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Comparison between Denoising Convolutional Neural Networks and Simple Convolutional Neural Networks for Denoising of Medical Images

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Abstract

In this study, we compare between Denoising Convolutional Neural Networks (DnCNN) and simple Convolutional Neural Networks (CNN). We apply these networks for small dataset of chest radiographs. Then, we evaluate them by visual observation as qualitative evaluation and Peak Signal to Noise Ratio (PSNR) as quantitative evaluation.

1. Introduction

Convolutional Neural Networks (CNN) are one method of Artificial Intelligence (AI), and CNN has enormous attention in recent years. Nowadays, it is used for various kinds of fields and products. Then, CNN is applied for medical images as well. For accurate diagnosis it is important to have good quality of medical images. However, medical imaging systems have trade-off relationships between filming time, radiation dose and quality of images. It is also important for patients to have less filming time and radiation dose. Therefore, noise would be generated in medical images.

Recently, CNN for denoising of medical images has been discussed. Denoising Convolutional Neural Networks (DnCNN) is one of the state-of-the-art denosing Networks [1].

In this study, we compare between DnCNN and simple CNN for denoising Gaussian noise on Chest Radiographs. Then, denoising by simple CNN showed better results than DnCNN. The result images of denoising by DnCNN had white spots that are not expected.

2. Convolutional Neural Networks

CNN is one of the most popular Neural Networks, and it is used for various studies.

In this study, we use simple CNN which has only two Convolutional layers. Kernel size is 3, batch size is 4, and activation function is ReLU. Figure 1 shows the structure of simple CNN that we use.

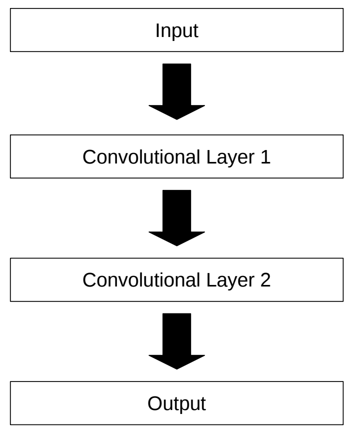

Figure 1: Structure of simple CNN.

3. Denoising Convolutional Neural Networks

DnCNN can be described one of the state-of-the-art denosing Networks. It has Convolution layer and repetition of Convolution and Batch Normalization layers.

In this study, Convolutional and Batch Normalization layers are repeated 16 times. Kernel size is 3, batch size is 4, and Activation function is ReLU. Figure 2 shows the structure of simple DnCNN that we use.

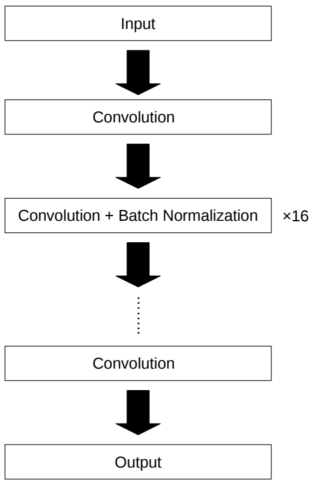

Figure 2: Structure of simple DnCNN.

4. Dataset

We use Japanese Society of Radiological Technology (JSRT) Database [2]. In this dataset, there are both of with and without nodule images. From this database, we use 200 images. The ratio of train data and test data is 3:1. Test data is used for validation as well. Image size is 256 $\times$ 256 pixels, and images are gray scale. The table2 shows the number of images with and without nodule in the dataset.

Table 1: Dataset.

	train data	test data
With nodule images	94	31
Without nodule images	56	19
Total	150	50

Then, we make noisy images by putting Gaussian noise on the dataset. Gaussian noise is one of the most common kinds of noise for medical images. We put Gaussian noise of standard deviation 50 and mean 0.

5. Peak Signal To Noise Ratio

We use Peak Signal to Noise Ratio (PSNR) as quantitative evaluation. PSNR can express degradation of images,and large number of PSNR means less degradation. In this study, PSNR is defined by the following equation [3].

$$PSNR = 10 \log_{10} \frac{MAX^2}{MSE} \quad (1)$$

MAX is the maximum pixel that the images can be. MSE is mean square error between original image and result image.

6. Results

First, we show the graphs about loss function. In this study, we use mean square error as loss function.

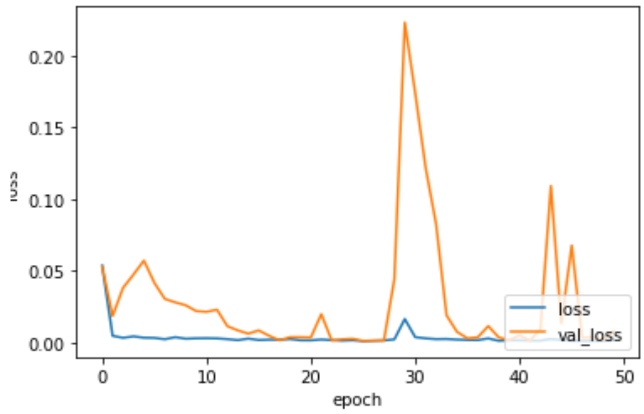

Figure 3: Loss of DnCNN.

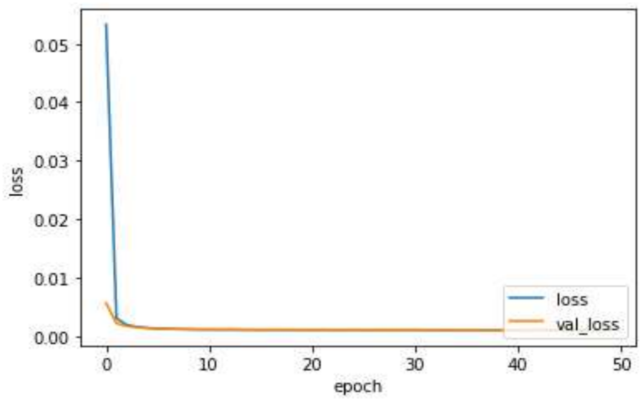

Figure 4: Loss of simple CNN.

The loss of train of DnCNN does not converge, and the loss of validation of DnCNN does not converge at all [Figure 3]. On the other hand, the loss of CNN converges about both of train data and validation data [Figure 4].

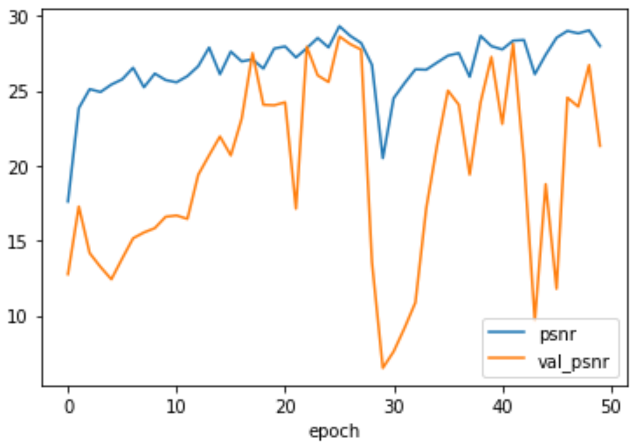

Figure 5: PSNR of DnCNN.

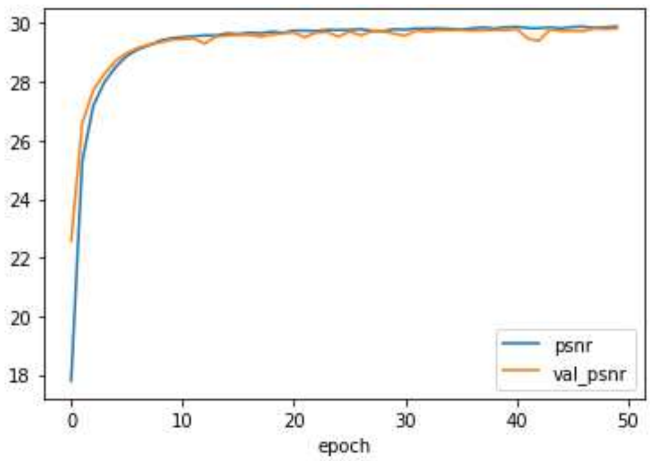

Figure 6: PSNR of simple CNN.

PSNR of DnCNN is not stable at all [Figure 5]. The highest PSNR of train data is 29.3015 and the highest PSNR of validation data is 28.6190. PSNR of CNN converges, and PSNR of train data indicates 29.8867 and PSNR of validation data indicates 29.8139 at 50th epochs [Figure 6]. Even the highest PSNRs of DnCNN are lower than PSNRs of CNN. Then, we show the processing time result compared between DnCNN and CNN [Table2].

Table 2: Processing Time.

DnCNN	2h47m
CNN	15m25s

We use GPU for processing both of DnCNN and CNN. Processing time of CNN is dramatically shorter than DnCNN.

Figure 7: Original Image.

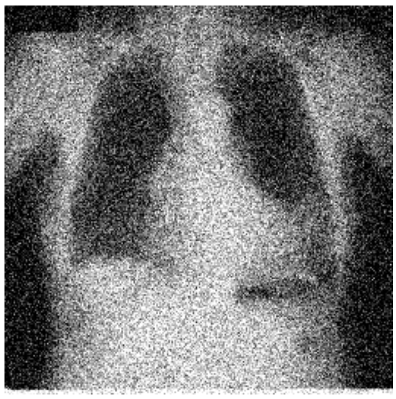

Figure 8: Noise image.

Figure 9: Denoising result image by simple CNN.

Figure 10: Denoising result image by DnCNN.

As we can compare between Figure 7, 8, and 10, about denoising result images by DnCNN we can see white spots that do not exist on original images. That white spots appear mainly background and the black space in lungs. Especially, white spots in lungs would be problems for diagnosis. On the other hand, result images by simple CNN have less white spots than DnCNN [Figure 9]. Even though we can still see Gaussian noises on result images and blurred noise in lungs aw well, denoising result images by simple CNN are better than DnCNN ones.

7. Conclusion

We could reduce Gaussian noise from noisy Chest Radiographs by using simple CNN. Simple CNN showed better results than DnCNN with small size of dataset. Moreover, Simple CNN processed rapidly compared with DnCNN. However, noise reduction is not enough yet. In the future, we will consider better network structures for denoising.

References

[1] Kai Zhang, Wangmeng Zuo, Yunjin Chen, Deyu Meng, and Lei Zhang,"Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising", IEEE Transactions on Image Processing, July 2017.

[2] Shiraishi J, Katsuragawa S, Ikezoe J, Matsumoto T, Kobayashi T, Komatsu K, Matsui M, Fujita H, Kodera Y, and Doi K, "Development of a digital image database for chest radiographs with and without a lung nodule: Receiver operating characteristic analysis of radiologists 'detection of pulmonary nodules" AJR 174, 71-74, 2000.

[3] Hiroshi Fujita,"Medical AI and Deep Learning Series No.3", Ohmsha, 2019.