Chest X-ray Images Classification Using Modified VGG-16 with Adaptive Histogram Equalization as Physical Layer

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Abstract

Pneumonia is a lung infection caused by a bacterial, viral, or fungal infection in one or both lungs. It is essential to diagnose pneumonia as soon as possible in order to get good treatments. A chest x-ray can help diagnose pneumonia, but the diagnosis can be subjective due to other reasons, such as unclear x-ray images. Therefore, using convolution neural networks to boost the classification of normal and pneumonia lungs has become a newly heated research topic. To achieve better accuracy and sooner diagnosing results, our study choose adaptive histogram equalization as the physical layer and VGG16 as a based convolution neural network to process the classification. The test results showed that our modified VGG16 with adaptive histogram equalization as a physical layer has increased the accuracy by 2% and decreased the training time by 20%. In the end, we realized that adding adaptive histogram equalization as the physical layer can increase training accuracy.

1 Introduction

1.1 Background

Pneumonia is described as lung tissue inflammation and consolidation caused by an infectious pathogen. It's a prevalent ailment that strikes people of all ages. In general, 12 cases per 1,000 people are attacked each year. The annual incidence of pneumococcal illness among Alaskan indigenous, for example, is estimated to be 6-34 times that of the entire US population. Pneumonia is the sixth highest cause of death in the United States, with a $23 billion treatment cost [1]. X-ray images are frequently used in medical diagnosis. Chest X-ray is the oldest form and most used way of diagnosing pneumonia. However, there exist other factors that affect the diagnosis, such as fuzzy x-ray images and other confusing lung diseases [2]. In this case, convolution neural networks are introduced to boost the diagnosis.

1.2 Related Works

Many convolution neural network models have been introduced in recent years. Research has shown that VGG16 is considered to be a typical convolution neural net architecture for classification, and there are many related works using this model. For example, Ankita Shelke et al. classify normal, pneumonia, and tuberculosis (TB) using VGG16, and they are able to get their accuracy to 95.9% [3]. Feng Xiong's team also adopted VGG16 as part of their study on the classification of normal lungs and pneumonia lungs, and their training data exceeds 5000 chest x-ray images [4]. While looking at comparisons between VGG16 and other methods, we found Rachna Jain et al. compared VGG16 to VGG19, ResNet50, and Inception-v3 in categorizing non-pneumonia and pneumonia lungs. The accuracies for these models are 87.28%, 88.46%, 77.56%, and 70.99% respectively [5]. In this case, we decided to use VGG16 as our start point. We modified the VGG16 model and added adaptive histogram equalization as a physical layer to help improve the accuracy.

2 Methods

2.1 Data Description

We choose to use open data, Mendeley Data, as our training data. The images are about 250KB, 1600*1900 pixels. There are 5232 chest X-ray images collected and labeled. Among these, we use 3883 depicting pneumonia and 1349 normal to train our neural network. And we use 390 pneumonia and 234 normal images to test our model [6].

2.2 Physical Layer

2.2.1 Histogram

A histogram is a graph that divides the number of data points into user-defined ranges. The histogram, which resembles a bar graph in appearance, compresses a set of data into an easily read visually by grouping data points into logical ranges or bins [7].

2.2.2 Histogram Equalization

Histogram Equalization [8] is used to manipulate the contrast of the image and enhance the image. When the image's useful data is represented by close contrast values, this method usually raises the global contrast of the image. The intensities upon this histogram can be more evenly distributed with this change. This permits low-contrast areas to obtain more contrast [9].

2.2.3 Adaptive Histogram Equalization

An adaptive Histogram is a sort of histogram that adapts to the adaptive method and differs from typical histogram equalization in that it computes multiple histograms, each corresponding to a distinct area of the image, and uses them to distribute the brightness values of the image. As a result, it's perfect for increasing local contrast and sharpening edge definitions in various sections of a picture. Below (Fig.1) shows the process result for our physical layer.

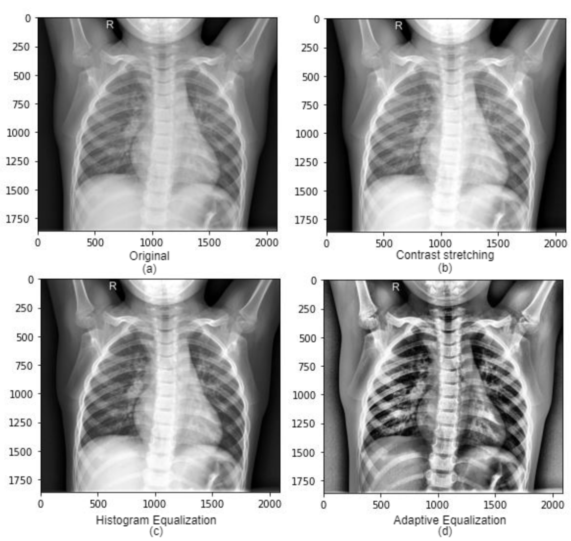


Figure 1: (a) is the original chest x-ray image; (b) is the result after contrast stretching; (c) is the results after we use Histogram Equalization; (d) is the final result with the adaptive Histogram Equalization.

2.3 Modified VGG-16 Architecture

We use modified VGG-16 architecture as our model. Specifically, we changed the three dense 4096 layers to dense 256, dense 128, and dense 2. And we delete the last 8 hidden layers of the modified VGG-16 architecture as our other model. The chosen optimizer algorithm is Adam. The learning rate is originally set to 1e 3 which is better than 1e 2. We also tried data augmentation with a random rotation of 30 degrees for the image, but it reduced the accuracy of the model.

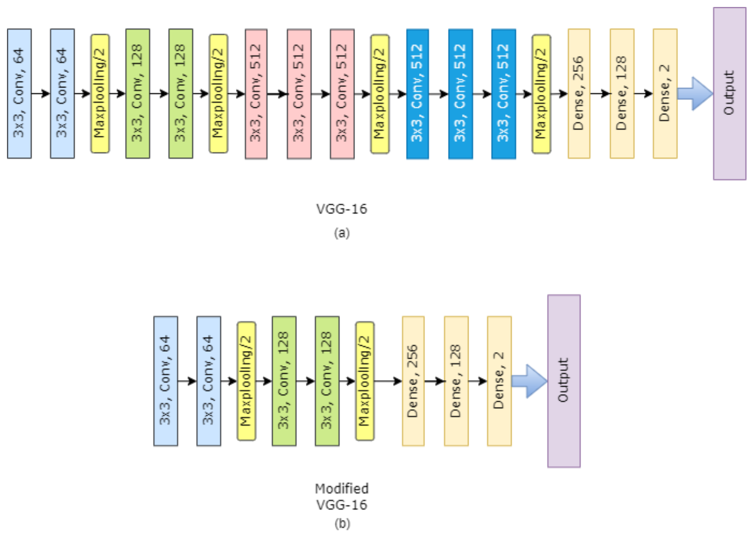
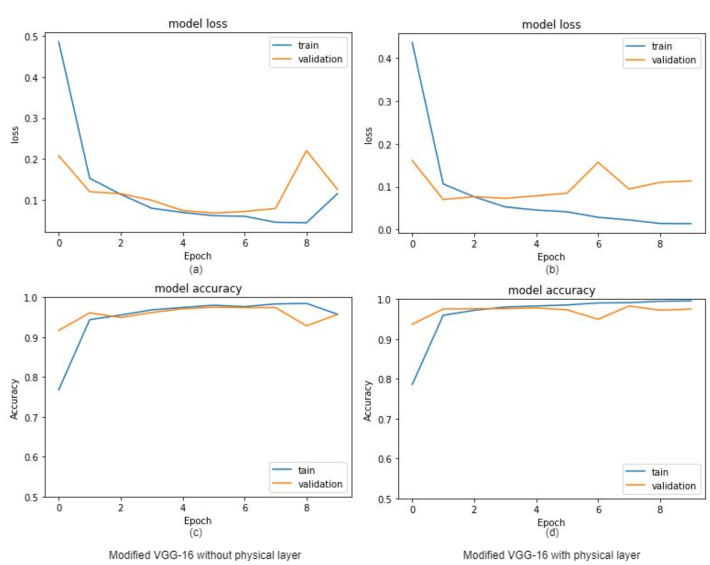


Figure 2: (a) is VGG16 architecture; (b) is modified VGG16 architecture.

3 Results and Comparison

The accuracy of the modified VGG-16 model without a physical layer could achieve 95.23%. And the accuracy of the modified VGG-16 model with a physical layer could achieve 97.52%. As for the other model, it could achieve 95.71% without a physical layer and 97.52% with a physical layer. Because our model has fewer layers than the modified VGG-16 model. So, it could reduce by 20% the running time.



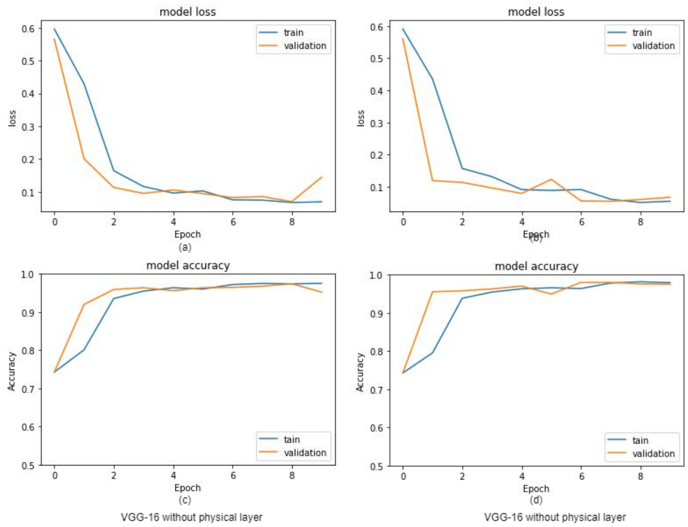


Figure 3: VGG16: (a) is the loss of the VGG-16 model without a physical layer. (b) is the loss of the VGG-16 model with the physical layer. (c) is the accuracy of the VGG-16 model without a physical layer. (d) is the accuracy of the VGG-16 model with the physical layer.

Figure 4: Our work: (a) is the loss of the modified VGG-16 model without a physical layer. (b) is the loss of a modified VGG-16 model with a physical layer. (c) is the accuracy of the modified VGG-16 model without a physical layer. (d) is the accuracy of the modified VGG-16 model with a physical layer.

4 Discussion

While training, at each run, we selected 1000 images from the data set to train the model. In the future, we will reduce the learning rate to keep the training model to get the final accuracy. As matter of fact, physical later is another important part of our study. And we can see from the results that adding this physical layer has boosted the accuracy. Since the physical layer is a contrast-enhancing technique, we are expecting to do more research on this aspect to find a better physical layer. For our future work, we could try adding a 3x3 gaussian filter to blur the image first. We would continue using VGG16 as a based model, and our other focus would be trying to increase the training efficiency.

5 Conclusion

In this project, As a result, our modified VGG16 model is more efficient and accurate than the VGG16 model. With the experiment, we found adaptive Histogram equalization is a good physical layer when classifying pneumonia and non-pneumonia chest x-ray images.

References

[1] Marrie, Thomas J. “Community-Acquired Pneumonia.” Clinical Infectious Diseases 18, no. 4 (1994): 501–13. http://www.jstor.org/stable/4457743.

[2] E. Ayan and H. M. Ünver, "Diagnosis of Pneumonia from Chest X-Ray Images Using Deep Learning," 2019 Scientific Meeting on Electrical-Electronics Biomedical Engineering and Computer Science (EBBT), 2019, pp. 1-5, doi: 10.1109/EBBT.2019.8741582.

[3] Shelke, Ankita, Madhura Inamdar, Vruddhi Shah, Amanshu Tiwari, Aafiya Hussain, Talha Chafekar, and Ninad Mehendale. “Chest X-Ray Classification Using Deep Learning for Automated COVID-19 Screening.” SN computer science. Springer Singapore, May 26, 2021. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC8152712/.

[4] Feng Xiong, Di He, Yujie Liu, Meijie Qi, Zhoufeng Zhang, and Lixin Liu "Pneumonia image classification based on convolutional neural network", Proc. SPIE 12057, Twelfth In-

ternational Conference on Information Optics and Photonics, 120573C (1 November 2021); https://doi.org/10.1117/12.2606413

[5] Jain, Rachna, Preeti Nagrath, Gaurav Kataria, V. Sirish Kaushik, and D. Jude Hemanth. “Pneumonia Detection in Chest x-Ray Images Using Convolutional Neural Networks and Transfer Learning.” Measurement. Elsevier, December 1, 2020.

[6] Kermany, Daniel; Zhang, Kang; Goldbaum, Michael (2018), “Labeled Optical Coherence Tomography (OCT) and Chest X-Ray Images for Classification”, Mendeley Data, V2, doi: 10.17632/rscbjbr9sj.2

[7] Chen, James. “Histogram Definition.” Investopedia. Investopedia, August 18, 2021.

[8] A. D. Fleming, S. Philip, K. A. Goatman, J. A. Olson and P. F. Sharp, "Automated microaneurysm detection using local contrast normalization and local vessel detection," in IEEE Transactions on Medical Imaging, vol. 25, no. 9, pp. 1223-1232, Sept. 2006, doi: 10.1109/TMI.2006.879953.

[9] Indumathi, G., and V. Sathananthavathi. “Microaneurysms Detection for Early Diagnosis of Diabetic Retinopathy Using Shape and Steerable Gaussian Features.” Telemedicine Technologies. Academic Press, May 10, 2019.