Self-supervised Learning for Small Shot COVID-19 Classification

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ABSTRACT

Recently, COVID-19 has become one of the most severe and widespread diseases with an increasing number of infections and deaths. An accurate and high-speed automatic classifier will increase the efficiency of diagnosis and reduce fatigue misdiagnosis. Given the contradiction that many previous classifiers require a large amount of data for training while it is difficult to collect the medical images of COVID-19 with labels, we propose a classification model based on self-supervised learning and transfer learning, which uses rotation and division as labels and then transfers the parameters to the classifier. It solves the overfitting problem caused by insufficient data set and improves the accuracy by nearly 30%

CCS CONCEPTS

• **Computing methodologies**; • **Artificial intelligence**; • **Computer vision**; • **Applied computing**; • **Life and medical sciences**; • **Computational biology**; • **Imaging**;

KEYWORDS

COVID-19, Deep Learning, Convolutional Neural Network, Self-supervised Learning

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1 INTRODUCTION

As a new type of coronavirus causing respiratory infectious diseases, COVID-19 has caused 111 million infections and 2.46 million deaths worldwide [1]. Due to the rapid increase in the number of infections, medical resources have been extremely insufficient, and the time for doctors to diagnose each patient has been greatly shortened. Diagnosing suspicious cases of COVID-19 as soon as possible and quarantining the patients quickly are of great significance to epidemic prevention [2][3]. Thus, it is urgent to explore a method for quickly determining whether a patient has COVID-19. The past ten years have seen the remarkable achievements of traditional artificial intelligence and modern deep learning methods in processing medical images [4][5][6]. Therefore, using Convolutional Neural Networks (CNN) as a classifier to analyze medical images of COVID-19 is a potential way to save the time of medical staff and experts and avoid delays in treatment [7].

Chest computed tomography (CT) scan is one of the most essential methods for doctors to diagnose the condition [8]. Many researchers have conducted diverse studies on CT image analysis and processing based on deep learning such as LSTM [9] and transfer learning [10]. However, it is difficult to obtain labeled medical images of COVID-19. The network that requires a large amount of training data is not quite practical. Self-supervised learning is becoming a key instrument in recent years due to its huge advantages in processing unlabeled data [11]. Self-supervised learning is performed without the supervision of any human annotations. It will automatically construct labels given only the input signals [12]. Several attempts based on self-supervised have been made and achieved great success [13]. Therefore, for the scarce number of COVID-19 medical images, using self-supervised learning to classify is a desirable approach to get a higher accuracy rate.

Inspired by the above analysis, in this paper, we propose a new self-supervised learning COVID-19 classification method for small shot scenario, where the training set for COVID-19 is lightweight size. This method overcomes the problem of overfitting and significantly improves the accuracy. The images are labeled with whether the image is the left lung or the right lung and whether it is rotated, and then they are inputted into the network for training. Subsequently, the parameters are transferred to another network with the same structure for classification. Through this method, the accuracy of the test set is improved by nearly 30%, and the highest accuracy of the training set reaches 95.31%

The rest paper is organized as follows. The related literature is reviewed in Section 2. Then, several different models are presented in Section 3. In Section 4, we introduce the data sets, experiments results and future discussion. Finally, our conclusions are drawn in Section 5.

2 LITERATURE REVIEW

Since the outbreak of the COVID-19 pandemic, researchers have continued to develop various methods to automatically classify COVID-19 medical images. Some of the previous related work can be summarized as follows:

Asmaa, Mohammed and Mehamed introduced a classification of COVID-19 using DeTraC deep convolutional neural network [14]. The DeTraC model partitioned the chest X-ray images into several sub-classes and assigned new labels to the new sets by decomposing, transferring, and composing, so as to address the problems caused by the intensity inhomogeneity in the images. Ioannis and Tzani proposed an automatic detection from X-ray images based on transferring learning [15]. They have verified that the significant biomarkers extracted from common pneumonia were related to the COVID-19 in X-ray images. Amine, Romain, Hua and Su created a multi-task classification for COVID-19 CT images with

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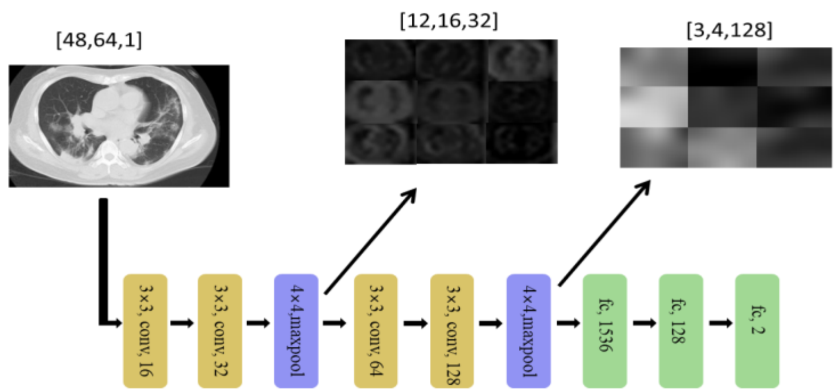

Figure 1: Structure of convolutional neural network

an accuracy of higher than 94.67% [16]. In the diagnosis of COVID-19 medical images, the CNN-based architectures mentioned above all have excellent performance.

Xingyi, Xuehai, Jinyu, Yichen, Shanghang and Pengtao demonstrated special methods based on multi-task learning and contrastive self-supervised learning to handle the complication that a small number of images are prone to overfitting [17]. They used lesion masks that were only provided by experienced radiologists and lung masks that were labeled manually. Compared to the proposed methods, our classification can automatically use rotation and segmentation as labels, contributing to significantly saving time and manpower for labeling.

3 MODEL

3.1 Study1: Traditional CNN based classification

The proposed framework is a traditional CNN, in which each layer has a batch normalization and residual structure (H(X) = F(x) + x). The complete architecture of the CNN is illustrated in Figure1.

3.2 Study2: Classifier based on CNN and transfer learning

Since finding large numbers of labeled samples of common pneumonia is much easier than finding COVID-19 samples, transfer learning is adopted in this study. We believe the features extracted by the common pneumonia classifier may be potential features of COVID-19. The process is presented as follows.

Algorithm 1 Detailed Steps of Study 2

Step1: Input chest X-ray image into the CNN network in Study1.
Step2: Iterate 30 epochs and then transfer the parameters to a new CNN network with the same structure.
Step3: Train multiple times to make the highest correct rate of the test set.

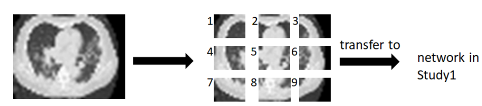

Figure 2: Labels for self-supervised learning in Study 3

3.3 Study3: CNN Self-Supervision by segmentation

With the purpose of extracting the location feature of the image (lung location), each image is divided into 3*3 small images of the same size, (Figure2) then they are numbered in the order of location, which is employed as a label for training. Finally, the parameters are transferred to the network in Study1 to classify.

3.4 Study4: CNN Self-Supervision by rotation and segmentation

In this study, a combination of rotation and division, instead of dividing the image, is adopted [18]. This suggests that after transfer learning, the amount of data in the training set has been expanded four times. Additionally, this model has two test sets: 1) 30% of the images randomly selected from the training set, and 2) 30% of the images randomly selected from the original data set. The specific steps are described as follows.

4 EXPERIMENTS

4.1 Datasets Organization

Due to the sudden outbreak of COVID-19, it is very difficult to find a considerable number of marked medical images. Thus, only 746 chest CT images of COVID-19 from GitHub [19] and 5232 X-ray images of common pneumonia from Kaggle [20] were collected (Table 1). The COVID-19 CT images were selected from clinical findings of COVID-19 from 216 patients in Tongji Hospital, Wuhan, China, and are labeled by a senior radiologist at the hospital [19]. The chest X-ray dataset contains retrospective cohorts' study which is part of patients' routine clinical care from Guangzhou Women

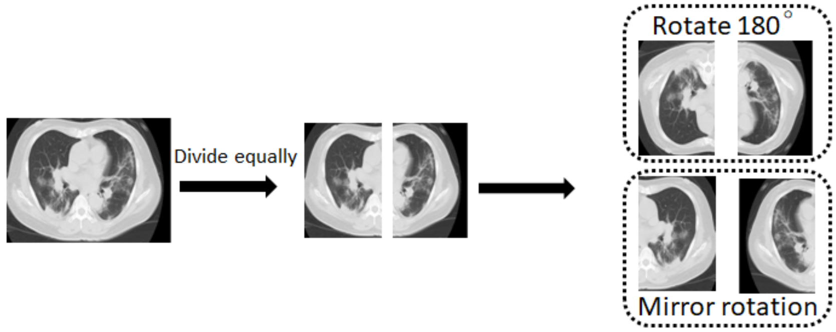

Figure 3: Labels for self-supervised learning in Study 4

Algorithm 2 Detailed Steps of Study 4

Step1: Divide the CT images into the left and right parts equally, denoted as set1.
Step2: Rotate the images in set1 by 180 degrees, denoted as set2, and record the mirror rotations as set3, as illustrated in Figure3.
Step3: Use set1 and set2 as the training set, and use left lung, right lung, left lung after rotation, and right lung after rotation as labels for training.
Step4: Transfer the parameters to a new CNN network with the same structure and use set1 and set3 as the training set.
Step5: Train multiple times to make the correct rate of the test set the highest.

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and Children's Medical Center, Guangzhou, China. The images were graded by two expert physicians and then checked by a third expert in this hospital [20].

Since the sample image has a wide range of resolutions from 1637 * 1225 pixels to 148 * 61 pixels, we used bilinear interpolation to resize the images into 48 * 64 pixels to facilitate network training. Besides, 30% of the total samples were randomly selected as the test set with the rest as the training set to assess the performance of the model.

4.2 Results

It can be observed from Figure 4 that although the accuracy of the training set climbs from 51.56% in the first epoch to the highest 92.18% in the 29th epoch, the accuracy of the test set is not high, only 57.93% in the 20th epoch. Meanwhile, the accuracy of the test set decreases from 65.25% to 61.43% as the epoch increases from 25 to 30, indicating that the model is overfitting.

As indicated by the experimental result on Study2, although the accuracy of the training set is better than Study1 with the highest

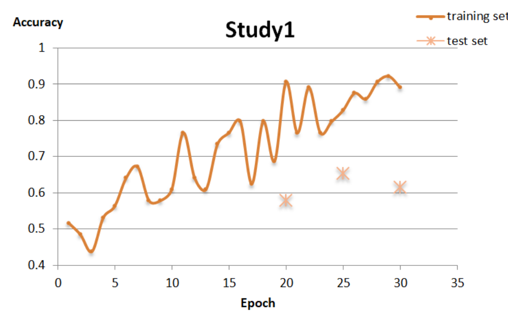

Figure 4: Result of study1

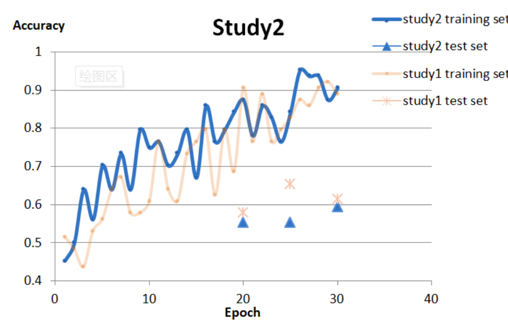

Figure 5: Result of study2

95.31%, the accuracy of the test set is lower, only 55.33%, and it slightly increases to 59.3% in the 30th epoch. This suggests that the features extracted from the chest X-ray images are not consistent with the CT images. A clear improvement of accuracy in the test set could not be identified in this model.

Table 1: Datasets

CT Images		X-ray Images		
normal	COVID-19	normal	virus	bacteria
397	349	1349	1345	2538
Total: 746		Total: 5232		

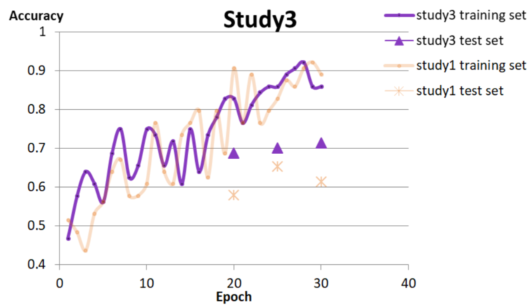

Figure 6: Result of study3

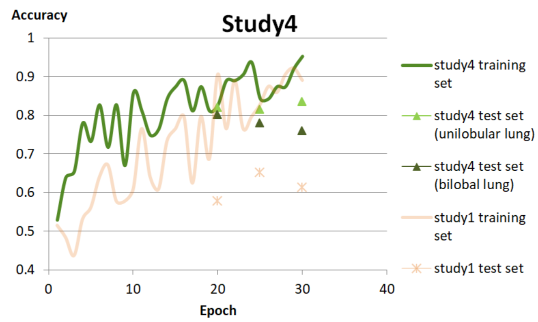

Figure 7: Result of study4

The next study is concerned with self-supervised learning. The results, as illustrated in Figure 6, indicate that the transfer of the parameters in self-supervised learning to the CNN model contributes to improving the accuracy of the test set. Compared with Study1, the accuracy of the test set is improved to 71.33%. However, there is still a gap compared with the accuracy of the training set close to 90%, reflecting that only using image segmentation is not the most appropriate method. Therefore, we choose to combine rotation and segmentation in the next study.

There is a significant improvement in the accuracy of the training set in Study4 (Figure 7), with the highest accuracy up to 95.31%. Although the accuracy of the bilobal lung suggests a tendency of overfitting from 80.14% to 76.12%, the accuracy of the unilobular lung shows an increasing trend from 82.06% to 83.54 % as the epoch increases. Moreover, there is not much difference with the accuracy of the training set in the 25th epoch, which is 84.38%. Therefore, the problem of overfitting is solved.

4.3 Evaluations

The results in this section reveal that in the case of a limited data set, traditional CNN will fall into overfitting and reduce the accuracy of the test set. The features extracted from the chest X-ray image did not help the feature extraction of the CT image and even resulted in lower accuracy of the test set. Therefore, it is not feasible to transfer the parameters from the X-ray image to the CT image to promote classification. As illustrated in Figure 8, the accuracy of the test set is significantly improved under self-supervised learning, among which, the label combined with segmentation and rotation

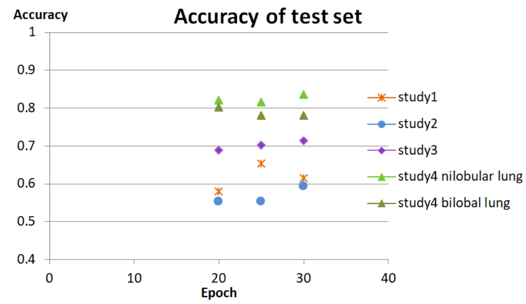

Figure 8: Accuracy of the test set

performed the best, with an improvement from 57.93% to 83.54% compared to Study1.

4.4 Further Discussion

For future directions of our current model, the accuracy would be improved from the following perspectives.

Hyperparameter adjustment. In all current studies, our batch size is 32. Since the training set size of each training network is different, appropriate adjustments for different networks may improve the accuracy. At the same time, changing the number of epochs of the network before transfer may also improve the accuracy to a certain extent.

Self-supervised representation. In self-supervised learning, only some combinations of image rotation and segmentation were performed, and the accuracy of the test set was significantly improved. If we try a large number of combinations or add other label representation methods in the future, the accuracy rate may be further improved.

Combination of single and double lobe lung images. We recommend that in future clinical diagnosis, the results of single lobe and double lobe should be combined, suggesting that each image should be classified three times (left lung, right lung, and both lungs) to minimize the false-negative rate and better control the epidemic.

5 CONCLUSIONS

An accurate and automatic COVID-19 classifier is of great significance to diagnose patients as soon as possible and save medical resources. In response to the scarcity of medical images for COVID-19, we propose four different models based on transfer learning and self-supervised learning. Although the result of transferring from the chest X-ray image is not ideal, the self-supervised learning model overcomes the overfitting problem, and the accuracy of the test set is improved by almost 30%. Regardless of the stated strengths of the proposed model, there are some issues not addressed in this paper, such as adjusting the best hyperparameters, improving the performance of self-supervised learning, and considering the combination of single and double lobe lung. These are considered in future work.

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