Chest X-Ray Image Classification and Deconvolution

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Abstract

This project discusses the impact of focal spot blur effect on pneumonia detection by using X-Ray images and attempts to retrieve clear images. We simulate this blurring effect by convolving clear images with a gaussian kernel and thus, generate a smeared set for comparison. Then, VGG-16 models are trained on both sets separately. The result shows that the classification network can achieve similar test accuracy on both sets. In addition, a U-Net model is built to recover blurred images. These reconstructed images demonstrate the effectiveness of neural networks.

1 Introduction

Nowadays, the diagnosis of pneumonia is a stressful task all over the world. According to WHO, pneumonia kills about 2 million children every year and is thought as the leading cause of childhood mortality. [1] To better protect our next generation, accurate and timely diagnosis may be necessary. Thus, we may want our X-Ray images to be classified automatically to accelerate pneumonia detection and alleviate doctors' pressure.

However, the X-Ray images are often affected by the focal spot blur effect caused by physical systems and that makes manual classification much harder. This focal spot blur effect can be modeled as the convolution between a high-resolution image and a gaussian kernel. [3] In this project, we are going to simulate this blurring effect and discuss its impact on classification network. In addition, another neural network was constructed to recover clear images as well.

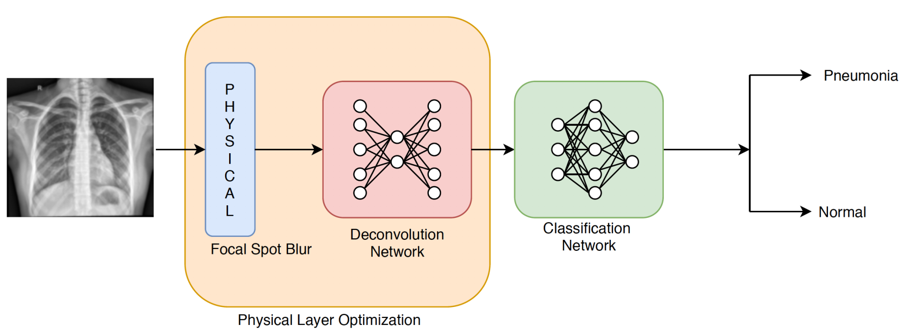

Figure 1: The general structure

2 Related Work

AI, especially convolutional neural network, is becoming a revolutionary tool in disease diagnosis. Daniel Kermany and his colleagues established a diagnostic tool based on a deep-learning framework for the screening of patients with common diseases. [1] Their research also provide the data we used in our project. However, when applying machine learning in clinical diagnosis, researchers have to face the difficulty of the lack of data. Transfer learning, which uses weights from networks trained on other data sets instead of completely training a new network, has been proven to be a efficient way to address this issue. [2]

Nagesh started to discuss focal spot deblurring for high resolution X-Ray detectors. He simulated this effect on real X-Ray images and used a conventional method called Wiener deconvolution to recover images. [3] In 2018, Jan Kuntz proposed to adopt U-Net for CT image deconvolution and demonstrated the advantage of CNN. [4]

3 Methods

3.1 Dataset

The X-Ray images used in this project are derived from pediatric patients of one to five years old from Guangzhou Women and Children's Medical Center, Guangzhou, China. [5] It contains 5573 3-channel X-Ray images and 3 categories (normal, bacterial and viral) in total. Nevertheless, this dataset is imbalanced, as it includes 2601 bacterial cases, 1353 viral cases and 1583 normal cases.

3.2 Focal Spot Blur Simulation

At first, since each picture has a different shape, we resized each image into a 224x224x3 RGB picture and each pixel value was normalized to belong to (0, 1). Then we convolved each image with a symmetric gaussian kernel$G(x, y)$ to generate a corresponding blurred set. The standard deviation σ of the gaussian kernel was set to 2.

$$G(x,y) = \frac{1}{2\pi\sigma^2} e^{\frac{-(x^2+y^2)}{\sigma^2}}$$

Figure 2: Guassian kernel

3.3 Classification

A VGG-16 model [6] was constructed for the classification task. Since transfer learning can achieve a higher accuracy with limited data, we pre-trained our convolutional layers on the ImageNet data set. We trained our fully-connected layer on both the original set and its blurred counterpart separately and got two models. Then, each model was tested on the corresponding test set to check whether the blurring fact will affect classification accuracy or not. Two classification task were conducted in total: ***Normal vs Pneumonia*** and ***Bacterial vs Viral***.

3.4 Image Deconvolution

A U-Net [7] network was constructed for the deblurring task. Though U-Net are mainly designed for image segmentation, it's deconvolutional layers, or transposed convolutional layers, are suitable for this task. Our model was trained with blurred images as input images and unblurred original images as references.

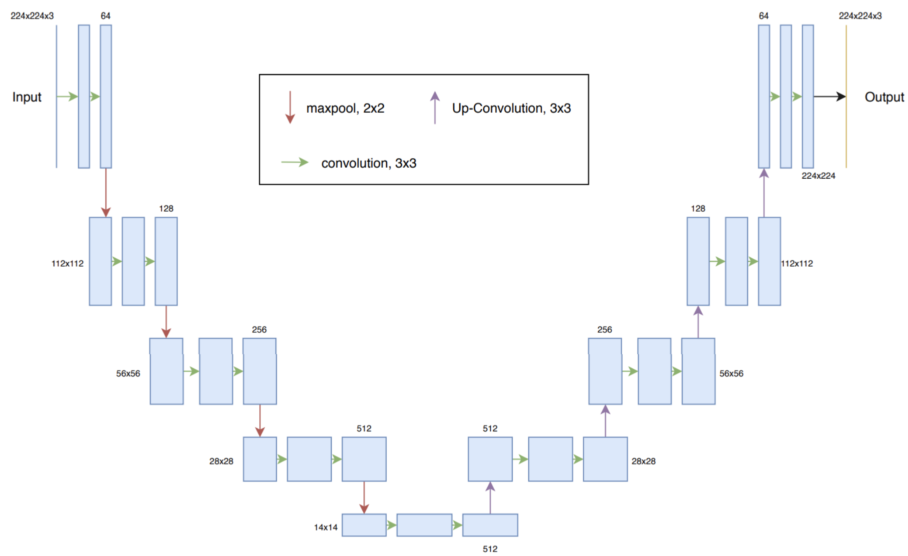

Figure 3: Architecture of the applied U-Net.

4 Results

4.1 Effects of Focal Spot Blur

In this section, we are going to discuss the impact of the focal spot blur we imposed on clear pictures. When classifying normal and pneumonia cases, we achieved a test accuracy of 87.50% on the original set and a test accuracy (after 10 epochs) of 87.02% on the blurred set. For the bacterial vs viral task, the test accuracy is quite similar as well.

Table 1: Test Accuracy(10 epochs)

	Original	Blurred
Normal vs Pneumonial	0.8750	0.8702
Bacterial vs Viral	0.9120	0.8974

The ROC curves also indicate a similar performance.

In general, the blurring effect does not affect classification a lot. As long as the networks are trained and tested on the same data set, they are quite able to detect the presence of pneumonia, no matter it is blurred or not.

4.2 Image Deconvolution

The U-Net network was trained for 30 epochs with an Adam optimizer with a default learning rate. And it did a good job. From the test images below, it is clear to see that the recovered images are much clearer and look nearly the same with the original images and the local details are largely recovered. When $\sigma = 1, 2$, the mean square errors of pixel value are 2.447×10^{-5} and 1.1102×10^{-4} separately.

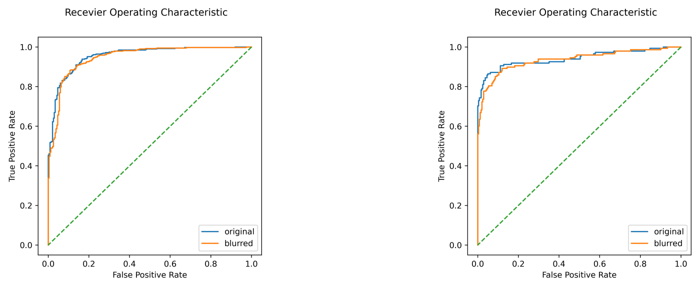

Figure 4: ROC Curves, the left curve derives from normal vs pneumonia task, while the right one is from bacterial vs viral task.

In fact, there is another evidence to prove this similarity. When we put the reconstructed test images ($\sigma = 2$) into the classification network (normal vs pneumonia) trained on the original image set, the test accuracy is 0.8670, quite the same with the original accuracy(0.8750). However, when we put the blurred images into the same network, the accuracy drops to 0.74.

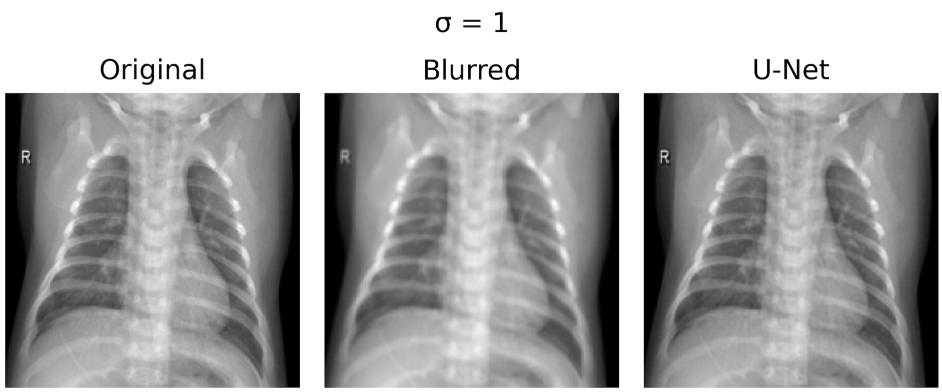

Figure 5: Recovered image I

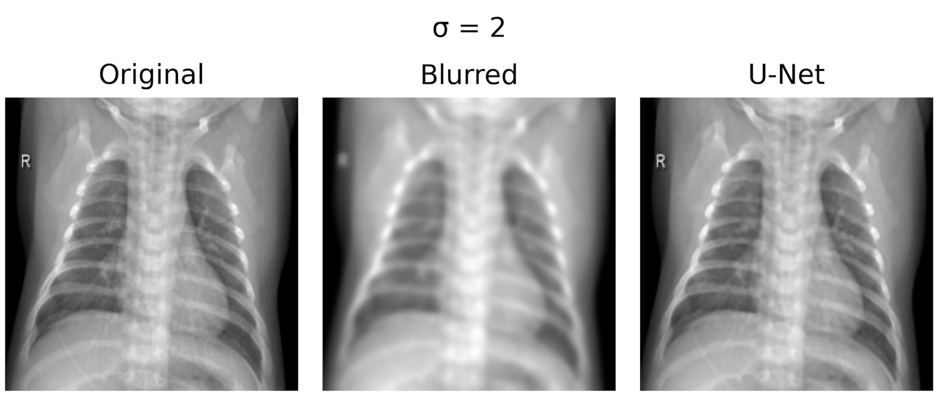

Figure 6: Recovered image II

5 Conclusion and Discussion

In this project, we firstly simulated the focal spot blur effect by convolving clear images with a gaussian kernel and indicated that this blurring effect will not interfere classification CNN a lot. Then, we built a U-Net network to recover the blurred images and the results demonstrate the advantage of U-Net, as the deblurred images are very satisfying.

However, these conclusions are based on ideal situations. We assumed that our image are affected by the blurring effect evenly, since our images are not big enough. We also neglected the influences of noise. In practice, the assumption that the focal spot blur effect can be modeled as a shift-invariant convolution are not valid all the time. When we have a large X-Ray detector with many more pixels, the blurring effect should be modeled as a shift-variant convolution, which means the convolution kernel are not consistent during the process. Besides, images with higher resolution are more likely to be affected by noise, which will make it much harder for us to get reference images.

In the future, we are going to search for X-Ray images with higher resolution and shift to shift-variant model instead. Nevertheless, this change may sharply increase the computational complexity and ask for more computational resources and better algorithms.

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