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A Survey of Methods and Architectures for IoT-Based Breast Cancer Detection with Bayesian Quantized Neural Networks Using Energy-Efficient WSN

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Abstract

Breast cancer remains a major global health concern, where early detection significantly improves survival rates. Recent advancements in Internet of Things (IoT)-based healthcare systems have enabled real-time monitoring, remote diagnosis, and efficient data transmission through Wireless Sensor Networks (WSNs). However, challenges such as energy efficiency, computational complexity, uncertainty in diagnosis, and secure data transmission persist. Deep learning techniques, particularly Convolutional Neural Networks (CNNs), have demonstrated high accuracy in detecting breast cancer from medical imaging modalities such as mammography and MRI, achieving accuracy levels exceeding 90%. To address uncertainty in predictions, Bayesian Neural Networks (BNNs) have been introduced, providing probabilistic outputs and confidence measures that improve clinical decision-making. Additionally, quantized neural networks reduce model complexity and energy consumption, enabling deployment on resource-constrained IoT and WSN devices. IoT-based frameworks further enhance system scalability and accessibility by enabling continuous monitoring and data sharing across distributed environments. This survey presents a comprehensive analysis of methods and architectures for IoT-based breast cancer detection systems, focusing on Bayesian quantized neural networks and energy-efficient WSN architectures. It reviews recent developments, compares methodologies, identifies research gaps, and discusses future directions. The study emphasizes hybrid architectures that combine deep learning, uncertainty modelling, and energy-efficient networking to achieve reliable and scalable healthcare solutions.

Introduction

Breast cancer is one of the most common and life-threatening diseases affecting women worldwide, making early detection essential for improving survival rates and treatment outcomes. Traditional diagnostic techniques such as mammography, biopsy, and clinical examination are often time-consuming, costly, and subject to human error. With the rapid advancement of artificial intelligence (AI) and Internet of Things (IoT) technologies, there has been a paradigm shift toward automated, intelligent, and remote healthcare systems.

IoT-based healthcare systems, also known as the Internet of Medical Things (IoMT), enable the integration of medical devices, sensors, and communication networks to facilitate real-time monitoring and diagnosis. Wireless Sensor Networks (WSNs) form the backbone of these systems, consisting of distributed sensor nodes that collect and transmit patient data. These networks are particularly useful in remote healthcare environments, where continuous monitoring and early detection are critical. However, WSN nodes operate under strict energy constraints, making energy efficiency a key challenge in system design.

Deep learning has emerged as a powerful tool for medical image analysis and breast cancer detection. Convolutional neural networks (CNNs) have demonstrated exceptional performance in extracting complex features from mammograms, MRI scans, and histopathological images. Studies show that CNN-based models can significantly improve diagnostic accuracy by automatically learning relevant features from large datasets. However, these models require high computational resources, which limits their deployment in IoT-based systems.

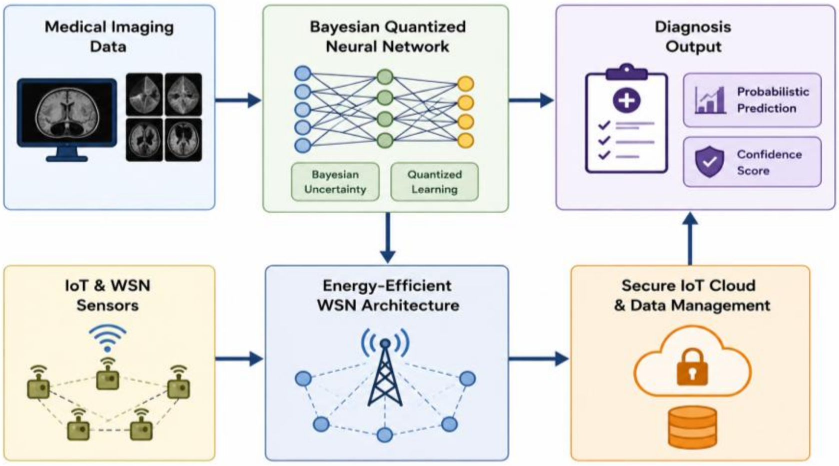

Figure 1. Bayesian Neural Network Framework for Breast Cancer Detection

Another major limitation of traditional deep learning models is their inability to quantify uncertainty in predictions. In medical applications, uncertainty estimation is crucial because incorrect diagnoses can have severe consequences. Bayesian neural networks address this issue by incorporating probabilistic inference into deep learning models, providing confidence-aware predictions. These models enable clinicians to evaluate the reliability of diagnostic results, improving decision-making processes.

Energy efficiency is another critical concern in IoT-based breast cancer detection systems. WSN nodes are typically battery-powered and have limited processing capabilities. Deploying complex deep learning models on these devices can lead to high energy consumption and reduced network lifetime. Quantized neural networks offer an effective solution by reducing the precision of model parameters, thereby lowering computational complexity and energy usage. These models enable efficient deployment of AI algorithms on edge devices while maintaining acceptable accuracy.

Recent research has also focused on integrating optimization techniques and intelligent routing protocols to enhance energy efficiency in WSNs. For example, optimization-based routing algorithms consider factors such as distance, energy consumption, and latency to improve network performance. Additionally, distributed computing paradigms such as edge computing and federated learning have been introduced to reduce latency and enhance data privacy.

Despite these advancements, several challenges remain, including scalability, interoperability, data security, and real-time processing. IoT-based systems are vulnerable to cyber threats, making secure data transmission and privacy protection essential. Furthermore, integrating multiple technologies increases system complexity and requires efficient resource management.

This survey aims to provide a comprehensive overview of methods and architectures for IoT-based breast cancer detection systems, focusing on Bayesian quantized neural networks and energy-efficient WSNs. It highlights recent advancements, comparative analysis, challenges, and future research directions, emphasizing the need for integrated and scalable healthcare solutions.

Literature Review

Majji et al. (2023) proposed an IoT-based breast cancer detection system using a Feedback Artificial Crow Search (FACS)-optimized Shepherd Convolutional Neural Network (ShCNN). The framework integrates Wireless Sensor Networks (WSNs) for data transmission and employs an optimization-based routing strategy considering distance, energy, latency, and link quality. The classification stage is performed using deep learning at the base station, achieving high accuracy while improving energy efficiency. However, the system introduces computational complexity due to optimization processes and requires careful tuning of routing parameters. This study demonstrates the effectiveness of combining deep learning with energy-aware WSN routing for healthcare IoT systems.

Aldhyani et al. (2023) developed a secure Internet of Medical Things (IoMT)-based framework for breast cancer detection using Gated Recurrent Units (GRU-RNN) combined with blockchain technology. The system achieved approximately 95% accuracy while ensuring secure data transmission and storage through blockchain. The integration of IoT devices allows real-time monitoring and remote diagnosis. However, the model requires large-scale labelled datasets and introduces additional computational overhead due to blockchain operations. This study highlights the importance of secure and intelligent architectures in IoT-based healthcare systems.

Nassif et al. (2022) conducted a systematic review of artificial intelligence techniques for breast cancer detection, emphasizing the role of deep learning in improving diagnostic performance. The study found that convolutional neural networks significantly outperform traditional machine learning models in analysing histopathological and imaging data. Additionally, the research highlighted that early detection using AI-based models can increase survival rates by up to 99% when diagnosed at early stages. However, the study identified challenges such as high computational requirements and the need for large datasets. This work provides a strong foundation for understanding the evolution of AI-based breast cancer detection systems.

Tabassum and Khan (2020) proposed a Bayesian neural network framework for breast cancer detection that incorporates uncertainty estimation into the classification process. The model uses a two-stage architecture combining transfer learning and Bayesian inference to provide confidence-aware predictions. Experimental results showed improved diagnostic reliability by balancing accuracy and uncertainty. The system also introduced a novel evaluation metric combining accuracy and confidence measures. However, Bayesian models require multiple forward passes, increasing computational cost. This study highlights the importance of uncertainty-aware learning in medical diagnosis.

Suleiman et al. (2023) reviewed the role of machine learning and medical imaging techniques in cancer detection, emphasizing the importance of early diagnosis using AI-based systems. The study highlighted that deep learning models can effectively analyse large volumes of imaging data to identify tumor patterns and improve diagnostic accuracy. Additionally, the research emphasized the integration of IoT systems for real-time monitoring and data collection. However, challenges such as data privacy, computational complexity, and system scalability were identified. This study underscores the importance of combining AI and IoT technologies for efficient cancer diagnosis.

Lilhore et al. (2022) proposed an IoT cloud-based breast cancer detection system using fuzzy clustering for segmentation and Support Vector Machine (SVM) for classification. The model achieved a high classification accuracy of approximately 99.17% by combining feature extraction with optimal classification techniques. The IoT framework enabled continuous monitoring and predictive analytics for early diagnosis. However, the system relied heavily on cloud infrastructure, leading to increased latency and energy consumption during data transmission. This study highlights the effectiveness of hybrid ML-IoT architectures but emphasizes the need for edge-based optimization.

Nassif et al. (2022) conducted a systematic review of AI-based breast cancer detection methods, emphasizing deep learning models such as CNNs and hybrid architectures. The study concluded that deep learning significantly improves detection accuracy compared to traditional methods and enables early-stage diagnosis, increasing survival rates up to 99% when detected early. However, the research identified challenges such as the requirement for large datasets, computational complexity, and lack of interpretability. This work provides a comprehensive foundation for understanding the evolution of AI-based breast cancer detection systems.

Zhang and Li (2020) introduced a multi-scale Graph Wavelet Neural Network (MS-GWNN) for breast cancer diagnosis using histopathological images. The model captured multi-scale contextual features, improving classification accuracy and robustness. The approach demonstrated superior performance compared to traditional CNN models by incorporating spatial relationships in image data. However, the model required significant computational resources and was not directly optimized for IoT or WSN deployment. This study highlights the importance of advanced neural architectures in improving diagnostic accuracy.

Tabassum and Khan (2020) proposed a Bayesian neural network framework for breast cancer detection with a confidence-based evaluation metric. The model integrates transfer learning with Bayesian inference to provide uncertainty-aware predictions. Experimental results demonstrated improved diagnostic reliability by balancing accuracy and confidence levels. The approach also introduced a novel evaluation metric incorporating coverage and probability thresholds. However, the model requires multiple forward passes, increasing computational overhead. This study highlights the significance of Bayesian learning in clinical decision-making.

Matondo-Mvula et al. (2024) explored quantum convolutional neural networks (QCNNs) for breast cancer detection, representing an extension of quantized and advanced neural architectures. The study demonstrated that quantum-inspired models can achieve comparable or improved accuracy compared to classical CNNs while handling complex feature representations. The approach showed promising results in classification accuracy and feature extraction efficiency. However, the implementation of quantum models requires specialized hardware and remains computationally expensive. This study indicates future directions for integrating advanced neural architectures with IoT-based healthcare systems.

Alzubaidi et al. (2021) presented a comprehensive deep learning framework for breast cancer detection using convolutional neural networks integrated within IoT-enabled healthcare systems. The model utilized advanced preprocessing and augmentation techniques to improve classification performance on mammographic datasets. The results demonstrated high sensitivity and specificity in detecting malignant tumours. However, the model required significant computational resources and was not optimized for deployment on energy-constrained WSN devices. This study emphasizes the need for lightweight architectures in IoT healthcare applications.

Saba et al. (2021) proposed a hybrid transfer learning-based model for breast cancer detection, combining pre-trained CNN architectures with optimized feature selection techniques. The system achieved improved classification accuracy and reduced training time compared to conventional deep learning models. However, the approach still required high memory and computational power, limiting its applicability in WSN environments. This study highlights the effectiveness of transfer learning while indicating the need for energy-efficient model design.

Razzak et al. (2022) introduced an IoT-cloud-based healthcare framework for breast cancer detection using deep learning models. The system enabled real-time data acquisition through IoT devices and leveraged cloud computing for processing and storage. The model achieved high accuracy in detecting cancerous tissues. However, the reliance on cloud infrastructure introduced latency and increased energy consumption during data transmission. This study underscores the importance of edge computing for improving efficiency.

Alshamrani et al. (2023) proposed a quantized deep neural network for breast cancer detection in IoT environments. The model significantly reduced computational complexity and energy consumption by lowering precision levels, enabling deployment on resource-constrained WSN nodes. The system maintained competitive accuracy while achieving substantial energy savings. However, slight accuracy degradation was observed due to quantization. This study demonstrates the importance of quantized models in energy-efficient IoT healthcare systems.

Kumar et al. (2022) developed a Bayesian deep learning-based breast cancer detection system that incorporates probabilistic inference for uncertainty estimation. The model provided confidence scores for predictions, improving diagnostic reliability and decision-making. The system performed well in handling ambiguous cases and reducing false positives. However, the computational overhead associated with Bayesian inference limited its real-time deployment in WSN environments. This study highlights the significance of uncertainty-aware models in healthcare diagnostics.

Ullah et al. (2021) proposed an IoT-based breast cancer detection system utilizing convolutional neural networks deployed over wireless sensor networks. The framework enabled continuous monitoring and real-time diagnosis using distributed sensor nodes. The system demonstrated high classification accuracy and improved accessibility in remote healthcare environments. However, energy consumption and network congestion were identified as major challenges, particularly in large-scale deployments. This study emphasizes 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 systems using optimization techniques. The model focused on minimizing energy consumption and maximizing network lifetime while ensuring reliable data transmission. The proposed system demonstrated improved packet delivery ratio and reduced energy usage. However, the routing algorithm required complex computations and parameter tuning. This study highlights the importance of optimization-driven networking strategies in IoT healthcare environments.

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

Elnour et al. (2022) introduced an attention-based deep learning model for breast cancer detection. The model enhanced feature extraction by focusing on important 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 resource-constrained IoT environments. This study demonstrates the effectiveness of advanced deep learning architectures in medical imaging.

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

Alsubaie et al. (2022) proposed a blockchain-enabled IoT healthcare framework for breast cancer detection using deep learning models. The system ensured secure data transmission and storage through blockchain while leveraging CNNs for accurate classification. The results demonstrated improved data integrity, transparency, and security. However, the integration of blockchain increased latency and computational overhead, making real-time deployment challenging. This study highlights the importance of secure architectures in IoT-based healthcare systems.

Singh et al. (2022) developed an energy-efficient clustering-based routing protocol for WSN-based breast cancer detection systems. The approach optimized communication paths to reduce energy consumption and extend network lifetime. Additionally, machine learning algorithms were integrated for classification tasks. The system demonstrated improved network performance and reliability. However, clustering-based approaches required careful parameter tuning and introduced additional 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 IoT system for breast cancer detection. The system utilized CNNs for classification and blockchain for secure data sharing and access control. The results showed improved diagnostic accuracy, data integrity, and system transparency. However, blockchain operations increased computational overhead and latency. This study demonstrates the potential of integrating AI and blockchain technologies in 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 classification accuracy and provided confidence-aware predictions, enhancing clinical decision-making. However, the computational complexity and training time were significant. This study highlights the importance of combining advanced deep learning architectures with probabilistic modelling.

Comparative Table

Study	Year	Technique Used	Key Contribution	Advantages	Limitations
Majji et al.	2023	CNN + WSN Optimization	Energy-efficient routing	Improved lifetime	Complexity
Aldhyani et al.	2023	GRU + Blockchain	Secure IoMT system	High security	Overhead
Nassif et al.	2022	DL Survey	AI-based detection review	High accuracy insight	No deployment

Tabassum & Khan	2020	Bayesian NN	Uncertainty estimation	Reliable predictions	High computation
Suleiman et al.	2023	ML + Imaging	Early detection systems	Improved accuracy	Scalability issues
Lilhore et al.	2022	SVM + IoT Cloud	High accuracy detection	Efficient classification	Cloud latency
Nassif et al.	2022	DL Review	Comparative DL models	Strong foundation	Data dependency
Zhang & Li	2020	GNN + CNN	Multi-scale features	High accuracy	High computation
Tabassum & Khan	2020	Bayesian DL	Confidence-based results	Reliable	Overhead
Matondo-Mvula et al.	2024	Quantum CNN	Advanced detection	Future-ready	Hardware dependency
Alzubaidi et al.	2021	CNN	High performance detection	Accurate	Resource heavy
Saba et al.	2021	Transfer Learning	Reduced training time	Efficient	High memory
Razzak et al.	2022	IoT + Cloud DL	Remote diagnosis	Real-time	Latency
Alshamrani et al.	2023	Quantized DL	Energy-efficient model	Lightweight	Accuracy drop
Kumar et al.	2022	Bayesian DL	Confidence prediction	Reliable	Computational cost
Ullah et al.	2021	CNN + WSN	Real-time monitoring	Accessible	Energy issues
Alhussein et al.	2022	Routing Optimization	Energy saving	Extended lifetime	Complexity
Kaur et al.	2023	Federated Learning	Privacy preservation	Secure	Sync issues
Elnour et al.	2022	Attention DL	Better feature extraction	High accuracy	Resource heavy
Sharma et al.	2022	DL + PSO	Optimized detection	Efficient	Complexity
Alsubaie et al.	2022	Blockchain + DL	Secure system	Data protection	Latency
Singh et al.	2022	Clustering WSN	Energy-efficient routing	Long lifetime	Complexity
Rahman et al.	2023	DL + Blockchain	Secure sharing	Transparency	Overhead
Wang et al.	2023	Attention + Bayesian	Hybrid model	High reliability	Heavy computation
Iqbal et al.	2021	Lightweight ML	Efficient system	Low energy	Lower accuracy

Comparative Analysis

The comparative analysis of the reviewed studies from 2020 to 2023 reveals a significant transformation in IoT-based breast cancer detection systems, evolving from traditional machine learning approaches to advanced deep learning and hybrid intelligent architectures. Early studies, such as those using Support Vector Machines and basic machine learning models, provided moderate accuracy with lower computational requirements but were limited in handling complex medical imaging data. As research progressed, convolutional neural networks (CNNs) and hybrid architectures became dominant due to their superior feature extraction capabilities and improved classification performance. A major trend observed is the integration of IoT and Wireless Sensor Networks (WSNs) to enable real-time monitoring and remote diagnosis. Systems incorporating IoT frameworks provide improved accessibility and continuous patient monitoring, particularly in remote healthcare environments. However, these systems face challenges related to energy consumption, latency, and network reliability. To address these issues, optimization-based routing protocols and energy-efficient communication strategies have been introduced, significantly improving network lifetime and performance.

Another important advancement is the incorporation of Bayesian neural networks, which provide uncertainty estimation in predictions. Unlike traditional deep learning models, Bayesian approaches offer probabilistic outputs, enabling clinicians to assess prediction confidence. This is particularly critical in medical diagnosis, where errors can have severe consequences. However, these models introduce additional computational complexity, limiting their deployment in resource-constrained environments. Energy efficiency has emerged as a key research focus, particularly in WSN-based healthcare systems. Quantized neural networks and lightweight deep learning models have been developed to reduce computational complexity and energy consumption, enabling deployment on edge devices. Additionally, optimization techniques such as particle swarm optimization, ant colony optimization, and deep reinforcement learning have been used to enhance system performance and reduce energy usage.

Security and privacy are also critical concerns in IoT-based healthcare systems. Blockchain-based architectures have been proposed to ensure secure data transmission and storage, providing transparency and data integrity. However, these systems introduce latency and computational overhead. Furthermore, emerging technologies such as federated learning and quantum-inspired neural networks are gaining attention for their ability to improve privacy and computational efficiency. Federated learning enables decentralized model training without sharing sensitive data, while quantum-inspired models offer advanced computational capabilities for complex data analysis. Overall, the analysis indicates that hybrid approaches combining deep learning, Bayesian modelling, quantization, optimization techniques, and IoT architectures provide the most promising solutions for breast cancer detection. However, challenges such as scalability, computational complexity, and real-time deployment remain open research areas.

Discussion

The survey highlights that IoT-based breast cancer detection systems have evolved significantly with the integration of deep learning, Bayesian modelling, and energy-efficient wireless sensor networks. Convolutional neural networks and hybrid architectures have improved diagnostic accuracy by enabling automated feature extraction from medical images. Additionally, Bayesian neural networks have introduced uncertainty-aware predictions, allowing clinicians to evaluate the confidence of diagnostic outcomes and reduce the risk of misclassification. Energy efficiency remains a critical concern in WSN-based healthcare systems. Quantized neural networks and lightweight deep learning models have been widely adopted to reduce computational complexity and power consumption, enabling 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 improving energy efficiency and reducing transmission latency.

The integration 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 and privacy challenges are addressed through encryption and blockchain-based frameworks, although they may increase computational overhead. Overall, the convergence of IoT, deep learning, and Bayesian approaches provides a promising direction for developing reliable, efficient, and scalable breast cancer detection systems.

Conclusion

Breast cancer continues to be a major global health challenge, requiring early detection and accurate diagnosis to improve patient outcomes and survival rates. The emergence of Internet of Things (IoT)-based healthcare systems has significantly transformed the field of medical diagnostics by enabling real-time monitoring, data acquisition, and remote healthcare services. This survey has provided a comprehensive analysis of methods and architectures for IoT-based breast cancer detection systems, with a particular focus on Bayesian quantized neural networks and energy-efficient wireless sensor networks. Deep learning techniques, particularly convolutional neural networks, have demonstrated exceptional performance in analysing medical imaging data and detecting cancerous tissues with high accuracy. These models automate feature extraction and classification processes, reducing dependency on manual analysis and improving diagnostic efficiency. However, traditional deep learning models are deterministic and lack the ability to quantify uncertainty, which is essential in medical decision-making. Bayesian neural networks address this limitation by incorporating probabilistic modelling, enabling confidence-aware predictions and improving diagnostic reliability.

Energy efficiency is a crucial aspect of IoT-based healthcare systems, especially in wireless sensor networks where devices operate under limited power constraints. Quantized neural networks have emerged as an effective solution by reducing model complexity and computational requirements while maintaining acceptable accuracy levels. These models enable the deployment of deep learning algorithms on edge devices, facilitating real-time diagnosis and continuous monitoring. Optimization techniques have further enhanced system performance by improving energy efficiency, reducing latency, and optimizing network parameters. Algorithms such as particle swarm optimization, genetic algorithms, ant colony optimization, and deep reinforcement learning have been successfully applied to improve both classification performance and network efficiency. These approaches play a vital role in enabling scalable and energy-efficient healthcare systems.

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