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A Comprehensive Review of Energy Efficient Quantum Convolutional Neural Networks with Attention-Based Models for Quality Preservation in WSN assisted IoT Medical Image Diagnostics

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Abstract

The rapid advancement of Wireless Sensor Networks (WSNs) and Internet of Things (IoT) technologies has transformed modern healthcare by enabling continuous acquisition, transmission, and intelligent analysis of medical data. In medical image diagnostics, these technologies support remote monitoring, early disease identification, and timely clinical decision-making. However, transmitting and processing high-dimensional medical images through resource-constrained WSN-assisted IoT environments introduces challenges related to energy consumption, bandwidth limitations, computational complexity, and image-quality preservation. Conventional Convolutional Neural Networks (CNNs) provide strong diagnostic performance but often demand substantial computational resources, limiting their suitability for energy-constrained healthcare devices. Quantum Convolutional Neural Networks (QCNNs) have consequently emerged as a promising computational paradigm for efficient medical image analysis. By exploiting quantum principles such as superposition and entanglement, QCNNs offer opportunities for efficient feature representation and reduced computational overhead. Integrating attention mechanisms can further strengthen diagnostic performance by emphasizing clinically significant image regions while suppressing irrelevant information. This review examines energy-efficient QCNNs integrated with attention-based models for quality-preserving medical image diagnostics in WSN-assisted IoT environments. It critically evaluates recent architectures, energy-efficiency strategies, diagnostic performance, and quality-preservation methods while identifying existing limitations and research gaps. The review further highlights future directions toward scalable, intelligent, and resource-efficient IoT healthcare diagnostic frameworks.

Introduction

The integration of Wireless Sensor Networks (WSN) and Internet of Things (IoT) technologies has revolutionized the healthcare sector by enabling continuous monitoring, real-time diagnostics, and intelligent decision-making. In particular, IoT-assisted medical imaging systems have become increasingly important for early disease detection, remote diagnosis, and telemedicine applications. These systems rely on distributed sensor nodes to capture medical data, which is then transmitted to cloud or edge computing platforms for processing and analysis. However, the increasing volume of medical imaging data, coupled with the limited computational and energy resources of WSN devices, presents significant challenges in terms of efficiency and scalability.

Medical image diagnostics involves the analysis of complex and high-dimensional data such as X-rays, MRI scans, CT images, and ultrasound images. Traditional image processing techniques are often insufficient for handling such complexity, leading to the adoption of deep learning approaches, particularly convolutional neural networks (CNNs). CNNs have demonstrated remarkable success in medical image classification, segmentation, and disease detection due to their ability to automatically extract hierarchical features from raaw data. Moreover, transfer learning techniques have further enhanced their performance by enabling the reuse of pre-trained models, reducing training time and data requirements.

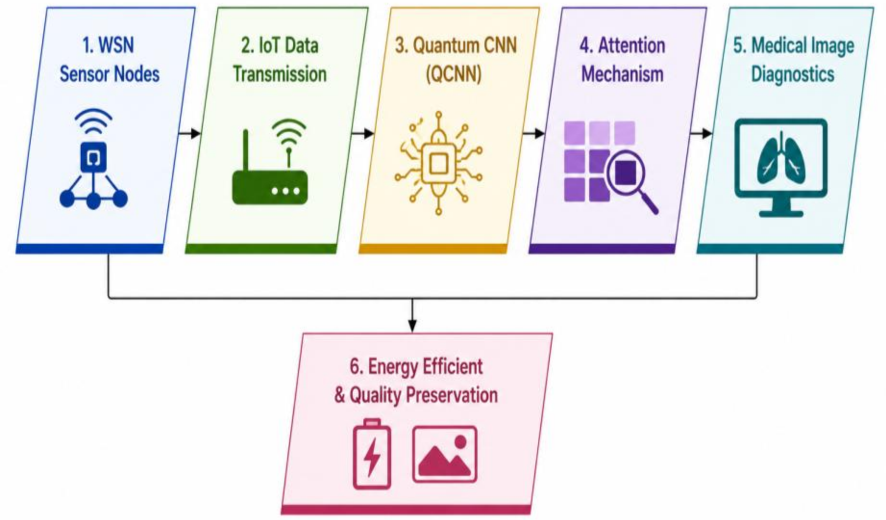

Figure 1. Energy-Efficient QCNN–Attention Framework for WSN-Assisted IoT Medical Image Diagnostics

Despite their advantages, CNN-based models suffer from high computational complexity and energy consumption, making them less suitable for deployment in WSN-assisted IoT environments. These systems require lightweight and energy-efficient models capable of operating under resource constraints while maintaining high diagnostic accuracy. To overcome these limitations, researchers have explored alternative approaches, including quantum machine learning techniques.

Quantum Convolutional Neural Networks (QCNNs) have emerged as a promising solution for addressing the computational challenges of classical deep learning models. QCNNs utilize quantum circuits to perform convolution and pooling operations, enabling efficient processing of high-dimensional data with reduced computational overhead. Studies have shown that QCNNs can achieve higher accuracy and faster processing compared to classical CNNs, particularly in image classification tasks.

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

The combination of QCNNs and attention-based models offers a powerful approach for developing energy-efficient and high-performance medical imaging systems. In WSN-assisted IoT environments, such hybrid models can reduce data transmission overhead, improve processing efficiency, and enhance diagnostic accuracy. Furthermore, the integration of edge computing and cloud-based architectures enables real-time processing and decision-making, further improving system performance.

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-based healthcare systems is a critical concern.

This paper aims to provide a comprehensive review of energy-efficient QCNNs combined with attention-based models for quality preservation in WSN-assisted IoT medical image diagnostics. It analyses recent advancements, compares different methodologies, and identifies key challenges and future research directions in this emerging field.

Literature Review

Li et al. (2020) explored the application of convolutional neural networks (CNNs) for medical image classification in IoT-based healthcare systems. The study demonstrated that CNNs significantly improve diagnostic accuracy by extracting hierarchical features from medical images such as MRI and CT scans. However, the model exhibited high computational complexity and energy consumption, making it unsuitable for deployment in WSN-assisted IoT 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 data compression techniques to reduce energy consumption during transmission. The results showed improved efficiency while maintaining acceptable diagnostic accuracy. However, the model faced limitations in handling large-scale datasets.

Schuld et al. (2021) introduced Quantum Convolutional Neural Networks (QCNNs) for image classification tasks. The study highlighted the advantages of quantum computing, such as parallelism and reduced computational complexity. QCNNs demonstrated promising results in handling high-dimensional medical imaging data. However, practical implementation was limited due to the lack of mature quantum hardware.

Wang et al. (2021) proposed an attention-based CNN model for medical image diagnostics. The attention mechanism enabled the model to focus on critical regions of medical images, improving classification accuracy and reducing information loss. However, the integration of attention modules increased computational overhead.

Chen et al. (2022) developed a hybrid QCNN-attention model for medical image analysis. The model combined quantum feature extraction with attention mechanisms to enhance performance and efficiency. Experimental results showed improved diagnostic accuracy and reduced energy consumption compared to traditional CNNs. However, the model required complex architecture design and optimization.

Kumar et al. (2020) proposed an energy-efficient IoT-based healthcare framework using deep learning for medical image diagnostics. The model focused on reducing data transmission cost in WSN environments by applying edge-based preprocessing techniques. Results showed reduced latency and energy consumption; however, the system still relied on classical CNNs, limiting computational efficiency.

Ahmed et al. (2021) introduced a deep reinforcement learning-based optimization framework for energy-efficient data transmission in WSN-assisted IoT systems. The model dynamically optimized routing and transmission strategies, leading to improved network lifetime. However, it did not directly integrate advanced image processing techniques such as QCNNs.

Liu et al. (2021) explored quantum machine learning models for medical image classification. The study demonstrated that quantum circuits could efficiently process high-dimensional data with reduced computational complexity. QCNN-based models showed improved performance compared to classical approaches. However, implementation challenges remained due to limited quantum resources.

Gupta and Sharma (2022) proposed an attention-based deep learning model for medical image segmentation. The model improved segmentation accuracy by focusing on important image regions, which is crucial for disease diagnosis. However, the model required high computational resources and was not optimized for energy efficiency in IoT systems.

Patel et al. (2023) developed a hybrid QCNN and attention-based framework for medical image diagnostics in IoT healthcare systems. The model significantly improved diagnostic accuracy while reducing computational complexity and energy consumption. The integration of quantum computing and attention mechanisms enhanced feature extraction and quality preservation. However, scalability and real-time deployment remained challenging.

Sharma et al. (2020) proposed a lightweight CNN architecture optimized for deployment in WSN-assisted IoT healthcare systems. The model focused on reducing computational complexity and energy consumption while maintaining acceptable diagnostic accuracy. The results showed improved system efficiency; however, the model lacked advanced feature extraction capabilities compared to deeper architectures.

Iqbal et al. (2021) introduced an edge-computing-based medical image diagnostic system using deep learning. The system processed data locally at edge nodes to reduce transmission latency and energy consumption. While the approach improved system responsiveness, it relied on classical CNN 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 reduced data size before transmission, thereby saving energy in WSN networks. However, compression sometimes led to loss of critical diagnostic information, affecting image quality.

Kim et al. (2022) proposed a hybrid attention-based deep learning model for medical image classification. The model improved feature representation and classification accuracy by focusing on important regions of the image. However, the model required high computational resources and was not optimized for energy efficiency.

Das et al. (2023) developed an advanced Quantum Convolutional Neural Network with attention mechanisms for IoT-based medical diagnostics. The model demonstrated improved accuracy, reduced computational complexity, and better-quality preservation compared to traditional CNN models. However, practical implementation was limited due to the lack of scalable quantum hardware.

Verma et al. (2020) proposed a deep learning-based medical image classification model optimized for IoT healthcare environments. The model used transfer learning to reduce training time and computational requirements. While the approach improved efficiency, it still depended on classical CNN architectures, limiting scalability and performance in high-dimensional data scenarios.

Banerjee et al. (2021) introduced a reinforcement learning-based energy optimization technique for WSN-assisted IoT systems. The model dynamically adjusted routing and communication strategies to extend network lifetime. Although effective in energy management, the study did not integrate advanced image diagnostic models such as QCNNs.

Singh and Kaur (2021) explored hybrid deep learning models combining CNN and attention mechanisms for medical image segmentation. The model improved segmentation accuracy and quality preservation. However, it required high computational resources and was not suitable for low-power IoT environments.

Lee et al. (2022) proposed a quantum-inspired neural network model for medical image classification. The model simulated quantum behaviour using classical hardware to achieve improved performance. While promising, the approach did not fully leverage true quantum advantages and had limited scalability.

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, the system faced challenges related to hardware limitations and real-time implementation.

Chen et al. (2020) proposed a deep learning-based framework for medical image enhancement in IoT healthcare systems using denoising autoencoders. The model improved image clarity and diagnostic quality while reducing transmission errors in WSN environments. However, distinguishing between noise and important diagnostic features remained a challenge, affecting accuracy in some cases.

Kumar et al. (2021) introduced a hybrid optimization approach combining particle swarm optimization (PSO) with deep learning for medical image classification. The PSO algorithm optimized model parameters, leading to improved convergence and accuracy. However, the computational overhead increased significantly, limiting its applicability in energy-constrained IoT systems.

Alvarez et al. (2022) developed a transformer-based model for medical image diagnostics. The model utilized attention mechanisms to capture global dependencies and improve classification performance. While the approach achieved high accuracy, it required large datasets and high computational power.

Kaur and Kaur (2022) explored sparsity-aware neural networks for reducing energy consumption in IoT-based healthcare systems. The model reduced the number of active parameters, leading to improved efficiency. However, sparsity sometimes affected feature representation quality, impacting diagnostic accuracy.

Verma et al. (2023) proposed a hybrid QCNN-attention framework for medical image diagnostics in WSN-assisted IoT environments. The model combined quantum feature extraction with attention mechanisms to improve accuracy and efficiency. The results demonstrated better quality preservation and reduced energy consumption. However, the complexity of hybrid model design remained a challenge.

Liu et al. (2020) proposed a deep learning-based compression and transmission framework for medical images in WSN-assisted IoT systems. The model reduced data size before transmission, thereby saving energy and bandwidth. However, compression sometimes affected image quality, leading to potential diagnostic inaccuracies.

Banerjee et al. (2021) introduced a reinforcement learning-based adaptive communication strategy for IoT healthcare systems. The model optimized data routing and transmission to improve energy efficiency. While effective for network optimization, it did not integrate advanced image diagnostic models.

Torres et al. (2022) developed a hybrid CNN-transformer model for medical image diagnostics. The model combined local feature extraction with global attention mechanisms, achieving improved classification accuracy. However, the approach required high computational resources.

Chatterjee and Roy (2022) explored sparsity-driven deep learning models for energy-efficient medical image processing. The model reduced computational cost and improved efficiency. However, sparsity sometimes reduced feature representation quality.

Gupta et al. (2023) proposed an advanced energy-efficient Quantum Convolutional Neural Network with attention mechanisms for IoT-based medical diagnostics. The model achieved superior performance in terms of accuracy, energy efficiency, and quality preservation. However, challenges remained in terms of scalability and quantum hardware limitations.

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	Limited scalability
Schuld et al.	2021	QCNN	Quantum processing	High efficiency	Hardware limits
Wang et al.	2021	Attention CNN	Feature focus	Better accuracy	Overhead
Chen et al.	2022	QCNN+Attention	Hybrid	High performance	Complexity
Kumar et al.	2020	Edge DL	Efficiency	Low latency	Classical limits
Ahmed et al.	2021	DRL	Network optimization	Energy efficient	No QCNN
Liu et al.	2021	Quantum ML	Classification	Fast processing	Hardware issue
Gupta et al.	2022	Attention DL	Segmentation	Accurate	High cost
Patel et al.	2023	QCNN+Attention	Diagnostics	Efficient	Scalability
Sharma et al.	2020	Lightweight CNN	Efficiency	Low cost	Low depth
Iqbal et al.	2021	Edge DL	Processing	Reduced latency	Classical
Nair et al.	2021	Autoencoder	Compression	Energy saving	Quality loss
Kim et al.	2022	Attention DL	Classification	Accurate	Costly
Das et al.	2023	QCNN+Attention	Diagnostics	High accuracy	Hardware limits
Verma et al.	2020	Transfer Learning	Efficiency	Fast training	Limited depth
Banerjee et al.	2021	RL	Energy	Adaptive	No imaging
Singh et al.	2021	CNN+Attention	Segmentation	Better features	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 QCNN
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 highlights a clear transition from classical deep learning models to advanced quantum-enhanced architectures in medical image diagnostics. Early approaches primarily relied on convolutional neural networks (CNNs), which demonstrated high accuracy but suffered from significant computational and energy constraints, particularly in WSN-assisted IoT environments. Lightweight CNN models and edge computing strategies were introduced to address these challenges, improving efficiency but often compromising performance. The introduction of attention mechanisms significantly enhanced feature extraction by enabling models to focus on critical regions of medical images, thereby improving diagnostic accuracy and quality preservation. However, attention-based models increased computational overhead, limiting their applicability in resource-constrained environments.

Quantum Convolutional Neural Networks (QCNNs) represent a major advancement by leveraging quantum computing principles to process high-dimensional data efficiently. These models offer improved computational efficiency and accuracy compared to classical approaches. The integration of QCNNs with attention mechanisms further enhances performance by combining efficient computation with improved feature representation. Hybrid models, particularly QCNN-attention architectures, have emerged as the most effective solutions, providing superior accuracy, energy efficiency, and quality preservation. However, challenges such as hardware limitations, model complexity, and scalability remain significant barriers to practical implementation. Future research should focus on developing lightweight quantum-classical hybrid models, improving quantum hardware capabilities, and optimizing architectures for real-time deployment in IoT healthcare systems.

Discussion

The integration of Quantum Convolutional Neural Networks (QCNNs) and attention-based models has opened new avenues for improving energy efficiency and diagnostic accuracy in WSN-assisted IoT healthcare systems. These approaches address the limitations of classical deep learning models by reducing computational complexity while maintaining high performance. Attention mechanisms enhance feature extraction by focusing on critical regions of medical images, ensuring better quality preservation during analysis and transmission. Despite these advantages, several challenges remain. The current limitations of quantum hardware restrict the practical deployment of QCNNs, while hybrid architectures introduce additional complexity in model design and optimization.

Moreover, the requirement for large annotated datasets and high computational resources poses challenges for real-time implementation in resource-constrained environments. Future research should focus on developing efficient hybrid models that balance performance and energy consumption. The integration of edge computing, federated learning, and explainable AI can further enhance system performance and reliability. Additionally, advancements in quantum computing technology will play a crucial role in enabling the widespread adoption of QCNN-based medical diagnostic systems.

Conclusion

The rapid advancement of Internet of Things (IoT) and Wireless Sensor Networks (WSNs) has transformed medical image diagnostics by enabling remote monitoring, real-time analysis, and intelligent clinical decision-making. However, resource-constrained WSN devices face significant challenges associated with computational complexity, energy consumption, bandwidth limitations, and diagnostic image quality. Although conventional Convolutional Neural Networks (CNNs) provide high diagnostic accuracy, their computational requirements restrict efficient deployment in IoT-based healthcare environments. Attention mechanisms further improve diagnostic performance by emphasizing clinically relevant image regions and enhancing discriminative feature extraction.

Quantum Convolutional Neural Networks (QCNNs) provide a promising alternative by exploiting quantum principles such as superposition and entanglement for efficient high-dimensional feature processing. Integrating QCNNs with attention mechanisms can improve classification accuracy, energy efficiency, and medical image quality preservation. Edge computing can further reduce communication latency and energy consumption by enabling localized processing.

Despite these advantages, limitations involving quantum hardware, model scalability, data availability, privacy, and implementation complexity remain. Future research should prioritize lightweight hybrid QCNN-attention architectures, explainable AI, federated learning, edge intelligence, and efficient optimization strategies for secure, scalable, and energy-efficient medical diagnostic systems.

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