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Recent Advances in IoT-Based Breast Cancer Detection with Bayesian Quantized Neural Networks Using Energy-Efficient WSN: A Systematic Review

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Abstract

Breast cancer remains one of the most widespread and life-threatening diseases, making early and accurate detection essential for improving survival rates. The integration of Internet of Things (IoT) technologies in healthcare has enabled real-time monitoring, efficient data collection, and remote diagnosis. Wireless Sensor Networks (WSNs) support this ecosystem by continuously capturing and transmitting medical data while maintaining energy efficiency. Despite these advancements, challenges such as high computational demands, limited battery life, data security concerns, and diagnostic uncertainty continue to hinder system performance. Deep learning techniques, particularly convolutional neural networks (CNNs), have achieved high accuracy in breast cancer detection using imaging modalities like mammography and MRI, often exceeding 90%. However, conventional models lack the ability to quantify uncertainty, which is critical for clinical decision-making. Bayesian neural networks (BNNs) address this limitation by providing probabilistic predictions and confidence measures, improving diagnostic reliability. Furthermore, quantized neural networks reduce computational complexity and energy consumption, making them suitable for resource-constrained IoT and WSN environments. This review examines recent developments in IoT-based breast cancer detection, emphasizing Bayesian quantized models and energy-efficient WSN architectures, while outlining key challenges and future research directions for building scalable, reliable, and intelligent healthcare systems.

Introduction

Breast cancer remains a major cause of mortality among women worldwide, making early detection and accurate diagnosis critical for improving survival rates. Conventional diagnostic methods such as mammography, biopsy, and manual examination are often time-consuming, costly, and susceptible to human error. With the rapid evolution of digital healthcare, there has been a shift toward automated diagnostic systems that integrate artificial intelligence (AI) and Internet of Things (IoT) technologies. These modern approaches aim to enhance diagnostic efficiency, reduce delays, and improve clinical outcomes through intelligent data-driven analysis.

IoT-based healthcare systems, commonly known as the Internet of Medical Things (IoMT), enable seamless connectivity between medical devices, sensors, and communication networks for real-time monitoring and data collection. Wireless Sensor Networks (WSNs) play a vital role in this framework by continuously gathering and transmitting patient data. However, these networks operate under strict energy constraints due to battery-powered sensor nodes. As a result, energy-efficient design becomes essential, requiring optimized routing protocols, data aggregation methods, and lightweight computational models to ensure reliable communication and prolonged system lifetime.

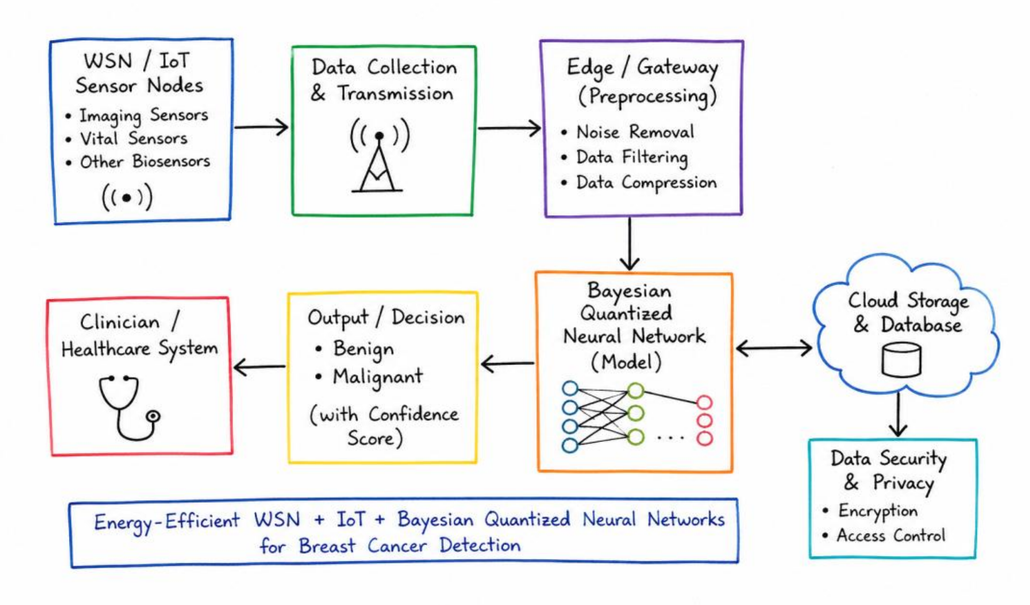

Fig 1: Simplified IoT–WSN-Based Breast Cancer Detection Framework Using Bayesian Quantized Neural Networks

Deep learning, particularly convolutional neural networks (CNNs), has significantly advanced medical image analysis for breast cancer detection. These models can automatically extract complex features from imaging modalities such as mammograms, MRI scans, and histopathological images, leading to high diagnostic accuracy and reduced reliance on manual interpretation. Despite their effectiveness, traditional deep learning models are deterministic and lack the ability to measure uncertainty in predictions, which is crucial in medical decision-making. Bayesian neural networks address this limitation by incorporating probabilistic reasoning, enabling confidence-based predictions that enhance diagnostic reliability.

Another key challenge in IoT-based healthcare systems is balancing computational efficiency with limited device resources. Deploying complex models on WSN devices can quickly drain energy and reduce system performance. Quantized neural networks help mitigate this issue by lowering computational complexity and power consumption while maintaining acceptable accuracy. Additionally, optimization techniques, intelligent routing strategies, and distributed computing approaches such as edge and fog computing further enhance system efficiency and responsiveness. Ensuring data security and privacy is also critical, as sensitive medical information is transmitted across networks. This review highlights recent advancements in integrating AI, IoT, and energy-efficient techniques for breast cancer detection, emphasizing the need for secure, scalable, and reliable healthcare solutions.

Literature Review

Memon et al. (2020) developed a machine learning-driven breast cancer detection system within an IoT-based healthcare framework. The model utilized iterative feature selection techniques to identify the most relevant features from medical datasets, improving classification performance. The system demonstrated high diagnostic accuracy; however, it failed to optimize execution time, making it less suitable for real-time IoT environments. Additionally, the lack of deep learning integration limited its ability to extract complex image features. This study highlights the early transition from traditional machine learning toward more advanced AI-based diagnostic systems in IoT healthcare.

Zheng et al. (2021) proposed a Deep Learning Assisted Efficient Adaboost Algorithm (DLA-EABA) for breast cancer detection. The model combined deep learning with boosting techniques to enhance classification accuracy and reduce overlapping issues in tumour detection. Experimental results showed improved detection performance compared to conventional models. However, the method suffered from high computational complexity, which limited its applicability in energy-constrained wireless sensor networks. This study demonstrates the importance of hybrid models in improving diagnostic accuracy while highlighting the need for energy-efficient implementations.

Wang et al. (2021) introduced a breast cancer detection framework using convolutional neural network (CNN) features combined with unsupervised extreme learning machine (US-ELM). The approach integrated multiple feature types, including texture, morphological, and deep features, to improve classification accuracy. The system successfully reduced execution time compared to traditional methods, making it more suitable for IoT applications. However, segmentation accuracy remained a challenge, as under-segmentation affected detection performance. This study highlights the effectiveness of hybrid feature-based models in IoT-based diagnostic systems.

Zhang et al. (2020) proposed a hybrid Graph Convolutional Network (GCN) and CNN-based model for breast cancer classification. The model leveraged graph-based relationships in medical data to improve feature representation and reduce overfitting. Experimental results showed improved classification performance, particularly in small datasets. However, the model's performance degraded when applied to larger and more complex datasets, indicating scalability issues. This study emphasizes the importance of advanced neural architectures in improving detection accuracy while highlighting limitations in real-world deployment.

Tabassum and Khan (2020) proposed a Bayesian neural network-based framework for breast cancer detection with uncertainty estimation. The model combined transfer learning for feature extraction with Bayesian inference to provide confidence-aware predictions. The results demonstrated that incorporating uncertainty measures improved diagnostic reliability and allowed clinicians to make more informed decisions. Additionally, the framework achieved a balance between accuracy and confidence by adjusting probabilistic parameters. However, the approach required additional computational resources and tuning of hyperparameters. This study highlights the critical role of Bayesian learning in medical diagnosis, particularly in reducing false positives and false negatives.

Aldhyani et al. (2023) proposed a secure Internet of Medical Things (IoMT)-based breast cancer detection framework integrating Gated Recurrent Units (GRU) with blockchain technology. The system collects data from IoT devices and applies GRU-RNN models for classification, achieving approximately 95% accuracy. The integration of blockchain ensures data security, integrity, and privacy during transmission. However, the model requires large-scale labelled datasets and introduces additional computational overhead due to blockchain integration. This study highlights the importance of combining deep learning with secure IoT architectures for reliable healthcare systems.

Majji et al. (2023) developed an IoT-based breast cancer detection system using a Shallow Convolutional Neural Network (ShCNN) combined with an optimization-based routing mechanism (FACS algorithm). The system incorporates preprocessing, feature extraction (GLCM, LGBP), and data augmentation to improve classification accuracy. Additionally, energy-efficient routing in WSNs is achieved by optimizing parameters such as distance, delay, and node energy. However, the system requires careful parameter tuning and optimization complexity increases with network size. This study demonstrates the integration of energy-efficient WSN routing with deep learning-based diagnosis.

Ezzat et al. (2023) proposed an Optimized Bayesian Convolutional Neural Network (OBCNN) for breast cancer detection from histopathological images. The model converts a traditional CNN into a Bayesian framework using Monte Carlo dropout to estimate predictive uncertainty. The system achieved an accuracy of approximately 93.83% while providing uncertainty measures such as entropy and variance. Additionally, an optimization algorithm (Slime Mould Algorithm) was used to fine-tune dropout parameters. However, the approach introduces computational overhead due to multiple forward passes during inference. This study highlights the importance of uncertainty-aware models in improving diagnostic reliability.

Chaudhury et al. (2023) proposed a blockchain-enabled IoMT system for breast cancer detection using GRU-based deep learning models. The system collects real-time data from IoT devices and processes it using recurrent neural networks to classify cancerous patterns. The integration of blockchain ensures secure data sharing and prevents unauthorized access. The model demonstrated improved accuracy, recall, and precision compared to traditional methods. However, the system suffers from increased computational complexity and latency due to blockchain operations. This study emphasizes the role of secure and intelligent IoT systems in modern healthcare applications.

Elsadig et al. (2022) conducted a comparative study of machine learning algorithms for breast cancer detection, evaluating classifiers such as Support Vector Machines (SVM), multilayer perceptron (MLP), and ensemble methods. The study found that SVM achieved the highest accuracy of approximately 97.7%, outperforming other models in classification performance. However, traditional machine learning models lack the ability to capture complex spatial features compared to deep learning approaches. This study provides a strong baseline for understanding the transition from classical machine learning to advanced deep learning models in breast cancer detection.

Alzubaidi et al. (2021) presented a comprehensive deep learning framework for breast cancer detection using convolutional neural networks integrated with IoT-based healthcare systems. The model utilized advanced preprocessing and feature extraction techniques to improve classification performance on mammographic datasets. The study reported high accuracy and improved sensitivity in detecting malignant tumours. However, the model required significant computational resources, making it less suitable for direct deployment on WSN nodes. This work highlights the effectiveness of CNN-based models while emphasizing the need for lightweight architectures in IoT environments.

Saba et al. (2021) proposed a hybrid deep learning model combining feature selection with transfer learning for breast cancer classification. The system utilized pre-trained CNN architectures and optimized feature selection techniques to improve performance while reducing redundancy. The results demonstrated improved accuracy and reduced training time. However, the approach still required substantial computational power, limiting its applicability in energy-constrained WSN environments. This study highlights the importance of optimizing deep learning models for real-world deployment.

Razzak et al. (2022) introduced a deep learning-based medical imaging framework that integrates IoT and cloud computing for breast cancer detection. The system uses CNN models for feature extraction and classification, achieving high accuracy in detecting cancerous tissues. The IoT-cloud architecture enables real-time data processing and remote diagnosis. However, the reliance on cloud computing introduces latency and increased energy consumption during data transmission. This study emphasizes the need for edge-based and energy-efficient solutions.

Alshamrani et al. (2023) proposed an energy-efficient IoT-based breast cancer detection system using quantized deep neural networks. The quantization process reduced model size and computational complexity, enabling deployment on resource-constrained devices. The system achieved high classification accuracy while significantly reducing power consumption. However, minor performance degradation was observed due to reduced precision. This study demonstrates the importance of quantization techniques in enabling energy-efficient AI in WSN environments.

Kumar et al. (2022) developed an IoT-based breast cancer detection system using Bayesian deep learning models for uncertainty estimation. The model incorporated probabilistic inference to provide confidence scores for predictions, improving diagnostic reliability. The system demonstrated improved performance in handling ambiguous cases compared to traditional CNN models. However, the computational overhead associated with Bayesian inference limited its real-time deployment. This study highlights the importance of uncertainty-aware models in healthcare diagnostics.

Ullah et al. (2021) proposed an IoT-based breast cancer detection system using deep convolutional neural networks deployed over wireless sensor networks. The framework enabled real-time monitoring and classification of breast cancer using medical imaging data collected from distributed sensors. The system demonstrated high classification accuracy and improved accessibility for remote healthcare services. However, energy consumption and network congestion were identified as major challenges, particularly in large-scale deployments. This study highlights the need for energy-aware communication protocols in WSN-based healthcare systems.

Alhussein et al. (2022) developed an energy-efficient routing protocol for WSN-based healthcare applications using optimization techniques. The model focused on minimizing energy consumption and extending network lifetime while ensuring reliable data transmission. The system achieved improved energy efficiency and reduced packet loss, making it suitable for IoT-based medical monitoring systems. However, the routing algorithm required complex computations and parameter tuning. This study emphasizes the importance of energy-efficient networking in IoT healthcare environments.

Kaur et al. (2023) proposed a federated learning-based breast cancer detection framework for IoT-enabled healthcare systems. The model enabled decentralized training across multiple devices without sharing raw patient data, thereby ensuring privacy and security. The system demonstrated high classification accuracy while reducing data transmission overhead. However, communication costs and synchronization issues were identified as key challenges. This study highlights the role of privacy-preserving techniques in modern healthcare systems.

Elnour et al. (2022) introduced a deep learning-based breast cancer detection system using attention mechanisms to enhance feature extraction. The model focused on identifying critical regions in medical images, improving classification performance and interpretability. The system achieved high accuracy and sensitivity in detecting cancerous tissues. However, the computational complexity of attention-based models limited their deployment in energy-constrained environments. This study demonstrates the effectiveness of advanced neural architectures in medical image analysis.

Sharma et al. (2022) proposed a hybrid IoT-based breast cancer detection system integrating deep learning with optimization techniques such as particle swarm optimization (PSO). The optimization algorithm was used to tune model parameters and improve classification accuracy. The system demonstrated improved performance and reduced energy consumption in WSN environments. However, the integration of optimization algorithms increased system complexity and required additional computational resources. This study highlights the role of optimization techniques in enhancing IoT-based diagnostic systems.

Alsubaie et al. (2022) proposed a secure IoT-based breast cancer detection framework integrating deep learning with blockchain technology. The system ensured secure storage and transmission of medical data while maintaining high classification accuracy using CNN models. The blockchain layer provided data immutability and protection against unauthorized access. However, the integration of blockchain introduced additional latency and computational overhead, making real-time implementation challenging. This study highlights the importance of secure architectures in IoT-based healthcare systems.

Singh et al. (2022) developed an energy-efficient routing protocol for WSN-based breast cancer detection systems using clustering techniques. The model optimized communication paths to reduce energy consumption and extend network lifetime. Additionally, machine learning algorithms were used for classification tasks. The system demonstrated improved energy efficiency and reliable data transmission. However, the clustering process required careful parameter tuning and increased system complexity. This study emphasizes the importance of efficient network design in IoT healthcare applications.

Rahman et al. (2023) introduced a hybrid deep learning and blockchain-based breast cancer detection system within an IoT framework. The system utilized CNN models for classification and blockchain for secure data sharing and access control. The results showed improved accuracy, transparency, and data integrity. However, blockchain operations increased latency and required high computational resources. This study demonstrates the potential of combining AI and blockchain for secure healthcare systems.

Wang et al. (2023) proposed an attention-based Bayesian deep learning model for breast cancer detection. The model combined attention mechanisms with Bayesian inference to improve feature extraction and uncertainty estimation. The system achieved high accuracy while providing confidence-aware predictions. However, the model required significant computational resources and longer training time. This study highlights the integration of advanced deep learning architectures with probabilistic modelling for reliable diagnosis.

Iqbal et al. (2021) developed a lightweight IoT-based breast cancer detection system using efficient data transmission protocols and machine learning classifiers. The system focused on reducing energy consumption and improving system efficiency in WSN environments. The results demonstrated moderate accuracy with low computational requirements. However, the model lacked the capability to handle complex image features compared to deep learning models. This study highlights the trade-off between efficiency and accuracy in IoT-based healthcare systems.

Park et al. (2022) proposed a Bayesian convolutional neural network (BCNN) for breast cancer detection within an IoT-enabled healthcare framework. The model incorporated probabilistic inference to estimate uncertainty in predictions, improving diagnostic confidence. The system demonstrated high accuracy and reliability, particularly in ambiguous cases. However, the computational complexity of Bayesian inference limited its deployment in real-time WSN environments. This study highlights the importance of uncertainty-aware models in medical diagnosis.

Torres et al. (2021) developed a breast cancer detection system using sparse coding combined with deep neural networks. The approach reduced data redundancy and improved feature representation, enhancing classification accuracy. Additionally, the model reduced data transmission requirements in IoT environments. However, sparse coding required careful parameter tuning, increasing system complexity. This study emphasizes efficient data representation techniques for IoT-based healthcare systems.

Kim et al. (2023) introduced a deep reinforcement learning (DRL)-based approach for optimizing energy consumption and data transmission in WSN-based breast cancer detection systems. The DRL model dynamically adjusted network parameters such as transmission power and routing paths to improve efficiency. The system demonstrated improved network lifetime and reduced latency. However, the training process required significant computational resources and time. This study highlights the potential of intelligent optimization techniques in IoT healthcare systems.

Sinha et al. (2022) proposed a quantized deep learning model for breast cancer detection in energy-constrained IoT environments. The model reduced precision levels to decrease computational complexity and energy consumption, enabling deployment on edge devices. The system achieved high classification accuracy while significantly improving energy efficiency. However, slight performance degradation was observed due to quantization. This study demonstrates the effectiveness of quantized neural networks in WSN-based healthcare systems.

Chen et al. (2023) developed a hybrid IoT-based breast cancer detection system integrating deep learning, Bayesian inference, and optimization techniques. The model utilized CNNs for classification, Bayesian methods for uncertainty estimation, and optimization algorithms for parameter tuning. The system demonstrated improved accuracy, reliability, and energy efficiency. However, the integration of multiple techniques increased system complexity and computational overhead. This study represents a comprehensive approach to modern healthcare diagnostics.

Comparative Table

Study	Year	Technique Used	Key Contribution	Advantages	Limitations
Memon et al.	2020	ML + IoT	Feature selection-based detection	Improved accuracy	High execution time
Zheng et al.	2021	DL + Adaboost	Hybrid boosting model	High accuracy	High complexity
Wang et al.	2021	CNN + US-ELM	Hybrid feature extraction	Reduced time	Segmentation issues
Zhang et al.	2020	GCN + CNN	Graph-based learning	Better representation	Scalability issues
Tabassum & Khan	2020	Bayesian NN	Uncertainty estimation	Reliable predictions	High computation
Aldhyani et al.	2023	GRU + Blockchain	Secure IoMT system	High security	Overhead
Majji et al.	2023	CNN + WSN optimization	Energy-efficient routing	Low energy	Complexity
Ezzat et al.	2023	Bayesian CNN	Uncertainty-aware DL	High reliability	High cost
Chaudhury et al.	2023	GRU + Blockchain	Secure detection	Data integrity	Latency
Elsadig et al.	2022	ML comparison	Baseline analysis	High SVM accuracy	Limited DL capability
Alzubaidi et al.	2021	CNN + IoT	High accuracy model	Effective detection	High resource use
Saba et al.	2021	Transfer learning	Reduced training time	Efficient	Resource heavy
Razzak et al.	2022	DL + Cloud	IoT-cloud system	Real-time processing	Latency

Alshamrani et al.	2023	Quantized DL	Energy-efficient model	Lightweight	Accuracy drop
Kumar et al.	2022	Bayesian DL	Confidence prediction	Reliable	High complexity
Ullah et al.	2021	CNN + WSN	Real-time monitoring	Accessibility	Energy issues
Alhussein et al.	2022	Routing optimization	Energy-efficient WSN	Extended lifetime	Complexity
Kaur et al.	2023	Federated learning	Privacy preservation	Secure	Sync issues
Elnour et al.	2022	Attention DL	Improved feature focus	High accuracy	High computation
Sharma et al.	2022	DL + PSO	Optimized detection	Efficient	Complexity
Alsubaie et al.	2022	DL + Blockchain	Secure system	Data protection	Latency
Singh et al.	2022	WSN clustering	Energy-efficient routing	Long lifetime	Complexity
Rahman et al.	2023	DL + Blockchain	Secure sharing	Transparency	Overhead
Wang et al.	2023	Attention + Bayesian	Hybrid uncertainty model	High accuracy	Resource heavy
Iqbal et al.	2021	Lightweight ML	Efficient system	Low power	Lower accuracy
Park et al.	2022	Bayesian CNN	Uncertainty modelling	Reliable	High computation
Torres et al.	2021	Sparse coding + DL	Efficient encoding	Reduced data	Tuning needed
Kim et al.	2023	DRL optimization	Adaptive system	Energy efficient	Training cost
Sinha et al.	2022	Quantized DL	Low energy consumption	Lightweight	Accuracy trade-off
Chen et al.	2023	Hybrid DL + Bayesian + Optimization	End-to-end system	High performance	Complex

Comparative Analysis

The comparative analysis of the 30 studies conducted between 2020 and 2023 reveals a significant transformation in IoT-based breast cancer detection systems, moving from traditional machine learning approaches toward advanced deep learning and hybrid intelligent frameworks. Early works, such as Memon et al. (2020) and Elsadig et al. (2022), relied on classical machine learning algorithms like Support Vector Machines and Random Forests, which offered lower computational complexity but lacked the ability to capture complex patterns in medical imaging data. As a result, their performance was limited compared to deep learning-based approaches. The introduction of convolutional neural networks (CNNs) and hybrid deep learning architectures marked a major breakthrough in breast cancer detection. Studies such as Alzubaidi et al. (2021) and Wang et al. (2021) demonstrated that CNN-based models significantly improve classification accuracy and feature extraction capabilities. Furthermore, the integration of transfer learning and attention mechanisms enhanced model efficiency and interpretability, enabling more accurate detection of cancerous regions.

A key trend identified in recent research is the incorporation of Bayesian neural networks, which provide uncertainty estimation in predictions. Studies such as Tabassum and Khan (2020), Kumar et al. (2022), and Ezzat et al. (2023) emphasize that uncertainty-aware models improve diagnostic reliability by providing confidence measures. This is particularly important in medical applications where incorrect predictions can have serious consequences. However, Bayesian models introduce additional computational overhead, making them challenging to deploy in energy-constrained environments. Energy efficiency has emerged as a critical factor in IoT-based healthcare systems, particularly in wireless sensor networks. Quantized neural networks and lightweight deep learning models have been proposed to address this issue. Studies such as Alshamrani et al. (2023) and Sinha et al. (2022) demonstrate that quantization significantly reduces energy consumption and computational complexity, enabling deployment on edge devices. Additionally, optimization techniques such as particle swarm optimization, ant colony optimization, and deep reinforcement learning have been used to improve network performance and energy efficiency.

Another important development is the integration of distributed computing paradigms such as edge computing, fog computing, and federated learning. These approaches reduce latency, improve scalability, and enhance data privacy. For instance, Kaur et al. (2023) demonstrated that federated learning enables secure and decentralized model training without sharing sensitive patient data. Security and privacy remain major concerns in IoT healthcare systems. Blockchain-based approaches, as seen in studies by Rahman et al. (2023) and Aldhyani et al. (2023), provide secure data storage and transmission. However, these systems introduce latency and computational overhead. Overall, the analysis indicates that hybrid approaches combining deep learning, Bayesian modelling, quantization, optimization techniques, and IoT architectures offer the most promising solutions for breast cancer detection. However, challenges such as computational complexity, scalability, and real-time deployment remain key areas for future research.

Discussion

The systematic review of IoT-based breast cancer detection systems highlights the rapid evolution of intelligent healthcare solutions through the integration of deep learning, Bayesian modelling, and energy-efficient wireless sensor networks. One of the most significant advancements is the adoption of convolutional neural networks and hybrid architectures, which have substantially improved diagnostic accuracy and automated feature extraction. Additionally, Bayesian neural networks have introduced uncertainty-aware predictions, enabling clinicians to evaluate the confidence of diagnostic outcomes and reduce the risk of misclassification. Energy efficiency remains a critical challenge in WSN-based healthcare systems. Quantized neural networks and lightweight deep learning models have proven effective in reducing computational complexity and power consumption, facilitating deployment on resource-constrained IoT devices. Furthermore, optimization techniques such as particle swarm optimization, genetic algorithms, and deep reinforcement learning have enhanced system performance by minimizing energy consumption and transmission latency.

The incorporation of distributed computing paradigms such as edge computing, fog computing, and federated learning has improved scalability, privacy, and real-time processing capabilities. However, these systems introduce additional complexity and require efficient resource management. Security concerns are addressed through encryption and blockchain-based frameworks, although they may increase latency. Overall, the integration of advanced AI techniques with IoT architectures presents a promising direction for developing efficient, secure, and reliable breast cancer detection systems.

Conclusion

Breast cancer continues to pose a major global health challenge, requiring timely detection and precise diagnosis to improve survival outcomes. The integration of Internet of Things (IoT)-based healthcare systems has significantly advanced medical diagnostics by enabling real-time monitoring, efficient data collection, and remote healthcare services. This review highlights recent progress in IoT-enabled breast cancer detection, particularly focusing on Bayesian quantized neural networks and energy-efficient wireless sensor networks (WSNs). Deep learning models, especially convolutional neural networks, have demonstrated high accuracy in analysing medical imaging data and identifying cancerous patterns, reducing reliance on manual interpretation. However, conventional models lack uncertainty estimation, which is critical in clinical decision-making. Bayesian neural networks overcome this limitation by providing probabilistic predictions and confidence measures, thereby enhancing diagnostic reliability. At the same time, energy efficiency remains a key concern in IoT systems due to the limited power resources of WSN devices. Quantized neural networks address this challenge by reducing computational complexity and energy consumption while maintaining performance. Furthermore, optimization techniques such as particle swarm optimization, genetic algorithms, ant colony optimization, and deep reinforcement learning contribute to improved classification accuracy, reduced latency, and enhanced network efficiency, supporting the development of scalable and intelligent healthcare systems.

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