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Abnormal breast identification by nine-layer convolutional neural network with parametric rectified linear unit and rank-based stochastic pooling

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ABSTRACT

Aim: Abnormal breast appears similar as dense breast in mammography, which makes it a challenge for radiologists to identify. Scholars have proposed numerous computer-vision and machine-learning based approaches. Nevertheless, the features were manually designed.
Method: In this study, the breast dataset was chosen as the open-access mini MIAS dataset. Cost-sensitive learning was used to balance the dataset. Data augmentation was used to increase the size of training set. We proposed an improved nine-layer convolutional neural network (CNN). In addition, we compared three activation functions: rectified linear unit (ReLU), leaky ReLU, and parametric ReLU. Besides, six pooling techniques were compared: average pooling, max pooling, stochastic pooling, rank-based average pooling, rank-based weighted pooling, and rank-based stochastic pooling.
Results: The results over 100 test set showed the combination of parametric ReLU and rank-based stochastic pooling performed the best, with sensitivity of 93.4%, specificity of 94.6%, precision of 94.5%, and accuracy of 94.0%. This result is better than six state-of-the-art breast cancer detection approaches.
Conclusion: Deep learning can provide better detection results than traditional artificial intelligence methods. We validate why we set the number of convolution layers as 2. We shall try to further improve the performance of this proposed method.

1. Background

Breast cancer develops from breast tissue. The risk causing breast cancer include modifiable risk factors and fixed risk factors [1]. The former one means people can change themselves, and the latter one means the factors that cannot be changed. Common risks include smoking, age, gender, hormonal birth control, dietary factors, radiation, shift-work, etc. In UK, about one in eight women will be diagnosed with breast cancer during lifetime [2].

The breast cancer staging considers the size of tumor, whether the tumor is metastasized, whether the tumor has spread to lymph nodes [3]. Stage 0 is a pre-cancerous condition, such as ductal/lobular carcinoma in situ. Stages 1–3 are tumors within the breast or nearby lymph nodes. For Stage 1A, the tumor is less than or equal to 2 centimeters, the lymph nodes are not affected. For Stage 1B, cancer may be found in axillary lymph. Stage 4 is metastatic cancer.

Digital mammography (DM) is the easiest approach for detecting breast cancer. The fatty issue appear black, however, the dense breast tissues appear white, the same color as breast masses or tumors, making the tumor may behind or overlap with dense breast tissues. Computer-vision based methods may provide better performance on DM images than human experts. Milosevic, Jankovic [4] proposed spatial gray level dependence (SGLD) matrix and gray-level co-occurrence matrix (GLCM) to detect abnormal breasts. Nakamura [5] detected abnormal breast via hybridization of biogeography-based optimization and particle swarm optimization (HBP). Gorgel, Sertbas [6] proposed a hybridized technique that combined spherical wavelet transform (SWT) and support vector machine (SVM). Liu [7] is the first to apply a weighted-type frac-

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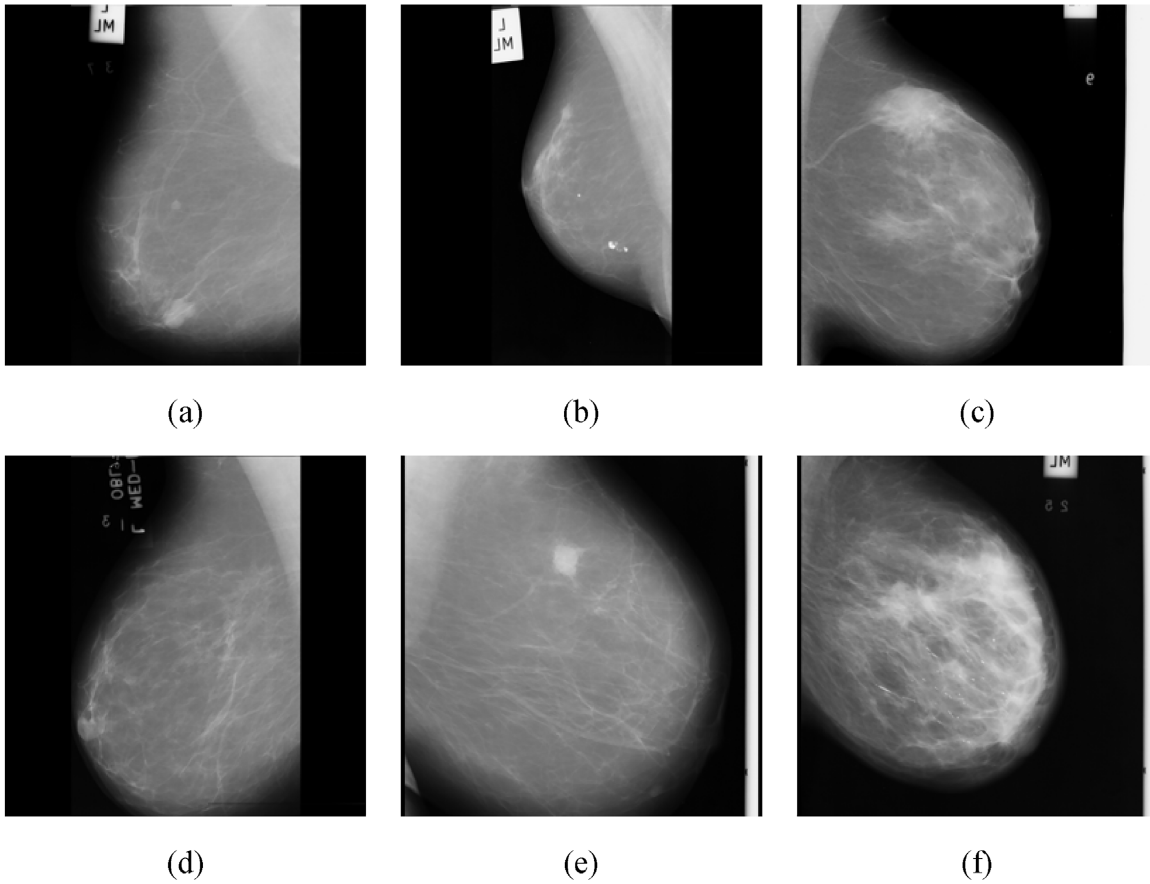

Fig. 1. six abnormal breast types: (a) Circumscribed Mass; (b) Asymmetry; (c) Architectural distortion; (d) Calcification; (e) Ill-defined masses; (f) Spiculated masses.

tional Fourier transform (WFrFT) and k-nearest neighbors (kNN) to extract features from DM images. Yang, Li [8] utilized the thin-plate spline (TPS) and maximum intensity projection (MIP). Rao [9] used a newly-proposed optimization algorithm, namely Jaya algorithm, to detect breast cancer. Wang, Zheng [10] used ensemble algorithm based on support vector machine. Banaie, Soltanian-Zadeh [11] suggested to extract spatiotemporal features from dynamic contrast-enhanced (DCE) magnetic resonance imaging (MRI). Wu [12] proposed a new improved biogeography-based optimization (IBBO) method.

We reviewed abovementioned literature, and all of them can identify abnormal breast automatically with high accuracy. Nevertheless, those methods need to manually determine how to extract feature. With the help of deep learning, we expect to determine the features in automatic way, i.e., present a data-driven method. The convolutional neural network (CNN) is the most popular tool in deep learning, and it has shown success in many academic and industrial fields, e.g., radar image segmentation [13], alcoholism detection [14], resolution enhancement [15], microorganism classification [16], etc. Face recognition [17,18] and plasma identification [19] are hot ways that scholars apply CNN to.

In this study, our contribution is to apply CNN to identify breast cancer in digital mammogram. Besides, to get better performance of CNN, we proposed two improvements. First, the leaky rectified linear unit was used to serve as the activation function. Second, the rank-based stochastic pooling was used to replace ordinary pooling technique. The experiments showed the effectiveness of this improved CNN.

The remainder of the paper is organized as follows: Section 2 contains the subjects and related preprocessing techniques, include cost-sensitive learning and data augmentation. Section 3 introduced the basic rational of convolutional neural network, and three activation functions and six pooling technologies were introduced and compared. Section 4 provides experiments, results, and discussions. Finally, Section 5 gives the concluding remarks.

2. Dataset

2.1. mini_MIAS dataset

The mini-MIAS database [20] was downloaded, which contains 322 single-breast mammogram images with sizes of 1024×1024. 209 are normal breasts, and 113 are abnormal breasts. We used mini_MIAS dataset because numerous published papers were based on this dataset. Hence, we can easily compare our method with them.

The abnormal breasts consist of six types shown in Fig. 1. In this study, our task is not predicting each abnormal brain to one of the six abnormal types. Instead, we treated all six abnormal types as one class "abnormal", and our aim is to detect abnormal breasts in the mammogram images. Note the spiculated masses represents sharp-point barbed tissues. These spiky tumors have spicules or elongated pieces of tissues sticking out from the perimeter. The spiculated masses exist on the periphery of the breast, not the center.

2.2. Cost-sensitive learning

The dataset is divided into training and set. Here the test set consists of 50 abnormal and 50 normal breast images. The training set consists of 63 abnormal and 159 normal images, as shown in Table 1. During the training stage, the imbalanced dataset (63