Breast Cancer Detection Using Transfer Learning in Convolutional Neural Networks

Shuyue Guan and Murray Loew
Department of Biomedical Engineering, George Washington University
Washington, D.C. USA

Motivation

For the U.S. women, breast cancer will be diagnosed among about 1 in 8 during their lifetime and it is the second leading reason for death [1].

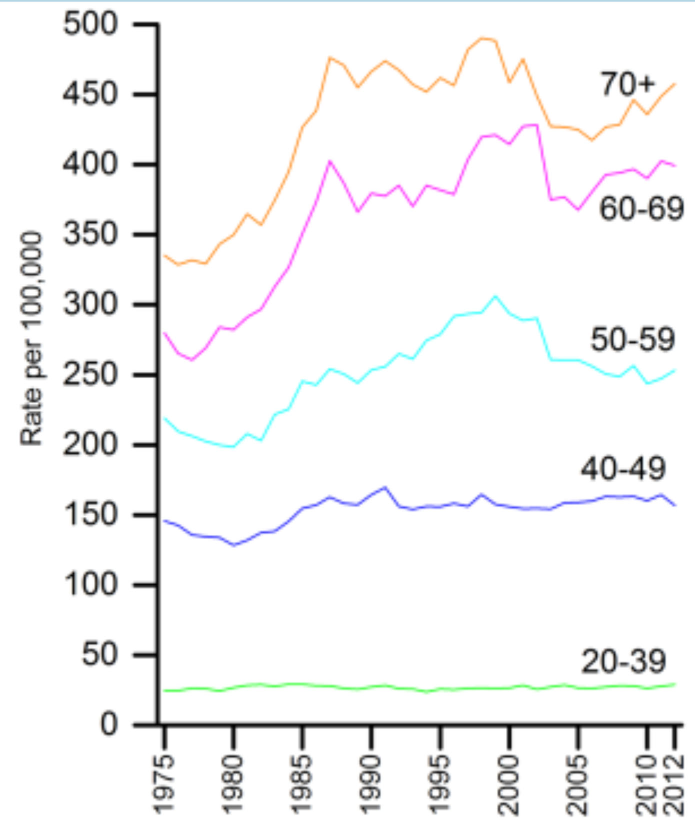


Fig.1. Incidence Rates of Female Breast Cancer by Age, U.S. (DeSantis, et al. 2015)

Convolutional Neural Network (CNN) is a promising method for breast cancer detection, which can improve treatment outcomes for breast cancer and longer survival times for the patients [2].

Fig.2. To reuse a pre-trained CNN model that has been trained by image datasets from other fields (WildML, 2015)

To train the CNN from scratch needs a huge number of labeled images [4]. Such a requirement often is infeasible for mammographic tumor images. An alternative solution is to apply transfer learning.

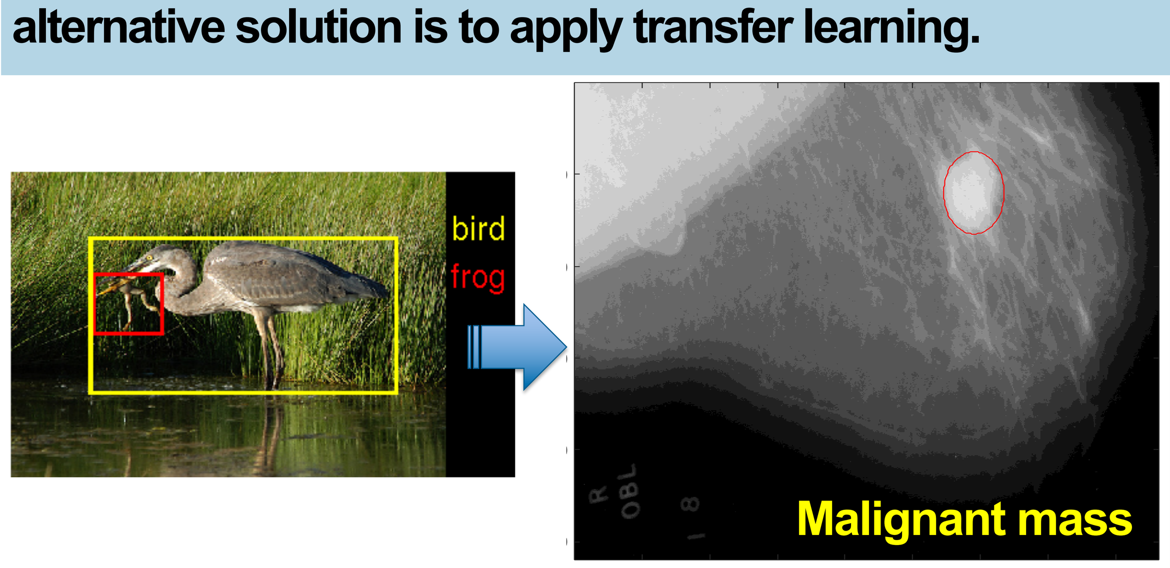


Fig.3. Transfer learning: the features learned from natural images could be transferred to medical images

DATA

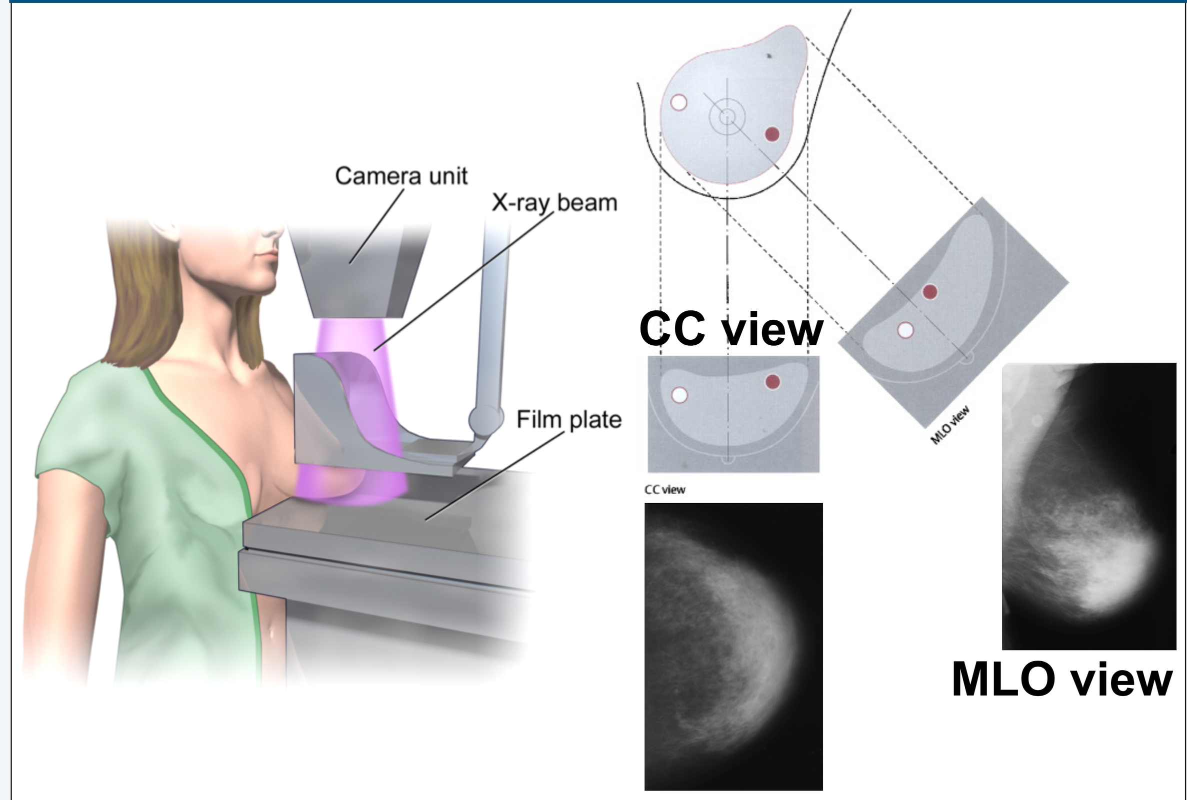


Fig.4. Mammography (BruceBlaus, 2014; Chung, 2008)

We firstly downloaded mammographic images from the DDSM database and cropped the Region of Interest images (ROIs) by given abnormal areas as ground-truth information.

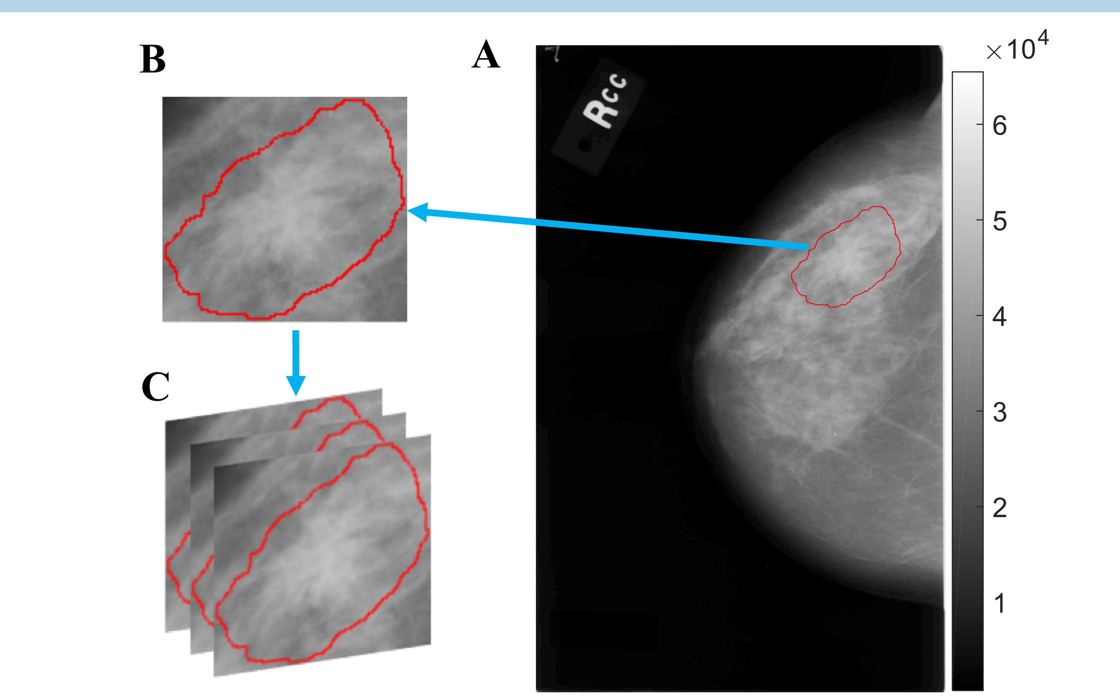
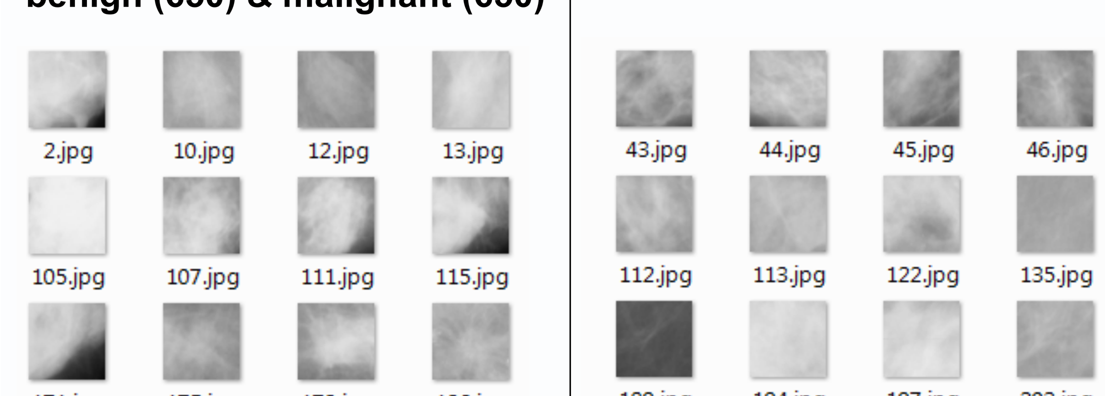


Fig.5. (A) A mammographic image from DDSM rendered in grayscale; (B) Cropped ROI by the given truth abnormality boundary; (C) Convert Grey to RGB image by duplication.

Training Sets for DDSM

Abnormal ROIs Resize: 300x300	Normal ROIs Resize: 300x300
1300 **benign (650) & malignant (650)**	**1300**



Validation: 10-fold cross
Classes: Binary

METHODS

The structure of CNN in transfer learning was the combination of the 13 convolutional layers in pre-trained VGG-16 model with a simple FC layer. All the weights in 5 convolutional blocks were imported from the pre-trained VGG-16 model and not changed ("weights frozen") during the training of this CNN.

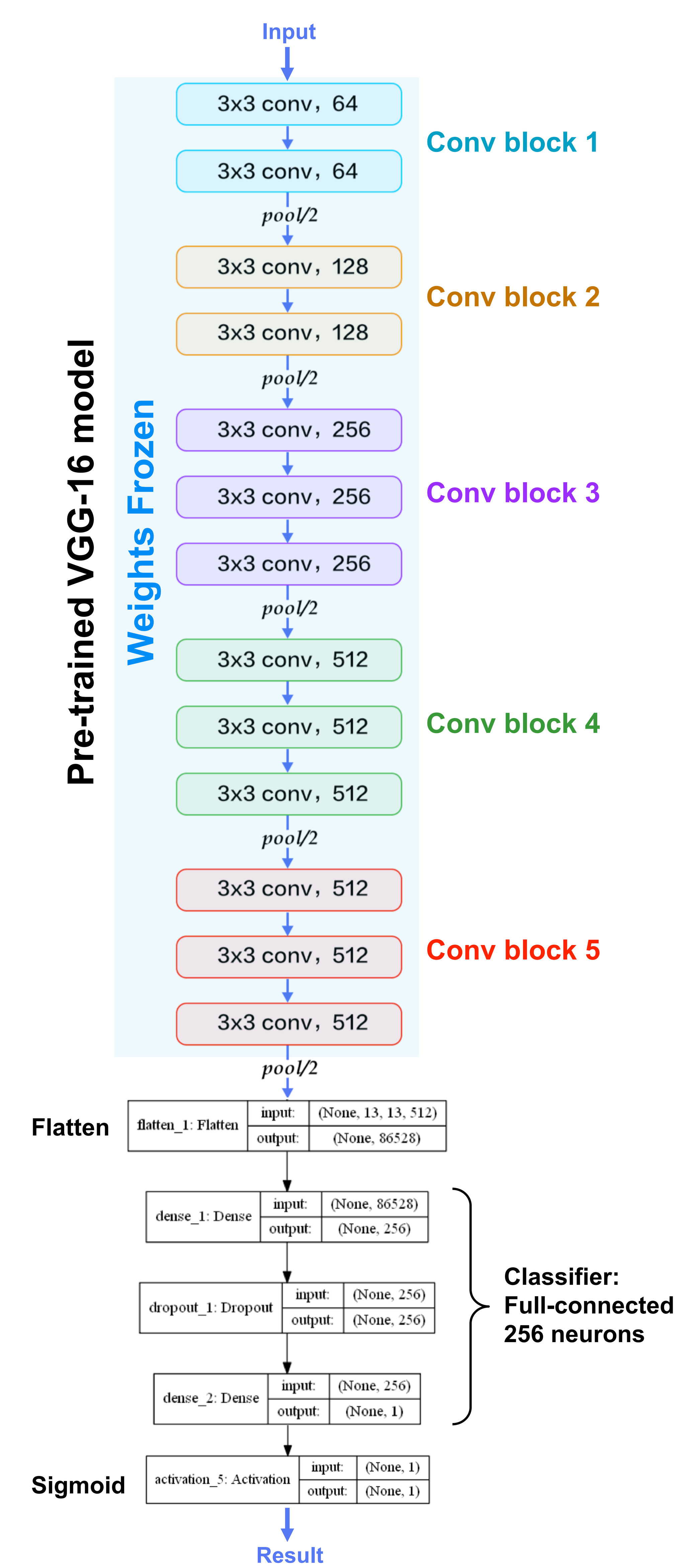


Fig.6. Transfer learning CNN architecture: only weights in the FC layer were randomly initialized and updated by training.

Such a training process can be seen as that the VGG-16 extracts features from input image and then these features were used to train a FC neural classifier.

RESULTS

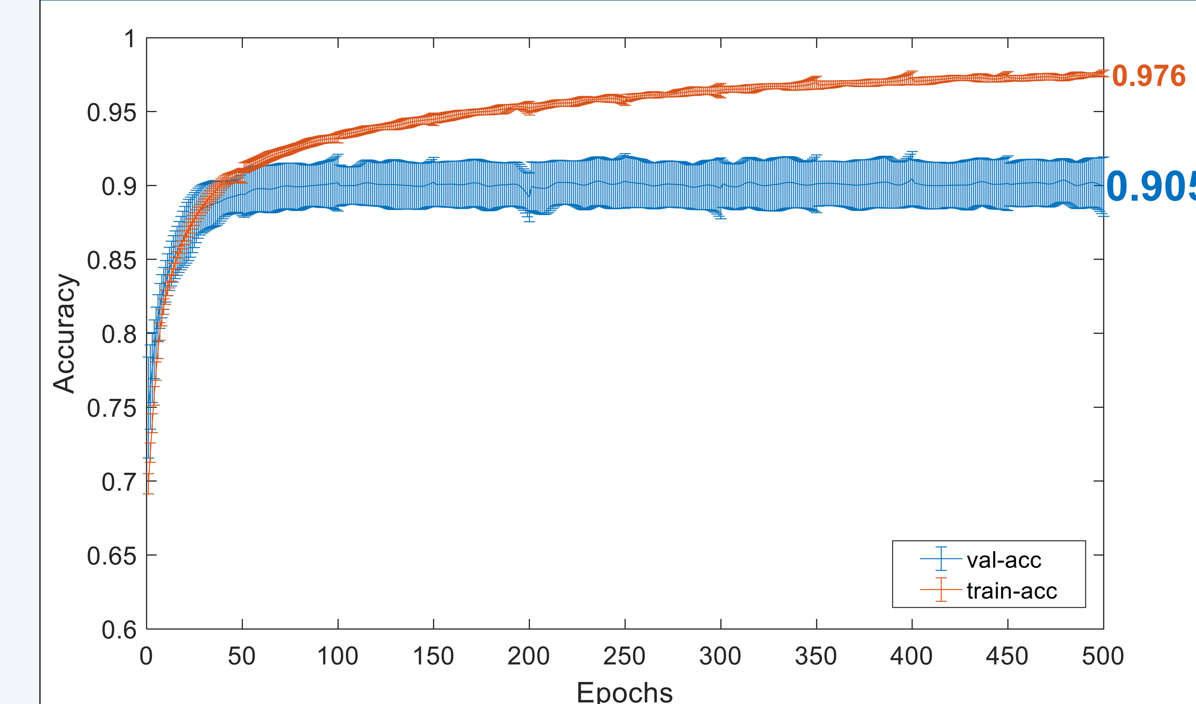
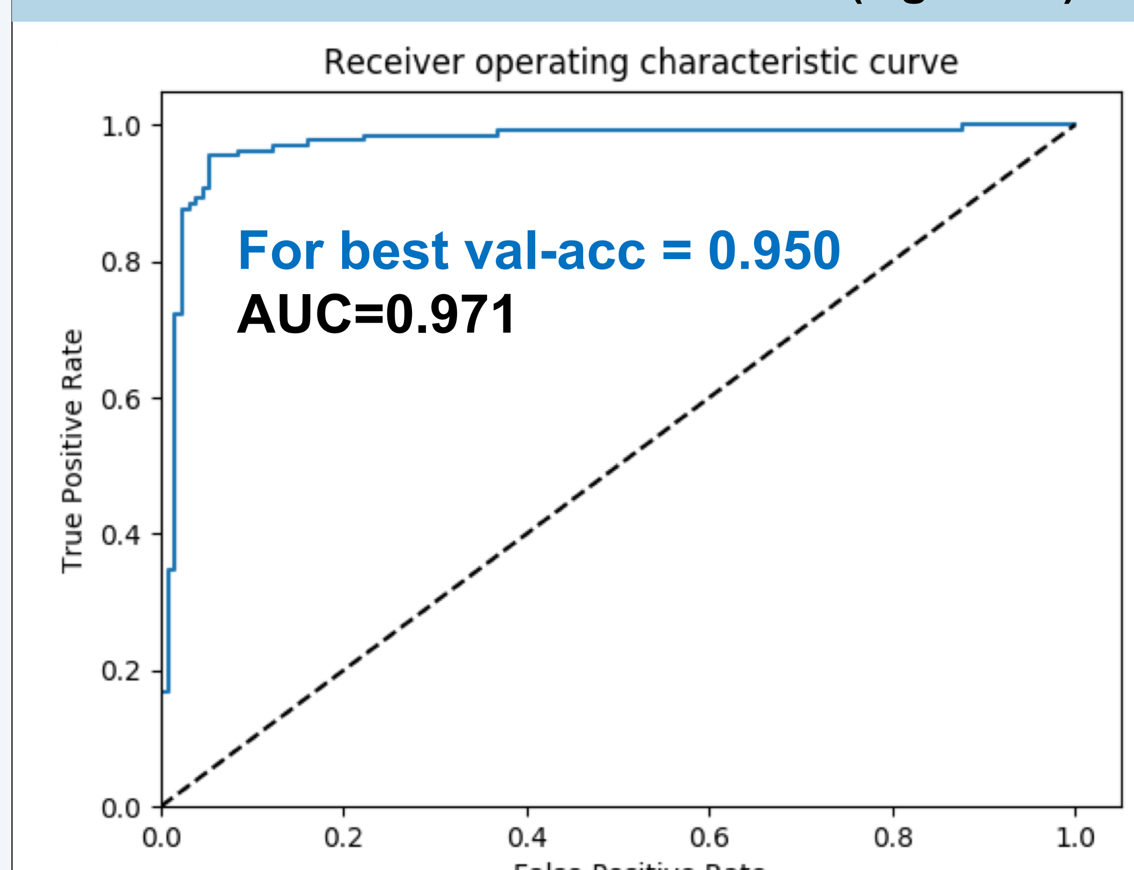


Fig.7. Result: the red curve is training accuracy and blue is validation accuracy. The center line is average through 10-cross validation accuracy.

After 100 epochs, the validation accuracy converged at about 0.905, and there was no obvious overfitting (Fig.7). The maximum validation accuracy that the classification model reached was 0.950 (Fig below).



DISCUSSION

Main method	Validation (# of images)	Accuracy %	AUC
Pre-trained CNN on LSVRC datasets & Fine-tuning + Two-step decision (Jiao et al., 2016)	2-fold cross (600)	(Ben-Mal) **96.7**	–
Pre-trained CNN with hand crafted features + RF (Dhungel et al., 2016)	5-fold cross (410)	(Ben-Mal) **91 ± 0.02**	**0.76**
Pre-trained AlexNet +Sparse MIL (Zhu et al., 2016)	5-fold cross (410)	(Mal-nonMal) **90.00 ± 0.02**	**0.85**
Pre-trained VGG-16 + one FC layer (Ours)	10-fold cross (2600)	(Abnorm-Norm) **90.5 ± 3.2**	**0.96**