An Efficient Optimization System for Early Breast Cancer Diagnosis based on Internet of Medical Things and Deep Learning

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Received: 10 June 2024 | Revised: 26 June 2024 | Accepted: 30 June 2024

 DOI: https://doi.org/10.48084/etasr.8080

ABSTRACT

Improving patient outcomes and treatment efficacy requires effective early detection of breast cancer. Recently, medical diagnostics has been transformed by merging the Internet of Things (IoT) technology with AI and ML methods. Better and faster diagnoses have been made possible by this revolutionary synergy, which allows the study of both real-time and historical data. Unfortunately, many people still die from breast cancer because modern diagnostics are not good enough to catch the disease in its early stages, even though medical science has come a long way. To overcome this obstacle, this study introduces a new medical diagnostic system that utilizes IoT to accurately distinguish between patients with and without tumors. The proposed model achieved 95% classification accuracy in differentiating between non-tumor and tumor instances by utilizing a Convolutional Neural Network (CNN) with hyperparameter adjustment. This approach can improve the accuracy and efficiency of breast cancer diagnosis by integrating medical devices with AI applications and healthcare infrastructure. In the long run, this study could help reduce breast cancer deaths by increasing early detection rates. This study can revolutionize healthcare delivery and improve patient outcomes on a global scale through continued innovation and collaboration with medical IoT technology.

Keywords-breast cancer classification; medical Internet of Things (IoT); deep learning; Convolutional Neural Network

I. INTRODUCTION

Deaths caused by breast cancer account for almost 36% of all female cancer deaths each year, making it the most common disease among women according to the World Health Organization (WHO). Breast cancer ranks second in both incidence and mortality rates among both sexes. Detecting breast cancer at an early stage is the most effective strategy to save lives and reduce healthcare expenditures [1]. As breast cancer detection and diagnostic technology evolves, patients have access to more effective and less invasive options. Mammography is very important for reducing the mortality rates of breast cancer. With the fast advancement of smart medical equipment, the healthcare sector is poised to reap the benefits of the Internet of Things (IoT) in several ways. Today, significant changes are happening in the healthcare sector around the world [2, 3]. Industrial IoT is one of the fastest-growing networks that can collect and share massive volumes of data from healthcare sensors [4]. Sometimes, it is referred to as Medical IoT (MioT), the Internet of Health Things (IoHT), or the Internet of Medical Things (IoMT). IoMT denotes an interconnected system of health systems, devices, apps, and services. Sensor nodes that collect data from the patient's body via smart portable devices are examined to determine their physical attributes. Integrating IoMT with AI methods allows fast and flexible medical data analysis and diagnosis while allowing distant and wireless devices to connect securely over the Internet. Telehealth services have allowed for effective illness identification, remote patient monitoring, and treatment for both patients and caregivers or medical professionals. The convergence of these technologies has brought about a new era in healthcare, known as Healthcare Industry 4.0. This study proposes an approach to improve and refine the selection of important features that can detect tumors early using Machine Learning (ML) techniques and optimizing the hyperparameters of a Convolutional Neural Network (CNN) model to achieve better classification results. Using sophisticated optimization methods, this framework provides a new way to fine-tune CNN parameters, which in turn improves performance, accuracy, and effectiveness in many applications, including medical diagnosis and image recognition.

II. RELATED WORKS

In [5], an IoT-based diagnostic system was proposed to reliably classify tumors as malignant or benign using a Support Vector Machine (SVM). In [6], ML was used to analyze big data from a healthcare network and create a disease prediction system. This study used several prognostic approaches based on data collected from a real medical facility in China between 2013 and 2015. In [7], inactive factor testing was used to successfully recover fragmented data, and CNN modifications were proposed to reduce the likelihood of creating unstructured multimodal data with medical diagnoses. In [8], an exhaustive evaluation of recommended healthcare diagnostic techniques was carried out. Big data strategies can help healthcare organizations manage their ever-expanding datasets. Despite the lack of a critical goal in this sector, this process starts with evaluating the state of big data in the medical sector. Predicting how ML and big data will impact healthcare systems is challenging.

Automated training and classification using breast cancer dataset features is possible with the use of Deep Learning (DL) [9]. Numerous studies have used the Wisconsin Prognostic Breast Cancer Chemotherapy (WPBCC) and WDBC criteria over the years [2]. Several studies have investigated breast cancer detection and ML, such as Naive Bayes (NB), Decision Tree (DT), Logistic Regression (LR), Random Forest (RF), and SVM, to implement various classification methods. Feature selection approaches have been used to assign the best features to increase projected accuracy. In [10], a method was proposed to increase early-stage breast cancer survival. In [11], deep CNN and computer-assisted diagnostics were used to detect breast cancer in its early stages. In [12], methodological and objective prediction markers were established in breast cancer classification. Based on the prognostic factor, two classifiers, K-Nearest-Neighbor (kNN) and NB, were used to detect breast cancer. In [13], four distinct approaches were devised to select features and identify cancer types, including NB, NN, DT, and LR. In [14, 15], three cancer classification methods were used, namely SVM, NB, and DT, using dimensionality reduction in feature selection to alleviate fitness issues.

According to [15], ML models should be prioritized for early breast cancer diagnosis. This study attempted to devise a method to help patients determine their own risk for the disease at an early stage. On the validation dataset, the proposed CNN approach achieved an accuracy of approximately 86%. In [16], DL was used to create a system that reduces noise and improves low-dose mammography images. Skilled practitioners may provide excellent results with low-dose mammography [17]. Thus, low-dose mammography will become more dependent on cutting-edge DL methods. In [18], multi-label image classification was used with a pre-trained CNN and applied end-to-end image representation learning to solve new problems. Furthermore, an issue-specific label selection method was proposed to determine the optimal level of confidence for each visual idea. This study showed that this method was useful and achieved better results than commonly used baselines on the following benchmark datasets: MIAS, INBreast, BCDR, and CBIS-DDSM [19, 20].

III. METHODOLOGY

A. Dataset

This study used a modified version of the PatchCamelyon (PCam) benchmark dataset. Originally, the PCam dataset contained duplicate images due to its probabilistic sampling method. However, the version used has been curated to exclude duplicate entries [21]. The PatchCamelyon benchmark dataset presents a novel and challenging task in image classification. It comprises a total of 327,680 color images, each with dimensions of 96×96 pixels. These images are extracted from histopathologic scans of lymph node sections. In particular, each image in the dataset is annotated with a binary label indicating the presence or absence of metastatic tissue. PCam represents a significant benchmark for ML models, occupying a space between the CIFAR10 and ImageNet datasets in terms of size and complexity. One of the key advantages of PCam is its trainability on a single GPU, making it accessible for researchers and practitioners with limited computational resources.

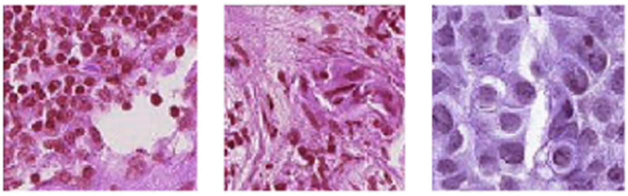

Fig. 1. A sample of the PatchCamelyon dataset.

B. Proposed IoMT-Based Framework

Figure 2 shows the framework of the proposed IoMT-based approach for diagnosing breast cancer. This approach is structured into three key stages. Initially, histopathological breast samples are obtained from patients for testing. Cell images captured by a microscopy imaging device are then transmitted to a cloud data server to offer additional functionality. Histopathological image samples, including annotations, are stored in the patient's health record database. Subsequently, the acquired sample features are analyzed using a custom-built CNN model. This framework prioritizes the use of cloud computing services to classify uploaded samples to minimize the consumption of computational resources and file storage. Finally, the results of breast cancer detection are relayed to the therapist's computer display or smartphone for verification and finalization, along with medical recommendations. Doctors can access the platform using desktop, laptop, or mobile devices through a web interface.

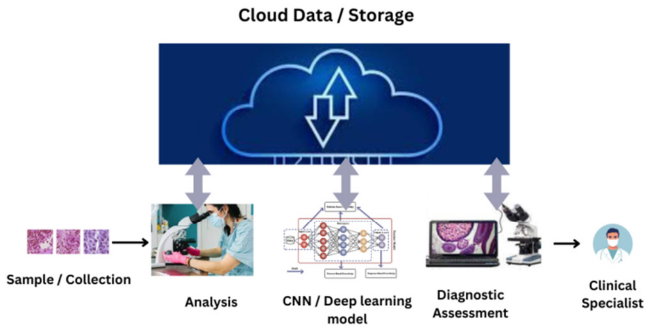

Fig. 2. IoMT framework for health monitoring.

The proposed method for breast cancer detection integrates MIoT technology with CNN to streamline the diagnostic process. Initially, mammogram images or breast tissue samples are collected by medical professionals as part of routine screening or diagnostic procedures. These samples are then subjected to analysis using a CNN DL model. The CNN model utilizes its sophisticated algorithms to examine the samples, identifying patterns and anomalies indicative of breast cancer. Then, the evaluated data is safely kept in the cloud, where it can be accessed and scaled without compromising data privacy or integrity. Remote access to test data and streamlined teamwork are possible with this cloud-based storage solution. After the examination is completed, a medical expert, usually a radiologist who specializes in the diagnosis of breast cancer, will perform a diagnostic evaluation. The radiologist then uses the results of the DL model to create a detailed diagnosis report. Integrating IoT technology with DL algorithms offers a sophisticated and efficient framework for breast cancer diagnosis, paving the way for improved patient outcomes and enhanced healthcare provision. This system can be accessed from any device with an Internet connection through a medical cloud service. Using the proposed method, the e-Health cloud application server may quickly identify breast cell cancer as data enter, and then communicate the findings to the nearby medical facility so that they can take the necessary medical measures. The user can run a proposed diagnostic in the prediction stage and relay the findings to the physician for a final clinical judgment.

C. Proposed Model

Figure 3 shows the design of the proposed CNN model for breast cancer diagnosis.

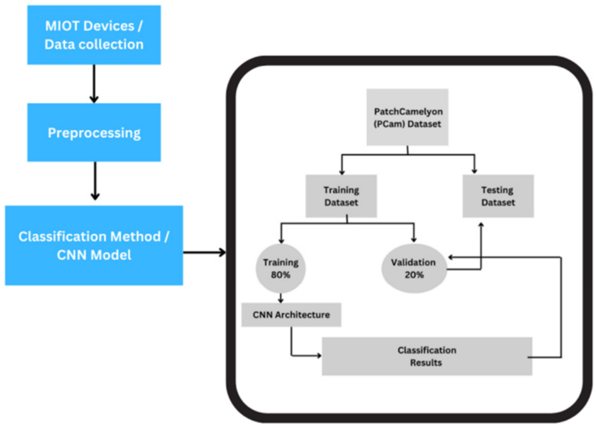

Fig. 3. Proposed CNN architecture for breast cancer classification.

The system uses IoMT devices to collect crucial data for breast cancer diagnosis. Subsequently, the collected data undergo preprocessing to enhance its quality and usability, ensuring optimal input for subsequent analysis. The core of the method is a CNN model that effectively discerns between breast tumor and non-tumor cases based on the preprocessed data. CNNs are particularly suited for this task because of their inherent ability to learn hierarchical features from complex data, such as medical images. By analyzing mammograms or other imaging data, CNNs can effectively identify patterns indicative of early-stage breast cancer with high accuracy and efficiency. The selection of CNNs for this problem is driven by several factors. Firstly, CNNs excel at image recognition tasks, making them well-suited for analyzing medical images such as mammograms. Their deep architecture allows them to automatically learn relevant features from the input data, eliminating the need for manual feature extraction. Additionally, CNNs have demonstrated state-of-the-art performance in various medical imaging tasks, including breast cancer detection. Their ability to generalize well to new data further enhances their suitability for real-world healthcare applications.

Integrating the proposed method into an MIoT environment improves the diagnostic process by enabling quick and accurate breast cancer detection. By connecting medical devices and systems through IoT technology, healthcare professionals can access and analyze patient data in real time, facilitating timely interventions and treatment decisions. Moreover, leveraging ML approaches such as CNNs within this IoT framework enables the interpretation of vast amounts of streaming medical data, leading to improved diagnostic accuracy and efficiency.

TABLE I. STRUCTURAL DESIGN OF THE CNN MODEL

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 96, 96, 32)	2432
conv2d_2 (Conv2D)	(None, 96, 96, 32)	9248
conv2d_3 (Conv2D)	(None, 96, 96, 32)	9248
batch_normalization_1	(None, 96, 96, 32)	128
max_pooling2d_1	(None, 48, 48, 32)	0
dropout_1	(None, 48, 48, 32)	0
conv2d_4 (Conv2D)	(None, 48, 48, 64)	18496
conv2d_5 (Conv2D)	(None, 48, 48, 64)	36928
conv2d_6 (Conv2D)	(None, 48, 48, 64)	36928
batch_normalization_2	(None, 48, 48, 64)	256
max_pooling2d_2	(None, 24, 24, 64)	0
dropout_2	(None, 24, 24, 64)	0
conv2d_7 (Conv2D)	(None, 24, 24, 128)	73856
conv2d_8 (Conv2D)	(None, 24, 24, 128)	147584
conv2d_9 (Conv2D)	(None, 24, 24, 128)	147584
batch_normalization_3	(None, 24, 24, 128)	512
max_pooling2d_3	(None, 12, 12, 128)	0
dropout_3	(None, 12, 12, 128)	0
flatten_1	(None, 18432)	0
dense_1 (Dense)	(None, 512)	9437696
batch_normalization_4	(None, 512)	2048
dropout_4	(None, 512)	0
dense_2 (Dense)	(None, 2)	1026

IV. RESULTS AND DISCUSSIONS

A. *CNN Model Results*

An independent test set was used to evaluate the CNN model with the optimal combination of hyperparameter settings. Based on these results, the proposed CNN model can reliably detect the occurrence of breast cancer. Since standard ML models are time-consuming, the proposed CNN model is suitable to replace them. Figure 4 shows the training accuracy and training loss of the proposed CNN.

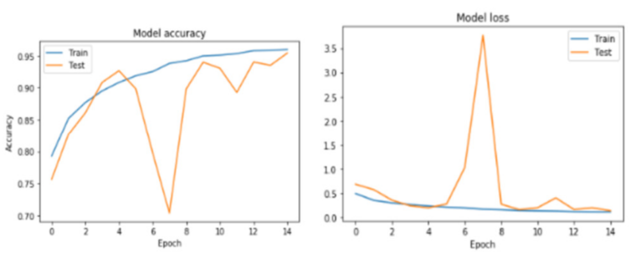

Fig. 4. Model training accuracy and loss results.

Figure 5 shows the confusion matrix of the CNN model, revealing its strong performance in binary image classification, especially for the category "No_tumor", with 7605 true positives indicating high accuracy. However, it also highlights a misclassification issue, with 395 false positives, where category "Has_tumor" images are incorrectly classified as "No_tumor". The matrix emphasizes the model's proficiency in identifying category "No_tumor" images while pointing to the need for further investigation into false and true negative values for a complete performance evaluation.

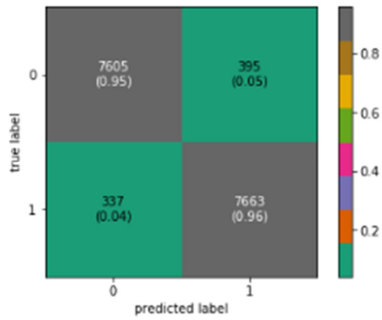

Fig. 5. Confusion matrix.

B. *Performance Evaluation Metrics*

The performance of the proposed CNN was evaluated using precision, recall, and F1-score. The model achieved high precision (0.96 for "No_tumor" and 0.95 for "Has_tumor") and recall (0.95 for "No_tumor" and 0.96 for "Has_tumor"), indicating strong accuracy in identifying both tumor and non-tumor cases. The F1-score of 0.95 for both classes highlight the model's balanced performance. This demonstrates the robustness and reliability of the model in early-stage breast cancer detection, improving diagnosis accuracy in breast cancer screening programs.

TABLE II. PROPOSED MODEL'S PERFORMANCE

	Precision	Recall	F1-score	Support
No-tumor	0.96	0.95	0.95	8000
Has-tumor	0.95	0.96	0.95	8000
Micro avg	0.95	0.95	0.95	16000
Macro avg	0.95	0.95	0.95	16000
Weighted avg	0.95	0.95	0.95	16000

Table II shows the performance metrics for the proposed model, including precision, recall, and F1-score for both "No-tumor" and "Has-tumor" classes, along with micro, macro, and weighted averages across all classes. The model demonstrates high accuracy with all metrics around 0.95. Precision, recall, and F1-score are metrics used to evaluate the performance of DL models. Precision (*P*) is given by:

$$P = \frac{TP}{TP+FP} \quad (1)$$

Precision (P) represents the proportion of true positive predictions out of all positive predictions. Recall is given by:

$$R = \frac{TP}{TP+FN} \quad (2)$$

and represents the proportion of true positive predictions out of all actual positives. F1-score is given by:

$$F1 = 2 \times \frac{P \times R}{P+R} \quad (3)$$

and represents the harmonic mean of precision and recall.

C. Discussion

This study introduced a novel medical IoT-based diagnostic system aimed at effectively identifying people with and without tumors within an IoT environment. This approach was specifically designed to address the challenges associated with early-stage breast cancer detection. Leveraging CNNs in conjunction with hyperparameter optimization, the proposed model demonstrated remarkable performance in distinguishing between tumor and non-tumor cases. The utilization of CNNs allowed for the extraction of intricate patterns and features from medical imaging data, allowing precise classification with a remarkable accuracy of 95%. This achievement surpasses the performance of conventional diagnostic methods and underscores the potential of advanced ML techniques to improve medical diagnosis and treatment.

D. Comparative Analysis

Comparative analysis with previous studies demonstrates the superiority of the proposed diagnostic model in terms of classification accuracy. The 95% accuracy rate signifies a substantial improvement over existing methods, highlighting the efficacy of CNNs in medical image analysis. This notable achievement has promising implications for early detection and intervention in cases of breast cancer, which could lead to better patient outcomes and survival rates. Furthermore, the scalability and adaptability of the proposed IoT-based diagnostic system make it suitable for deployment in diverse healthcare settings, catering to the evolving needs of patients and clinicians. This study adds to the current body of information by presenting a new technique that provides improved accuracy rates, while previous studies have made substantial progress in improving diagnostic skills. Improving patient outcomes in clinical practice and the effectiveness of breast cancer screening programs is an ultimate goal. To achieve this, research should take advantage of previous studies and use cutting-edge technology.

TABLE III. COMPARATIVE ANALYSIS

Reference	Dataset	Accuracy
[22]	ICIAR	92.50%
[23]	BreakHis	84.60%
[24]	Bioimaging	88.90%
[25]	Bioimaging	83.30%
Proposed model	PatchCamelyon	95%

V. CONCLUSION

This study explores the integration of ML models, particularly CNNs, within an IoT framework for the detection of breast cancer. Demonstrating superior accuracy compared to traditional methods, the proposed CNN-based approach facilitates early and accurate identification of breast cancer, enabling timely intervention. Despite challenges such as dataset variability, the proposed method proved effective in real-world scenarios, achieving a classification accuracy of 95%. Moving forward, collaborative efforts between healthcare professionals and technology experts are crucial to advance diagnostic systems and ultimately improve patient outcomes in breast cancer management. Future work will focus on expanding the dataset diversity and improving the robustness of the model to further enhance diagnostic accuracy. Additionally, the integration of advanced ML techniques and real-time data processing will pave the way for more responsive and adaptive breast cancer detection systems.

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