Breast Ultrasound Image Classification and Segmentation Using Convolutional Neural Networks

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Abstract. Due to the shortage and uneven distribution of medical resources all over the world, breast cancer diagnosis and treatment is a fundamental but vital problem, especially in developing countries. Breast ultrasound image classification and segmentation method by using Convolutional Neural Networks (CNN) can be a new efficient solution in early analysis and diagnosis. What's more, the diagnosing of diversity of cancers is challenge in itself and the training of data-driven based CNN model also highly relay on dataset. In this paper, we first build a breast ultrasound dataset (with 1418 normal and 1182 cancerous samples) labeled by three radiologists from XiangYa Hospital of Hunan Province. And then, we propose a two-stage Computer-Aided Diagnosis (CAD) system to diagnose the breast cancer automatically. Firstly, the system utilize a pre-trained ResNet generated with transfer learning approach to excluded normal candidates, and then use an improved Mask R-CNN model for the accurate tumor segmentation. Experimental results show that the proposed system can achieve 98.72% precision and 98.05% recall for classification, and 85% (1.2% improvement) mAP and 82.7% (3.1% improvement) F1-Measure than the original Mask R-CNN model.

Keywords: Breast ultrasound image · Breast ultrasound dataset
Image classification · Tumor segmentation

1 Introduction

As a leading cause of death for women worldwide, breast cancer has caused a wide public concern, while detection and treatment at an early stage are essencial to effectively overcome this burden. Over the last decades, benefit from the development of Convolutional Neural Networks (CNN) in the field of image classification and segmentation, enhanced the importance of medical imaging

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(such as ultrasound, mammography, X-ray) for the early detection, diagnosis and treatment of this disease.

Ultrasound and mammography imaging technology are often used as the common and effective method in early diagnosis of breast cancer [1]. By contrast, ultrasound is more useful and effective than mammography due to following advantages [6,20,33,35]. (1) It is safer without radiation, cheaper, faster and possible to increase the number of detected nodules. (2) It is more sensitive to detect abnormalities in dense breasts. Traditional breast cancer diagnosis depends on the expertise of radiologists, results in subject diagnosis. Additionally, radiologists are overwhelmed with the data need to be analyzed due to the dramatic increase in the number of patients.

Nowdays, some Computer-Aided Diagnosis (CAD) systems have been developed to assist radiologists to diagnose breast cancer in ultrasound images. Different studies [8,39] have shown that CAD is an important tool to improve the diagnostic sensitivity and specificity. Comparable results are produced with less time, and the inter-/intra- observer variations are reduced to some extent. Considering the different types of complicated breast tumors in ultrasound images, traditional CAD systems [5,9,11] may be not robust enough and do not take heterogenity of different tumors into account. Furthermore, such methods do not balance the accuracy, speed, and level of automation especially when the dataset is complex. Such deviations make it difficult to accurately segment and classify breast images. Several drawbacks of these methods are as follows.

(1) Lack of public dataset in breast ultrasound area limited the development of CAD for breast cancer. Accurate labeling of dataset may also affect the diagnosis performance in this filed.
(2) Classification and segmentation methods in other fields can not be used directly in ultrasound images, especially when complex lesion objects need to be dealt with.

In this paper, to address the aforementioned drawbacks, we first build a breast ultrasound dataset, which consists of 2600 images (1418 and 1182 for normal and cancerous, respectively) obtained from four different devices. Then we conduct the image classification and lesion segmentation based on the state-of-the-art methods in other fields, followed by modifying some structures to adapt to our ultrasound dataset. Specifically, in order to validate the accuracy and sensitivity of classification and segmentation methods, some classification methods: LeNet [18], AlexNet [17], ZFNet [40] and ResNet [14], and segmentation methods: FCN-AlexNet [28], U-Net [26] and Mask-RCNN [13] are used and verified in our dataset.

The contributions of this paper are listed as follows.

(1) A breast ultrasound dataset is constructed, in which the images and tumors are all labeled by three radiologists to reduce the inter-/intra- observer variations.

(2) We investigate a novel CAD system for image classification and segmentation, which modifies ResNet [14] and Mask R-CNN [13] methods to adapt to our dataset.

The rest of this paper is organized as follows. Background and related research of breast ultrasound image classification and segmentation are reviewed in Sect. 2. Our dataset is explained in detail in Sect. 3. Breast ultrasound image classification and segmentation methods are described in Sect. 4. Experiments results of image classification and segmentation are presented in Sect. 5. Finally, this paper is concluded in Sect. 6.

2 Related Work

2.1 Ultrasound Image Classification

Nowdays, some popular classification methods [25,27,31,38] such as SVM, AdaBoost and K-means are employed to learn statical information of tumor regions and background. Besides, many other classification methods and CAD systems are also proposed. Some of them focused on image classification and others are tumor classification. Huynh et al. [3] realize the use of transfer learning approach for ultrasound breast image classification. Shi et al. [29] develop a stacked deep polynomial network (S-DPN) algorithm based representation learning method for tumor classification with small ultrasound imaging. Uniyal et al. [32] classify ultrasound-based breast malignant lesions with considering the ultrasound radio frequency (RF) time series analysis. In addition, Moon et al. [22] propose a CAD classification system based on speckle patterns on automated breast ultrasound imaging and achieves high sensitivity and accuracy. Flores et al. [10] compile distinct morphological and texture features to improve the classification accuracy of breast lesions on ultrasonography. Byra et al. [4] improve classification accuracy in ultrasound breast lesions by using the segmented quantitative ultrasound maps of homodyned K distribution parameters, which showed that the analysis of internal changes in lesion parametric maps lead to a better classification of breast tumors.

Although these methods performance well in tumor classification with high accuracy and sensitivity, the process may be a little cumbersome with considering the features extracted from images and difference between tumor and background. In our work, each image is labeled as cancerous or normal one without considering the tumor category, which is restricted by the label obtained. Some classification network structures, such as LeNet [18], AlexNet [17], ZFNet [40] and ResNet [14] are chosen and adapted to our dataset for automated feature extraction and classification.

2.2 Ultrasound Image Segmentation

Image segmentation methods are categorised into four groups [6]: thresholding-based [15,16], active contour model [24,34], Markov random field [23,37] and neural network [12,21,30]. Despite the good segmentation performance, some limitations still exist in these methods. Threshold based methods are simple but may not perform well for only considering the gray level statistics and the segment performance are vulnerable to threshold chosen. Active contour models can detect edge closed and continuous, but the initialization point is hard to choose and segmentation accuracy may decrease in pseudo-edge and noisy conditions. MRF model may have better segmentation performance, but at the cost of a time-consuming and complex process.

In order to achieve satisfactory segmentation accuracy in complex situations, a tumor segmentation model considering the prior knowledge learning is proposed in [36]. Meanwhile, the computerized image segmentation results often require various case-by-case user interventions to improve the contour correctness, which unfortunately remains quite difficult to address [2].

The neural network methods directly uncover features from the training data, and employ these features in lesion segmentation from ultrasound images. Marcomini et al. [21] realize segmentation and classification of nodules in breast ultrasound digital images using the artificial neural network models. Su et al. [30] apply a fast scanning deep convolutional neural network (fcnn) to pixel-wise region segmentation in histopathological breast cancer images. Gomez et al. [12] present an evolutionary segmentation approach for breast lesions on ultrasound based on pulse-coupled neural network (pcnn) model and an adaptive differential evolution algorithm (JADE). Dhungel et al. [7] explore the use of deep learning methods as potential functions in structured prediction models for breast masses segmentation from mammograms. However, some limitations exist in these methods due to the complicated characteristics of breast ultrasound images, especially when the intensity inhomogeneity or coarse texture occurs in the tumor. In addition, the design and tuning of overall performance of the conventional CADx framework tends to be very arduous.

In this study, we investigate three state-of-the-art network structures for breast ultrasound tumor segmentation, Patch-based U-Net [26], transfer learning approach with a pretrained FCN-AlexNet [28] and a modified Mask-RCNN [13]. Then we compare the segmentation performances in our dataset with these algorithms.

3 Dataset Description

Collected from XiangYa Hospital of Hunan Province in 2016 and 2017, our dataset contains a total of 2600 images with a mean image size of $390 * 443$ pixels, 1182 and 1418 with and without tumor area, respectively. From the 1182 cancerous images (collected from 394 patients), 890 were invasive ductal carcinomas, 164 were invasive carcinomas, 73 were non-special type invasive carcinomas, and 55 were other unspecified malignant lesions. It is note that one or more tumors in each cancerous image. Since this dataset was obtained from different systems such as PHILIPS, SIEMENS, HITACHI and ALOKA, each image label and lesion area are annotated and voted by three doctors to reduce

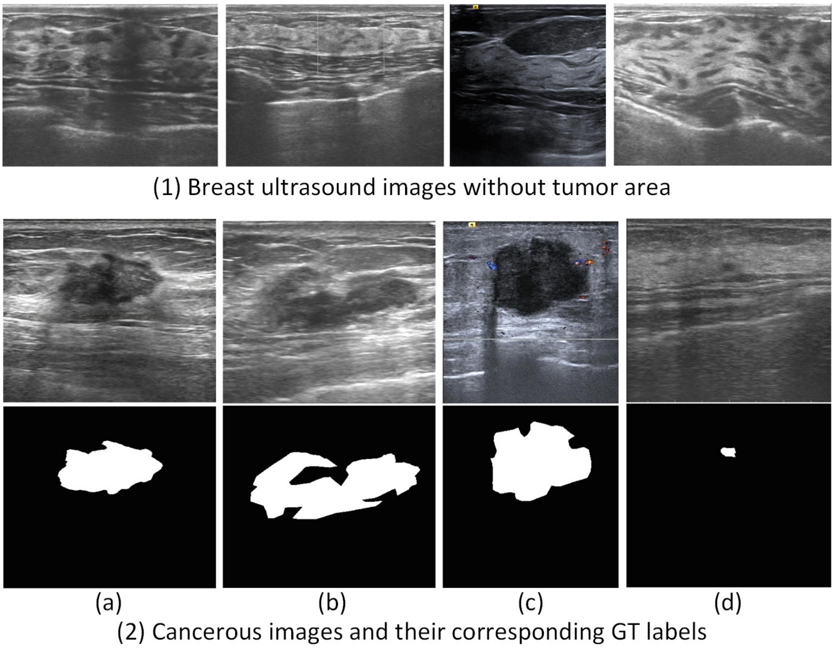

Fig. 1. Breast ultrasound images examples and their ground truth labels. (1) shows the normal images without tumor area in our dataset. (2) exhibits some cancerous images and their ground truth labels of our dataset, where (a), (b), (c), (d) show the example of invasive ductal carcinoma images, non-special type invasive carcinoma images, images with invasive carcinoma and images with other unspecified malignant lesions, respectively.

the difference among them. Some examples of normal and cancerous images in our dataset are illustrated in Fig. 2, where (1) depict the normal images in our dataset, (2a), (2b), (2c), (2d) show the example of invasive ductal carcinoma images, non-special type invasive carcinoma images, images with invasive carcinoma and images with other unspecified malignant lesions, respectively. Our dataset and the respective delineation of the breast lesions will be public for research purposes.

As Fig. 1 shows, tumor areas in our dataset are complicated with irregular shapes and various sizes. Moreover, speckle noise, image quality and image aspect ratio are completely different between different images taken by different devices in different times. Our dataset are used to show the effectiveness of our classification and segmentation method and compare with other state-of-the-art methods in experiments. Due to the limitation in malignant and benign label in our dataset, classification or segmentation of one candidate image mainly depends on whether there is a lesion area.

4 The Proposed CAD System

In this section, we introduce a CAD system based on ResNet and Mask R-CNN to classify and segment ultrasound images in our dataset, where two stages are incorporated: (1) feature extraction and normal candidates exclusion and (2) accurate tumor segmentation using improved Mask R-CNN. The framework of our proposed CAD system is illustrated in Fig. 1.

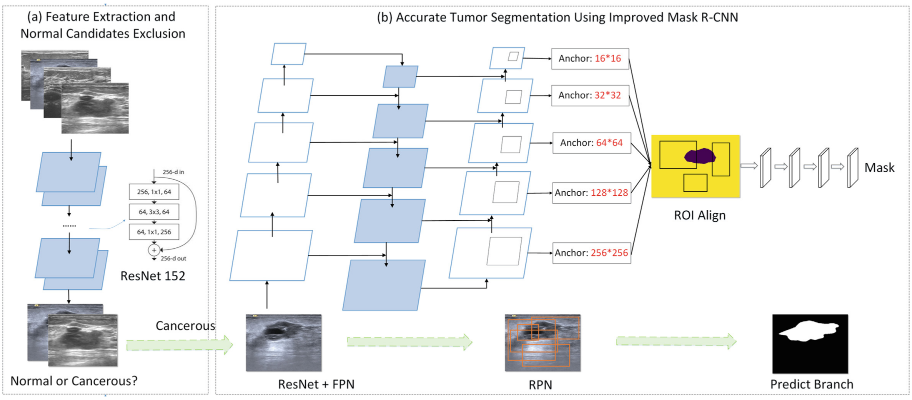

Fig. 2. The framework of our tumor classification and segmentation system.

4.1 Feature Extraction and Normal Candidates Exclusion

As illustrated in most previous works, a good feature extraction network should be deep enough with many convolution layers such that multi-level features can be learned. Further, different filter sizes can output feature maps which accurately represent the spatial arrangement of activations. Inspired by the successful use of ResNet in feature extraction and classification tasks [13], this structure is also used in our image classification tasks (shown in Fig. 2(a)), where a transfer learning approach with the pre-trained parameters from ResNet are used in our dataset. In this way, all images are fed into this network and output their predicted labels, while normal images can be excluded before tumor segmentation.

4.2 Accurate Tumor Segmentation Using Improved Mask R-CNN

After normal candidates exclusion, all images labeled by cancerous as the inputs to the Mask R-CNN for tumor segmentation. Despite the fact that multi-scale (5 anchor sizes for 5 feature maps respectively) and multi-ratio (1:1, 1:2, 2:1) anchors have been taken into account in the original method, there is still a large room for improvement over considering the difference and diversity of different feature maps.

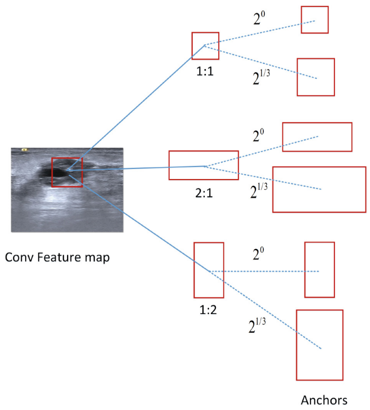

Fig. 3. Illustration of anchors in the improved Mask R-CNN

Owing to the huge difference over object scales in our candidate images (lesions range in size from 16 * 10 to 956 * 676), anchors with different scales and ratios are taking into account (illustrated in Fig. 2(b)), where the size of anchors are modified to (16 * 16, 32 * 32, 64 * 64, 128 * 128, 256 * 256) correspondingly. In spired by the anchors setting in [19], we also add two anchors sizes of 2^0 and $2^{1/3}$ of the original set of 3 aspect ratio anchors at each level (shown in Fig. 3). Thus, there are 6 anchors per level and across levels they cover the scale range 16–322 pixels with respect to the resized input.

In this way, the large proportion of big tumor region in small images can also be handled. Thus, each feature map generates 30 scales, and the RoIAlign layer and three branches are followed to generate accurate segmentation results.

5 Experimental Results and Discussion

In this section, a diverse set of experiments are introduced to evaluate the performance of our CAD system on our dataset. The performance of classification are evaluated by using Precision, Recall and F2 (depicts the classification results emphasize on Recall), mAP (mean Average Precision) and F1-meature are selected to measure the segmentation performance. and then 5-flod and 10-fold cross validation are used in classification and segmentation tasks, respectively. The performance metric measures are calculated by following equations:

$$F_2 = \frac{(1+2^2) \times P \times R}{2^2 \times P + R} \tag{1}$$

$$mAP = \frac{TPs}{TPs + FPs} \tag{2}$$

$$F1\text{-}measure = \frac{2 \times TPs}{2 \times TPs + FPs + FNs} \tag{3}$$

Where P and R represent the Precision and Recall respectively, TPs refers the number of pixels in tumor area labeled as tumors, FPs is the number of pixels in backgrounds labeled as tumors, FNs is the number of pixels in tumors masked as backgrounds.

5.1 Image Classification Results

All images are resized to 224 * 224 before feeding into different networks, learning rate are set to 0.001 in all methods, while epoches are 20, 20, 20, 65 in LeNet, ZF Net, AlexNet and ResNet networks, respectively. The image classification results of these methods are shown in Table 1. From this table, we observe that the ResNet method achieves the hightest Precision (95.84%), Recall (99.41%) and F_2 measure (99.23%) among these four classification methods, which demonstrate the robust feature extraction and classification ability are performed in this deepest network. By using this structure, most normal images are excluded before tumor segmentation in the next stage.

Table 1. The comparison of different methods in classification

Method	*Precision*	*Recall*	F_2
LeNet	0.7532	0.8207	0.8062
ZF net	0.8988	0.9107	0.9082
AlexNet	0.9260	0.9328	0.9314
ResNet	**0.9872**	**0.9805**	**0.9818**

5.2 Image Segmentation Results

To evaluate the segmentation performance of our method, we set hyper-parameters following existing Mask R-CNN [13]. In the training process, a RoI is considered as positive if it has IoU with a ground-truth box of at least 0.5 and negative otherwise. ResNet50 backbone are chosen to adjust to our dataset, all Images are resized as 512 * 512 pixels, each mini-batch has 2 images per GPU and each image has one sampled RoI at least, with a ratio of 1:3 positives to negatives, learning rate and epoches are set as 0.005 and 1500. For the U-net training implementation, learning rate and epoches are 0.0001 and 300, while 0.001 and 60 in the implementation of FCN-AlexNet. In particular, dropout rate is set to 33% in FCN implementation.

The quantitative comparison among our method and the state-of-the-art methods [26,28] is shown in Table 2, where Mask R-CNN achieves competitive results and our method has much higher mAP (85.0% *vs.* 83.8%) and F1-measure (82.7% *vs.* 79.6%) than the original Mask R-CNN method benefit from using more anchor scales. In addition, some special results, such as image with small tumor, image with big tumor, multi-tumor and tumor in complex background,

Table 2. The comparison of different methods in segmentation

Method	*mAP*	*F1-measure*
U-net	0.7370	0.6924
FCN-AlexNet	0.8241	0.7743
Mask R-CNN	0.8376	0.7962
Ours	**0.8501**	**0.8270**

are selected to illustrate the segmentation performance in our dataset. As shown in Fig. 4, our method achieves the better segmentation results in most instances, even in complex environment with large background noise.

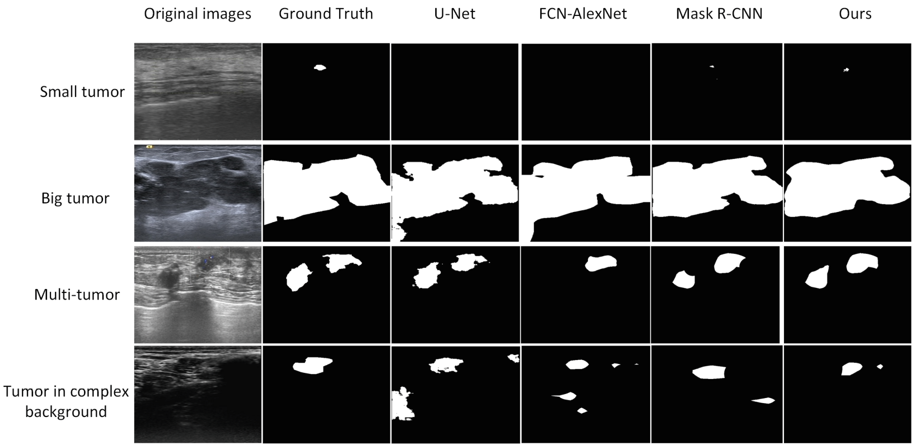

Fig. 4. The segmentation results comparison under four different conditions.

6 Conclusion

In this study, we analyze a CAD system for image classification and segmentation based on our breast ultrasound dataset. We first use a transfer learning approach with the pretrained ResNet structure in image classification, after this stage, all images can be labeled by normal or cancerous one and the normal candidates can be excluded. Then the improved Mask R-CNN method is developed to segment tumor areas in cancerous candidates. Experimental results show that our two-stage method can realize the better performance both in classification and segmentation tasks, where the Precision and Recall in classification tasks can reach to 98.72% and 98.05%, and a slight improvement on mAP of 85.0% *vs.* 83.8% and F1-Measure of 82.7% *vs.* 79.6% when compared with using the original Mask R-CNN method.

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