Application of deep neural networks for bone-suppressed digital radiography

Eunpyeong Park

Advisor: Prof. Ho Kyung Kim

Radiation Imaging Laboratory,

Pusan National University, South Korea

Outline

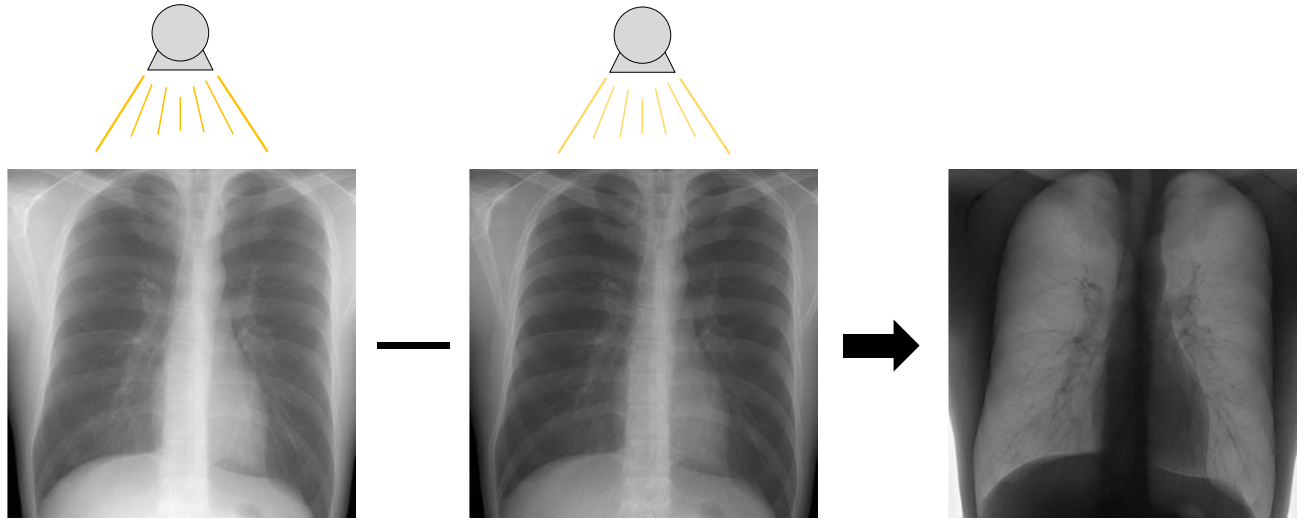
I. Introduction
- Objective
- Type of neural network

II. Method
- DNN (Deep neural network)
- SSIM (Structural similarity index)

III. Results & Discussion
- Dropout
- Parameters

IV. Conclusion

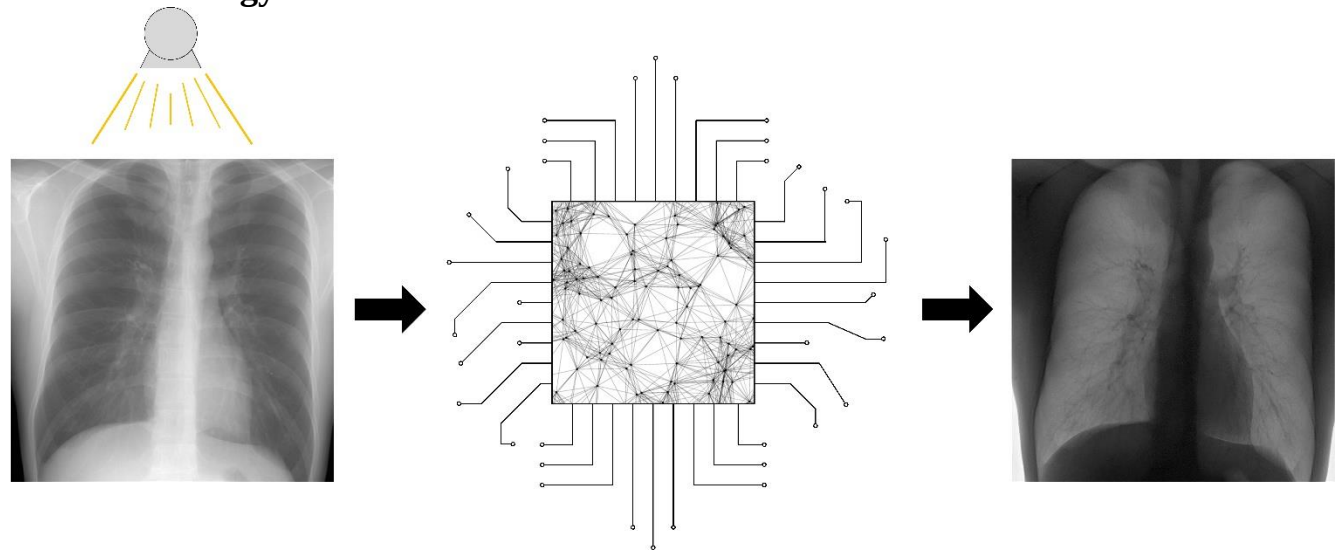
Introduction



High Energy **Low Energy**

Dual-Energy Imaging (**DEI**)

Machine Learning (**N**eural **N**etwork)



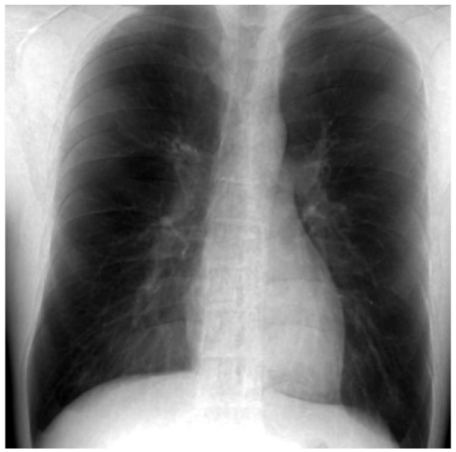
Objective

HE

$-\quad w \times$

LE

$=$



DE

HE

$-\quad w \times \left[W_{DNN} * \right.$

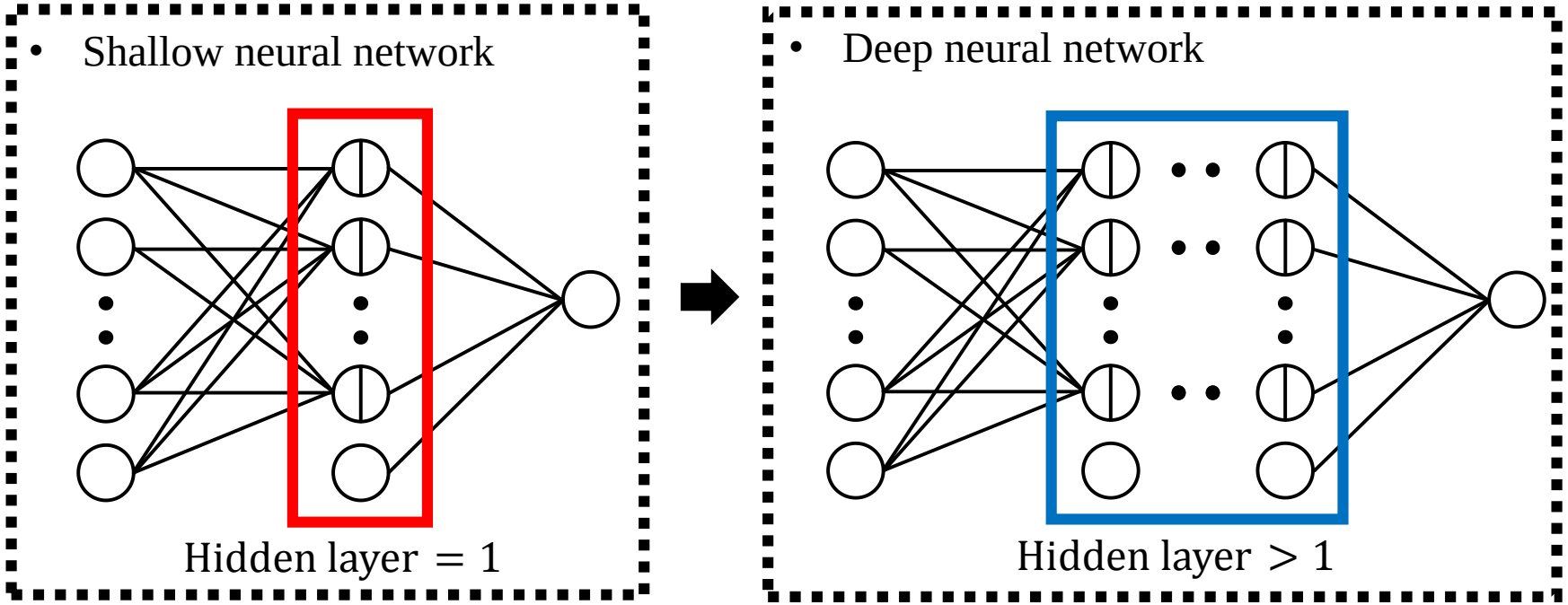
$\left. \right]$

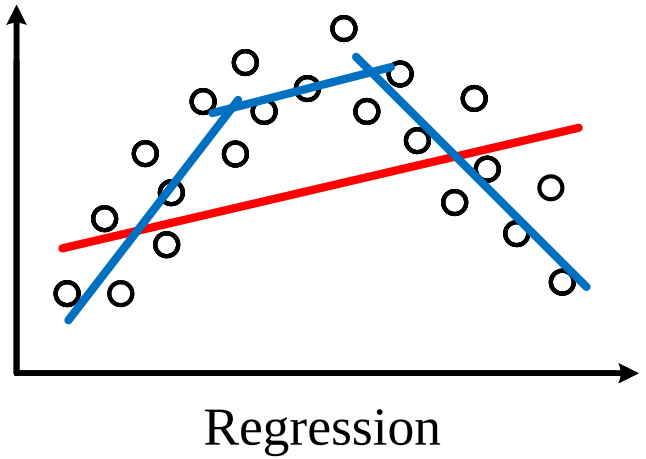
HE

$=$

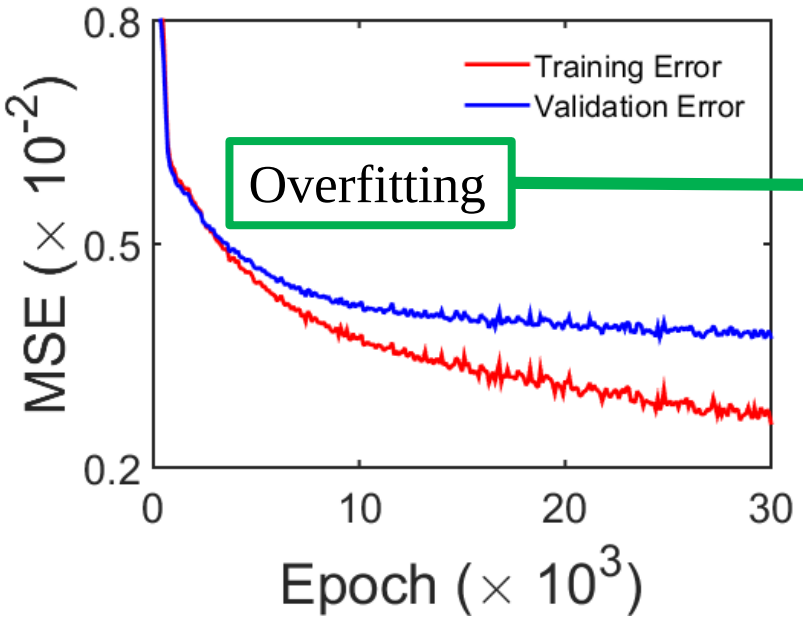
DNN-DE

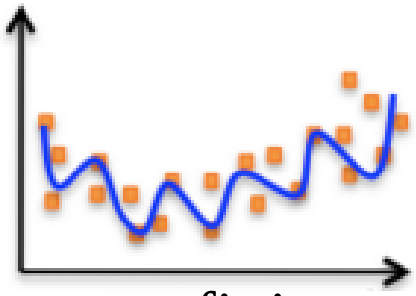
Type of neural network





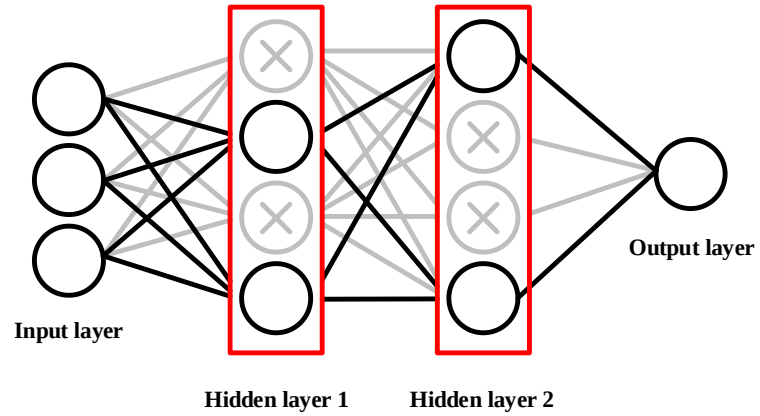
DNN (Dropout)

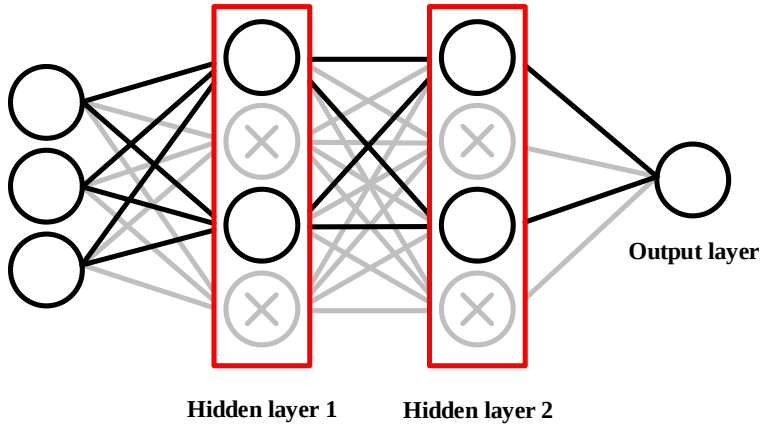




overfitting

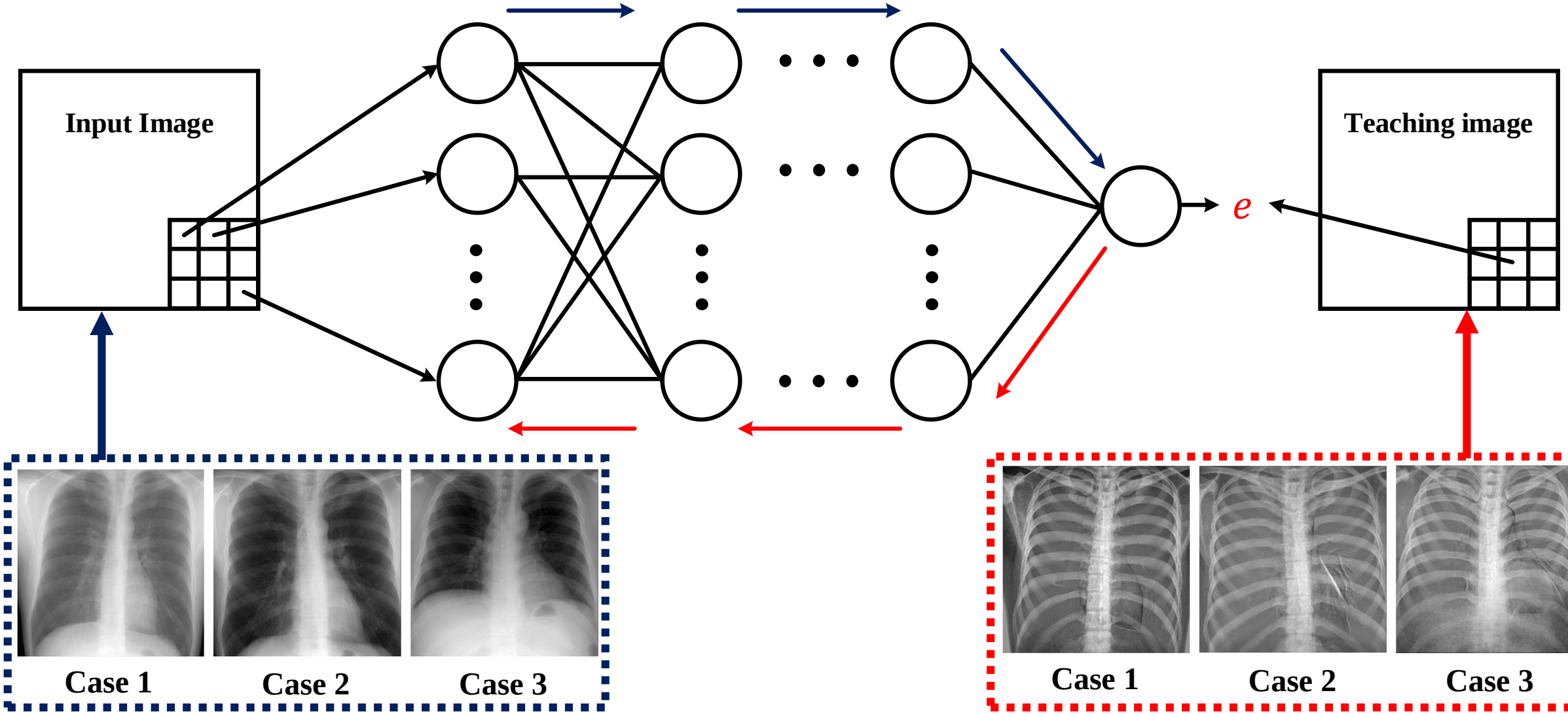
Dropout



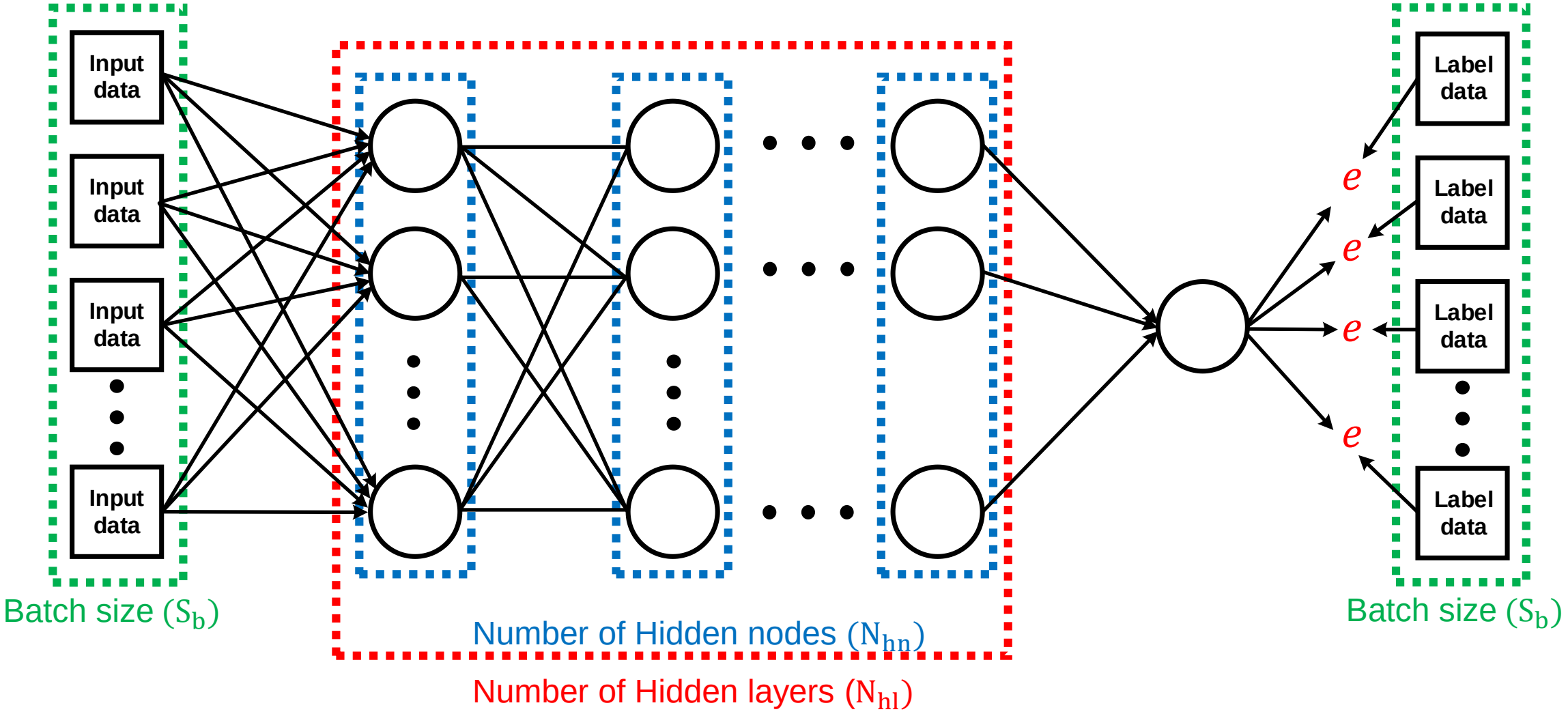


- Various neural network architectures.
- To improve the generalization ability of DNN.

DNN (Deep neural network)



DNN (Parameters)



SSIM (Structural similarity index)

$$\mathrm{SSIM}(x,y) = [I(x,y)] \cdot [c(x,y)] \cdot [s(x,y)]$$

Intensity

$$I(x,y) = \frac{2\mu_x\mu_y + C_1}{\mu_x^2 + \mu_y^2 + C_1}$$

Contrast

$$c(x,y) = \frac{2\sigma_x\sigma_y + C_2}{\sigma_x^2 + \sigma_y^2 + C_2}$$

Structure

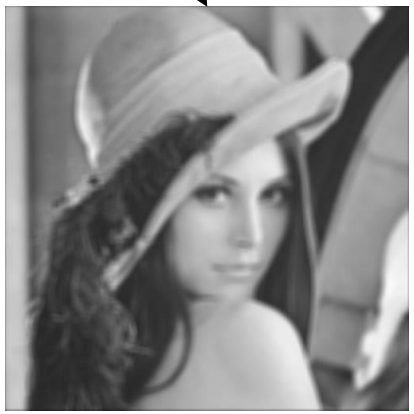
$$s(x,y) = \frac{\sigma_{xy} + C_3}{\sigma_x\sigma_y + C_3}$$

Pixel intensity $= \mu_x, \mu_y$ Pixel contrast $= \sigma_x, \sigma_y$

$$\mathrm{SSIM}(x,y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$$

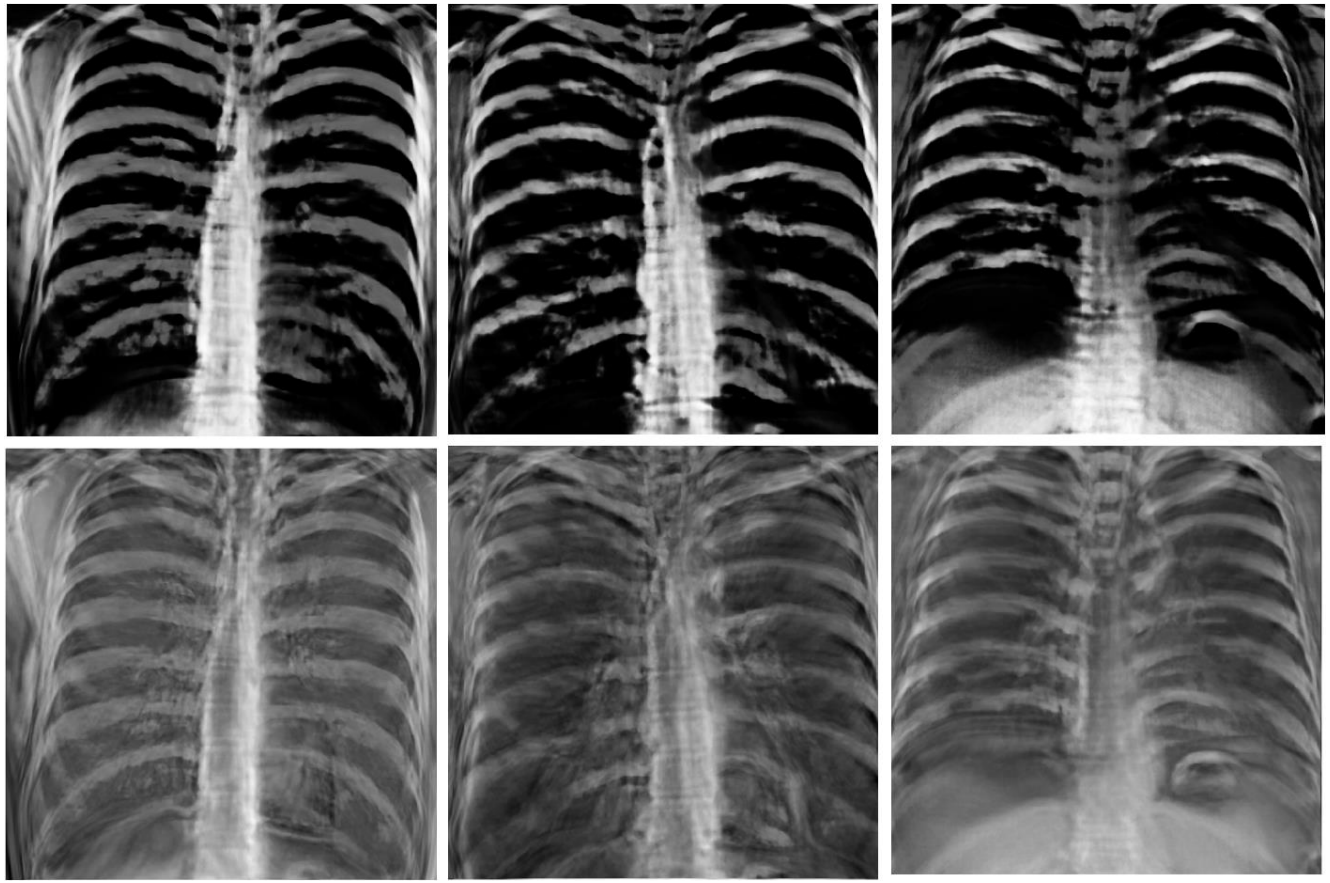
Reference image

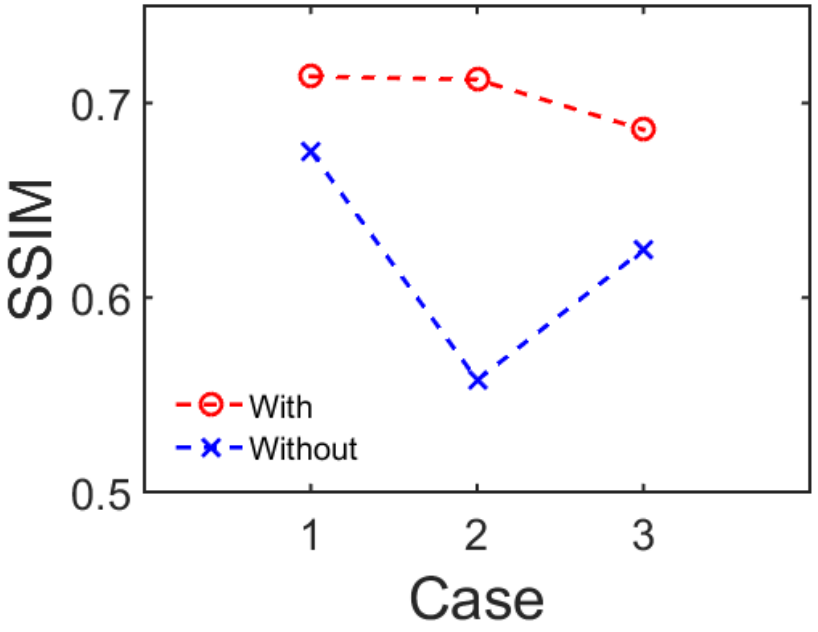
Contrast-stretched image
SSIM : 0.8882



Blurred image
SSIM : 0.6087

Results (Dropout)

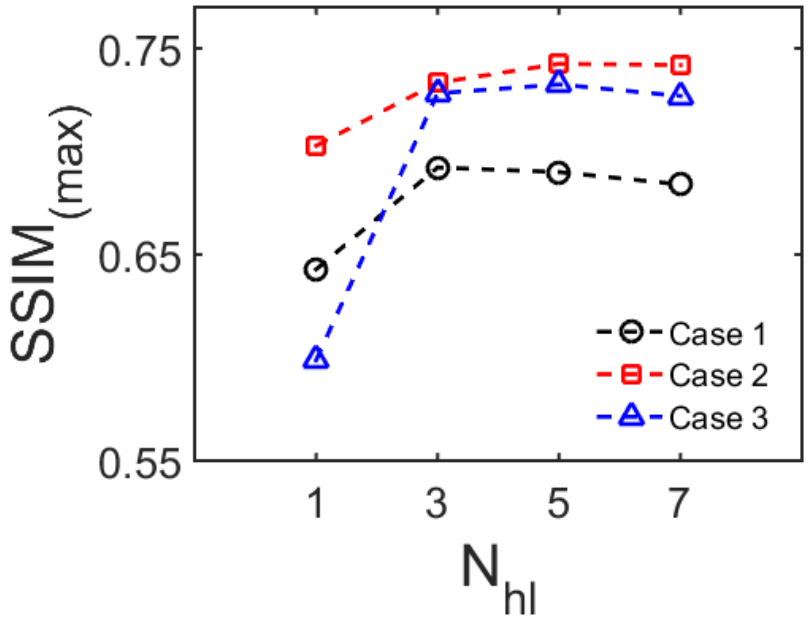




- Using the dropout technique, The generalization ability of DNN has improved.

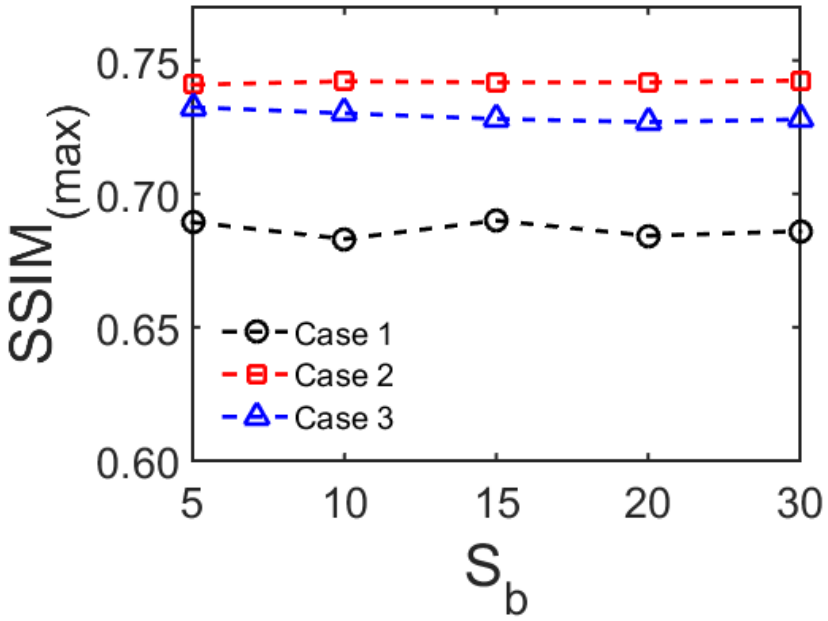
Results (Hidden layers, Batch sizes)

Batch	Hidden layer	Hidden node	Learning rate
20	1,3,5,7	200	10^{-3}



- The number of hidden layers and the performance of the DNN are independent of each other.

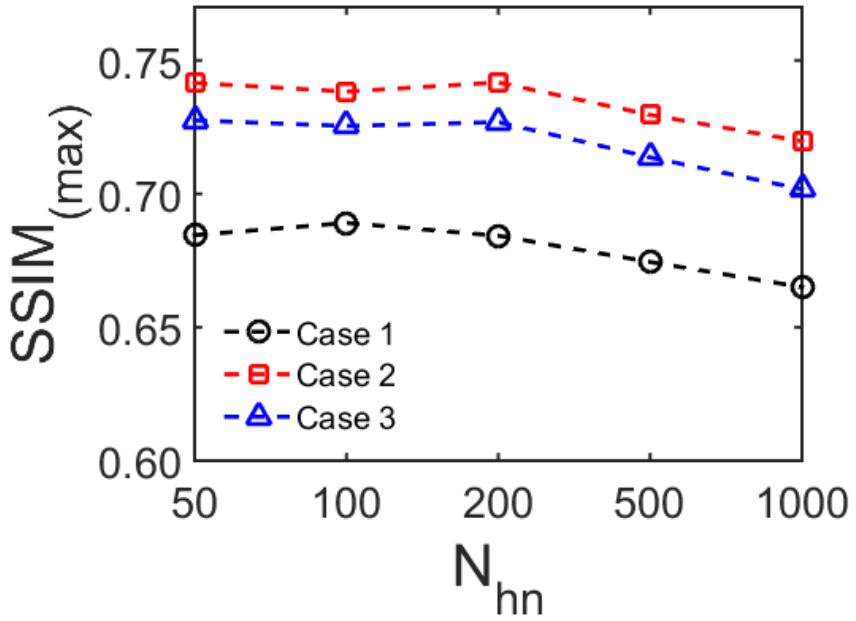
Batch	Hidden layer	Hidden node	Learning rate
5, 10, 15, 20, 30	5	200	10^{-3}



- The batch sizes and the performance of the DNN are independent of each other.

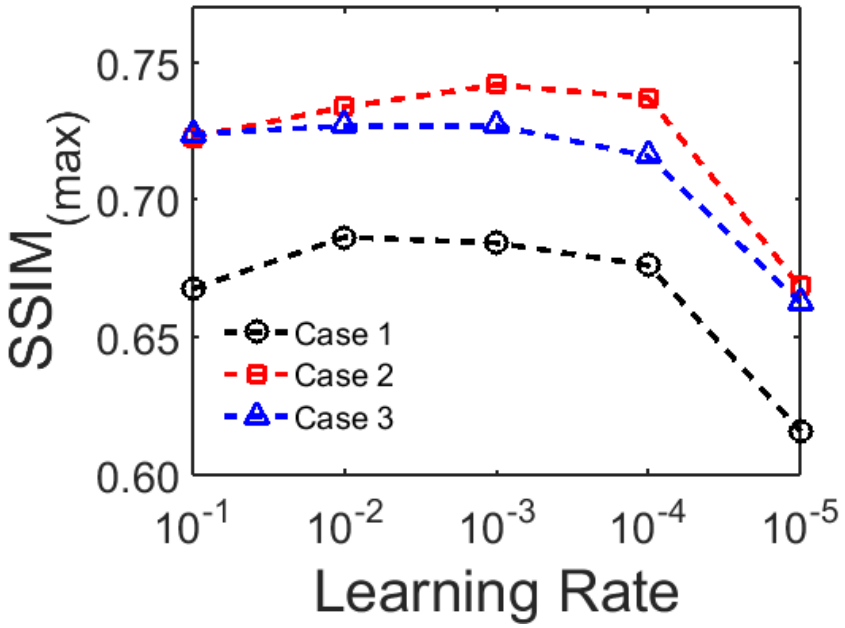
Results (Hidden nodes, Learning rates)

Batch	Hidden layer	Hidden node	Learning rate
20	5	50, 100, 200, 500, 1000	10^{-3}



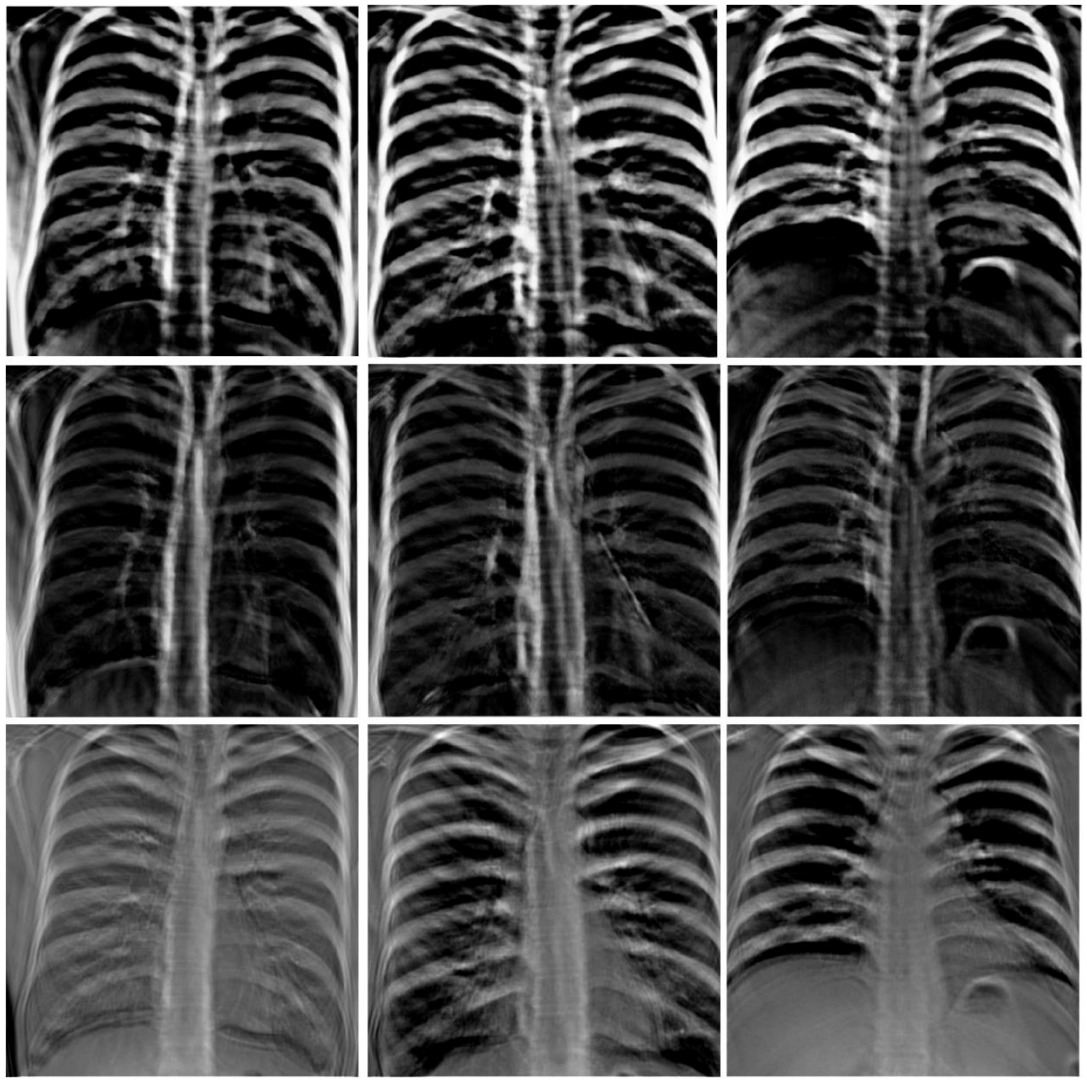
- The number of hidden nodes and the performance of DNN are related to each other.

Batch	Hidden layer	Hidden node	Learning rate
20	5	200	$10^{-1}, 10^{-2}, 10^{-3}, 10^{-4}, 10^{-5}$

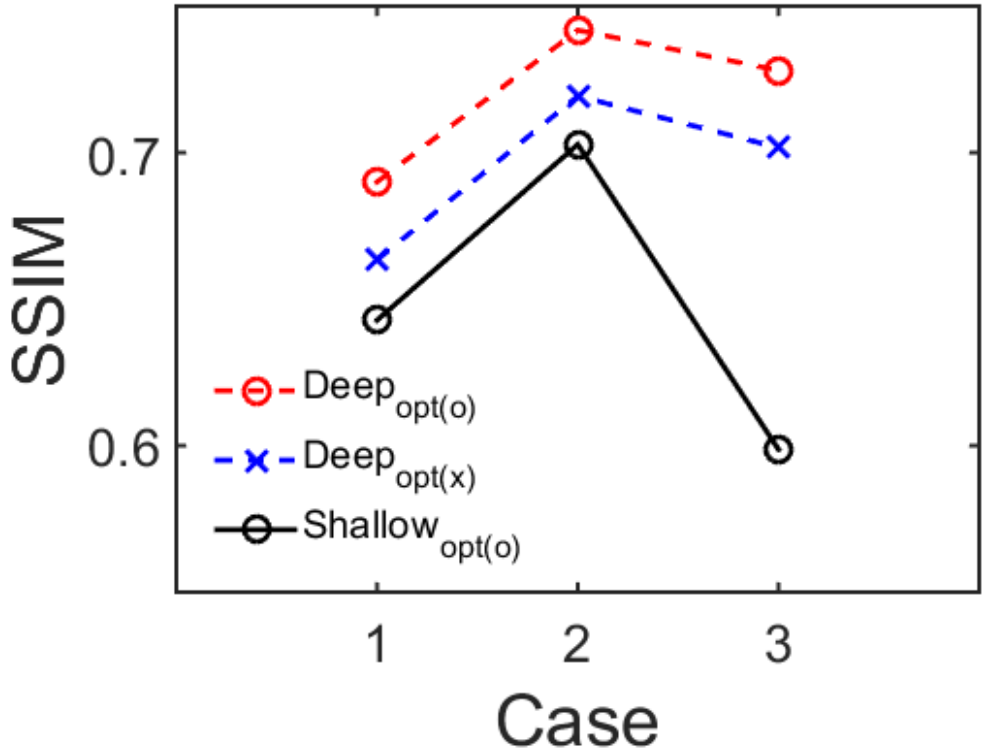


- The learning rates and the performance of DNN are related to each other.

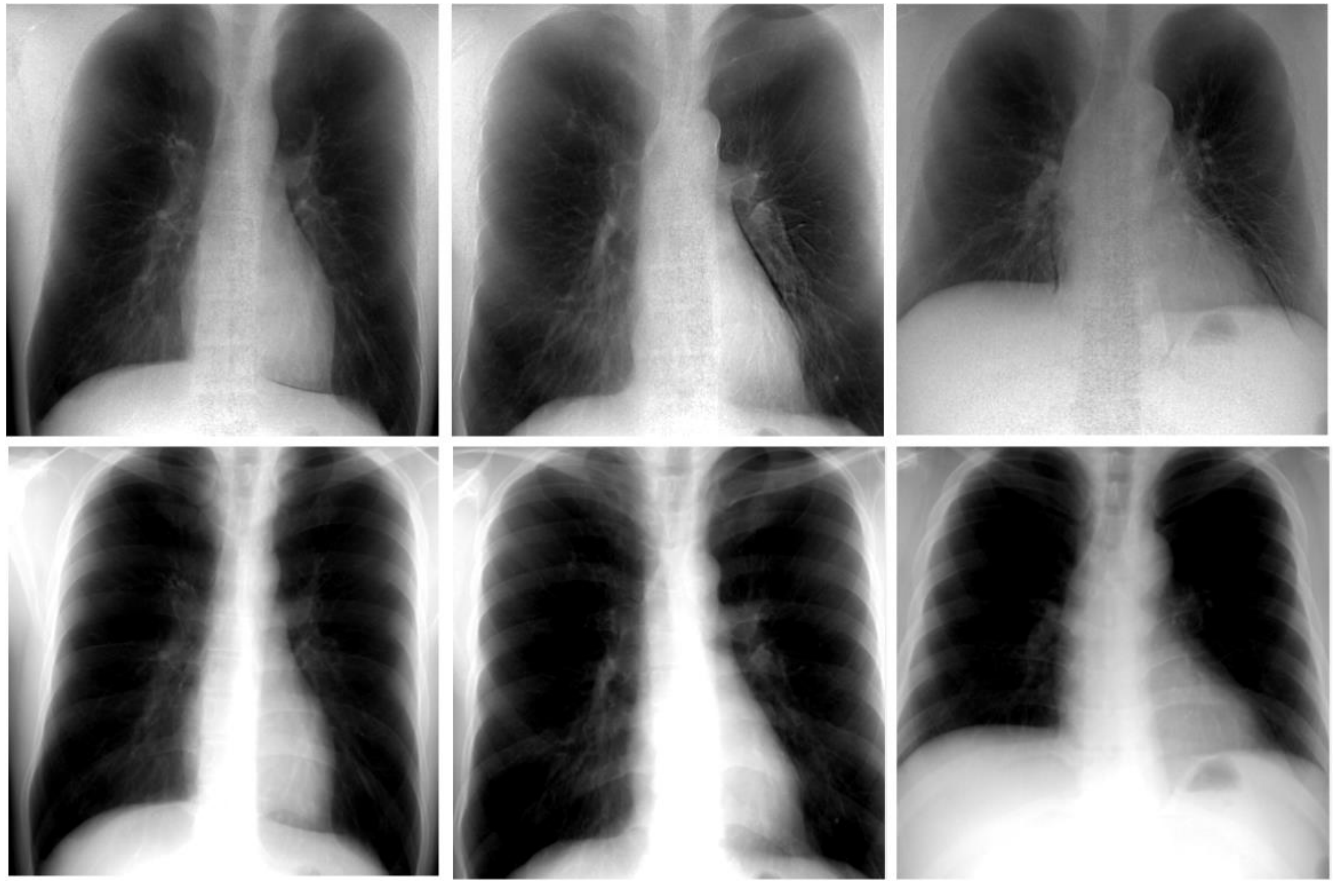
Results

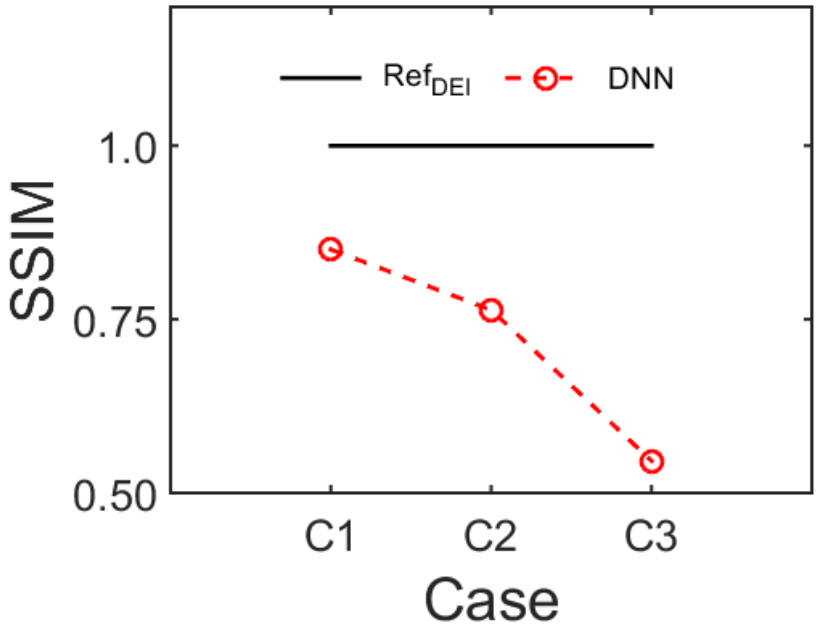


	$Deep_{opt(o)}$	$Deep_{opt(x)}$	$Shallow_{opt(o)}$
Hidden nodes	200	500	200
Learning rate	10^{-3}	10^{-1}	10^{-3}



Discussion





- Due to different subtraction algorithm, SSIM performance is poor between the reference image(DEI) and the DNN image.

Conclusion

- N_{hl} and S_b, N_{hn} and the learning rate

- The best parameters of the DNN investigated in this study were: $N_{hl} = 3\sim5$, $N_{hn} = 50\sim200$, $S_b = 15\sim20$, the learning rate $= 10^{-2} \sim 10^{-3}$

- The study with original-sized radiographs will be a future study.

- We will study subtraction algorithms for quantitative evaluation.

Thanks for your kind attention