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Original Article

Use of BEGAN and GAN for pneumothorax image augmentation and labeling

Ming-Chi Wu[1,2], Chiun-Li Chin[3], Po-Wei Hsu[3], Meng-Fang Wu[3*]

[1] *School of Medicine, Chung Shan Medical University, Taichung, Taiwan*
[2] *Department of Medical Imaging, Chung Shan Medical University Hospital, Taichung, Taiwan*
[3] *Department of Medical Informatics, Chung Shan Medical University, Taichung, Taiwan*

Background: As medical technology advances and becomes more complex, it is important to understand how to use it to make accurate diagnoses. Misjudgment may delay treatment, leading to worsening condition or even death. A pneumothorax occurs when there is rupture of bullae or blebs in the lungs, which causes air to accumulate in the pleural cavity, increasing pressure within the pleural space and resulting in collapse of the lungs. If not diagnosed in time, pneumothorax can result in death due to dyspnea. Most hospitals use chest X-ray images for diagnosis. In this paper, Generative Adversarial Network (GAN) was applied to improve the quality of X-ray images of the thoracic cavity, determine the position of characteristic labels of the chest, and generate labeled images of pneumothoraces.
Methods: GAN uses combined multiple loss functions to improve the authenticity of labeled images. With Boundary Equilibrium Generative Adversarial Network (BEGAN), image data increased. We evaluated whether this enhances the quality of the labeled images.
Results and conclusion: GAN training improves the accuracy of labeling and increased image data improves the quality of labeled images.

Keywords: Pneumothorax, labeled image, GAN, loss function, BEGAN

Introduction

A pneumothorax occurs when there is rupture of lung bullae or blebs and air accumulates in the pleural cavity, increasing pressure within the pleural space and causing partial or complete collapse of the lungs. When blood flow is affected, collapse of the lungs causes tension pneumothorax, which is life-threatening. Without immediate treatment a patient may die. Pneumothorax can be divided by cause into traumatic pneumothorax and spontaneous pneumothorax. With about 3,400 patients per year requiring hospitalization for spontaneous pneumothorax in Taiwan,[1] this is not an uncommon condition.

Spontaneous pneumothorax can also be divided into primary, secondary, catamenial, and neonatal types. It mainly occurs in young people from teenagers to adults aged around 30 (mainly thin tall males who are smokers), in people with chronic obstructive pulmonary disease (COPD), and in the elderly aged around 60. In the COPD group and elderly groups, the bubbles associated with pneumothorax are more numerous and larger (usually greater than 2.5 cm) and often coexist with lung lesions.[2,3] Catamenial spontaneous pneumothorax more commonly occurs in the first

* Correspondence Author: Meng-Fang Wu
Address: No. 110, Sec. 1, Jianguo North Road, South District, Taichung, Taiwan
Tel: +886-917-128-036
E-mail: s0917128036@gmail.com

or last 72 hours of menstruation in 30 to 40-year-old childbearing women.[4]

X-ray, tomography, and chest ultrasound are used to detect a pneumothorax. X-ray images can capture the entire lung to define the area of gas distribution and determine the positions of the endotracheal and chest tubes. X-ray imaging is convenient and cost-effective. Therefore, it is the most commonly used medical tool for pneumothorax diagnosis. Compared with X-ray imaging, tomography takes longer and costs more. Although a chest ultrasound can confirm the presence or absence of pneumothorax, not all hospitals have access to an ultrasound machine.[5] Nevertheless, misdiagnosis due to subjective evaluation or inexperience of the doctor and lack of timely judgment due to high false positive rate may lead to worsening condition and shock. In view of the severity of pneumothorax, the aim of this paper is to use a Generative Adversarial Network (GAN) trained through unsupervised learning[6] to auto-label pneumothorax features and Boundary Equilibrium Generative Adversarial Network (BEGAN)[7] to amplify the data, increase the number of pneumothorax images, and improve the accuracy of GAN labeling. This model is expected to help doctors to promptly and accurately detect pneumothoraces and reduce the diagnosis or observation time, enabling treatment to begin as soon as possible.

1.1 Related work

In 2007, Hamza-lup et al.[8] proposed deep learning for pneumothorax detection and localization in chest radiographs. Pneumothorax is a critical condition that requires timely communication and immediate action. To prevent morbidity and mortality, early detection is crucial. We studied the characteristics of three deep learning techniques: (i) convolutional neural networks (CNN), (ii) multiple instance learning, and (iii) fully convolutional networks. They all failed to clearly label the locations of pneumothorax features, meaning that they cannot be used to assess the severity of disease.

In 2018, Kim, Kim, and Jun[9] proposed automated diagnosis of pneumothorax with an ensemble of CNN and multi-sized chest radiography images. Pneumothorax is a relatively common disease but, in some cases, it may be difficult to identify based on chest radiography. In this paper, we propose a novel method for detecting pneumothorax on chest radiographs. Our ensemble model of identical CNN with three different sizes of radiographs makes use of CNN to improve the clarity of images. However, if labeling is not absolutely accurate, doctors may underestimate or ignore the severity of disease.

In 2017, Liu and Xiang[10] proposed a deep learning model to improve image analysis of the lung with a classification algorithm based on CNN that consisted of three convolutional layers, three subsampling layers, and one fully connected layer. The network parameters were regulated through a back-propagation algorithm, which also improved the back-propagation process.

In 2019, Liu and He[11] demonstrated the shortcomings of CT imaging for the diagnosis of lung tumors including doctor's subjective evaluation, which results in a high number of false positives. The great advances in the field of computer vision make lung cancer computer-aided diagnosis and screening possible.

All these methods use CNN for amplification of chest images. Although such methods enhance the image, they do not help the doctor to immediately locate sites in the lung or label the affected areas of the lung. We used GAN to label images of spontaneous pneumothorax. Different from CNN and traditional red dot labeling, our system automatically labeled pneumothorax images without intervention by doctors. This method will help doctors to more rapidly select appropriate treatment. In the next section, we introduce the GAN architecture and training process. Experimental devices and training experiments are presented in Section 3 and conclusions in Section 4.

Methods

As the pneumothorax imaging dataset was insufficient, we used BEGAN to amplify the data and generate a large number of pneumothorax images. Then, we provided the images to an experienced doctor to mark the areas of pneumothorax with red dots. Finally, the labeled pneumothorax images were

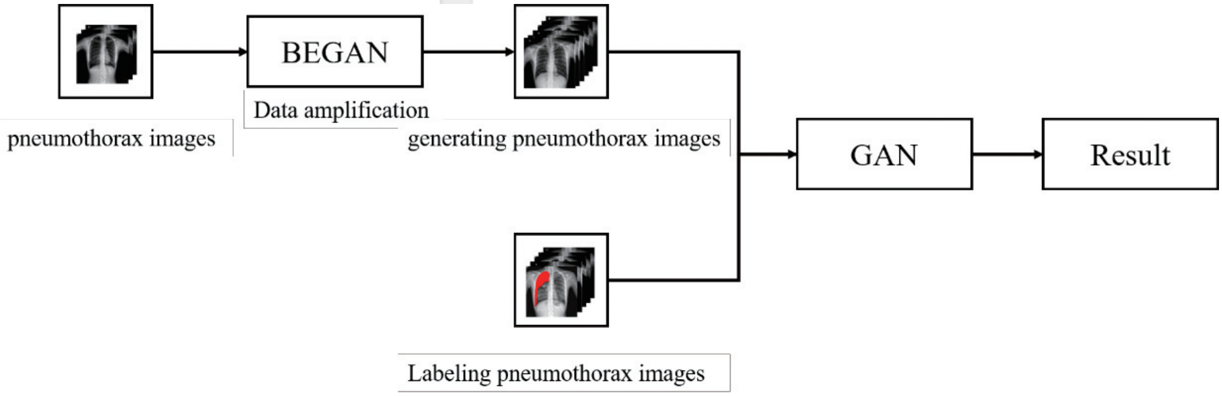


Figure 1. System flowchart

used for training our proposed GAN model (Figure 1).

2.1. BEGAN

The goal of GAN is to transform the distribution of the generated imaging data into the distribution of the original imaging data. The reconstruction error produced by BEGAN during the generation of images is similar to the reconstruction error in the distribution of original imaging data, such that the distributions of data are similar between the generated and original images.

The generator of BEGAN consists of a convolutional network for creating images. The generator's loss function is defined by the image reconstruction error. The goal of the generator is to minimize the error and find the best approximation of the original image. The discriminator acts as an automatic encoder. The original image is decoded and encoded to produce an image and the error in the original image reconstruction process is used to define the loss function of the discriminator. The purpose of the discriminator is to determine the similarity between the generated image and the original image. The loss function of the discriminator in the process of automatic encoding is used to adjust the parameters of the generator, thereby enhancing the training results of the generator and generating similar pneumothorax images. The diagram of BEGAN architecture is shown in Figure 2.

2.2. Generative adversarial networks

Our proposed GAN[12] method includes three models: generation, identification, and VGG-19 models. To improve the authenticity of generated images, we added five loss functions to the GAN architecture, each with a different goal.

The generator has a 12-layer convolutional structure. The characteristics of the pneumothorax are extracted by the convolutional layers to generate a labeled pneumothorax image. The two loss functions produced in the generated network are color loss and total variation loss functions. The color loss function calculates the color difference between the generated labeled image and the original image and evaluates the brightness and contrast of

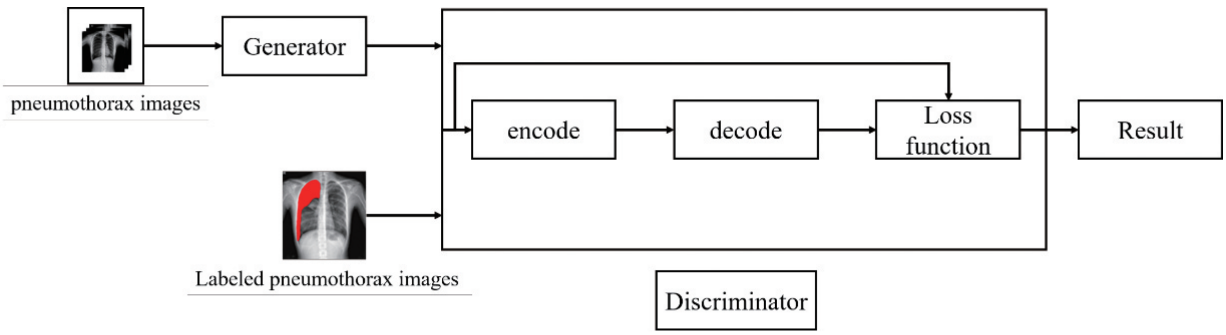


Figure 2. BEGAN architecture

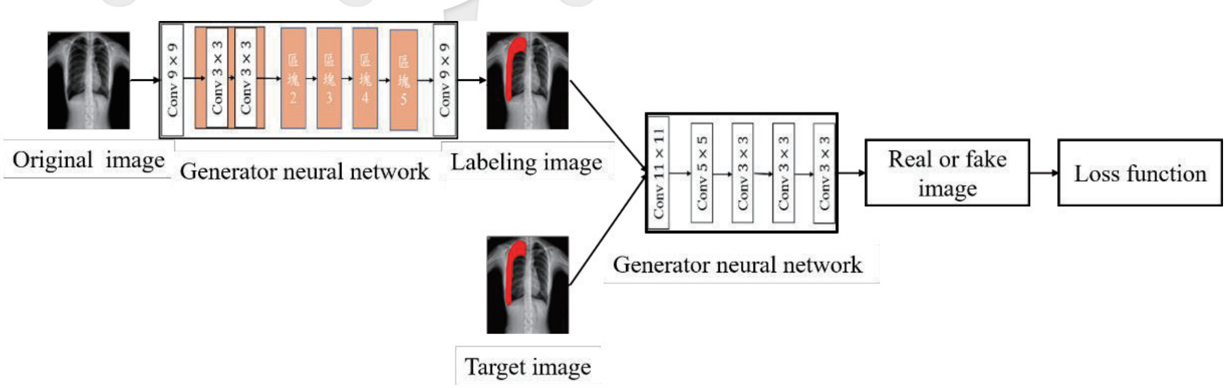


Figure 3. GAN architecture

the two images. The total variation loss function removes the noise from the generated labeled image.

The discriminator has a 5-layer convolutional structure that is used to distinguish a true image from a false one produced by the generator. The product of the discriminator will be presented to the generator for reference. After the generator adjusts the parameters, a new pneumothorax image is created and submitted to the discriminator to determine texture loss. Texture loss occurs during the process, with the goal of learning the textures of the original image.

The goal of VGG-19 is for the generated labeled image to approximate the original image. In this model, there is content loss with calculation of Euclidean distances between the features of the generated labeled image and those of the original image to enable the two images to correspond.

Through constant contention between the generated model and the identification model and the loss function generated by VGG-19, we defined total loss function, then assigned weights to the loss functions generated above and added them together. Our goal was to minimize the total loss function and thereby improve the authenticity of the generated image, while training a model that can generate labeled pneumothorax images. The GAN architecture is shown in Figure 3.

Experimental results

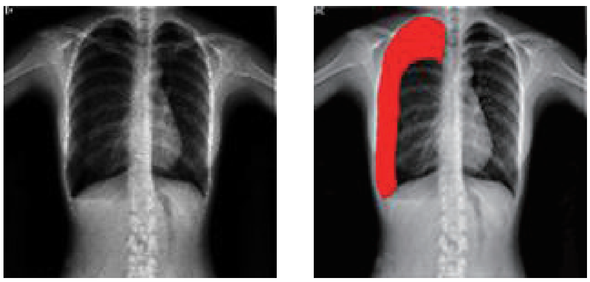
In this section, we describe the hardware environment and dataset used for training and testing. Finally, we discuss the results obtained with the GAN model and the training results after data amplification by the BEGAN model.

3.1. Setting up the environment

We used Anaconda 3 to construct TensorFlow and create the Python 3 environment. Our experiment was run on a DGX-2 machine equipped with two 2.7 GHz CPUs, 1.5 TB RAM, and 16 Nvidia Tesla V100 GPUs..

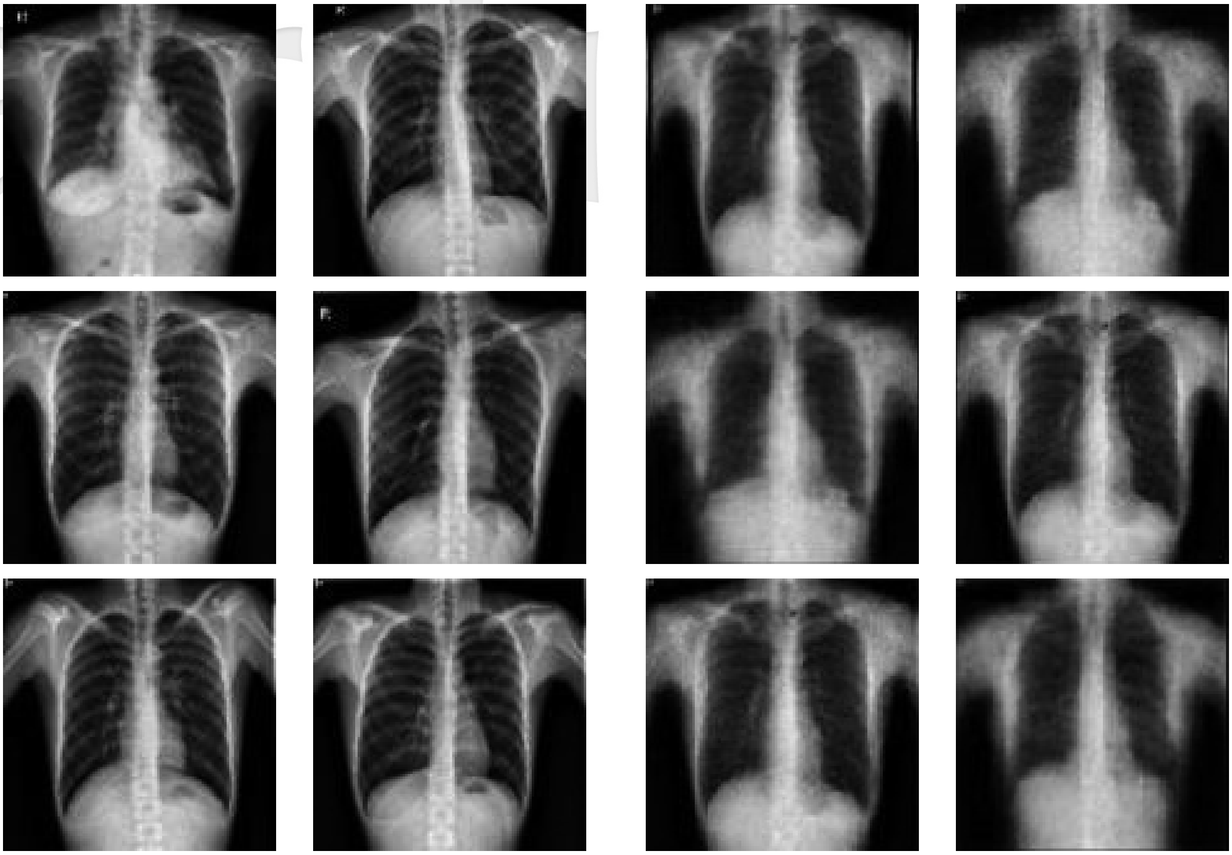
3.2. Dataset

A total of 100 chest X-ray images of pneumothorax were collected from the Department of Radiology of Chung Shan Medical University Hospital. Labeled images of pneumothorax and unlabeled images were used in the training process. Images were sent to an experienced doctor, who labeled the features of pneumothorax with red dots. Approximately 90% of the data was used as training data and the remaining 10% as test data. The lungs expand to fill the entire chest when a person inhales and some of the microvessels above the lungs expand throughout the chest on X-ray images. When a pneumothorax



(a) (b)

Figure 4. Area of pneumothorax with and without labeling



(a) (b)

Figure 5. Detailed pneumothorax images (a) and original pneumothorax images (b) generated by BEGAN

occurs, the area of the chest cavity vacated by the collapsed lungs appears transparent on chest X-ray images. This area was subjectively labeled by a doctor, as shown in Figure 4.

3.3. Amplification of the pneumothorax image dataset

As the number of pneumothorax images was insufficient for the model to generate pneumothorax images, we expanded our dataset using BEGAN, then trained BEGAN for 81,000 iterations, input noise into the trained BEGAN model, and again input GAN training data. The generated pneumothorax images are shown in Figure 5.

3.4. Experimental results

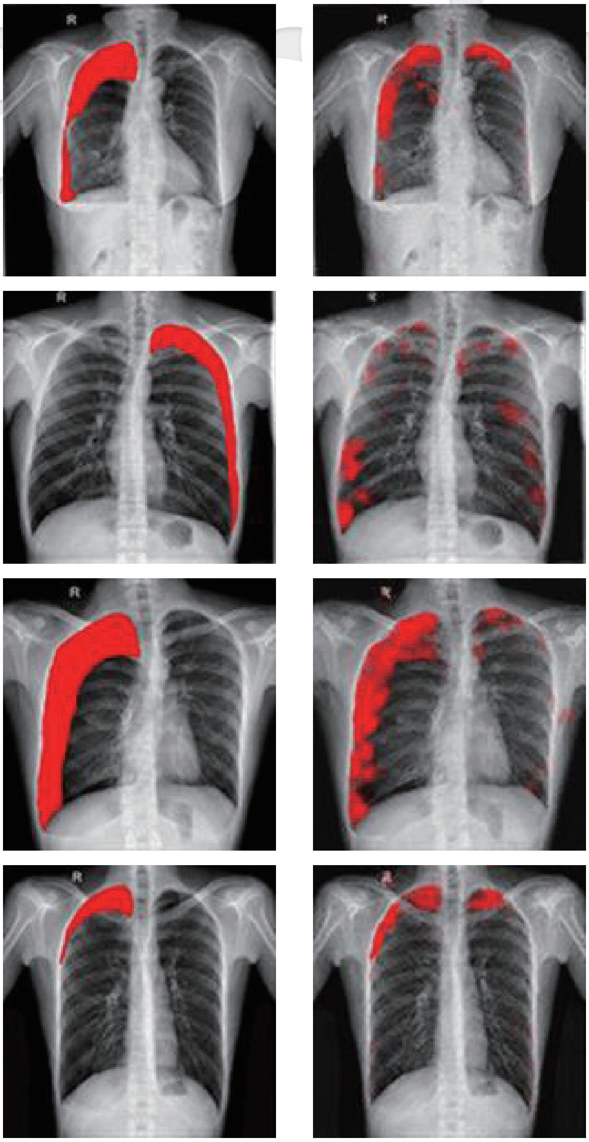
i. Training results without data amplification

In this experiment, a pneumothorax label generator model was developed using the original GAN training dataset for 500,000 iterations. During the testing process, we dropped the unlabeled and untrained test images into the trained pneumothorax label generator model. The results of the four test images that we selected are shown in Figure 6.

The test images labeled by the doctor are on the left and the test images labeled by the model are on the right. The image labeling results were quite unsatisfactory. Areas of labeled pneumothorax features were inconsistent in size and position with those on the doctor's labeled images. Moreover, some areas with no pneumothorax features were labeled.

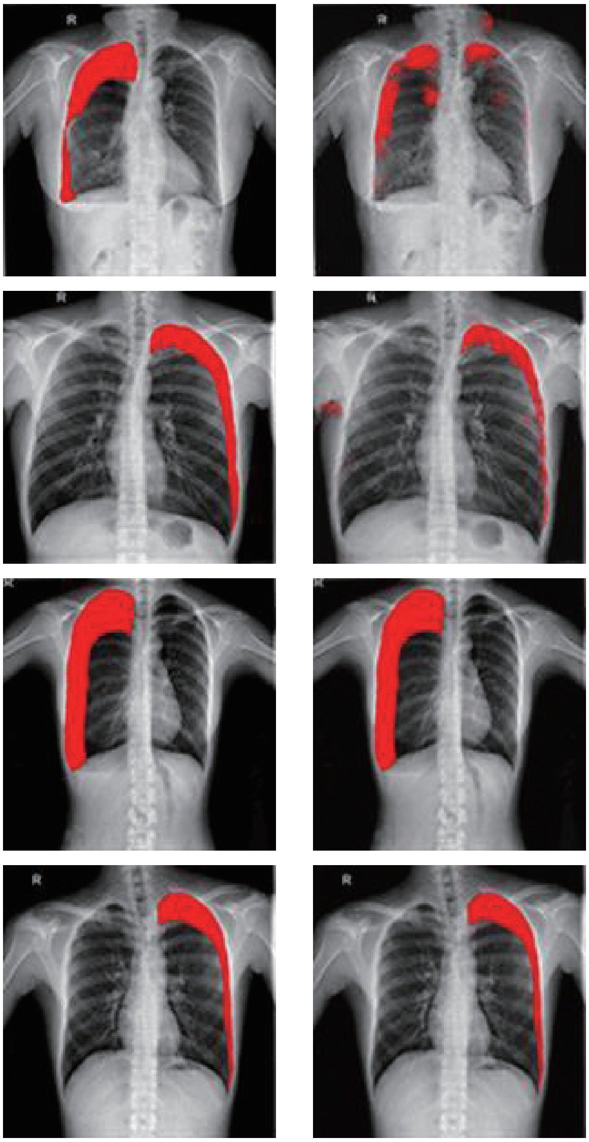
ii. Training results with data amplification

In this experiment, we increased the number of pneumothorax X-ray images through BEGAN, amplified the pneumothorax image dataset, and re-entered it into GAN. We also trained GAN for 500,000 iterations to develop the pneumothorax label generator model. We input the unlabeled



(a) (b)

Figure 6. Test results of image auto-labeling using the dataset of original images (a) compared with images labeled by doctor (b)



(a) (b)

Figure 7. Test results of image auto-labeling after data amplification (a) compared with images labeled by doctor (b)

and untrained test images into the trained model. The results of four selected images are shown in Figure 7. The test images labeled by the doctor are shown on the left and the test images labeled by the model are shown on the right. The labeled pneumothorax features in the first image are in the right and wrong positions, while the pneumothorax features in the remaining 3 images are clearly and fairly accurately labeled. Using the same parameter settings and 500,000 training iterations, the labeling results were better with data amplification than without data amplification.

Conclusion

Pneumothorax causes failure of the lungs to expand normally due to bullae or bleb rupture, allowing air to enter the chest cavity. If severe, it may lead to death. In clinical practice, it is difficult for doctors to make a judgement regarding pneumothorax from X-ray images, especially for those with less experience. Therefore, we proposed a GAN model for learning the characteristics of labeled pneumothorax, with a BEGAN model to generate more images of pneumothorax and enhance the accuracy of GAN model learning and feature labeling. In order to improve the authenticity of generated images, we introduced a loss function to adjust the training parameters. During the experiment, the results achieved with the original training dataset were not ideal. When the training dataset was expanded, the labeling results significantly improved. Therefore, we believe that increasing the amount of data improves GAN model learning and helps doctors to label the area of gas diffusion quickly and accurately to determine the position and size of the pneumothorax. This, in turn, lead to reductions in misdiagnoses, as well as time needed to make a diagnosis and to start treatment.

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