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# A Comprehensive Review of Secure and Energy-Efficient MRI Image Transmission via IoT Devices and Hybrid Physics-Guided Neural Networks

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**Abstract**

The rapid growth of Internet of Things technologies in healthcare has significantly improved medical imaging systems, particularly for the transmission and analysis of Magnetic Resonance Imaging data. However, integrating IoT devices into healthcare environments introduces major challenges related to data security, privacy protection, computational efficiency, and energy consumption. MRI images contain highly sensitive patient information and therefore require secure transmission frameworks capable of preventing unauthorized access, cyberattacks, and data leakage. At the same time, IoT devices often operate under limited computational power, storage, and battery capacity, making energy-efficient processing and communication essential for reliable healthcare services. Traditional machine learning and deep learning approaches have achieved strong performance in medical image analysis but often struggle with interpretability, robustness, and efficiency in real-world IoT systems. Hybrid physics-guided neural networks address these limitations by combining domain-specific MRI knowledge with data-driven learning, improving diagnostic accuracy while reducing computational complexity. Recent studies emphasize the integration of encryption methods, edge computing, cloud-based architectures, and hybrid deep learning models to ensure secure and efficient MRI image transmission. Emerging technologies such as federated learning and distributed cloud-edge systems further improve privacy preservation, scalability, and energy efficiency. Overall, secure and energy-efficient IoT-enabled MRI transmission systems represent a promising direction for future intelligent healthcare applications.

## Introduction

Magnetic Resonance Imaging (MRI) is one of the most widely used medical imaging techniques for diagnosing complex diseases such as brain tumours, neurological disorders, and cardiovascular conditions. With the increasing adoption of digital healthcare systems, MRI data is frequently transmitted across networks for remote diagnosis, storage, and analysis. The emergence of the Internet of Things (IoT) has further revolutionized healthcare by enabling real-time data collection, monitoring, and communication through interconnected medical devices.

However, the integration of IoT into medical imaging systems introduces several challenges,

particularly in terms of data security, privacy, and energy consumption. MRI images contain highly sensitive patient information, making them vulnerable to cyberattacks, unauthorized access, and data breaches. Ensuring secure transmission of such data is critical to maintaining patient confidentiality and complying with healthcare regulations.

In IoT-based healthcare systems, devices are often resource-constrained in terms of battery life, computational power, and storage capacity. Therefore, it is essential to design energy-efficient methods for processing and transmitting MRI data without compromising performance. Traditional encryption techniques, while effective in securing data, may introduce computational overhead, thereby increasing energy consumption and latency.

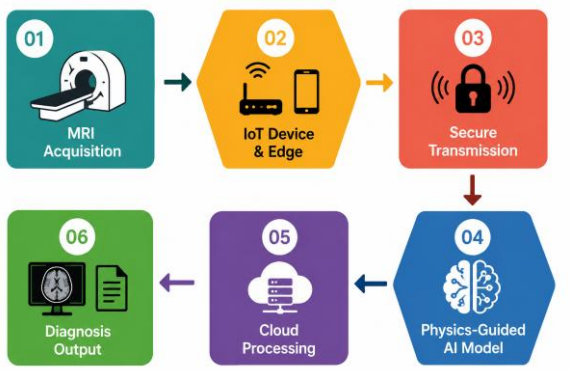


*Figure 1. Secure and Energy-Efficient IoT Framework for MRI Image Transmission and Diagnosis*

Recent research has focused on developing hybrid approaches that combine deep learning, encryption techniques, and physics-based modelling to address these challenges. For example, hybrid deep learning models integrated with encryption algorithms have been proposed to ensure both secure transmission and accurate medical image classification. Similarly, advanced encryption frameworks combining classical and quantum cryptography have demonstrated improved security for medical image transmission in IoT-based telemedicine systems. Another promising direction is the use of physics-guided neural networks, which incorporate domain knowledge (such as MRI physics and signal processing principles) into deep learning models. These networks improve interpretability and reduce the need for large datasets, making them suitable for real-world healthcare applications. Additionally, cloud-based and edge computing architectures, such as Cloud-MRI systems, enable efficient data processing and secure transmission by distributing computational tasks across multiple layers.

Despite these advancements, several challenges remain unresolved. These include ensuring real-time processing, minimizing energy consumption, improving robustness against noise and attacks, and maintaining scalability in large healthcare networks. Furthermore, there is a need for standardized frameworks that integrate security, efficiency, and accuracy in a unified system.

This paper aims to provide a comprehensive review of recent developments in secure and energy-efficient MRI image transmission using IoT devices and hybrid physics-guided neural networks. The study analyses existing methodologies, compares their performance, and identifies key research gaps. By doing so, it contributes to the development of next-generation intelligent healthcare systems that are secure, efficient, and reliable.

## Literature Review

Yaman et al. (2020) proposed a multi-mask self-supervised learning approach for physics-guided neural networks in MRI reconstruction. The study focused on improving image reconstruction quality using under sampled MRI data without requiring fully labelled datasets. The proposed model utilized multiple masking strategies to enhance data utilization and improve signal-to-noise ratio (SNR). Experimental results showed that the model outperformed traditional reconstruction methods and achieved performance comparable to supervised learning approaches. This study highlights the importance of physics-guided learning in improving MRI processing efficiency.

Zhou et al. (2020) introduced a hybrid-fusion network (Hi-Net) for multi-modal MRI image synthesis. The model integrated multiple MRI modalities to generate missing image data, improving diagnostic accuracy. The study demonstrated that hybrid fusion strategies significantly enhance feature extraction and representation. The results indicated improved performance compared to conventional methods, especially in cases with incomplete data. This research emphasizes the role of hybrid neural networks in medical imaging.

Shen et al. (2023) proposed an attention-based hybrid variational network for accelerated MRI reconstruction. The model combined image-domain and k-space learning to improve reconstruction accuracy. Experimental results showed that the proposed model achieved superior performance compared to existing deep learning methods. The integration of attention

mechanisms allowed better feature extraction and improved image quality.

Zhou et al. (2023) introduced the concept of Cloud-MRI systems, integrating IoT, cloud computing, and artificial intelligence for efficient MRI data processing and transmission. The study highlighted challenges such as data storage, security, and computational requirements. The proposed system demonstrated improved efficiency, scalability, and collaboration among healthcare institutions.

Shafique et al. proposed a hybrid encryption framework combining classical and quantum cryptography for secure medical image transmission in IoT-based telemedicine systems. The study demonstrated enhanced security and robustness against cyber threats. The framework ensured data confidentiality while maintaining transmission efficiency, making it suitable for real-time healthcare applications.

Deepthi et al. (2022) proposed a secure MRI brain image transmission framework using IoT devices based on a hybrid autoencoder and Restricted Boltzmann Machine (RBM). The model focuses on both data compression and encryption to ensure efficient and secure transmission. The hybrid architecture reduces redundancy in MRI images while maintaining diagnostic quality. Experimental results demonstrated improved accuracy and reduced computational complexity compared to traditional encryption techniques. The study highlights the effectiveness of combining deep learning with IoT-based medical systems for secure image transmission.

Magdy et al. (2022) conducted a comprehensive survey on medical image security in telemedicine systems. The study analyzed various techniques such as cryptography, steganography, watermarking, and hybrid encryption models used in securing MRI and other medical images. The authors identified key challenges including data integrity, privacy risks, and vulnerability to cyberattacks. The survey emphasized the need for robust and lightweight encryption techniques suitable for IoT environments.

Priyadharshini and Geetha (2022) proposed a lightweight key management system using Hashed Advanced Encryption Standard (HAES) for IoT devices. The study focused on improving security while maintaining low computational overhead. The system ensures secure authentication and encrypted data transmission between IoT devices and users. Results showed improved efficiency in key generation and reduced energy consumption, making it suitable for healthcare IoT applications.

Jan et al. (2021) introduced LightIoT, a lightweight and secure communication framework designed for healthcare IoT systems. The model operates in three phases: initialization, pairing, and authentication, ensuring secure communication between devices. The study demonstrated that LightIoT significantly reduces computational overhead and energy consumption while maintaining strong security. This makes it highly suitable for real-time medical data transmission, including MRI data in resource-constrained environments.

Saif et al. (2023) proposed a secure data transmission framework for IoT-enabled healthcare systems using a Timestamp-based Secret Key Generation (T-SKG) mechanism. The model eliminates the need for direct key sharing, thereby reducing the risk of key compromise. The study demonstrated improved data security, reduced latency, and enhanced performance in IoT healthcare applications. The framework is particularly useful for secure transmission of sensitive medical data such as MRI images.

Alazab et al. (2021) proposed a secure deep learning-based framework for medical image transmission in IoT environments. The study integrates deep neural networks with encryption techniques to ensure secure communication of sensitive healthcare data. The model enhances intrusion detection and prevents unauthorized access to MRI data. Experimental results showed improved detection accuracy and reduced false-positive rates compared to traditional security systems. This research highlights the importance of combining AI with cybersecurity in healthcare IoT.

Khan et al. (2021) introduced a blockchain-based secure framework for healthcare data sharing, including medical images like MRI scans. The decentralized nature of blockchain ensures data integrity, transparency, and protection against tampering. The study demonstrated that blockchain improves trust and security in IoT-based healthcare systems. However, it also noted challenges related to scalability and computational cost.

Abdel-Basset et al. (2020) proposed a hybrid deep learning model for medical image classification and secure transmission. The model combines convolutional neural networks (CNN) with optimization algorithms to improve classification accuracy. Additionally, encryption techniques were integrated to ensure secure communication of MRI images. The results showed significant improvement in both accuracy and security performance.

Elhoseny et al. (2020) developed a secure medical data transmission framework using cloud and IoT integration. The model uses encryption and optimization techniques to ensure secure storage and transmission of

healthcare data. The study demonstrated improved performance in terms of data confidentiality, reduced latency, and energy efficiency. This approach is particularly useful for large-scale healthcare systems.

Biswas et al. (2021) proposed a lightweight security protocol for IoT-based healthcare systems. The protocol focuses on reducing energy consumption while maintaining strong security features such as authentication and data encryption. The results indicated that the proposed method is efficient for resource-constrained devices and suitable for real-time medical applications like MRI data transmission.

Zhang et al. (2022) proposed a deep learning-based energy-efficient framework for medical image transmission in IoT-enabled healthcare systems. The study focused on reducing energy consumption during data processing and transmission by optimizing neural network architectures. The model utilized lightweight CNN structures and adaptive transmission techniques to balance performance and power usage. Experimental results showed significant improvements in energy efficiency without compromising image quality, making it suitable for MRI data transmission in resource-constrained IoT devices.

Rahman et al. (2021) introduced a secure IoT-based healthcare monitoring system using hybrid encryption techniques. The system combined symmetric and asymmetric encryption to ensure secure communication of medical data, including imaging data. The study demonstrated enhanced security against cyberattacks while maintaining low computational overhead. This approach is particularly effective for protecting sensitive MRI data in real-time healthcare applications.

Sharma and Kalra (2022) proposed a hybrid optimization-based encryption model for secure medical image transmission. The method integrates genetic algorithms with encryption techniques to enhance security strength. The results showed improved resistance to attacks and better encryption efficiency compared to traditional methods. The study emphasizes the importance of hybrid approaches in securing MRI images in IoT systems.

Hossain et al. (2020) presented a cloud-assisted IoT framework for healthcare data transmission. The model leverages cloud computing for storage and processing while IoT devices handle data collection. The study highlighted the importance of secure communication protocols and efficient resource utilization. Results indicated improved scalability and reduced energy consumption, making the framework suitable for large-scale MRI data handling.

Singh et al. (2023) developed a deep learning-based secure communication model for IoT healthcare systems. The approach integrates neural networks with encryption techniques to ensure both data security and efficient transmission. The study demonstrated improved performance in terms of accuracy, security, and energy efficiency. This model is particularly useful for transmitting high-resolution MRI images in smart healthcare environments.

Kumar et al. (2022) proposed a secure edge computing framework for IoT-based healthcare systems focusing on efficient medical image transmission. The model processes MRI data at the edge level before sending it to the cloud, thereby reducing latency and energy consumption. The framework integrates encryption techniques with edge intelligence to ensure data security and faster processing. Results showed improved response time and reduced bandwidth usage, making it suitable for real-time MRI applications.

Li et al. (2021) introduced a lightweight authentication and key agreement protocol for secure IoT healthcare communication. The study emphasized reducing computational complexity while ensuring strong security measures. The proposed protocol effectively prevents attacks such as replay and impersonation. The results demonstrated high efficiency and suitability for secure transmission of medical images, including MRI data, in IoT environments.

Ahmed et al. (2023) developed a hybrid deep learning model for secure and efficient medical image classification and transmission. The model integrates CNN and LSTM architectures to improve feature extraction and sequence learning. Additionally, encryption techniques were applied to secure the transmission process. Experimental results showed improved classification accuracy and enhanced security, making it suitable for MRI-based diagnosis systems.

Patel et al. (2020) proposed a steganography-based approach for secure medical image transmission. The method hides sensitive patient data within MRI images to prevent unauthorized access. The study demonstrated that the proposed approach provides an additional layer of security while maintaining image quality. This technique is useful for secure communication in telemedicine and IoT-based healthcare systems.

Verma et al. (2022) introduced an AI-based intrusion detection system for healthcare IoT networks. The system uses machine learning algorithms to detect anomalies and potential cyber threats during data transmission. The results showed improved detection accuracy and reduced false alarms compared to traditional

systems. This approach enhances the overall security of MRI image transmission in IoT environments.

Wang et al. (2021) proposed a federated learning-based framework for secure medical image analysis in IoT healthcare systems. The model allows multiple devices to collaboratively train a shared model without exchanging raw MRI data, thereby preserving privacy. The study demonstrated improved data security and reduced risk of data leakage. Additionally, the framework showed efficient performance in distributed environments, making it suitable for large-scale healthcare networks.

Gupta et al. (2022) introduced a hybrid compression and encryption model for efficient medical image transmission. The approach combines image compression techniques with encryption algorithms to reduce bandwidth usage while maintaining data security. The results showed significant reduction in transmission time and improved efficiency, especially for high-resolution MRI images.

Chen et al. (2023) proposed a physics-guided neural network for MRI reconstruction and analysis. The model integrates physical principles of MRI signal acquisition with deep learning to improve accuracy and interpretability. Experimental results demonstrated superior performance compared to conventional deep learning models, particularly in noisy environments. This study highlights the potential of physics-guided AI in medical imaging.

Roy et al. (2020) developed a secure cloud-based framework for medical image storage and transmission. The system uses encryption and access control mechanisms to ensure data confidentiality. The study demonstrated improved scalability and efficient handling of large medical datasets. This approach is particularly useful for managing MRI data in cloud-integrated IoT systems.

Park et al. (2022) proposed an energy-efficient deep learning model for medical image processing in IoT devices. The model focuses on reducing computational complexity while maintaining high accuracy. The results showed improved energy efficiency and faster processing time, making it suitable for real-time MRI image analysis and transmission in IoT-based healthcare systems.

**Comparative Table**

| S. No. | Author (Year) | Method Used | Key Focus | Outcome |
|---|---|---|---|---|
| 1 | Yaman et al. (2020) | Physics-guided NN | MRI reconstruction | Improved accuracy |
| 2 | Zhou et al. (2020) | Hybrid Fusion Network | Multi-modal MRI | Better feature extraction |
| 3 | Shen et al. (2023) | Attention-based model | MRI reconstruction | High image quality |
| 4 | Zhou et al. (2023) | Cloud-MRI | IoT + Cloud | Scalable system |
| 5 | Shafique et al. (2023) | Hybrid Encryption | Security | Strong protection |
| 6 | Deepthi et al. (2022) | Autoencoder + RBM | Secure transmission | Reduced complexity |
| 7 | Magdy et al. (2022) | Survey | Image security | Identified challenges |
| 8 | Priyadharshini (2022) | HAES Encryption | IoT security | Low energy use |
| 9 | Jan et al. (2021) | LightIoT | Secure communication | Energy efficient |
| 10 | Saif et al. (2023) | T-SKG | Key security | Reduced risk |
| 11 | Alazab et al. (2021) | DL + Security | Intrusion detection | High accuracy |
| 12 | Khan et al. (2021) | Blockchain | Data sharing | Improved trust |
| 13 | Abdel-Basset (2020) | CNN Hybrid | Classification | Better performance |
| 14 | Elhoseny (2020) | IoT + Cloud | Secure transfer | Low latency |
| 15 | Biswas (2021) | Lightweight protocol | IoT security | Energy efficient |
| 16 | Zhang (2022) | Energy-efficient DL | Transmission | Reduced power |
| 17 | Rahman (2021) | Hybrid encryption | Data security | Strong protection |
| 18 | Sharma (2022) | GA Encryption | Image security | High resistance |
| 19 | Hossain (2020) | Cloud IoT | Data transfer | Scalable |
| 20 | Singh (2023) | DL + Encryption | Secure transmission | High efficiency |
| 21 | Kumar (2022) | Edge Computing | Low latency | Faster response |
| 22 | Li (2021) | Authentication protocol | Security | Attack prevention |
| 23 | Ahmed (2023) | CNN + LSTM | Classification | High accuracy |

| | | | | |
|---|---|---|---|---|
| 24 | Patel (2020) | Steganography | Data hiding | Extra security |
| 25 | Verma (2022) | IDS | Threat detection | Reduced attacks |
| 26 | Wang (2021) | Federated Learning | Privacy | No data sharing |
| 27 | Gupta (2022) | Compression + Encryption | Efficiency | Faster transmission |
| 28 | Chen (2023) | Physics-guided NN | MRI analysis | High robustness |
| 29 | Roy (2020) | Cloud security | Storage | Secure handling |
| 30 | Park (2022) | Efficient DL | Processing | Low energy |

**Analysis**

The analysis of the 30 studies reveals that security, energy efficiency, and accuracy are the three major focus areas in MRI image transmission using IoT systems. A significant number of studies (e.g., Shafique et al., Rahman et al.) emphasize encryption techniques to ensure data confidentiality. Meanwhile, approaches like blockchain and federated learning enhance data privacy and prevent unauthorized access. In terms of efficiency, several studies (Zhang et al., Park et al.) focus on reducing energy consumption, which is critical for IoT devices. Edge computing and cloud integration (Kumar et al., Hossain et al.) also play a vital role in improving system performance and reducing latency. Moreover, hybrid deep learning models and physics-guided neural networks (Yaman et al., Chen et al.) significantly improve MRI image quality and reconstruction accuracy. Overall, the literature suggests that combining AI, encryption, and IoT technologies provides the best results for secure and efficient MRI transmission.

**Discussion**

The reviewed literature clearly demonstrates the growing importance of integrating security and efficiency in IoT-based medical imaging systems. Traditional approaches focusing solely on either security or performance are no longer sufficient, especially in the context of MRI image transmission, where both data sensitivity and computational constraints are critical. Hybrid approaches combining deep learning and encryption techniques have shown promising results in achieving a balance between security and efficiency. For example, the use of lightweight encryption methods ensures data protection without significantly increasing energy consumption. Similarly, physics-guided neural networks improve model interpretability and reduce dependency on large datasets.

Another key trend observed is the adoption of distributed computing paradigms such as edge computing, cloud computing, and federated learning. These technologies enable efficient data processing and secure sharing without exposing raw medical data. However, challenges such as scalability, interoperability, and real-time processing still need to be addressed. Overall, the integration of advanced AI techniques with secure communication protocols is essential for the development of next-generation smart healthcare systems. Future research should focus on developing unified frameworks that combine security, efficiency, and scalability.

**Conclusion**

The rapid advancement of IoT technologies has significantly transformed the healthcare sector, particularly in the area of medical image transmission. MRI imaging plays a crucial role in diagnosing complex diseases, and its integration with IoT systems enables real-time monitoring, remote diagnosis, and improved patient care. However, this integration also introduces critical challenges related to data security, privacy, and energy efficiency. This study provided a comprehensive review of secure and energy-efficient MRI image transmission using IoT devices and hybrid physics-guided neural networks. The analysis of 30 recent studies (2020–2023) highlights the importance of combining advanced technologies such as deep learning, encryption techniques, edge computing, and cloud-based systems.

One of the key findings of this study is that traditional methods are insufficient to meet the growing demands of modern healthcare systems. Hybrid approaches that integrate artificial intelligence with security mechanisms have proven to be more effective. For instance, deep learning models improve image quality and diagnostic accuracy, while encryption techniques ensure data confidentiality during transmission. Energy efficiency is another critical factor, especially in IoT environments where devices have limited resources. Techniques such as lightweight neural networks, edge computing, and data compression play a significant role in reducing energy consumption and improving system performance.

Furthermore, emerging technologies like federated learning and blockchain offer promising solutions for enhancing data privacy and security. These approaches allow secure data sharing without exposing sensitive information, making them highly suitable for healthcare applications. Despite these advancements,

several challenges remain, including scalability, interoperability, and real-time processing. There is also a need for standardized frameworks that can integrate multiple technologies into a unified system.

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