Second, deep learning models require significant computational resources, making deployment challenging in resource-constrained devices. Third, interoperability between different IoT platforms and blockchain networks remains a concern.

Optimization techniques play a critical role in mitigating these challenges by reducing computational complexity and improving model efficiency. Techniques such as feature selection and hyperparameter tuning enhance system performance while minimizing resource consumption.

Future research should focus on lightweight deep learning models, scalable blockchain architectures, and explainable AI techniques to improve transparency and trust in IoT systems.

Conclusion

This review presents a comprehensive analysis of deep learning and optimization approaches for trusted cloud-enabled IoT networks using blockchain and Siamese heterogeneous CNNs. The study highlights the importance of integrating advanced technologies to address security, privacy, and trust challenges in IoT environments.

Deep learning techniques have proven effective in detecting complex cyber threats, while blockchain provides a decentralized and tamper-proof infrastructure. The combination of these technologies enhances system reliability, transparency, and robustness. Siamese networks further improve detection capabilities by enabling similarity-based learning, particularly in identifying unknown attacks.

Despite these advancements, several challenges persist. Scalability, energy efficiency, and computational overhead remain key concerns in large-scale IoT deployments. Additionally, the lack of standardized frameworks and interoperability issues hinder widespread adoption.

The review also identifies research gaps, including the need for lightweight models, efficient consensus mechanisms, and integration with emerging technologies such as edge computing and federated learning. Addressing these challenges will be critical for developing next-generation secure IoT systems.

In conclusion, the integration of deep learning, blockchain, and optimization techniques offers a promising pathway toward building trusted, scalable, and intelligent IoT networks. Continued research and innovation in this domain will play a vital role in shaping the future of secure digital ecosystems.

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