BME 548L Final Project: Classification of Lung CT Image With COVID-19 Using Neural Networks

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1 Introduction

By November 23, 2020, SARS-Cov-2 (COVID-19) has 58,437,864 cases worldwide and has caused 1,384,897 death according to JHU. It has caused tremendous health and economic loss to the human beings. Trace back to December 1, 2020, when the COVID outbreak started in Wuhan, China, patients could not be diagnosed accurately because of the lack of testing kits. The normal PCR testing kits need at least two weeks to be put into production, which means that we have a window when the virus is spreading while we cannot identify whether we are infected. It turns out that it took Wuhan one month and New York City two months to receive enough testing kits. In these periods, the lung CT image has served as the most efficient approach for diagnosis. Experienced radiologists can easily identify the ground glass opacity in lung CT so that they can confirm the case without using PCR testing. I have designed a model that could assist the diagnosis of COVID 19 (or possible other virus in the future) from a single CT image.

Figure 1: JHU dashboard of COVID-19 by November 23, 2020 [1]

2 Related work

He et al. has studied the binary COVID-19 classification results from several hundreds of lung CT images under different popular pretrained models using self-trans approach [2]. They have developed a method, which can achieve a high diagnose accuracy with limited number of train data. Chen, Jun et al. also found out using Unet++ for 46,096 CT images training could achieved a comparable performance to that of expert radiologist [3]. For this project, I want to focus on how the simple self-designed model will perform, how illumination could affect the accuracy, and how size and ratio of sample could affect the result.

3 Methods

3.1 Image pre-processing

I built a dataset of 3502 lung CT images from the datasets provided by Angelov et al.[4], Zhao et al.[5], and Aya Khaled [6]. The dataset includes 1876 COVID-positive cases and 1626 Non-COVID cases. I reshaped all the data into 224x224 and split the data into train and test with the ratio of 4:1 (2802 train and 700 test). I stacked the original one channel image to three (same value for RGB) for the purpose of implementing ResNet 50 and for better training result. The master dataset is from four different sources, some of which shows the CT images of single patient at multiple voxel locations and some only shows one image per patient. All data are put together and shuffled to ensure the randomness of the train dataset.

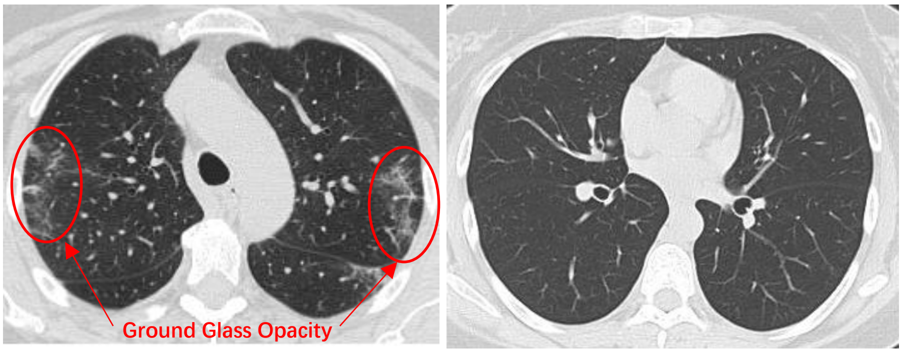

Figure 2: Lung CT image of a patient with COVID 19 (Left) and lung CT image of a healthy person (Right). Ground glass opacity could easily be identified in COVID-positive patients.

3.2 Classification on self-established dataset with self-designed network and ResNet50

For the self-designed network, I performed the training both on 3D and 2D. The structure is shown below. It outputs the binary classification of the data. The images vary a lot at different voxel locations and are low in resolution so that it introduces the difficulties in extracting features. The 3D model maps exactly the 2D model by stacking to three layers.

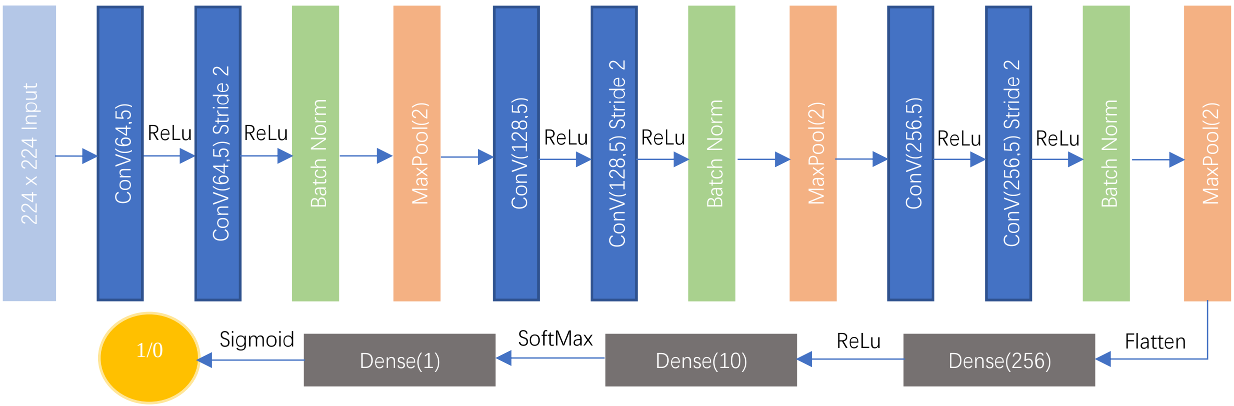

Figure 3: Self-designed CNN model structure.

I used the tf.keras.applications.resnet50 function to incorporate the ResNet50, the ResNet 50 is fifty layers deep, with identity mapping and residual mapping to ensure the high accuracy when the network goes deep. I ran the training for 30 epochs on the same dataset as well. This model fits the dataset well and could extract the finest details (ground glass opacity) to ensure its accuracy.

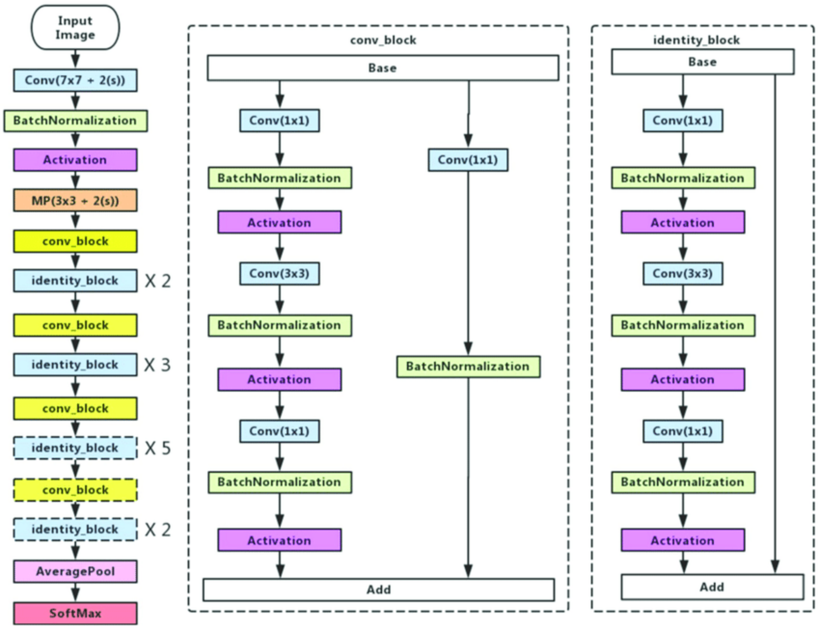

Figure 4: ResNet 50 architecture [7]

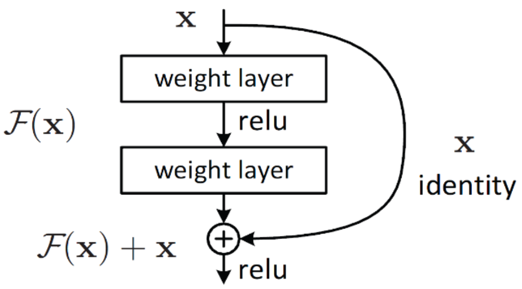

Figure 5: ResNet 50 mapping logic.[8]

3.3 Optimization of Illumination

Radiologists always put the CT image into a plane backlight to analyze the details since the bright part of the image appears to be transparent physically. So, I added a physical layer to the model to simulate the illumination on the image. I tested the model with constant and uniform input illumination phase and with trained input illumination. Different training results under these two different illumination setting are provided and compared in the below section.

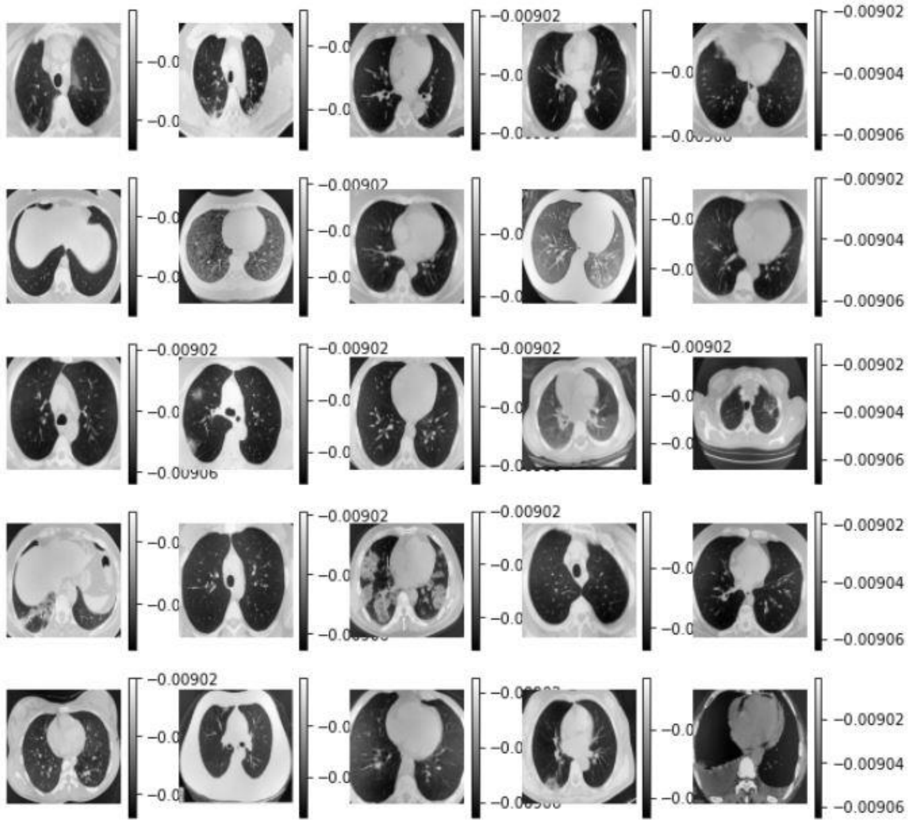

Figure 6: 25 example CT images after passing through the trained illumination layer.

<u>3.4 Classification under different dataset sizes.</u>

During the very early phase of the pandemic outbreak, we usually have limited (e.g. hundreds of) CT data to train our model. I want to study how the sample size and ratio of infected cases could affect the training result. I have set the illumination to be trainable and all the data to be 3D. All trainings are run using ResNet 50 for thirty epochs. I decreased the entire dataset size and maintain the same positive/negative ratio first and then decreased the ratio of positive cases in the entire sample.

4 Results

<u>4.1 Classification results of original images with self-designed network and ResNet50</u>

	ResNet 50	My Model
Train ACC	99.06%	85.31%
Train Loss	0.0253	0.4469
Test ACC	79.94%	60.31%
Test Loss	1.4162	1.3955

Table 1: Training results using different models.

The above table shows the training results under my model and ResNet 50. The training result is much better under ResNet 50 .The ResNet model could achieve 79.94% testing accuracy with 2802 train data for 30 epochs. The around-eighty testing accuracy could effectively and efficiently assist the doctors to diagnose the COVID-19. My model could achieve 85.31% training accuracy but had really bad performance under testing. The Theoretically, more train data could lead the testing result close to the training result.

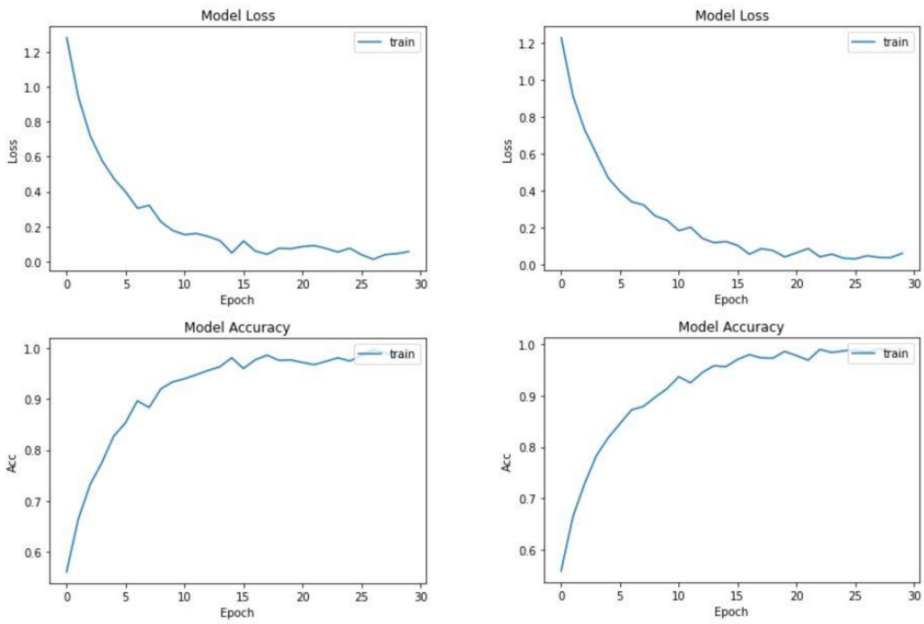

Figure 7: Training results with constant illumination (Left) and trained illumination (Right).

The training result under trainable illumination shows a smoother loss/accuracy curve compared with the training result with constant input illumination.

<u>4.2 Classification results after training illumination</u>

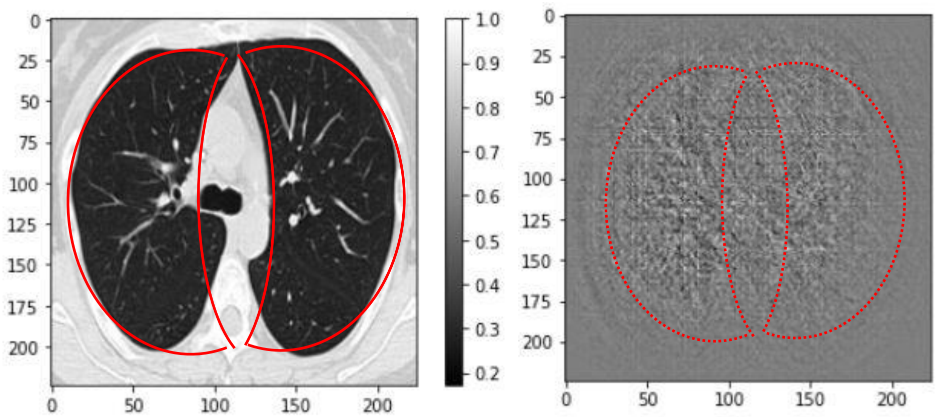

Figure 8: Processed CT image example, 224x224 pixels (Left) and trained illumination (Right). Strengthened illumination are identified within the red outlines.

The plots above show that the regions that provide most ground glass opacity details correspond to the regions trained to have strengthened illumination input (the regions within the red outlines. This is consistent with the fact that more illumination on the sample gives more detail information because of higher SNR, as long as it is not overexposed (maximum gray scale under 255).

4.3 Classification result under different dataset sizes.

	Control Case	Case 1	Case2	Case3
COVID	1876	1527	624	349
Non-COVID	1626	1229	1229	397
Positive Ratio	53.57%	55.57%	33.68%	46.78%
Train ACC	99.06%	98.62%	92.15%	83.61%
Train Loss	0.0253	0.0417	0.2177	1.0104
Test ACC	79.94%	74.65%	68.83%	67.79%
Test Loss	1.4162	1.5519	1.4968	2.3168

Table 2: Training results under different sample size and positive case ratio.

5 Discussion

5.1 Classification results of original images with self-designed network and ResNet50

The self-designed model ends up with a testing accuracy of 60.31%, which is statistically meaningless for doing a binary classification. It is possible that my model performs better when I modify the dataset I use (e.g. specify the size/voxel location of the CT image so that the images do not differ by a lot). The training result is much better under ResNet 50 because of its much more complexed structure and logics.

5.2 Results of classification under different dataset sizes.

The sample size experiment shows that the positive case ratio contributes more to the testing accuracy compared with the sample size. However, in order to achieve an effective testing accuracy, we also want the sample size to be large enough. Several hundreds of positive lung CT scans could already train an acceptable model under a reasonable ratio.

6 Conclusion and Future Work

The self-designed model cannot achieve a satisfied accuracy under both illumination settings. The ResNet 50 works great and can achieve a 79.94% testing accuracy under both illumination settings. The trained illumination gives the model a higher accuracy compared with constant illumination.

In real cases, doctors have access to at least ten CT images for a patient. Future works could also include a function that inputs all CT images of one patient to increase the testing accuracy. Also, in order to achieve higher testing accuracy, we need to incorporate more CT images with a reasonable positive case ratio and run for more epochs. Other models like Inception V and VGG19 might have better performance for this binary classification of CT image and should be tested in future works.

Reference

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