The Classification of Mammogram Using Convolutional Neural Network with Specific Image Preprocessing for Breast Cancer Detection

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***Abstract*—The incidence rate of breast cancer continued to rise in the last few decades. Current screening strategy of breast cancer is based on classic X-ray imaging. The sensitivity and specificity of the diagnosis are largely depend on the experiences of the radiologists, and uncertain diagnosis is quite frequent because of resolution limitations and the concerns of lawsuits arisen from wrong diagnosis or undetected lesions. The convolutional neural network is an effective technique for classification in deep learning model. In this study, we utilized median filter, contrast-limited adaptive histogram equalization, and data augmentation to preprocess over 9,000 mammograms, and trained a classified model by using convolutional neural network. The experiment results demonstrated that the accuracy of model with preprocessed images significantly outperformed the model without preprocessed images.**

Keywords-mammograms; breast cancer detection; convolution neural network; deep learning

I. INTRODUCTION

According to the public health survey of the Ministry of Health and Welfare in Taiwan [1], breast cancer is the most dangerous cancer for Taiwanese females. The incidence rate was about 69.1% per 100,000 peoples and the probability of malignant tumors is still increasing Figure 1. There's a good chance of recovery if the breast cancer is detected in early stages with a 5-year survival rate of above 90%.

Mammography has been used to detect early stage breast cancer. In Taiwan, females older than 45 years old are recommended for a screening mammogram biannually. The Breast Imaging Reporting and Data System (BI-RADS) is an international standard for categorizing the stages of breast cancer in mammography. Table I shows the all categories of BI-RADS.

Some lesions may be ignored by the radiologists because of the deficiency of experiences or technical interferences. Sometimes, the examinees may be categorized for further recall for another examination due to insufficient information on the mammograms or avoidance of a possible legal conflicts because of the possibility of making a false positive diagnosis. These situations may cause delay of an early intervention.

Convolutional neural network (CNN) in deep learning is one of the most effective technique for image classification [2]. We are conducting a study which utilizes the median filter, contrast-limited adaptive histogram equalization, and data augmentation method to preprocess the mammograms and train a classified model by using the CNN. This will build an aiding system for breast cancer staging and detection benign and malignant breast tissues.

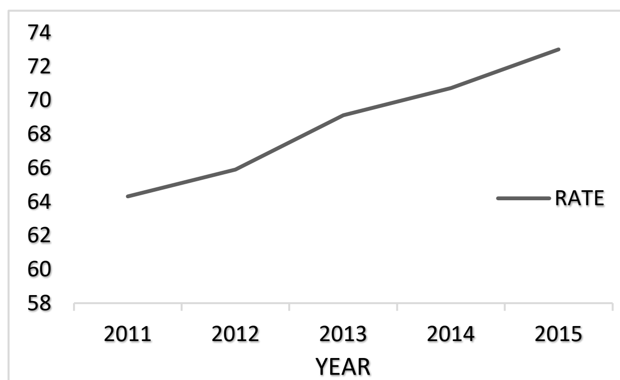

Figure 1. The incidences of malignant tumor [1].

TABLE I. THE CATEGORY OF BI-RADS

Category	Means
0	Incomplete
1	Negative
2	Benign findings
3	Probably benign
4	Suspicious abnormality
5	Highly suspicious of malignancy
6	Known biopsy with proven malignancy

978-1-7281-0831-5/19/$31.00 ©2019 IEEE

II. Previous Works

A. Literature Review

A list of previous works conducted by medical scientists are summarized in Table II.

TABLE II. LITERATURE REVIEW

Ref.	Area of image	Preprocessing method	Evaluation
Geras et al.	Whole image	Gaussian noise	macROC
BAKKOURI & AFDEL	Region of interest	Data augmentation Gaussian pyramid scaling	Accuracy ROC curve Sensitivity Specificity
Carneiro et al.	Whole image	Data augmentation Local contrast normalized Otsu algorithm	Accuracy
Wei et al.	Whole image	Data augmentation	Patient score Patient Level
Zhou, Zaninovich, Gregory	Region of interest	Data augmentation	Recall rate Accuracy
Zhang et al.	Whole image	Data augmentation	ROC curve auROC

Deep learning with CNN with preprocessing strategy has emerged as one of the most powerful approach in image classification [3].

Geras et al [4] used the Deep CNN to classify mammogram images into BI-RADS 0, 1, and 2 using normalization and data augmentation for preprocessing. The four angles of images (R-MLO, L-MLO, R-CC, and L-CC) were constructed into the same network architecture and concatenated each network's output. The performance was enhanced along with data increment.

Bakkouri and Afdel [5] used the CNN to classify the benign and malignant tumors with an accuracy of 97.26% with data preprocessed with the Gaussian pyramid multi-scaling and data augmentation.

Carneiro et al [6] used transfer learning model technique to classify the mammograms with an accuracy of 97%. The images were preprocessed with local contrast normalization and background removed with the Otsu algorithm.

Wei et al [7] used the CNN to classify breast cancer histopathological images preprocessed by using data augmentation method. The approach successfully reached a patient recognition rate of 97%.

Zhou, Zaninovich and Gregory [8] used the CNN to detect and classify mammograms with the cropped and data augmentation method used for image preprocessing. For the identification of calcifications, the study demonstrated a recall accuracy of 100% and test accuracy of 100%. For the masses, the study demonstrated a recall rate of 50% and an accuracy rate of 75%.

Zhang et al. [9] used the CNN and transfer learning method to classify mammograms using data augmentation method. The AlexNet model and the transfer learning method were used to obtain the feature maps. The result showed an auROC of with data augmentation and auROC of 0.62 without data augmentation.

Data augmentation is an ideal approach for increasing the size of data also shown to increase the accuracy of classification [10] and thus the power of discrimination while transfer learning has an advantage of shorter training time. These two approaches are always used to improve the model performance.

Another approach that may enhance the performance of deep learning is the use of image de-noise strategy. Use of the contrast limited adaptive histogram equalization(CLAHE) [11] reduces the chance of a noise amplification problem which is common when using the Adaptive histogram Equalization (AHE) that over amplifying the contrast of the images. Pisano et al. [12] adopt the CLAHE to improve the detection of spiculations on dense mammograms. Akila et al. [13] found CLAHE offered better enhancements on masses and microcalcifications. Figure 2 demonstrates the imaged preprocessed with CLAHE and without CLAHE.

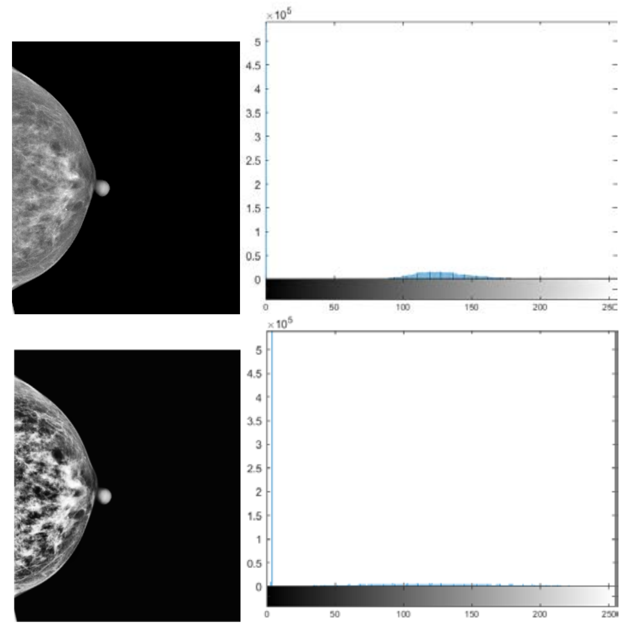

Figure 2. Up: Histogram without using CLAHE; Bottom: histogram using CLAHE.

B. Data Statisctis

A total of 2363 examinees with BI-RADS 0, 1, 2, 3, 4, and 5 were collected from a teaching hospital in Taiwan and 9927 images with resolution 2294*1914 were obtained. Four views including R-MLO, L-MLO, R-CC, and L-CC were available for most of the examinees.

C. Image Preprocessing, Data Augmentation, and Filtering

In order to enhance the contrast of the images, we adopted the CLAHE to preprocess our mammograms. This method reduces the chance of a noise amplification problem that is common when using the Adaptive histogram Equalization (AHE) which over amplifying the contrast of the images. The CLAHE reduces amplification noises by limiting the slope of cumulative distribution function (CDF). The slope of CDF corresponds to the height of probability density function. Thus, the CLAHE clipped the histogram before CDF computation. The part of the histogram that exceeds the clip will not be discarded but to be redistributed. The CLAHE process is briefly described as follows. First, the images are divided to several non-overlapping images called tiles. Second, histogram of each tile is calculated. Third, histogram will be clipped according to the value of clip limit until its height does not exceed the clip limit. Finally, the neighboring tiles will combine with each other with bilinear interpolation to eliminate boundaries.

Another problem in our mammogram study is that most of the examinees have benign tissues. This underlaid an unbalance data structure for the development of a model that discriminate malignancy. We adopt the data augmentation method to resolve the problem. We flipped the images of malignant tumors horizontally and vertically. This generates more images with tumors present in different orientations.

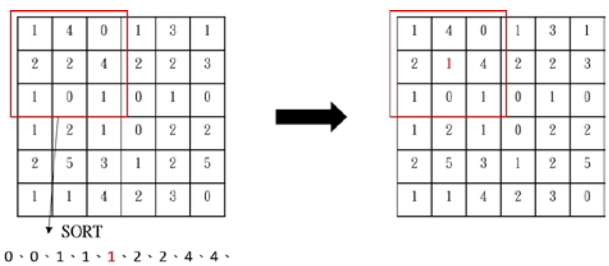

Figure 3. Median filter processing.

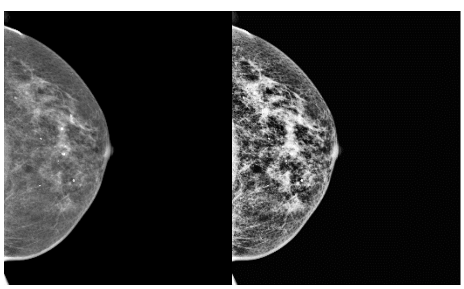

Figure 4. Left: without preprocessing with median filter and CLAHE; Right: with preprocessing with median filter and CLAHE.

Filtering methods have been used to improve image quality, remove the noise, and preserves the edges within an image [14]. Median filter, a nonlinear filter method that preserves edges which are the most important part of a visual appearance, was used to improve the image quality and remove salt and pepper noises by replacing each pixel value with the median of neighboring pixel. Sukassini and Velmurugan [15] compared the performance of median filter and mean filter in removing noises. Their results showed that median filter is better than mean filter in removing noises in the mammograms. Figure 3 briefly explains the median filter process: define filter size, sort pixel value inside filter size, and replace specific pixel value. Increment of the size of filter indicates an effective noise removal [16].

Figure 4 demonstrates the pre-processing effects using median filter and CLAHE achieved by MATLAB function. Our research process is summarized in Figure 5.

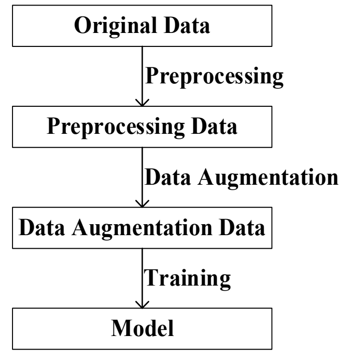

Figure 5. Research process.

D. *Transfer Learning*

Transfer Learning, also called fine-tuning, uses a larger dataset to train a model (pre-train model). After training, the model modifies the number of classification categories, and then another dataset is added for further training [17].

Levy and Jain [18] showed that transfer learning can be used to improve the model performance. In our study, we adopt a transfer learning model without pre-trained weights [4]. This model consists 13 convolutional layers and 4 pooling layers. The architecture is showed in Table III.

We trained this network with Adam optimizer with a learning rate 0.0001 and Rectified Linear Unit (ReLu) activation function and dropout rate 0.5 on a computer with two Nvidia RTX 2080TI GPUs, each with 11GB memory and an Intel i7-7900X CPU.

TABLE III. MODEL ARCHITECTURE

	Kernel size	**strides**	**filters**
Convolution	3*3	2*2	32
Max_pooling	3*3	3*3	32
Convolution	3*3	2*2	64
Convolution(repeat*2)	3*3	1*1	64
Max_pooling	2*2	2*2	64
Convolution(repeat*3)	3*3	1*1	128
Max_pooling	2*2	2*2	128
Convolution(repeat*3)	3*3	1*2	128
Max_pooling	2*2	2*2	128
Convolution(repeat*3)	3*3	1*2	256
FC Neural Network		1024	
FC Neural Network		2	

III. RESULTS

A. *Model Performance*

We choosed 70% of the dataset as training data, 10% of dataset as validation data, 20% of dataset as testing data. We defined BI-RADS 0,1,2,3 as benign and BI-RADS 4,5 as malignant. We used one-hot encoding to encode these two categories. The model accuracy was 0.823 in testing dataset. With the use of image preprocessing approach, the sensitivity, specificity, and F1 score were 0.91, 0.57, 0.88. Without image preprocessing approach, the sensitivity, specificity, and F1 score were 0.79, 0, 0.88. these results are showed in Table IV and Table V.

IV. CONCLUSION

Preprocessing improve the sensitivity and specificity of transfer learning model for BI-RADS categorization.

TABLE IV. RESULTS WITH PREPROCESSING

Predict class	**Actual class**	
	0(benign)	**1(malignant)**
0(benign)	685	115
1(malignant)	65	152
Sensitivity	0.913	
specificity	0.569	
PPV	0.856	
NPV	0.70	
FPR	0.43	
F1 score	0.883	

TABLE V. RESULTS WITHOUT PREPROCESSING

Predict class	**Actual class**	
	0(benign)	**1(malignant)**
0(benign)	800	0
1(malignant)	217	0
Sensitivity	0.786	
specificity	0	
PPV	1	
NPV	0	
FPR	0	
F1 score	0.880	

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