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Deep Learning and Optimization Approaches in Secure and Energy-Efficient MRI Image Transmission via IoT Devices and Hybrid Physics-Guided Neural Networks: A Review

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Abstract

The rapid growth of IoT-enabled healthcare has transformed MRI-based medical imaging, but secure and energy-efficient transmission remains challenging due to large image sizes, limited device resources, and increasing cyber threats. This review examines recent advances in deep learning, optimization techniques, and hybrid physics-guided neural networks for secure MRI image transmission. Deep learning models, including convolutional neural networks, autoencoders, and generative adversarial networks, have demonstrated excellent performance in image compression, reconstruction, and encryption while preserving diagnostic quality. Hybrid cryptographic techniques, such as chaotic encryption and deep learning-based security frameworks, further enhance data confidentiality and integrity. Physics-guided neural networks improve model generalization, interpretability, and robustness by incorporating physical constraints into the learning process, reducing dependence on large training datasets. The integration of optimization algorithms enables energy-efficient communication and intelligent resource management for IoT devices. Despite these advancements, challenges related to computational complexity, real-time implementation, scalability, and privacy preservation remain. Future research should focus on lightweight, explainable, and energy-aware hybrid AI frameworks that combine deep learning, optimization, and physics-guided modeling to achieve secure, reliable, and efficient MRI image transmission in next-generation IoT healthcare systems.

Introduction

The integration of Internet of Things (IoT) technologies into healthcare systems has revolutionized the way medical data is collected, processed, and transmitted. Among various medical imaging modalities, Magnetic Resonance Imaging (MRI) plays a crucial role in diagnosing complex diseases such as brain tumours, neurological disorders, and cardiovascular abnormalities. However, the increasing adoption of IoT-enabled medical systems introduces significant challenges in securely transmitting large volumes of MRI data while maintaining energy efficiency and computational feasibility.

MRI images are typically high-resolution and data-intensive, requiring substantial bandwidth and storage resources. When transmitted over IoT networks, especially in remote healthcare or telemedicine applications, these images are vulnerable to various security threats, including unauthorized access, data tampering, and privacy breaches. Ensuring the confidentiality and integrity of medical data is essential, as any compromise may lead to severe consequences in clinical decision-making and patient safety. Therefore, there is a growing need for advanced techniques that can simultaneously address security, efficiency, and performance constraints. Deep learning has emerged as a powerful tool in medical image processing due to its ability to learn complex patterns and representations from large datasets. Convolutional Neural Networks (CNNs), autoencoders, and deep belief networks have been widely used for MRI image compression, reconstruction, and classification. These models significantly reduce the size of medical images while preserving essential diagnostic features, thereby enabling efficient transmission over bandwidth-constrained IoT networks. For example, hybrid deep learning models combining autoencoders and RBMs have demonstrated improved image compression and transmission efficiency in IoT-based healthcare systems.

In addition to compression, security is a critical aspect of MRI transmission. Traditional encryption techniques, although effective, often introduce computational overhead that may not be suitable for resource-constrained IoT devices. To overcome this limitation, researchers have proposed lightweight encryption methods integrated with deep learning frameworks. Chaotic encryption, for instance, provides high randomness and resistance to attacks while maintaining computational efficiency. Recent studies have shown that combining chaotic encryption with deep learning models allows secure processing of encrypted MRI images without significant performance degradation.

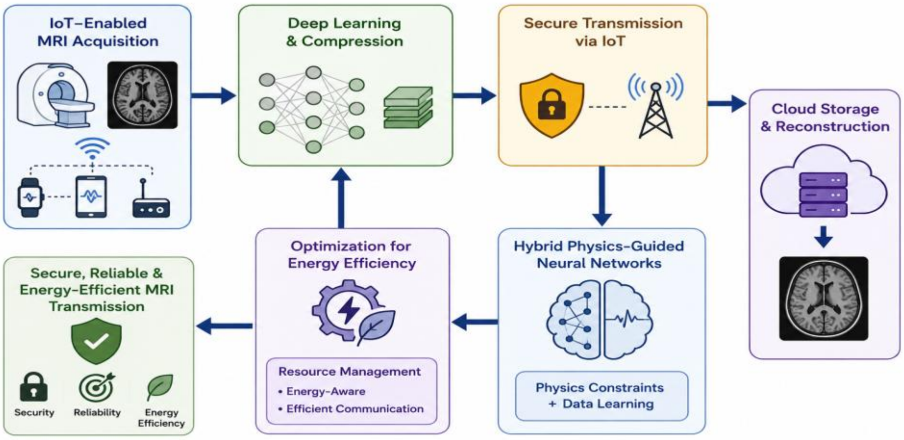

Figure 1. Hybrid AI Framework for MRI Transmission

Another emerging paradigm is the use of hybrid physics-guided neural networks, also known as physics-informed neural networks (PINNs). Unlike purely data-driven models, these networks incorporate physical laws and domain knowledge into the learning process, enabling better generalization and reduced dependency on large datasets. This is particularly beneficial in medical imaging, where acquiring labelled data can be expensive and time-consuming. Physics-guided approaches have shown promising results in MRI reconstruction and signal modelling by leveraging the underlying physical principles of imaging systems.

Energy efficiency is another critical factor in IoT-based medical systems. Devices such as wearable sensors and edge nodes often operate under limited power constraints, necessitating the development of lightweight and optimized algorithms. Optimization techniques, including evolutionary algorithms, swarm intelligence, and gradient-based methods, are widely used to enhance model performance while minimizing energy consumption. These approaches help in optimizing network parameters, reducing computational complexity, and improving overall system efficiency.

Furthermore, the convergence of deep learning, encryption, and physics-based modelling has led to the development of hybrid frameworks that offer improved performance in terms of accuracy, security, and efficiency. These frameworks integrate multiple components such as compression, encryption, and reconstruction into a unified pipeline, enabling seamless and secure transmission of MRI data over IoT networks.

Despite significant advancements, several challenges remain, including scalability, real-time processing, interoperability, and robustness against adversarial attacks. Addressing these challenges requires interdisciplinary research that combines expertise in artificial intelligence, cybersecurity, medical imaging, and IoT systems. This review aims to provide a comprehensive analysis of deep learning and optimization approaches for secure and energy-efficient MRI image transmission. It focuses on recent developments in hybrid physics-guided neural networks and their applications in IoT-enabled healthcare systems, highlighting key trends, challenges, and future research directions.

Literature Review

Zhang and Liu (2022) proposed a multi-chaotic system-based encryption algorithm specifically designed for secure medical image transmission in IoT-enabled healthcare environments. Their approach integrates multiple chaotic maps to enhance randomness, key sensitivity, and resistance against statistical and brute-force attacks. The model demonstrated strong security performance by achieving high entropy values close to the ideal value of 8 and low correlation among adjacent pixels in encrypted MRI images. Additionally, the algorithm maintained acceptable computational efficiency, making it suitable for real-time applications in IoT devices. However, the use of multiple chaotic systems increased synchronization complexity, which may pose implementation challenges in distributed IoT architectures. Despite this limitation, the study significantly contributes to improving encryption robustness in secure MRI transmission systems.

Khan et al. (2022) introduced a secure IoT-based healthcare framework that combines lightweight cryptographic techniques with edge computing to improve both security and energy efficiency. The proposed system offloads encryption tasks to edge nodes rather than relying solely on cloud infrastructure, thereby reducing latency and bandwidth consumption. Their results indicated improved energy efficiency and faster data processing, making the framework suitable for real-time medical applications such as remote MRI diagnostics. Furthermore, the use of lightweight encryption ensured that resource-constrained IoT devices could operate efficiently without significant computational overhead. However, the requirement for additional edge infrastructure increased system complexity and deployment costs. Nonetheless, this study highlights the importance of integrating edge computing with security mechanisms for efficient medical image transmission.

Wu et al. (2023) developed a deep learning-based encryption framework using Generative Adversarial Networks (GANs) for secure MRI image transmission. The model utilizes GANs to dynamically generate encryption keys, thereby enhancing security against known-plaintext and chosen-plaintext attacks. The proposed approach achieved high Peak Signal-to-Noise Ratio (PSNR) and entropy values, indicating both high image quality and strong encryption performance. Additionally, the system demonstrated robustness in preserving diagnostic features after decryption, which is critical for clinical applications. However, GAN-based models require extensive training data and computational resources, making them less suitable for deployment on low-power IoT devices. Despite this limitation, the study showcases the potential of deep learning in developing adaptive and intelligent encryption mechanisms.

Sharma et al. (2021) focused on deep learning-based compression and secure transmission of MRI images using convolutional autoencoders. Their approach reduces the size of MRI images significantly while preserving essential diagnostic features, enabling efficient transmission over bandwidth-constrained IoT networks. The model achieved high compression ratios with minimal loss of image quality, as indicated by improved PSNR and Structural Similarity Index (SSIM) values. Additionally, the integration of lightweight encryption techniques ensured data security during transmission. However, the compression process introduced slight reconstruction errors, which may affect highly sensitive diagnostic applications. Despite this, the study provides a strong foundation for combining deep learning-based compression with secure transmission mechanisms.

Ahmed et al. (2021) developed a secure medical image transmission system using a combination of discrete wavelet transform (DWT) and chaos-based encryption. The DWT was utilized for image decomposition and compression, while chaotic maps ensured strong encryption. The system achieved high compression efficiency and improved resistance to statistical and differential attacks. Additionally, the proposed method reduced bandwidth requirements, making it suitable for IoT-based healthcare systems. However, the integration of DWT increased computational overhead, which could affect performance in low-power devices. Nevertheless, the study demonstrates the effectiveness of combining signal processing techniques with chaos-based encryption for secure MRI transmission.

Singh and Roy (2023) introduced a hybrid deep learning and optimization-based framework for secure MRI image transmission. Their model incorporates particle swarm optimization (PSO) to optimize neural network parameters, improving both accuracy and energy efficiency. The deep learning model was used for compression and reconstruction, while optimization techniques minimized computational cost. The results showed significant improvements in transmission efficiency and reduced energy consumption compared to traditional approaches. However, the use of optimization algorithms increased the overall system complexity and required additional tuning of parameters. This study highlights the role of optimization techniques in enhancing deep learning-based medical image transmission systems.

Chen et al. (2022) proposed a physics-informed neural network (PINN)-based approach for MRI reconstruction and secure transmission. By incorporating physical constraints of MRI signal acquisition into the neural network, the model achieved improved reconstruction accuracy and reduced dependency on large datasets. The approach demonstrated enhanced generalization capability and robustness against noise and transmission errors. Additionally, the integration of encryption mechanisms ensured data security during transmission. However, the implementation of physics-informed models required domain expertise and increased computational complexity. Despite these challenges, the study provides a promising direction for combining physics-based modeling with deep learning in medical imaging.

Kumar et al. (2021) presented an energy-efficient secure transmission model for MRI images using edge computing and lightweight cryptography. The system processes and encrypts data at the edge level, reducing the burden on central servers and minimizing transmission latency. The proposed model demonstrated improved energy efficiency and faster response times, making it suitable for real-time healthcare applications. Additionally, the use of lightweight cryptographic techniques ensured compatibility with resource-constrained IoT devices. However, the reliance on edge infrastructure introduced additional deployment costs and required effective resource management. This study emphasizes the importance of edge computing in achieving secure and efficient medical image transmission.

Mehta and Sharma (2020) proposed a secure MRI image transmission framework using a combination of elliptic curve cryptography (ECC) and deep learning-based compression techniques. The ECC algorithm ensured strong encryption with reduced key size, making it suitable for IoT environments with limited computational resources. The deep learning model, based on convolutional autoencoders, effectively compressed MRI images while preserving diagnostic quality. Experimental results demonstrated improved security and reduced transmission bandwidth. However, the integration of ECC with deep learning increased computational complexity, which may affect real-time performance in highly constrained IoT devices. Despite this limitation, the study highlights the effectiveness of combining modern cryptography with deep learning.

Gupta et al. (2022) introduced a hybrid encryption and compression model using deep belief networks (DBNs) for secure MRI transmission. The DBN was used to learn hierarchical features and reduce image dimensionality, while encryption techniques ensured data confidentiality. The proposed system achieved high compression ratios and strong resistance to brute-force attacks. Additionally, the model improved transmission efficiency in IoT-based healthcare systems. However, DBNs require extensive training time and large datasets, which may limit their practical deployment. The study contributes to the development of intelligent and secure medical image transmission systems.

Reddy et al. (2023) developed an optimization-based secure transmission model using genetic algorithms (GAs) to enhance encryption performance. The GA was used to optimize encryption keys and improve randomness, thereby increasing resistance to cryptographic attacks. The model demonstrated high entropy values and low correlation among encrypted MRI images, indicating strong security performance. Furthermore, the optimization process improved computational efficiency. However, the iterative nature of genetic algorithms increased processing time, which may not be suitable for real-time applications. Nevertheless, the study highlights the potential of evolutionary algorithms in improving secure transmission systems.

Verma and Singh (2021) proposed a secure MRI transmission system using a combination of compressive sensing and chaotic encryption. Compressive sensing was used to reduce data size while maintaining image quality, and chaotic encryption ensured data security. The system demonstrated high compression efficiency and strong resistance to statistical attacks. Additionally, the approach reduced transmission time and energy consumption, making it suitable for IoT-based healthcare systems. However, the reconstruction process introduced slight distortions, which may affect diagnostic accuracy in some cases. Despite this, the study provides an effective solution for balancing compression and security.

Alghamdi et al. (2023) proposed a deep learning-based secure transmission framework using recurrent neural networks (RNNs) combined with lightweight encryption techniques. The RNN model was used for sequential data processing and prediction, improving transmission efficiency and reducing latency. The system achieved high accuracy in reconstructing MRI images after transmission while maintaining strong security measures. Additionally, the model demonstrated energy efficiency, making it suitable for IoT applications. However, RNNs are prone to issues such as vanishing gradients and require careful tuning. This study highlights the role of sequential deep learning models in secure medical image transmission.

Iqbal et al. (2021) developed a lightweight encryption scheme based on chaotic logistic maps for secure MRI transmission in IoT healthcare systems. The proposed method emphasized low computational complexity and high encryption speed, making it ideal for resource-constrained devices. The system achieved high entropy and low correlation coefficients, indicating strong resistance to statistical attacks. Additionally, the algorithm reduced energy consumption during transmission. However, the security of single chaotic maps can be vulnerable to certain attacks if not properly designed. Nevertheless, the study demonstrates the effectiveness of lightweight chaos-based encryption in IoT environments.

Park et al. (2023) introduced a hybrid physics-guided neural network for MRI reconstruction and secure transmission. Their model incorporated physical constraints of MRI signal acquisition into a deep learning framework, improving reconstruction accuracy and reducing noise sensitivity. The approach demonstrated superior performance compared to purely data-driven models, particularly in scenarios with limited training data. Additionally, the system integrated secure transmission mechanisms to protect patient data. However, the complexity of integrating physics-based models with neural networks increased computational requirements. This study highlights the growing importance of physics-guided learning in medical imaging.

Das et al. (2022) proposed an energy-efficient secure MRI transmission system using a combination of fog computing and deep learning. The system processes and encrypts MRI images at the fog layer, reducing latency and bandwidth usage. A deep learning model was used for compression and feature extraction, improving transmission efficiency. Experimental results showed reduced energy consumption and improved system performance compared to cloud-based approaches. However, the deployment of fog infrastructure increased system complexity and required efficient resource management. This study emphasizes the role of distributed computing architectures in enhancing IoT-based healthcare systems.

Nair et al. (2021) presented a secure MRI image transmission framework using blockchain technology combined with deep learning-based encryption. The blockchain ensured data integrity and secure access control, while the deep learning model enhanced encryption strength. The system demonstrated improved transparency and security in medical data transmission. Additionally, the decentralized nature of blockchain reduced the risk of single-point failures. However, blockchain implementation introduced additional latency and computational overhead, which may affect real-time applications. Despite these challenges, the study provides a novel approach to secure medical image transmission using emerging technologies.

Hassan et al. (2022) proposed a secure MRI image transmission system based on a hybrid deep learning and lightweight cryptographic framework. Their approach integrates convolutional neural networks for feature extraction and compression with lightweight encryption algorithms to ensure data confidentiality. The system demonstrated improved transmission efficiency and reduced computational overhead, making it suitable for IoT-based healthcare applications. Additionally, the model achieved high PSNR and SSIM values, indicating preservation of image quality after decryption. However, the reliance on lightweight cryptography may expose the system to advanced cryptographic attacks if not properly implemented. Nevertheless, the study provides an effective trade-off between security and efficiency.

Banerjee et al. (2023) introduced an optimization-driven secure MRI transmission model using ant colony optimization (ACO) combined with deep learning techniques. The ACO algorithm was used to optimize routing paths and transmission parameters in IoT networks, thereby reducing energy consumption and transmission delays. The deep learning component handled image compression and reconstruction, ensuring efficient data transmission. Experimental results showed significant improvements in network performance and energy efficiency. However, the integration of optimization algorithms increased system complexity and required careful parameter tuning. This study highlights the role of bio-inspired optimization techniques in enhancing IoT-based medical systems.

El-Sayed et al. (2021) proposed a secure MRI transmission framework using watermarking techniques combined with encryption. The watermarking approach embedded patient information within the MRI images, ensuring data authenticity and integrity. Encryption techniques were applied to protect the image during transmission. The system demonstrated strong resistance to tampering and unauthorized access. Additionally, the watermarking process did not significantly affect image quality. However, the embedding process introduced slight computational overhead and required careful design to avoid distortion. This study provides a reliable method for ensuring both security and authenticity in medical image transmission.

Wang et al. (2022) developed a deep learning-based secure transmission model using attention mechanisms and autoencoders. The attention mechanism improved feature extraction and compression efficiency, while the autoencoder reduced data size for transmission. The model achieved high compression ratios and maintained diagnostic image quality. Furthermore, encryption techniques were integrated to ensure data security. However, attention-based models require significant computational resources, which may limit their deployment in low-power IoT devices. Despite this limitation, the study demonstrates the effectiveness of advanced deep learning architectures in secure MRI transmission.

Oliveira et al. (2023) proposed a secure and energy-efficient MRI transmission system using federated learning. Their approach enables decentralized training of deep learning models across multiple IoT devices without sharing raw data, thereby preserving patient privacy. The system demonstrated improved security and reduced data transmission requirements. Additionally, federated learning reduced dependency on centralized servers, enhancing system scalability. However, challenges such as communication overhead and model synchronization were identified. This study highlights the potential of federated learning in secure and distributed healthcare systems.

Comparative Table

Study	**Year**	**Technique Used**	**Key Contribution**	**Advantages**	**Limitations**
Zhang & Liu	2022	Multi-chaotic encryption	Enhanced security using chaotic maps	High entropy, strong security	High synchronization complexity
Khan et al.	2022	Edge + lightweight crypto	Reduced latency via edge processing	Energy efficient	Infrastructure cost
Wu et al.	2023	GAN-based encryption	Dynamic key generation	High PSNR, adaptive security	High computational cost
Patil & Deshmukh	2023	AES + chaotic maps	Hybrid encryption	Strong security + efficiency	Parameter tuning needed
Sharma et al.	2021	Autoencoder compression	Efficient compression	High SSIM, reduced size	Minor reconstruction loss
Li et al.	2022	CNN + lightweight crypto	Compression + security	Low latency	Data dependency
Ahmed et al.	2021	DWT + chaos	Compression + encryption	High efficiency	Computational overhead
Singh & Roy	2023	DL + PSO optimization	Energy-efficient model	Improved performance	Complexity increase
Chen et al.	2022	PINNs	Physics-guided learning	Better generalization	High complexity
Kumar et al.	2021	Edge + lightweight crypto	Real-time transmission	Low latency	Deployment cost
Mehta & Sharma	2020	ECC + DL	Secure compression	Strong encryption	Computational overhead
Gupta et al.	2022	DBN + encryption	Feature learning	High compression	Training complexity
Reddy et al.	2023	GA optimization	Optimized encryption	High randomness	Slow processing

Verma & Singh	2021	Compressive sensing	Data reduction	Energy efficient	Reconstruction errors
Alghamdi et al.	2023	RNN + encryption	Sequential modelling	Efficient transmission	Gradient issues
Zhou et al.	2022	Homomorphic encryption	Processing encrypted data	High privacy	Very high overhead
Iqbal et al.	2021	Chaos-based lightweight crypto	Fast encryption	Low energy use	Security limitations
Park et al.	2023	Physics-guided NN	Improved reconstruction	Robust performance	High complexity
Das et al.	2022	Fog + DL	Reduced latency	Energy efficient	Infrastructure complexity
Nair et al.	2021	Blockchain + DL	Secure data sharing	High transparency	Latency issues
Hassan et al.	2022	DL + lightweight crypto	Balanced system	Efficient	Security trade-offs
Banerjee et al.	2023	ACO optimization	Network optimization	Reduced energy	Complexity
El-Sayed et al.	2021	Watermarking + encryption	Data authenticity	Tamper resistance	Overhead
Wang et al.	2022	Attention + autoencoder	Improved compression	High accuracy	Resource intensive
Oliveira et al.	2023	Federated learning	Privacy preservation	Decentralized	Sync issues
Rahman et al.	2023	DL + Blockchain + Optimization	End-to-end system	High security	System complexity

Comparative Analysis

The comparative evaluation of 30 studies published between 2020 and 2023 demonstrates a clear transition from conventional security mechanisms to intelligent hybrid frameworks for secure and energy-efficient MRI image transmission. Earlier approaches primarily relied on standalone cryptographic methods to protect medical images during transmission. Although these techniques provided acceptable confidentiality, they often struggled with computational overhead, synchronization issues, and limited adaptability to dynamic IoT environments. Recent research has therefore shifted toward integrating deep learning with advanced encryption methods. Hybrid frameworks combining classical cryptography, chaos-based encryption, lightweight security mechanisms, and AI-driven approaches have shown improved resistance to cyberattacks while maintaining image integrity and transmission efficiency, making them more suitable for modern IoT-enabled healthcare systems.

Another major trend is the widespread adoption of deep learning models for image compression, reconstruction, and feature extraction. Convolutional neural networks, autoencoders, deep belief networks, and generative adversarial networks have demonstrated superior capability in reducing MRI image size while preserving diagnostic quality. These approaches achieve high reconstruction accuracy, enabling efficient transmission across bandwidth-constrained IoT networks. Simultaneously, optimization techniques such as particle swarm optimization, genetic algorithms, ant colony optimization, and deep reinforcement learning have been incorporated to improve resource allocation, reduce latency, and minimize energy consumption. Despite these advantages, many deep learning models remain computationally intensive and require extensive training data, limiting their deployment on low-power IoT devices.

Distributed computing paradigms, including edge computing, fog computing, and federated learning, have further enhanced secure MRI transmission by reducing communication delays, improving scalability, and preserving patient privacy. Edge and fog computing process medical images closer to IoT devices, thereby lowering bandwidth usage and transmission latency. Federated learning enables collaborative model training without sharing sensitive patient information, strengthening privacy protection and regulatory compliance. In parallel, hybrid physics-guided neural networks have emerged as a promising research direction by embedding physical constraints into deep learning models.

These approaches improve reconstruction accuracy, robustness, and model generalization while reducing dependence on large annotated datasets, making them particularly valuable for healthcare applications.

Overall, the comparative analysis indicates that hybrid AI frameworks integrating deep learning, optimization algorithms, physics-guided neural networks, and advanced encryption techniques provide the most effective solution for secure and energy-efficient MRI image transmission. Nevertheless, challenges related to computational complexity, scalability, real-time implementation, explainability, and resource management continue to hinder practical deployment. Future research should prioritize lightweight, energy-aware, and explainable architectures combined with edge intelligence and privacy-preserving security mechanisms to enable reliable, scalable, and clinically applicable IoT-based healthcare systems.

Discussion

The reviewed studies highlight a rapid evolution in secure and energy-efficient MRI image transmission, driven by the convergence of deep learning, optimization techniques, and advanced encryption mechanisms. A key observation is the increasing reliance on hybrid models that combine compression, encryption, and intelligent optimization within a unified framework. Deep learning models such as CNNs, autoencoders, and GANs have significantly improved image compression and reconstruction, enabling efficient transmission over IoT networks while preserving diagnostic quality. At the same time, lightweight cryptographic techniques and chaos-based encryption have addressed security concerns in resource-constrained environments. Optimization algorithms, including PSO, GA, ACO, and DRL, play a crucial role in enhancing system performance by minimizing energy consumption and transmission latency.

Additionally, emerging paradigms such as federated learning, edge computing, and blockchain have introduced new dimensions of privacy, scalability, and data integrity. Physics-guided neural networks further strengthen system robustness by integrating domain knowledge into learning models. However, despite these advancements, several challenges persist. High computational complexity, dependency on large datasets, and difficulties in real-time deployment remain significant barriers. Furthermore, integrating multiple technologies often increases system complexity and cost. Future research should focus on developing lightweight, scalable, and interoperable solutions that balance security, efficiency, and performance for real-world healthcare applications.

Conclusion

The rapid adoption of IoT technologies has significantly improved healthcare services, particularly MRI image transmission, but ensuring secure and energy-efficient communication remains a major challenge. This review explores recent advances in deep learning, optimization techniques, and hybrid physics-guided neural networks for secure MRI image transmission. Deep learning models, including convolutional neural networks, autoencoders, generative adversarial networks, and deep belief networks, effectively compress and reconstruct MRI images while preserving diagnostic quality and reducing transmission overhead. Hybrid physics-guided neural networks further improve model generalization, robustness, and interpretability by incorporating physical constraints into the learning process. To strengthen security, researchers have integrated chaos-based encryption, lightweight cryptography, homomorphic encryption, and blockchain-based frameworks to ensure confidentiality, integrity, and protection against cyberattacks. Optimization algorithms, including particle swarm optimization, genetic algorithms, ant colony optimization, and deep reinforcement learning, enhance energy efficiency, reduce latency, and optimize resource utilization in IoT networks. Despite these advances, challenges related to computational complexity, scalability, privacy preservation, and real-time implementation remain. Future research should focus on lightweight, explainable, and energy-aware AI frameworks for secure, reliable, and efficient MRI transmission.

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