Medical Image Processing with Deep Learning

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Introduction

Why do we use deep learning in medical imaging?
Deep learning has been a tremendous success in image processing and has many applications such as image reconstruction, object detection etc. As the performance of deep neural network is reaching or even surpassing human performance, it brings possibilities to apply it to medical imaging area.

Why do we study mammograms?
Breast cancer is the most common disease for women worldwide. The mortality of breast cancer largely depends on whether the lesion could be detected at an early stage. Mammography is the process of using low-energy X-rays to examine human breast for diagnosis and screening. We need well-trained radiologists to examine the CT images traditionally, which is costly and time-consuming. Adopting computer aided detection system can accelerate the diagnosing process as well as enhancing the diagnosis accuracy.

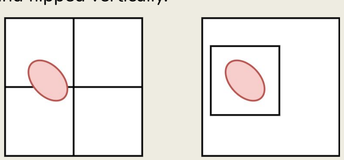
Research Objectives

- Classify mammograms into three categories
- Automatically detect tumor without prior information of the presence of a cancerous lesion

Materials and Methods

Data
We trained our neural network on mini-MIAS database of mammograms. The database contains 322 CT images (1024×1024) in total with labels. Each image is labelled as normal (healthy), benign or malignant and the label contains the coordinates of the tumor center and the radius of the tumor.

Data Augmentation
As the database has only 322 images, which is far from enough for training a neural network, we applied some data augmentation techniques before feeding the data into the neural network. The original images are cut into small image patches (128×128 and 256×256), rotated by certain degrees and flipped vertically.



More subpictures
Do not keep edges
Break tumor

Fewer subpictures
Keep edges
Do not break tumor

Cutting images centered at tumor (as in right figure) obtains the best results by now. (shown in the Performance part)

Model

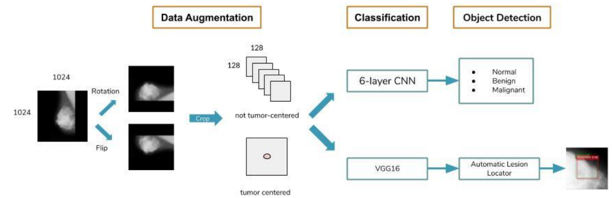


Figure1. Flowchart

Classification
We used a convolutional neural network for classification. The neural network consists of 4 convolutional layers, 1 pooling layer and 1 fully connected layer. Instead of using the usual convolutional layer, we replaced two of them with depthwise convolutional layers which could reduce the number of parameters needed to train.

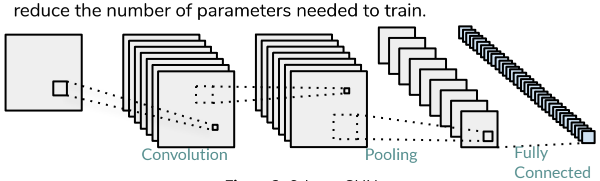


Figure2. 6-layer CNN

Automatic Lesion Detection
We use SSD (single Shot Multibox Detector) which is a popular algorithm for object detection to detect the tumor in abnormal images. We modified the model and our preprocessed images and labels are fed into the algorithm. **Figure 3** is the abstract and **Figure 4** is the whole architecture.

It is based on the VGG16 with several layers appended for automatic object detection. VGG16 is a convolutional neural network for classification which has been shown to have a remarkable performance in classification.

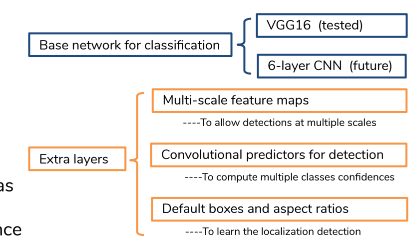


Figure3. The abstract of SSD

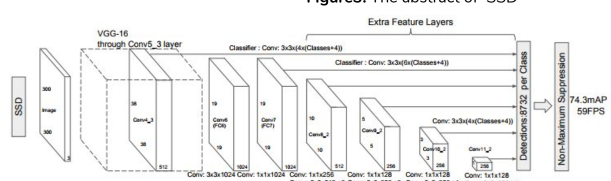
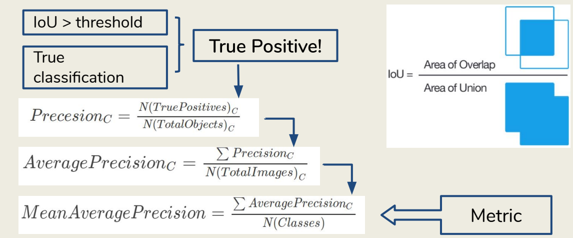


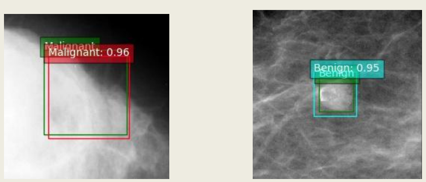
Figure4. The architecture of SSD

Performance



Test set			All sets (Train+Validation+Test)		
Benign	AP	0.8	Benign	AP	0.879
Malignant	AP	0.806	Malignant	AP	0.907
	mAP	0.803		mAP	0.902

In original SSD paper, the author performed experiment on PASCAL VOC2007 and VOC2012 databases, and the highest mAP is also around 0.8. However, there is a great gap on database sizes of their experiments(20000) and ours(700). Therefore, it is expected that with more mammogram data, better results will be achieved.



Future Work

- Use some other datasets to test our model
- Combine our classification model with SSD to decrease the computing time

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