VOL. 24, NO. 1, 2025, 57-60
elektrika.utm.my
ISSN 0128-4428

ELEKTRIKA
Journal of Electrical Engineering

Leveraging EfficientNet-CNN for Accurate Diagnosis of Breast Cancer from Ultrasound Images

Alyssa April Dellow and **Saiful Izzuan Hussain***

Department of Mathematical Sciences, Faculty of Science and Technology, Universiti Kebangsaan Malaysia, 43600 Bangi, Selangor, Malaysia.

*Corresponding author: sih@ukm.edu.my

Abstract: Breast cancer is one of the most common malignancies in women worldwide. Because early detection is essential for effective treatment, researchers have investigated a number of methods to aid radiologists in the early detection of breast cancer. Convolutional neural networks (CNNs) are a promising method for diagnosing breast cancer when applied to the analysis of breast ultrasound images. This study investigates the classification of benign, malignant, and normal breast ultrasound images using CNN models with transfer learning, specifically the EfficientNetB0 architecture. 780 breast ultrasound images were extracted from the BUSI database. Although the EfficientNet architecture has fewer parameters than other CNN models, it provides faster and more accurate results, which is one of its main advantages. EfficientNetB0 architecture achieved 83.33 percent accuracy, demonstrating its ability to accurately classify breast ultrasound images.

Keywords: Breast cancer, Convolutional neural networks (CNNs), EfficientNetB0

Article History: received 3 November 2024; accepted 12 February 2025; published 30 April 2025

1. INTRODUCTION

According to the Centers for Disease Control and Prevention [1], breast cancer is the most common cancer among women in the United States, along with skin cancer, and this cancer is also the most common disease cause of cancer deaths among women. However, men can also develop breast cancer, although this is rare. Breast cancer screening involves examining the breasts for cancer before symptoms appear. This helps in the early detection of breast cancer and allows for immediate treatment to reduce mortality rates. Although this screening is often performed using mammograms, ultrasound is one of the most commonly used alternatives. A cancerous (malignant) or noncancerous (benign) tumor can be detected by an ultrasound image. Ultrasound is an imaging test that uses sound waves to see the inside of a person's breast to determine if there are any problems with the breast [2].

Usually, an ultrasound is performed when changes are detected that are not visible on a mammogram. These changes may not appear on mammograms because mammograms sometimes cannot see through patients' dense breast tissue. Therefore, the cancer may not be detected until it gets larger. Unfortunately, by that time, the cancer would most likely have spread. Ultrasound is noninvasive, is well tolerated by women, and is radiation-free. Therefore, it is a commonly used method for the diagnosis of breast cancer. Ultrasound is a highly effective diagnostic tool in dense breast tissue, often detecting breast tumors missed by mammography [3]. Other imaging modalities, such as magnetic resonance imaging (MRI) and mammography, are less portable and more expensive than ultrasonography [4].

Ultrasound can be used to determine whether problems detected by mammograms and physical breast exams are fluid-filled cysts or solid tumors. They can also be used in individuals younger than 25 years and pregnant women because no radiation is used. Therefore, ultrasound examinations do not pose a risk to these individuals. After thoroughly reviewing breast ultrasound images, radiologists can determine whether or not a cancerous tumor is present in a patient's breast. Manual detection of breast cancer from ultrasound images by radiologists is a time-consuming task in which human error can occur. This process can take up to several weeks, depending on the facilities available and the experience of the radiologist. The detection of breast cancer should actually be rapid to allow for immediate treatment.

As the number of breast cancer cases increases every year, measures need to be taken to develop existing technologies such as artificial intelligence (AI) that can help to diagnose patients. AI is a device with the ability to function like human intelligence. It is capable of learning things, making inferences, and improving its progress [5]. AI methods are used to develop automated systems for diagnosing and predicting different types of diseases. AI models can make quantitative assessments of details in medical images that cannot be detected by specialists with the naked eye [6,7].

A CNN is capable of automatically detecting data features that meet the requirements of a particular task [9]. Usually, CNNs are produced with a fixed resource budget. When more resources are available, CNNs are scaled up to achieve higher accuracy. The accuracy of a CNN model depends on the design of its layers in addition to the training model. Examples of CNNs used for the diagnosis of cancer, COVID -19 or osteoporosis are ResNet, MobileNet, GoogLeNet and many others. The scale of a CNN can be increased by adding the number of layers. Scaling of these architectures is done by arbitrarily increasing the width or depth of the CNNs. Also, using higher resolution input images can be used for training and testing. However, this common scaling method requires complicated manual tuning. [8] shows that radiologists with four years of breast imaging experience had a lower area under the curve (AUC) value than CNNs, while radiologists with 8 and 20 years of experience had an AUC value comparable to CNNs. This shows that a radiologist's experience is a factor that leads to different levels of performance. Thus, radiologist experience is crucial for early detection of breast cancer.

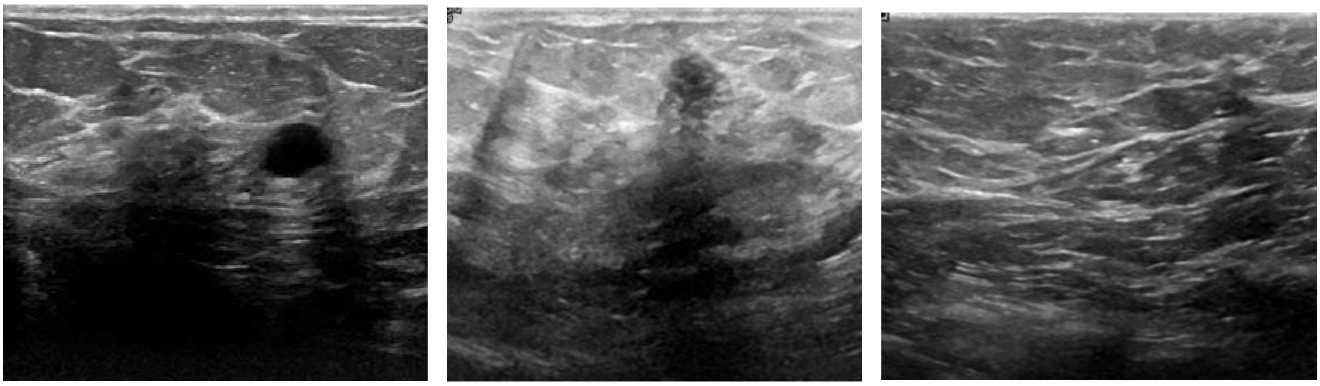
A CNN model family known as EfficientNet is said to be able to outperform the accuracy of existing architectures by a factor of ten, although it is smaller in size. The EfficientNet model presented [10] consists of eight variants, namely EfficientNetB0, EfficientNetB1, EfficientNetB2, EfficientNetB3, EfficientNetB4, EfficientNetB5, EfficientNetB6, and EfficientNetB7. In particular, EfficientNetB7 can achieve 84.3% accuracy on ImageNet, 6.1 times faster than ConvNet, which was the best architecture at the time, although EfficientNet is 8.4 times smaller. EfficientNets use a different composite scaling method than the usual method. This composite scaling method performs uniform scaling of the width, depth, and resolution of the network using a fixed scaling coefficient. In this study, EfficientNetB0 is used to classify the BUSI dataset. This research's EfficientNet architecture was trained to use the Swish activation function in each hidden layer and Softmax in the output layer.

2. METHODOLOGY

This section discusses the approach used in this study. First of all, a description of the dataset used and how it is handled is laid out. Then, descriptions of the EfficientNet architecture, ways to improve its performance and valuation metrics used to evaluate model performance are also discussed.

2.1 Data

The Breast Ultrasound Images Dataset (Dataset BUSI), a public available dataset, is used for training, validation, and testing of the EfficientNet architecture. The BUSI dataset provides annotated breast ultrasound images online and can be used for any scientific study. The dataset contains a total of 780 ultrasound images from 600 female patients between the ages of 25 and 75. It consists of three classes, including 437 benign images, 210 malignant images, and 133 normal images. All images were acquired by [11] from Baheya Hospital using LOGIQ E9 and LOGIQ E9 Agile ultrasound system. Ultrasound images are in PNG format and have an average size of 500*500 pixels. Examples of breast ultrasound images of classes (a) benign, (b) malignant and (c) normal are shown in Figure 1.



(a) (b) (c)

Figure 1. Three classes of breast ultrasound images benign (a), malignant (b) and normal (c)

The BUSI dataset is further divided into three categories with a ratio of 60:30:10, namely the images to be used for training, validating and testing the EfficientNet architecture. The appropriate ratio for the training, validation, and testing dataset was determined through trial and error, running the code several times with different ratios to obtain a combination that performs best. Therefore, the number of benign, malignant, and normal ultrasound images used for training, validation, and testing variants can be found in Table 1 below.

Table 1. Classification of ultrasound images by category

Category	Benign	Malignant	Normal	Total
Training	262	126	80	468
Validation	131	63	40	234
Testing	44	21	13	78

2.2 EfficientNet Framework

EfficientNet is a family of CNN architectures that offer superior performance and efficiency compared to other leading-edge models. In 2019, Google AI researchers developed the EfficientNet architecture, which is used in numerous computer vision applications, including medical imaging. The EfficientNet architecture combines multiple techniques to achieve better performance with fewer parameters than alternative models. It uses a composite scaling method that evenly scales the depth, width and resolution of the network to achieve an optimal balance between performance and efficiency [10]. EfficientNet models differ in their scaling coefficients, which determine the depth, width, and resolution of the network. The scaling coefficients are represented by three parameters. The parameter scales the network depth, scales the network width, and scales the image resolution. The composite scaling method ensures that the scaling coefficients are balanced for optimal performance and efficiency.

EfficientNetB0 is the base model of the EfficientNet family. It has fewer parameters than other modern CNN models and is therefore more efficient. EfficientNetB0 has significantly fewer parameters than ResNet50, another widely used CNN architecture that has 25 million parameters. EfficientNetB0 consists of a root convolutional layer followed by several blocks, each containing a number of convolutional layers and pooling layers. The blocks are organized hierarchically, with the first blocks extracting low-level features and the later blocks extracting higher-level features. EfficientNetB0 optimizes network depth, width and resolution using a novel composite scaling method. This method ensures that scaling coefficients are balanced for optimal performance and efficiency. EfficientNetB0 achieves peak performance on a wide range of computer vision tasks while requiring significantly fewer parameters than other models. To evaluate the performance of the architecture in classifying breast ultrasound images into three classes, several evaluation metrics were observed. The performance of each variant is compared in terms of accuracy (1), precision (2), recall (3) and F1-score (4). Also, the confusion matrix, loss curve, and receiver operating characteristic curve (ROC) are considered.

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN} \tag{1}$$

$$Precision = \frac{TP}{TP+FP} \tag{2}$$

$$Recall = \frac{TP}{TP+FN} \tag{3}$$

$$F1_{score} = 2 * \frac{Precision*Recall}{Precision+Recall} \tag{4}$$

As the model progresses through the training phase, a plot of the training and validation loss curve can illustrate the performance of the model with respect to the training and validation data set. Good models usually have a loss curve that starts with a high loss value and then gradually flattens out. This flattening of the curve indicates that additional training time no longer improves the performance of the model. Usually, the validation loss value is slightly higher than the training loss value. ROC is a graph in which the recall rate, also known as the true positive rate (TPR), is plotted against the false positive rate (FPR). A classifier with a curve closer to the upper left corner is able to perform better. The AUC value, on the other hand, measures the area under the ROC curve and represents the degree of separability, i.e., the performance of the classifier. AUC values range from 0 to 1, with higher AUC values indicating that the model is better able to classify individual data into the correct class. Equation (5) and (6) from [12] show the formulas for specificity and FPR, respectively.

$$Specificity = \frac{TN}{TN+FP} \tag{5}$$

$$FPR = 1 - Specificity = \frac{FP}{FP+TN} \tag{6}$$

3. DISCUSSION

The result of EfficientNetB0 is shown in Table 2 while the ROC curve is displayed in Figure 2. The first reported performance metric is accuracy, which measures the proportion of correctly classified images relative to the total number of images in the training set. In this case, the accuracy of the model was determined to be 82.05%, meaning that it correctly classified the majority of images in the dataset. The following two performance indicators are precision and recall. Precision quantifies the proportion of true positive classifications (i.e., the proportion of images correctly classified as cancerous) among all positively classified images. (i.e., both true and false positive images). In this case, the precision of the model was 84.00%, meaning that it correctly identified a large proportion of malignant images.

Table 2. EfficientNet evaluation metrics

EfficientNet	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
EfficientNetB0	82.05	84.00	82.00	81.00

Recall, on the other hand, evaluates the number of true positives divided by the number of true positives plus the number of false negatives. In this case, the model's hit rate was determined to be 82.00%, meaning that it correctly identified the majority of cancerous images in the dataset. The F1 score is a measure of the overall performance of the model that takes into account both accuracy and retrievability. It is obtained by calculating the harmonic mean of precision and recall. In this case, the F1 score of the model was found to be 81.00%, indicating a balanced relationship between precision and recall.

Overall, these results indicate that the model was able to classify breast ultrasound images as malignant or nonmalignant with a high degree of accuracy, precision, recall, and F1 score. However, it is important to note that the performance of the model may vary depending on the dataset used and the image features within that dataset. Further evaluation and validation may be required to ensure the reliability and applicability of the model.

4. CONCLUSION

In this study, we investigated the classification potential of breast ultrasound images using CNN with transfer learning over EfficientNetB0. The results of this study suggest that EfficientNets are ideally suited for use in the medical field, as they can reduce the amount of radiological assessment required by medical professionals. One of the main advantages of using EfficientNets is the ability to classify a large number of images in less time than radiologists can manually. This is a crucial aspect of breast cancer diagnosis, as timely and accurate detection is critical for successful treatment of the disease. EfficientNets can help in the early detection of breast cancer and enable faster and more effective intervention. In addition, the results of this research demonstrate the potential of EfficientNetB0 for automating the classification of breast ultrasound images. This has the potential to revolutionize medical image analysis and enable faster and more accurate diagnosis of breast cancer. While the results of this study are encouraging, more research is needed to develop and refine the use of EfficientNets in breast cancer diagnosis. Continued investigation and development of efficient and accurate algorithms is needed to enable widespread adoption of this architecture. We anticipate that the results of this study will stimulate and encourage further research in this area, ultimately leading to better medical care for breast cancer patients.

ACKNOWLEDGMENT

Part of this work was supported by the grant FRGS/1/2020/STG06/UKM/03/1.

REFERENCES

[1] Centers for Disease Control and Prevention, Breast Cancer. 2020. [Online]. Available: https://www.cdc.gov/cancer/breast/basic_info/index .htm

[2] Johns Ouahabi, A. (Ed.). Signal and image multiresolution analysis. John Wiley & Sons. 2012.

[3] Sood, R.; Rositch, A.F.; Shakoor, D.; Ambinder, E.; Pool, K.-L.; Pollack, E.; Mollura, D.J.; Mullen, L.A.; Harvey,

[4] S.C. Ultrasound for breast cancer detection globally: A systematic review and meta-analysis. J. Glob. Oncol. 5, 1– 17. 2019.

[5] Byra, M. Breast mass classification with transfer learning based on scaling of deep representations. Biomed. Signal Process. Control, 69, 102828. 2021.

[6] Azman, B. M., Hussain, S. I., Azmi, N. A., Abd Ghani, M. Z. A., & Norlen, N. I. D. Prediction of distant recurrence in breast cancer using a deep neural network. Revista Internacional de Métodos Numéricos para Cálculo y Diseño en Ingeniería, 38(1). 2022.

[7] L. Q. Zhou, X. L. Wu, S. Y. Huang, G. G. Wu, H. R. Ye et al., “Lymph Node Metastasis Prediction from Primary Breast Cancer US Images Using Deep Learning,” Radiology, vol. 294, no. 1, pp. 19-28, 2020.

[8] Hussain, S. I., & Ruza, N. (2022). Automated Deep Learning of COVID-19 and Pneumonia Detection Using Google AutoML. Intelligent Automation & Soft Computing, 31(2).

[9] T. Fujioka, K. Kubota, M. Mori, Y. Kikuchi, L. Katsuta et al., “Distinction between benign and malignant breast masses at breast ultrasound using deep learning method with convolutional neural network,” Japanese Journal of Radiology, vol. 37, no. 6, pp. 466–472, 2019.

[10] W. Al-Dhabyani, M. Gomaa, H. Khaled and A. Fahmy, “Deep learning Approaches for Data Augmentation and Classification of Breast Masses using Ultrasound Images,” International Journal of Advanced Computer Science and Applications, vol. 10, no. 5, pp. 618-627, 2019.

[11] M. Tan and Q. Le, “EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks,” International Conference on Machine Learning, pp. 6105-6114, 2019.

[12] W. Al-Dhabyani, M. Gomaa, H. Khaled and A. Fahmy, “Dataset of breast ultrasound images,” Data in Brief, vol. 28, pp. 104863, 2020.

[13] N. K. Chowdhury, M. A. Kabir, M. M. Rahman and N. Rezoana, “ECOVNet: A highly effective ensemble based deep learning model for detecting COVID-19,” Peer J Computer Science, 2020.