Deep Learning Based Mass Detection in Mammograms

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Overview

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Introduction

Medical imaging has been a revolutionary way for medical professionals to diagnose and treat medical diseases over the past decades.

- a complex task $\rightarrow$ extensively trained medical professionals with long-time clinical experience

Many researches apply the Convolutional Neural Networks (CNN) based methods to Computer Aided Detection (CADe) and Computer Aided Diagnosis (CADx) of medical images.

- reducing radiologists' workload
- accelerating the diagnosis process
- improving the diagnosis accuracy

Introduction

Among medical applications, detecting lesions in **mammography**, the primary imaging technique used for breast screening process, is gaining the increasing attention during recent years.

There are mainly four types of abnormality patterns in mammograms:

- **Mass**
- Calcification
- Asymmetry
- Architectural distortion

Introduction

Objective

We present a **Faster R-CNN** model with a series of modules, which are **feature pyramid networks** (FPN), **focal loss** (FL), and **non-local operation** (NL), for effectively detecting masses in mammograms.

Overview

Methods

- Faster R-CNN
- Feature Pyramid Networks (FPN)
- Focal Loss (FL)
- Non-Local Neural Networks (NL)

Faster R-CNN

An effective Region proposals with CNNs (R-CNN) model was first introduced in 2014[1]. The enhanced version, **Faster R-CNN**, improved the overall detection performance and significantly reduced the processing overhead[2].

[1] Girshick et al. "Rich feature hierarchies for accurate object detection and semantic segmentation" *CVPR'14*

[2] Ren et al. "Faster r-cnn: Towards real-time object detection with region proposal networks" *NIPS'15*

Faster R-CNN

Faster R-CNN is a two-stage deep-learning-based object detection model.

1. a **backbone network** to calculate feature maps → region candidates generated by region proposal networks (RPN)
2. a CNN-based network is used to classify the object class and detect the bounding box

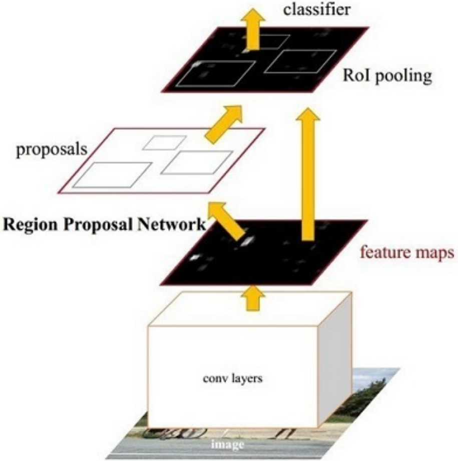

Figure: Faster R-CNN

Feature Pyramid Networks (FPN)

Feature Pyramid Networks (FPN) is a multi-scale algorithm for object detection[3].

Identifying mass lesions from a **dense background** requires specialists to observe **more areas**.

If a mass lies within a **clear background**, a **smaller and more local** receptive field is possibly adequate to locate it.

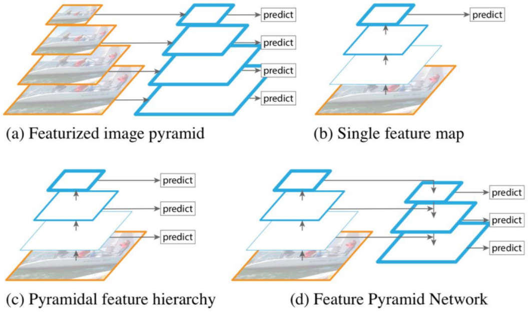

Figure: FPN (Fig. d)

[3] Lin et al. "Feature pyramid networks for object detection" *CVPR'17*

Focal Loss (FL)

Focal Loss (FL) is a state-of-the-art loss function, utilizing a weighting strategy and focuses on "**hard examples**" (masses with bright backgrounds)[4].

$$FL(\mathcal{p}) = -(1-\mathcal{p})^{\gamma}\log(\mathcal{p}), \tag{2.1}$$

where

$$\mathcal{p} = \begin{cases} p & \text{if } y = 1 \\ 1-p & \text{otherwize,} \end{cases} \tag{2.2}$$

where $y \in \{-1, +1\}$ refers to the ground-truth binary class; $p \in [0, 1]$ denotes the predicted probability of the class with label $y = 1$; γ is a focusing variable, which is not less than 0.

[4] Lin et al. "Focal loss for dense object detection" *ICCV'17*

Non-Local Neural Networks

The Non-local Means (NL-means) is a traditional computer vision algorithm originally used for image denoising.

Non-local neural networks applies the NL-means idea to the modern deep learning architecture and has demonstrated its effective capacity of capturing long-range dependencies ,i.e., global information[5].

[5] Wang et al. "Non-local neural networks" *CVPR'18*

Overview

Evaluation

- Datasets
- Settings and Parameters
- Effectiveness of Modules
- Prediction Results

Datasets

1. Curated Breast Imaging Subset of Digital Database for Screening Mammography (CBIS-DDSM)[6]
   - ∼1,600 images for mass lesions
2. INbreast[7]
   - 115 patient cases, of which 90 cases are from women with both breasts and 25 cases are from mastectomy cases
3. Breast Cancer Digital repository (BCD)[8]
   - 535 mass images

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[6] Lee et al. "A curated mammography data set for use in computer-aided detection and diagnosis research" *Scientific data'17*

[7] Moreira et al. "Inbreast: toward a full-field digital mammographic database" *Academic radiology'12*

[8] Lopez et al. "BCDR: a breast cancer digital repository" *ICEM'12*

Datasets

The CBIS-DDSM data are **randomly** split as training, validation and test data with the percentage of **60%**, **20%**, and **20%**, respectively. The other two public datasets (INbreast and BCD) along with the separated training subset of CBIS-DDSM constitute the training set, while the remaining validation and test subsets of CBIS-DDSM are respectively sole validation and test sets.

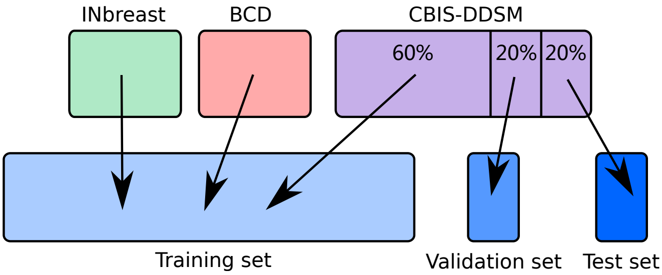


Figure: Utilization of public datasets.

Settings and Parameters

- Backbone network in Faster R-CNN: **ResNet-50** where the hyper-parameters are loaded from the pre-trained model on ImageNet
- Each original training image is down-sampled to a small size to ensure that the short edge has **1200** pixels
- Optimizer: **ADAM**
- Initial learning rate: **0.01**, with **4** epochs for warm up
- Steps in each epoch: **500**
- # of epochs in training process: **200**

Effectiveness of Modules

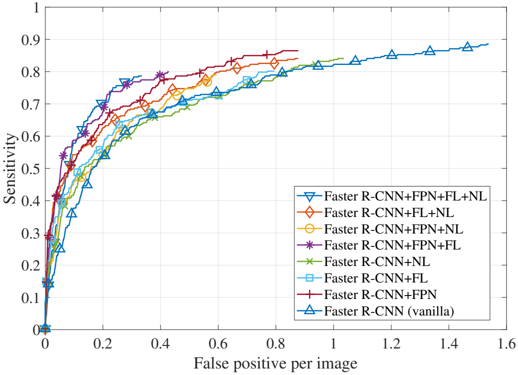


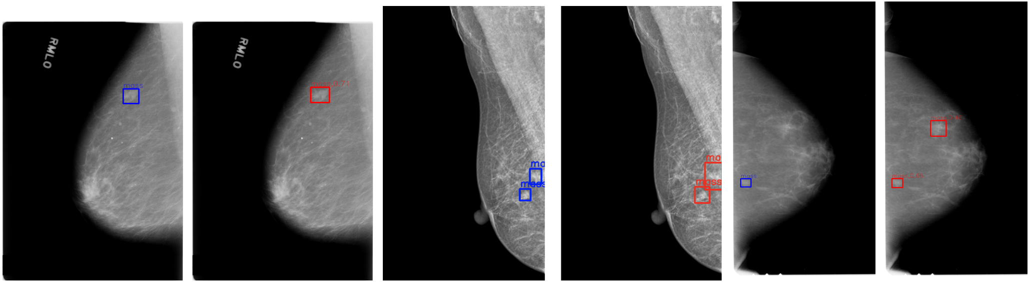
Figure: FROC curves of different models. “FL” = focal loss; “NL” = non-local operation; “vanilla” = the original Faster R-CNN model.

Prediction Results

Table: Prediction results of different models. "FL" = focal loss; "NL" = non-local operation; "vanilla" = the original Faster R-CNN model; "AP" = Average Precision

Method	AP	Recall
Faster R-CNN (vanilla)	0.762	0.950
Faster R-CNN+FPN	0.789	0.965
Faster R-CNN+FPN+FL+NL	**0.805**	**0.977**

Prediction Results



(a) One mass is successfully predicted.

(b) Multiple masses are successfully predicted.

(c) One prediction is correct while one false positive occurs.

Figure: Example prediction results of mass detection in mammograms. Bounding boxes in ground truth are labeled in blue, and the predicted masses are highlighted in red bounding boxes, respectively.

Overview

Datasets

Studies have shown that breast density has been a risk of breast cancer in woman is in relation to the higher breast density.

Moreover, ethnic difference on breast density is especially significant on women older than 50 years old.

We are now constructing our private dataset by collaborating with Shenzhen People's Hospital, Guangdong, China. Investigating how much the race difference will impact the prediction performance of deep learning models is one of our next research directions.

Overview

Conclusion

A Faster R-CNN model integrated with FPN, focal loss, and non-local operation, is evaluated and demonstrated for effectively detecting masses in mammograms.

Three public datasets, DDSM, INbreast, and BCD are utilized. The individual and joint effectiveness of modules are evaluated.

The FROC curve shows that the Faster R-CNN model with all three modules is the best model. The best detection results on our dataset are 0.805 in Average Precision (AP), and 0.977 in recall, respectively.

THANK YOU
Q&A

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