Using Generative Adversarial Networks and Transfer Learning for Breast Cancer Detection by Convolutional Neural Networks

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INTRODUCTION

In recent years, developments in machine learning have provided alternative methods for feature extraction; one is to learn features from whole images directly through a Convolutional Neural Network (CNN), however, to obtain a sufficient number of images to train a CNN classifier is difficult because the true positives are scarce in the datasets and expert labeling is expensive.

We proposed two deep-learning based solutions to the lack of training images:

1)To generate synthetic mammographic images for training by the Generative Adversarial Network (GAN). (Fig.1)

2)To apply transfer learning in CNN. (Fig.2)

Then, we combined the two technologies together. That is to apply GAN for image augmentation and transfer learning in CNN for breast cancer detection.

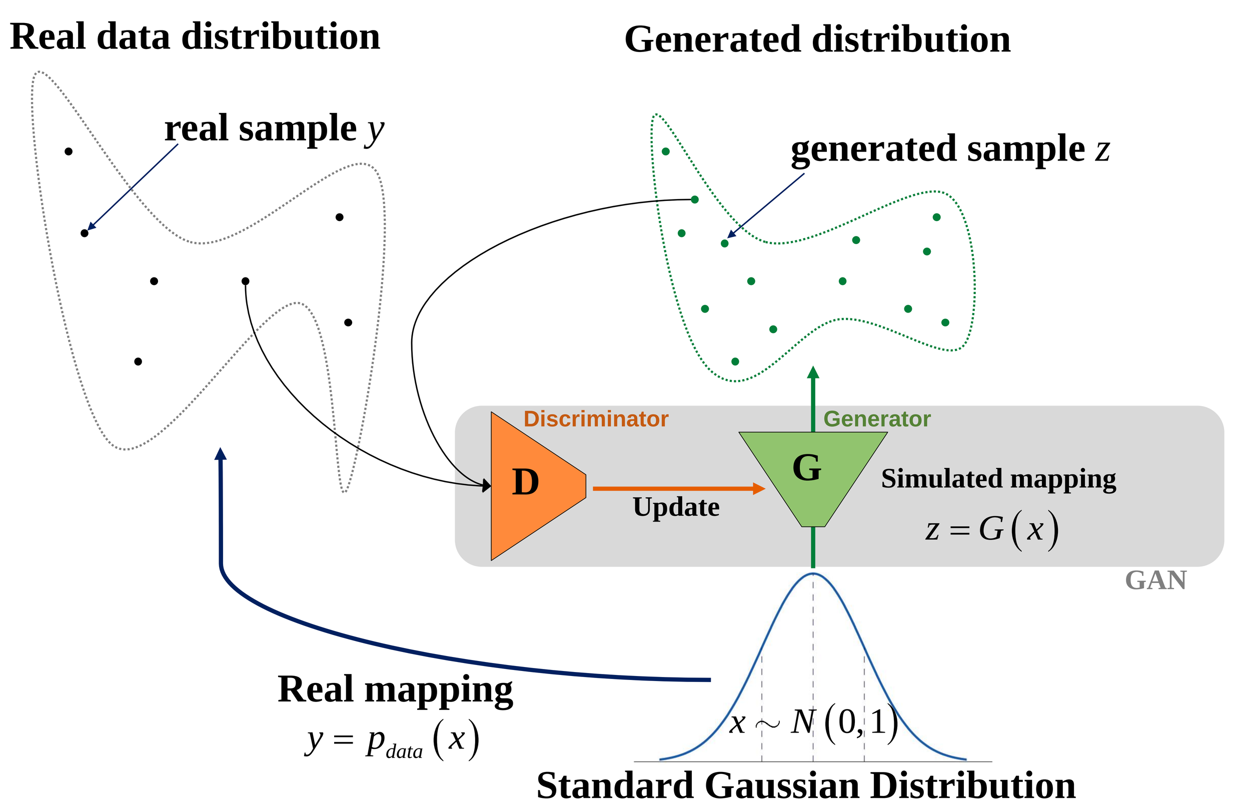

Fig.1. The principle of GAN

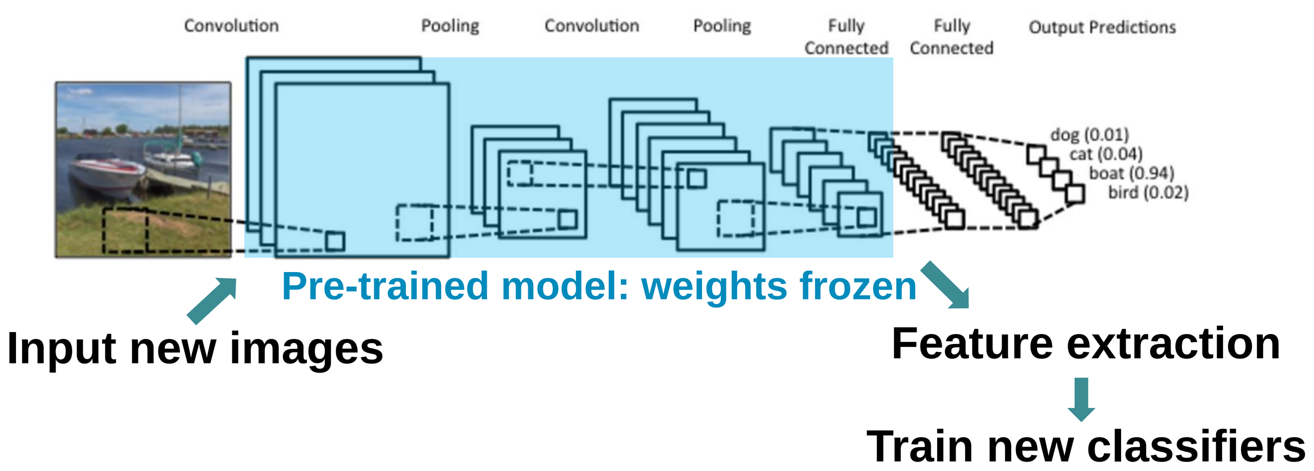

Fig.2. To reuse a pre-trained CNN model that has been trained by image datasets from other fields (WildML, 2015)

MATERIALS

In this study, we used mammogram from the Digital Database for Screening Mammography (DDSM). We used the regions of interest of images (ROIs) instead of entire images to train our neural-network models. These ROIs are cropped rectangle-shape images and obtained by:

- **For <u>abnormal ROIs</u> from images containing abnormalities, they are the minimum rectangle-shape areas surrounding the whole given ground truth boundaries.**

- **For <u>normal ROIs</u>, they are also rectangle-shape images and their sizes are approximately the average size of abnormal ROIs. In DDSM, the average size of abnormal ROIs is 506.02 × 503.90 pixels, so the cropping size for normal ROIs was chosen to be 505 × 505 pixels. Their locations are selected randomly on normal breast areas. We cropped only one ROI from an entire normal breast image.**

We resized the ROIs by resampling and made them to RGB (3-layer cubes) by duplication (Fig. 3).

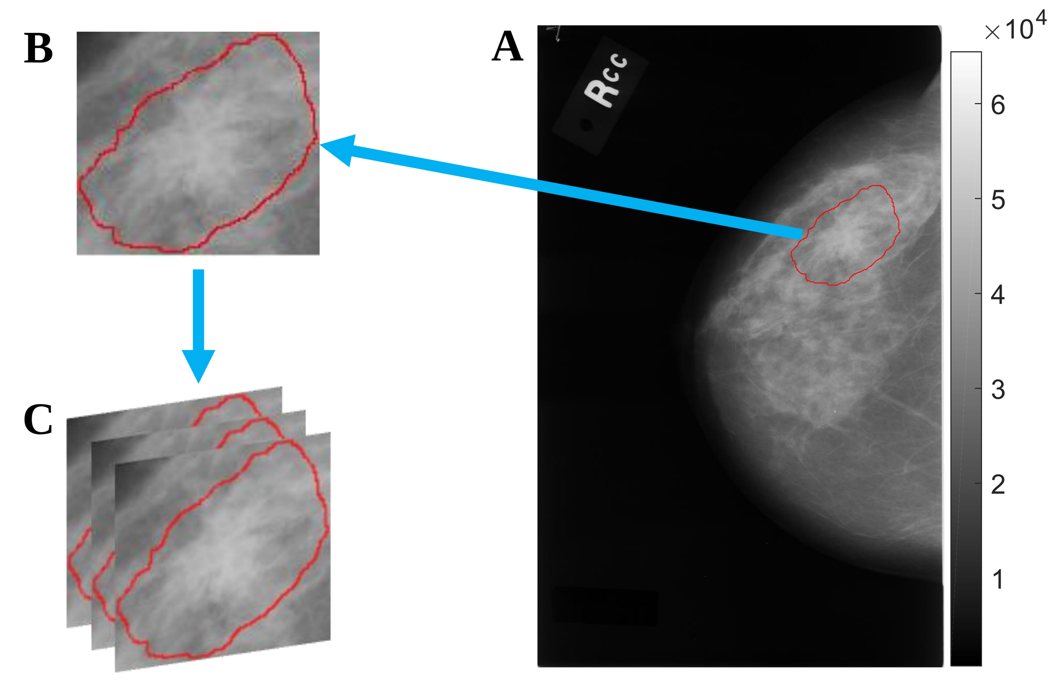

Fig.3. (A) A mammographic image from DDSM rendered in grayscale; (B) Cropped ROI by the given truth abnormality boundary; (C) Convert Grey to RGB image by duplication.

METHODS

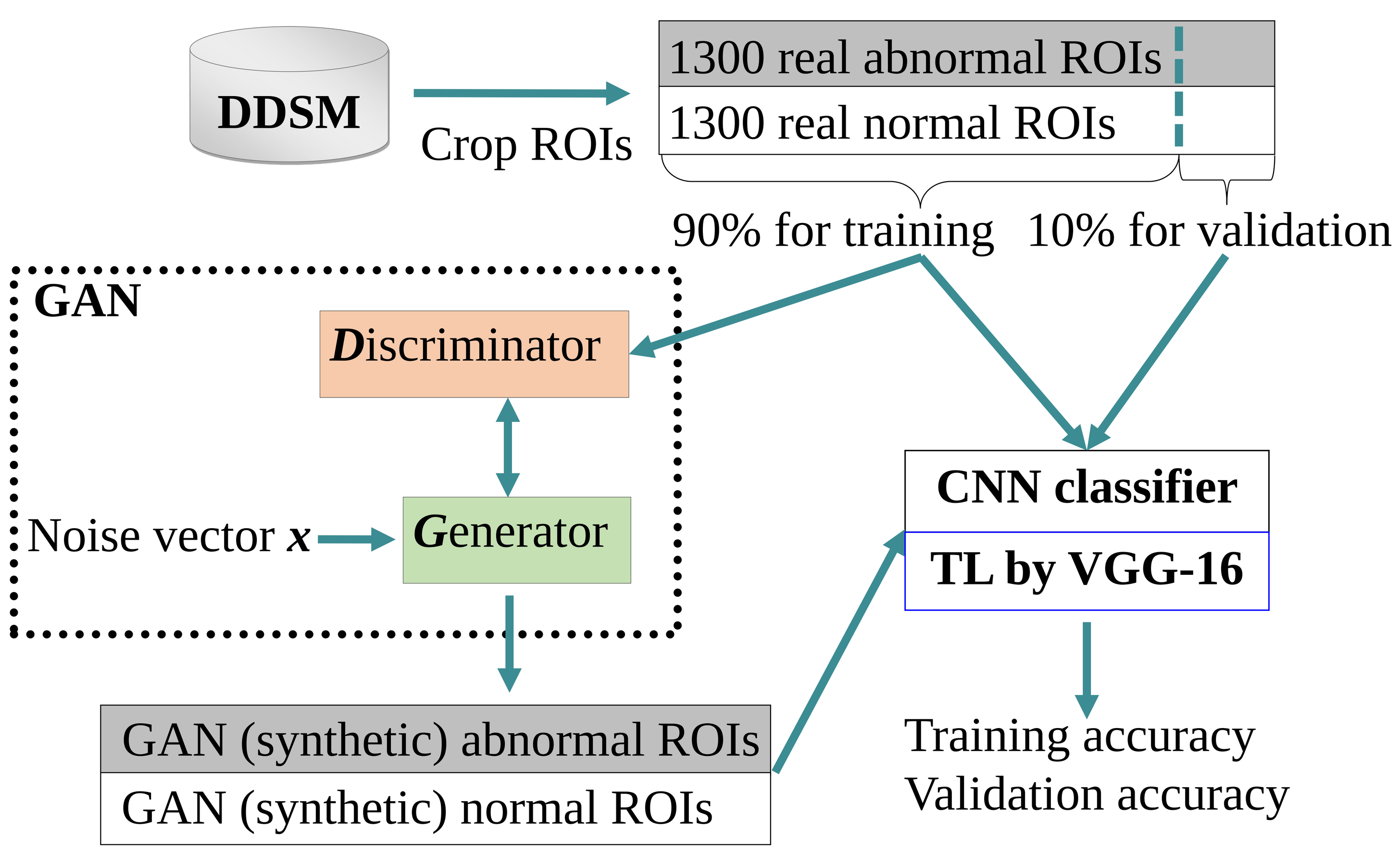

Fig.4. The flowchart of our experiment plan. CNN classifiers were trained by data including real and GAN ROIs. Validation data for the classifier were real ROIs that were never used for training. The real and GAN ROIs were also used to Transfer Learning by pre-trained VGG-16 model.

Set#	Dataset for training	Validation	Classifier Model	
1	1170 Real abnormal ROIs 1170 Real normal ROIs	130 Real abnormal ROIs 130 Real normal ROIs	CNN	TL model by VGG-16
2	1170 GAN abnormal ROIs 1170 GAN normal ROIs			
3	Set 1 + Set 2			
4	Set 1 + double Set 2			

Table 1. Training plans.

RESULTS

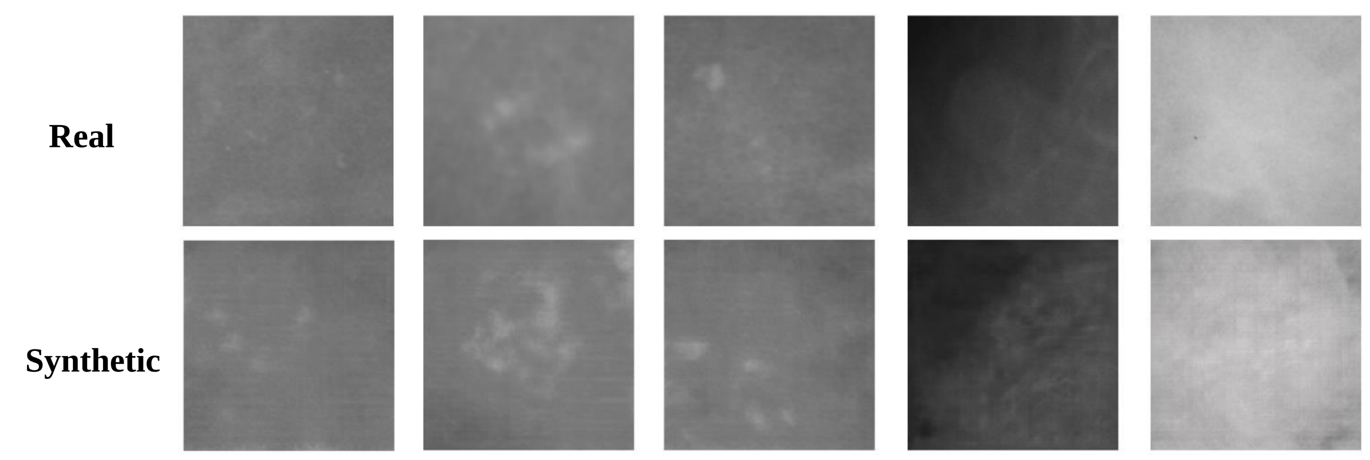

Fig.5. (Top row) Real abnormal ROIs; (Bottom row) synthetic abnormal ROIs generated from GAN.

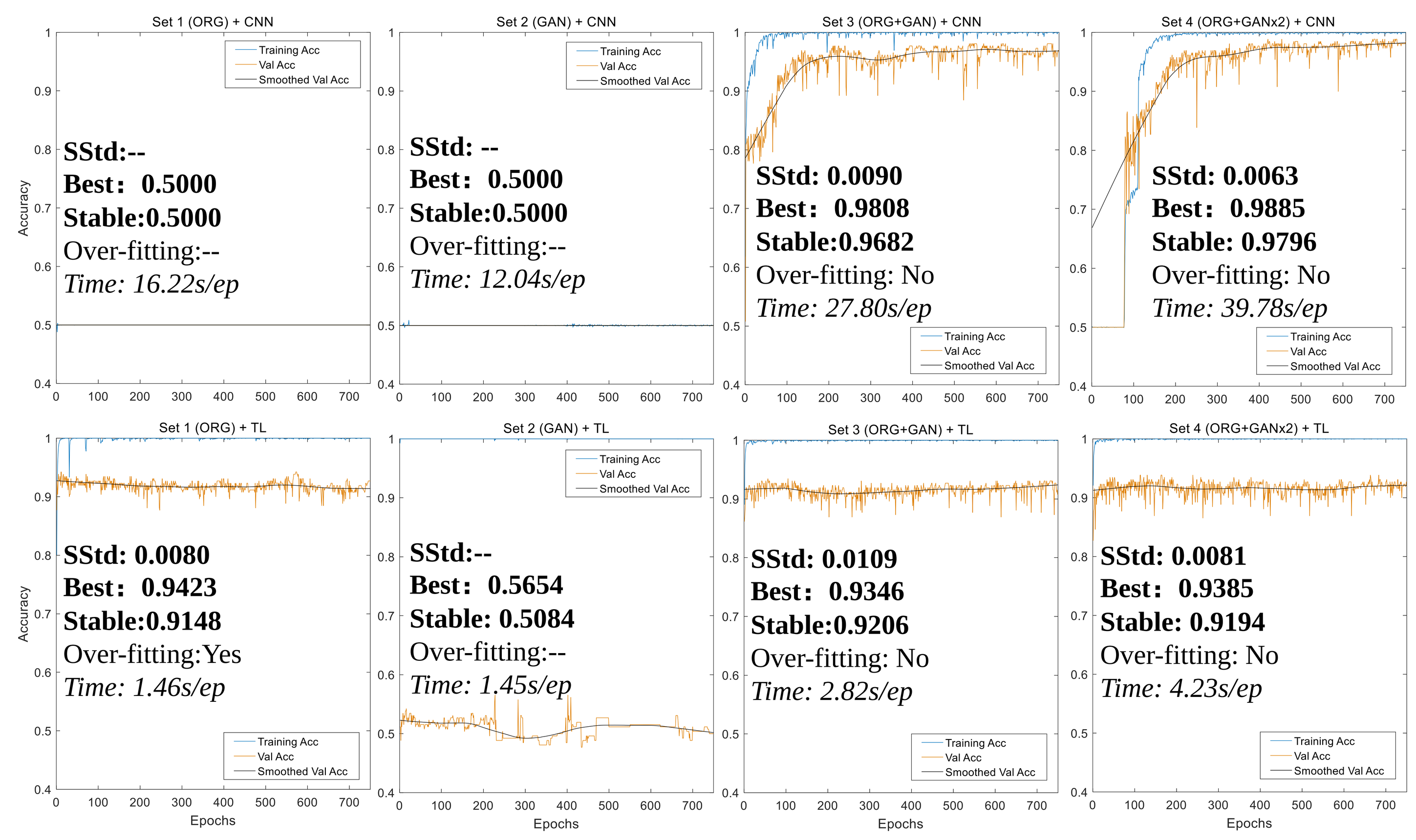

Fig.6. Training accuracy and validation accuracy for four training datasets. **<u>SStd</u>**: the standard deviation of validation accuracy after 600 epochs), **<u>Best</u>**: maximum validation accuracy, **<u>Stable</u>**: average validation accuracy after 600 epochs, **<u>Over-fitting</u>**: if the value of average validation accuracy after 400 epochs minus average validation accuracy before 400 epochs is negative.

CONCLUSIONS

- **<u>GAN-based image augmentation</u>**: to classify the normal ROIs and abnormal (tumor) ROIs from DDSM, adding GAN generated ROIs in training data can help the classifier prevent from over-fitting and the validation accuracy using mixture ROIs reached at most (best) 98.85%. Therefore, GAN could be promising image augmentation method.
- **<u>Transfer learning in CNN</u>**: the pre-trained CNN model (VGG-16) can automatically extract features from mammographic images, and a good NN-classifier (achieves stable average validation accuracy about 91.48% for classifying abnormal vs. normal cases in the DDSM database) can be trained by only real ROIs.
- **<u>Combining the two deep-learning based technologies together</u>**: to apply GAN for image augmentation and then use transfer learning in CNN for detection. Although to train the transfer learning model by adding GAN ROIs did not perform better than to train the CNN by adding GAN ROIs, the speed of training transfer learning model was about 10 times faster than CNN training.

In summary, adding GAN ROIs can help training avoid over-fitting and image augmentation by GAN is necessary to train CNN classifiers from scratch. On the other hand, transfer learning is necessary to be applied for training on pure ORG ROIs. To apply GAN to augment training images for training CNN classifier obtained the best classification performance.