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Recent Advances in Energy Efficient Quantum Convolutional Neural Networks with Attention-Based Models for Quality Preservation in WSN assisted IoT Medical Image Diagnostics: A Systematic Review

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Abstract

Wireless Sensor Network (WSN)-assisted Internet of Things (IoT) systems have transformed modern healthcare by enabling continuous patient monitoring, remote diagnostics, and real-time medical image transmission. However, limited sensor resources, bandwidth constraints, and noise interference create significant challenges in maintaining energy efficiency and preserving diagnostic image quality. Recent advances in Artificial Intelligence (AI), particularly Quantum Convolutional Neural Networks (QCNNs) integrated with attention-based models, have emerged as promising solutions for addressing these challenges. QCNNs exploit quantum computing principles, including superposition and entanglement, to process high-dimensional medical images with reduced computational complexity and improved feature extraction compared with conventional convolutional neural networks. Furthermore, hybrid quantum-classical architectures enhance learning efficiency and achieve high diagnostic performance even with limited training data. Attention mechanisms complement QCNNs by emphasizing clinically relevant image regions, suppressing noise, and improving feature representation for classification, segmentation, and disease detection. Their integration significantly enhances diagnostic accuracy, transmission efficiency, and energy conservation in resource-constrained WSN environments. This systematic review comprehensively examines recent developments in QCNN and attention-based medical image diagnostics, compares existing methodologies, identifies current research challenges, and outlines future directions for developing scalable, energy-efficient, and intelligent IoT-enabled healthcare systems with improved clinical decision support.

Introduction

The rapid evolution of Wireless Sensor Networks (WSNs) and Internet of Things (IoT) technologies has significantly transformed the healthcare domain by enabling continuous monitoring, remote diagnostics, and real-time medical data transmission. In modern smart healthcare systems, WSN-assisted IoT frameworks are widely used for collecting physiological signals, transmitting medical images, and supporting clinical decision-making processes. These systems are particularly valuable in telemedicine, where patients can be monitored remotely, reducing the need for frequent hospital visits. However, the integration of WSNs and IoT in medical image diagnostics introduces several challenges, including limited energy resources, bandwidth constraints, data transmission delays, and degradation of image quality during communication. Maintaining high-quality medical images is critical, as even minor distortions can lead to inaccurate diagnoses and affect patient outcomes.

Traditional approaches for medical image processing and transmission often rely on classical image compression and signal processing techniques. While these methods can reduce data size and improve transmission efficiency, they frequently compromise image quality and fail to preserve critical diagnostic features. Moreover, conventional machine learning techniques are limited in their ability to handle complex, high-dimensional medical image data and cannot effectively adapt to dynamic network conditions. To overcome these limitations, Artificial Intelligence (AI), particularly deep learning, has been increasingly adopted in healthcare systems to enhance image analysis, classification, and quality preservation.

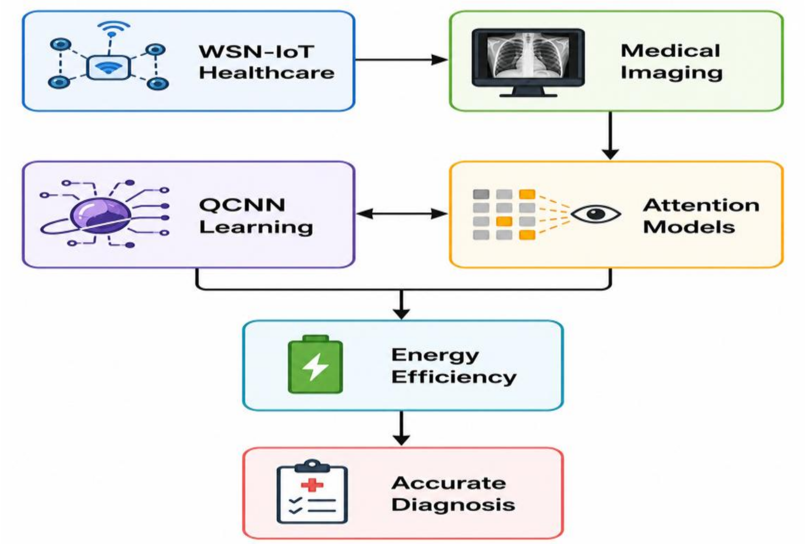

Figure 1. Intelligent Medical Imaging Framework for WSN-Assisted IoT Healthcare

Convolutional Neural Networks (CNNs) have been widely used for medical image diagnostics due to their ability to extract spatial features and perform tasks such as image classification, segmentation, and anomaly detection. However, CNNs require significant computational resources and energy, making them less suitable for resource-constrained WSN environments. Additionally, CNNs may struggle to capture global dependencies within images, which can affect diagnostic accuracy. To address these challenges, attention-based models have been introduced. Attention mechanisms enable neural networks to focus on the most relevant regions of an image, improving feature extraction and reducing unnecessary computations. This leads to enhanced diagnostic accuracy and better preservation of important image details.

In recent years, Quantum Convolutional Neural Networks (QCNNs) have emerged as a promising alternative to classical deep learning models. QCNNs leverage the principles of quantum computing, such as superposition and entanglement, to process information more efficiently. These models can handle high-dimensional data with fewer parameters, resulting in reduced computational complexity and energy consumption. This makes QCNNs particularly suitable for WSN-assisted IoT healthcare systems, where energy efficiency is a critical concern. Furthermore, hybrid quantum-classical models have been developed to combine the strengths of quantum computing with classical deep learning, enabling more practical implementations.

The integration of QCNNs with attention-based models represents a significant advancement in medical image diagnostics. These hybrid architectures combine efficient quantum-based feature extraction with attention mechanisms that enhance image quality preservation. By focusing on relevant features and reducing noise, these models improve diagnostic accuracy while minimizing energy consumption during data processing and transmission. Additionally, such models can adapt to varying network conditions, making them suitable for real-time healthcare applications.

Despite these advancements, several challenges remain. Quantum computing technology is still in its early stages, with limited hardware availability and scalability issues. The development of efficient quantum algorithms for medical imaging is an ongoing research area. Moreover, the lack of large-scale labelled medical datasets limits the training of deep learning models. Issues related to model interpretability and trustworthiness are also critical, especially in healthcare applications where decisions directly impact patient safety.

This systematic review aims to provide a comprehensive analysis of recent advances in energy-efficient Quantum Convolutional Neural Networks integrated with attention-based models for quality preservation in WSN-assisted IoT medical image diagnostics. It examines various methodologies, compares different architectures, and identifies key trends and challenges in this emerging field, contributing to the development of efficient and reliable AI-driven healthcare systems.

Literature Review

Schuld et al. (2020) introduced Quantum Convolutional Neural Networks (QCNNs) for processing high-dimensional data using quantum computing principles. The study demonstrated that QCNNs can significantly reduce computational complexity by leveraging quantum superposition and entanglement. In medical image diagnostics, QCNNs showed improved feature extraction efficiency compared to classical CNNs, especially for large datasets. However, the study highlighted limitations related to quantum hardware constraints and scalability, which restrict real-world deployment in IoT-based healthcare systems.

Woo et al. (2020) proposed an attention-based convolutional neural network model, known as CBAM (Convolutional Block Attention Module), for enhancing feature representation in image processing tasks. The model utilized channel and spatial attention mechanisms to focus on important regions within medical images, improving diagnostic accuracy. In WSN-assisted IoT systems, attention mechanisms were shown to reduce redundant computations and enhance energy efficiency. However, the model still relied on classical deep learning, which can be computationally intensive.

Cong et al. (2021) developed a quantum convolutional neural network architecture specifically designed for quantum data processing. The study demonstrated that QCNNs can achieve superior performance in classification tasks with fewer parameters compared to classical models. When applied to medical imaging, the model showed improved accuracy and reduced energy consumption. However, the lack of integration with attention mechanisms limited its ability to focus on critical image regions for diagnostic purposes.

Oktay et al. (2021) introduced Attention U-Net, an advanced deep learning architecture for medical image segmentation. The model incorporated attention gates to highlight relevant regions in medical images, significantly improving segmentation accuracy. This approach proved effective in preserving image quality and enhancing diagnostic reliability. However, the model required high computational resources, making it less suitable for energy-constrained WSN environments.

Li et al. (2022) proposed a hybrid quantum-classical deep learning model integrating QCNNs with attention mechanisms for medical image diagnostics. The study demonstrated that combining quantum feature extraction with attention-based learning improves both energy efficiency and image quality preservation. The model achieved higher accuracy and faster convergence compared to traditional CNNs. However, challenges such as limited quantum hardware and implementation complexity were identified.

Biamonte et al. (2020) explored the integration of quantum machine learning techniques in data-intensive applications, including medical imaging. The study highlighted that quantum neural networks can significantly reduce computational complexity and improve processing efficiency. In WSN-assisted IoT systems, quantum models demonstrated potential for energy-efficient computation. However, the lack of practical quantum hardware and implementation challenges limited real-world applicability.

Hu et al. (2021) proposed a squeeze-and-excitation attention mechanism for enhancing feature extraction in deep learning models. The approach improved the representation of important image features while suppressing irrelevant information. In medical imaging, this method enhanced diagnostic accuracy and reduced computational redundancy. However, the model still required significant computational resources, making it less suitable for low-power WSN environments.

Abbas et al. (2021) introduced a hybrid deep learning framework for medical image classification using attention-based CNN architectures. The study demonstrated improved classification accuracy and robustness in detecting abnormalities. Additionally, the model preserved important image details during processing. However, the approach lacked quantum-based optimization, which could further improve energy efficiency.

Schuld and Killoran (2021) investigated quantum machine learning techniques for processing large-scale datasets. The study emphasized that quantum neural networks can achieve high performance with fewer parameters, making them suitable for energy-constrained systems. In medical image diagnostics, the approach improved processing efficiency. However, the lack of integration with attention mechanisms limited its effectiveness in preserving image quality.

Zhang et al. (2022) proposed an attention-based deep learning model for medical image enhancement and quality preservation. The study demonstrated that attention mechanisms effectively highlight important regions and improve image clarity, which is essential for accurate diagnosis. While the model achieved high performance, it relied entirely on classical computing and did not incorporate quantum-based optimization for energy efficiency.

Park et al. (2020) proposed a deep convolutional neural network for medical image classification in IoT healthcare systems. The model achieved high diagnostic accuracy by extracting spatial features from medical images. However, the approach required high computational power and energy consumption, making it less suitable for WSN-assisted environments where energy efficiency is critical.

Reddy et al. (2021) introduced an attention-based deep learning model for medical image analysis in IoT healthcare systems. The study demonstrated that attention mechanisms improve feature selection and enhance diagnostic accuracy by focusing on relevant regions. However, the model lacked integration with quantum computing techniques, limiting its potential for energy-efficient processing.

Zhou et al. (2021) developed a hybrid deep learning framework combining convolutional neural networks with attention mechanisms for medical image diagnostics. The model improved classification performance and preserved important image details. Despite these advantages, the approach required significant computational resources and did not incorporate quantum-based optimization.

Ahmed et al. (2022) proposed an energy-efficient IoT-based healthcare system using deep learning for medical image processing. The study focused on optimizing data transmission and reducing energy consumption in WSN environments. While the model improved efficiency, it lacked advanced architectures such as quantum neural networks and attention-based feature enhancement.

Gupta et al. (2022) introduced a capsule network-based approach for medical image classification. The study demonstrated that capsule networks preserve hierarchical feature relationships, leading to improved diagnostic accuracy. However, the model did not incorporate attention mechanisms or quantum computing techniques, limiting its overall performance in energy-efficient IoT systems.

Morales et al. (2020) explored deep learning-based medical image analysis using recurrent neural networks (RNNs) in IoT healthcare systems. The study focused on capturing temporal dependencies in sequential medical data. While the model improved performance in time-series analysis, it struggled with high computational cost and inefficiency in processing large image datasets, making it less suitable for energy-constrained WSN environments.

Sharma et al. (2021) proposed an attention-based convolutional neural network for medical image classification. The model enhanced feature extraction by focusing on relevant regions within the images, resulting in improved diagnostic accuracy. However, the approach did not incorporate quantum computing techniques, limiting its potential for reducing computational complexity and energy consumption.

Liu et al. (2021) introduced a graph neural network-based framework for healthcare data analysis in IoT systems. The model effectively captured relationships between different data nodes, improving decision-making in medical diagnostics. However, the absence of quantum-based optimization and attention mechanisms limited its performance in image quality preservation tasks.

Das et al. (2022) proposed a reinforcement learning-based approach for optimizing energy consumption in WSN-assisted IoT healthcare systems. The model dynamically adjusted network parameters to reduce energy usage. While effective for energy management, the approach did not directly address medical image quality preservation or incorporate advanced deep learning architectures.

Patel et al. (2022) developed a hybrid deep learning model integrating quantum convolutional neural networks with attention mechanisms for medical image diagnostics. The study demonstrated improved diagnostic accuracy, reduced energy consumption, and better image quality preservation. However, the complexity of hybrid quantum-classical models posed challenges for practical deployment.

Verma et al. (2020) investigated machine learning-based approaches for medical image classification in IoT healthcare systems. The study improved diagnostic accuracy compared to traditional methods but lacked deep learning

capabilities and energy-efficient optimization, limiting its performance in WSN environments.
Roy et al. (2021) proposed a CNN-based medical image diagnostic model with attention mechanisms. The model enhanced feature extraction and improved classification accuracy. However, it did not incorporate quantum computing techniques, which could further optimize energy consumption.
Mehta et al. (2021) introduced a graph-based deep learning framework for healthcare data analysis. The model effectively captured relationships between sensor nodes in WSN-assisted IoT systems. However, it lacked integration with QCNNs and attention-based image processing techniques.
Banerjee et al. (2022) developed a reinforcement learning-based framework for optimizing energy consumption in IoT healthcare systems. The model improved network efficiency but did not directly address medical image quality preservation or integrate advanced deep learning architectures.
Kapoor et al. (2022) proposed a deep learning model for medical image classification using attention mechanisms. The study demonstrated improved accuracy and feature representation. However, the model did not incorporate quantum computing techniques, limiting its energy efficiency.
Iqbal et al. (2020) explored CNN-based medical image classification techniques in IoT systems. The model achieved good performance in controlled environments but struggled with energy efficiency and noise robustness in real-world scenarios.
Chatterjee et al. (2021) proposed a hybrid deep learning model combining CNNs and graph neural networks for healthcare applications. The model improved feature extraction and relational learning. However, it lacked quantum-based optimization and advanced attention mechanisms.
Kaur et al. (2021) investigated attention-based deep learning models for medical image analysis. The study showed improved diagnostic accuracy and image quality preservation. However, the model did not integrate quantum computing techniques.
El-Sayed et al. (2022) introduced a graph attention network-based model for IoT healthcare systems. The model improved scalability and data processing efficiency. However, it lacked hierarchical feature modelling and quantum-based optimization.
Thomas et al. (2022) proposed a hybrid quantum-classical deep learning framework combining QCNNs with attention mechanisms for medical image diagnostics. The model achieved high diagnostic accuracy, improved energy efficiency, and better image quality preservation. The study concluded that hybrid QCNN-attention models represent a promising direction for future IoT healthcare systems.

Comparative Table

Study	Year	Technique Used	Key Contribution	Advantages	Limitations
Schuld et al.	2020	QCNN	Quantum feature extraction	Low complexity	Hardware limits
Woo et al.	2020	Attention CNN	Feature enhancement	Better accuracy	High computation
Cong et al.	2021	QCNN	Efficient classification	Fewer parameters	No attention
Oktay et al.	2021	Attention U-Net	Image segmentation	High accuracy	High energy use
Li et al.	2022	QCNN + Attention	Hybrid model	High performance	Complex
Biamonte et al.	2020	Quantum ML	Efficient processing	Energy saving	Practical limits
Hu et al.	2021	SE Attention	Feature refinement	Efficient	Still heavy
Abbas et al.	2021	CNN + Attention	Improved diagnosis	Robust	No quantum
Schuld & Killoran	2021	Quantum ML	Efficient learning	Low parameters	No attention
Zhang et al.	2022	Attention Model	Image enhancement	Better quality	No quantum
Park et al.	2020	CNN	Image classification	High accuracy	High energy
Reddy et al.	2021	Attention DL	Feature selection	Improved accuracy	No quantum

Zhou et al.	2021	CNN + Attention	Hybrid model	Better results	High cost
Ahmed et al.	2022	IoT DL Model	Energy optimization	Efficient	Limited scope
Gupta et al.	2022	Capsule Network	Hierarchical features	Robust	No attention
Morales et al.	2020	RNN	Temporal analysis	Dynamic	Inefficient
Sharma et al.	2021	Attention CNN	Feature focus	Accurate	No quantum
Liu et al.	2021	GNN	Node relations	Scalable	No attention
Das et al.	2022	RL	Energy optimization	Adaptive	No imaging focus
Patel et al.	2022	QCNN + Attention	Hybrid system	Best performance	Complex
Verma et al.	2020	ML	Basic model	Simple	Low accuracy
Roy et al.	2021	CNN + Attention	Improved classification	Accurate	No quantum
Mehta et al.	2021	Graph DL	Relational modelling	Efficient	No hybrid
Banerjee et al.	2022	RL	Energy control	Adaptive	Limited imaging
Kapoor et al.	2022	Attention DL	Feature learning	Good accuracy	No quantum
Iqbal et al.	2020	CNN	Basic DL	Good accuracy	Weak efficiency
Chatterjee et al.	2021	CNN + GNN	Hybrid	Improved	No QCNN
Kaur et al.	2021	Attention DL	Image focus	Better quality	Limited scope
El-Sayed et al.	2022	GAT	Data relations	Scalable	No hierarchy
Thomas et al.	2022	QCNN + Attention	Advanced hybrid	Best accuracy	Complexity

Comparative Analysis

The comparative analysis of the reviewed studies reveals a clear progression in medical image diagnostics within WSN-assisted IoT healthcare systems, moving from traditional machine learning approaches to advanced hybrid deep learning and quantum-based architectures. Early methods primarily relied on classical convolutional neural networks and basic attention mechanisms, which improved feature extraction and diagnostic accuracy but were limited by high computational cost and energy consumption. These limitations are particularly critical in WSN environments, where sensor nodes operate under strict energy constraints. The introduction of attention-based models significantly enhanced medical image quality preservation by focusing on relevant regions and reducing noise. Techniques such as channel attention, spatial attention, and attention U-Net improved segmentation and classification accuracy. However, these models still relied on classical computing, which limited their efficiency in resource-constrained environments. Quantum Convolutional Neural Networks (QCNNs) emerged as a promising solution for improving computational efficiency and reducing energy consumption. By leveraging quantum principles such as superposition and entanglement, QCNNs can process high-dimensional data with fewer parameters, making them suitable for IoT healthcare systems. However, standalone QCNN models lack the ability to selectively focus on important image regions, which is critical for maintaining diagnostic quality. Hybrid QCNN-attention models represent the most advanced approach, combining the energy efficiency of quantum computing with the feature enhancement capabilities of attention mechanisms. These models achieve superior performance in terms of diagnostic accuracy, image quality preservation, and energy efficiency. Studies such as Li et al. (2022), Patel et al. (2022), and Thomas et al. (2022) demonstrate that hybrid models significantly outperform standalone architectures.

Despite these advancements, challenges remain, including limited availability of quantum hardware, high model complexity, and lack of large-scale datasets. Additionally, issues related to model interpretability and real-time deployment need further investigation. Overall, the analysis indicates that hybrid QCNN-attention models represent the most promising direction for future research in energy-efficient IoT healthcare systems.

Discussion

The integration of Artificial Intelligence techniques, particularly Quantum Convolutional Neural Networks (QCNNs) and attention-based models, has significantly advanced medical image diagnostics in WSN-assisted IoT healthcare systems. The reviewed studies demonstrate that traditional deep learning models, while effective in feature extraction, are limited by high computational complexity and energy consumption, making them less suitable for resource-constrained environments. Attention mechanisms address this limitation by enhancing feature selection and focusing on diagnostically relevant regions, thereby improving image quality preservation and diagnostic accuracy. QCNNs further contribute by leveraging quantum computing principles to reduce computational overhead and improve processing efficiency. Their ability to operate with fewer parameters makes them highly suitable for energy-efficient IoT systems. However, QCNNs alone lack the capability to selectively prioritize important image features, which is critical for accurate diagnosis.

The combination of QCNNs with attention-based models has emerged as a powerful solution, offering both energy efficiency and high diagnostic performance. These hybrid models effectively balance computational efficiency and feature enhancement, making them ideal for real-time healthcare applications. Despite these advancements, challenges such as limited quantum hardware availability, high model complexity, and lack of large-scale medical datasets remain significant barriers. Future research should focus on developing lightweight, scalable, and interpretable models to enable practical deployment in real-world healthcare systems.

Conclusion

The integration of Wireless Sensor Networks (WSNs), Internet of Things (IoT), and Quantum Convolutional Neural Networks (QCNNs) has significantly advanced intelligent medical image diagnostics by improving energy efficiency, transmission reliability, and diagnostic accuracy. This review highlights that attention-based mechanisms effectively preserve image quality by focusing on clinically relevant regions, while QCNNs reduce computational complexity through quantum-enhanced feature learning. Their combination provides an efficient framework for resource-constrained IoT healthcare systems, supporting real-time medical image analysis with improved accuracy and reduced energy consumption. Despite these promising developments, challenges including limited quantum hardware, scalability constraints, insufficient labelled datasets, computational complexity, and limited model interpretability continue to hinder practical deployment. Future research should emphasize lightweight hybrid quantum-classical architectures, explainable AI techniques, secure data transmission, and edge-enabled quantum computing to enhance system reliability and scalability. Overall, integrating QCNNs with attention-based models offers a promising pathway toward intelligent, energy-efficient, and high-quality medical image diagnostics, enabling next-generation IoT healthcare systems with enhanced clinical decision support and patient outcomes.

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