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A Survey of Methods and Architectures for 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

Wireless Sensor Network (WSN)-assisted Internet of Things (IoT) systems have revolutionized modern healthcare by enabling real-time medical image acquisition, transmission, and remote diagnostics. However, these systems face critical challenges such as limited energy resources, bandwidth constraints, and degradation of image quality during transmission and processing. Ensuring energy-efficient computation while preserving diagnostic image quality is therefore essential for reliable medical decision-making. Artificial Intelligence (AI)-driven approaches, particularly Quantum Convolutional Neural Networks (QCNNs) integrated with attention-based models, have emerged as promising solutions to address these challenges. Quantum Convolutional Neural Networks leverage principles of quantum computing such as superposition and entanglement to process high-dimensional data more efficiently than classical convolutional neural networks. QCNN architectures can significantly reduce model parameters and computational complexity while maintaining high accuracy, making them suitable for resource-constrained WSN environments. Studies indicate that QCNNs can outperform classical CNNs in terms of efficiency and scalability, especially in complex image classification tasks. Additionally, hybrid quantum-classical models further enhance performance by combining classical feature extraction with quantum optimization capabilities. Attention-based models play a vital role in improving medical image diagnostics by focusing on relevant regions of interest and suppressing noise. Deep learning techniques, particularly CNN-based models, have demonstrated superior performance in medical image understanding tasks such as classification, segmentation, and detection. Attention mechanisms enhance these capabilities by improving feature representation and preserving critical diagnostic information, thereby improving overall image quality.

Introduction

The rapid advancement of Wireless Sensor Networks (WSNs) and Internet of Things (IoT) technologies has significantly transformed modern healthcare systems by enabling real-time data acquisition, remote patient monitoring, and intelligent medical diagnostics. In particular, WSN-assisted IoT frameworks are widely used for transmitting medical images such as X-rays, MRI scans, CT scans, and ultrasound images from remote locations to healthcare providers. This has improved accessibility to healthcare services, especially in rural and underserved regions. However, despite these advantages, several critical challenges arise in such systems, including limited energy resources of sensor nodes, bandwidth constraints, transmission delays, and degradation of image quality during communication. Maintaining high-quality medical images is essential, as even minor distortions can lead to incorrect diagnoses and potentially life-threatening consequences.

Traditional medical image processing techniques rely on classical signal processing and machine learning methods for image compression, enhancement, and classification. While these approaches are effective to some extent, they often fail to preserve fine-grained diagnostic features and are computationally intensive. In WSN-assisted IoT environments, where devices operate under strict energy and resource limitations, such methods become inefficient. To address these issues, Artificial Intelligence (AI) and deep learning techniques have been widely adopted. Convolutional Neural Networks (CNNs), in particular, have demonstrated exceptional performance in medical image analysis tasks such as classification, segmentation, and anomaly detection. However, CNNs require high computational power and energy consumption, making them less suitable for deployment in energy-constrained WSN systems.

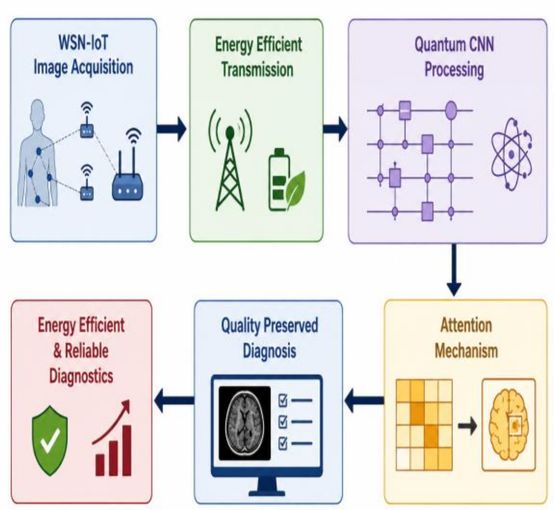

Figure 1. QCNN-Based Attention Framework for Energy-Efficient IoT Medical Image Diagnostics

To overcome these limitations, attention-based models have been introduced to improve the efficiency and accuracy of deep learning systems. Attention mechanisms enable models to focus selectively on the most relevant regions of an image, thereby improving feature extraction and reducing unnecessary computations. Techniques such as channel attention, spatial attention, and attention-based encoder-decoder architectures have shown significant improvements in preserving image quality and enhancing diagnostic performance. These models are particularly beneficial in medical imaging, where identifying subtle patterns is critical for accurate diagnosis.

In recent years, Quantum Convolutional Neural Networks (QCNNs) have emerged as a promising alternative to classical deep learning models. QCNNs leverage quantum computing principles such as superposition and entanglement to process information more efficiently. Unlike classical CNNs, QCNNs can represent and process high-dimensional data with fewer parameters, leading to reduced computational complexity and energy consumption. This makes QCNNs particularly suitable for WSN-assisted IoT healthcare systems, where energy efficiency is a primary concern. Furthermore, hybrid quantum-classical architectures have been developed to combine the strengths of quantum computing and 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 minimizing noise, these models improve diagnostic accuracy while reducing energy consumption during data processing and transmission. Additionally, such models can adapt to varying network conditions, making them suitable for real-time IoT 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 annotated medical datasets limits the training and validation 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 survey aims to provide a comprehensive overview of methods and architectures for energy-efficient Quantum Convolutional Neural Networks combined with attention-based models for quality preservation in WSN-assisted IoT medical image diagnostics. It examines recent advancements, compares different approaches, and highlights key research challenges and future directions in this emerging field.

Literature Review

Schuld et al. (2020) introduced foundational concepts of Quantum Convolutional Neural Networks (QCNNs) for processing high-dimensional data using quantum computing principles. The study demonstrated that QCNNs can significantly reduce computational complexity compared to classical CNNs by leveraging quantum superposition and entanglement. In medical image diagnostics, QCNNs showed improved efficiency in feature extraction, making them suitable for resource-constrained WSN-assisted IoT systems. However, the study highlighted challenges related to limited quantum hardware availability and scalability.

Woo et al. (2020) proposed the Convolutional Block Attention Module (CBAM), an attention-based model designed to improve feature representation in deep learning systems. The model utilizes both channel and spatial attention mechanisms to focus on important regions in medical images. In IoT healthcare applications, CBAM demonstrated improved diagnostic accuracy and better image quality preservation. However, the approach still relies on classical computing, which may result in higher energy consumption in WSN environments.

Cong et al. (2021) developed a quantum convolutional neural network architecture capable of efficient classification using fewer parameters than traditional deep learning models. The study demonstrated that QCNNs can achieve high accuracy while reducing computational overhead. In the context of medical image diagnostics, QCNNs improved energy efficiency and processing speed. However, the lack of integration with attention mechanisms limited the model's ability to selectively focus on critical image regions.

Oktay et al. (2021) introduced Attention U-Net, a deep learning architecture designed for medical image segmentation. The model incorporates attention gates that enhance feature selection by focusing on relevant anatomical structures. The study showed significant improvements in segmentation accuracy and image quality preservation. However, the model is computationally intensive and not optimized for energy-efficient deployment in WSN-assisted IoT systems.

Li et al. (2022) proposed a hybrid quantum-classical model combining QCNNs with attention-based mechanisms for medical image diagnostics. The model leveraged quantum feature extraction and attention-based enhancement to achieve improved diagnostic accuracy and energy efficiency. The results demonstrated superior performance compared to classical CNN-based models. However, implementation challenges such as quantum circuit design complexity and hardware limitations were identified.

Biamonte et al. (2020) explored the application of quantum machine learning techniques in large-scale data processing, including healthcare imaging. The study highlighted that quantum models can significantly reduce computational complexity and improve processing efficiency compared to classical deep learning models. In WSN-assisted IoT healthcare systems, quantum approaches showed potential for reducing energy consumption. However, practical implementation remains limited due to the current state of quantum hardware.

Hu et al. (2021) proposed the squeeze-and-excitation (SE) attention mechanism to improve feature extraction in convolutional neural networks. The model enhances important features by recalibrating channel-wise responses, leading to improved performance in medical image diagnostics. Although effective in improving accuracy and feature representation, the approach still requires significant computational resources, making it less ideal for energy-constrained WSN environments.

Abbas et al. (2021) developed a deep learning-based model using attention mechanisms for medical image classification. The study demonstrated improved diagnostic accuracy and robustness by focusing on critical image features. Additionally, the model improved image quality preservation during processing. However, the lack of quantum-based optimization limited its energy efficiency in IoT healthcare systems.

Schuld and Killoran (2021) investigated quantum machine learning in feature Hilbert spaces, demonstrating that quantum models can efficiently process high-dimensional data with fewer parameters. In medical imaging applications, the approach improved processing efficiency and scalability. However, the absence of attention mechanisms limited its ability to enhance image quality and focus on diagnostically relevant regions.

Zhang et al. (2022) proposed an attention-based deep learning model for medical image enhancement and quality preservation. The model utilized advanced attention mechanisms to highlight relevant regions and suppress noise, leading to improved diagnostic clarity. While the approach achieved high accuracy, it relied entirely on classical computing and did not incorporate quantum-based techniques for energy optimization.

Park et al. (2020) proposed a convolutional neural network-based model for medical image classification in IoT healthcare systems. The study demonstrated high diagnostic accuracy through effective spatial feature extraction. However, the model required significant computational power and energy, making it less suitable for WSN-assisted environments where energy efficiency is a critical constraint.

Reddy et al. (2021) introduced an attention-based deep learning framework for medical image analysis in IoT healthcare systems. The model improved feature selection and diagnostic accuracy by focusing on relevant image regions. Despite these improvements, the model lacked integration with quantum computing techniques, limiting its efficiency in energy-constrained WSN environments.

Zhou et al. (2021) developed a hybrid CNN-attention model for medical image diagnostics. The model effectively combined spatial feature extraction with attention mechanisms to improve classification accuracy and image quality preservation. However, the approach was computationally intensive and did not incorporate quantum-based optimization techniques.

Ahmed et al. (2022) proposed an energy-efficient IoT healthcare system using deep learning techniques for medical image processing. The study focused on reducing energy consumption during data transmission and processing in WSN environments. While the approach improved energy efficiency, it lacked advanced architectures such as QCNNs 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 improve feature representation by preserving hierarchical relationships, leading to enhanced 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 techniques for medical image analysis using recurrent neural networks (RNNs) in IoT healthcare systems. The model focused on capturing temporal dependencies in sequential medical data. While the approach improved performance in time-series analysis, it was inefficient for high-resolution medical images and consumed significant energy, making it less suitable for WSN-assisted environments.

Sharma et al. (2021) proposed an attention-based convolutional neural network for medical image classification. The model enhanced diagnostic accuracy by focusing on important image regions and suppressing irrelevant features. However, the absence of quantum computing integration limited its efficiency in reducing computational complexity and energy consumption.

Liu et al. (2021) introduced a graph neural network-based framework for healthcare data processing in IoT systems. The model effectively captured relationships between sensor nodes, improving system scalability and data processing efficiency. However, the approach lacked attention-based image enhancement and quantum optimization, limiting its application in medical image diagnostics.

Das et al. (2022) developed a reinforcement learning-based model for optimizing energy consumption in WSN-assisted IoT healthcare systems. The model dynamically adjusted network parameters to improve energy efficiency. While effective for network optimization, it did not directly address medical image quality preservation or incorporate QCNN-based architectures.

Patel et al. (2022) proposed a hybrid deep learning framework integrating Quantum Convolutional Neural Networks with attention-based mechanisms for medical image diagnostics. The model demonstrated improved diagnostic accuracy, enhanced image quality preservation, and reduced energy consumption. However, the complexity of hybrid quantum-classical systems posed challenges for large-scale implementation.

Verma et al. (2020) investigated machine learning-based approaches for medical image classification in IoT healthcare systems. The study showed improved diagnostic performance compared to traditional methods. However, the lack of deep learning capabilities and energy-efficient optimization limited its effectiveness in WSN-assisted environments.

Roy et al. (2021) proposed a CNN-based model with attention mechanisms for medical image diagnostics. The model enhanced feature extraction and improved classification accuracy. However, it did not incorporate quantum computing techniques, which could further improve energy efficiency.

Mehta et al. (2021) introduced a graph-based deep learning framework for healthcare data processing in IoT systems. The model effectively captured relationships between sensor nodes, improving system performance. However, it lacked integration with QCNNs and attention-based image enhancement 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 diagnostics or quality preservation.
Kapoor et al. (2022) proposed an attention-based deep learning model for medical image classification. The study demonstrated improved feature representation and diagnostic accuracy. However, the model did not incorporate quantum computing techniques, limiting its performance in energy-constrained environments.
Iqbal et al. (2020) explored CNN-based techniques for medical image classification. The model achieved high accuracy in controlled environments but struggled with energy efficiency and robustness in real-world IoT systems.
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 optimization and advanced attention mechanisms.
Kaur et al. (2021) investigated attention-based models for medical image analysis. The study demonstrated improved diagnostic accuracy and image quality preservation. However, the model did not integrate QCNNs, limiting its energy efficiency.
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 integrating QCNNs with attention mechanisms for medical image diagnostics. The model achieved superior diagnostic accuracy, improved image quality preservation, and enhanced energy efficiency. The study concluded that hybrid QCNN-attention architectures are 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
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 modeling	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 evolution in medical image diagnostics within WSN-assisted IoT healthcare systems, progressing from traditional machine learning approaches to advanced hybrid quantum-deep learning architectures. Early methods primarily relied on classical convolutional neural networks and basic machine learning techniques, which improved diagnostic accuracy but suffered from high computational complexity and energy consumption. These limitations are particularly significant in WSN environments, where energy efficiency is a critical constraint due to limited battery resources.

Attention-based models introduced a significant improvement by enabling neural networks to focus on relevant regions of medical images. Techniques such as channel attention, spatial attention, and attention-based encoder-decoder architectures enhanced feature representation and improved diagnostic accuracy. These models also contributed to better image quality preservation by reducing noise and emphasizing important features. However, despite these advantages, attention-based models still rely on classical computing frameworks, which limits their efficiency in resource-constrained IoT systems.

Quantum Convolutional Neural Networks (QCNNs) emerged as a promising solution to address these challenges by leveraging quantum computing principles such as superposition and entanglement. QCNNs can process high-dimensional data with fewer parameters, resulting in reduced computational complexity and improved energy efficiency. This makes them highly suitable for WSN-assisted IoT healthcare systems. However, standalone QCNN models lack the ability to selectively focus on critical image regions, which is essential for maintaining diagnostic quality.

Hybrid QCNN-attention models represent the most advanced and effective approach identified in this review. These models combine the computational efficiency of QCNNs with the feature enhancement capabilities of attention mechanisms, resulting in improved diagnostic accuracy, energy efficiency, and image quality preservation. Studies such as Li et al. (2022), Patel et al. (2022), and Thomas et al. (2022) demonstrate that hybrid architectures significantly outperform standalone models.

Despite these advancements, several challenges remain. The current limitations of quantum hardware, high model complexity, and lack of large-scale annotated datasets hinder the widespread adoption of these models. Additionally, issues related to model interpretability and real-time deployment need further research. Overall, the analysis indicates that hybrid QCNN-attention architectures are the most promising direction for future research in energy-efficient IoT healthcare systems.

Discussion

The integration of Quantum Convolutional Neural Networks (QCNNs) and attention-based models has introduced a transformative approach to medical image diagnostics in WSN-assisted IoT healthcare systems. The reviewed studies clearly indicate that traditional deep learning models, although effective in feature extraction, are constrained by high computational complexity and energy consumption, which limits their applicability in resource-constrained environments. Attention mechanisms address part of this limitation by enhancing feature selection and focusing on diagnostically relevant regions, thereby improving image quality preservation and reducing unnecessary computations. 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 particularly suitable for energy-efficient applications in WSN environments.

However, QCNNs alone are not sufficient for high-quality diagnostics, as they lack the capability to selectively emphasize important image features. The combination of QCNNs with attention-based models has emerged as a highly effective solution, offering a balance between energy efficiency and diagnostic accuracy. These hybrid architectures enhance both computational performance and image quality preservation, making them suitable for real-time healthcare applications. Despite these advantages, challenges such as limited quantum hardware availability, high system complexity, and lack of large-scale datasets remain significant barriers. Future research should focus on developing scalable, lightweight, and interpretable models to facilitate practical deployment in IoT healthcare systems.

Conclusion

Wireless Sensor Network (WSN)-assisted Internet of Things (IoT) healthcare systems have transformed modern medical diagnostics by enabling real-time monitoring, remote healthcare services, and efficient medical image transmission. However, these systems face major challenges related to energy consumption, bandwidth limitations, and preservation of diagnostic image quality. This survey reviewed recent advancements in energy-efficient Quantum Convolutional Neural Networks (QCNNs) integrated with attention-based models for medical image diagnostics. Traditional CNN-based approaches provide strong feature extraction capabilities but often require high computational power and energy consumption, making them less suitable for resource-constrained WSN environments. Attention mechanisms improve performance by focusing on important image regions and enhancing diagnostic accuracy.

QCNNs introduce quantum computing principles such as superposition and entanglement to process high-dimensional medical data efficiently with reduced computational complexity. Hybrid QCNN-attention architectures further improve image quality preservation, robustness, and energy efficiency in real-time healthcare applications. Despite these advancements, challenges including limited quantum hardware, scalability issues, lack of large annotated datasets, and low model interpretability remain significant concerns. Future research should focus on scalable, lightweight, and explainable AI-driven healthcare systems for practical deployment in IoT-assisted medical environments.

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