A Convolutional Neural Network on X-Ray Images for Pneumonia Diagnosis

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Abstract. The application of AI in general and Deep learning, in particular, is becoming increasingly popular in human life. AI has been able to replace people in many fields, with data already synthesized and stored by computers that will help AI become smarter. One of the areas where AI can be applied very well is the medical field, especially X-ray imaging. In this study, we propose a convolutional network architecture to classify chest X-ray images as well as apply explanatory methods to trained models to support disease diagnosis. The proposed method provides insight into medical imaging to support the diagnosis of Pneumonia.

Keywords: AI · Deep learning · Chest X-ray · X-ray imaging · Pneumonia · Convolutional neural network

1 Introduction

The lungs are a part of the body with the main role of exchanging gases - bringing oxygen from the air into the pulmonary veins, and carbon dioxide from the pulmonary arteries. Besides, the lungs also have some other secondary abilities, which help metabolize some biochemicals, filter some toxins in the blood. The lungs are also a store of blood.

Because the lungs are the organs in direct contact with the external environment, they are very susceptible to bacterial, viruses, etc.: dry cough, cough with phlegm, difficulty breathing, ... with pathologies from pneumonia, bronchial tablets, ... to more severe tuberculosis, lung cancer [1]. In particular, SARS, COVID-19 (a virus causes acute respiratory infections in humans) over 16,601,552 people in the world have been infected and 655,214 people have died. Symptoms of Covid-19 disease appear very quickly within 14 days, if not treated promptly, it will lead to complications such as respiratory failure, arrhythmia,

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blood infection, liver failure, kidney failure, ... can lead to death [11]. Early detection and timely treatment are the best way to prevent disease progression and increase the patient's chance of survival.

Chest radiography is one of the most common types of diagnostic radiology exams, which is critical for screening and diagnosis of many different thoracic diseases [13]. Diagnosing abnormalities in an x-ray image requires a lot of expertise and the quality of the diagnosis can sometimes affect the outcome (an error may occur).

Today, the application of AI to human health care is the application that is most concerned today. Machine learning, deep learning has become an effective tool for image classification, image segmentation [9,10]. In particular convolutional networks, have rapidly become a methodology of choice for analyzing medical images [14]. And this is also a very effective tool for doctors to diagnose abnormalities of lung X-ray faster and faster.

2 Related Work

Recently, a deep learning model has been found suitable or superior to human expert radiologists in diagnosing 10 or more pathologies on chest radiography. The success of AI in imaging has fueled growing debate on the future role of radiologists in an era in which deep-learning models are capable of performing diagnostic tasks. Automated critical guessing and speculation around the radiologist's comprehensive diagnostic interpretation skills can be replicated in algorithms. However, AI is also affected by some disadvantages including deviations due to limited training data, lack of cross-population popularity, and the inability of deep learning models to contextualize.

The author in [2] describe to detect lung X-ray images showing signs of tuberculosis or healthy, we use two different machine learning models, AlexNet and GoogLeNet, and use over 1007 back-chest X-rays labeled for distribution. assorted images. As a result, an in-depth study can accurately classify tuberculosis during a chest X-ray with an AUC of 0.99.

The author in [3] describes based on the deep convulsive neural network (CNN) to detect specific diseases such as lymph node or lung cancer through X-ray images, this model is trained on more than 200,000 supervised X-rays. of data sets and achieve certain success.

The author in [4] describes a machine-learning study that uses the CNN network to detect abnormalities in X-ray images of lower extremities for clinical and treatment use in musculoskeletal disorders. The model is based on a large dataset of 93,455 x-rays of the lower extremities of each body part, with each test labeled normal or abnormal. A dense, interconnected CNN dense 161 layer has achieved AUC-ROC of 0.880 (sensitivity = 0.714, specificity = 0.961) in this unusual classification task.

The author in [5] describes research, three types of deep neural networks (e.g., CNN, DNN, and SAE) are designed for lung cancer calcification. Those networks are applied to the CT image classification task with some modification for the benign and malignant lung nodules. Those networks were evaluated on the LIDC-IDRI database. The experimental results show that the CNN network archived the best performance with an accuracy of 84.15%, sensitivity of 83.96%, and specificity of 84.32%, which has the best result among the three networks.

3 Theoretical Modeling

Most clinical techniques are based on anomaly analysis of lung X-ray images for diagnosis and treatment cite 13. Diagnosing anomalies in an x-ray image require a lot of specialist knowledge, and the quality of the diagnosis also sometimes affects the result (error may occur). Diagnosis results are not shared and doctors have to look back from the beginning when there is an image to diagnose. The quality of diagnosis depends on the expertise and experience of each doctor. This is a problem for doctors as the number of X-rays to diagnose increases. In places where access to skilled radiologists is limited, diagnosis of results can be delayed and affect the patient's treatment

We propose a method to classify pneumonia and normal patients from Chest X-ray images with CNN architectural model [7,8]. The intended method will be a good tool for diagnosing medical imaging diseases.

We train a CNN architectural model that contains a Convolutional class followed by a Max-Pooling class of 2 × 2 dimensions connected to the full class. [6]. The output of the Max-Pooling layer will form a 1D, array that forms the matrix input for the fully connected layer. Our convolution layer contains 64 filters or nuclei, the filter itself is a 3 × 3 integer matrix.

Furthermore, CNN was performed with a default learning rate of 0.000001 and ran 100 times over a period 1 day. And we used the input of size 150 × 150, a shallow architecture that should be able to work well in this task.

We calculated binary cross-entropy losses during the training using the formula 1. The goal is to compare the probability distribution volume with the real label.

$$-\frac{1}{N}\sum_{i=1}^{N} y_i \log(\hat{y_i}) + (1 - y_i)\log(1 - \hat{y_i}) \tag{1}$$

Where y_i and $\hat{y_i}$ denote the label and the predictive results respectively.

After establishing an abnormal detection system on the chest X-ray, the system was evaluated by the following method:

We calculated the overall accuracy, the area according to the characteristic curve (ROC-AUC) [12]. Each row of matrices represents instances in a predictive class while each column represents instances in an actual class (or vice versa). The name of the confusion matrix comes from the fact that it makes it easy to see whether the system is confusing two layers (usually mislabeled as another class).

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 150, 150, 32)      320
_________________________________________________________________
batch_normalization (BatchNo (None, 150, 150, 32)      128
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 75, 75, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 75, 75, 64)        18496
_________________________________________________________________
dropout (Dropout)            (None, 75, 75, 64)        0
_________________________________________________________________
batch_normalization_1 (Batch (None, 75, 75, 64)        256
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 38, 38, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 38, 38, 64)        36928
_________________________________________________________________
batch_normalization_2 (Batch (None, 38, 38, 64)        256
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 19, 19, 64)        0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 19, 19, 128)       73856
_________________________________________________________________
dropout_1 (Dropout)          (None, 19, 19, 128)       0
_________________________________________________________________
batch_normalization_3 (Batch (None, 19, 19, 128)       512
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 10, 10, 128)       0
_________________________________________________________________
conv2d_4 (Conv2D)            (None, 10, 10, 256)       295168
_________________________________________________________________
dropout_2 (Dropout)          (None, 10, 10, 256)       0
_________________________________________________________________
batch_normalization_4 (Batch (None, 10, 10, 256)       1024
_________________________________________________________________
max_pooling2d_4 (MaxPooling2 (None, 5, 5, 256)         0
_________________________________________________________________
flatten (Flatten)            (None, 6400)              0
_________________________________________________________________
dense (Dense)                (None, 128)               819328
_________________________________________________________________
dropout_3 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 129
=================================================================
Total params: 1,246,401
Trainable params: 1,245,313
Non-trainable params: 1,088
```

Fig. 1. Model 1

The accuracy of the model is calculated by the ratio between the total number of correctly detected lungs (normal and abnormal lung)/the total number of detected lung images, according to formula 2:

$$ACC\,(M) = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

Inside:

TP (True Positive) - the number of abnormal-labeled lung images correctly classified into abnormal layers.

FP (False Positive) - number of normal labeled lung images incorrectly classified into abnormal layers.

FN (False Negative) - the number of abnormal labeled lung images that are incorrectly classified into normal layers.

TN (True Negative) - the number of normal labeled lung images correctly classified into the normal layer.

4 Tool

We experimented with Keras is an open-source neural network written in the Python language. It is run on Windows 64-bit system with 8G memory. Keras has several advantages: simple, easy to use, runs on both CPU and GPU and is very powerful. So we choose Keras to study.

5 Experimental Results

5.1 Dataset

CheXpert is a dataset of 224,316 chest X-ray images of 65,240 patients who underwent an X-ray examination at Stanford University Medical Center from October 2002 to July 2017, both at the control center. Inpatient and outpatient treatment [3]. We used this dataset including 2 folders (Train, Val), and each folder will be the corresponding categories (Pneumonia/Normal). The Train folder contains 7599 images of chest X-rays with 1082 images of normal lungs and 6517 images of patients with pneumonia. The Val folder contains 234 images of chest X-rays with 38 images of normal lungs and 196 images of patients with pneumonia. The sample of chest X-ray image shown in Fig. 2 includes pneumonia (left) and normal (right).

5.2 Scenario 1

We have conducted on model 1 consisting of 5 classes. Coaching and validation in coaching are shown in Fig. 1. The model's performance for the categorical assignment was assessed by an ACC accuracy of 0.84 shown in Fig. 3.

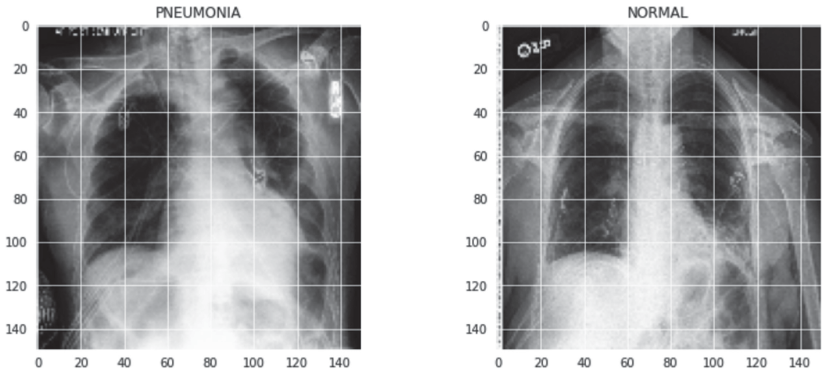

Fig. 2. Image in the dataset

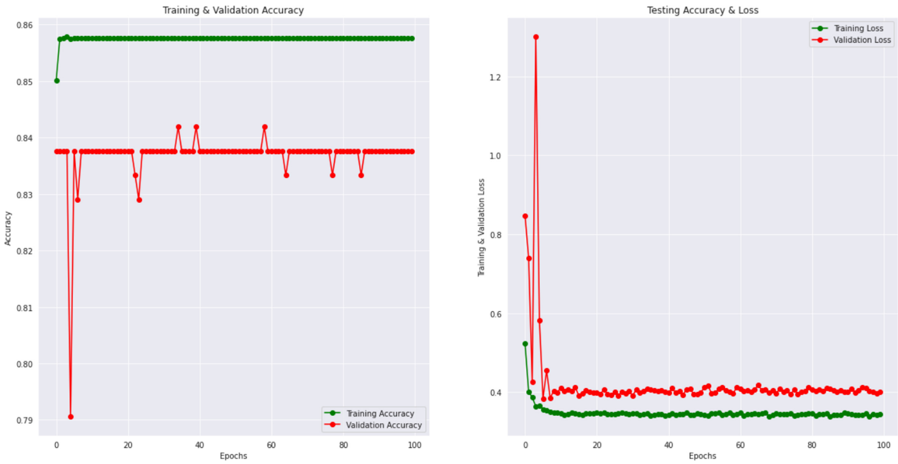

Fig. 3. ACC-Model 1

5.3 Scenario 2

We have conducted on model 2 consisting of 4 classes. Coaching and validation in coaching are shown in Fig. 4. The model's performance for the categorical assignment was assessed by an ACC accuracy of 0.8375 shown in Fig. 5.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 150, 150, 32)      320
_________________________________________________________________
batch_normalization (BatchNo (None, 150, 150, 32)      128
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 75, 75, 32)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 75, 75, 64)        18496
_________________________________________________________________
batch_normalization_1 (Batch (None, 75, 75, 64)        256
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 38, 38, 64)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 38, 38, 128)       73856
_________________________________________________________________
dropout (Dropout)            (None, 38, 38, 128)       0
_________________________________________________________________
batch_normalization_2 (Batch (None, 38, 38, 128)       512
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 19, 19, 128)       0
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 19, 19, 256)       295168
_________________________________________________________________
dropout_1 (Dropout)          (None, 19, 19, 256)       0
_________________________________________________________________
batch_normalization_3 (Batch (None, 19, 19, 256)       1024
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 10, 10, 256)       0
_________________________________________________________________
flatten (Flatten)            (None, 25600)             0
_________________________________________________________________
dense (Dense)                (None, 128)               3276928
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 129
=================================================================
Total params: 3,666,817
Trainable params: 3,665,857
Non-trainable params: 960
```

Fig. 4. Model 2

5.4 Scenario 3

We have conducted on model 3 consisting of 3 classes. Coaching and validation in coaching are shown in Fig. 6. The model's performance for the categorical assignment was assessed by an ACC accuracy of 0.8375 shown in Fig. 7.

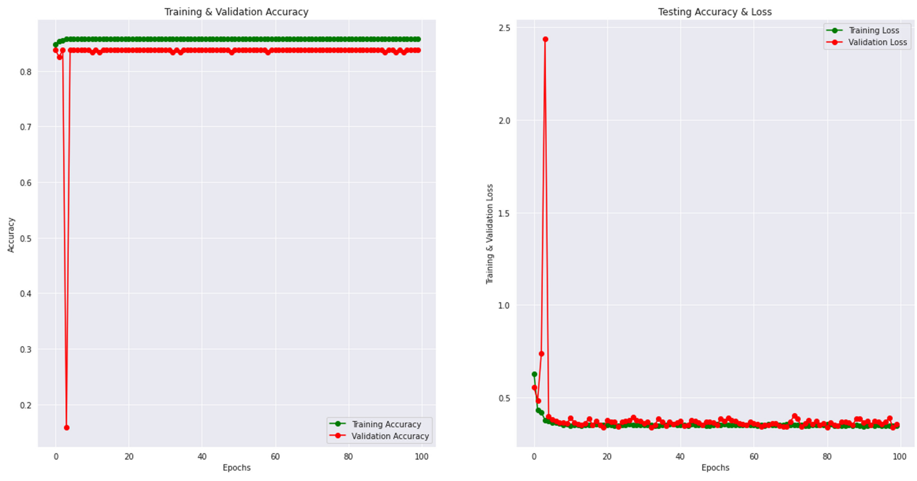

Fig. 5. Accuracy M2

After conducting experiments on 3 models, we have the following summary table: Fig. 8

We see that in the above 3 models CNN, model 1 with ACC has the best accuracy and error is very low. So we have chosen model 1 as the training model. It is quite good for classifying abnormalities on a chest X-ray (Fig. 9).

However, a major downside in medical image processing with deep learning is the limited dataset size compared to the computer vision domain. And due to the similarity between the X-ray images of normal lungs and pneumonia, there is confusion in the classification of X-ray images of normal lungs. Specifically, in Fig. 10, the X-ray image of a normal lung in the episode Val is similar to Fig. 11, which is an X-ray image of pneumonia in Train episode.

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 150, 150, 64)      640
_________________________________________________________________
batch_normalization (BatchNo (None, 150, 150, 64)      256
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 75, 75, 64)        0
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 75, 75, 128)       73856
_________________________________________________________________
dropout (Dropout)            (None, 75, 75, 128)       0
_________________________________________________________________
batch_normalization_1 (Batch (None, 75, 75, 128)       512
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 38, 38, 128)       0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 38, 38, 256)       295168
_________________________________________________________________
dropout_1 (Dropout)          (None, 38, 38, 256)       0
_________________________________________________________________
batch_normalization_2 (Batch (None, 38, 38, 256)       1024
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 19, 19, 256)       0
_________________________________________________________________
flatten (Flatten)            (None, 92416)             0
_________________________________________________________________
dense (Dense)                (None, 128)               11829376
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 129
=================================================================
Total params: 12,200,961
Trainable params: 12,200,065
Non-trainable params: 896
```

Fig. 6. Model 3

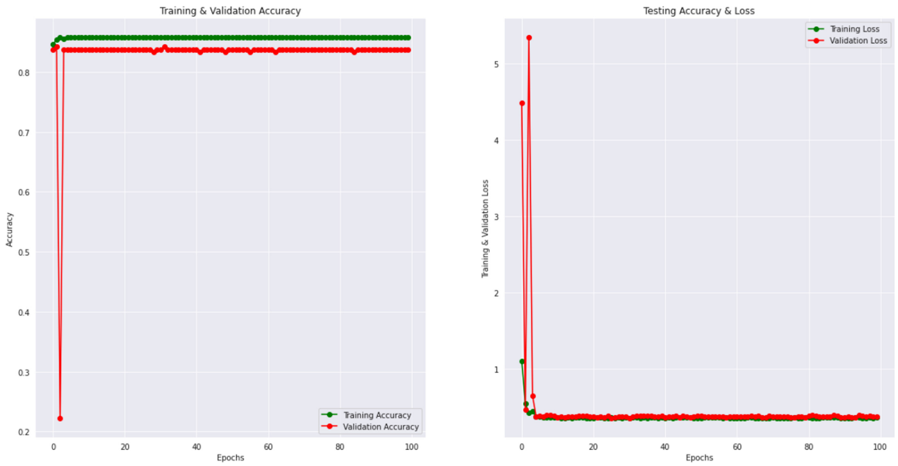

Fig. 7. Accuracy M3

Model	Number of layers	ACC_Val
Model 1	5 layers	8.382
Model 2	4 layers	8.376
Model 3	3 layers	8.376

Fig. 8. Compare the results

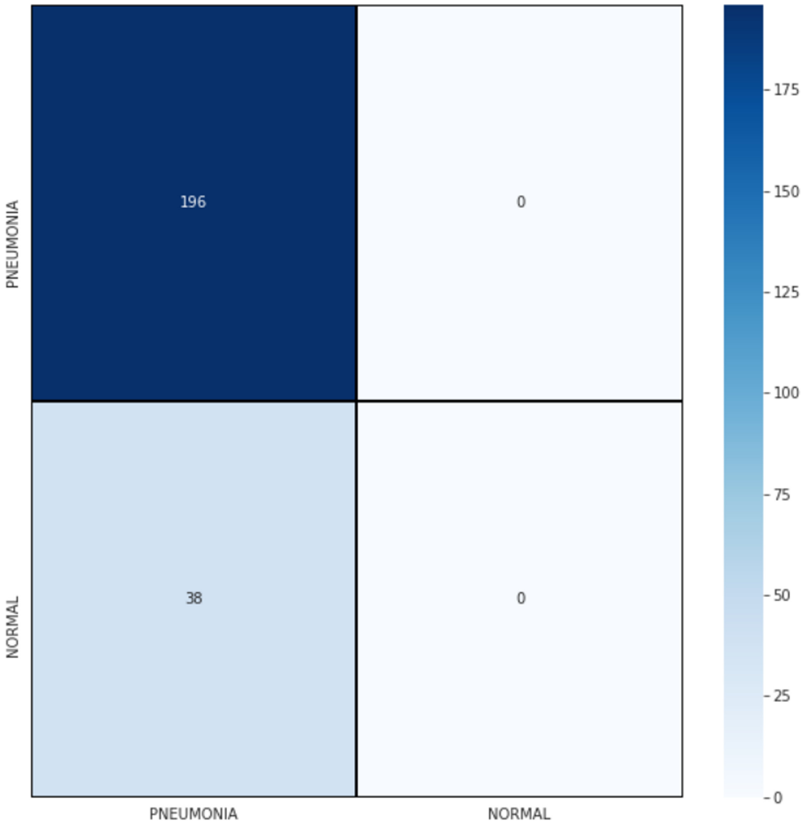

Fig. 9. Confusion matrix

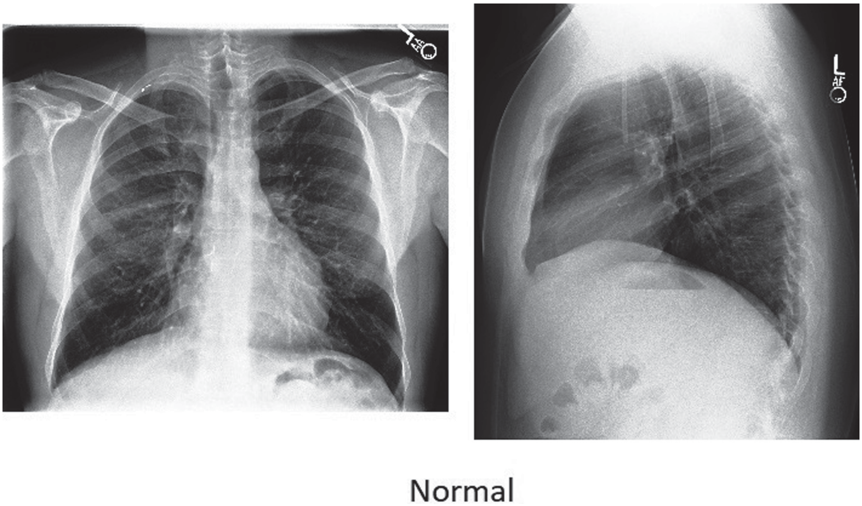

Fig. 10. Normal

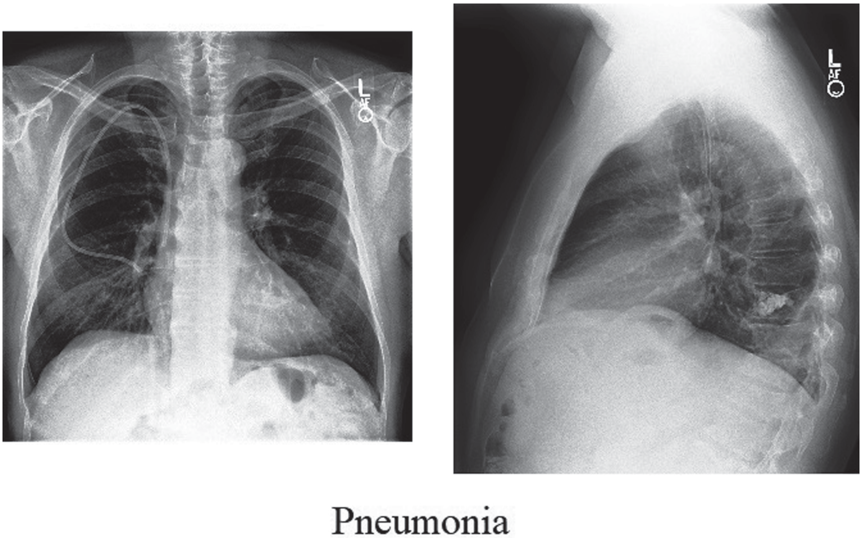

Fig. 11. Pneumonia

6 Conclusion

Lung image recognition plays an important role in medical imaging. This helps to quickly detect serious illnesses in the lung image. Especially in the current situation of the COVID-19 epidemic, photo identification has proven to be important. The faster the disease is identified, the more effective it will be. Our study is expected to play a part in the early detection of lung x-ray abnormalities. We trained our CNN model with nearly exactly classified pneumonia cases during each validation. However, due to limited resources and time, we have only been researched on the CheXpert dataset. In the future, more in-depth studies on larger datasets are expected to contribute to improving machine learning performance on medical imaging data.

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