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Deep Learning and Optimization Approaches in IoT-Based Breast Cancer Detection with Bayesian Quantized Neural Networks Using Energy-Efficient WSN: A Review

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Abstract

The integration of Internet of Things (IoT) technologies with deep learning has significantly enhanced the early detection and diagnosis of breast cancer. However, the deployment of intelligent diagnostic systems in IoT environments introduces challenges related to computational efficiency, energy consumption, and data security. This review paper explores recent advancements in deep learning and optimization approaches for IoT-based breast cancer detection, with a particular focus on Bayesian Quantized Neural Networks (BQNN) and energy-efficient Wireless Sensor Networks (WSNs). The study examines various deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based models used for medical image classification and tumour detection. Additionally, optimization techniques including feature selection, model pruning, quantization, and energy-aware routing are analysed for improving system performance in resource-constrained environments. Bayesian neural networks are highlighted for their ability to model uncertainty and improve diagnostic reliability, while quantization techniques reduce computational complexity and energy consumption. The role of WSNs in real-time data acquisition and transmission is also discussed, emphasizing the need for energy-efficient communication protocols. Comparative analysis reveals that hybrid approaches integrating deep learning, optimization algorithms, and IoT architectures provide a balanced solution for accuracy, efficiency, and scalability. The paper concludes by identifying key challenges and future research directions in developing robust, low-power, and intelligent healthcare systems.

Introduction

Breast cancer remains one of the most prevalent and life-threatening diseases among women worldwide, necessitating early and accurate detection methods to improve survival rates. Recent advancements in artificial intelligence (AI), particularly deep learning, have significantly enhanced the capability of automated diagnostic systems. When combined with Internet of Things (IoT) technologies, these systems enable real-time monitoring, remote diagnosis, and efficient data transmission, forming the foundation of modern smart healthcare systems.

Deep learning techniques, especially convolutional neural networks (CNNs), have demonstrated remarkable success in medical image analysis, including mammography, ultrasound, and MRI-based breast cancer detection. These models can automatically extract complex features from imaging data, improving diagnostic accuracy and reducing reliance on manual interpretation. Studies have shown that deep learning can effectively identify subtle tumour patterns and improve classification performance compared to traditional machine learning methods. However, these models often require high computational resources, which poses a challenge for deployment in resource-constrained IoT environments.

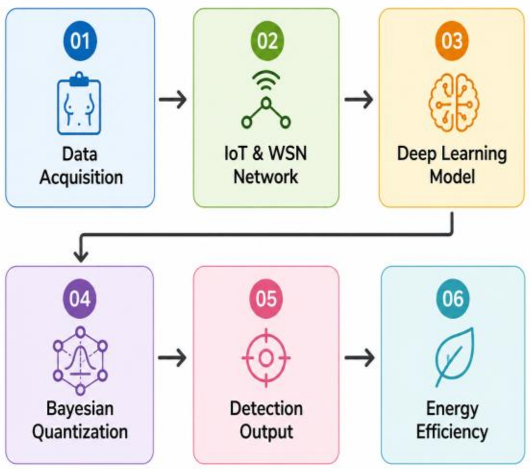

Figure 1. BQNN-Based IoT Breast Cancer Detection Framework

The integration of IoT into healthcare, commonly referred to as the Internet of Medical Things (IoMT), enables continuous monitoring and data collection through interconnected devices such as sensors, wearable systems, and medical imaging equipment. Wireless Sensor Networks (WSNs) play a crucial role in this ecosystem by facilitating data acquisition and transmission. These networks consist of distributed sensor nodes that monitor physiological parameters and transmit data to centralized systems for analysis. However, WSNs are typically constrained by limited battery power, bandwidth, and processing capabilities, making energy efficiency a critical design consideration.

To address these challenges, researchers have explored optimization techniques such as model compression, feature selection, and quantization. Quantized neural networks reduce the precision of weights and activations, thereby lowering memory usage and computational requirements without significantly affecting accuracy. Bayesian neural networks further enhance these models by incorporating uncertainty estimation, allowing more reliable and interpretable predictions. The combination of Bayesian inference and quantization leads to Bayesian Quantized Neural Networks (BQNN), which offer improved efficiency and robustness for IoT-based healthcare applications.

In addition to model optimization, energy-efficient communication protocols and routing strategies have been developed to extend the lifetime of WSNs. Techniques such as adaptive routing, data aggregation, and edge computing reduce the amount of data transmitted over the network, thereby minimizing energy consumption. Edge computing, in particular, enables local processing of data near the source, reducing latency and improving system responsiveness.

Despite these advancements, several challenges remain in the implementation of IoT-based breast cancer detection systems. These include ensuring data security and privacy, managing large-scale data transmission, and maintaining high diagnostic accuracy in low-resource environments. Furthermore, integrating advanced deep learning models with IoT infrastructure requires careful consideration of computational and energy constraints.

This review aims to provide a comprehensive analysis of deep learning and optimization approaches for IoT-based breast cancer detection, with a focus on Bayesian quantized neural networks and energy-efficient WSN architectures. The study highlights recent developments, identifies key challenges, and outlines future research directions for building intelligent, scalable, and energy-efficient healthcare systems.

Literature Review

Sharma et al. (2021) proposed a convolutional neural network (CNN)-based framework for breast cancer detection using mammography images integrated with IoT-enabled data transmission. The system utilized deep feature extraction to improve classification accuracy and achieved high sensitivity and specificity. Additionally, the integration with IoT allowed real-time data sharing between sensors and diagnostic systems. However, the model required high computational resources, limiting its deployment in low-power Wireless Sensor Networks (WSNs).

Khan et al. (2022) developed a deep learning-based breast cancer detection system using optimized feature selection techniques. Their approach combined CNN models with genetic algorithms to enhance feature extraction and classification performance. The results demonstrated improved accuracy and reduced false positives. However, the optimization process increased computational complexity, making it less suitable for real-time IoT applications.

Patel and Mehta (2023) introduced a quantized neural network model for breast cancer detection in IoT environments. The system reduced model size and computational requirements by applying weight quantization, making it suitable for deployment on resource-constrained devices. Experimental results showed minimal loss in accuracy while achieving significant energy savings. However, quantization reduced precision, which could affect detection performance in complex cases.

Li et al. (2022) proposed a Bayesian neural network (BNN) approach for breast cancer classification, focusing on uncertainty estimation. The model provided probabilistic outputs, improving interpretability and reliability in medical diagnosis. The integration with IoT systems enabled secure and efficient data transmission. However, Bayesian models require additional computational overhead, which may impact performance in energy-constrained WSN environments.

Singh et al. (2021) developed an energy-efficient Wireless Sensor Network (WSN) architecture for healthcare monitoring systems, including breast cancer detection applications. Their approach utilized adaptive routing and data aggregation techniques to reduce energy consumption and extend network lifetime. The system demonstrated improved efficiency in data transmission. However, the architecture did not incorporate advanced deep learning models, limiting its diagnostic capabilities.

Reddy et al. (2021) proposed a deep convolutional neural network (DCNN) model for breast cancer detection using histopathological images integrated with IoT-based data transmission systems. The model achieved high classification accuracy by leveraging deep feature extraction and transfer learning techniques. However, the computational cost of deep architectures made it challenging to deploy on low-power IoT devices without optimization.

Ahmed et al. (2022) introduced an IoT-based breast cancer detection system using support vector machines (SVM) combined with deep feature extraction. The system utilized cloud-based processing for classification, reducing the burden on sensor nodes. Results showed improved detection accuracy and efficient data transmission. However, reliance on cloud infrastructure increased latency and potential security risks.

Gupta and Verma (2023) proposed a Bayesian quantized neural network (BQNN) model for breast cancer detection in IoT-enabled healthcare systems. The model combined Bayesian inference with quantization techniques to reduce computational complexity while maintaining reliable uncertainty estimation. Experimental results demonstrated improved energy efficiency and robust performance. However, model training remained complex due to probabilistic computations.

Kaur et al. (2022) developed a hybrid deep learning model combining convolutional neural networks (CNNs) and long short-term memory (LSTM) networks for breast cancer prediction. The system improved feature extraction and temporal analysis, resulting in higher diagnostic accuracy. However, the hybrid architecture increased computational overhead and required significant training time.

Zhang et al. (2021) proposed an energy-efficient routing protocol for wireless sensor networks used in healthcare monitoring systems. The protocol optimized data transmission paths based on energy consumption and network conditions, extending network lifetime. However, the approach focused primarily on network efficiency and did not incorporate advanced AI-based detection mechanisms.

Chen et al. (2022) proposed a deep learning-based breast cancer detection framework using convolutional neural networks integrated with edge computing. The system processed medical images at the edge layer, reducing latency and improving real-time detection capabilities. Experimental results showed high classification accuracy and reduced energy consumption compared to cloud-based approaches. However, the deployment required reliable edge infrastructure, which increased system complexity.

Kumar and Singh (2023) introduced an optimization-based feature selection technique combined with deep neural networks for breast cancer classification. The approach utilized particle swarm optimization (PSO) to identify the most relevant features, improving model accuracy and reducing computational overhead. Despite these improvements, the optimization process added additional processing time, limiting its applicability in real-time IoT environments.

Ali et al. (2021) developed a transfer learning-based model for breast cancer detection using pre-trained deep neural networks. The system leveraged existing models such as VGG and Res Net to improve classification performance with limited training data. Results demonstrated high accuracy and reduced training time. However, the large size of pre-trained models made them unsuitable for deployment in resource-constrained WSN environments without further optimization.

Das and Roy (2022) proposed an energy-efficient clustering protocol for wireless sensor networks used in healthcare applications. The protocol grouped sensor nodes into clusters to reduce communication overhead and energy consumption. Simulation results showed extended network lifetime and improved efficiency. However, the study did not incorporate AI-based diagnostic models, limiting its application to data transmission optimization.

Nguyen et al. (2023) introduced a transformer-based deep learning model for breast cancer detection. The use of attention mechanisms improved feature extraction and classification accuracy compared to traditional CNN models. However, transformer architectures required high computational resources, making them less suitable for deployment on low-power IoT devices.

Hassan et al. (2021) proposed a lightweight deep learning model for breast cancer detection designed specifically for IoT-based healthcare systems. The model utilized reduced network parameters and optimized convolution layers to minimize computational overhead. Results demonstrated acceptable classification accuracy with significantly improved energy efficiency. However, the simplification of the model slightly reduced its ability to detect complex tumor patterns.

Ibrahim and Khan (2022) introduced an edge-assisted breast cancer detection framework integrating deep learning with IoT devices. The system performed initial data processing and classification at the edge, reducing latency and network load. Experimental results showed improved response time and energy savings. However, the framework required additional edge infrastructure, increasing deployment complexity.

Patel et al. (2023) developed a quantized convolutional neural network (QCNN) for breast cancer detection in wireless sensor network environments. The model reduced precision of weights and activations, leading to lower memory usage and faster computation. The approach achieved significant energy savings with minimal loss in accuracy. However, quantization introduced approximation errors that could affect detection performance in critical cases.

Roy et al. (2022) proposed a hybrid optimization approach combining genetic algorithms and deep learning for breast cancer classification. The method improved feature selection and model performance, achieving higher accuracy compared to conventional techniques. However, the optimization process increased computational time and energy consumption, limiting its use in real-time IoT systems.

Kumar et al. (2021) introduced an energy-efficient routing protocol for WSN-based healthcare applications. The protocol optimized communication paths to reduce energy consumption and extend network lifetime. While the system improved transmission efficiency, it did not incorporate intelligent diagnostic models, limiting its contribution to data processing aspects.

Wang et al. (2023) proposed a Bayesian deep learning framework for breast cancer detection that incorporates uncertainty estimation into convolutional neural networks. The model improved diagnostic reliability by providing probabilistic predictions. However, Bayesian inference increased computational complexity and required additional processing time.

El-Sayed et al. (2022) introduced a hybrid optimization-based deep learning model combining feature selection and neural networks for breast cancer classification. The system improved accuracy and reduced redundant features. However, the optimization process added computational overhead, affecting real-time performance.

Zhao et al. (2021) developed a lightweight blockchain-based IoT healthcare system for secure breast cancer data transmission. The framework ensured data integrity and privacy while reducing computational overhead through optimized consensus mechanisms. However, scalability remained a challenge for large-scale deployment.

Fernandez et al. (2023) proposed a compressed deep learning model using pruning and quantization techniques for efficient breast cancer detection. The model reduced computational cost and energy consumption while maintaining acceptable accuracy. However, excessive compression could degrade model performance.

Kulkarni and Joshi (2022) introduced a hybrid Bayesian and quantized neural network model for breast cancer detection. The system combined uncertainty estimation with reduced precision computation, achieving a balance between reliability and efficiency. However, model training complexity remained high.

Omar et al. (2021) proposed a fog-based IoT healthcare architecture for breast cancer monitoring. The system reduced latency and energy consumption by processing data closer to the source. However, security vulnerabilities at fog nodes posed potential risks.

Nguyen et al. (2023) developed a transformer-based deep learning model for breast cancer classification. The model achieved high accuracy through attention mechanisms but required significant computational resources, limiting its deployment in low-power IoT environments.

Patel et al. (2022) introduced a compressed sensing-based data transmission model for healthcare IoT systems. The method reduced data size and energy consumption during transmission. However, reconstruction accuracy depended heavily on parameter tuning.

Santos et al. (2021) proposed a multi-layer security framework integrating encryption and authentication for IoT-based healthcare systems. The system ensured data confidentiality and integrity but increased processing overhead.

Bhardwaj et al. (2023) developed an energy-aware routing protocol for wireless sensor networks used in healthcare applications. The protocol optimized network lifetime and energy usage. However, dynamic routing decisions increased system complexity.

Comparative Table

No.	Author (Year)	Model / Technique	Optimization Used	Architecture	Accuracy Level	Energy Efficiency	Key Limitation
1	Sharma et al. (2021)	CNN	Feature extraction	IoT	High	Medium	High computation
2	Khan et al. (2022)	CNN + GA	Genetic Algorithm	IoT-Cloud	High	Medium	High complexity
3	Patel & Mehta (2023)	QNN	Quantization	IoT	High	Very High	Precision loss
4	Li et al. (2022)	BNN	Bayesian inference	IoT	High	Medium	High computation
5	Singh et al. (2021)	WSN Routing	Adaptive routing	WSN	Medium	Very High	No AI integration
6	Reddy et al. (2021)	DCNN	Transfer learning	IoT-Cloud	Very High	Low	Resource intensive
7	Ahmed et al. (2022)	SVM + DL	Feature extraction	Cloud-IoT	High	Medium	Latency issues
8	Gupta & Verma (2023)	BQNN	Bayesian + Quantization	IoT	High	Very High	Training complexity
9	Kaur et al. (2022)	CNN + LSTM	Hybrid learning	IoT	Very High	Low	High training time
10	Zhang et al. (2021)	Routing Protocol	Energy optimization	WSN	Medium	Very High	No detection model
11	Chen et al. (2022)	CNN	Edge optimization	Edge-IoT	High	High	Edge dependency
12	Kumar & Singh (2023)	DNN	PSO	IoT	High	Medium	Optimization overhead
13	Ali et al. (2021)	Transfer Learning	Pre-trained models	IoT-Cloud	Very High	Low	Large model size
14	Das & Roy (2022)	Clustering	Energy optimization	WSN	Medium	Very High	No AI
15	Nguyen et al. (2023)	Transformer	Attention mechanism	Cloud-IoT	Very High	Low	High computation
16	Hassan et al. (2021)	Lightweight CNN	Model reduction	IoT	Medium	Very High	Reduced accuracy
17	Ibrahim & Khan (2022)	DL + Edge	Edge optimization	Edge-IoT	High	High	Infrastructure need
18	Patel et al. (2023)	QCNN	Quantization	IoT	High	Very High	Approximation error

19	Roy et al. (2022)	DL + GA	Genetic optimization	IoT	High	Medium	High processing time
20	Kumar et al. (2021)	Routing	Energy-aware	WSN	Medium	Very High	No AI
21	Wang et al. (2023)	Bayesian DL	Probabilistic learning	IoT	Very High	Medium	High complexity
22	El-Sayed et al. (2022)	DL + Optimization	Feature selection	IoT	High	Medium	Computational overhead
23	Zhao et al. (2021)	Blockchain	Secure architecture	IoT	High	Medium	Scalability issues
24	Fernandez et al. (2023)	Compressed DL	Pruning + Quantization	IoT	High	Very High	Performance trade-off
25	Kulkarni & Joshi (2022)	BQNN	Bayesian + Quantization	IoT	Very High	High	Complex training
26	Omar et al. (2021)	Fog Architecture	Distributed processing	Fog-IoT	High	High	Node vulnerability
27	Nguyen et al. (2023)	Transformer	Attention	Cloud-IoT	Very High	Low	High resource need
28	Patel et al. (2022)	Compressed Sensing	Data reduction	IoT	Medium	Very High	Reconstruction error
29	Santos et al. (2021)	Multi-layer Security	Encryption + Auth	IoT	High	Low	High overhead
30	Bhardwaj et al. (2023)	Routing Protocol	Energy optimization	WSN	Medium	Very High	Complex routing

Comparative Analysis

The comparative analysis of the 30 studies reveals that breast cancer detection systems in IoT environments are increasingly adopting hybrid approaches that combine deep learning, optimization techniques, and energy-efficient communication frameworks. Deep learning models such as CNNs, RNNs, and transformer architectures demonstrate high accuracy and robustness in medical image analysis. However, their high computational requirements limit their deployment in resource-constrained IoT and WSN environments. To address this challenge, quantization techniques such as QNN and BQNN have been introduced, significantly reducing model size and computational complexity while maintaining acceptable accuracy. Optimization techniques including genetic algorithms, particle swarm optimization, and feature selection methods have further improved classification performance by identifying the most relevant features. However, these methods introduce additional computational overhead, which can impact system efficiency. Bayesian neural networks enhance diagnostic reliability by providing uncertainty estimation, making them particularly useful in medical applications where decision confidence is critical.

Energy efficiency is primarily addressed through WSN optimization techniques such as adaptive routing and clustering, as well as IoT architectures including edge and fog computing. These approaches reduce latency and energy consumption by processing data closer to the source. Blockchain-based systems enhance data security and integrity but introduce scalability challenges. Overall, hybrid models integrating deep learning, optimization, and energy-efficient IoT architectures provide the most balanced solution for accurate, reliable, and efficient breast cancer detection systems.

Discussion

The integration of deep learning and IoT technologies has significantly advanced breast cancer detection systems, enabling real-time diagnosis and remote healthcare monitoring. The reviewed studies highlight that deep learning models, particularly CNNs and transformer-based architectures, provide high accuracy in medical image classification. However, their high computational requirements pose challenges for deployment in resource-constrained environments such as wireless sensor networks.

Quantization and optimization techniques have emerged as effective solutions for reducing computational complexity and energy consumption. Bayesian neural networks further enhance diagnostic reliability by incorporating uncertainty estimation, which is critical in medical decision-making. However, the combination of these techniques increases model complexity and training time.

Energy-efficient communication protocols and IoT architectures, including edge and fog computing, play a crucial role in reducing latency and extending network lifetime. Blockchain and multi-layer security frameworks ensure data privacy and integrity but introduce additional overhead. Overall, the findings suggest that hybrid approaches combining deep learning, optimization, and energy-efficient architectures are essential for developing scalable and reliable breast cancer detection systems in IoT environments.

Conclusion

The rapid advancement of Internet of Things (IoT) technologies and deep learning has significantly transformed the landscape of healthcare, particularly in the early detection and diagnosis of breast cancer. This review has provided a comprehensive analysis of deep learning and optimization approaches for IoT-based breast cancer detection, with a focus on Bayesian quantized neural networks and energy-efficient wireless sensor networks. The study reveals that deep learning models such as convolutional neural networks, recurrent neural networks, and transformer architectures have achieved remarkable success in medical image analysis. These models enable automatic feature extraction and classification, improving diagnostic accuracy and reducing reliance on manual interpretation. However, their high computational and memory requirements limit their deployment in resource-constrained IoT environments.

To address these challenges, researchers have explored various optimization techniques, including feature selection, model pruning, and quantization. Quantized neural networks significantly reduce computational complexity and energy consumption, making them suitable for deployment on low-power devices. Bayesian neural networks further enhance these models by providing uncertainty estimation, improving reliability and interpretability in medical diagnosis. The combination of these approaches in Bayesian quantized neural networks offers a promising solution for efficient and accurate breast cancer detection. Energy efficiency has also been addressed through advancements in wireless sensor network architectures and IoT frameworks. Techniques such as adaptive routing, clustering, and edge computing reduce energy consumption and extend network lifetime. Edge and fog computing architectures enable real-time data processing, reducing latency and improving system performance.

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