A Method for Classifying Medical Images using Transfer Learning: A Pilot Study on Histopathology of Breast Cancer

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Abstract**—** The advance of deep learning has made huge changes in computer vision and produced various off-the-shelf trained models. Particularly, Convolutional Neural Network (CNN) has been widely used to build image classification model which allow researchers transfer the pre-trained learning model for other classifications. We propose a transfer learning method to detect breast cancer using histopathology images based on Google's Inception v3 model which were initially trained for the classification of non-medical images. The pilot study shows the feasibility of transfer learning in the detection of breast cancer with AUC of 0.93.

Keywords – Breast cancer, Transfer learning, Inception v3, Convolutional Neural Network, Deep Learning

I. Introduction

Breast Cancer Facts & Figures reported 1.7 million breast cancer cases in 2012 as breast cancer is the most common female cancer in 140 of 184 countries [1]. Early detection of breast cancer is an important factor in survival, since the five-year survival rate of stage 3(75.8%) and stage 4(34.0%) decreases rapidly compared to the survival rate of stage 0 to 2 (98.3% ~ 91.8%). The detection of breast cancer has been determined by specialists' pathologic diagnosis that is influenced by doctor's experience and other external factors.

To solve this problem, computer-assisted analysis methods have been applied in medical imaging including machine learning algorithms [2-5]. Especially, deep neural network has shown outperformance in image analysis due to the development of computing resources [6-8].

However, the performance of deep learning depends on the amount and the quality of data to build the learning model for the target application. In this paper, we propose a method to solve the limited amount of training data by the use of data augmentation and transfer learning which utilizes pre-trained learning model with other image sets. We investigated the feasibility of transfer learning in clinical decision by applying Google's Inception v3 model to classification of histopathological images of breast cancer.

II. Related Works

Recent studies have leveraged machine learning techniques in medical image analysis. Various algorithms have achieved high performance in nucleus segmentation and classification with breast cancer images [2-5]. Spanhol et al. published a data set, named as BreaKH, for histopathological classification of breast cancer and suggested a test protocol by which the experiment obtained 80% to 85% accuracy using SVM, LBP(Local Binary Pattern), and GLCM(Gray Level Co-occurrence Matrix)[5]. Convolutional Neural Network(CNN) is known to achieve high performance in image recognition and natural language processing through pattern analysis. CNN is a specific type of neural network, which is a feed-forward neural network with convolutional layer, pooling layers and fully connected layers as its hidden layer. Due to its outstanding performance, CNN is used widely in many fields, especially in computer vision. Deep cascade CNN was utilized to detect cells mitosis in breast histopathological image[9].

Recent research using transfer learning have obtained prominent results in image analysis. Transfer learning is a method that trains a pre-trained model, which is already learned in a specific domain, to another knowledge domain. Transfer

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learning method is known to be very useful when the data is not enough or trainng time and computing resources are restricted. AlexNet was transferred for the classification of breast cancer histopathological image with higher accuracy than normal CNN's performance in [6]. Wei et al. proposed BiCNN model based on the GoogLeNet that outperformed LeNet, AlexNet and VGG-16 [8]. Esteva et al. Proposed CNN-PA that diagnoses skin cancer using transfer learning[10]. In recent studies, Google Inception v3 is reported as the outstanding CNN model, which is designed for image classification task and trained for the ImageNet's Large Visual Recognition Challenge(LVRC) data [12]. Google Inception v3 model outperformed VGGNet [13], GoogLeNet [14], PreLU [15] and BN-Inception [16] in error rate.

In classification of hispathological images, the magnification of images is another issue in the use of machine learning. Bayramoglu et al. proposed a model that can learn and predict the decision of disease regardless of different magnifications [7].

III. Methods

A. DataSet

In this paper, we used BreaKHis database composed of 7909 microscopic biopsy images of benign and malignant breast tumor acquired on 82 patients [5]. BreaKHis is collected using different magnifying factors (40X, 100X, 200X, and 400X) and contains 2,480 benign and 5,429 malignant images. Table 1 shows the distribution of the dataset.

TABLE I. Distribution of the dataset [5]

Magnification	Benign	Malignant	Total
40x	625	1,370	1,995
100x	644	1,437	2,081
200x	623	1,390	2,013
400x	588	1,232	1,820
Total	2,480	5,429	7,909
# Patients	24	58	82

We trained with images of lowest magnifying factors (40X) to verify the ability to identify the ROI (region of interest) in the whole image, since the enlarged images already revealed the information of ROI. Therefore, we used 625 images of benign tumor, 1,397 images of malignant tumor collected using magnifying factor 40x for training. Training set is composed of 438 images of benign, 960 images of malignant and validation set is composed of 187 images of benign, 410 images of malignant.

B. Preprocessing

CNN needs sufficient amount of data to achieve prominent performance. We applied data augmentation techniques to compliment the insufficient data in training. Rotated images by 90°, 180°, 270°, mirrored(flipped left-right, top-bottom) images and randomly distorted images were added to the original dataset. Consequently, the initial data set, which was composed of 438 images of benign class and 960 images of malignant class, was augmented to total of 11,184 images (3,504 benign images and 7,680 malignant images).

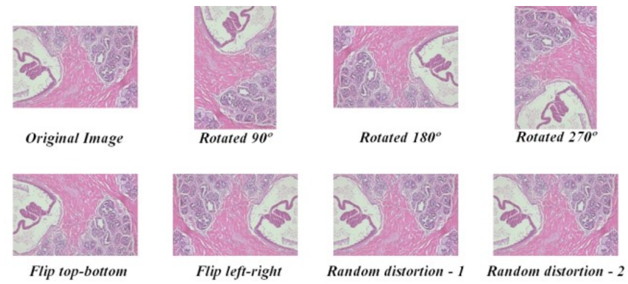


Figure 1. Example of augmented images by rotating, flipping, and random distortion.

C. Transfer Learning

In this paper, we built deep convolutional neural network(CNN, ConvNet) model to classify breast cancer histopathological images to malignant and benign class. In addition to data augmentation, we applied transfer learning technique to overcome the insufficient data and training time.

As a pre-trained model in trasfer learning, we utilized Google's Inception v3 using python API provided by TensorFlow [17]. The architecture of traditional CNN [11] and Google's Inception v3 were depicted in Figure 2.

Figure 3 shows overall workflow of the proposed method utilizing data augmentation and transfer learning to classify histopathological images of breast cancer.

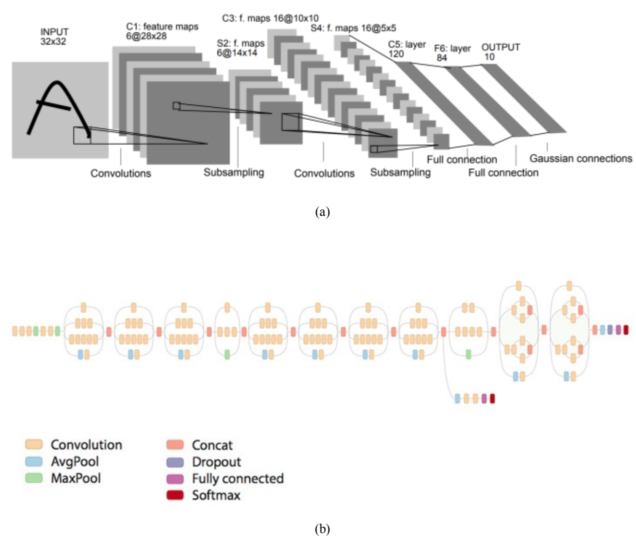


Figure 2. Architecture of traditional CNN and Google's Inception v3: (a) traditional CNN architecture for recognizing hand-writings, and (b) the architecture of Inception v3 model.

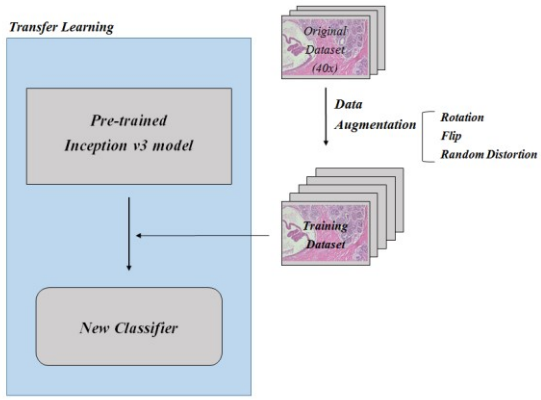
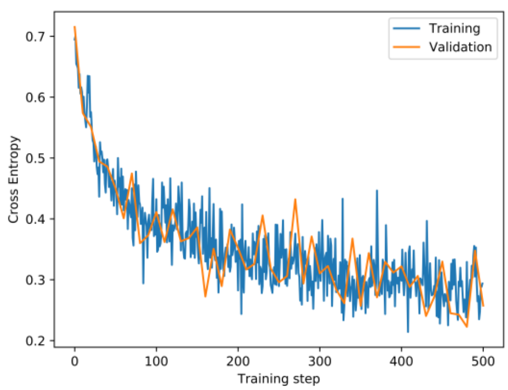


Figure 3. Overall workflow of proposed method using transfer learning. and data augmentation.

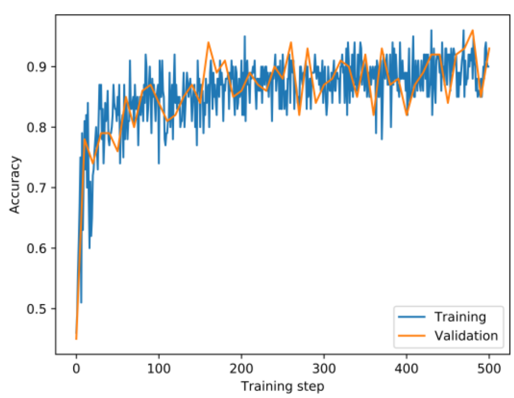
IV. Results

A. Training accuracy & Cross-entropy

We measured the training accuracy and cross-entropy during the training steps as shown in Figure 4.



(a)



(b)

Figure 4. (a) Cross-entropy and (b) accuracy of training model. Orange curve indicates the training cross-entropy/accuracy and blue curve indicates the validation cross-entropy/accuracy.

Training accuracy increased as training proceeds and the fianl accuray was 0.89 at 500 training steps. Cross-entropy is used as cost function, which is calculated as formula (1).

$$H(x) = H(p) = -\sum_i p(xi)\log\big(p(xi)\big) \qquad (1)$$

B. Optimizing Cut-off

Classification task to assist medical diagnosis has asymmetric misclassification cost, since the cost for missed detection of breast cancer (false negative) is higher than the false positive classification. Optimizing cut-off value method is used for such asymmetric misclassification cost.

In general, the classifier computes the probability that a training data belongs to a particular class using cut-off value over which the sample is classified to a positive class. Therefore, tuned cut-off value adjusts the weight on each class in learning. Figure 5 and Table II show the change of classification accuracy according to various cut-off values. Cut-off value is set to the score of malignant, which is the probability that a record belongs to malignant tumor class.

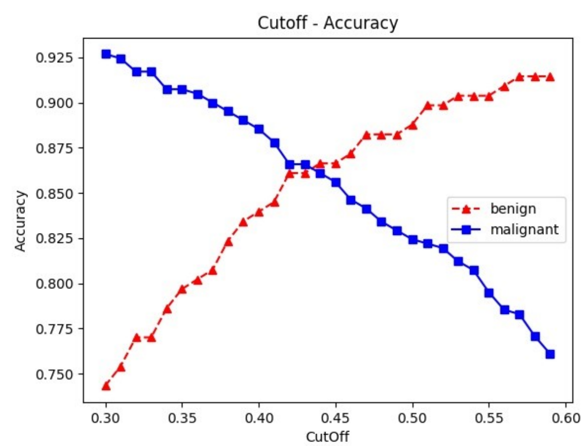


Figure 5. Classification accuracy and cutoff values.

TABLE II Classification Accuracy by different cut-off values

	Classification Accuracy	
Cut-off	Benign	Malignant
0.3	0.74	0.93
0.4	0.83	0.89
0.5	0.89	0.82
0.6	0.91	0.76

C. ROC curve

ROC curve of the proposed method with cut-off value of 0.4 is shown in Figure 6. Area Under the Curve(AUC) of malignant was 0.93 and AUC of benign was also 0.93.

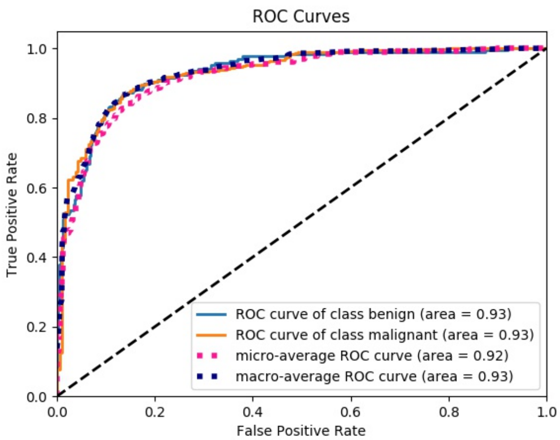


Figure 6. ROC curves of our model, with cutoff value 0.4

V. CONCLUSION

In this work, we have proposed classification of breast cancer histopathological images based on transfer learning technique. We retrained Google's Inception v3 model with breast cancer microscopic biopsy images and our trained model performed classification in accuracy of 0.83 for benign class and 0.89 for malignant class. In this study, we investigated and demonstrated the feasibility of transfer learning in medical diagnosis by retraining a model pre-trained on irrelative knowledge domain to target domain.

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