Early pleural effusion detection from respiratory diseases including COVID-19 via deep learning

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***Abstract*—Pleural effusion is the build-up of excess fluid between the pleura layers around the lung. This fluid may be transudative or exudative. Pneumonia and cancer are common exudative causes of pleural effusion. Other causes include tuberculosis and recently discovered COVID-19. Physicians are able to diagnose pleural effusion through the use of chest radiographs. In this work, we propose, instead, the early detection of pleural effusion from tuberculosis, pneumonia, and COVID-19 diseases on chest radiographs using deep learning. The performance results show that the early detection of pleural effusion from pneumonia and tuberculosis have the highest accuracy. They further show that the deep learning architecture can distinguish bacterial pneumonia and COVID-19 diseases from pleural effusion the best.**

***Index Terms*—Chest radiographs, COVID-19, deep learning, pleural effusion, pneumonia, tuberculosis**

I. Introduction

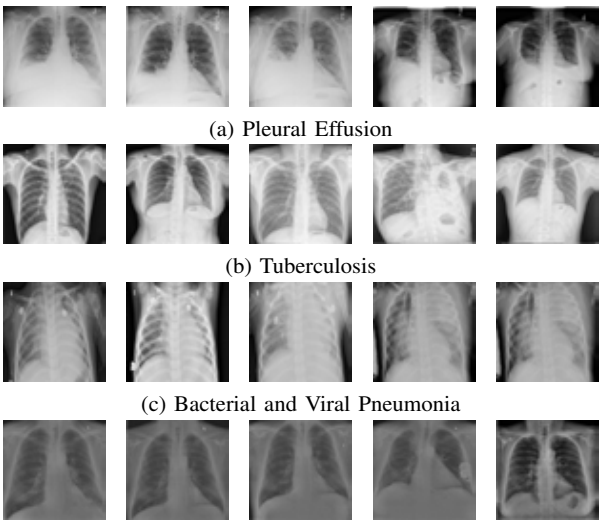
A radiograph is often used as an important part of the examination of certain diseases including those with high mortality. Doctors use chest radiographs, for example, in the diagnose of diseases like pneumonia and tuberculosis. Early treatment of them are important as they may lead to more serious complications such as septic shock and pleural effusion.

COVID-19 is a type of coronavirus disease discovered for the first time in December 2019 in Wuhan City, China. Known to be a result of SARS-CoV-2 virus, COVID-19 may also lead to life-threatening complications such as pneumonia and acute respiratory distress syndrome (ARDS).

Examining these complications require an experienced radiologists as distinguishing chest pathologies can sometimes be a tough task. It is therefore crucial to have enough radiologists in the hospitals to alleviate their workload against growing number of patients.

Researchers have proposed the use of deep learning methods for various medical imaging tasks such as age-related macular degeneration and diabetic macular edema detection [1], and malignant pigmented skin lesions detection [2] or as an alternative to interpreting chest radiographs for various conditions by radiologists [3].

The aim of this paper is to use a deep learning architecture for early detection of pleural effusion from pneumonia, tuberculosis and COVID-19 diseases. Several chest X-rays containing these conditions are shown in Figure 1. The goal is to use a ResNet-18 deep learning architecture to detect tuberculosis, pneumonia, and COVID-19 respiratory diseases before they evolve into pleural effusion. In addition, we carry out an experiment to differentiate chest radiographs containing pneumonia, COVID-19 and pleural effusion diseases. This multiclass detection will allow to separately detect pneumonia and COVID-19 cases from pleural effusion.



(a) Pleural Effusion

(b) Tuberculosis

(c) Bacterial and Viral Pneumonia

(d) COVID-19

Fig. 1. Sample chest radiographs

The organization of this paper is section II summarizes some of the recent work on the detection of pleural effusion, pneumonia, tuberculosis and COVID-19 diseases using deep learning. Section III overviews the preprocessing and classification model details. Section IV details the hardware implementation. Section V gives the details of the datasets used for performance evaluation. Section VI reports the early pleural effusion detection results. Section VII analyzes the detection performance results reported and section VIII gives the conclusions of this study.

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II. Related Work

There have been several studies on the detection of pleural effusion, pneumonia, tuberculosis and COVID-19 diseases using deep learning. In this section, we would like to summarize some of them.

A. Pleural effusion detection via deep learning

Bar [4] researched identifying different pathologies, including right pleural effusion, on chest radiographs using convolutional neural networks trained on nonmedical data. Singh et al. [5] assessed how deep learning helps for the detection of abnormalities, such as pleural effusions, on frontal chest radiographs and the stability or change of these findings on follow-up chest radiographs. Anavi et al. [6] investigated combining metadata with image features for image retrieval of X-ray chest pathologies, including left and right pleural effusion. Rajpurkar et al. [3] reported the deep learning performance of chest radiograph pathology detection, including pleural effusion, and compared these with radiologists. Butt [7] detected COVID-19 and influenza viral pneumonia diseases from computed tomography (CT) chest scans using deep learning and compared the results to reverse-transcription polymerase chain reaction (RT-PCR) detection. Becher et al. [8] evaluated the feasibility of detection and classification of some pathological patterns, such as effusion, with deep learning using tuberculosis chest X-ray images. Lakhani [9] investigated the use of deep learning methods to detect tuberculosis on chest radiographs containing pleural effusion, miliary and cavitation.

B. Tuberculosis detection via deep learning

Hwang et al. [10] developed an automatic detection algorithm for active pulmonary tuberculosis using deep learning methods and compared its performance to physicians. Hwang [11] investigated an automated system for tuberculosis screening using deep convolutional neural networks trained on chest X-rays. Stirenko et al. [12] used deep learning on lung segmented and augmented datasets to analyze chest X-rays for tuberculosis.

C. Pneumonia detection via deep learning

Among the studies on pneumonia detection using deep learning, Zech et al. [13] assessed the generalization of convolutional neural networks in detecting pneumonia across three different hospitals systems. Stephen [14] extracted features from a chest X-ray image using convolutional neural networks to the detect the presence of pneumonia.

D. COVID-19 detection via deep learning

Researchers have started studying the detection of recent epidemic COVID-19 on chest radiographs using deep learning. Among them, Li et al. [15] developed a deep learning model to distinguish COVID-19 from pneumonia on chest CT images. Apostolopoulos [16] utilized a convolutional neural network architecture to automatically differentiate COVID-19 from bacterial pneumonia on X-ray images.

III. Method

A. Preprocessing

The images of the datasets have different resolutions and thus have been resized to $224\times224\times3$.

B. Classification

For early pleural effusion detection from respiratory diseases, we have used a ResNet model. This model has eighteen layers. We pre-trained this model on ImageNet dataset. This dataset contains approximately one million images.

IV. Implementation

We trained the ResNet-18 deep learning architecture using a single NVIDIA GeForce GTX 1080Ti GPU with Caffe deep learning framework.

V. Datasets

We used four public datasets for early pleural effusion detection from images containing respiratory diseases.

The dataset of Kermany et al. [17] contains 5232 chest X-ray images. 3883 of these are chest X-rays containing pneumonia (2538 bacterial and 1345 viral). 1349 images of this dataset are from patients with no pneumonia. The dataset of [18] contains 108948 frontal view X-ray images in 14 classes of thoracic diseases, including pleural effusion. The dataset of [19] includes 123 frontal view X-rays images of COVID-19 collected from websites and publications. The datasets of [20] are from Montgomery County in the USA and Shenzhen in China. The set from Montgomery county has 138 frontal chest X-rays. 58 of these images contain tuberculosis and 80 of them do not. Shenzhen set has 662 frontal chest X-ray images. 336 of these contain tuberculosis and 326 contain no tuberculosis.

Table I lists the number of images in each of the four datasets.

TABLE I
Dataset details.

Dataset	No. of Images
Kermany et al. [17]	5332
Wang et al. [18]	108948
Cohen [19]	123
Jager et al. [20]	800

VI. Performance Evaluation

A. Early detection of pleural effusion from pneumonia

We have evaluated the classification performance of early detection of pleural effusion from pneumonia. We have used 324 chest X-ray images of patients having pleural effusion and pneumonia from the datasets of [17] and [18], respectively, to train the ResNet-18 architecture. We have tested the performance using 76 images from the same datasets.

The accuracy of the ResNet-18 model is 99%, its sensitivity is 98% and its specificity is 100%. The area under the region of convergence (ROC) curve (AUC) is 94% (see Table II).

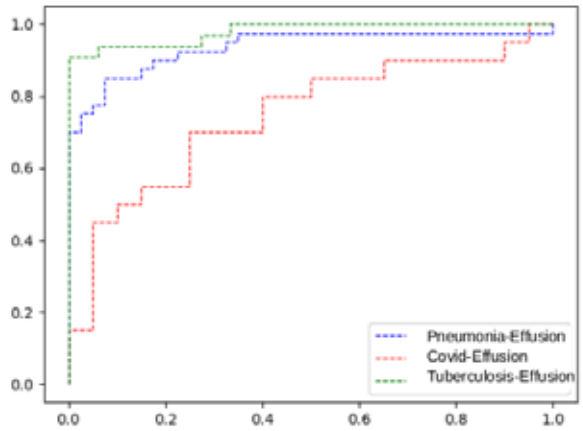

Fig. 2. Comparison of the ROC curves for three cases of early detection.

TABLE II
PLEURAL EFFUSION FROM PNEUMONIA.

AUC	Accuracy	Sensitivity	Specificity
94%	99%	98%	100%

B. Early detection of pleural effusion from COVID-19

We have also evaluated the early detection of pleural effusion from COVID-19 using ResNet-18 architecture. We have trained this architecture using 168 chest X-ray images of patients having COVID-19 and 168 images of patients having pleural effusion. We have tested it using 38 chest X-ray images of patients having COVID-19 and 38 chest X-ray images of patients having pleural effusion.

The accuracy of the ResNet-18 model here is 75%, its sensitivity is 92% and its specificity is 68%. The AUC is 75% (see Table III).

TABLE III
PLEURAL EFFUSION FROM COVID-19.

AUC	Accuracy	Sensitivity	Specificity
75%	75%	92%	68%

C. Early detection of pleural effusion from tuberculosis

We next report the classification performance of early detection of pleural effusion from tuberculosis. We have trained the ResNet-18 architecture using 273 images containing tuberculosis and 273 images containing pleural effusion. We have tested its performance using 63 chest X-ray images containing tuberculosis and 63 containing pleural effusion.

The accuracy of this classification is 100%, its sensitivity is 100% and its specificity is 100%, as also listed in Table IV. The AUC is 98%.

Next, we would like the compare and analyze the ROC curves of the three cases to have a better understanding on their relative performance. Figure 2 shows this comparison.

TABLE IV
PLEURAL EFFUSION FROM TUBERCULOSIS.

AUC	Accuracy	Sensitivity	Specificity
98%	100%	100%	100%

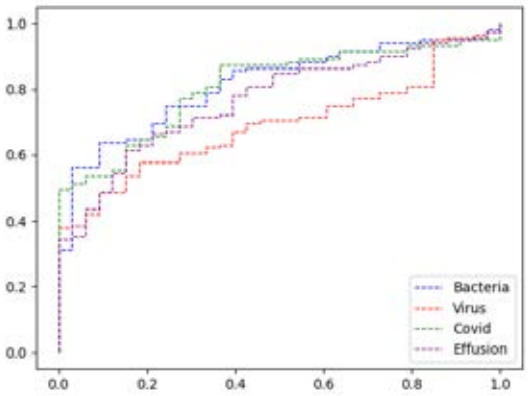

Fig. 3. ROC curves for multiclass detection.

We observe from this figure that out of three early detection cases, the early detection of pleural effusion from pneumonia has the best detection performance.

D. Multiclass detection

In this section, we would like to report on a multiclass performance comparison using ResNet-18 involving COVID-19, tuberculosis, bacterial pneumonia, viral pneumonia, and pleural effusion diseases.

For this experiment, we used 168 chest X-ray images containing COVID-19, 273 images containing tuberculosis, 273 images containing bacterial pneumonia, 273 images containing viral pneumonia and 270 images having pleural effusion to train the ResNet-18 architecture. To test it, we used 37 chest X-ray images images having COVID-19, 63 images having tuberculosis, 63 images having bacterial pneumonia, 63 images having viral pneumonia and 62 images having pleural effusion.

The accuracy of bacterial pneumonia classification is 83%, its sensitivity is 100% and its specificity is 82%, as listed in Table V. The AUC is 81%. For viral pneumonia classification, the accuracy is 82%, the sensitivity is 88% and the specificity is 82%. The AUC is 69%. COVID-19 disease classification has an accuracy of 82%, sensitivity of 100% and a specificity of 82%. The AUC for it is 81%. Finally, the accuracy of pleural effusion classification is 82%, its sensitivity is 78%, and the specificity is 82%. Here, the AUC is 77%.

We observe from the results of Table V that the ResNet-18 architecture performs best for the detection of bacterial pneumonia and COVID-19 diseases.

We next plot the ROC curves for multiclass detection of bacterial and vital pneumonia, COVID-19, and pleural effusion

TABLE V
MULTICLASS DETECTION.

Disease	AUC	Accuracy	Sensitivity	Specificity
Bacterial Pneumonia	81%	83%	100%	82%
Viral Pneumonia	69%	82%	88%	82%
COVID-19	81%	82%	100%	82%
Pleural effusion	77%	82%	78%	82%

diseases. From this plot (see Figure 3), we again see that the best performances of ResNet-18 architecture are for the detections of bacterial pneumonia and COVID-19 diseases.

VII. DISCUSSIONS

We used chest radiographs for early and automated detection of pleural effusion from three types of respiratory diseases, namely pneumonia, COVID-19 and tuberculosis. We trained the images first using the datasets of Kermany et al. [17], Wang et al. [18], Cohen [19], and Jager et al. [20]. Then, we used ResNet-18 deep learning architecture to test the images for early pleural effusion detection. As the idea is to detect the disease before it evolves into pleural effusion, we created separate performance metrics of each disease. The performance results show that ResNet-18 architecture is able to detect pneumonia and tuberculosis the best before they convert into pleural effusion. They also show that the early detection of COVID-19 is the worst of the three. To distinguish between bacterial and viral pneumonia, COVID-19, and pleural effusion diseases, we ran additional experiments. We showed that out of these four, COVID-19 and bacterial pneumonia have the highest detection rate whereas viral pneumonia and pleural effusion have the lowest.

VIII. CONCLUSIONS

We performed early pleural effusion detection from pneumonia, COVID-19, and tuberculosis diseases using chest radiographs. In addition, we investigated a multiclass detection of bacterial and viral pneumonia, COVID-19 and pleural effusion diseases. We used the ResNet-18 deep learning architecture for the detections. We evaluated the detection performance using accuracy, sensitivity, specificity and the area under the ROC curve performance metrics. The performance results show that early detection of pneumonia and tuberculosis diseases has the highest accuracy whereas that of COVID-19 has the lowest. The results also show that among the bacterial and viral pneumonia, COVID-19, and pleural effusion diseases, the architecture is able to detect the bacterial pneumonia and COVID-19 diseases the best.

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