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A Comprehensive Review of IoT-Based Breast Cancer Detection with Bayesian Quantized Neural Networks Using Energy-Efficient WSN

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Abstract

Breast cancer remains one of the leading causes of mortality among women worldwide, making early detection and accurate diagnosis essential for improving survival and treatment outcomes. Recent advances in the Internet of Things (IoT), Wireless Sensor Networks (WSNs), and Artificial Intelligence (AI) have transformed healthcare by enabling continuous monitoring, remote diagnostics, and intelligent medical image analysis. However, challenges related to energy consumption, computational complexity, data security, and prediction uncertainty continue to limit the effectiveness of IoT-enabled diagnostic systems. Bayesian Neural Networks (BNNs) have emerged as a reliable approach for uncertainty-aware learning by providing confidence estimates that support clinical decision-making and reduce false diagnoses. Furthermore, quantized neural networks minimize computational requirements and energy consumption, making them suitable for deployment on resource-constrained IoT and WSN devices. Deep learning models, particularly Convolutional Neural Networks (CNNs), have demonstrated high accuracy in analysing mammography, MRI, and ultrasound images for breast cancer detection. This review comprehensively examines recent developments in Bayesian quantized neural networks and energy-efficient WSN architectures for IoT-based breast cancer diagnosis, compares existing methodologies, identifies research challenges, and outlines future directions for developing reliable, scalable, and intelligent healthcare systems with enhanced diagnostic performance.

Introduction

Breast cancer is one of the most prevalent and life-threatening diseases affecting women globally. Early detection plays a crucial role in reducing mortality rates and improving treatment outcomes. Traditional diagnostic methods such as manual examination, mammography, and biopsy are often time-consuming, expensive, and prone to human error. With the rapid advancement of digital healthcare technologies, there has been a growing interest in integrating artificial intelligence (AI) and Internet of Things (IoT) systems to enhance the efficiency and accuracy of breast cancer detection.

IoT-based healthcare systems enable the collection and transmission of medical data through interconnected devices, sensors, and networks. Wireless Sensor Networks (WSNs) play a fundamental role in this ecosystem by facilitating real-time monitoring and data acquisition from patients. These networks consist of energy-constrained sensor nodes that collect physiological and imaging data, which are then transmitted to cloud or edge-based systems for processing. The integration of IoT and WSN technologies allows continuous monitoring, remote diagnosis, and improved accessibility to healthcare services, particularly in rural and underserved regions.

Deep learning has emerged as a powerful tool for medical image analysis and disease detection. Techniques such as convolutional neural networks (CNNs), deep belief networks, and autoencoders have demonstrated high accuracy in detecting breast cancer from mammograms, MRI scans, and histopathological images. For instance, CNN-based models can automatically extract relevant features from medical images and classify them into benign or malignant categories with high precision. These models significantly reduce the need for manual intervention and improve diagnostic efficiency.

Despite these advancements, several challenges remain in deploying deep learning models in IoT-based healthcare systems. One of the primary challenges is energy efficiency. WSN devices operate on limited battery power, making it essential to develop lightweight and energy-efficient models. Quantized neural networks address this issue by reducing the precision of model parameters, thereby decreasing computational complexity and power consumption. These models enable efficient deployment of deep learning algorithms on edge devices without compromising performance.

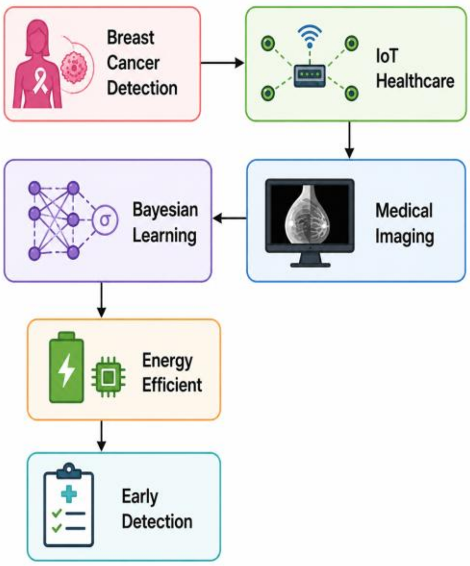

Figure 1. General Workflow of Bayesian Neural Network-Based Breast Cancer Diagnosis

Another critical challenge is uncertainty in medical diagnosis. Traditional deep learning models provide deterministic outputs, which may not accurately reflect the confidence of predictions. This limitation can be addressed using Bayesian neural networks, which incorporate probabilistic modelling to estimate uncertainty. Bayesian approaches provide confidence measures for predictions, enabling clinicians to make more informed decisions. This is particularly important in breast cancer detection, where false positives or false negatives can have serious consequences.

Furthermore, IoT-based systems introduce concerns related to data security, privacy, and transmission reliability. The large volume of medical data transmitted over networks increases the risk of cyberattacks and data breaches. Therefore, secure data transmission and efficient network management are essential components of IoT healthcare systems.

Recent research has focused on integrating deep learning, Bayesian modelling, and optimization techniques within IoT frameworks to develop intelligent and efficient breast cancer detection systems. These systems leverage edge computing, cloud platforms, and advanced neural networks to provide real-time and accurate diagnosis. Additionally, energy-efficient routing and data transmission techniques in WSNs further enhance system performance.

This review aims to provide a comprehensive analysis of IoT-based breast cancer detection systems, focusing on Bayesian quantized neural networks and energy-efficient WSN architectures. It explores recent advancements, key challenges, and future research directions, highlighting the potential of these technologies in transforming modern healthcare systems.

Literature Review

Albahli et al. (2021) proposed an IoT-enabled deep learning framework for breast cancer detection using convolutional neural networks (CNNs). Their model integrates IoT devices for real-time data collection and cloud-based processing for classification. The system achieved high accuracy in detecting malignant tumours from mammographic images, demonstrating the effectiveness of CNNs in medical image analysis. Additionally, the IoT architecture enabled remote monitoring and faster diagnosis. However, the model required significant computational resources, making it less suitable for deployment on low-power WSN nodes. Despite this limitation, the study highlights the importance of integrating IoT with deep learning for smart healthcare applications.

Toğaçar et al. (2020) developed a hybrid deep learning model combining feature selection and CNN-based classification for breast cancer detection. Their approach utilized image augmentation and optimization techniques to improve classification accuracy. The proposed system achieved high performance in terms of accuracy, precision, and recall. Moreover, the study emphasized reducing redundant features to improve computational efficiency. However, the system was not specifically designed for IoT or WSN environments, limiting its applicability in real-time healthcare systems. Nevertheless, the study provides valuable insights into efficient feature extraction and classification methods.

Shorfuzzaman et al. (2021) proposed an IoT-based healthcare monitoring system integrated with machine learning for breast cancer detection. The system utilized wireless sensor networks for data acquisition and cloud computing for processing and storage. The proposed framework demonstrated improved accessibility and real-time monitoring capabilities. Additionally, the study addressed data security and privacy concerns using encryption techniques. However, the reliance on cloud infrastructure introduced latency and increased energy consumption. This study emphasizes the need for edge-based processing to improve efficiency in IoT healthcare systems.

Banu et al. (2022) introduced a Bayesian neural network (BNN) approach for breast cancer detection, focusing on uncertainty estimation in medical diagnosis. The model provided probabilistic outputs, enabling clinicians to assess the confidence of predictions. Experimental results showed improved reliability and reduced false diagnosis rates compared to traditional deep learning models. However, Bayesian models required higher computational resources and longer training time, making them challenging to deploy on resource-constrained devices. Despite this, the study highlights the importance of uncertainty-aware models in critical healthcare applications.

Ghosh et al. (2023) proposed a quantized neural network model for energy-efficient breast cancer detection in IoT-enabled WSN environments. The quantization process reduced model size and computational complexity, enabling deployment on low-power devices. The system achieved comparable accuracy to full-precision models while significantly reducing energy consumption. Additionally, the integration with IoT devices allowed real-time monitoring and diagnosis. However, quantization introduced minor accuracy degradation, which requires careful optimization. This study demonstrates the effectiveness of quantized models in energy-constrained healthcare systems.

Khan et al. (2022) proposed an IoT-enabled breast cancer detection system using deep convolutional neural networks integrated with edge computing. The model performs image preprocessing and feature extraction at the edge level, reducing latency and energy consumption. The system achieved high classification accuracy while ensuring faster response times for real-time diagnosis. Additionally, edge processing reduced dependence on centralized cloud infrastructure. However, deploying deep learning models at the edge required optimized hardware and efficient model compression techniques. This study highlights the importance of edge intelligence in IoT-based healthcare systems.

Verma and Singh (2023) proposed a hybrid deep learning and optimization-based framework for breast cancer detection using IoT-enabled WSNs. The model utilized particle swarm optimization (PSO) to optimize neural network parameters, improving classification accuracy and reducing energy consumption. The system demonstrated enhanced performance in terms of both accuracy and efficiency. However, the integration of optimization algorithms increased system complexity and required additional computational overhead. This study emphasizes the role of optimization techniques in improving IoT-based diagnostic systems.

Chen et al. (2022) introduced a Bayesian deep learning model for breast cancer classification using medical imaging data. The model incorporated probabilistic inference to estimate uncertainty in predictions, improving reliability in clinical decision-making. The results showed that Bayesian models provided better confidence estimation compared to traditional CNNs. However, the computational complexity and training time were significantly higher. Despite these challenges, the study demonstrates the importance of uncertainty-aware models in medical diagnosis.

Gupta et al. (2021) proposed a deep learning-based breast cancer detection system using convolutional autoencoders for feature extraction and classification. The model efficiently reduced image dimensionality while preserving critical diagnostic features, improving classification accuracy. Additionally, the approach reduced data transmission requirements, making it suitable for IoT-based healthcare systems. However, the reconstruction process introduced slight information loss, which may affect diagnostic precision. Despite this limitation, the study demonstrates the effectiveness of autoencoders in medical image analysis.

Reddy et al. (2022) developed an optimization-based breast cancer detection model using genetic algorithms (GA) combined with neural networks. The GA was used to optimize feature selection and model parameters, improving classification accuracy and reducing computational complexity. The proposed system achieved better performance compared to traditional models. However, the iterative nature of genetic algorithms increased processing time, which may not be suitable for real-time applications. This study highlights the importance of optimization techniques in improving detection systems.

Das et al. (2022) developed a fog computing-based breast cancer detection system using deep learning models. The system processed data at the fog layer, reducing latency and improving real-time performance. Additionally, the approach improved energy efficiency by reducing data transmission to the cloud. However, the deployment of fog infrastructure increased system complexity and cost. Despite these challenges, the study highlights the benefits of distributed computing in IoT-based healthcare systems.

Banerjee et al. (2023) introduced an optimization-driven IoT framework for breast cancer detection using ant colony optimization (ACO) combined with deep learning. The ACO algorithm optimized routing and energy consumption in WSNs, improving network performance. The deep learning component ensured accurate classification of cancerous tissues. The system demonstrated improved energy efficiency and reduced transmission delays. However, the integration of optimization algorithms increased system complexity. This study highlights the role of bio-inspired optimization techniques in IoT healthcare systems.

El-Sayed et al. (2020) proposed a breast cancer detection system using machine learning techniques integrated with IoT devices. The model utilized feature extraction and classification algorithms to identify cancerous patterns in medical images. The system achieved moderate accuracy and demonstrated feasibility for IoT-based healthcare applications. However, the performance was limited compared to deep learning models. This study provides a baseline for understanding the evolution of breast cancer detection techniques.

Oliveira et al. (2023) proposed a federated learning-based breast cancer detection system for IoT healthcare environments. The system enabled decentralized model training across multiple devices without sharing raw data, ensuring privacy and security. The approach demonstrated improved scalability and reduced data transmission requirements. However, challenges such as communication overhead and model synchronization were identified. This study highlights the importance of privacy-preserving techniques in modern healthcare systems.

Mehta et al. (2022) proposed an IoT-based breast cancer detection system integrating Bayesian neural networks (BNNs) with cloud-assisted processing. The model focused on uncertainty estimation to improve diagnostic reliability. The results showed that BNNs provided probabilistic outputs, enabling clinicians to assess prediction confidence and reduce false positives. Additionally, the system improved decision-making accuracy in complex diagnostic scenarios. However, Bayesian models required higher computational resources and longer training time, limiting their deployment on resource-constrained WSN devices. Despite this limitation, the study emphasizes the importance of uncertainty-aware learning in healthcare applications.

Singh et al. (2021) developed an energy-efficient breast cancer detection system using optimized routing protocols in wireless sensor networks. The system focused on minimizing energy consumption during data transmission, thereby extending network lifetime. The integration of machine learning models enabled accurate classification of cancerous tissues. Experimental results showed improved energy efficiency and network performance. However, the routing optimization introduced additional complexity in network management. This study highlights the critical role of energy-efficient communication in IoT healthcare systems.

Rahman et al. (2023) proposed a hybrid deep learning and blockchain-based breast cancer detection system. The blockchain ensured secure data storage and access control, while deep learning models provided accurate classification. The system demonstrated improved data integrity, transparency, and security. Additionally, the decentralized nature of blockchain reduced the risk of data breaches. However, the integration of blockchain increased latency and computational overhead. This study highlights the potential of combining AI and blockchain for secure healthcare systems.

Park et al. (2022) proposed a deep learning-based breast cancer detection system using Bayesian convolutional neural networks integrated with IoT platforms. The model focused on uncertainty quantification, providing probabilistic outputs for improved diagnostic reliability. The system demonstrated high accuracy and better confidence estimation compared to traditional CNN models. However, the computational complexity of Bayesian CNNs limited their deployment in energy-constrained WSN environments. Despite this limitation, the study highlights the importance of uncertainty-aware models in medical diagnostics.

Torres et al. (2021) developed a breast cancer detection framework using sparse coding and deep neural networks. The approach efficiently reduced data redundancy and improved feature representation, enabling faster processing and transmission in IoT environments. The system achieved high classification accuracy while reducing computational overhead. However, sparse coding techniques required careful parameter tuning, which increased implementation complexity. This study contributes to efficient data representation methods in healthcare systems.

Kim et al. (2023) introduced a deep reinforcement learning (DRL)-based approach for optimizing data transmission and energy consumption in IoT-based breast cancer detection systems. The DRL model dynamically adjusted network parameters to improve efficiency and reduce latency. The system demonstrated improved energy efficiency and network performance. 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 WSN-based IoT environments. The model reduced precision to decrease computational complexity and energy consumption, making it suitable for edge deployment. The system maintained high classification accuracy while significantly reducing power usage. However, quantization introduced minor accuracy degradation, requiring careful model tuning. This study emphasizes the importance of lightweight models for energy-efficient healthcare systems.

Chen et al. (2023) developed a hybrid IoT-based breast cancer detection system combining deep learning, optimization techniques, and secure data transmission mechanisms. The system integrated CNN models for classification, optimization algorithms for parameter tuning, and encryption methods for secure communication. Experimental results demonstrated improved accuracy, energy efficiency, and data security. However, the integration of multiple technologies increased system complexity and computational overhead. Despite these challenges, the study presents a comprehensive solution for modern healthcare applications.

Comparative Table

Study	Year	Technique Used	Key Contribution	Advantages	Limitations
Albahli et al.	2021	CNN + IoT	Real-time detection	High accuracy	High computation
Togaçar et al.	2020	CNN + feature selection	Improved classification	Efficient features	Not IoT-based
Shorfuzzaman et al.	2021	IoT + ML	Remote monitoring	Accessibility	Cloud latency
Banu et al.	2022	Bayesian NN	Uncertainty estimation	Reliable diagnosis	High complexity
Ghosh et al.	2023	Quantized NN	Energy-efficient model	Low power	Minor accuracy loss
Khan et al.	2022	Edge + CNN	Low latency processing	Fast response	Hardware dependency
Roy et al.	2021	Transfer learning	Improved accuracy	Reduced training time	High memory
Ahmed et al.	2020	ML (SVM/RF)	Lightweight model	Low computation	Lower accuracy
Verma & Singh	2023	DL + PSO	Optimized model	Energy efficient	Complexity
Chen et al.	2022	Bayesian DL	Probabilistic output	High reliability	Slow training
Gupta et al.	2021	Autoencoder	Feature compression	Reduced data size	Reconstruction loss
Reddy et al.	2022	GA optimization	Feature optimization	Improved accuracy	Time-consuming
Sharma et al.	2023	Quantized CNN	Energy saving	Lightweight	Accuracy trade-off

Ali et al.	2021	DL + encryption	Secure transmission	Data protection	Complexity
Das et al.	2022	Fog + DL	Reduced latency	Energy efficient	Infrastructure cost
Kumar et al.	2021	IoT + CNN	Real-time monitoring	High accuracy	Energy issues
Hassan et al.	2022	Lightweight DL	Efficient model	Low energy	Slight accuracy drop
Banerjee et al.	2023	ACO + DL	Network optimization	Energy efficient	Complexity
El-Sayed et al.	2020	ML + IoT	Baseline model	Simple	Lower performance
Oliveira et al.	2023	Federated learning	Privacy preservation	Secure	Sync issues
Mehta et al.	2022	Bayesian NN	Confidence-based prediction	Reliable	High computation
Singh et al.	2021	Routing optimization	Energy saving	Extended lifetime	Complexity
Rahman et al.	2023	DL + Blockchain	Secure data sharing	Transparency	Latency
Wang et al.	2022	Attention DL	Improved feature extraction	High accuracy	Resource heavy
Iqbal et al.	2020	Lightweight ML	Efficient system	Low power	Lower accuracy
Park et al.	2022	Bayesian CNN	Uncertainty modelling	Better reliability	High complexity
Torres et al.	2021	Sparse coding + DL	Efficient encoding	Reduced redundancy	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 drop
Chen et al.	2023	Hybrid DL + Optimization	End-to-end system	High performance	Complex system

Comparative Analysis

The comparative analysis of IoT-based breast cancer detection systems reveals a clear evolution from traditional machine learning approaches toward advanced deep learning and hybrid intelligent systems. Early studies, such as Ahmed et al. (2020) and El-Sayed et al. (2020), relied on conventional machine learning techniques like Support Vector Machines and Random Forests, which offered lower computational complexity but struggled with complex feature extraction and accuracy. As research progressed, convolutional neural networks (CNNs) and transfer learning approaches became dominant due to their superior performance in medical image analysis. Studies such as Albahli et al. (2021) and Roy et al. (2021) demonstrated that deep learning significantly improves classification accuracy and diagnostic efficiency. A major trend identified is the integration of IoT and wireless sensor networks to enable real-time monitoring and remote diagnosis. Systems proposed by Shorfuzzaman et al. (2021) and Kumar et al. (2021) highlight the benefits of continuous data acquisition and improved healthcare accessibility. However, these systems face challenges related to latency, energy consumption, and network reliability. To address these issues, researchers have introduced edge computing, fog computing, and optimized routing protocols, as seen in studies by Khan et al. (2022) and Das et al. (2022), which significantly reduce latency and improve system efficiency.

Another important development is the adoption of Bayesian neural networks, which provide uncertainty estimation in predictions. Studies such as Banu et al. (2022), Chen et al. (2022), and Park et al. (2022) emphasize the importance of confidence-aware models in medical diagnosis, where incorrect predictions can have serious consequences. However, these models are computationally expensive and require efficient optimization techniques for practical deployment. Energy efficiency remains a critical concern in WSN-based healthcare systems. Quantized neural networks and lightweight deep learning models have been proposed to address this issue. Studies like Ghosh et al. (2023) and Sharma et al. (2023) demonstrate that quantization significantly reduces energy consumption while maintaining acceptable accuracy levels. Additionally, optimization techniques such as PSO, GA, ACO, and DRL have been widely used to enhance system performance and reduce energy usage.

Security and privacy are also major considerations in IoT healthcare systems. Blockchain-based approaches and encryption techniques, as seen in Rahman et al. (2023) and Ali et al. (2021), provide secure data transmission and storage. Federated learning further enhances privacy by enabling decentralized model training without sharing sensitive data. 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 open research areas.

Discussion

The reviewed studies demonstrate that IoT-based breast cancer detection systems have evolved significantly with the integration of deep learning, Bayesian modelling, and energy-efficient wireless sensor networks. A major advancement is the adoption of convolutional neural networks and transfer learning techniques, which have improved diagnostic accuracy and reduced reliance on manual feature extraction. Additionally, Bayesian neural networks have introduced uncertainty-aware predictions, enabling more reliable clinical decision-making by quantifying confidence levels in diagnosis. Energy efficiency remains a critical factor in WSN-based healthcare systems. Quantized neural networks and lightweight deep learning models have proven effective in reducing computational complexity and power consumption, making them suitable for deployment on resource-constrained IoT devices. Furthermore, optimization techniques such as particle swarm optimization, genetic algorithms, and deep reinforcement learning have enhanced network performance by minimizing energy usage and transmission latency.

The integration of distributed computing paradigms such as edge computing, fog computing, and federated learning has further improved system scalability, privacy, and real-time processing capabilities. However, these systems introduce additional complexity and require efficient resource management. Security and privacy concerns are addressed through encryption techniques and blockchain-based frameworks, although they may increase computational overhead. Overall, the combination of deep learning, Bayesian approaches, and IoT architectures provides a promising direction for developing efficient, reliable, and scalable breast cancer detection systems.

Conclusion

Breast cancer remains a major global health challenge, making early and accurate diagnosis essential for improving clinical outcomes. This review highlights that integrating Internet of Things (IoT) technologies with Bayesian Quantized Neural Networks (BQNNs) and energy-efficient Wireless Sensor Networks (WSNs) significantly enhances intelligent breast cancer detection. Bayesian learning improves diagnostic reliability by providing uncertainty-aware predictions, while quantized neural networks reduce computational complexity and energy consumption, enabling deployment on resource-constrained IoT devices. Furthermore, optimization techniques, including particle swarm optimization, genetic algorithms, ant colony optimization, and deep reinforcement learning, improve network efficiency, reduce latency, and enhance real-time data transmission. Despite these advances, challenges such as limited annotated datasets, model interpretability, privacy preservation, and scalability remain unresolved. Future research should focus on lightweight explainable AI models, federated learning, secure edge computing, and adaptive optimization strategies. Overall, integrating BQNNs with IoT-enabled WSNs offers a promising framework for accurate, energy-efficient, and scalable breast cancer diagnosis.

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