

Faster Region Convolutional Neural Networks Applied to Ultrasonic Images for Breast Lesion Detection and Classification

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Abstract—According to the global cancer data report of the International Agency for Research on Cancer, breast cancer already becomes a common and widespread disease around the world and is also the leading cause of death from cancer in women. Compared with mammograms and magnetic resonance imaging, breast ultrasound imaging is a universal and inexpensive test method for breast lesion screening without additional risk from radiation. However, most radiologists still need support and assistance from the computer-aided diagnosis systems for the detection and classification of breast cancer in ultrasonic images by improving the differentiation between malignant and benign lesions. In this paper, we propose a lesion detection and classification algorithm for breast cancer using Faster Region Convolutional Neural Networks (Faster R-CNN) applied to ultrasonic images. The proposed algorithm is capable of locating breast lesions with a bounding box and characterizing the detected lesion as malignant or benign. An open-access series of ultrasonic data of breast lesions is used for training and testing the Faster R-CNN, and the examination result shows that the algorithm is capable of precisely locate and characterize the breast lesion with the accuracy of more than 95%.

Keywords—*Medical Ultrasonic Imaging, Breast Lesion, Faster R-CNN*

I. INTRODUCTION

Global Cancer Observatory (GCO), a web-based platform of the International Agency for Research on Cancer (IARC), published an official statistical report of cancer for each country worldwide [1]. The report indicates that breast cancer already becomes the most commonly diagnosed cancer in women with a high incidence (46.3%, that about half of the women under the threat of breast cancer), and this disease is the most widespread cancer in 156 of the 185 countries. Nowadays, breast cancer is also the leading cause of cancer death in women with high mortality (13.0%). Figure 1 showed the worldwide incidence and mortality rates of different cancer of all age females in 2018.

Finding breast lesions early and getting treatment as soon as possible are the most critical strategies to prevent deaths from this cancer. Mammograms, magnetic resonance imaging (MRI), and breast ultrasound are the foremost methods for breast cancer screening in the hospital and medical centers. Breast ultrasound utilizes the echoes of sound waves to make an image that can show specific changes inside the breast like the fluid-filled cysts. Compared with other screening approaches of breast lesions, the ultrasound equipment is easy and convenient to

obtain for most hospitals and medical centers and is more affordable. Moreover, ultrasound is safe for the patient because of avoiding get exposed to radiation. Therefore, ultrasound is widely available for people with high universalization in the early detection of breast cancer.

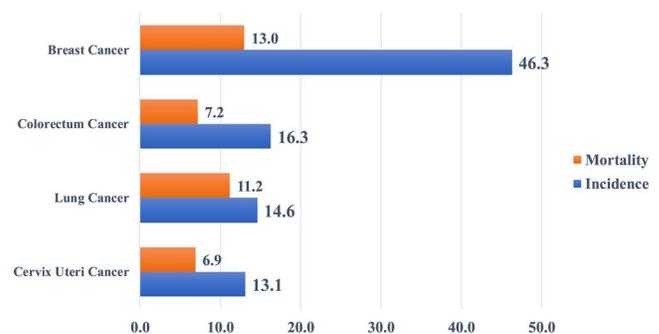


Figure 1. Estimated age-standardized incidence and mortality rates in 2018, worldwide, females, all ages. (Data from GCO, IARC [1])

With the widely available imaging screening methods of breast cancer, the American College of Radiology (ACR) proposed a standardized reporting system, Breast Imaging Reporting and Data System (BI-RADS) [2, 3]. This standardized reporting system of breast cancer indicates several features of the lesions in ultrasound images, such as shape, orientation, margin, and lesion boundary. However, the quality of the acquired ultrasound breast images heavily depends on the experience of the radiologists and devices of screening. Furthermore, the analysis of the ultrasound images is not straightforward and requires a profound knowledge of breast lesions. Therefore, radiologists try to adapt several Computer-aided Diagnoses (CADx) systems to improve the accuracy and precision of breast cancer detection and classification. CADx systems usually use hand-crafted features for the classification of breast lesions and have an excellent performance in practical application [4, 5]. With the growth of machine learning and neural networks, CADx with automatic feature extraction replaces the traditional hand-crafted methods [6, 7, 8, 9, 10]. In this paper, we will introduce an object detection and classification algorithm called faster Region Convolutional Neural Networks (Faster R-CNN) [11] into CADx systems for screening and diagnosis of breast cancer.

Open Access Series of Breast Ultrasound Data (OASBUD) provides the raw radio-frequency of ultrasonic echoes for the training and testing of our detection and classification neural networks model [12]. Figure 2 shows six examples of breast ultrasound images with preliminary signal processing. These raw radio-frequency data of ultrasonic echoes were collected by an experienced radiologist in two years. This database also includes a manually labeled Regions of Interest (ROI) to indicate the location and shape of these breast lesions. The ROI is labeled by a white line in Figure 2. OASBUD provides two ranking systems for classification and diagnosis: one is a simplified classification system that only has two classes, malignant and benign tumors. Another one is following the BI-RADS standard. In this study, we will apply faster R-CNN on the OASBUD dataset for the detection and classification of breast lesions.

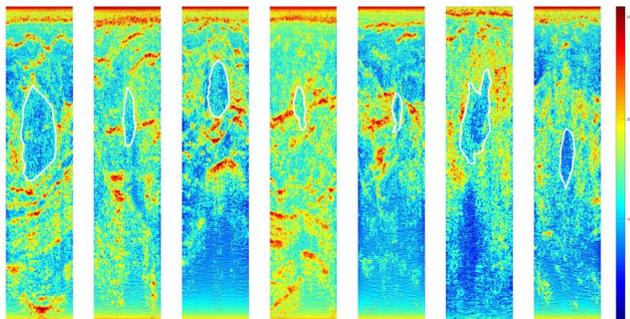


Figure 2. Ultrasound images of breast cancer with lesions circled in white lines

Section II of this paper introduces the Open Access Series of Breast Ultrasound Data (OASBUD) and Breast Imaging Reporting and Data System (BI-RADS). In Section III, the proposed model of the algorithm, faster region convolutional neural networks, is introduced with its framework. Section IV shows the validation output of the proposed faster R-CNN model after training and testing by the data from OASBUD. Section V concludes this paper and summarizes our work.

II. BACKGROUND

A. Open Access Series of Breast Ultrasound Database

Open Access Series of Breast Ultrasound Data (OASBUD) provides an open-source database of the raw radio-frequency (RF) ultrasonic echoes acquired from malignant and benign breast lesions. These raw radio-frequency data were collected by an experienced radiologist in the ultrasonic examination of breast lesions in two years. This database includes scans from 52 malignant and 46 benign breast lesions recorded in a group of 78 women. For each collection, two independent orthogonal scans were acquired for the analysis purpose.

OASBUD stores the data of each patient as a structure with seven fields in the OASBUD.mat, a data file of MATLAB. Table I shows the fields. The ID is the identification of these 100 examples with radio-frequency data and labels. The RF1 and RF2 are the matrices of 510 columns and the number of rows that matched the penetration depth. The RF1 and RF2 record the radio-frequency data of two independent orthogonal scans. The Region of Interest (ROI) marks the area of breast lesions. BI-RADS and Class is the label for the database, and these labels

will play a significant role in the training and testing of convolutional neural network models.

TABLE I. FIELDS AND DESCRIPTION OF OASBUD

Fields	Description
id	Identification of examples
rf1	First scan plane
rf2	Second scan plane
roi1	Region of interest of the first plane
roi2	Region of interest of the second plane
birads	Categories of BI-RADS system
class	0 – Benign, 1 – Malignant

B. Breast Imaging Reporting and Data System

With the widely available of breast ultrasound and other imaging screening methods, American College of Radiology (ACR) propose a standardized reporting system, breast imaging reporting and data system (BI-RADS), for making a diagnosis with more detail. This standardized reporting and data system of breast imaging related to several features of the lesion, such as shape, orientation, margin, magnitude, and lesion boundary. This standardized reporting system for breast imaging has full application in hospitals and medical centers around the world.

BI-RADS classify all the breast lesion into six categories. Category 0 means that the screening of breast lesions is incomplete and needs additional images for diagnosis. Category 1, Category 2, and Category 3 mean that the breast lesions are benign, which has a lower likelihood, from 0% to 2%, of malignancy. The patients of these categories only need routine screening and short-interval follow-up surveillance. Category 4 means that the breast lesions is suspicious, and this category has four subcategories, 4A, 4B, 4C, based on the different likelihood, from 2% to 95%, of the malignancy. If the likelihood of a breast lesion is higher than 95%, this lesion is not suspicious but highly suggestive of malignancy. These patients need tissue diagnosis for precise examination results to verify the diagnosis based on imaging. The breast lesions below to Category 6 is the malignancy which known Biopsy-Proven, and need surgical excision when clinically appropriate. In this paper, we combine Category 1, Category 2, Category 3, Category 4A, and Category 4B as the class named benign, and Category 4C, Category 5, and Category 6 belong to the class called malignant.

III. FASTER REGION CONVOLUTIONAL NEURAL NETWORKS

Compared with some traditional signal processing methods, which work on the frequency domain, image processing is more straightforward and understandable for diagnosis. Traditional signal processing of ultrasound images can find the breast lesion quickly because of its exclusive representation in the frequency domain of ultrasound images, but it is hard to classify the breast lesion into different categories for diagnosis. The image processing algorithm not only can locate the breast lesion on the ultrasound image but also can classify the breast lesion for assessment. For the detection and characterization of breast lesions, two stages are essential for the implementation of the algorithm. First, we will confirm the existence of breast lesions

on the ultrasound image and locate the proposal region of the breast lesion. Next, we will classify the breast lesion into different classes by convolutional neural networks (CNN). In this implementation, we use three independent neural networks for feature maps extraction, selection of the region proposals, and the classification of these regions.

The algorithm, faster region convolutional networks (faster R-CNN), import region proposal networks (RPN) to replace the traditional algorithm of region selection. RPN can execute on CPU and GPU with higher effectiveness, and it will decrease the time of the process of training and testing. In the practical examination, the time of generating all proposal regions for an ultrasound image is around ten milliseconds with RPN, almost reduce 99.5% time for region selection and workload for further processing. Algorithm 1 will show the pseudocode of faster R-CNN and illustrates the essential implementation.

Algorithm 1 Faster Region Convolutional Neural Networks

```

feature maps = process(image)
ROIs = region_proposal(image)
for ROI in ROIs
    patch = roi_pooling(feature maps, ROIs)
    results = detector2(patch)

```

A. Convolutional Layers

Faster R-CNN will extract the feature maps first by a group of convolutional layers. This process will also reduce the workloads of the generation of region proposal. In our work, we use the VGG16 model, which has 13 Conv layers, 13 Relu layers, and 4 Pooling layers.

B. Region Proposal Networks

The flow chart of region proposal networks shown in Figure 3 has two independent paths. One is to classify the anchors to classes. Another one is to calculate the bias of the bounding box regression for anchors. The proposal layer will combine the information of anchors and the bias value of bounding box regression to locate the region proposal of breast lesions.

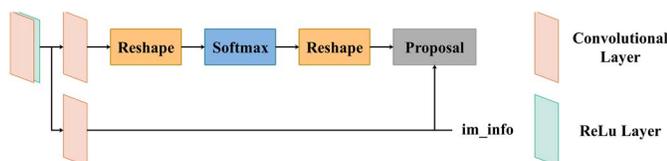


Figure 3. Flowchart of Region Proposal Networks of Faster R-CNN

Anchors: The anchor is a matrix $(x1, x2, y1, y2)$ that can represent a rectangle with different sizes at different locations. $(x1, y1)$ is the coordinate of the top-left point of rectangle, and $(x2, y2)$ is the coordinate of the bottom-right point. Region proposal networks generate many anchors on the ultrasound image, and convolutional neural networks will separate the anchors of the foreground (objects) from the background for the detection of lesions. The anchors of the foreground will contain the lesion that we want to detect and classify.

Bounding Box Regression: Bounding box regression will calculate the value of bias to minimize the difference between the positive anchors and ground truth. We define a rectangle window as (x, y, w, h) , which indicates the position and size of

the box. (x, y) is the coordinate of the center of the window, and (w, h) is the width and height of it. In Figure 4, the red box is the window of ground truth, and the green box is the positive anchors extracted by the activation function.

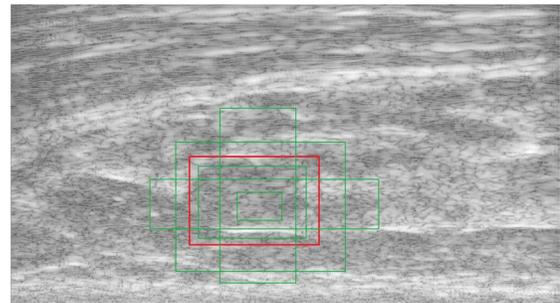


Figure 4. Bounding box regression (red box is the ground truth, and the green box is the positive anchors)

These positive anchors, the green boxes, have differences with the ground truth, the red box. We need to find a function and corresponding weights to adjust the green box of positive anchors for nearing the ground truth.

C. ROI Pooling and Classification

ROI pooling layer, shown in Figure 5, will collect region proposals and generate the proposal feature maps. ROI pooling layer has two inputs, the original feature maps and the output region proposal of RPN. ROI pooling layer is an essential component for solving the problem that the sizes of the region proposals are different. With ROI pooling, the networks will generate the same size output for further neural networks of classification without loss of the information of proposals.

The classification of breast lesions will be completed by the activation function, softmax, and neural networks will calculate the confidence of different classes of the same breast lesion. Furthermore, the proposal will have additional bounding box regression for a precise rectangle to locate the breast lesion.

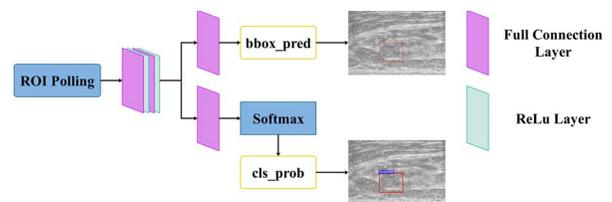


Figure 5. ROI Pooling and Classification

IV. RESULT

In OASBUD dataset, there are 200 ultrasonic images for training and testing of our region proposal networks (RPN) and convolutional neural networks. The training dataset includes 112 ultrasound images of breast lesions (56% of the OASBUD database). The validation dataset consists of 48 ultrasound images (24% of all ultrasound images), and the test dataset has 40 images (20%). These three sets are independent and do not have any duplicate images. The training set and validation set will be utilized for the training process to get the optimal weights, and the test set will be used for the evaluation of our model. According to the OASBUD documentation, each ultrasound image of OABUD has one single region of interest,

thus we will reserve the bounding box with the highest confidence.

The training process includes two stages. In the first stage, we will train the RPN with the initial trained model, VGG16. With this RPN, we will collect the proposals and train the faster R-CNN for the first time. These weights and parameters will feed to the next stage as the initial model and repeat the process. Figure 6 shows the result of the training process after 10,000 iterations. The total loss is the combination of $loss_cls$ and $loss_box$ of these two stages. The parameter, $loss_cls$, indicates the error rate of the classification of the breast lesions. The $loss_box$ shows the difference in location between prediction and ground truth. This result indicates the deviation of detection.

```
speed: 1.239s / iter
iter: 10000 / 40000, total loss: 0.046770
>>> rpn_loss_cls: 0.000445
>>> rpn_loss_box: 0.002817
>>> loss_cls: 0.031350
>>> loss_box: 0.012158
```

Figure 6. Training result of region proposal networks and faster R-CNN

Figure 7 shows an examination result of the same tumor. The red rectangle indicates the location of the lesion, and the confidence of benign for this tumor is 0.183, which means that the algorithm believes that the likelihood that the lesion is a benign tumor only is 18.3%. However, the likelihood that the lesion is a malignant tumor will be 90.2%. The different confidence for different classes is fundamental for the classification of breast lesions. Therefore, the breast lesion located by the red rectangle box is malignant because of its high confidence for the malignant tumor. We evaluate our model by the test set, 40 ultrasound images of breast lesions. The accuracy is 95%, the precision is 100%, and the recall is 89.5%.

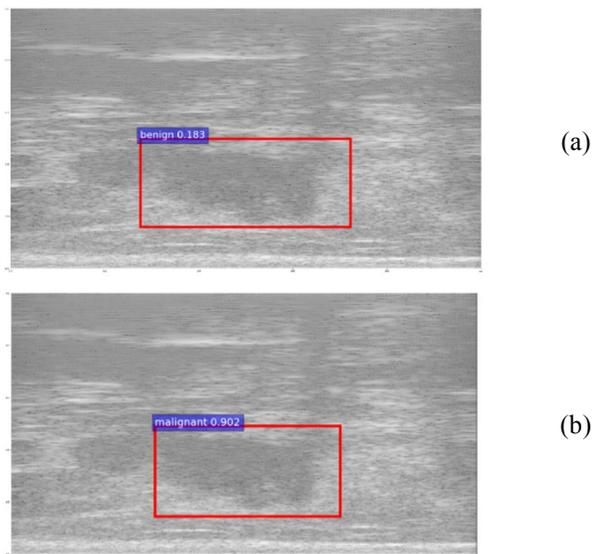


Figure 7. The confidence level of benign and malignant tumors labeled in a detection result

V. CONCLUSION

In this paper, we implemented a breast lesion detection and classification algorithm based on faster R-CNN in ultrasound images. Compared with other approaches [4, 5], Faster RCNN significantly improve the performance of generation of region proposal by RPN (Region Proposal Networks). Therefore, our model based on Faster RCNN will execute faster and obtain a better performance (accuracy more than 95%). OASBUD, the standard database of raw radio frequency data of breast lesion, has 200 examples which is small for training and testing of our model. However, the result shows that with the limited number of training data, faster R-CNN is capable of detecting and characterize the breast lesion with decent precision. In the future work, we will extend the database of breast lesion and also apply our algorithm and model to other screening images, such as X-Ray images and MRI images.

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