Breast Cancer Detection

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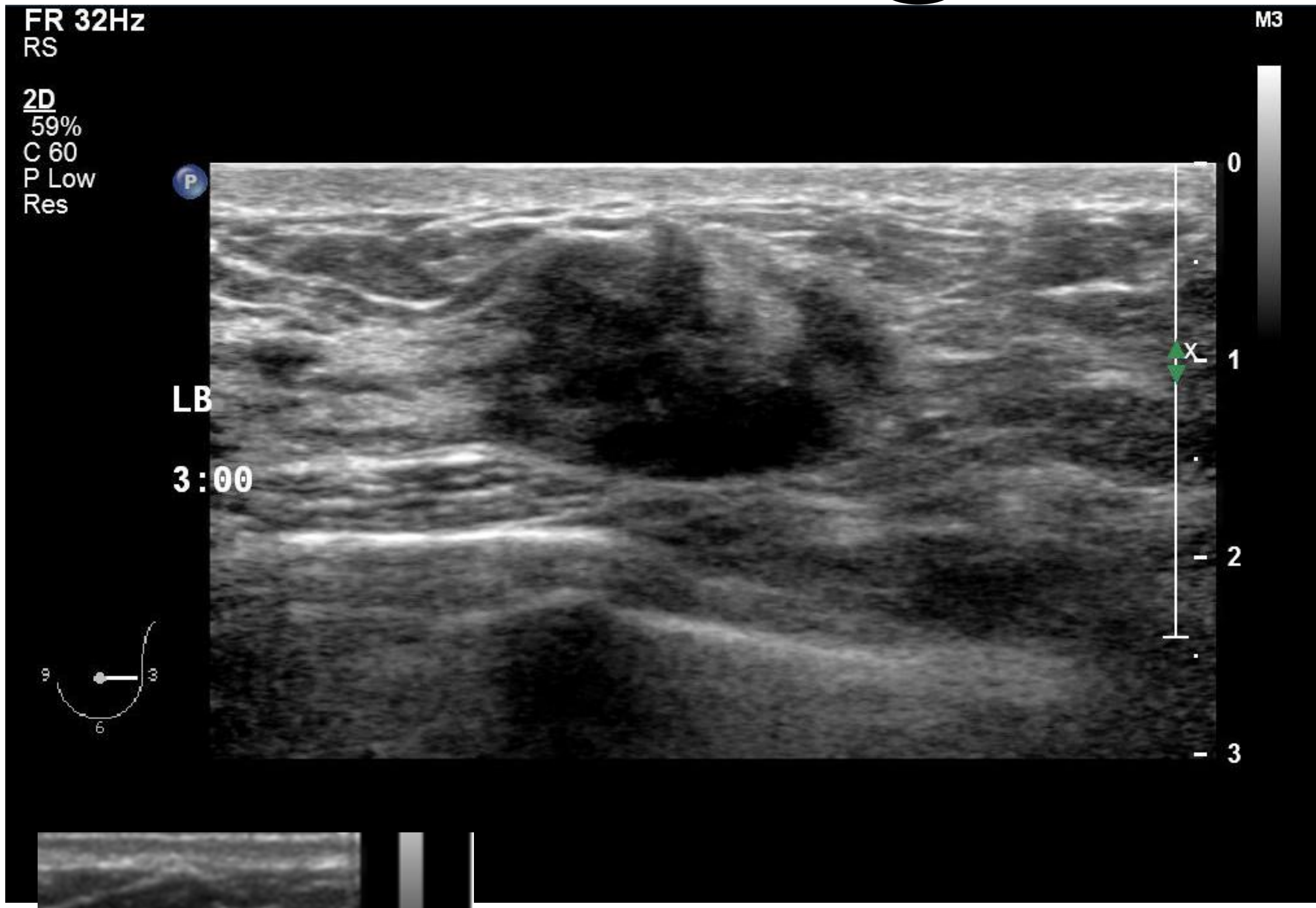
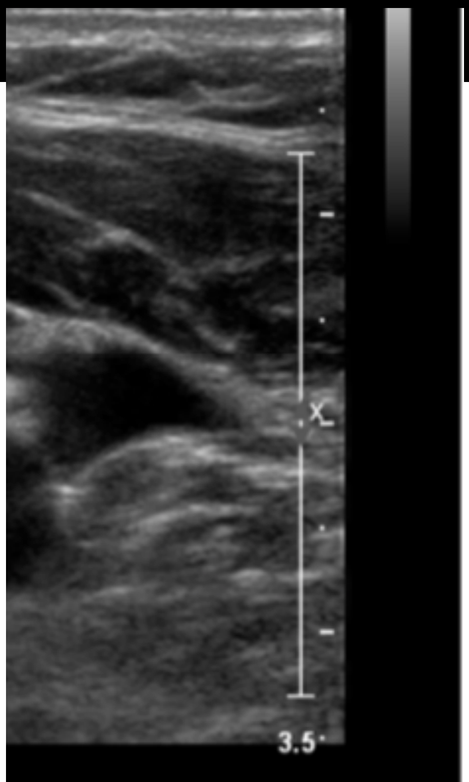
Work process

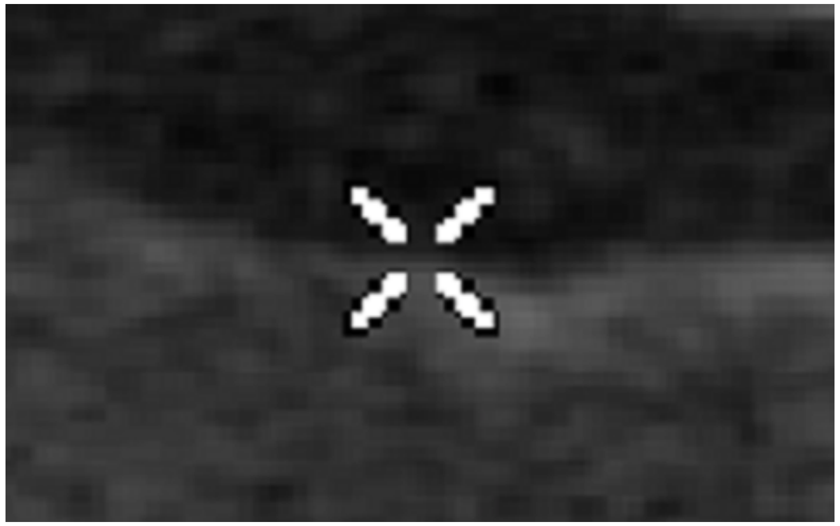
- Pre-process ultrasound images. Data normalization, balance and augmentation.
- Build up classifiers with deep neural networks.
- Training and testing.

Data Pre-processing

- Remove useless annotations from ultrasound images, such as the tick bars and fiducial markers added by radiologists.
- Image restore.
- Data normalization and augmentation.







- We used the following methods to remove antifacts:

- Apply 2D connected component algorithm on the binary image, resulting in a labelled image with K components.

- Identify the texture region as the largest 2D connected component in the labelled image and subtracted it from the image to get the “possible artifact” regions.

- Plot the histogram of the “possible artifact” regions and divided the histogram into three parts [0,100], [101,200], [201,255], respectively.

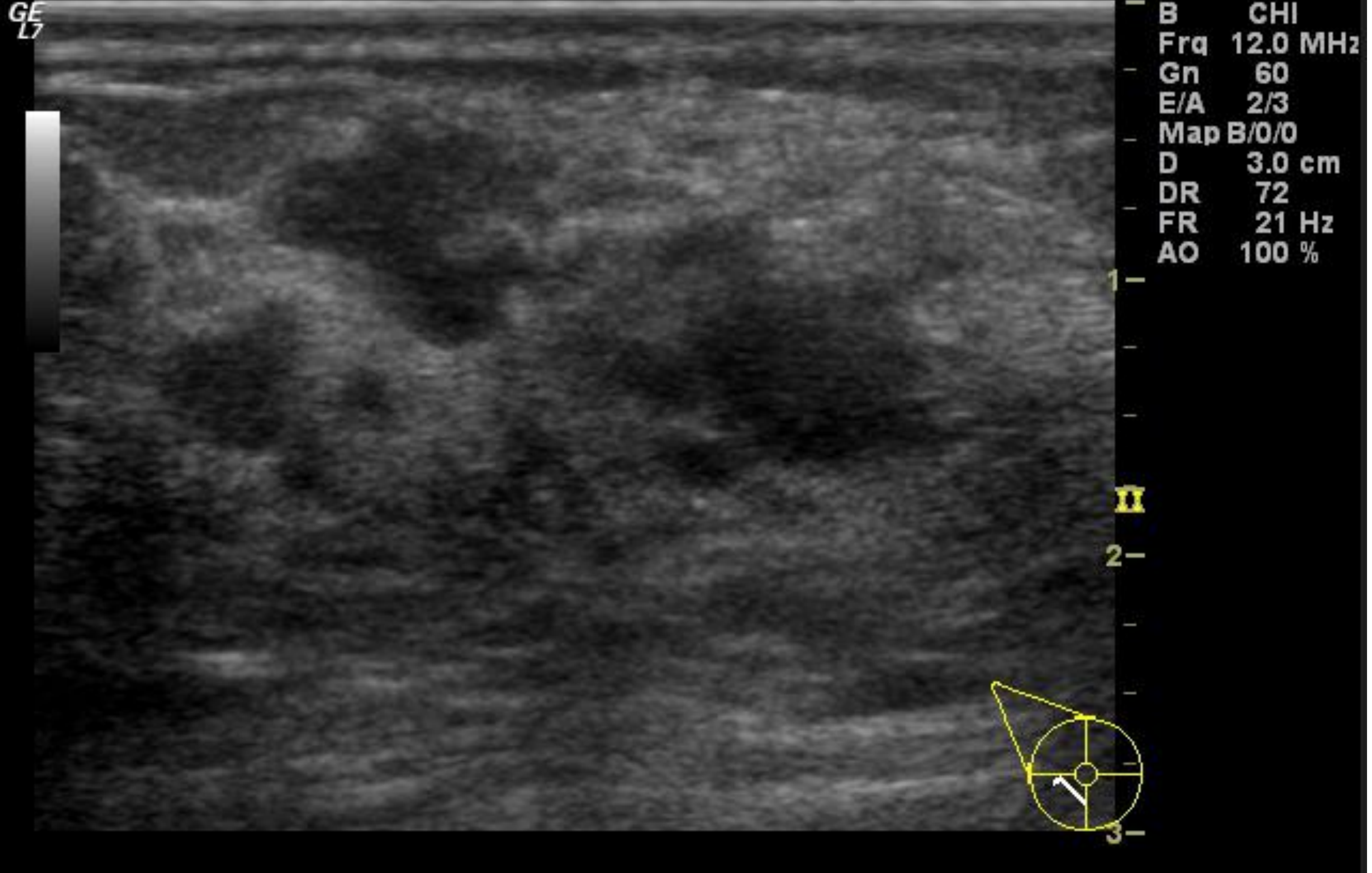
- Take the histogram peaks in each of the three parts as the intensity levels of the artifacts and subtract from the original image to generate the artifact-removed image.

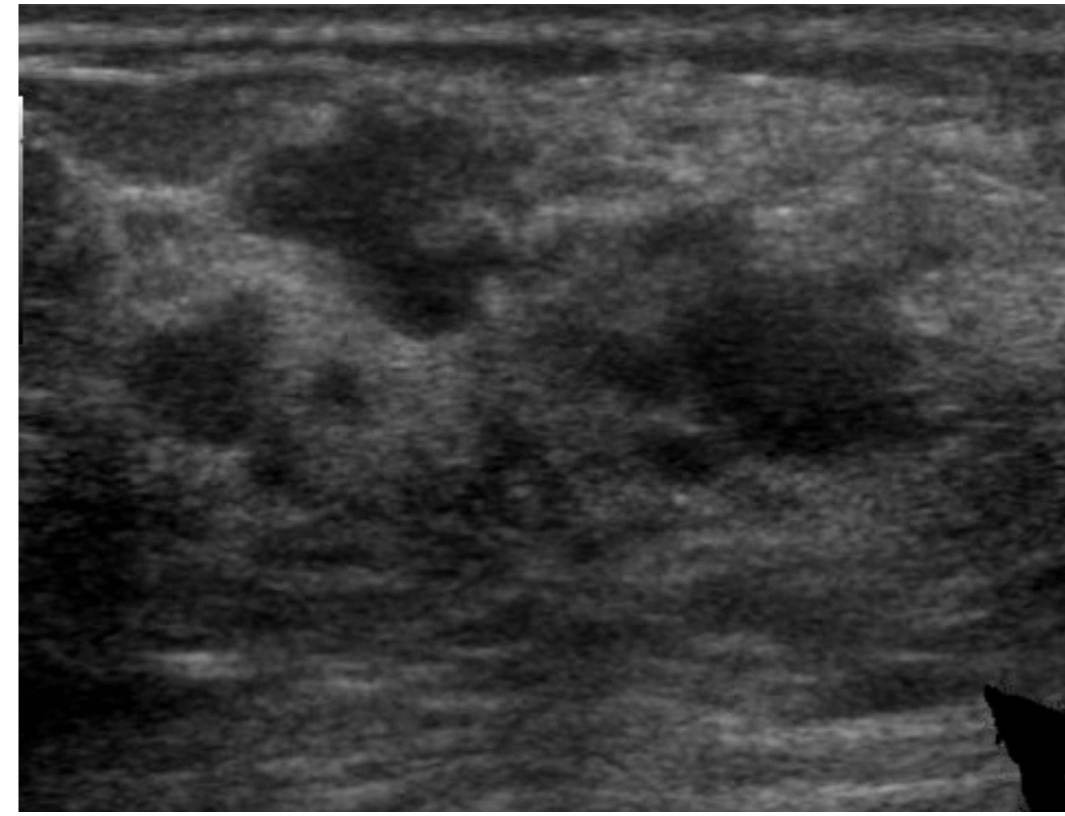
- We used the “Inpaint” function in OpenCV to restore the images. The restore method is Navier-Stokes based method [Navier01].

- Cut the texture areas from the original images.

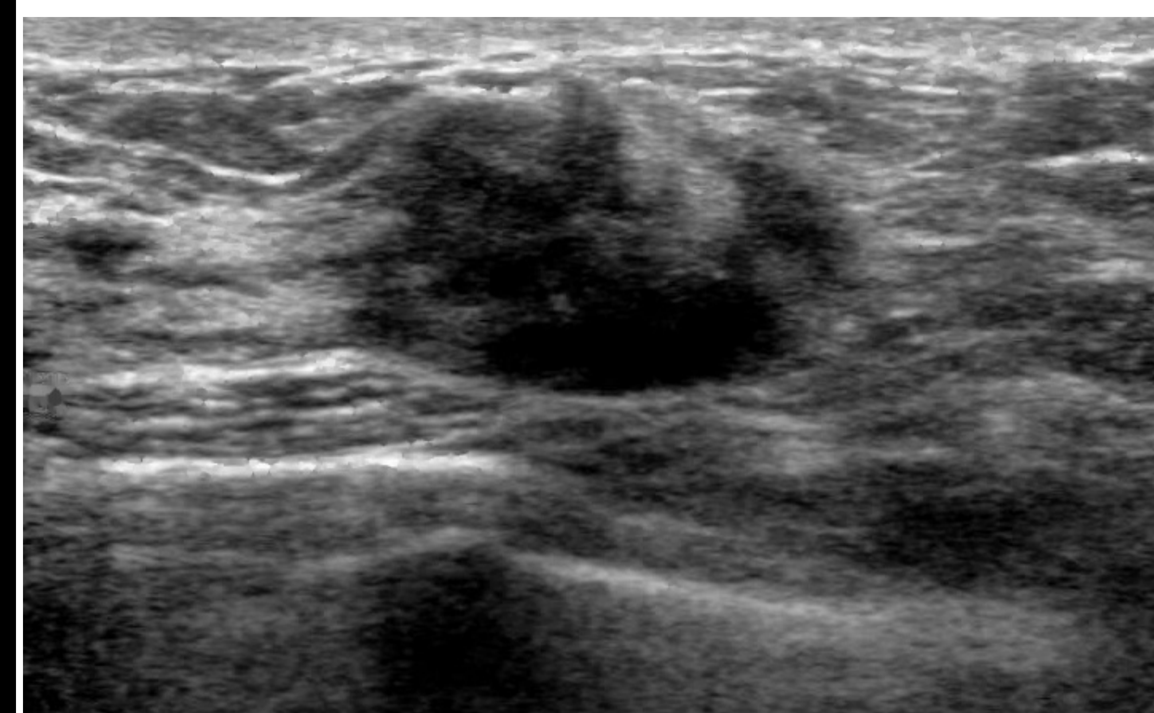
- All images were resized to size 512 * 512 to fit the input of neural networks.

- Applied flipping, rotating and color jitter for augmentation. Made the four classes have equal numbers of images.


GE
L7
B CHI
Frq 12.0 MHz
Gn 60
E/A 2/3
Map B/0/0
D 3.0 cm
DR 72
FR 21 Hz
AO 100 %
1
2
3




FR 32Hz
RS
2D
59%
C 60
P Low
Res
M3
P
LB
3:00
0
1
2
3
9
3
6



Classification

- The input is a 512 * 512 size image and three clinical diagnostic data: age, HER2, P53.
- First, we trained a simple SVM classifier with only the clinical diagnostic data, and reached the f1-score of 0.56.
- Then we trained a simple VGG network with only the ultrasound images, and reached the f1-score of 0.39. For one patient with several ultrasound images, we predict the label of each image and vote to the final result.

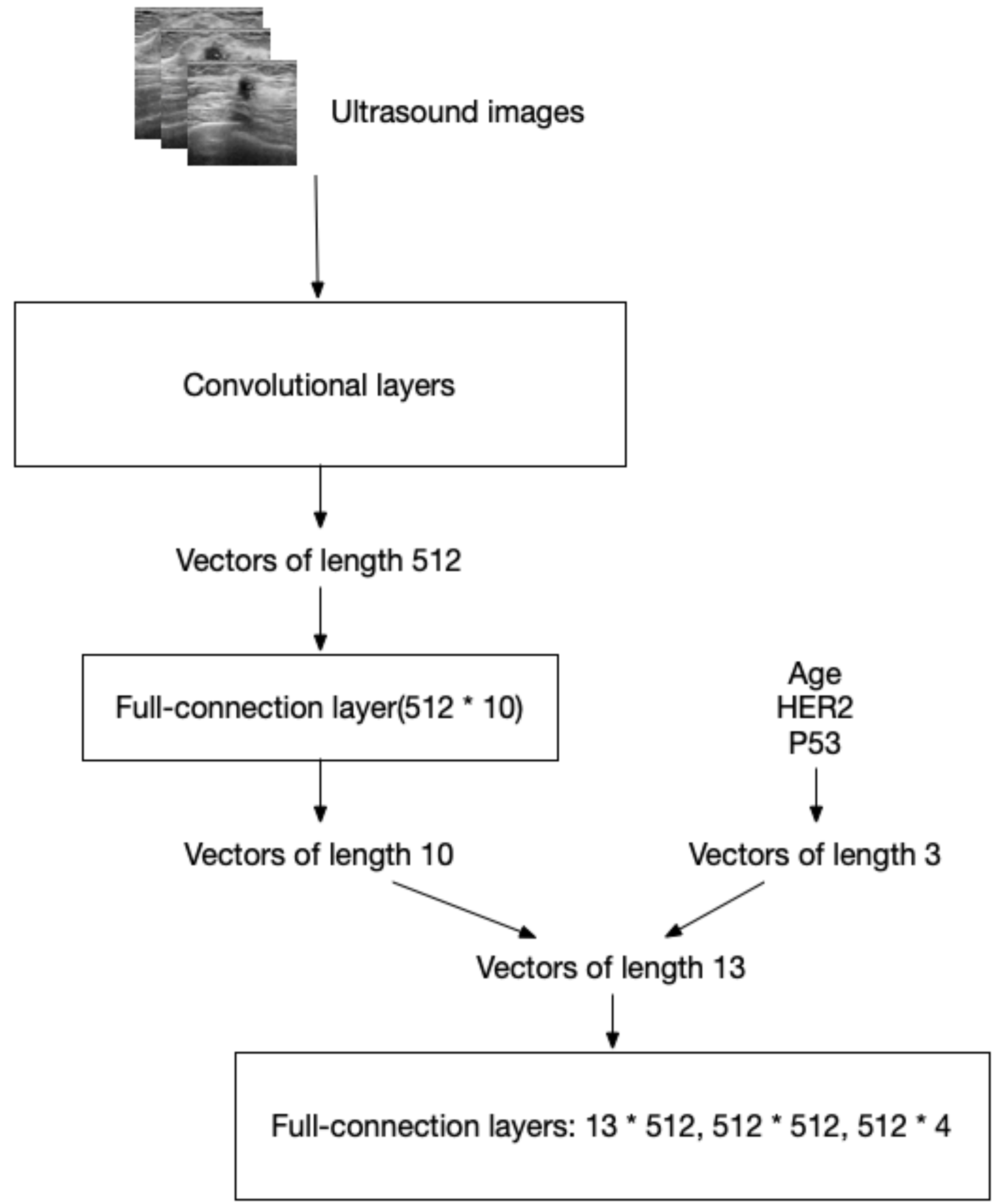
- Extract the features of the images(vectors of length 512) from the feature-layers output of neural networks.

- Dimensionality reduction to vectors of length 5. According to experiments results, PCA outperforms t-SNE.

- Combine this vector with the three clinical diagnostic data to vectors of length 8. These vectors were then sent to train the SVM classifier.

- The best result of this method is 0.625.

- According to the advice of the teaching assistant, we tried another method which only use the neural network.
- This method reached the f1-score of 0.639, which outperforms the last method.



- The neural networks were implemented with Pytorch.

- We then tried another network DRN(Dilated Residual Networks), which captures both the global and local features without losing the perception field. This network outperformed VGG with f1-score 0.667. (Rank 6 currently)

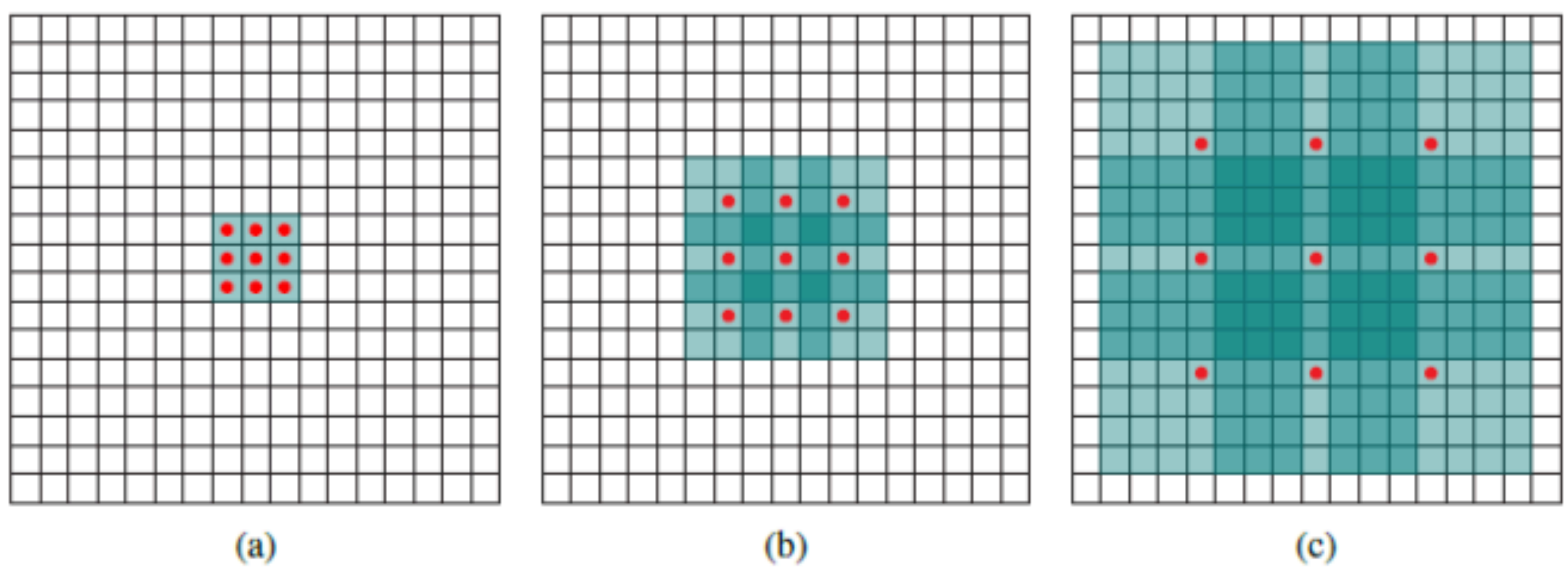


Figure 1: Systematic dilation supports exponential expansion of the receptive field without loss of resolution or coverage. (a) F_1 is produced from F_0 by a 1-dilated convolution; each element in F_1 has a receptive field of 3×3. (b) F_2 is produced from F_1 by a 2-dilated convolution; each element in F_2 has a receptive field of 7×7. (c) F_3 is produced from F_2 by a 4-dilated convolution; each element in F_3 has a receptive field of 15×15. The number of parameters associated with each layer is identical. The receptive field grows exponentially while the number of parameters grows linearly.

- Any questions?
- We still want to try some semi-supervised methods with the unannotated data.
- Our biendata group name is: quanbucaofei.
- All code can be found at:https://github.com/xindubawukong/SOA_cancer_detection
- All experiments are carried out on a computer with two GTX 1080 GPUs.

References

- [1]Simonyan, K. and Zisserman, A., 2014. Very deep convolutional networks for large-scale image recognition. arXiv preprint arXiv:1409.1556.

- [2]Yu, F., Koltun, V. and Funkhouser, T., 2017. Dilated residual networks. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 472-480).

- [3]Chi, J., Walia, E., Babyn, P., Wang, J., Groot, G. and Eramian, M., 2017. Thyroid nodule classification in ultrasound images by fine-tuning deep convolutional neural network. *Journal of digital imaging*, *30*(4), pp.477-486.

Thank you!