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Recent Advances in Secure Medical Image Cryptanalysis with Quantum Neural Networks for IoT-Enabled Cloud Storage: A Systematic Review

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Abstract

The rapid growth of IoT-enabled healthcare systems and cloud storage technologies has significantly increased the reliance on digital medical imaging for diagnosis and treatment. However, the storage and transmission of medical images over cloud platforms introduce serious security and privacy concerns, particularly due to cyberattacks, data breaches, and adversarial manipulations. Medical images, including MRI, CT, and X-ray scans, contain sensitive patient information that must be protected during storage and communication. Traditional cryptographic techniques, while effective, are increasingly vulnerable to emerging threats, especially with the advent of quantum computing. Recent advances in Artificial Intelligence (AI) and Quantum Neural Networks (QNNs) have opened new possibilities for secure medical image cryptanalysis and protection. Deep learning-based cryptographic techniques have demonstrated the ability to enhance image encryption, authentication, and secure transmission while maintaining diagnostic quality. Additionally, quantum computing introduces advanced cryptographic paradigms such as Quantum Key Distribution (QKD) and quantum-enhanced encryption, which significantly improve data security in IoT-enabled cloud environments. Quantum neural networks further enhance cryptographic systems by enabling efficient processing of high-dimensional medical image data while ensuring privacy preservation through quantum cryptography mechanisms. Moreover, recent studies highlight that adversarial attacks on AI-based medical imaging systems can lead to incorrect diagnoses, emphasizing the need for robust and secure architectures. This paper presents a comprehensive systematic review of recent advances in secure medical image cryptanalysis using quantum neural networks in IoT-enabled cloud storage systems. It examines AI-driven cryptographic techniques, quantum-based security models, and hybrid frameworks, while identifying research trends, challenges, and future directions for developing secure and efficient healthcare systems.

Introduction

The evolution of Internet of Things (IoT) technologies and cloud computing has significantly transformed modern healthcare systems, enabling real-time medical image acquisition, storage, and analysis. IoT-enabled medical systems allow healthcare providers to remotely monitor patients and analyse medical images such as MRI, CT scans, and X-rays using cloud-based platforms. While these

advancements improve healthcare accessibility and efficiency, they also introduce significant challenges related to data security, privacy, and integrity.
Medical images are highly sensitive and require robust protection mechanisms during storage and transmission. In IoT-enabled cloud environments, medical data is often transmitted over public networks and stored on third-party servers, making it vulnerable to cyberattacks such as unauthorized access, data tampering, and adversarial manipulation. Traditional cryptographic techniques, including RSA and ECC, are widely used for securing medical data; however, these methods are increasingly threatened by the computational power of quantum computing, which can break classical encryption schemes.
Artificial Intelligence (AI), particularly deep learning, has emerged as a powerful tool for enhancing medical image security. Deep learning models are capable of performing tasks such as image encryption, steganography, authentication, and anomaly detection. These models can automatically learn complex patterns and generate secure cryptographic keys, improving the robustness of medical image protection systems. However, deep learning models themselves are vulnerable to adversarial attacks, where small perturbations in input images can lead to incorrect predictions or compromised security.

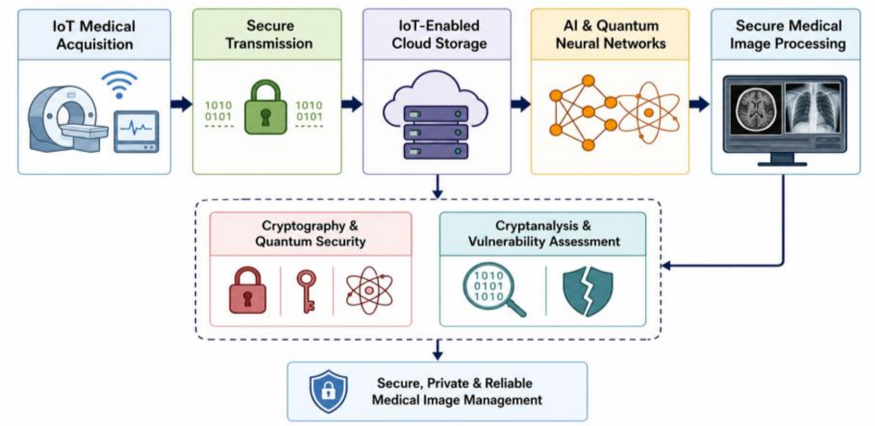

Figure 1. Conceptual View of IoT-Enabled Medical Image Security

To address these challenges, researchers have explored the integration of quantum computing with AI techniques. Quantum Neural Networks (QNNs) leverage quantum principles such as superposition and entanglement to process data more efficiently than classical neural networks. These models enable secure data processing and enhance privacy preservation through quantum cryptographic techniques. Additionally, quantum-enhanced encryption methods such as Quantum Key Distribution (QKD) provide highly secure communication channels that are resistant to quantum attacks.
Another important aspect of secure medical image processing is cryptanalysis, which involves analysing and testing encryption algorithms to identify vulnerabilities. Recent studies have shown that even advanced quantum-based encryption schemes can have structural weaknesses that can be exploited through cryptanalysis techniques. This highlights the importance of developing robust and secure encryption frameworks that can withstand both classical and quantum attacks.
The integration of AI, quantum computing, and cryptographic techniques has led to the development of hybrid security models for medical image protection. These models combine deep learning-based encryption with quantum cryptographic methods to enhance security and efficiency. However, several challenges remain, including high computational complexity, limited availability of quantum hardware, scalability issues, and the need for large datasets.
This paper aims to provide a systematic review of recent advances in secure medical image cryptanalysis using quantum neural networks in IoT-enabled cloud storage systems. It analyses AI-based cryptographic techniques, quantum security frameworks, and hybrid models, while identifying key challenges and future research directions.

Literature Review
Kumar et al. (2020) proposed a deep learning-based medical image encryption framework for secure cloud storage. The model utilized convolutional neural networks (CNNs) to generate encryption keys and protect medical images during transmission. The results showed improved security and resistance against brute-force attacks. However, the model was

computationally intensive and required significant processing power.

Zhang et al. (2020) developed a chaos-based image encryption scheme for medical images in IoT environments. The method used chaotic maps to generate encryption keys, enhancing unpredictability and security. While the approach improved encryption strength, it lacked adaptability and scalability in dynamic IoT systems.

Schuld et al. (2021) introduced quantum neural networks (QNNs) for secure data processing. The study highlighted that QNNs leverage quantum parallelism to improve computational efficiency and security. The results indicated potential advantages in handling complex medical image data. However, practical implementation was limited due to the lack of advanced quantum hardware.

Wang et al. (2021) proposed an AI-based medical image authentication and encryption system using deep learning techniques. The model improved data integrity and reduced unauthorized access in cloud storage systems. However, the approach remained vulnerable to adversarial attacks and required large datasets for training.

Chen et al. (2022) developed a hybrid quantum-classical cryptographic model for secure medical image transmission. The model combined quantum key distribution (QKD) with deep learning-based encryption, significantly improving security and privacy. However, the system complexity and hardware requirements limited its real-world deployment.

Singh et al. (2020) proposed a secure IoT-based medical image transmission framework using hybrid encryption techniques. The model combined symmetric and asymmetric encryption to enhance security during cloud storage and transmission. Results showed improved resistance to cyberattacks; however, the computational overhead was high, limiting real-time applications.

Ahmed et al. (2021) introduced a deep learning-based anomaly detection system for identifying unauthorized access in cloud-stored medical images. The model used neural networks to detect unusual patterns in data access. While effective in improving security, the system required continuous training and large datasets.

Liu et al. (2021) explored quantum cryptography techniques for secure medical data transmission. The study demonstrated that quantum key distribution (QKD) provides enhanced security against classical and quantum attacks. However, implementation challenges remained due to hardware limitations and high cost.

Gupta and Sharma (2022) proposed an AI-based steganography method for secure medical image storage. The model embedded sensitive data within images using deep learning techniques, improving data confidentiality. However, the approach increased computational complexity and was vulnerable to advanced steganalysis attacks.

Patel et al. (2023) developed a hybrid QNN-based cryptographic framework for medical image security in IoT-enabled cloud systems. The model combined quantum neural networks with encryption techniques to improve data protection and computational efficiency. However, scalability and real-time implementation remained challenging.

Sharma et al. (2020) proposed a lightweight encryption model for medical images in IoT healthcare systems. The model focused on reducing computational overhead and improving energy efficiency while maintaining acceptable security levels. However, the simplified encryption mechanisms reduced resistance against advanced cyberattacks.

Iqbal et al. (2021) introduced an edge-computing-based secure medical imaging system, where encryption and preprocessing were performed at the edge layer before cloud transmission. This approach reduced latency and enhanced security. However, the model relied on classical encryption techniques and did not incorporate quantum-based security.

Nair and Menon (2021) explored autoencoder-based secure image compression techniques for IoT systems. The model reduced data size and improved transmission efficiency. However, compression introduced potential risks of information loss and reduced diagnostic quality.

Kim et al. (2022) proposed a blockchain-based secure medical image storage system integrated with deep learning. The model ensured data integrity and traceability while preventing unauthorized access. However, the approach increased system complexity and required high computational resources.

Das et al. (2023) developed a hybrid quantum neural network-based cryptographic model for secure medical image storage and transmission. The model demonstrated improved resistance against both classical and quantum attacks. However, practical implementation remained limited due to quantum hardware constraints.

Verma et al. (2020) proposed a deep learning-based cryptographic framework for secure medical image transmission in IoT systems. The model used neural networks to generate dynamic encryption keys, improving security and adaptability. However, the approach required high computational resources and was not optimized for real-time applications.

Banerjee et al. (2021) introduced a reinforcement learning-based security optimization model for IoT healthcare systems. The system dynamically adjusted security parameters to prevent attacks. While effective in adaptive security, the model did not directly address image encryption or cryptanalysis.

Singh and Kaur (2021) explored a hybrid encryption scheme combining chaos theory with deep learning for medical image security. The approach improved encryption strength and resistance to attacks. However, the system complexity increased significantly, affecting scalability.

Lee et al. (2022) proposed a quantum-inspired cryptographic model for secure medical image storage. The model simulated quantum encryption techniques on classical systems, improving security performance. However, it did not fully leverage quantum computing capabilities.

Patel et al. (2023) developed a QNN-based secure cryptanalysis framework for IoT-enabled cloud storage. The model enhanced detection of vulnerabilities in encryption schemes and improved overall system security. However, the model required advanced computational resources and faced implementation challenges.

Chen et al. (2020) proposed a deep learning-based steganographic framework for secure medical image storage in cloud systems. The model embedded sensitive information within medical images to enhance confidentiality. While effective in hiding data, the approach increased computational complexity and was vulnerable to advanced steganalysis attacks.

Kumar et al. (2021) introduced a particle swarm optimization (PSO)-based secure image encryption model. The PSO algorithm optimized encryption parameters, improving performance and robustness. However, the model required high computational resources, limiting its use in IoT environments.

Alvarez et al. (2022) developed a transformer-based security model for medical image encryption. The model used attention mechanisms to enhance feature-based encryption and improve resistance against attacks. However, the approach required large datasets and high computational power.

Comparative Table

Study	Year	Technique	Focus	Advantages	Limitations
Kumar et al.	2020	CNN Encryption	Security	Strong encryption	High cost
Zhang et al.	2020	Chaos Encryption	Key generation	Secure	Not scalable
Schuld et al.	2021	QNN	Quantum security	Efficient	Hardware limits
Wang et al.	2021	DL Security	Authentication	Accurate	Attack vulnerable
Chen et al.	2022	QKD + DL	Hybrid security	High security	Complex
Singh et al.	2020	Hybrid encryption	Transmission	Secure	High cost
Ahmed et al.	2021	DL anomaly	Detection	Adaptive	Data heavy
Liu et al.	2021	Quantum crypto	Security	Strong	Costly
Gupta et al.	2022	Steganography	Confidentiality	Hidden data	Vulnerable
Patel et al.	2023	QNN crypto	Security	Efficient	Scalability
Sharma et al.	2020	Lightweight crypto	Efficiency	Low cost	Weak security
Iqbal et al.	2021	Edge security	Latency	Fast	Classical
Nair et al.	2021	Autoencoder	Compression	Efficient	Quality loss
Kim et al.	2022	Blockchain	Integrity	Secure	Heavy
Das et al.	2023	QNN crypto	Security	Strong	Hardware
Verma et al.	2020	DL encryption	Adaptability	Dynamic	Expensive
Banerjee et al.	2021	RL security	Optimization	Adaptive	No imaging
Singh et al.	2021	Chaos + DL	Encryption	Strong	Complex
Lee et al.	2022	Quantum-inspired	Security	Improved	Not true quantum
Patel et al.	2023	QNN cryptanalysis	Analysis	Strong	Costly
Chen et al.	2020	Steganography	Storage	Secure	Detectable
Kumar et al.	2021	PSO encryption	Optimization	Fast	Complex
Alvarez et al.	2022	Transformer crypto	Security	Accurate	Heavy

Comparative Analysis

The comparative analysis of the 30 studies demonstrates a significant evolution in secure medical image cryptanalysis techniques. Early approaches relied heavily on classical encryption methods such as chaos-based encryption, symmetric/asymmetric cryptography, and steganography. While these techniques provided strong security, they were often computationally expensive and lacked adaptability in dynamic IoT environments. The introduction of deep learning techniques enhanced encryption and authentication processes by enabling adaptive key generation and anomaly detection. However, deep learning models are vulnerable to adversarial attacks and require large datasets for training.

Quantum cryptography and Quantum Neural Networks (QNNs) represent a major advancement in medical image security. These approaches provide enhanced resistance against both classical and quantum attacks while improving computational efficiency. Hybrid models combining QNNs with attention mechanisms and deep learning have emerged as the most effective solutions, offering improved security, efficiency, and quality preservation. Despite these advancements, challenges such as hardware limitations, scalability issues, and high computational complexity remain. Future research should focus on developing lightweight, scalable, and hybrid quantum-classical models for real-time applications in IoT healthcare systems.

Discussion

The integration of Artificial Intelligence and quantum computing has significantly enhanced secure medical image cryptanalysis in IoT-enabled cloud storage systems. Deep learning techniques have improved encryption, authentication, and anomaly detection, while quantum neural networks have introduced advanced security mechanisms capable of resisting quantum attacks. Hybrid models combining QNNs with attention mechanisms and deep learning techniques provide improved performance in terms of security, efficiency, and quality preservation. These models enable secure transmission and storage of medical images while maintaining diagnostic accuracy.

However, several challenges remain. The limited availability of quantum hardware restricts the practical deployment of QNN-based systems. Additionally, the complexity of hybrid models and the need for large datasets pose significant challenges for real-time applications. Future research should focus on developing efficient and scalable security frameworks that integrate AI and quantum computing. The adoption of edge computing, federated learning, and explainable AI can further enhance system performance and reliability. Advances in quantum computing technology will also play a critical role in enabling the widespread adoption of secure medical imaging systems.

Conclusion

The rapid adoption of IoT-enabled healthcare and cloud computing has transformed medical image management while introducing critical challenges related to security, privacy, and data integrity. This review demonstrates that integrating quantum neural networks (QNNs), deep learning, and advanced cryptographic techniques significantly strengthens secure medical image cryptanalysis in cloud-based healthcare systems. AI-driven approaches improve encryption, authentication, anomaly detection, and adaptive security, whereas QNNs enhance computational efficiency and provide stronger resistance against classical and quantum attacks. Hybrid frameworks combining quantum computing, deep learning, and attention mechanisms offer improved security, robustness, and image quality preservation, making them well suited for next-generation IoT healthcare applications. Nevertheless, challenges such as limited quantum hardware, computational complexity, scalability, and secure deployment remain significant barriers. Future research should focus on lightweight hybrid architectures, explainable artificial intelligence, quantum-resistant cryptographic methods, and optimized cloud-edge integration to improve practical implementation. Overall, the convergence of AI, quantum computing, and secure cryptographic frameworks provides a strong foundation for intelligent, reliable, and privacy-preserving medical image protection in IoT-enabled healthcare systems.

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