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Deep Learning Approaches for Classification of Breast Cancer in Ultrasound (US) Images

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ABSTRACT: Breast cancer is one of the deadliest cancer types affecting women worldwide. As with all types of cancer, early detection of breast cancer is of vital importance. Early diagnosis plays an important role in reducing deaths and fighting cancer. Ultrasound (US) imaging is a painless and common technique used in the early detection of breast cancer. In this article, deep learning-based approaches for the classification of breast US images have been extensively reviewed. Classification performance of breast US images of architectures such as AlexNet, VGG, ResNet, GoogleNet and EfficientNet, which are among the most basic CNN architectures, has been compared. Then, transformer models, which are one of the most popular deep learning architectures these days and show similar performance to the performance of CNN' architectures in medical images, are examined. BUSI, the only publicly available dataset, was used in experimental studies. Experimental studies have shown that the transformer and CNN models successfully classify US images of the breast. It has been observed that vision transformer model outperforms other models with 88.6% accuracy, 90.1% precison, 87.4% recall and 88.7% F1-score. This study shows that deep learning architectures are successful in classification of US images and can be used in the clinic experiments in the near future.

Keywords: Deep learning, breast cancer, classification, breast cancer classification, transformer, CNN, VGG, ResNet

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INTRODUCTION

Breast cancer is the most common type of cancer in women and is the leading cause of cancer-related deaths. Breast cancer is associated with a tumor that occurs due to the alteration and uncontrolled proliferation of one of the cell groups that make up the breast tissue. As in all types of cancer, in breast cancer, the cancerous tissue first spreads to its immediate surroundings. In breast cancer, the cancerous tissue, which can spread to the lymph nodes close to the breast, then spreads to other organs and passes into an incurable stage. In women, more than 2.26 million new cases of breast cancer and 685 000 deaths were recorded in 2020 (Siegel et al., 2022). As with all cancers, early detection of breast cancer can prevent the spread of cancer and even ensure that it is effectively treated and controlled. In studies, early diagnosis of breast cancer reduces breast-cancer-related deaths by 40% (Seely and Alhassan 2018). Such statistical information strongly emphasizes the vital importance of early diagnosis. Compared to other methods such as mammography and biopsy in the diagnosis of breast cancer, ultrasound imaging (US) has advantages such as painless, comfortable, and real-time operation. It is a popular imaging system especially for preliminary diagnosis. As in other imaging methods, the experience of the radiologist in breast cancer is the most decisive factor for the correct diagnosis in US.

Computer aided diagnosis systems (CAD) have been developed for a long time to diagnose many types of cancer (Pacal et al., 2020, Kilicarslan et al., 2021, Wang et al., 2021). CAD systems based on mammography images, pathology images, and US images have been developed for the diagnosis of breast cancers, but most of these systems were based on conventional machine-based systems. These systems lack accuracy and precision but are particularly lacking in generalizability (Pacal and Karaboga 2021). Recently, almost all these problems have been resolved with deep learning-based systems. Deep learning can learn from the experience of many specialist physicians, especially in medical image processing, and can be used effectively to improve outcomes based on a physician (Ozkok and Celik 2022). Thus, besides helping the specialist physician, it can make a serious contribution to the diagnosis of breast cancer. Deep learning architectures being fed with big data, having high generalization capabilities and discovering more useful features from data have made it a popular research area (Lecun et al., 2015). The adventure of deep learning, which started with object detection and classification, has taken the most remarkable place in many fields such as medical image processing, natural language processing, defense industry and autonomous vehicles.

Convolutional neural networks (CNNs) are the most important architecture that makes deep learning architectures popular in every field (Lecun et al., 2015). CNN architectures can extract useful features from raw data, learn from it, and carry out on many important tasks such as detection, classification and prediction (Işık and Artuner 2020, Ozkok and Celik 2021). The main advantage of CNNs is that they automatically detect important features without any human supervision (Pacal et al., 2022). CNN architectures, which achieved significant success firstly in object classification, later takes a place in many areas. CNNs are widely used in many fields such as computer vision, speech processing, face recognition and medical image processing. With the ever-increasing success of CNNs, both deep learning architectures have become popular and have gained a place in many fields. CNNs are used in almost all algorithms based on deep learning. In recent years, CNNs can be used in a hybrid structure with many deep learning architectures (Bayat and Isık 2022).

There are many deep learning-based approaches for diagnosing breast cancer using US images. These approaches are all CNN-based approaches and are generally studies done in the last few years. Some of the prominent studies among these approaches are as follows. Ragab et al (Ragab et al., 2022) proposed the Ensemble Deep Learning Effective Clinical Decision Support System for the diagnosis of breast cancer. This system offers a way to assist radiologists and healthcare professionals using US images. In the proposed method, three of the popular deep learning models are selected for feature extraction and a more powerful machine learning technique is presented for breast cancer detection. In another similar study, Zhang et al. (Zhang et al., 2021) presented a multitasking learning-based method for segmenting and classifying breast US images. In this method, soft and hard attention mechanisms are used simultaneously for the tasks. In this method, a dense CNN encoder is used in the classification process, and a decoder is also included. This decoder provides up sampling. Later, these units relate to attention-gated (AG) units with soft attention mechanism. The proposed model follows a successful path in the classification of US images. Eroglu et al. (Eroğlu et al., 2021) proposed a hybrid CNN-based method for the diagnosis of breast cancer using US images. This hybrid model has separately acquired and combined the features of AlexNet, MobileNetV2 and ResNet50 models. Thus, the proposed method has been used more successfully than single models in the diagnosis of breast cancer. Ayana et al. (Ayana et al., 2022) presented a new transfer learning-based approach that includes multiple CNN models for early detection of breast cancer from US images. To do this, he used features learned from the large natural image dataset ImageNet (Russakovsky et al., 2015). They then used the weights trained on the cancer cell line microscopic image dataset for transfer learning to train the breast US images. The main purpose here is to achieve more successful results than models trained with transfer learning.

Joshi et al. (Chandra et al., 2022) presented a novel approach to the classification of breast US images. This approach is a new method based on deep learning for the pre-diagnosis of breast cancer. This proposed technique used different data augmentation techniques and transfer learning to increase model performance. The proposed method used two different breast US datasets. In the experimental results of this technique, the model showed accurate and fast prediction performance on the test set, and it seemed that deep learning will be promising to help radiologists in clinical applications in the future. Pourasad et al. (Pourasad et al., 2021) designed a method for diagnosing breast tumors on US images. The proposed approach includes six techniques to detect and segment ultrasound images. First, the features of the images were extracted using the fractal method, while the k-nearest neighbor, support vector machine, decision tree and Naive Bayes classification techniques were used to classify the images. Finally, CNN architecture was used to classify breast cancer based on direct US images. Considering the experimental results of the proposed method, it seems that deep learning techniques offer successful results. Jabeen et al. (Jabeen et al., 2022) proposed a deep learning-based system for the classification of breast cancer in US images. The proposed deep learning model is based on a DarkNet53 model and several deep learning techniques. In the final stage, the best selected features are combined using a new probabilistic serial approach. This method gave remarkable results on the public dataset. In conclusion, studies in the literature show that deep learning approaches can be used for early detection of breast cancer from breast US images.

In this study, we used deep learning methods to classify US images for early detection of breast cancer. We examined the performance of the most popular and current deep learning methods on the BUSI (Al-Dhabyani et al., 2020) US public dataset. We employed transfer learning and data augmentation techniques to increase the performance of deep learning models. We conducted a detailed study for transformer, which is the most popular deep learning technique in medical image processing. Our aim here is to automatically recognize tumors in breast US images with the help of deep learning, and thus to assist radiologists. The rest of the article is organized as follows. Section 2 covers the deep learning approaches, dataset and training procedures used for breast cancer diagnosis. Section 3 presents the experiments, which contains the setup, experimental results, and comparisons. Finally, some remarks and conclusions are given in Section 4.

MATERIALS AND METHODS

Dataset and data augmentation

In deep learning architectures, the model and a sufficient dataset are the two most basic elements. A sufficient dataset is essential to the performance of data-hungry deep learning architectures. In particular, the generalization ability of a trained model on the test dataset depends on the training data. Therefore, data-hungry deep learning architectures are often trained with high-scale data. This study employs the Breast Ultrasound Images Dataset (Dataset BUSI) to classify breast cancer (Al-Dhabyani). This dataset was collected from 600 female patients aged 25-75 years in 2018. Each image is 500x500 pixels in size and consists of 780 images in total. This dataset consists of three categories: normal (133 images), malignant (210 images), and benign (487 images). In addition, ground truth images of each breast US image are available. This is for use of US images in segmentation or detection. Figure 1 shows examples from the BUSI dataset.

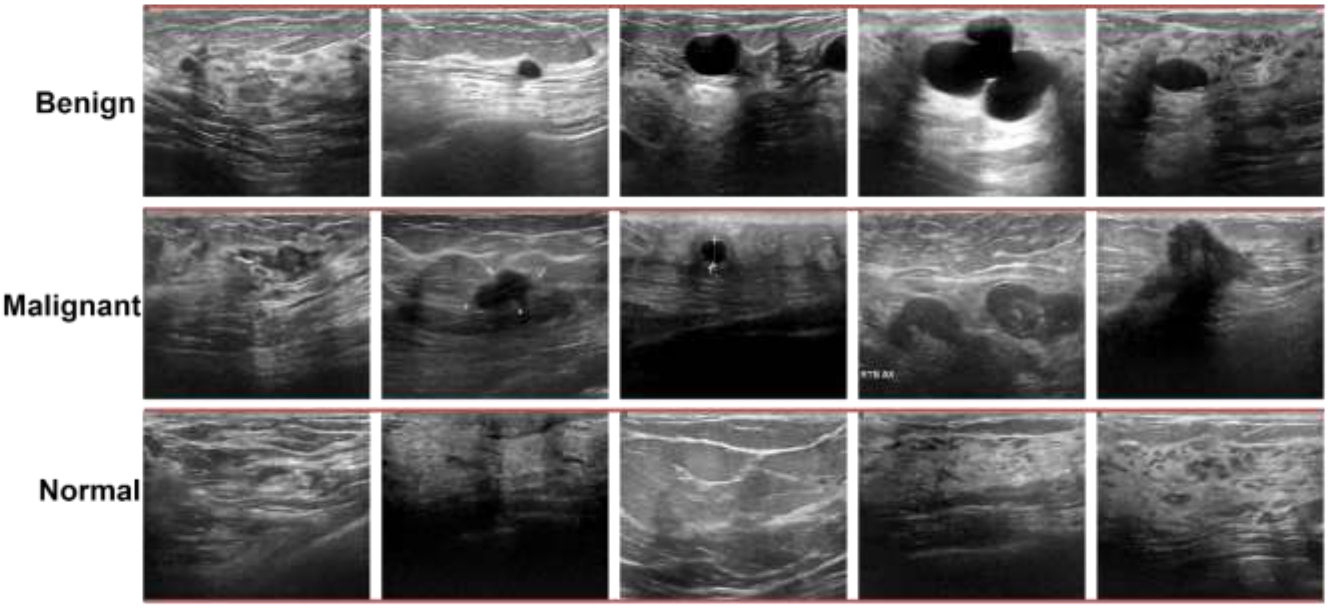

Figure 1. Some US images of the BUSI dataset

BUSI dataset is not fully sufficient for training deep learning architectures. Therefore, simple data augmentation techniques such as horizontal flip, vertical flip and rotation were used during the training. The aim here is to focus on the performance of deep learning architectures rather than the performance of dataset augmentation techniques. Therefore, by applying simple data augmentation techniques, the dataset has been made suitable for the deep learning environment. In this study, we divided the BUSI dataset into three parts: training, validation, and testing. 70% of the dataset is training data, 15% is validation and the remaining 15% is test data. The test data was never used in the training operations, but only for the evaluation of the model, so that the generalization ability of the model was tested on unseen data.

Convolutional neural networks (CNNs)

CNNs are the most popular and interesting of the deep learning architectures. CNNs are a multilayer neural network frequently used in image analysis and consist of an input layer, an output layer, and a hidden deep layer. A CNN architecture accepts images as input and could automatically extract features without the need for handcrafted feature extraction methods and approaches. CNNs take their name from their most basic layer, the convolution layer. The other base layers are pooling, activation, dropout, Fully Connected (FC) Layers. Each layer performs a different task assigned to it.

Brief summaries of each layer are as follows. **The convolution layer** is used to automatically extract features by applying a linear process called convolution. Discoveries of the most useful features take place in this layer with the help of filters. **The activation function** is the only construct that decides whether a selected neuron is activated or not (Kiliçarslan and Celik 2021). Therefore, it plays an important role in the training of the network. **The pooling layer** is the unit where different techniques are applied for the discovery of features, that is, subsampling. Various pooling techniques such as maximum, minimum, and average are used. A **drop layer** is one of the regularization techniques. It is used to randomly omit some neurons in the hidden layers. Thus, the number of parameters of the network is reduced. **The fully connected (FC) layer** may contain more than one convolutional or pooling layer. It consists of a series of fully connected layers that transform and connect every neuron in one layer to every neuron in the other layer in fully connected layers (Adem and Kılıçarslan 2021).

In this study, we give a brief explanation of some popular and basic deep learning architectures. We only give figures for some architectures, because all these models are quite common and popular. Our aim is to examine which models are more successful by making a short and concise explanation and to compare the performance of the models accordingly.

In this study, several popular CNN architectures were used to classify US breast tumor images. Our aim here is to examine which architecture is more successful. As it is known, CNN architectures have been continuously developed to classify ImageNet (Russakovsky et al., 2015) images more successfully. **AlexNet** (Krizhevsky et al., 2012) comes as one of the most basic architectures of these CNN architectures. AlexNet won the ImageNet large-scale image recognition competition in 2012. In this model, the depth of the network is increased compared to its first architect, LeNet-5.VGG architecture is another CNN model used. **VGG** (Simonyan and Zisserman 2015) architecture is another popular CNN architecture used in this study. VGG stands for Visual Geometry Group; it is a standard CNN architecture with multiple layers. While VGG16 architectures consist of 16 layers, on the other hand, VGG19 states that it consists of 19 layers. Developed as a deep neural network, VGG is currently still one of the most popular image recognition architectures. Figure 2 shows the VGG16 architecture.

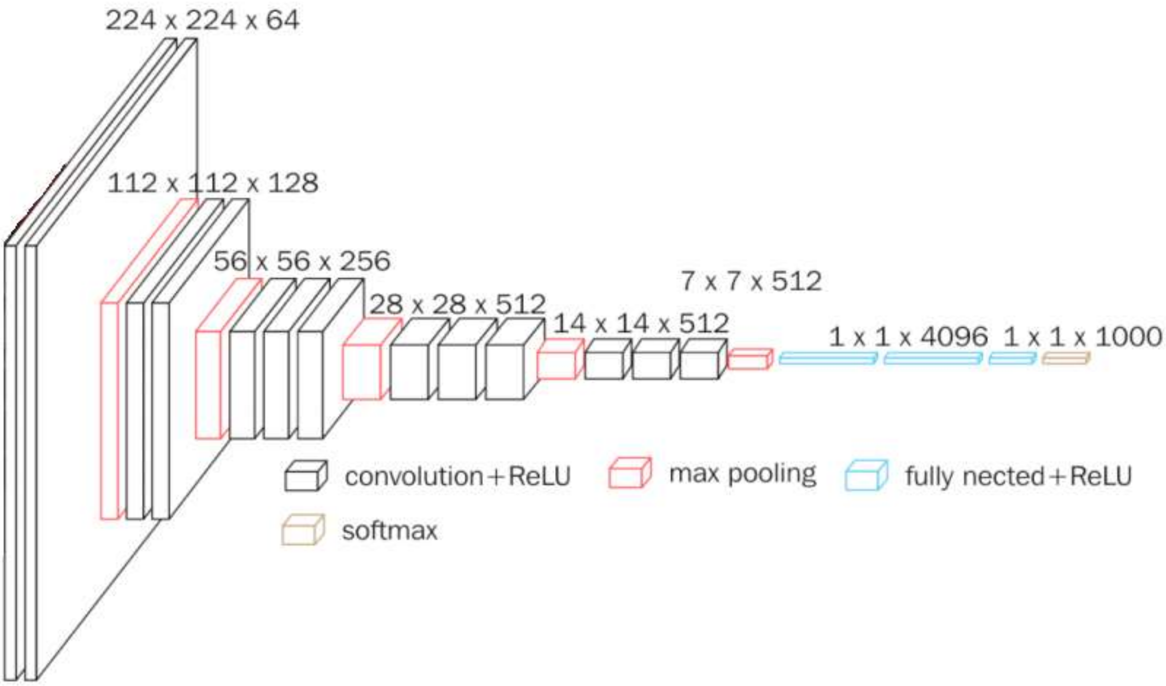

Figure 2. The VGG16 model architecture

Another architecture, **GoogLeNet** (Szegedy et al., 2015), has 22 layers, a variant of the Inception Network, a CNN developed by researchers at Google. The GoogLeNet architecture is a high-performance network that is frequently used in computer vision tasks such as image classification and object detection. Another popular **ResNet** (He et al., 2016) is a deep convolutional neural network that stacks residual blocks to form a network. ResNet architecture is a high-performance network that is frequently used in many object detection algorithms and object recognition. According to the number of layers of ResNet networks; It can be divided into models such as ResNet-34, ResNet-50 and ResNet-101. Another network used in this study is the **EfficientNet** (Tan et al., 2020) model. This network is suggested from Google Research, Brain team. Being a deep network, EfficientNet has made a significant contribution to the literature by introducing a new scaling method that equally scales all the depth, width, and resolution dimensions of the network. Later, many architectures were based on this idea of scaling.

In recent years, the **transformer** (Vaswani et al., 2017) model has managed to become one of the main elements of advances in deep learning and deep neural networks. In fact, transformers used for advanced applications in natural language processing soon found their way into computer vision, where they gradually replaced convolutional neural networks (CNN) for many complex tasks. The most up-to-date architecture used in the study is transformers. These structures use a new architecture called 'Attention Is All You Need'. In other words, they use the attention mechanism. Transformer is an architecture to convert one string to another with the help of two parts (Encoder and Decoder), but it does not rely on recurrence and convolutions to produce an output. Figure 2 demonstrates the A transformer (Attention Is All You Need) architecture.

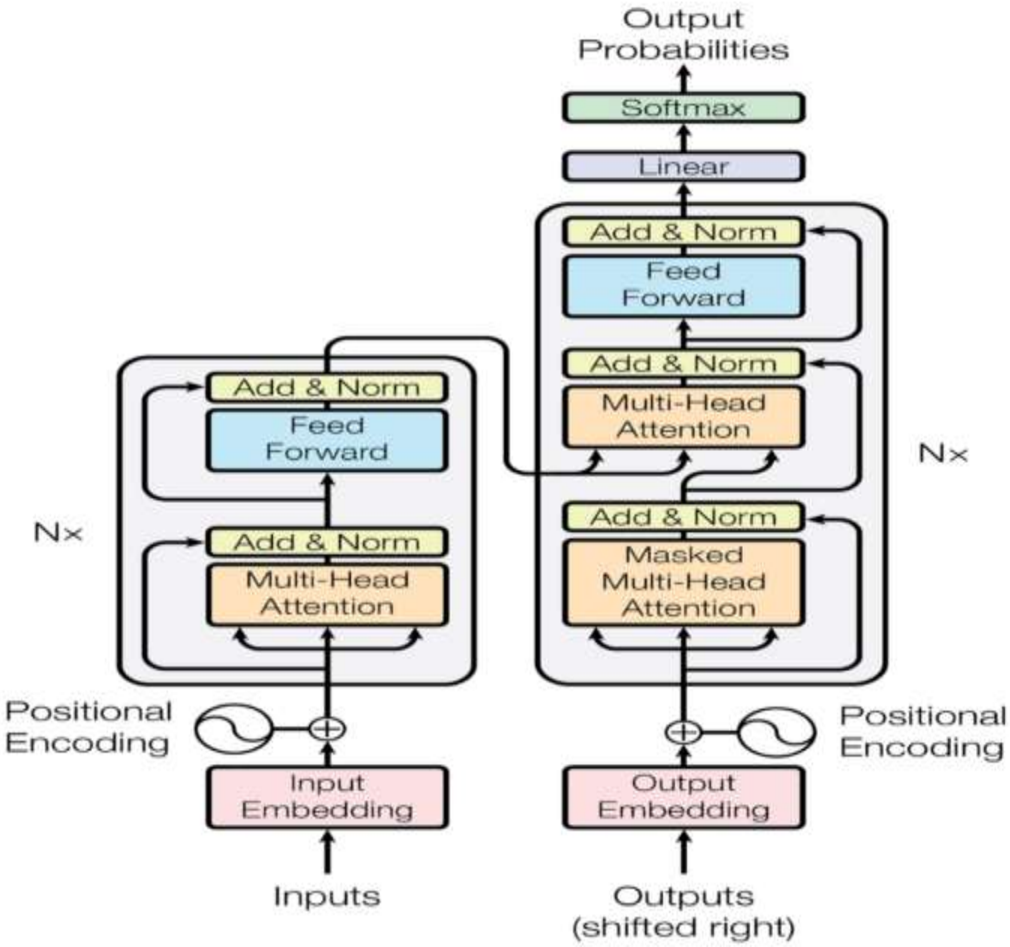

Figure 3. The transformer - model architecture

Training

To conduct the experimental results more objectively, we performed the following steps. Most studies that classify tumors from breast US images have used several deep learning architectures, and in general these architectures are outdated but popular ones. For example, VGG and ResNet architectures are frequently used. We conducted a wider study using both popular and current architectures. These architectures are AlexNet, VGG, GoogleNet, ResNet, EfficientNet and transformers, respectively. To conduct a more stable experiment in these architectures, SGD optimizer, 0.001 learning rate and 0.9 momentum are used the same in all architectures. Transfer learning was used because the BUSI dataset contains insufficient number of US images. Transfer learning is the process of transferring the weights of a model trained in one area to a different area. It also allows convergence to occur with less epoch and is often used in small datasets. In this study, we performed transfer learning by using ImageNet weights of each model. In addition to these, basic data augmentation techniques such as flip and rotation were used during the training. Furthermore, most studies do not have clear information on how the dataset is distributed in training, validation, and testing. It is stated in studies that it is generally used for 80% training and 20% for testing. Experimental results are difficult to interpret because there is no clear statement for validation. In this study, we used much clearer expressions compared to other studies. In this study, the first 15% of the data was used for the test set, the second 15% for the validation, and the remaining, 70% of the dataset, employed for the training data. The distribution showing the training, validation and test data of the data set used in our study is given in Table 1.

Table 1. Information on how the BUSI dataset is employed in this study

BUSI Dataset	Normal	Benign	Malignant
Number of test images	20 (1-20) sequence	65 (1-65) sequence	32 (1-32) sequence
Number of validation images	20 (21-40) sequence	65 (66-130) sequence	32 (33-64) sequence
Number of training images	93 (41-133) sequence	307 (131-437) sequence	146 (65-210) sequence

As can be seen in Table 1, the number of US images used in training, validation and testing and which image ranges are used are clearly indicated. Thus, a more objective experiment can be performed.

RESULTS AND DISCUSSION

Experimental setup

In this study, all experiments were carried out with a PC with the following specifications. The most up-to-date version of Linux, Ubuntu 22.04, which is the most suitable operating system for deep learning platforms, was used. Hardware-wise, this computer consists of Intel® Core™ i7-12700K Processor (25M Cache, up to 5.00 GHz) processor, 64 GB DDR5 (5200Mhz) RAM and NVIDIA RTX 3090 graphics card. The NVIDIA RTX 3090 graphics card contains 10496 CUDA cores, 328 tensor cores, and uses a 384-bit memory interface with 24GB of GDDR6X memory. Python was used as programming language, PyTorch and NVIDIA CUDA Toolkit 11.7 were used as framework.

Performance metrics

Evaluation or performance metrics are used to determine the generalization performance of a deep learning model. These metrics are the metrics that are common in measuring the performance of the model and especially its generalization ability. The most used metrics are Accuracy, Precision, Recall, and F1 score, and we used these metrics in our experimental study. Accuracy is the ratio of correct guesses to the total number of guesses. Precision is the ratio of correct positive predictions to total positive predictions. Recall, also known as Sensitivity or True Positive Ratio (TPR), determines the ratio of correct positive predictions to total predictions in a specific actual class. Finally, the F1- score gives the weighted average between precision and recall. The mathematical formulas of these metrics are given in the equations below.

$$Accuracy = \frac{Number\ of\ correct\ predictions}{Number\ of\ total\ predictions} \tag{1}$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \tag{2}$$

$$Recall = Sensitivity = \frac{True\ Positive}{True\ Positive + False\ Negative} \tag{3}$$

$$F1 = \frac{2 * Precision * Recall}{Precision + Recall} \tag{4}$$

Experimental results and discussion

Although many studies have been presented for the diagnosis of breast cancer from US images, the objectivity of the studies is decreasing for the following two reasons. It is difficult to evaluate models with these data, as most of the studies include private datasets. Another reason is that many studies do not have detailed explanations of how the BUSI dataset is used. In this study, we explained in detail which data are used in training, validation, and testing in the BUSI dataset because the dataset has a very high effect on model performance. In addition, we conducted experiments to determine whether the diagnosis of breast cancer from US images would be successful with popular and current deep learning models. Experimental results for each model are shown in Table 2.

Table 2. Experimental results for each deep learning model

Model name	Accuracy	Precision	Recall
AlexNet	0.795	0.801	0.796
VGG16	0.854	0.858	0.855
VGG19	0.786	0.797	0.786
GoogleNet	0.756	0.772	0.759
ResNet18	0.826	0.835	0.828
ResNet34	0.838	0.854	0.834
ResNet50	0.831	0.864	0.829
ResNet101	0.847	0.875	0.831
EfficientNet	0.856	0.867	0.843
Swin_Transformer	0.819	0.819	0.796
Vision_Transformer	**0.886**	**0.901**	**0.874**

Considering Table 2, it is seen that the models performed successfully on the test data. As it is known, in deep learning approaches, repeatability cannot be guaranteed in the training process of the models. The main reason for this is that even if the same seeds are used, different results are obtained between CPU and GPU executions. It also arises from non-deterministic sources such as randomness. Therefore, we performed 5 runs for each model in our experiments and then gave the average. Thus, we have presented more stable results. Considering experiment results, VGG16, which is one of the popular architectures, seems to be quite successful. In ResNet architectures, the performance increased in proportion to the depth of the model. AlexNet and GoogleNet architectures showed less performance compared to other architectures. Transformers, which are excluded from CNN architectures, seem to be more successful. Transformers, which have recently become as popular as CNN in medical image processing, showed their success here as well. Vision transformers models are quite successful in classifying breast US images in all metrics compared to other models. Figure 4 shows the performance of the F1 metric for each model.

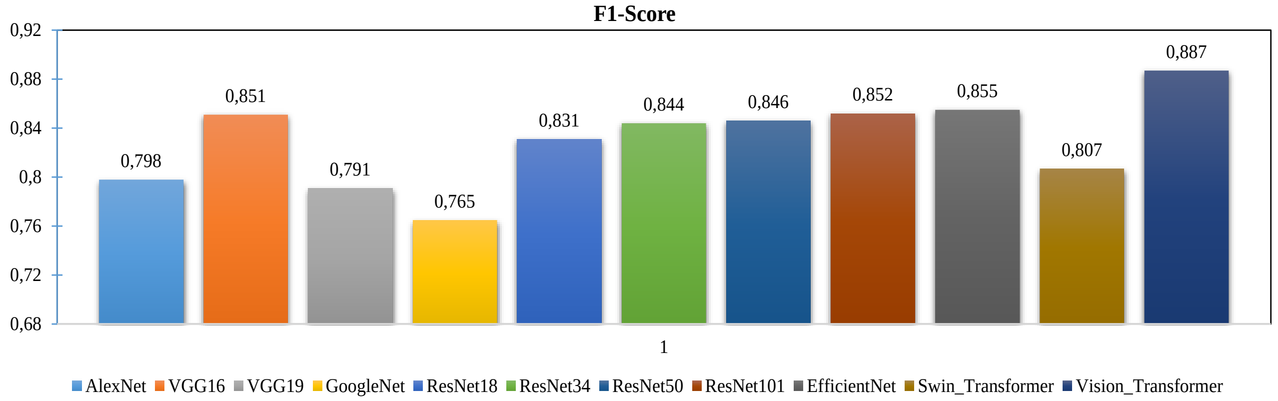

Figure 4. The F1-score of the experimental results of each model

As seen in Figure 4, the vision transformer model is quite successful compared to other models. Since the F1 metric is the harmonic average of the precision and recall metrics, it is more robust in measuring performance compared to other metrics. Therefore, in short, the vision transformer model has successfully classified breast US images with a rate of close to 89%. Then, in the F1 metric, EfficientNet with 85.5%, ResNet101 with 85.2% and VGG16 with 85.1%, respectively, are more successful than other models. Although the VGG architecture does not have as deep a structure as the ResNet101 architecture, it has shown the same performance as ResNet101 in terms of performance. On the other hand, GoogleNet architecture showed the lowest performance with an F1-score of 76.5%. Deep models did not perform well in performance because the BUSI dataset is a small dataset and the number of images per class is also small. Even if data augmentation techniques are applied, deep models can show the desired performance with the sufficient dataset. It is predicted that there will be an increase in the performance of deeper architectures if the dataset is large-scale.

Although very simple data augmentation techniques such as flip and rotate were used during the training in this study, the performance of the models can be said to be quite good. The success of these models can be more than 90% (F1-score) with pre-processing and different data augmentation techniques before the training, together with the data augmentation techniques applied during the training. It could be increased even more with the use of techniques such as hyper-parameter optimization and ensemble learning methods. In addition to all these, if the data imbalance problem in the BUSI dataset is removed, the performance will increase even more.

CONCLUSION

In this study, we applied deep learning methods in the diagnosis of breast cancer and made a detailed comparison. Early detection of breast cancer is of vital importance. Ultrasound (US) imaging is one of the most common methods used in the early diagnosis of breast cancer. Classification of breast US images was performed using the basic CNN architectures available in the literature and transformer structures, which have become very popular in medical image processing today. Simple data augmentation techniques and transition learning were used to increase the performance of the models. Experimental studies were applied on the BUSI data set, which is publicly available in the literature. Experimental studies have revealed that deep learning techniques for classification of breast US images are quite successful, and the vision transformer model is more successful than other models. In future studies, it is planned to present more specific models for the early detection of breast cancer from US images. In this context, it is considered to propose a high-performance transformer model together with a wider review of transformer models.

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