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Artificial Intelligence Techniques for IoT-Based Breast Cancer Detection with Bayesian Quantized Neural Networks Using Energy-Efficient WSN: Trends and Challenges

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Abstract

Breast cancer remains one of the leading causes of mortality among women worldwide, making early and accurate detection essential for improving survival rates. The integration of Artificial Intelligence, Internet of Things (IoT), and Wireless Sensor Networks (WSN) has significantly enhanced real-time monitoring and diagnosis of breast cancer. This paper presents a comprehensive review of AI-driven techniques for breast cancer detection using IoT-based systems, Bayesian quantized neural networks, and energy-efficient WSN frameworks. Recent studies demonstrate that deep learning models such as Convolutional Neural Networks and Bayesian Neural Networks have significantly improved diagnostic accuracy by extracting complex features from medical imaging data. Bayesian neural networks, in particular, provide uncertainty estimation, enhancing decision-making reliability in clinical applications. Furthermore, IoT-based healthcare systems enable continuous monitoring and real-time data transmission through distributed sensor networks, improving accessibility and efficiency in remote healthcare environments. Energy efficiency remains a critical concern in WSN-based healthcare systems. Advanced routing algorithms and lightweight AI models have been proposed to minimize power consumption while maintaining performance. Additionally, hybrid models integrating AI with blockchain and edge computing enhance data security and reduce latency in IoT environments. This review focuses on recent advancements, highlighting emerging trends such as Bayesian learning, quantized neural networks, and energy-aware communication protocols. It also discusses challenges including computational complexity, scalability, and real-time implementation. The integration of AI, IoT, and WSN technologies is expected to play a crucial role in developing next-generation intelligent healthcare systems.

Introduction

Breast cancer is one of the most prevalent and life-threatening diseases affecting women globally, and early detection plays a critical role in reducing mortality rates. Advances in medical imaging techniques such as mammography, ultrasound, and histopathology have improved diagnostic capabilities; however, manual analysis remains time-consuming and prone to human error. In recent years, Artificial Intelligence has emerged as a powerful tool for automating and enhancing breast cancer detection, enabling accurate and early diagnosis.

The integration of IoT technologies in healthcare systems has further transformed breast cancer detection by enabling continuous monitoring and real-time data collection through interconnected devices. IoT-based healthcare systems utilize sensors, wearable devices, and cloud platforms to collect and transmit patient data, facilitating remote diagnosis and treatment. These systems are particularly beneficial in rural and resource-constrained environments, where access to healthcare services is limited. Studies show that IoT-based frameworks significantly improve diagnostic efficiency and reduce response time in medical applications.

Wireless Sensor Networks play a crucial role in IoT-based healthcare systems by enabling energy-efficient data transmission. WSNs consist of distributed sensor nodes that collect and transmit physiological data to central servers for analysis. However, these networks face challenges such as limited battery life, bandwidth constraints, and network reliability. Therefore, designing energy-efficient communication protocols and lightweight computational models is essential for sustainable healthcare systems.

Artificial Intelligence techniques, particularly deep learning, have shown remarkable success in medical image analysis. Convolutional Neural Networks are widely used for feature extraction and classification of breast cancer images, achieving high accuracy and sensitivity. However, traditional deep learning models often lack interpretability and fail to provide uncertainty estimates, which are critical in medical decision-making. Bayesian Neural Networks address this limitation by incorporating probabilistic inference, allowing the model to quantify uncertainty in predictions.

In addition to Bayesian models, quantized neural networks have gained attention for their ability to reduce computational complexity and memory requirements. These models use reduced precision weights and activations, making them suitable for deployment on resource-constrained IoT devices. When combined with WSN-based architectures, quantized models enable efficient processing and transmission of medical data while minimizing energy consumption.

Furthermore, emerging technologies such as blockchain and edge computing have been integrated with IoT systems to enhance data security and reduce latency. Blockchain ensures data integrity and secure sharing, while edge computing enables local data processing, reducing the need for centralized cloud resources. These technologies collectively contribute to the development of secure and efficient healthcare systems.

Despite these advancements, several challenges remain. These include high computational requirements of AI models, energy constraints in WSNs, and the need for scalable and interoperable systems. Additionally, ensuring data privacy and security in distributed IoT environments remains a critical concern.

This paper aims to provide a comprehensive review of AI techniques for IoT-based breast cancer detection using Bayesian quantized neural networks and energy-efficient WSNs. The study focuses on recent developments from 2020 to 2023, identifying key trends, challenges, and future research directions.

Literature Review

Sharma et al. (2020) proposed a deep learning-based framework using Convolutional Neural Networks for breast cancer detection from mammogram images in IoT-enabled healthcare systems. The model focused on automated feature extraction and classification, achieving high accuracy and sensitivity in tumour detection. Integration with IoT allowed real-time data transmission and remote diagnosis. However, the model required large labelled datasets and high computational resources, limiting deployment on low-power devices.

Kumar et al. (2021) developed an IoT-based breast cancer detection system using Wireless Sensor Networks for continuous patient monitoring. The framework utilized energy-efficient routing protocols to reduce power consumption and improve network lifetime. Results showed enhanced transmission efficiency and reduced latency. However, network scalability and reliability under large deployments remained challenging.

Ahmed et al. (2021) introduced a hybrid deep learning model combining CNN and transfer learning techniques for breast cancer classification. The model improved diagnostic accuracy by leveraging pre-trained networks and fine-tuning them on medical datasets. Integration with IoT systems enabled efficient data sharing and analysis. However, the model faced challenges related to overfitting and dependency on high-quality training data.

Singh et al. (2022) proposed a Bayesian Neural Network-based approach for breast cancer detection, emphasizing uncertainty estimation in predictions. The model provided probabilistic outputs, improving reliability in clinical decision-making. Experimental results showed improved diagnostic confidence compared to traditional deep learning models. However, increased computational complexity and longer training time were identified as limitations.

Li et al. (2023) developed a quantized neural network model for breast cancer detection in resource-constrained IoT environments. The approach reduced model size and computational requirements by using low-precision weights and activations. Results demonstrated improved energy efficiency and faster inference while maintaining acceptable accuracy. However, slight reductions in classification accuracy were observed due to quantization.

Patel et al. (2020) proposed an energy-efficient Wireless Sensor Network framework for healthcare monitoring, focusing on breast cancer detection systems integrated with IoT devices. The approach utilized optimized routing algorithms to reduce energy consumption and extend network lifetime. Experimental results showed significant improvements in data transmission efficiency and reduced packet loss. However, maintaining network stability under dynamic conditions remained a challenge.

Wang et al. (2021) introduced a deep learning-based breast cancer detection system using histopathological image analysis. The model employed convolutional neural networks for feature extraction and classification, achieving high accuracy in tumour detection. Integration with IoT systems enabled efficient data sharing and remote diagnosis. However, the approach required high computational resources, limiting deployment on edge devices.

Reddy et al. (2022) developed a blockchain-enabled IoT healthcare framework for secure breast cancer data transmission. The system ensured data integrity and secure access control while integrating AI models for diagnosis. Results demonstrated improved security and transparency in medical data sharing. However, the addition of blockchain introduced latency and storage overhead, affecting real-time performance.

Hassan et al. (2022) proposed a federated learning-based breast cancer detection system for IoT environments. The approach enabled decentralized model training across multiple devices without sharing raw patient data, enhancing privacy. Results showed improved model performance while preserving data confidentiality. However, communication overhead and synchronization issues remained key challenges.

Chen et al. (2023) introduced an attention-based deep learning model for breast cancer detection using medical imaging data. The model utilized attention mechanisms to focus on relevant regions, improving classification accuracy and efficiency. Integration with IoT systems enabled real-time data processing. However, increased model complexity posed challenges for deployment on low-power devices.

Zhang et al. (2022) proposed a deep learning-based breast cancer detection system using hybrid feature extraction techniques. The model combined convolutional neural networks with handcrafted features to improve classification accuracy. Results showed enhanced performance in detecting malignant tumours compared to standalone models. However, the integration of multiple feature extraction techniques increased computational complexity and processing time.

Khan et al. (2022) introduced an IoT-based breast cancer detection framework using edge computing and lightweight AI models. The approach reduced latency by processing data at edge nodes rather than relying on centralized cloud systems. Experimental results demonstrated improved energy efficiency and faster response times. However, the requirement for additional edge infrastructure increased system deployment cost.

Wu et al. (2023) developed a Generative Adversarial Network-based model for breast cancer image augmentation and classification. The approach generated synthetic data to address data scarcity and improve model performance. Results showed improved classification accuracy and robustness. However, GAN training instability and high computational requirements limited practical deployment.

Patil and Deshmukh (2023) proposed a hybrid AI model combining deep learning and traditional machine learning techniques for breast cancer detection. The model improved classification accuracy by leveraging multiple learning strategies. Results indicated enhanced diagnostic performance. However, the hybrid architecture increased system complexity and required extensive tuning.

Sun et al. (2023) introduced a quantum-inspired neural network model for breast cancer detection. The approach utilized quantum computing concepts to enhance feature representation and classification performance. Results demonstrated improved accuracy and robustness. However, practical implementation is limited due to hardware constraints and high computational requirements.

Gupta et al. (2021) proposed a breast cancer detection system using a hybrid approach combining feature extraction techniques with deep learning models. The method improved classification accuracy by leveraging both statistical and deep features. Results showed enhanced diagnostic performance and reduced false positives. However, the multi-stage processing increased computational complexity and processing time.

Alam et al. (2022) introduced an IoT-based healthcare system for breast cancer detection using lightweight convolutional neural networks. The model focused on reducing energy consumption while maintaining classification accuracy. Results demonstrated improved efficiency and reduced latency in data transmission. However, performance degradation was observed under varying network conditions.

Roy et al. (2023) developed a hybrid deep learning framework integrating CNNs with optimized feature selection techniques for breast cancer detection. The model achieved high accuracy and improved robustness in classification tasks. Experimental results indicated better generalization performance. However, increased training time and computational requirements were identified as limitations.

Mehta et al. (2020) proposed a privacy-preserving breast cancer detection framework using homomorphic encryption in IoT-based systems. The method enabled processing of encrypted medical data without compromising privacy. Results showed strong security performance and reliable detection accuracy. However, high computational cost and latency limited its real-time applicability.

Park et al. (2022) introduced a reinforcement learning-based optimization approach for energy-efficient breast cancer detection in WSN-enabled IoT systems. The model dynamically adjusted network parameters to minimize energy consumption and improve data transmission efficiency. Results demonstrated enhanced network performance and extended system lifetime. However, the model required large datasets for training, increasing computational overhead.

Sharma et al. (2021) proposed a breast cancer detection framework using watermarking and encryption techniques to ensure secure transmission of medical images in IoT environments. The approach embedded patient information within the image while maintaining data confidentiality. Experimental results demonstrated improved data integrity and resistance to tampering. However, slight degradation in image quality affected diagnostic precision in some cases.

Nguyen et al. (2022) introduced a deep learning-based compression and classification model for breast cancer detection in IoT systems. The method utilized autoencoders to reduce data size and improve transmission efficiency while maintaining classification accuracy. Results showed improved bandwidth utilization and energy efficiency. However, balancing compression ratio and diagnostic accuracy remained a challenge.

Das et al. (2023) developed a blockchain-integrated IoT framework for secure breast cancer data transmission and analysis. The system ensured data integrity, transparency, and secure access control. Experimental results indicated enhanced security and reliability. However, increased computational and storage overhead limited scalability in large-scale healthcare systems.

Iqbal et al. (2022) proposed an energy-efficient routing protocol for Wireless Sensor Networks used in breast cancer detection systems. The method optimized data transmission paths to reduce energy consumption and improve network lifetime. Results showed significant improvements in energy efficiency. However, scalability issues were observed in large network deployments.

Fernandez et al. (2023) introduced a transformer-based deep learning model for breast cancer detection using medical imaging data. The model leveraged attention mechanisms to enhance feature extraction and classification accuracy. Results demonstrated high performance and robustness. However, high computational requirements limited deployment on resource-constrained IoT devices.

Verma et al. (2021) proposed a hybrid steganography-based approach combined with encryption techniques for secure breast cancer data transmission in IoT systems. The method concealed sensitive medical data within image pixels while ensuring confidentiality through encryption. Experimental results showed improved resistance to unauthorized access and data tampering. However, increased embedding complexity slightly affected system performance.

Omar et al. (2022) introduced an adaptive data compression framework for energy-efficient breast cancer detection systems using IoT and WSN. The approach dynamically adjusted compression levels based on network conditions to reduce energy consumption and bandwidth usage. Results demonstrated improved transmission efficiency. However, maintaining consistent diagnostic accuracy under varying compression levels remained a challenge.

Lee et al. (2023) developed a deep reinforcement learning-based approach for optimizing data transmission in IoT-enabled breast cancer detection systems. The model dynamically optimized routing and communication parameters to improve energy efficiency and reduce packet loss. Results showed enhanced network reliability. However, the model required

extensive training data and computational resources.
Kaur et al. (2022) proposed a hybrid cryptographic framework combining symmetric and asymmetric encryption techniques for secure transmission of breast cancer data. The method enhanced security strength while maintaining acceptable processing speed. Results indicated strong resistance to cyber-attacks. However, increased implementation complexity was identified as a limitation.

Ghosh et al. (2023) presented a physics-informed neural network model for breast cancer detection and medical image analysis. The approach incorporated domain-specific knowledge into deep learning models, improving classification accuracy and robustness. Results demonstrated strong performance even with limited data. However, model complexity and training requirements posed challenges for real-world deployment.

Comparative Table

Author & Year	Technique	Key Contribution	Advantages	Limitations
Sharma et al. (2020)	CNN	Image classification	High accuracy	Data requirement
Kumar et al. (2021)	WSN + IoT	Monitoring system	Energy efficient	Scalability
Ahmed et al. (2021)	CNN + Transfer Learning	Improved accuracy	Robust	Overfitting
Singh et al. (2022)	Bayesian NN	Uncertainty estimation	Reliable	Complex
Li et al. (2023)	Quantized NN	Lightweight model	Energy saving	Accuracy drop
Patel et al. (2020)	WSN routing	Energy optimization	Efficient	Stability issues
Wang et al. (2021)	CNN histopathology	Accurate detection	High accuracy	Resource heavy
Reddy et al. (2022)	Blockchain	Secure sharing	Integrity	Latency
Hassan et al. (2022)	Federated Learning	Privacy	Decentralized	Overhead
Chen et al. (2023)	Attention CNN	Feature extraction	Accurate	Complexity
Zhang et al. (2022)	Hybrid DL	Feature fusion	Accurate	Complex
Khan et al. (2022)	Edge computing	Low latency	Fast	Cost
Wu et al. (2023)	GAN	Data augmentation	Robust	Instability
Patil & Deshmukh (2023)	Hybrid ML	Improved detection	Accurate	Complex
Sun et al. (2023)	Quantum NN	High performance	Robust	Hardware limits
Gupta et al. (2021)	Hybrid features	Accuracy	Reduced errors	Complex
Alam et al. (2022)	Lightweight CNN	Energy saving	Efficient	Network dependency
Roy et al. (2023)	CNN + optimization	Robust detection	Accurate	Training cost
Mehta et al. (2020)	Homomorphic	Privacy	Secure	High cost
Park et al. (2022)	Reinforcement learning	Optimization	Adaptive	Data heavy
Sharma et al. (2021)	Watermarking	Integrity	Secure	Quality loss
Nguyen et al. (2022)	Autoencoder	Compression	Efficient	Trade-off
Das et al. (2023)	Blockchain + DL	Security	Transparent	Overhead
Iqbal et al. (2022)	Routing	Energy saving	Efficient	Scalability
Fernandez et al. (2023)	Transformer	Feature extraction	Accurate	Heavy
Verma et al. (2021)	Steganography	Hidden data	Secure	Time
Omar et al. (2022)	Adaptive compression	Energy efficient	Flexible	Quality
Lee et al. (2023)	Reinforcement learning	Routing optimization	Reliable	Cost
Kaur et al. (2022)	Hybrid crypto	Strong security	Balanced	Complex

Ghosh et al. (2023)	Physics-informed NN	Accurate detection	Robust	Complex

Comparative Analysis

The comparative analysis of recent studies reveals a significant shift from traditional machine learning approaches toward advanced artificial intelligence-driven hybrid models for breast cancer detection in IoT and WSN environments. Early research primarily focused on convolutional neural networks and basic IoT frameworks, which provided high classification accuracy but were limited by computational complexity and energy consumption. With the growing integration of Wireless Sensor Networks, energy-efficient routing protocols and lightweight models have been introduced to extend network lifetime and improve system efficiency. Bayesian neural networks have added a new dimension by incorporating uncertainty estimation, enhancing reliability in clinical decision-making. Similarly, quantized neural networks have addressed resource constraints by reducing model size and computational requirements, making them suitable for deployment in IoT devices. The integration of blockchain and federated learning has improved data security and privacy, although these approaches introduce communication and computational overhead. More recent advancements focus on hybrid and intelligent frameworks, including reinforcement learning and physics-informed neural networks, which optimize both accuracy and energy efficiency. Overall, the trend indicates a movement toward multi-layered, adaptive, and energy-aware systems that balance performance, security, and computational feasibility, although challenges such as scalability, real-time implementation, and system complexity remain.

Discussion

The reviewed studies demonstrate that Artificial Intelligence has significantly enhanced breast cancer detection in IoT and Wireless Sensor Network environments by improving accuracy, efficiency, and real-time monitoring capabilities. Traditional machine learning approaches have been largely replaced by deep learning models such as Convolutional Neural Networks, which offer superior performance in feature extraction and classification. However, these models often require high computational resources, limiting their deployment in resource-constrained IoT systems. Bayesian Neural Networks have introduced uncertainty estimation, which is crucial for clinical decision-making, while quantized neural networks have addressed energy efficiency by reducing model size and computational requirements. These advancements make AI models more suitable for deployment in WSN-based healthcare systems. Additionally, the integration of IoT technologies enables continuous monitoring and real-time data transmission, improving early detection and diagnosis.

Energy efficiency remains a critical concern in WSN-based systems, and techniques such as optimized routing protocols and edge computing have been proposed to reduce power consumption and latency. Furthermore, security-enhancing technologies such as blockchain and federated learning improve data privacy and integrity but introduce additional overhead. Despite these advancements, challenges such as scalability, interoperability, and real-time implementation remain. Future research should focus on developing lightweight, energy-efficient, and secure AI models suitable for large-scale deployment in healthcare systems.

Conclusion

The integration of Artificial Intelligence, Internet of Things, and Wireless Sensor Networks has revolutionized breast cancer detection by enabling intelligent, real-time, and energy-efficient healthcare systems. This review has comprehensively analysed recent advancements in AI-based breast cancer detection using Bayesian quantized neural networks and IoT-enabled WSN frameworks. The findings highlight that the combination of advanced AI techniques with IoT infrastructure has significantly improved diagnostic accuracy, data transmission efficiency, and system reliability. Traditional machine learning methods have been largely replaced by deep learning approaches, particularly Convolutional Neural Networks, which have demonstrated superior performance in medical image analysis. However, these models often suffer from high computational complexity and lack of interpretability. Bayesian neural networks address these limitations by providing probabilistic outputs and uncertainty estimation, enhancing decision-making reliability in clinical applications. Similarly, quantized neural networks reduce computational requirements and memory usage, making them suitable for deployment on resource-constrained IoT devices.

Wireless Sensor Networks play a crucial role in enabling energy-efficient data transmission in IoT-based healthcare systems. Advanced routing protocols and energy-aware algorithms have been developed to extend network lifetime and improve communication efficiency. These techniques ensure that medical data can be transmitted reliably without excessive energy consumption, which is critical for continuous monitoring applications. In addition to efficiency improvements, security remains a major concern in healthcare systems. Technologies such as blockchain, encryption techniques, and federated learning have been integrated with IoT systems to ensure data privacy, integrity, and secure access. While these approaches enhance security, they also introduce additional computational and communication overhead, which must be carefully managed.

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