BREAST CANCER DIAGNOSIS BY USING DEEP LEARNING

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Abstract: Breast cancer is one of the most common and serious types of cancer, especially in women. Definitive treatment of breast cancer may vary depending on early, rapid, and accurate diagnosis. The need for scientific studies that can contribute to early diagnosis continues today. It is a fact that studies are being carried out to use deep learning methods in every field of medicine and developments are being made every day. In this study, a deep learning application that can diagnose breast cancer and classify benign, malignant and normally cancerous tumors was implemented using the deep convolutional neural networks (DCNN) method. Training and testing results show that the pre-trained DCNN model proposed in the study has a very promising performance in breast cancer diagnosis.

Keywords: Deep Learning, Pre-Trained, CNN, GoogleNet, TL, Breast Cancer

INTRODUCTION AND THEORETICAL FRAMEWORK

Breast cancer is a type of cancer that occurs in breast cells. It can occur in both men and women, but is more common in women. Diagnosing breast cancer typically involves a combination of physical examination, imaging tests (such as mammography, ultrasound, and MRI), and tissue sampling (such as biopsies). These tests help doctors determine if there are any abnormalities or cancerous cells in the breast tissue. Although misdiagnosis can occur with any medical condition, it is important to remember that the diagnostic process for breast cancer is quite extensive and involves multiple tests to minimize the chance of misdiagnosis. However, some cases of misdiagnosis may still occur depending on various factors, such as the interpretation of test results or the presence of similar conditions. Early diagnosis and treatment of breast cancer is crucial to increasing the chances of successful outcomes. Regular screenings and self-exams can help detect breast cancer at an early stage when it is more treatable.

Artificial intelligence (AI) has shown great potential in aiding breast cancer diagnosis. Deep learning methods, a subset of artificial intelligence, have been particularly useful in analyzing medical images and identifying patterns that may indicate the presence of cancer. Convolutional Neural Networks (CNNs), a type of deep learning model, have shown promising results in detecting breast cancer from ultrasound images and other imaging techniques. CNN has been used in many studies to date in the diagnosis of breast cancer and successful results have been obtained (Agnes et al., 2020; Lei et al., 2021; Desai and Shah 2021). The advantage of DCNNs lies in their ability to learn and recognize complex patterns in medical images; This can aid early detection and reduce the likelihood of misdiagnosis. However, it is important to remember that artificial intelligence cannot replace human doctors but rather is a tool to help them make more accurate and effective diagnoses (Nogay and Adeli, 2020; Nogay et al., 2021).

In this study, breast cancer diagnosis and classification were developed with a DCNN tested with ultrasound images. The remaining parts of the study are organized as follows. After the introduction section, the purpose and scope of the study are revealed. In the next section, information is given about the method and data set used in the study. Finally, the findings obtained in the study are presented. In the conclusion section, the results obtained and future directions are discussed.

AIM

The aim of this study is to perform triple classification for breast cancer diagnosis with a DCNN model trained and tested with ultrasound images.

SCOPE

This study is a deep learning application that is trained and tested with a data set consisting of ultrasound images and segmentation images (mask) of these images. In this application, the aim is to diagnose breast cancer by making a triple classification. In the triple classification, there are benign, malignant and normal categories.

METHODOLOGY

Obtaining the data set

The ultrasound images obtained in the study and the mask (segmentation result image) images of these images were created in 2018 and published on the international database Kaggle.com. More detailed information can be obtained from https://www.kaggle.com/datasets/aryashah2k/breast-ultrasound-images-dataset (Al-Dhabyani et al., 2019). In the study, 780 ultrasound images of 600 female patients and segmentation result (mask) images of these images were used. Images are divided into three groups: benign, malignant and normal. Some ultrasound images may have more than one segmentation image. According to this situation, the total image data is 1578 in total, 891 for benign, 421 for malignant and 266 for normal. Figure 1 shows three ultrasound images of benign, malignant and normal conditions from the data set and the mask images of these images (Buda et al., 2020).

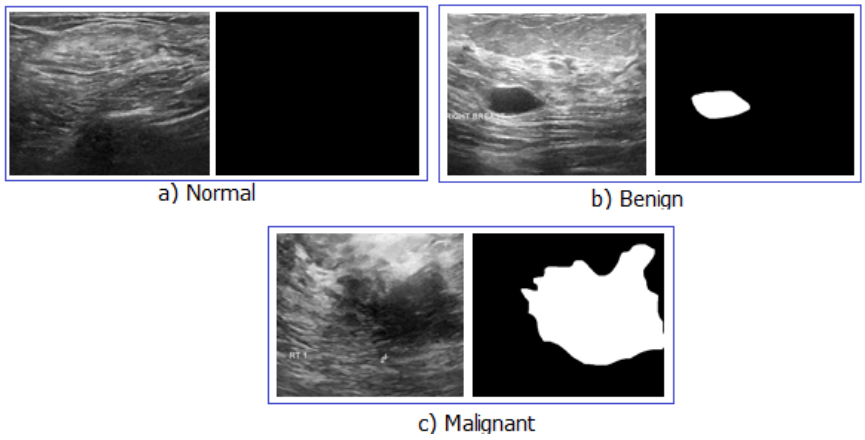

Figure 1. Example Ultrasound Images in the Dataset

Transfer Learning (TL)

Transfer learning (TL) is a powerful technique in deep learning in which knowledge gained from solving one problem is applied to a different problem. It involves leveraging pre-trained models on large-scale datasets and then fine-tuning them for specific tasks. The idea is that the learned representations of the pre-trained model can be generalized and applied to new tasks, saving time and computational resources. Using transfer

learning, models can start with a good knowledge base and then specialize in specific tasks, leading to increased performance, faster training times, and reduced data requirements. This is a technique that helps artificial intelligence systems become more efficient and versatile (Zhu et al., 2020), Tuncer et al. 2020; Yu and Wang, 2019).

Deep Convolutional Neural Network Model

In this experimental deep learning application, the GoogleNet pre-trained model was used by using the transfer learning method. GoogleNet is a deep learning model designed by Szegedy and colleagues in 2015 to participate in the ImageNet competition. With its success in the competition, this CNN model has been used in many scientific studies thanks to the transfer learning approach (Szegedy et al. 2015). According to the Transfer Learning method, the last three layers of the GoogleNet CNN model were revised in accordance with the purposes of our study. Structural information and revised layers about the GoogleNet CNN pre-trained model are shown in Table 1.

Table 1. Structural Information of the Proposed Pre-Trained DCNN Model

Input Image	**224x224x3**
Number of Convolution Layer	57
Number of Pooling	14
Number of Fully Connected	1
Number of Dropouts	1
Number of Normalization	2
Number of Activation Function (ReLu)	57
Total number of all layers	144
Rearranged layers via transfer learning	Classification, Softmax and Last Fully Connected

Training and testing of the model

The GoogleNet pre-trained DCNN model applied for the study is trained with the previously separated training data, which is 75% of the whole data until it reaches the minimum value of the missing value. In the Softmax layer, input images are assigned to one of the K classes with the cross entropy function. After the training process is completed, the proposed CNN model is tested with test data that is randomly selected and separated from all data. In equation (1), N represents the sample size, K represents the number of classes, tij represents the i sample in class j, and yij represents the output for sample j in class i (Bishop 2006). Table 2 shows the limitations of the training and testing process.

$$Loss = -\sum_{i=1}^{N}\sum_{j=1}^{K} t_{ij} \ln y_{ij} \quad (1)$$

Table 2. Limitations for the Training and Testing Process

Maximum epoch	**30**
Maximum iteration	840
Iteration per epoch	28
Validation Frequency	5 Iteration
Initial learning rate	0.0001
Mini batch size	42
Learning rate schedule	Constant

RESULTS

As a result of the testing process, graphical, numerical, and matrix results were obtained. Table 3 shows the training and test results, accuracy rates, and losses. Accuracy rate and loss curves are given in Figure 2, and the confusion matrix is given in Figure 3. According to the test results obtained, it is seen that an accuracy rate of 89.34 was reached.

Table 3. The Results of the Proposed DCNN Model

Training Accuracy (%)	Testing Accuracy (%)	Training Loss	Testing Loss	Epoch	Iteration
95.24	89.34	0.1139	0.2682	30	840

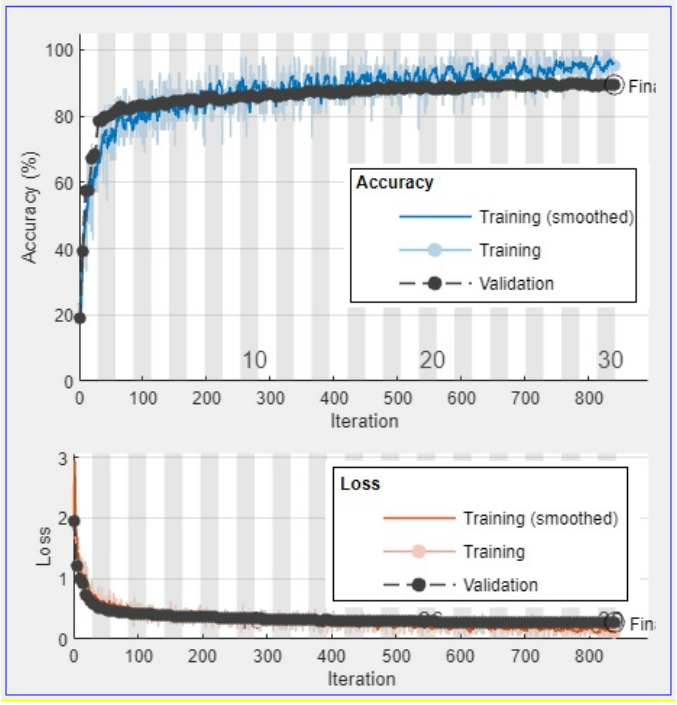

Figure 2. Loss and Accuracy Curves of the Proposed DCNN Model

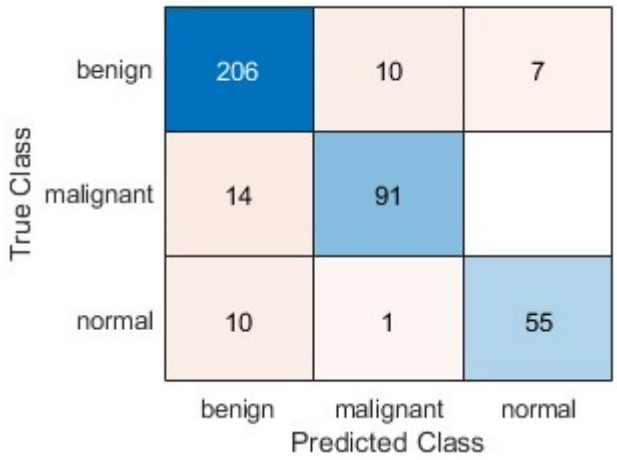

Figure 3. The Confusion Matrix Obtained as a Result of the Test Process

CONCLUSION

In this study, the pre-trained GoogleNet model, which is a deep learning technique for breast cancer diagnosis, was applied by revising the last three layers using the transfer learning approach. Achieving an accuracy rate of 89.34% for breast cancer diagnosis seems quite impressive. Using 1578 ultrasound images to train the model is a significant amount of data from which the model can learn and can contribute to the model's ability to make accurate predictions. The accuracy rate of 89.34% shows that the model has good performance but there is always room for improvement. As with all AI models, the model's performance needs to be continually evaluated and improved by incorporating more diverse and representative data. Overall, this deep learning study reveals promising results and demonstrates the potential of artificial intelligence in medical diagnosis.

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