Milestone Report for COMP 4471

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1. Introduction

The 2019 novel coronavirus (COVID-19) has become a pandemic[14] in 2020, deprived thousands of hundred of people's lives. According to a study about COVID-19[2], this disease presents several unique imaging features. Although polymerase chain reaction (PCR) is currently adopted as the main diagnosis method, the Chest X-ray scans of the infected patients may present characteristic features, which are hardly visible to human eyes[13]. In order to accelerate the diagnosis of this rapidly spreading disease. We proposed a convolutional neural networks (CNN) based model to classify Chest X-ray scans into different types of infection. We will first classify them into healthy and pneumonia scans and then further augment the model by classifying COVID-19 scans from the pneumonia scans. Our model feeds the pre-processed data into a CNN network to extract features of different types of scans to make rough prediction of whether the patient has caught pneumonia. Then we will further augment the model to classify COVID-19 scans from the pneumonia scans with the help of transfer learning techniques[3]. Finally it will be able to make diagnosis based on the raw input of Chest X-ray scans images. In this way, our project makes practical contributions to contain this ongoing pandemic.

2. Problem Statement

The problem we are going to resolve in this project is that we want to construct a model that can automatically augment the Chest X-ray scans by suppressing bones shadow and then classify the pneumonia scans from normal scans. Finally further distinguish COVID-19 scans from the pneumonia scans.
Firstly, we pre-process the Chest X-ray scans into a bone-suppressed version, in order to display the lung lobe more clearly to the network[8].

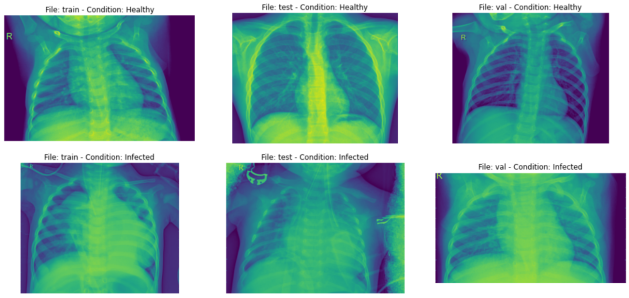

Figure 1. The data we used in Phase 1.

Moreover, we want to train our model on a well-labeled Chest X-ray scans dataset (contains 5863 images)[10] provided by University of California San Diego to classify the pneumonia scans from normal scans. And then we plan to further augment this tuned model to classify COVID-19 scans from the pneumonia scans, with the support of a dataset (contains 2905 images)[4] provided by Qatar University and the University of Dhaka.
According to the transmission property of COVID-19 [1][14], our model is required to effectively identify the infected patients with a low false negatives rate. Apart from that, due to the great impact brought by COVID-19 on medical system across the world[5][6][18], a relatively low rate of false positives is also required. Thus for the evaluation part, a model with both high precision and high recall is desirable[15]:

$$P = \frac{TP}{TP + FP} \tag{1}$$

$$R = \frac{TP}{TP + FN} \tag{2}$$

Where P denotes the precision; R denotes the recall; TP, FP, FN are true positives, false positives and false negatives respectively.

As for the expected result, we have reviewed previous models developed on the dataset provided by University of California San Diego[10] , the best of them has achieved 98% recall and 79% precision with undesirable accuracy of 83% on the task of classifying pneumonia scans from healthy lung scans. We want to fine tune our model to be able to achieve overall accuracy of at least 95%. We expect to achieve 90% on both precision and recall. Besides, limited number of models have focused on implementing the classification of COVID-19 scans, thus we plan to enable our model to distinguish COVID-19 scans from the pneumonia scans as well. Hopefully, we can achieve at least 95% recall and 90% precision in classifying COVID-19 scans.

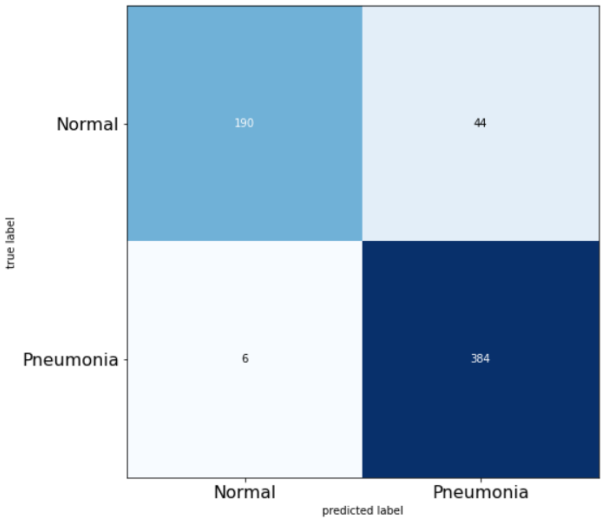

Figure 2. The chart denoting the precision and recall of our model.

3. Technical Approach

We decided to proceed our project gradually, thus divided the whole project into two phases. In Phase 1, we only focus on classifying the pneumonia scans from normal scans. In Phase 2, we step further to classify COVID-19 scans from the pneumonia scans.

3.1. Pre-processing

We plan to utilize the existing bone suppression model[3][8] to augment the original dataset[10] into a set of bone-suppressed version of Chest X-ray scans. Besides in order to resolve the imbalanced data issue in the original dataset[10], we utilized downsampling of large classes and data augmentation on small classes to achieve a balanced dataset[11].

3.2. Phase 1: classification of the pneumonia scans

In this phase we focus on the dataset provided by University of California San Diego[10], which has labeled classes of normal scans, bacterial pneumonia scans and viral pneumonia scans. We plan to apply the VGG-16 network[17] first to accomplish the task. We will adjust the parameters based on the overall accuracy, precision and recall to obtain a desirable model.

3.3. Phase 2: classification of COVID-19 pneumonia scans

In this phase, we focus on distinguishing COVID-19 scans from other types of pneumonia scans. Thus we will only utilize the COVID-19 scans and viral pneumonia scans in the dataset provided by Qatar University and the University of Dhaka. Besides, we will insert some bacterial pneumonia scans into the original dataset to make the problem setting more complete. Hopefully we can come up with a classifier focusing on COVID-19. Since the dataset is relatively small (219 COVID-19 scans and 1345 viral pneumonia scans)[4], we decided to apply transfer learning from the fine-tuned model generated from Phase 1. The images in the two datasets used in Phase 1 and 2 are inherently similar to each others, therefore we planned to fine-tune a few layers and apply linear classifiers on the top layer[9].

4. Intermediate Result

For the pre-processing part, we firstly skipped the deep learning based bone suppression approach, simply train our model on the original dataset. The result for Phase 1 turned out to be satisfactory and therefore we decided to reserve the bone suppression technique for Phase 2 as a way to augment the data.

Currently we have completed the goal of Phase 1, which is classifying pneumonia scans from normal scans. The intermediate result of Phase 1 is quite satisfactory: We attained 92% accuracy on test set, with 98% recall and 90% precision (statistics is shown in Figure 2), which beats the gold winner in Kaggle on this dataset. The network we use currently is VGG-16[17]. We will test on other useful networks to see if we can further improve our result.

For the intermediate result of Phase 2, we have already completed the data collection work. Data augmentation such as sliding, rotating the images will be applied to resolve the

inherent imbalanced problem in the original data.

After this first dive into this project, we found some interesting points that worth discussing about: Initially, we opt for classifying viral pneumonia scans and bacterial pneumonia scans. However, the experiments carried out later proved that it is not likely to be successful for CNN to classify viral scans from bacterial scans directly. No matter how we tuned our parameters, the accuracy is always around 50%, which denotes that the model is actually random guessing about the result. A follow-up study on this phenomenon was carried out and we found that image segmentation of the lungs is required to achieve the goal of distinguishing bacterial pneumonia scans from the viral pneumonia scans[7]. Then we decided to change our primitive goal of classifying bacterial type, viral type and normal scans in Phase 1 into classifying catching pneumonia or not. We further researched the possibility of classifying COVID-19 scans from other types of pneumonia. The result is positive, COVID-19 scans do have unique imaging features that can be distinguished from other viral pneumonia scans and bacterial pneumonia scans[12][16]. Thus we will continue on Phase 2 and hopefully come up with a model that can outperform the existing model on accuracy, precision and recall.

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