JTE HCM-UTE
ISSN: 2615-9740

JOURNAL OF TECHNICAL EDUCATION SCIENCE
Ho Chi Minh City University of Technology and Engineering
Website: https://jte.edu.vn
Email: jte@hcmute.edu.vn

Design of a Telemedicine System for Classification of Breast Cancer Images

Thanh-Tam Nguyen[1], **Thanh-Hai Nguyen**[1*], **Tin-Trung Nguyen**[2]
[1]*Ho Chi Minh City University of Technology and Engineering, Vietnam*
[2]*Ho Chi Minh City Oncology Hospital, Vietnam*

[*]Corresponding author. *Email: nthai@hcmute.edu.vn*

ARTICLE INFO

Received:	19/07/2025
Revised:	30/07/2025
Accepted:	21/08/2025
Published:	28/02/2026

KEYWORDS

Telemedicine system;
Breast cancer classification;
EfficientNet-B7 model;
DICOM standard;
Protocols for information exchange.

ABSTRACT

Breast cancer is one of complex breast lesions. Therefore, accurate diagnosis to determine whether there is cancer disease or not, to determine which stage is a challenge for most doctors. This article proposes a telemedicine system for diagnosing breast cancer disease using EfficientNet-B7 in AI model, in which three image sets of Benign, Malignant and Normal are used. The main points are that, this telemedicine system is designed and calculated suitably so that a DICOM image can be transmitted from the image collected place to a server for classification and diagnosis, in which protocols and storage parts in this system are carefully selected and tested for its efficiency. Furthermore, layers and coefficients of the EfficientNet-B7 model are calculated and selected to increase the classification performance. Thus, the overall system results produced an accuracy of about 89.58%, which is a significant result for a complex and challenging system. Thus, the system can be improved in the future by enhancing the image sets, updating the deep learning network appropriately, and configuring a powerful enough server system.

Doi: https://doi.org/10.54644/jte.2025.1969

Copyright © JTE. This is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial 4.0 International License which permits unrestricted use, distribution, and reproduction in any medium for non-commercial purpose, provided the original work is properly cited.

1. Introduction

Breast cancer is one of the causes leading death in women worldwide, in which an incidence is increasing, especially among young people in Vietnam. According to recent statistics [1], each year in Vietnam, approximately 22,000 people are diagnosed with the breast cancer and there are more than 9,000 deaths, accounting for 25.8% of all cancer cases in women. Moreover, according to data of Bach Mai Hospital in Vietnam, nearly 70% of patients are diagnosed at late stages (III-IV), which significantly reduces the chance of successful treatment. Therefore, the main reason may be the lack of a large-scale screening system and limited highly specialized resources. Furthermore, Bach Mai Hospital receives more than 5,000 patients per day, which puts great pressure on the team of diagnostic imaging doctors [2].

In recent years, Artificial Intelligence (AI) has been applied to remote diagnostic systems which is considered a breakthrough in the medical field [3]. In particular, recent researches from Sweden, Germany, South Korea and some other countries have demonstrated that AI not only improves the accuracy of early breast cancer detection by up to 20%, but also reduces the workload for doctors by 44% [4]. Several large Vietnamese hospitals, including Bach Mai Hospital and the Hospital of Thai Binh Medical University, have successfully implemented AI solutions like Cadai-BTM for interpreting ultrasound images. This not only help the automatically diagnostic process, also support doctors in better diagnosing X-ray or ultrasound breast images [2], [5].

Traditional diagnostic methods are mainly based on mammography or ultrasound imaging [6], and this requires doctors with high skills to be able to detect small lesions such as microcalcifications or tumors less than 1 cm in diameter [7]. However, subjectivity of doctors in image reading and overloaded working can sometimes lead to errors in diagnosing breast cancer images. In particular, a research from Lund University in Sweden indicates that about 15% to 30% of breast cancer cases have been missed in routine screening [8]. This is obvious that it is very unfortunate and dangerous for many patients.

With increasing workload and pressure to doctors at hospitals, this can lead to inaccurate diagnosis results. Therefore, a remote diagnostic system integrated with AI is a solution for improving accuracy and also reduce the workload for doctors. It means that the integration of AI into a telemedicine system is reshaping the approach to breast cancer globally. Recent researches have shown that AI not only improves diagnostic accuracy, but also provides diagnostic results of up to 94.5% compared to 88% for traditional diagnosis [9]. Furthermore, the use of the AI-based telemedicine system reduces the number of visits by approximately 40% compared to in-person visits. In Vietnam, where the rate of late detection of breast cancer is up to 70% [1], this telemedicine system promises to narrow the gap in access to quality healthcare services.

In recent years, many deep learning models for image analysis have been developed, particularly YOLO, ResNet-50 and other models have been applied for different lesion recognition. One research is that YOLOv6 combined with Federated Learning (FedL) using BreakHis and BUSI datasets achieved 98% accuracy in benign and malignant tissue classification [10]. In particular, this federated learning for model training on multiple servers without sharing patient data due to information security. Meanwhile, MammoScreen with an FDA-cleared AI solution has been employed a top-down approach for evaluating the entire mammogram and a bottom-up approach for analyzing each suspicious region, resulting in a 44% reduction in physician workload [4].

Recent healthcare systems have been developed for assisting doctors in medical diagnosis and treatment [11], [12] and AI is one of the technologies developed in some of these systems. Google Health is developing the Med-PaLM 2 system, which is a medical-specific Large Language Model (LLM) for analyzing results of test, images, and then recommending treatment regimens. In India, a trial of the IBM Watson system achieved 90% agreement with the decision of a panel of experts in the treatment of early-stage breast cancer [13]. These systems use reinforcement learning to continuously update from new clinical data for optimizing personalized treatment recommendations. In particular, Google Health's AI-powered system reduced 5.7% of false positives and 9.4% of false negatives compared to traditional methods. Another study is that with the analysis of 44,755 ultrasound images and AUROC 0.976, the system detected lesions with very small sizes from 0.5mm to 2mm that are easily missed by the human eye [14].

The EfficientNet model has been developed through several stages and the EfficientNet-B7 model achieves higher accuracy than some other deep learning models. Furthermore, EfficientNet-B7 not only produces good accuracy with image data, but also has a network size 8.4 times smaller and 6.1 times faster than some other deep learning networks [15]. In recent studies, the EfficientNet model has been combined with other algorithms for application in many different classification fields. In particular, Lung-EfficientNet was proposed for classifying lung cancer based on a set of CT scan images and produced results with an accuracy of 99.10% [16]. Another research is that EfficientNet family U-Net models have been applied for segmenting renal tumors on CT-scan images and achieved high accuracy results using tumor segmentation [17], [18]. In the telemedicine breast cancer imaging diagnosis system, we used EfficientNet-B7 for image classification for evaluating the remote classification results.

This article is organized as follows: Section 2 briefly describes the proposed methods and materials, including building hardware architecture of the telemedicine system, image processing, AI model using EfficientNet-B7, protocols for interfacing input-output blocks. In Section 3, the results of methods for classifying using this system and result evaluations. The final section is the conclusion points.

2. Materials and Methods

This article proposes a telemedicine diagnosis system using an EfficientNet-B7 model to support doctors in classifying breast cancer images. It means that the system needs to ensure the transmission and processing of standard medical images over the internet to the server to produce breast cancer image classification results. Moreover, with this telemedicine system, doctors in many remote locations can join to perform diagnosis and receive this classification result for urgent case of dangerous and complicated diseases.

Furthermore, this telemedicine breast cancer diagnosis system will be designed using a web platform to help doctors easily access on different devices such as mobile phone or computer with the web. An important problem is that the computer application has good security and hardware support with a web application which is compatible with a variety of the different devices, and is also easy to access anytime. Moreover, in this study, the choice of a web-based system is easy for remote access. Therefore, this system is designed with the following basic requirements: 1. Operate on a server in the Internet environment and provides access anytime, anywhere; 2. Support DICOM protocol and the ability to upload JPEG images; 3. Allow user communication based on a web platform; 4. Provide output results including lesion type, risk level of benign or malignant.

2.1. Hardware architecture of the telemedicine system

Figure 1 shows a proposed telemedicine system for remote breast cancer image classification. This system encompasses the core components, interacting peripheral devices, and the connections between them. In particular, the system is composed of three main components: 1. Picture Archiving and Communication System server (PACS) for images; 2. Web server for data connection with the AI model and PACS; 3. AI model for image classification.

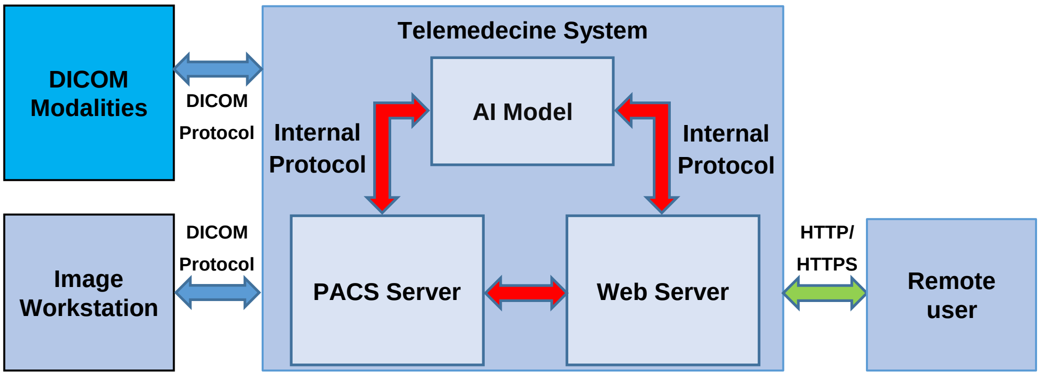


Figure 1. *Representation of the telemedicine system for classification of breast cancer images using a AI model*.

Therefore, this telemedicine system connects to peripheral devices such as X-ray imaging equipment, image viewing devices, and terminal devices for remote access. Details of each component in the system are described as follows:

(i) PACS server can receive and store images, particularly the images are uploaded from medical imaging devices with DICOM standard. Moreover, the system allows uploading the images in JPEG format for storing and processing. This server also interfaces with terminals, other components in the system through protocols and APIs.

(ii) Web server is to provide web services for creating an access interface for users. In particular, the web interface is built using modern web technology, providing high adaptability to many different types of terminal devices.

(iii) AI model is applied an EfficientNet-B7 model trained for classifying mammogram images. In particular, when receiving a request from the web server, the AI model performs the classification process and then returns classified results through the system's internal protocols.

(iv) Peripheral devices connected to the above system include: DICOM Modalities being breast X-ray imaging devices compatible with the DICOM standard; Imaging workstations for doctors to view images; remote users such as doctors or patients can access remotely via the website.

2.2. Description of EfficientNet-B7 model

In this system, the AI model plays an important role in the telemedicine diagnosis system of breast cancer problems. In particular, EfficientNet-B7 is used in the AI model for classifying 3 types of breast cancer lesions such as Benign, Malignant and Normal. Moreover, EfficientNet-B7 is one of the models suitable for breast cancer image classification. In particular, the Fully Connected (FC) and Classifier layers at the output of the pre-trained models are tuned to the breast cancer image sets for better classification performance. In this EfficientNet-B7 model, a Transfer Learning (TL) method is used with the Efficientnet-B7 pre-trained on ImageNet. In addition, EfficientNet-B7 features a compound scaling method, which allows the depth, width, and resolution of the network to be adjusted simultaneously. Thus, the compound scaling formula is defined as follows:

$$d = \alpha^{\phi}, w = \beta^{\phi}, r = \gamma^{\phi} \quad (1)$$

in which α, β, γ are the scaling factors for depth, width, and resolution, respectively and ϕ is the compound coefficient.

EfficientNet-B7 is designed with scaling factors of α, β, γ determined through a neural architecture search and their following values are α=1.2, β=1.1, γ=1.15. In addition, EfficientNet-B7 uses a baseline network with the following parameters: input resolution=224×224, width=1, depth=1.

For high performance of classifying three types of breast lesions such as Benign, Malignant and Normal, we changed the final FC layer of the pre-trained EfficientNet-B7 model to an output layer with three units. In particular, the original FC layer was replaced by a subnetwork consisting of two Dense layers with a ReLU activation layer. In addition to this, determining the hyper-parameters for the pre-trained model is an important contribution. This process includes fine-tuning parameters such as batch size, number of epochs, optimizer, and learning rate to suit the training process:

- Batch size = 32: Each training run will process 32 data samples.
- Epochs = 100: The entire dataset will be passed through the model 100 times. The training process will end after completing 100 epochs.
- Optimizer = Adam: The Adam optimizer is chosen for its good adaptability and high performance in deep learning problems.
- Learning rate = 0.001: This learning rate determines the degree to which the model's weights are adjusted in each training step.

After training the model, we will evaluate its performance and accuracy to ensure its reliability. Evaluation criteria during training includes Loss Function (LF) using the CrossEntropyLoss function; a popular choice for classification problems. Thus, this function, which measures the difference between the model’s predictions and the actual labels, is expressed as follows:

$$loss(x, y) = -\sum_{i=1}^{C} x_i \log(y_i) \quad (2)$$

in which $loss(x,y)$ is the value of the loss function, representing the error between the predicted value and the actual value. C is the number of classes. x_i is the actual label of the i^{th} class. If class i is the actual class of the data sample, $x_i = 1$, otherwise $x_i = 0$. y_i is the prediction probability of the model for the i^{th} class.

Accuracy is calculated as the percentage of correct predictions over the total number of data samples. In each epoch, accuracy is calculated for both the training dataset and the testing dataset.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

in which TP: Number of correctly predicted positive samples. TN: Number of correctly predicted negative samples. FP: Number of incorrectly predicted negative samples. FN: Number of incorrectly predicted positive samples.

2.3. Image processing

For better classification performance, the breast cancer images need to be preprocessed for extracting regions containing many features, as well as to synchronize the image size as described in Figure 2. Furthermore, the original image of the system is in DICOM format and has a large size and this is not suitable for the input of the AI classifier. Moreover, the original image contains some unnecessary background image information that may affect the classification accuracy. Therefore, image preprocessing is necessary before being fed into the system with the AI model as described in Figure 2.

In Figure 2, before being classified by the EfficientNet-B7 model, the images from PACS are processed through 3 steps: First, the original image in DICOM format is converted to JPEG format for matching the input format of the EfficientNet-B7 and the JPEG image still keep its unchanged size; Next, the JPEG image is automatically cropped to focus on the part of breast object and also remove unnecessary components such as patient information and image background; Finally, the image is resized to be suitable to the input of the AI classifier.

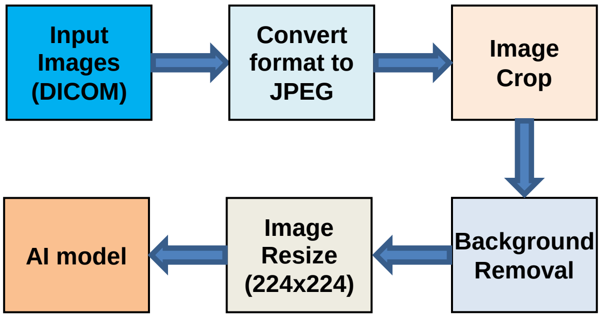


Figure 2. *Representation of Image pre-processing*

2.4. Describing internal protocols of the system core

Protocols in the telemedicine system play an important role. Therefore, in this system, we describe and propose some methods for the protocols to be compatible with the DICOM imaging system. In order for the parts of the system as described in Figure 1 to interact and exchange information each other, internal protocols are needed to perform this function. In the proposed system, the internal protocols, managing the communication between the PACS server, the web interface server and the EfficientNet-B7 model are the important part of the telemedicine system for breast cancer diagnosis. In particular, the PACS server, which stores medical images, relies on protocols to securely transmit relevant breast imaging studies to the web interface server upon user request. Therefore, the web interface server uses its own protocols to forward these images to the AI model for analysis, assigning tasks and the expected output format. Finally, the protocols determine how the AI model communicates its diagnostic predictions back to the web interface server, which then presents these results to the remote healthcare doctors. In this system, the internal communication paths are standardized to ensure data security and this will increase processing efficiency. With this good communication, the workflow will be highly reliable throughout the image retrieval process, as well as AI-assisted diagnosis.

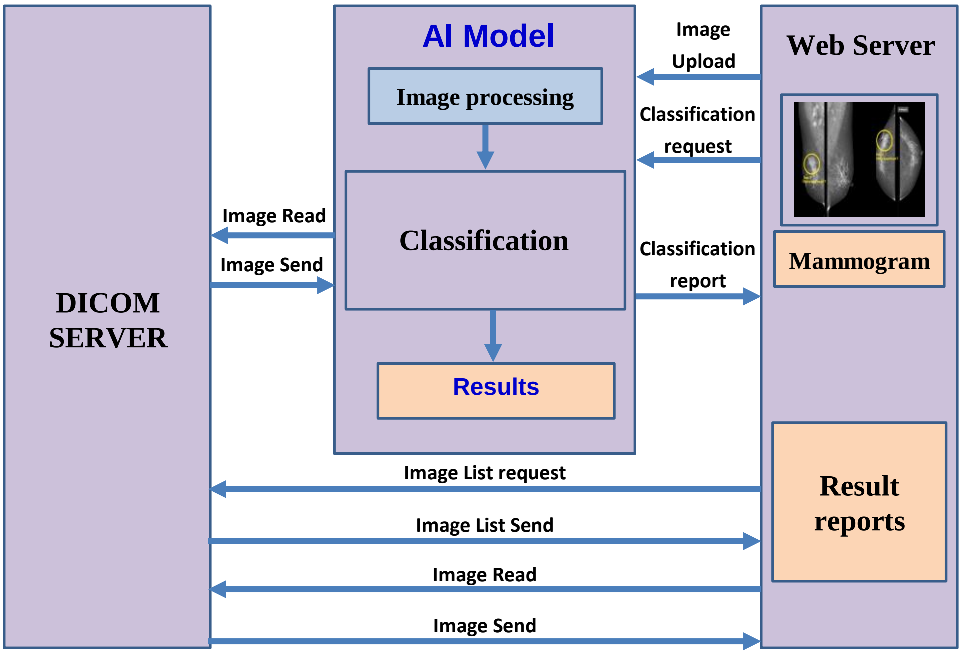


Figure 3. *Description of the internal protocols for information exchange between three main components in the system core.*

JTE HCM-UTE
ISSN: 2615-9740
JOURNAL OF TECHNICAL EDUCATION SCIENCE
Ho Chi Minh City University of Technology and Engineering
Website: https://jte.edu.vn
Email: jte@hcmute.edu.vn

In this article, the AI model is designed to use the internal protocols for establishing to exchange information and coordinate with other components in the core of the system as depicted in Figure 3. In particular, the types of messages exchanged between the components need to be determined. In addition, the system is designed to interface with external peripherals such as X-ray devices, image display devices, and user terminals through appropriate protocols. Including the DICOM protocol for communication between the system and X-ray devices, DICOM image display devices already have the support of the protocol as a common standard in medicine. Image communication with user terminals uses the HTTP/HTTPS standard protocol for websites. The use of standard and popular protocols for external communications allows the system to be easily deployed and connected to existing medical facilities' equipment.

To process images before classification, the AI model needs to get images from the PACS server. Therefore, the communication between the AI model and the PACS needs to provide messages for performing this function. Meanwhile, the Web server needs not only to exchange images with the PACS server, but also to access the list of images stored on the server and other information which display on the web interface for users. Meanwhile, the communication between the web server and the AI model needs to provide a means to request the AI model for performing diagnosis and then returning results for generating user reports.

Furthermore, the proposed system is built using parameters for operating at the highest performance. Therefore, the specific system parameters relate to image size, storage capacity and other parameters which are determined based on the expected input data set, usage requirements and other system factors as described in Table 1.

Table 1. *Technical specifications of the telemedicine diagnostic system*.

No.	Parameters	Value
1	Storage capacity	200GByte
2	Transmission bandwidth	100Mbps
3	Maximum file size for upload	10Mbyte
4	Processing time	<20s

2.5. Data acquisition

In this study, DICOM mammogram images collected from the Oncology Hospital in Vietnam are used to train the AI model. For image collection, a strictly designed process is carried out to ensure the validity of the dataset as shown in Figure 4. First, the DICOM mammogram images are collected from the hospital's PACS image storage device and they are anonymized to protect patient privacy. Next, the dataset is annotated by some radiologists through a labelling tool on the hospital's computer. Finally, the annotated images are stored as a dataset.

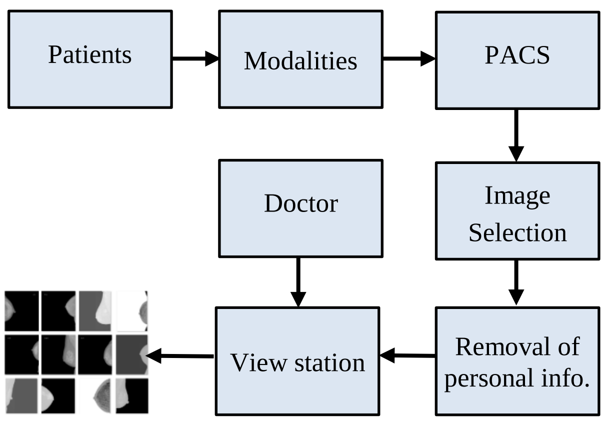
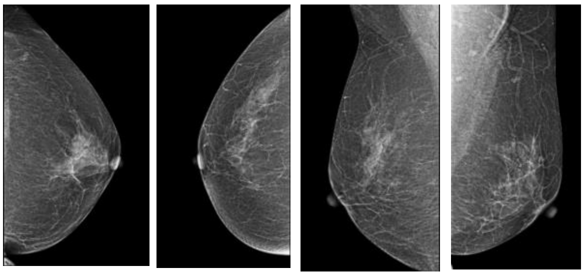


Figure 4. *Data collection diagram at the Ho Chi Minh City Oncology Hospital*.

In this step, more than 4000 DICOM mammogram images from 2018 to 2023 in the PACS server of the Ho Chi Minh City Oncology Hospital DICOM system were selected. In particular, these images were collected on devices from the vendor SIEMENS. For ensuring patient privacy on the images such as identifiable patient information in the DICOM tags are completely erased. It means that only necessary information such as patient age and sex are retained. In addition to DICOM metadata, relevant information such as the angle and perspective of the image may appear in the images for preprocessing and feature extraction. Some sample images collected from the Ho Chi Minh City Oncology Hospital are shown in Figure 5. In addition, all are digital images collected from the DICOM system and unnecessary personal information has been removed. After preprocessing the images, the detailed information about the collected image set is described in Table 2.



(a) (b) (c) (d)

Figure 5. *Sample images of a patient's exam at the Ho Chi Minh City Oncology Hospital: (a) Left CC; (b) Right CC; (c) Right MLO; (d) Left MLO*

Table 2. *Representation of the detail information of an image after preprocessing.*

No.	Parameters	Value
1	Number of Images	4034
2	Image size	1024×1024
3	Format	DICOM
4	File size	8.8MB

For the purpose of this study, the image collection was diagnosed and classified by specialists into three primary categories: normal (no lesions), benign, and malignant, as presented in Table 3. To ensure a balance in the number of images during training, images from the original image set were reselected with a number of 800 images per category.

Table 3. *Representation of the number of lesion types in the image set*

No.	Classification	Number of Images	Training	Testing
1	Normal	1815	640	160
2	Benign	877	640	160
3	Malignant	838	640	160

3. Results and Discussion

After completion of the telemedicine diagnosis system, the results are obtained for evaluating and we would like to show two main independent aspects: Classification accuracy of the EfficientNet-B7 model; Operational parameters of the telemedicine system. Therefore, each aspect is evaluated through many parameters for determining the effectiveness of the proposed methods, as well as the level of meeting the requirements. During this evaluation, the system indicators some problems, including accuracy, system reliability, transmission parameters, processing time, delay, protocols and other parameters.

3.1. Result of Breast cancer classification

In this article, the classification accuracy is evaluated through the confusion matrix, in which the image sets are collected from the Ho Chi Minh city Oncology Hospital and the test dataset is completely independent of the dataset for training, with a quantity ratio of 8:2. Basically, there are 3 types of image sets such as Benign, Malignant and Normal. Therefore, the training results of the EfficientNet-B7 model are evaluated by the Loss and Accuracy functions.

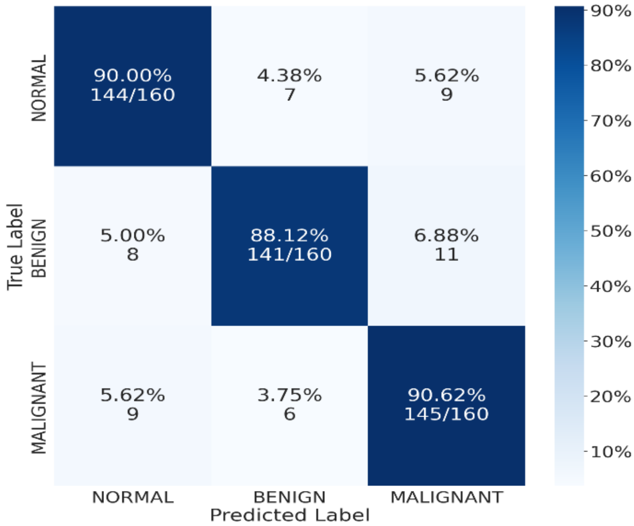


Figure 6. *Representation of the confusion matrix for three types of lesion such as Benign, Malignant and Normal.*

Figure 6 presents the confusion matrix, showing the model's classification ability for three breast lesion categories: Benign, Malignant and Normal. In particular, the EfficientNet-B7 model predicted related to correction and mistake as shown in Table 4. It means that when classifying, the category of Benign has 141 of True Positive and in case of False Positive, it recognizes 11 Benign to Malignant and 8 Benign to Normal, it is similar to the categories of Malignant and Normal.

Table 4. *Representation of the prediction related to the classification using the confusion matrix.*

Categories	Number of Images	True Positive	False Positive	
Normal	160	144	7 to Benign	9 to Malignant
Benign	160	141	8 to Normal	11 to Malignant
Malignant	160	145	9 to Normal	6 to Benign

Analysis of the training results shows that the AI model with EfficientNet-B7 achieves high training accuracy, particularly converging at around 97%, indicating good learning ability on the training data. However, the accuracy on the test set is only around 89.58 % and this may be a small problem related to constructing new data. The difference between the training and testing accuracy may be due to the fact that the data set used is real data, has a large difference in quality and is collected from different devices. The precision and F1-score are showed in Table 5.

Table 5. *Representation of the precision and F1-score.*

Categories	Precision	recall	f1-score
Normal	0.8944	0.9000	0.8972
Benign	0.9156	0.8812	0.8981
Malignant	0.8788	0.9062	0.8923

JTE
HCM-UTE
ISSN: 2615-9740
JOURNAL OF TECHNICAL EDUCATION SCIENCE
Ho Chi Minh City University of Technology and Engineering
Website: https://jte.edu.vn
Email: jte@hcmute.edu.vn

3.2. Result of Telemedicine model

The system is evaluated for telemedicine functionality through comprehensive tests of data transmission, stability, and system bandwidth through the following detailed test steps.

- Simulated data transmission: Simulate the transmission of a diverse set of test images through the system, simulating various network conditions such as different bandwidths or latency.
- Latency measurement: Measure the time required for images to be uploaded, processed by the AI model, and displayed; Record these delays.
- Error rate assessment: Introduce controlled errors during the simulated transmission such as packet loss to evaluate the system's robustness and error handling; monitor for data corruption or system failures.
- System uptime monitoring: monitor the uptime and stability of the web interface server and AI model over a period of time and record any errors.
- Qualitative evaluation: Evaluate the user experience of the web interface in terms of ease of use and clarity of presentation results.

The evaluation steps provided data for calculating specific parameters as follows: Average latency for processing images and delivering results; Transmission error rate or system failure rate under stress; System uptime rate. In addition, this protocol provides a framework for evaluating a telemedicine system for breast cancer diagnosis based on EfficientNet-B7. Thus, specific parameters and thresholds for acceptable performance will be determined based on the requirements and context of the intended application. During the evaluation of the imaging data, the real DICOM data are collected.

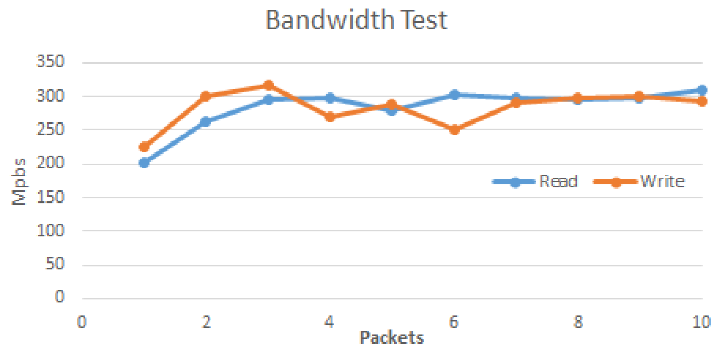


Figure 7. *Measurement results of the system bandwidth.*

Figure 7 shows the results of testing the telemedicine system. In particular, the graph shows that the system Read/Write speed is always above the allowable limit of 200Mbps and the average speed is 284Mbps.

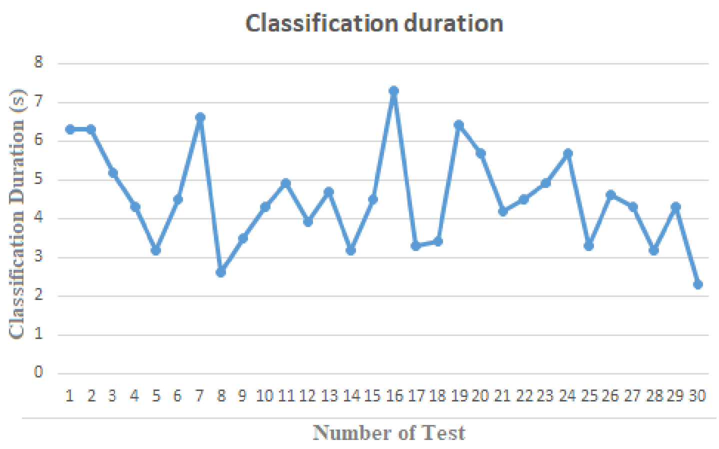


Figure 8. *Measurement results of the classification duration.*

Figure 8 shows the test results of the system's classification time with 30 trials. In particular, the results show that the longest classification time is 7.3s and the fastest is 2.3s and the average classification time is 4.514s.

Table 6. *Representation of the system evaluation results.*

Parameter	Number of Test	Result	Standard deviation
Accuracy	1500	84%	-
Bandwidth	-	284Mbps	32.23
Fault ratio	1500	0.47%	-
Average classification duration	30	4.514s	1.52

The results are presented in Table 6, in which the system meets the requirements of a system for practical remote diagnosis. However, to achieve higher performance and accuracy, some techniques need to be followed such as: input image quality related to substandard lighting, noisy images; The requirement of large computational resources for the training process is a barrier for units with limited infrastructure.

This result is comparable to other telemedicine systems for breast cancer diagnosis. For example, VinDr AI's solution for breast cancer diagnosis - VinDr-Mammo system has a practical BI-RADS classification accuracy of over 80% [19]. Other technical parameters of similar systems are not published, making comparison difficult.

3.3. Discussion

In recent years, deep learning networks have attracted researchers for image classification in different fields, in which medical images for diagnosis support are classified. A study utilizing YOLOv6 combined with Federated Learning (FedL) on the BreakHis and BUSI datasets achieved a remarkable 98% accuracy in differentiating between benign and malignant tissues [10]. A research is that general an AI-based diagnostic systems produced a report to reach an accuracy as high as 94.5% [14]. Although, our results of the proposed telemedicine system have not yet reached this state-of-the-art threshold, its strength points are to complete the telemedicine system architecture from input data to end results. In particular, the performance of our proposed AI model presents a nuanced picture and the 89.58% accuracy is a significant step towards automated diagnosis. In addition, our work addresses the practical challenge of integrating the model within a telemedicine infrastructure, including PACS server communication, web-based user access, and defined internal protocols for data exchange. Focusing on telemedicine the system for application is a key contribution in this article.

Moreover, our research aligns with developing the telemedicine system using AI model in medicine area for reducing diagnostic errors and physician workload. Although, we did not directly measure error reduction using the telemedicine compared to doctor diagnosis, the high accuracy in identifying the Normal cases of 92% precision as shown in Figure 5 is very significant. Thus, it means that our proposed system could effectively produce a significant number of right cases and this can allow specialists to focus on more ambiguous or potentially malignant ones. In addition, it aligns with the 44% reduction in physician workload reported by MammoScreen [20].

In this article, the classification accuracy of the EfficientNet-B7 model in the telemedicine system is not the highest compared to previous researches, but our telemedicine system has made a significant contribution by presenting a complete, practical, and efficient telemedicine system designed for real-world deployment. In particular, the system's architecture is robust and its performance can allow to apply for clinical testing. Therefore, this system can focus on enhancing and improving its diagnostic accuracy to be able to apple at Vietnam hospitals.

4. Conclusions

This article proposes a telemedicine system for classifying breast cancer images using an EfficientNet-B7 model and this system can be applied for classifying breast lesions at hospitals in Vietnam. In the proposed telemedicine system with the EfficientNet-B7 model, a dataset of DICOM mammogram images from the Oncology Hospital in Ho Chi Minh City were used to train this EfficientNet-B7. The results produced a high training accuracy of approximately 97%. However, the validation accuracy on the test set was just 89.58%.

The importance is that the telemedicine system demonstrated robust performance, meeting the technical requirements for practical deployment. In particular, it achieved an average data transmission speed of 284Mbps, which is higher than the 200Mbps requirement and also an average classification time of 4.514 seconds per image. These results illustrate the system's capability to operate efficiently for real clinical applications and this can provide timely support for many doctors in remote diagnosis at the same time. In addition to this, our telemedicine system shows great promise in reducing physician workload and improving diagnostic access. This system can focus on enhancing the model's accuracy, in which image sets should be obtained more and AI model should be improved and upgraded.

Acknowledgments

We would like to thank the Ho Chi Minh City University of Technology and Engineering (HCM-UTE), Vietnam.

Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] World Health Organization, "Vietnam source: Globocan 2022," 2022. [Online]. Available: https://gco.iarc.who.int/media/globocan/factsheets/populations/704-viet-nam-fact-sheet.pdf

[2] Vietnamnews, "Bach Mai Hospital leads digital transformation in healthcare," *Vietnamnews*, 2025. [Online]. Available: https://vietnamnews.vn/opinion/1693875/bach-mai-hospital-leads-digital-transformation-in-healthcare.html. Accessed: Jun. 18, 2025.

[3] K. N. Ramanto and A. A. Parikesit, "The usage of deep learning algorithm in medical diagnostic of breast cancer," *Malays. J. Fundam. Appl. Sci.*, vol. 15, 2019, doi: 10.11113/mjfas.v15n2.1231.

[4] Y. Deng *et al.*, "A new framework to reduce doctor's workload for medical image annotation," *IEEE Access*, vol. 7, pp. 107097–107104, 2019, doi: 10.1109/ACCESS.2019.2917932.

[5] N. N. Trung, "Updating and upgrading the features of artificial intelligence (AI) applications in early diagnosis of breast cancer with Korean experts at Thai Binh University of Medicine and Pharmacy Hospital," *Thai Binh Univ. Med. Pharm. Web Portal*, 2025. [Online]. Available: https://tbump.edu.vn/tin-hoat-dong/cap-nhat-nang-cap-tinh-nang-cua-ung-dung-tri-tue-nhan-tao-ai-trong-chan-doan-som-ung-thu-vu-cung-cac-chuyen-gia-han-quoc-tai-benh-vien-dai-hoc-y-thai-binh-298.html. Accessed: Jun. 16, 2025.

[6] S. A. A. Karim, U. H. Mohamad, and N. E. N. Puteri, "Discovery of interpretable patterns of breast cancer diagnosis via class association rule mining (CARM) with SHAP-based explainable AI (XAI)," *Malays. J. Fundam. Appl. Sci.*, vol. 21, 2025, doi: 10.11113/mjfas.v21n3.3792.

[7] J. Yan *et al.*, "Diagnosis and treatment of breast cancer in the precision medicine era," in *Precision Medicine*, T. Huang, Ed. New York, NY, USA: Springer, 2020, pp. 53–61, doi: 10.1007/978-1-0716-0904-0_5.

[8] K. K. Evans, R. L. Birdwell, and J. M. Wolfe, "If you don't find it often, you often don't find it: why some cancers are missed in breast cancer screening," *PLoS One*, vol. 8, 2013, Art. no. e64366, doi: 10.1371/journal.pone.0064366.

[9] M. Issaiy, D. Zarei, and A. Saghazadeh, "Artificial intelligence and acute appendicitis: A systematic review of diagnostic and prognostic models," *World J. Emerg. Surg.*, vol. 18, 2023, Art. no. 59, doi: 10.1186/s13017-023-00527-2.

[10] C. Gupta *et al.*, "Applying YOLOv6 as an ensemble federated learning framework to classify breast cancer pathology images," *Sci. Rep.*, vol. 15, 2025, Art. no. 3769, doi: 10.1038/s41598-024-80187-7.

[11] A. Kapoor, P. Nambisan, and E. Baker, "Mobile applications for breast cancer survivorship and self-management: A systematic review," *Health Informatics J.*, vol. 26, pp. 2892–2905, 2020, doi: 10.1177/1460458220950853.

[12] J. V. Johansson and E. Engström, "'Humans think outside the pixels' – Radiologists' perceptions of using artificial intelligence for breast cancer detection in mammography screening in a clinical setting," *Health Informatics J.*, vol. 30, 2024, Art. no. 14604582241275020, doi: 10.1177/14604582241275020.

[13] N. Zhou *et al.*, "Concordance study between IBM Watson for Oncology and clinical practice for patients with cancer in China," *Oncologist*, vol. 24, pp. 812–819, 2019, doi: 10.1634/theoncologist.2018-0255.

[14] Y. Shen *et al.*, "Artificial intelligence system reduces false-positive findings in the interpretation of breast ultrasound exams," *MedRxiv*, 2021, doi: 10.1101/2021.04.28.21256203.

[15] M. Tan and Q. V. Le, "EfficientNet: Rethinking model scaling for convolutional neural networks," 2020. [Online]. Available: https://arxiv.org/abs/1905.11946

[16] R. Raza *et al.*, "Lung-EffNet: Lung cancer classification using EfficientNet from CT-scan images," *Eng. Appl. Artif. Intell.*, vol. 126, 2023, Art. no. 106902, doi: 10.1016/j.engappai.2023.106902.
[17] A. Abdelrahman and S. Viriri, "EfficientNet family U-Net models for deep learning semantic segmentation of kidney tumors on CT images," *Front. Comput. Sci.*, vol. 5, 2023, doi: 10.3389/fcomp.2023.1235622.
[18] Y. Sun, Z. Zhu, and B. Honarvar Shakibaei Asli, "Automated classification and segmentation and feature extraction from breast imaging data," *Electronics*, vol. 13, 2024, doi: 10.3390/electronics13193814.
[19] VinDr, "VinDr – Solutions for medical data," [Online]. Available: https://vindr.ai/. Accessed: Aug. 1, 2025.
[20] K. Lang *et al.*, "Artificial intelligence-supported screen reading versus standard double reading in the Mammography Screening with Artificial Intelligence trial (MASAI): a clinical safety analysis of a randomised, controlled, non-inferiority, single-blinded screening," *Lancet Oncol.*, vol. 24, pp. 936–944, 2023, doi: 10.1016/S1470-2045(23)00298-X.

Thanh-Tam Nguyen is a lecturer at School of Biomedical Engineering, International University Vietnam National University - Ho Chi Minh City, Vietnam. He received the B.E. and the M.E degrees in Electronic and Telecommunication Engineering from Ho Chi Minh City University of Technology, Viet Nam, in 2002 and 2004, respectively. He's currently working toward the Ph.D. degree in Electronic Engineering at Ho Chi Minh City University of Technology and Engineering, Viet Nam.
His main research interests include Telemedicine, Machine learning, Telecommunication, Medical Instrumentation.
Email: tamnt.ncs@hcmute.edu.vn. ORCID: https://orcid.org/0000-0002-7920-1651

Thanh-Hai Nguyen is a lecturer in Department of Industrial Electronics and Biomedical Engineering, Faculty of Electrical – Electronics Engineering, HCMC University of Technology and Engineering, Ho Chi Minh City, Vietnam. He received the B.S. degree in Engineering of Electrical and Electronics from Ho Chi Minh City University of Technology and Education (currently Ho Chi Minh City University of Technology and Engineering), Vietnam, and the M.E, degree in Electronic-Telecommunication from Ho Chi Minh City University of Technology, Vietnam. He obtained his Ph.D. in Electrical and Electronics Engineering from University of Technology, Sydney, Australia. His main research interests include Signal-Image processing, Biomedical Engineering, Smart wheelchairs, Machine Learning, Artificial Intelligence.
Email: nthai@hcmute.edu.vn. ORCID: https://orcid.org/0000-0003-3270-6975

Tin-Trung Nguyen is working in Department of Radiology, Ho Chi Minh City Oncology Hospital, Ho Chi Minh City, Vietnam.
His main research interests include Telemedicine, Breast cancer, Lung cancer.
Email: nguyentintrung.dr@gmail.com. ORCID: https://orcid.org/0000-0002-8894-4289