최적화된 심층모형을 이용한 저배율 조직병리학적 이미지 기반 다종 유방암 분류법

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Low Magnification Histopathological Images for Multi-Class Breast Cancer Classification Using Optimized Deep Model

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Abstract - Surgery open biopsy is considered a gold standard to examine the presence of cancer. However, to assess accurately, a subjective measure involving experienced pathologists is required. Therefore, to assist the pathologists in accommodating their workload, a deep neural network may have a promising role to classify the cancers not only into benign and malignant but also into the subset of those cancer types. This study presents a deep model to categorize the breast cancer histopathological images into eight classes, such as adenosis, fibroadenoma, phyllodes tumor, tubular adenoma, ductal carcinoma, lobular carcinoma, mucinous carcinoma, and papillary carcinoma using 40× magnification BreaKHis dataset. The classification assigning a pre-trained InceptionV3 model and adaptive gradient algorithm optimizer along with data augmentations and learning rate scheduler has been accomplished. The results represented by training, validation, and test accuracies and losses indicate that the model classifier is feasible to categorize the breast cancer histopathological images into adenosis, fibroadenoma, phyllodes tumor, tubular adenoma, ductal carcinoma, lobular carcinoma, mucinous carcinoma, and papillary carcinoma. Additionally, an advanced study is essential to improve the classifier ability.

1. Introduction

The procedure to screen the breast tissue can be possible with the modality imaging techniques invasively, i.e., magnetic resonance imaging (MRI), X-ray, ultrasound (US), optical tomography, and computed tomography (CT) [1]. However, those modalities have a common deficiency in image acquisition. For instance, CT can provide adequate information on the dense tissue, in contrast, MRI may offer satisfactory reconstructed images for soft tissue. Moreover, the US has an issue with the speckle and optical tomography has a low resolution of the reconstructed images [2]. Hence, the biopsy techniques, such as fine-needle aspiration, core needle biopsy, vacuum-assisted, and surgical (open) biopsy (SOB), are considered essential procedures to accurately diagnose almost all cancer types, including breast cancer.

By performing the biopsy, pathologists who are experts in microscopical image analysis are required. Nevertheless, this analysis is time-consuming, inconvenient, and not effective concerning the cost. Additionally, the pathologists' perspective is affected by endurance and fatigue. Thus, to overcome such problems, the deep model with a convolutional neural network (CNN) may provide the decent capability to evaluate the breast cancer histopathological images. This study performed a pre-trained weight and model assigning InceptionV3 with an adaptive gradient algorithm (Adagrad) optimizer, a learning rate scheduler, and data augmentation to establish a classifier for categorizing the breast cancer histopathological images into adenosis (A), fibroadenoma (F), phyllodes tumor (PT), tubular adenoma (TA), ductal carcinoma (DC), lobular carcinoma (LC), mucinous carcinoma (MC), and papillary carcinoma (PC) using 40× magnification BreaKHis dataset [3].

2. Methods

The 40× magnification BreaKHis dataset has 114, 253, 109, and 149 images of A, F, PT, and TA, respectively. Also, it contains 864, 156, 205, and 145 images of DC, LC, MC, and PC. A, F, PT, and TA are non-cancerous, while DC, LC, MC, and PC are cancerous.

To balance the dataset, we employed ten image augmentations, namely 10, 20, 30, 90, 180, 270, 340, and 350 degrees rotations, as well as horizontal and vertical flips. These augmentations offered 1000 images for each class. Then, we split the dataset into training and test datasets using 80:20; thus, the training images were 800, meanwhile, the test images were 200 for each class. Using 800 training images, again, we split the dataset into training and validation images utilizing an 80:20 ratio. Hence, we had 640 training images and 160 validation images. To avoid overfitting, we increased the number of training images to 2560 images with shear, height shift, and width shift data augmentations. Table 1 shows the training, validation, and test dataset in summary.

Table 1. Datasets in this study

Cancer Type	Training	Validation	Test
A, F, PT, TA, DC, LC, MC, and PC	2560	160	200

InceptionV3 model by substituting its last layer with 8 classes was applied. Likewise, we employed 150 epochs, 100 batch sizes, softmax activation function, cross-entropy loss function, and Adagrad optimizer. Additionally, a learning rate scheduler with 10-3 as an initial learning rate, as well as a decay rate of 0.96, was used.

3. Results and Discussions

Figure 1 depicts the accuracies and losses of training and validation in every epoch. Our model can overcome the overfitting problem; thus our classifier is considered feasible to classify breast cancer into 8 classes. In addition Table 2 shows the training, validation, and test accuracies and losses, respectively. We can achieve high overall accuracy (test accuracy) at 97.75% with a low loss of 8.81%. Moreover,

Figure 2 presents the confusion matrix to provide comprehensive results of this study. With these results, we have demonstrated that our model is beneficial for classifying the breast cancer histopathological images into A, F, PT, TA, DC, LC, MC, and PC using a 40× magnification BreaKHis dataset.

Table 2. Results of this study

Metric	Training (%)	Validation (%)	Test (%)
Accuracy	99.68	99.00	97.75
Loss	2.02	2.86	8.81

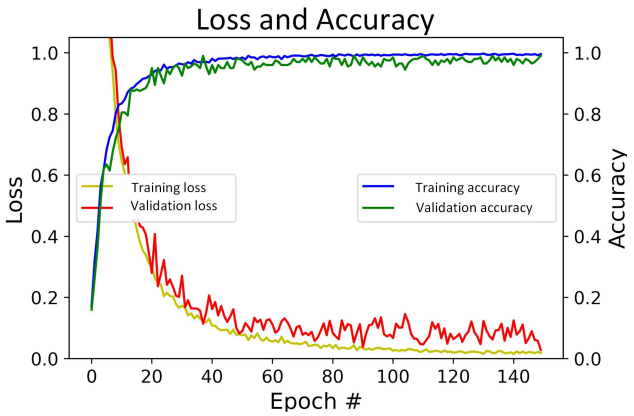

Figure 1. Training and validation accuracies and losses

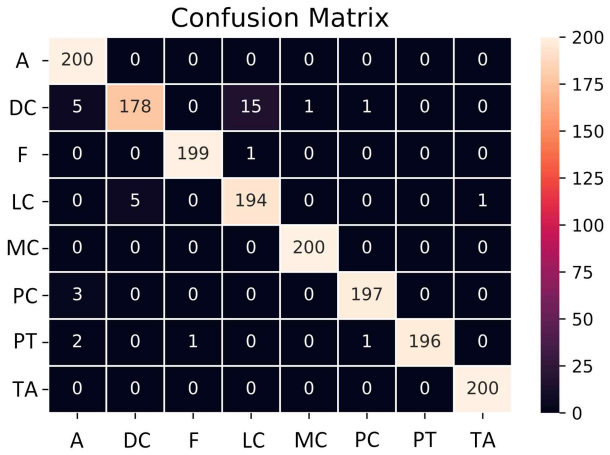

Figure 2. Confusion matrix

4. Conclusions and Future Works

We have designed the classifier with InceptionV3 to categorize breast cancer into A, F, PT, TA, DC, LC, MC, and PC using a 40× magnification BreaKHis dataset. The results indicated that the preliminary model in this study is promising to be extended for breast image classification to obtain improved accuracy with less loss. The future study is recommended to implement k-fold cross-validation and fine-tune the classifier model with several optimizers and hyperparameters to discover the best model. Moreover, 100×, 200×, and 400× magnifications are considered to apply for enhancing the overall accuracy.

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