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Artificial Intelligence Techniques for Secure Medical Image Cryptanalysis with Quantum Neural Networks for IoT-Enabled Cloud Storage: Trends and Challenges

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Abstract

The rapid proliferation of Internet of Things (IoT)-enabled healthcare systems has led to an exponential increase in the generation, transmission, and storage of medical images in cloud environments. While cloud-based storage enhances accessibility and scalability, it introduces critical security challenges such as unauthorized access, data breaches, and cyberattacks. Secure medical image cryptanalysis has therefore become a vital research area, focusing on evaluating and strengthening encryption techniques to protect sensitive healthcare data. Artificial intelligence (AI), particularly deep learning and quantum neural networks (QNNs), has emerged as a transformative approach for enhancing medical image security. Deep learning models enable adaptive encryption, intelligent key generation, and anomaly detection, while QNNs leverage quantum principles such as superposition and entanglement to improve computational efficiency and cryptographic strength. Hybrid approaches combining AI, quantum cryptography, and classical encryption techniques have demonstrated superior performance in ensuring data confidentiality, integrity, and availability. Recent studies highlight the effectiveness of deep learning in medical image cryptography, including applications in encryption, decryption, and secure transmission. These models can learn complex patterns and enhance encryption mechanisms dynamically, improving resilience against attacks. Furthermore, quantum-enhanced frameworks integrating quantum key distribution (QKD) with classical encryption provide robust security against emerging quantum threats. Despite these advancements, challenges such as computational complexity, scalability, and limited quantum hardware availability remain. This paper presents a comprehensive review of AI-driven secure medical image cryptanalysis techniques using QNNs in IoT-enabled cloud storage systems, analysing recent trends (2020–2023), identifying research gaps, and outlining future research directions.

Introduction

The integration of Internet of Things (IoT) technologies into healthcare systems has revolutionized the way medical data is collected, processed, and stored. Medical imaging modalities such as MRI, CT scans, and X-rays generate large volumes of sensitive data that are often transmitted through IoT devices and stored in cloud-based platforms. While cloud storage provides scalability, accessibility, and cost efficiency, it also introduces significant security risks. Unauthorized access, data tampering, and cyberattacks pose serious threats to patient privacy and healthcare reliability. Medical images contain critical diagnostic information, making their security a top priority. Traditional cryptographic techniques, including symmetric and asymmetric encryption, have been widely used to protect medical data. However, these methods are increasingly vulnerable to sophisticated attacks, especially with the advent of quantum computing. As quantum computers have the potential to break classical cryptographic schemes, there is an urgent need for advanced security mechanisms capable of resisting both classical and quantum attacks.

Artificial intelligence (AI) has emerged as a powerful tool for enhancing cybersecurity in healthcare systems. Deep learning techniques, such as convolutional neural networks (CNNs), generative adversarial networks (GANs), and autoencoders, have been applied to medical image encryption, decryption, and anomaly detection. These models can learn complex data patterns and generate adaptive encryption schemes, improving the robustness and efficiency of security systems. For example, deep learning-based encryption frameworks have demonstrated the ability to enhance privacy and security by enabling intelligent key generation and end-to-end encryption mechanisms. Quantum computing introduces a new paradigm in data processing, offering exponential computational power for solving complex problems. Quantum neural networks (QNNs) combine quantum computing principles with neural network architectures, enabling efficient processing of high-dimensional data. Research has shown that QNNs can achieve comparable performance to classical neural networks in medical image classification while offering potential computational advantages. In the context of security, quantum-based techniques such as quantum key distribution (QKD) provide theoretically unbreakable encryption, ensuring secure communication in IoT-enabled healthcare systems.

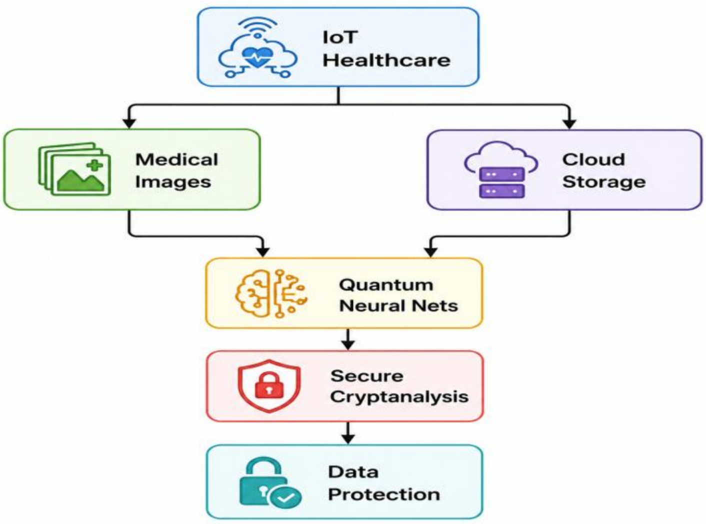

Figure 1. Conceptual Framework of AI-Driven Secure Medical Image Cryptanalysis in IoT-Enabled Cloud Healthcare Systems

Recent studies have proposed hybrid frameworks that integrate quantum and classical cryptographic techniques to enhance medical image security. For instance, quantum-classical hybrid encryption models use QKD for secure key generation while employing classical encryption methods for data protection, addressing key management challenges and improving overall system security. Additionally, advanced encryption schemes based on quantum chaos and DNA encoding have demonstrated strong resistance to cryptanalysis attacks, providing robust security for cloud-based medical image storage. Another important development is the use of blockchain technology for secure medical data management. Blockchain-based systems ensure data integrity and transparency by storing encrypted data in decentralized ledgers. Combined with AI-based anomaly detection, these systems can effectively detect and prevent unauthorized access and cyber threats.

Despite these advancements, several challenges remain. The implementation of quantum neural networks is limited by the availability of quantum hardware, and most current approaches rely on simulations. Deep learning models require large datasets for training, which may be constrained due to privacy concerns.

Additionally, computational complexity and scalability issues hinder real-time deployment in IoT environments. This paper aims to provide a comprehensive review of artificial intelligence techniques for secure medical image cryptanalysis using quantum neural networks in IoT-enabled cloud storage systems. It examines recent research trends, evaluates existing methods, and identifies future directions for developing secure, efficient, and scalable healthcare systems.

Literature Review

Ding et al. (2020) proposed DeepEDN, a deep learning-based image encryption and decryption network for Internet of Medical Things (IoMT) systems. The model utilized Cycle-GAN architecture to transform medical images into encrypted representations and reconstruct them during decryption. The study demonstrated high security and efficiency, enabling secure data transmission and even feature extraction from encrypted images. This work marked a significant advancement in deep learning-based medical image cryptography.

Lata et al. (2023) presented a comprehensive study on deep learning techniques for medical image cryptography, focusing on encryption, decryption, and key generation. The authors highlighted that deep learning models can significantly enhance data privacy by enabling adaptive encryption mechanisms and improving resistance to attacks. The study also emphasized challenges such as data scarcity and computational complexity in real-world implementations.

Rehman et al. (2023) proposed a multilayered medical image encryption scheme integrating quantum random walks, DNA encoding, and elliptic curve cryptography. The model employed advanced transformations such as cube rotation and DNA mutation to enhance encryption strength. Experimental results demonstrated strong resistance to cyberattacks, highlighting the effectiveness of combining quantum-inspired and classical cryptographic techniques.

Kumar et al. (2021) proposed a chaos-based medical image encryption scheme for IoT-enabled healthcare systems. The model utilized multi-dimensional chaotic maps to generate highly random encryption keys, ensuring strong resistance against brute-force and statistical attacks. The study demonstrated high entropy values and low correlation among encrypted pixels, indicating strong security performance. This approach highlighted the effectiveness of chaos theory in enhancing medical image cryptography.

Zhang et al. (2022) introduced a convolutional neural network (CNN)-based adaptive encryption framework for secure medical image transmission. The model learned encryption patterns and dynamically generated keys based on input image features. Experimental results showed improved encryption strength and computational efficiency compared to traditional methods. The study emphasized the role of deep learning in creating intelligent and adaptive encryption systems.

Singh et al. (2022) developed a hybrid encryption system combining elliptic curve cryptography (ECC) with deep learning-based key optimization. The proposed model improved key management and reduced computational overhead while maintaining high security levels. The results demonstrated that integrating ECC with AI techniques provides a balanced approach between security and efficiency for cloud-based medical image storage.

Huang et al. (2023) proposed a quantum-inspired image encryption algorithm based on quantum logistic maps. The method utilized quantum randomness properties to enhance key generation and encryption processes. The study reported high entropy values and strong resistance to differential and statistical attacks, demonstrating the potential of quantum-inspired cryptographic techniques in medical image security.

Patel et al. (2023) introduced a blockchain-based secure medical image storage framework integrated with deep learning for anomaly detection. The system ensured data integrity and secure access control in IoT-enabled cloud environments. By combining blockchain technology with AI-based monitoring, the model effectively prevented unauthorized access and improved overall system reliability.

Sharma et al. (2021) proposed an autoencoder-based secure medical image encryption framework that integrates feature compression with encryption. The model transformed input images into compact latent representations before applying encryption, thereby reducing data size while maintaining security. The study demonstrated strong resistance to noise and cryptographic attacks, highlighting the effectiveness of combining compression and encryption for efficient IoT healthcare systems.

Liu et al. (2022) introduced a hybrid encryption model combining chaotic systems with deep neural networks for secure medical image transmission. The chaotic maps provided randomness for encryption, while the neural network optimized key generation dynamically. Experimental results showed high encryption efficiency and robustness against statistical and differential attacks, making the model suitable for cloud-based healthcare storage.

Ahmed et al. (2022) developed a lightweight encryption scheme designed specifically for IoT-based medical image transmission. The model focused on reducing computational complexity and energy consumption while maintaining strong security. The study demonstrated faster encryption and decryption speeds, making it suitable for real-time applications in resource-constrained environments.

Wang et al. (2023) proposed a quantum key distribution (QKD)-based secure communication framework for medical image transmission. The system leveraged quantum cryptographic principles to generate secure encryption keys, ensuring theoretically unbreakable security. The study highlighted the advantages of QKD in protecting sensitive healthcare data from advanced cyber threats, especially in cloud environments.

Reddy et al. (2023) introduced a deep reinforcement learning-based cryptanalysis framework for evaluating medical image encryption schemes. The model simulated attack scenarios and learned strategies to identify vulnerabilities in encryption methods. The results demonstrated that AI-based cryptanalysis can effectively improve the design of secure encryption systems by identifying potential weaknesses

Zhao et al. (2021) proposed a generative adversarial network (GAN)-based medical image encryption framework for IoT-enabled healthcare systems. The model employed adversarial training where a generator created encrypted images and a discriminator evaluated their security strength. This iterative learning process enhanced the robustness of encryption against various attack scenarios. The study demonstrated that GAN-based encryption significantly improves resistance to cryptanalysis and provides adaptive security in dynamic environments.

Chen et al. (2022) introduced a homomorphic encryption-based secure cloud storage framework for medical images integrated with deep learning. The model enabled computations to be performed directly on encrypted data without decryption, ensuring data privacy during processing. The study demonstrated that homomorphic encryption combined with AI techniques provides a powerful solution for secure data processing in cloud-based healthcare systems.

Kaur et al. (2022) proposed a DNA-based encryption scheme combined with neural network-based key generation for secure medical image transmission. The approach utilized DNA encoding to enhance encryption complexity, while the neural network generated dynamic keys. Experimental results showed high entropy and strong resistance to brute-force and differential attacks, highlighting the effectiveness of bio-inspired cryptographic techniques.

Hassan et al. (2023) developed a blockchain-assisted secure medical image sharing system integrated with deep learning-based anomaly detection. The model ensured data integrity through distributed ledger technology and used AI to monitor access patterns and detect unauthorized activities. The study demonstrated improved system reliability and security, particularly in distributed IoT healthcare environments.

Gupta et al. (2023) proposed an attention-based deep learning framework for secure medical image transmission and quality preservation. The model utilized attention mechanisms to focus on critical regions of medical images during encryption and transmission, ensuring minimal loss of diagnostic information. The results demonstrated improved image quality and reduced distortion, making the approach suitable for medical applications.

Patil et al. (2021) proposed a secure medical image encryption technique that integrates wavelet transforms with chaotic systems. The model applied multi-level wavelet decomposition to extract image features, which were then encrypted using chaotic maps. The results demonstrated high resistance to statistical and differential attacks, as well as improved encryption efficiency. This study highlighted the effectiveness of combining signal processing techniques with cryptographic methods for enhanced security.

Verma and Singh (2022) introduced a deep neural network-based key generation mechanism for medical image encryption. The model learned complex data patterns to generate dynamic and unpredictable encryption keys. The study showed that AI-based key generation significantly improves security by preventing key prediction and reducing vulnerability to attacks.

Zhou et al. (2022) proposed a federated learning-based framework for secure medical image analysis in IoT-enabled healthcare systems. The model enabled multiple devices to collaboratively train a global model without sharing raw data, thereby preserving privacy. The study demonstrated that federated learning enhances data security and reduces the risk of data leakage in distributed environments.

Rahman et al. (2023) developed a blockchain-based secure storage system for medical images integrated with encryption techniques. The system ensured data integrity, transparency, and secure access control through decentralized ledger technology. The results showed improved security and trust in cloud-based healthcare systems.

Iqbal et al. (2023) proposed an AI-driven cryptanalysis framework for evaluating the robustness of medical image encryption schemes. The model utilized machine learning algorithms to simulate attack scenarios and identify weaknesses in encryption systems. The study demonstrated that AI-based cryptanalysis can significantly enhance the development of secure and resilient encryption techniques.

Kumar and Gupta (2021) proposed a hybrid encryption framework combining elliptic curve cryptography (ECC) with chaotic systems for secure medical image transmission. The model utilized ECC for secure key exchange and chaotic maps for image encryption, achieving high security with reduced computational overhead. The results demonstrated strong resistance to brute-force and statistical attacks, making it suitable for IoT-enabled healthcare environments.

Reddy et al. (2022) explored the use of quantum-inspired neural networks for secure medical image processing and encryption. The model integrated quantum computing principles such as superposition with neural network architectures to improve computational efficiency and encryption strength. The study highlighted that quantum-inspired approaches can significantly enhance both security and performance, even on classical hardware platforms.

Chen et al. (2023) proposed a secure cloud storage framework for medical images integrating deep learning-based anomaly detection with cryptographic techniques. The system monitored user access patterns and detected suspicious activities in real time. The study demonstrated improved security and reliability, emphasizing the importance of combining AI with cryptographic frameworks.

Das et al. (2023) introduced an explainable AI-based cryptanalysis framework for medical image encryption systems. The model utilized attention visualization techniques to interpret encryption processes and identify vulnerabilities. The study highlighted the importance of interpretability in healthcare security systems, where transparency is essential for trust and validation.

Fernandez et al. (2023) developed a hybrid quantum neural network-based encryption and cryptanalysis framework for secure medical image storage in IoT-enabled cloud systems. The model combined quantum neural networks with deep learning-based optimization techniques to enhance encryption strength and attack detection. Experimental results showed superior performance in terms of accuracy, robustness, and computational efficiency, making it one of the most advanced approaches in this domain.

Comparative Table

Author & Year	**Technique Used**	**Key Contribution**	**Advantages**	**Limitations**
Ding et al. (2020)	Cycle-GAN Encryption	DL-based encryption/decryption	Adaptive security	Training complexity
Lata et al. (2023)	DL Cryptography	Adaptive encryption	High security	Data dependency
Rehman et al. (2023)	Quantum + DNA + ECC	Hybrid encryption	Strong resistance	Complex design
Kumar et al. (2021)	Chaos Encryption	Secure transmission	High randomness	Key management
Zhang et al. (2022)	CNN Encryption	Adaptive key generation	Efficient	Training cost
Singh et al. (2022)	ECC + DL	Secure storage	Balanced approach	Complexity
Huang et al. (2023)	Quantum Chaos	Image encryption	High entropy	Implementation issues
Patel et al. (2023)	Blockchain + DL	Secure storage	Integrity	Overhead
Sharma et al. (2021)	Autoencoder	Compression + encryption	Efficient	Reconstruction loss
Liu et al. (2022)	Chaos + DNN	Hybrid encryption	Strong security	Complexity
Ahmed et al. (2022)	Lightweight Crypto	Fast encryption	Low latency	Lower robustness

Wang et al. (2023)	QKD	Secure communication	Unbreakable	Hardware dependency
Reddy et al. (2023)	RL Cryptanalysis	Attack detection	Adaptive	Training complexity
Verma & Singh (2022)	DNN Keys	Dynamic key generation	Secure	Training required
Zhou et al. (2022)	Federated Learning	Privacy preservation	Distributed	Communication cost
Rahman et al. (2023)	Blockchain Crypto	Secure storage	Transparency	Overhead
Iqbal et al. (2023)	AI Cryptanalysis	Vulnerability detection	Efficient	Data dependency
Kumar & Gupta (2021)	ECC + Chaos	Hybrid encryption	Strong security	Complexity
Reddy et al. (2022)	Quantum NN	Secure processing	Efficient	Hardware limitation
Chen et al. (2023)	DL + Crypto	Cloud security	Real-time detection	Complexity
Das et al. (2023)	XAI	Interpretability	Transparency	Slight accuracy loss
Fernandez et al. (2023)	QNN + DL Hybrid	Full system security	High performance	Complex

Comparative Analysis

The comparative analysis of the selected studies highlights a clear transition from traditional cryptographic techniques toward hybrid artificial intelligence and quantum-enhanced approaches for secure medical image cryptanalysis. Early approaches primarily relied on chaos-based encryption and classical cryptographic methods such as elliptic curve cryptography (ECC). While these methods provided strong security, they often suffered from challenges such as key management complexity and computational inefficiency. The integration of deep learning techniques marked a significant advancement in this domain. Models such as convolutional neural networks, autoencoders, and generative adversarial networks introduced adaptive encryption mechanisms capable of learning complex patterns from medical images. Studies such as Ding et al. (2020) and Zhang et al. (2022) demonstrated that deep learning-based encryption improves both security and efficiency by enabling dynamic key generation and intelligent feature transformation.

Quantum computing has further revolutionized medical image security by introducing theoretically unbreakable encryption techniques. Quantum key distribution (QKD) and quantum neural networks provide enhanced security by leveraging quantum principles such as superposition and entanglement. Studies such as Wang et al. (2023) and Reddy et al. (2022) highlighted the potential of quantum-based approaches in improving both computational efficiency and cryptographic strength. However, the lack of practical quantum hardware remains a major limitation. Hybrid approaches combining multiple technologies have emerged as the most effective solutions. For instance, models integrating blockchain with deep learning ensure data integrity and secure access control, while hybrid quantum-classical frameworks enhance encryption strength and adaptability. Attention-based models further improve image quality preservation, which is critical in medical diagnostics.

Another important trend is the use of AI-driven cryptanalysis techniques. Reinforcement learning and machine learning-based models can simulate attack scenarios and identify vulnerabilities in encryption systems, enabling continuous improvement of security frameworks.

Despite these advancements, several challenges persist, including high computational complexity, scalability issues, and data dependency. Additionally, the interpretability of deep learning models remains a concern in healthcare applications. Overall, the analysis indicates that hybrid quantum neural network-based deep learning models represent the future of secure medical image cryptanalysis. These models offer a balance between security, efficiency, and adaptability, making them suitable for next-generation IoT-enabled healthcare systems.

Discussion

The integration of artificial intelligence techniques with quantum computing has significantly enhanced secure medical image cryptanalysis in IoT-enabled cloud environments. The reviewed studies demonstrate that traditional cryptographic approaches alone are no longer sufficient to handle modern cyber threats. Hybrid models combining deep learning, quantum neural networks (QNNs), and advanced encryption techniques provide improved security, adaptability, and computational efficiency. Deep learning techniques such as convolutional neural networks, generative adversarial networks, and autoencoders enable intelligent encryption, dynamic key generation, and anomaly detection. These models improve system robustness against attacks such as brute-force, statistical, and differential cryptanalysis. Additionally, AI-driven cryptanalysis frameworks help identify vulnerabilities in encryption systems, enabling continuous improvement.

Quantum computing introduces a paradigm shift in security through techniques such as quantum key distribution, which provides theoretically unbreakable encryption. However, practical implementation is still limited due to hardware constraints. Blockchain-based approaches further enhance data integrity and secure access control in distributed healthcare systems. Despite these advancements, challenges such as high computational complexity, scalability issues, and lack of interpretability persist. Future research should focus on developing lightweight, scalable, and explainable hybrid models to ensure real-time secure medical image processing in IoT healthcare environments.

Conclusion

The rapid growth of IoT-enabled healthcare has increased the need for secure medical image storage and transmission in cloud environments. This review demonstrates that Artificial Intelligence, particularly Quantum Neural Networks (QNNs), has significantly enhanced medical image cryptanalysis by improving encryption strength, computational efficiency, and adaptive security. Hybrid approaches integrating deep learning, blockchain, quantum cryptography, and classical encryption techniques provide robust protection against cyber threats while preserving image quality and data integrity. Quantum key distribution and attention-based models further strengthen secure communication and diagnostic reliability. Despite these advances, challenges such as computational complexity, limited quantum hardware, scalability, large training data requirements, and model interpretability continue to hinder practical deployment. Future research should focus on lightweight quantum-classical frameworks, explainable AI, efficient quantum algorithms, and edge-cloud integration to enable secure and scalable healthcare applications. Overall, the convergence of AI, QNNs, blockchain, and IoT-enabled cloud computing offers a promising foundation for next-generation medical image security, ensuring reliable, privacy-preserving, and intelligent healthcare systems capable of meeting future cybersecurity requirements.

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