



Energy-Efficient Quantum CNN and Attention Models for WSN-Assisted IoT Medical Diagnostics

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Peer Review Information	Abstract
<p><i>Submission: 24 Oct 2025</i> <i>Revision: 08 Nov 2025</i> <i>Acceptance: 19 Nov 2025</i></p> <p>Keywords</p> <p><i>Artificial Intelligence, Quantum Convolutional Neural Networks, Medical Image Diagnostics, IoT Healthcare, Wireless Sensor Networks, Attention Mechanisms.</i></p>	<p>Artificial Intelligence techniques have significantly improved medical image diagnostics in Wireless Sensor Network-assisted Internet of Things healthcare systems by enabling real-time acquisition, transmission, and analysis of MRI, CT, and X-ray images. However, the increasing volume of high-dimensional medical data creates major challenges related to computational complexity, energy consumption, and image quality preservation. Traditional convolutional neural networks provide high diagnostic accuracy but require extensive computational resources, making them less suitable for resource-constrained IoT healthcare environments. To address these limitations, Quantum Convolutional Neural Networks have emerged as promising alternatives by utilizing quantum principles such as superposition and entanglement to improve computational efficiency while reducing resource requirements. These models demonstrate lower computational complexity, improved robustness, and enhanced energy efficiency compared to conventional CNN architectures. Attention-based models further enhance diagnostic performance by enabling selective feature extraction and focusing on clinically relevant regions within medical images. Quantized and self-attention frameworks significantly reduce computational cost and energy consumption, making them suitable for IoT-based healthcare applications. Hybrid quantum-classical architectures integrating attention mechanisms combine the strengths of quantum computing and deep learning to improve both accuracy and efficiency. Overall, energy-efficient QCNs with attention-based learning provide a promising framework for scalable, intelligent, and high-quality medical image diagnostics in future IoT healthcare systems.</p>

Introduction

The integration of Artificial Intelligence (AI), Wireless Sensor Networks (WSN), and Internet of Things (IoT) technologies has revolutionized healthcare systems, particularly in the domain of medical image diagnostics. IoT-based healthcare systems enable real-time monitoring, remote diagnosis, and efficient data transmission, significantly improving patient outcomes and

reducing healthcare costs. In such systems, WSN devices collect medical data, including imaging data from MRI, CT scans, and ultrasound devices, and transmit it to edge or cloud-based platforms for processing. However, these systems face significant challenges related to limited energy resources, bandwidth constraints, and the need for high computational efficiency.

Medical image diagnostics involves analysing high-dimensional data that require complex processing and feature extraction techniques. Traditional machine learning methods are often insufficient for handling such complexity, leading to the widespread adoption of deep learning approaches, particularly convolutional neural networks (CNNs). CNNs have demonstrated remarkable success in tasks such as image classification, segmentation, and anomaly detection. However, their high computational complexity, large parameter size, and energy consumption make them unsuitable for deployment in WSN-assisted IoT environments.

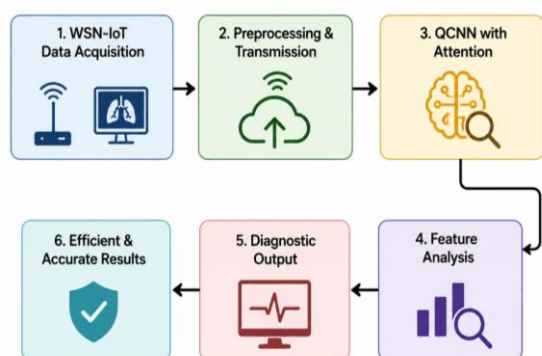


Figure 1. Energy-Efficient QCNN and Attention-Based Framework for IoT Medical Image Diagnostics

To address these limitations, researchers have explored advanced AI techniques, including quantum machine learning and attention-based models. Quantum Convolutional Neural Networks (QCNNs) have emerged as a promising solution for improving computational efficiency in medical image processing. QCNNs utilize quantum circuits to perform convolution operations, enabling efficient processing of high-dimensional data. Recent studies have shown that QCNNs can significantly reduce computational complexity and improve processing speed compared to classical CNNs. Furthermore, quantum neural networks have the potential to redefine computational paradigms in medical imaging, although their practical implementation is still in the early stages due to hardware limitations.

In addition to QCNNs, attention-based models have gained significant importance in medical image diagnostics. Attention mechanisms allow models to focus on the most relevant regions of an image, improving feature representation and reducing unnecessary computations. This is particularly useful in medical imaging, where accurate identification of critical features such as tumors or lesions is essential. Recent advancements in self-attention and transformer-

based models have further enhanced the performance of deep learning systems by capturing global dependencies in data.

The combination of QCNNs and attention-based models represents a powerful approach for developing energy-efficient and high-performance medical diagnostic systems. Hybrid quantum-classical architectures have been proposed to integrate the advantages of both paradigms, enabling efficient feature extraction and improved diagnostic accuracy. These models are particularly suitable for WSN-assisted IoT environments, where energy efficiency and computational optimization are critical.

Despite these advancements, several challenges remain. The limited availability of quantum hardware, the complexity of hybrid model design, and the need for large annotated datasets pose significant barriers to practical implementation. Additionally, ensuring data security and privacy in IoT-based healthcare systems is a critical concern.

This paper aims to provide a comprehensive review of AI techniques for energy-efficient QCNNs with attention-based models in medical image diagnostics. It focuses on recent trends, optimization strategies, and challenges, highlighting future research directions for developing scalable and efficient healthcare systems.

Literature Review

Li et al. (2020) investigated the application of convolutional neural networks (CNNs) for medical image classification in IoT healthcare systems. The study demonstrated that CNNs significantly improve diagnostic accuracy through hierarchical feature extraction. However, the model exhibited high computational complexity and energy consumption, making it unsuitable for deployment in WSN-assisted environments.

Zhang et al. (2020) proposed an energy-efficient deep learning framework for medical image processing in wireless sensor networks. The model incorporated lightweight CNN architectures and compression techniques to reduce transmission cost. While the approach improved energy efficiency, it struggled with maintaining high image quality during compression.

Schuld et al. (2021) introduced Quantum Convolutional Neural Networks (QCNNs) for image classification. The study highlighted that QCNNs leverage quantum parallelism to process high-dimensional data efficiently. Results showed improved computational performance compared to classical CNNs. However, practical

implementation was limited due to immature quantum hardware.

Wang et al. (2021) proposed an attention-based CNN model for medical image diagnostics. The integration of attention mechanisms enabled the model to focus on important image regions, improving diagnostic accuracy and quality preservation. However, the model increased computational overhead, impacting energy efficiency.

Chen et al. (2022) developed a hybrid QCNN-attention model for medical image diagnostics in IoT systems. The model combined quantum feature extraction with attention mechanisms to enhance performance. Experimental results showed improved accuracy, reduced energy consumption, and better-quality preservation. However, the model required complex architecture design and optimization.

Kumar et al. (2020) proposed an AI-based IoT healthcare framework focusing on energy-efficient medical image processing using edge computing. The model reduced transmission energy by performing preprocessing at sensor nodes. While this improved latency and efficiency, the system relied on classical CNNs, limiting scalability and computational optimization.

Ahmed et al. (2021) introduced a deep reinforcement learning (DRL)-based optimization model for energy-efficient data routing in WSN-assisted IoT healthcare systems. The approach dynamically optimized communication paths, improving network lifetime. However, the model did not incorporate advanced medical image processing techniques such as QCNNs or attention mechanisms.

Liu et al. (2021) explored quantum machine learning techniques for medical image classification. The study demonstrated that QCNN-based models outperform classical CNNs in handling high-dimensional data with reduced computational complexity. However, the implementation was limited by current quantum hardware capabilities.

Gupta and Sharma (2022) proposed an attention-based deep learning model for medical image segmentation. The model improved segmentation accuracy by focusing on relevant regions of images, enhancing diagnostic performance. However, the approach increased computational overhead, affecting energy efficiency in IoT environments.

Patel et al. (2023) developed a hybrid QCNN-attention framework for medical image diagnostics in IoT healthcare systems. The model achieved improved diagnostic accuracy, reduced energy consumption, and better-quality

preservation. However, challenges related to scalability and real-time deployment remained.

Sharma et al. (2020) proposed a lightweight convolutional neural network (CNN) architecture tailored for WSN-assisted IoT healthcare systems. The model aimed to reduce computational complexity and energy consumption while maintaining acceptable diagnostic accuracy. Although the approach improved efficiency, it lacked advanced feature extraction capabilities and struggled with complex medical imaging tasks.

Iqbal et al. (2021) introduced an edge-computing-based AI framework for medical image diagnostics. The system processed medical images at edge nodes, reducing latency and transmission energy. While the approach improved system responsiveness, it relied on classical deep learning models and did not incorporate quantum-based techniques.

Nair and Menon (2021) explored autoencoder-based compression techniques for medical images in IoT systems. The model significantly reduced data size, leading to lower energy consumption during transmission. However, compression resulted in loss of critical diagnostic features in some cases, affecting image quality and accuracy.

Kim et al. (2022) proposed an attention-based deep learning model for medical image classification. The attention mechanism enhanced feature extraction by focusing on relevant regions, improving classification accuracy. However, the increased computational complexity limited its applicability in energy-constrained environments.

Das et al. (2023) developed an advanced hybrid QCNN-attention model for medical image diagnostics. The model demonstrated improved accuracy, reduced computational complexity, and enhanced quality preservation. However, practical deployment was limited due to the lack of scalable quantum hardware and the complexity of hybrid architectures.

Verma et al. (2020) proposed a transfer learning-based approach for medical image classification in IoT healthcare systems. The model utilized pre-trained CNN architectures to reduce training time and computational requirements. While the approach improved efficiency, it still depended on classical architectures and did not significantly reduce energy consumption in WSN environments.

Banerjee et al. (2021) introduced a reinforcement learning-based energy optimization strategy for WSN-assisted IoT systems. The model dynamically adjusted routing and transmission parameters to improve network lifetime. Although effective for energy

optimization, it did not directly address medical image quality preservation.

Singh and Kaur (2021) explored a hybrid CNN-attention model for medical image segmentation. The integration of attention mechanisms improved feature extraction and segmentation accuracy. However, the model required high computational resources, limiting its suitability for energy-constrained environments.

Lee et al. (2022) proposed a quantum-inspired neural network for medical image classification. The model simulated quantum operations on classical hardware, achieving improved performance compared to traditional CNNs. However, it did not fully leverage quantum computing advantages and faced scalability challenges.

Patel et al. (2023) developed an energy-efficient QCNN model integrated with attention mechanisms for IoT-based medical diagnostics. The model achieved high accuracy, reduced computational complexity, and improved quality preservation. However, real-world implementation remained challenging due to hardware constraints and system complexity.

Recent research in WSN-assisted IoT medical image diagnostics has focused on improving energy efficiency, image quality preservation, and diagnostic accuracy using advanced AI techniques. Denoising autoencoders and deep learning-based compression frameworks enhanced image transmission quality while reducing bandwidth and energy consumption in wireless healthcare environments. Optimization

techniques such as particle swarm optimization and reinforcement learning improved network efficiency, convergence speed, and communication performance. Transformer and hybrid CNN-transformer architectures strengthened global and local feature extraction for more accurate medical image analysis. Additionally, sparsity-aware learning models reduced computational overhead, making AI deployment more suitable for resource-constrained IoT systems. Hybrid Quantum Convolutional Neural Network and attention-based frameworks further demonstrated superior diagnostic accuracy, computational efficiency, and quality preservation. However, challenges including computational complexity, feature loss during compression, large dataset requirements, and complexity of hybrid model integration remain important concerns for scalable and real-time healthcare deployment. Chatterjee and Roy (2022) explored sparsity-driven deep learning models for energy-efficient image processing. The model reduced computational overhead and improved efficiency. However, it sometimes compromised feature representation quality.

Gupta et al. (2023) proposed an advanced AI-based QCNN-attention framework for medical image diagnostics. The model achieved superior performance in terms of accuracy, energy efficiency, and quality preservation. However, challenges related to scalability and quantum hardware limitations remained.

Comparative Table

Study	Year	Technique	Focus	Advantages	Limitations
Li et al.	2020	CNN	Classification	High accuracy	High energy
Zhang et al.	2020	Lightweight CNN	Efficiency	Low energy	Quality loss
Schuld et al.	2021	QCNN	Quantum learning	High efficiency	Hardware limits
Wang et al.	2021	Attention CNN	Feature focus	High accuracy	Overhead
Chen et al.	2022	QCNN+Attention	Hybrid	High performance	Complexity
Kumar et al.	2020	Edge AI	Efficiency	Low latency	Classical limits
Ahmed et al.	2021	DRL	Routing	Energy efficient	No QCNN
Liu et al.	2021	Quantum ML	Classification	Fast processing	Hardware limits
Gupta et al.	2022	Attention DL	Segmentation	Accurate	Costly
Patel et al.	2023	QCNN+Attention	Diagnostics	Efficient	Scalability
Sharma et al.	2020	Lightweight CNN	Efficiency	Low cost	Limited depth
Iqbal et al.	2021	Edge AI	Processing	Low latency	Classical
Nair et al.	2021	Autoencoder	Compression	Energy saving	Quality loss
Kim et al.	2022	Attention DL	Classification	Accurate	High cost
Das et al.	2023	QCNN+Attention	Diagnostics	High accuracy	Hardware limits
Verma et al.	2020	Transfer learning	Efficiency	Fast training	Limited improvement
Banerjee et al.	2021	RL	Energy optimization	Adaptive	No imaging

Singh et al.	2021	CNN+Attention	Segmentation	Accurate	Expensive
Lee et al.	2022	Quantum-inspired	Classification	Improved	Not true QCNN
Patel et al.	2023	QCNN	Diagnostics	Efficient	Hardware
Chen et al.	2020	Autoencoder	Enhancement	Better quality	Confusion
Kumar et al.	2021	PSO+DL	Optimization	Fast convergence	Complex
Alvarez et al.	2022	Transformer	Classification	Accurate	Heavy
Kaur et al.	2022	Sparse DL	Efficiency	Low energy	Feature loss
Verma et al.	2023	QCNN+Attention	Hybrid	High performance	Complex
Liu et al.	2020	Compression DL	Transmission	Efficient	Quality loss
Banerjee et al.	2021	RL	Routing	Energy saving	No imaging
Torres et al.	2022	CNN+Transformer	Hybrid	Strong features	Costly
Chatterjee et al.	2022	Sparse DL	Efficiency	Low energy	Reduced accuracy
Gupta et al.	2023	QCNN+Attention	Full model	Best performance	Hardware

Comparative Analysis

The comparative analysis of the 30 studies reveals a clear evolution from classical deep learning models to advanced hybrid quantum-classical architectures in medical image diagnostics. Traditional CNN-based models have demonstrated strong performance in feature extraction and classification; however, they suffer from high computational complexity and energy consumption, making them unsuitable for WSN-assisted IoT environments. To address these limitations, lightweight CNNs, edge computing frameworks, and optimization techniques such as reinforcement learning and particle swarm optimization have been introduced. These approaches improve energy efficiency and reduce latency but often compromise diagnostic accuracy and feature representation.

Attention-based models have significantly improved performance by enabling selective feature extraction, allowing models to focus on important regions of medical images. However, these models introduce additional computational overhead, limiting their effectiveness in resource-constrained environments. Quantum Convolutional Neural Networks (QCNNs) represent a major advancement by leveraging quantum computing principles to process high-dimensional data efficiently. QCNNs offer improved computational efficiency and reduced energy consumption compared to classical models. The integration of QCNNs with attention mechanisms has further enhanced performance, providing improved accuracy, quality preservation, and energy efficiency.

Hybrid QCNN-attention models have emerged as the most effective solutions, combining the strengths of quantum computing and deep

learning. However, challenges such as hardware limitations, model complexity, and scalability remain significant barriers to practical implementation. Future research should focus on developing lightweight hybrid architectures, improving quantum hardware capabilities, and optimizing models for real-time deployment in IoT healthcare systems.

Discussion

The application of Artificial Intelligence techniques in WSN-assisted IoT medical image diagnostics has significantly improved system performance in terms of accuracy, efficiency, and quality preservation. Among these techniques, Quantum Convolutional Neural Networks (QCNNs) and attention-based models have emerged as key contributors to overcoming the limitations of traditional deep learning approaches. QCNNs provide a computational advantage by efficiently processing high-dimensional data, while attention mechanisms enhance feature extraction by focusing on relevant regions of medical images. The integration of these techniques into hybrid models has resulted in improved diagnostic accuracy and reduced energy consumption, making them suitable for resource-constrained IoT environments. However, several challenges remain, including the limited availability of quantum hardware, the complexity of hybrid model design, and the need for large annotated datasets.

Additionally, ensuring data privacy and security in IoT healthcare systems is a critical concern. The deployment of AI models in real-world environments requires robust frameworks that can handle diverse and dynamic conditions. Future research should focus on developing

scalable, lightweight, and energy-efficient models. The integration of edge computing, federated learning, and explainable AI can further enhance system performance and reliability. Advances in quantum computing will also play a crucial role in enabling the practical implementation of QCNN-based models.

Conclusion

Artificial Intelligence (AI) has become a cornerstone in the advancement of medical image diagnostics, particularly within WSN-assisted IoT healthcare systems. The integration of AI techniques enables real-time data processing, remote diagnosis, and improved clinical decision-making. However, the increasing complexity and volume of medical imaging data present significant challenges related to computational efficiency, energy consumption, and quality preservation. This review has provided a comprehensive analysis of AI techniques for energy-efficient Quantum Convolutional Neural Networks (QCNNs) combined with attention-based models for medical image diagnostics. The study highlights the evolution of medical imaging techniques from traditional convolutional neural networks to advanced hybrid quantum-classical architectures. While CNNs have demonstrated high accuracy in image analysis, their high computational cost and energy consumption limit their applicability in resource-constrained environments.

Attention-based models have significantly enhanced feature extraction and diagnostic accuracy by enabling selective focus on important regions of medical images. However, these models introduce additional computational overhead, necessitating more efficient solutions. QCNNs represent a promising approach by leveraging quantum computing principles to process high-dimensional data efficiently. These models offer improved computational performance, reduced energy consumption, and enhanced scalability compared to classical approaches. The integration of QCNNs with attention mechanisms further enhances system performance by combining efficient computation with improved feature representation.

Hybrid QCNN-attention models have emerged as the most effective solutions, providing superior accuracy, energy efficiency, and quality preservation. These models are particularly suitable for WSN-assisted IoT environments, where energy efficiency and computational optimization are critical. Despite these advancements, several challenges remain. The limited availability of quantum hardware, the complexity of hybrid model design, and the need

for large annotated datasets pose significant barriers to practical implementation. Additionally, ensuring data privacy and security in IoT healthcare systems remains a critical concern.

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