An Enhanced Artificial Intelligence and Deep Learning Assisted Breast Cancer Classification and Diagnosis Based on the Internet of Medical Things (IOMTs)

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ABSTRACT

Early detection of breast cancer can increase treatment opportunities and patient survival rates. Various screening methods with computer-aided detection systems have been developed for the effective diagnosis and treatment of breast cancer. An effective early diagnosis of breast cancer can lead to better patient outcomes and improved treatment success. In recent years, IoT technology, combined with Artificial Intelligence and Machine Learning (ML) methods, has completely revolutionized modern medical diagnostics. The combination of these novel system elements enables faster and better diagnoses through

their ability to process data. Many people continue to die from breast cancer because the present diagnostic methods fail to detect the disease at its initial stages, despite significant advances in medical science. This study presents an IoT-based medical diagnostic system that distinguishes between patients who have tumors and those who do not. The proposed model performs tumor versus non-tumor identification with a 95% accuracy rate through a CNN with optimized hyperparameters. Medical staff can use this technology to enhance the accuracy of breast cancer diagnosis through the combination of medical devices with AI applications and healthcare infrastructure. This approach has the potential to reduce breast cancer deaths through its effective early detection, which could be established in the long term. Medical IoT technology, along with continuous innovation, can transform healthcare delivery while improving worldwide patient outcomes.

Keywords-breast cancer classification; Medical Internet of Things (MioT); deep learning; Convolutional Neural Network (CNN)

I. INTRODUCTION

Each year, breast cancer is responsible for 35.8% of all cancer deaths in women, holding the second-highest position of occurrence in females. Early breast cancer detection offers the maximum life-saving potential along with cost-saving advantages in medical care [1]. Early breast cancer detection with AI models allows patients to obtain treatments that deliver superior results with reduced invasiveness [2]. Genetic research offers better assessments to identify the risk of breast cancer if supported by mammography, decreasing breast cancer mortality [3]. Due to advances in Internet of Medical Things (IoMT) devices, breast cancer screening can achieve significantly improved results, offering substantial transformations in healthcare operations [4].

In [5], an improved CNN-based breast cancer detection model showed that females who underwent breast imaging and open biopsy had a very low risk of rescreen failure of 1.08 (94% CI: 1.07–1.02), 1.82 (93% CI: 1.12–1.17), and 1.19 (95% CI: 1.89–1.70). In [6], IoMT devices were combined with a deep learning model to detect affected regions during screening. This model involved a sensor node to collect the real-time patient body data through a smart portable device. Medical data processing for breast cancer diagnoses is separated into spatial and temporal sample data that capture important features [7]. In [8], SVM and DBN models were compared to assess the accuracy of breast cancer detection, achieving accuracies of 82.34% and 92.4%, respectively. In [9], a CNN had a loss of 2.08 (93% CI: 2.12–2.12), 1.92 (95% CI: 1.24–1.37) [9].

In [10], an IoMT-based breast cancer diagnostic system used a CNN. In [11], an SVM model with the Fuzzy Clustering Algorithm (FCM) significantly improved breast cancer detection using image screening, helping to distinguish benign from potentially malignant tumors. In [12], a gradient method was used for backpropagation to fine-tune the parameters of each layer. The study in [13] discussed various feature selection techniques and machine learning models in the detection of breast cancer. In [14], additional modifications were applied to a CNN to minimize unstructured multimodal data and improve the medical diagnosis of breast cancer. The implementation of big data methods helps healthcare institutions control their growing information, but forecasting future changes brought about by ML and big data technology to healthcare systems remains complicated to determine [15]. In [16], a Deep Learning (DL) breast cancer detection technique was used for breast cancer. In [17], a DL model was presented to detect breast cancer and identify the risk of other organs based on histopathological images. Feature selection approaches can improve accuracy, leading to improved patient survival rates.

II. METHODOLOGY

This study used the histo-pathologic breast cancer detection PatchCamelyon (PCam) benchmark dataset to train and test the proposed model, obtained from [18]. PCam contains images of breast cancer patients at various stages. A total of 327,680 color images were considered, each with dimensions of 224×224 pixels and annotated with a binary label indicating the presence or absence of tumor tissue.

The proposed CNN model consists of an Input layer, Convolutional, Pooling, Normalization/Regularization, and Dense layers, and an Output layer, as follows:

- The Input layer takes images of breast tissue mammograms after preprocessing, which involved resizing images, pixel normalization at 0–1, and flipping to augment the dataset to improve generalization.
- Convolutional layers are utilized for feature extraction. Convolutional layers apply multiple kernels to understand and relocate spatial patterns: breast cancerous image shapes, irregularities, and the texture of mammograms. 3×3 filters are used with Rectified Linear Unit (ReLU) with an $(x) = max(0, x)$ activation function. These layers are as follows:
  - Convolutional layer 1: Filters, kernel, and max_P ReLU: 32, 3×3, and 2×2.
  - Convolutional layer 2: Filters, kernel, and max_P ReLU: 64, 3×3, and 2×2.
  - Convolutional layer 3: Filters, kernel, and max_P ReLU: 12, 3×3, and 2×2.
- Normalization/Regularization: This layer is essential to stabilize learning and accelerate convergence.
- The Dense layer (256, ReLU) is utilized before binary classification, with a standard Dropout of 0.5 to prevent overfitting.

To validate the performance of the proposed classification model, the dataset was split into training and testing sets with a ratio of 80:20. The model was optimized with the Adam optimizer based on binary cross-entropy loss and trained for 50 epochs with a batch size of 32. All layers have a convolution kernel step size of 1.

Cloud computing services were utilized to upload the samples. The results of breast cancer detection can be accessible to the therapist's computer display for a diagnostic analysis. Figures 1 and 2 represent the proposed framework for breast cancer diagnosis, performing breast cancer detection through the recommended optimized CNN model.

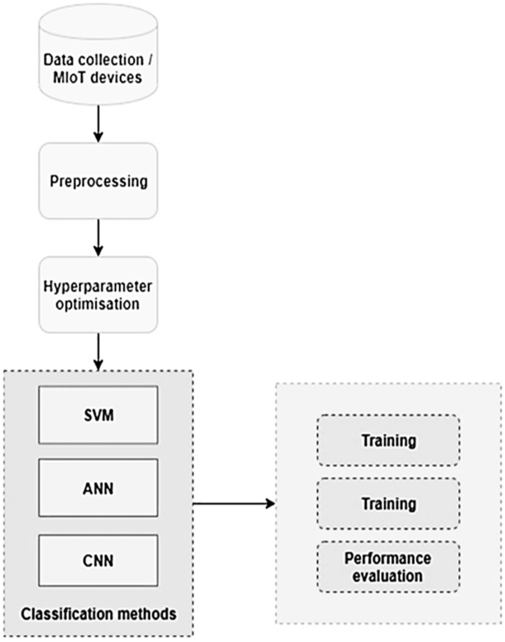

Fig. 1. Proposed framework for breast cancer detection.

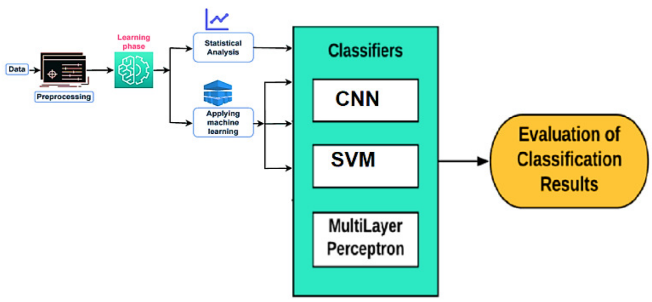

Fig. 2. Proposed ML-based model for cancer detection.

The proposed CNN model performed particularly well in this task due to its inherent ability to learn hierarchical features from complex data. By analyzing imaging data, the proposed CNN model can effectively identify early-stage breast cancer patterns with high accuracy and efficiency. The CNN can automatically learn relevant features from the input data, eliminating the need for manual feature extraction. The selection of a feature vector follows the extraction of important elements, as the proposed model is trained after an optimal phase of parameter optimization with feature vectors. After training, the model was tested for its performance on data from the previously separated test set.

III. RESULTS AND DISCUSSIONS

An independent test set was used to evaluate and select the best-performing network model with the optimal mix of hyperparameters. The results show that the proposed CNN model can reliably predict the occurrence of breast cancer and differentiate between tumor and non-tumor cases. Standard pre-trained deep learning models require significant computational resources, while the proposed CNN is simpler to fit IoMT devices with limited resources. The training of the supervised patch-level feature extractors was performed using data divided into a patch-level classification task.

Figure 3 shows the training accuracy and loss to describe the effectiveness of the training process. The data were augmented to generate additional training samples and employ validation sets to assess the efficiency of model training. Accuracy, sensitivity, and specificity were used to determine the performance of the model on the test data. A 5-fold cross-validation was performed to ensure the performance of the model.

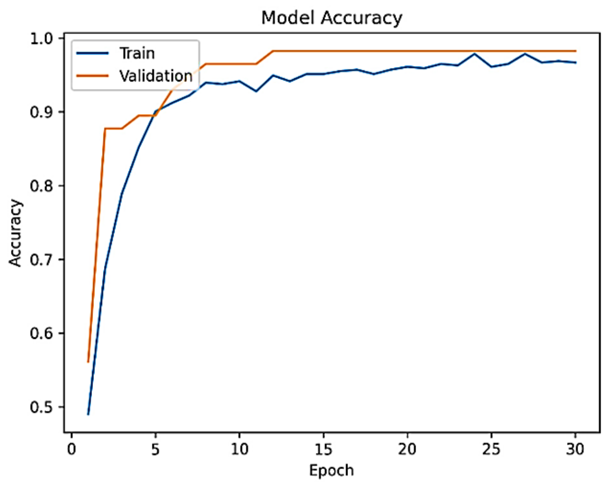

Fig. 3. Model accuracy in training and validation.

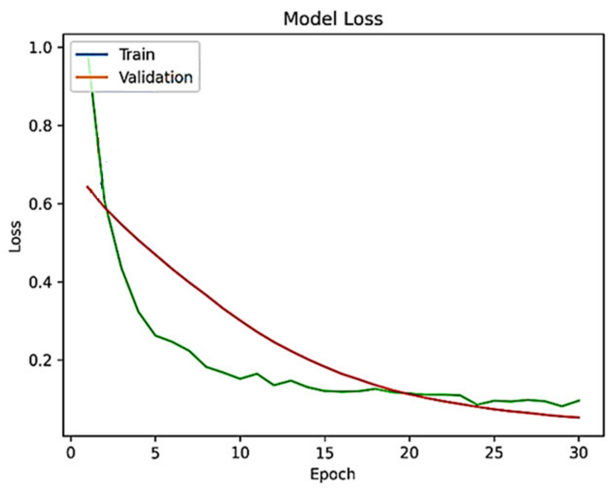

Fig. 4. Model loss in training and validation.

The confusion matrix of the CNN model, shown in Figure 5, demonstrates its classification performance. Image patches were used to extract features. The stride length in extracting patches used in feature extraction was 224 pixels (no overlap). The model demonstrates its strong performance in binary classification, especially for the Normal category, with 7605 true positives indicating high accuracy. However, it also highlights a misclassification issue, with 395 false positives where category Disease images are incorrectly classified as Normal. The matrix emphasizes the model's proficiency in identifying Normal images while pointing to the need for further investigation into false negative and true negative cases for a complete performance assessment.

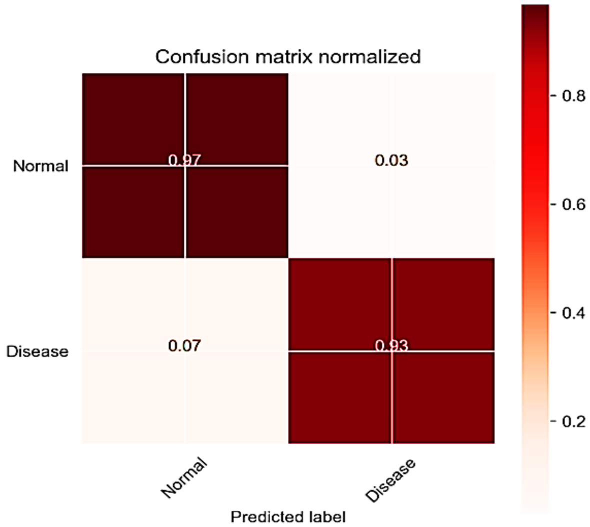

Fig. 5. Normalized confusion matrix of the proposed CNN model.

A. Performance Evaluation Metric

The performance of the proposed deep learning model was evaluated using precision, recall, and F1-score. The model achieved high precision and recall, indicating strong accuracy in identifying both tumor and non-tumor cases. Comparative analysis with previous studies revealed the superiority of the proposed diagnostic model in terms of classification accuracy, as the achievement of 95% accuracy signifies a substantial improvement over existing methods [4, 21], highlighting the efficacy of CNNs in medical image analysis. This notable achievement holds promising implications for early detection and intervention in breast cancer cases, potentially leading to improved patient outcomes and survival rates.

Table I shows the results of some previous studies that outperform the proposed model but with more complicated architectures, making it more difficult to apply to low-resource IoMT settings.

TABLE I. PERFORMANCE OF EXISTING MODELS

Study	Method	Accuracy	Precision	Recall	F1-score
[19]	TL	99.53%	99.53%	100%	99.40%
[20]	DL	97.13%	97.2%	97.20%	97.10%

The scalability and adaptability of the proposed IoT-based diagnostic system make it suitable for deployment in various healthcare settings, catering to the evolving needs of patients and clinicians alike. This study helps better understand the changing landscape of breast cancer detection approaches, as it shows significant improvements compared to previous techniques, offering improved accuracy rates that can improve diagnostic performance.

The ultimate goal is to improve patient outcomes in clinical practice and the effectiveness of breast cancer screening methods. The F1-scores of 0.95 for both classes highlight the model's balanced performance. This demonstrates the robustness and reliability of the proposed model in early-stage breast cancer detection, improving diagnostic accuracy and patient care in breast cancer screening. The misclassifications shown in the confusion matrix stress the need for additional research on false negatives and false positives to implement a comprehensive performance analysis that can lead to more improvements.

IV. CONCLUSION

Breast cancer is a common type of cancer, and many ML models have been proposed to examine its diagnostic variables. This study examined three key algorithms, CNN, SVM, and ANN (MLP), on the PatchCamelyon (PCam) benchmark dataset, with the goal of accurate and reliable breast cancer classification. The proposed DL-based CNN model outperformed conventional ML and ANN models in the detection of breast cancer, achieving better results. Statistical tests showed that performance differences were significant at $p = 0.018$. In the sphere of scientific works in the healthcare field, especially in IoMT applications, the feature selection procedure can bring different results based on other datasets, locations, and lifestyles of people, which requires further research. Overall, the proposed model works successfully to detect breast cancer, but more research is needed to further reduce false negative and positive cases.

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