Image Generation of Lung Nodules based on Generative Adversarial Network

Wanle Chi[1,2,*], Yun Huoy Choo[2], Ong Sing Goh[2], and Dafeng Gong[1,2]

[1] College of artificial intelligence, Wenzhou Polytechnic, Wenzhou, Zhejiang 325035, China

[2] Faculty of Information and Communication Technology, Universiti Teknikal Malaysia Melaka (UTeM), Malacca 76100, Malaysia

*chiokchi@163.com

Abstract

Lung nodule images are very helpful for machine learning method to aided diagnosis lung disease. Because radiation is harmful to human health, it is difficult for researchers to obtain a large number of nodule image datasets. For machine learning algorithm, the number of data sets will greatly affect the final training effect. In addition, the nodule images datasets are very imbalanced. Healthy images are usually dominant, and the number of sick samples is relatively small. This paper proposes a method to enhance and balance lung nodule datasets by generating nodule images using Generative Adversarial Network(GAN). The paper proposes a W-CapsuleGAN method. In the LUNA16 datasets, the result of experiment shows that the algorithm of paper is more effective than other approaches.

Keywords

LUNA16; Lung Nodules; Generative Adversarial Network; Image Generation; CapsuleNets; Wasserstein Distance.

1. Introduction

With the emergence of deep learning, researchers are committed to applying the deep learning algorithm to the field of medical imaging, effectively realizing the combination of medical industry and computer.

For computer aided diagnosis, the number of data sets required for deep learning will greatly affect the final training effect. Due to the privacy of patients, it is difficult for researchers to obtain a large number of medical image data sets. In addition, the acquisition of medical images is often accompanied by radiation harmful to human health, and the cost is extremely high. At the same time, because healthy organizations are usually dominant and highly repetitive, they usually over represent normal categories, which may lead to slow convergence or over fitting of the model[1,2,3].

The medical image data set is very imbalanced. Taking LIDC-IDRI as an example, only 314 of 1086 CT cases have lung diseases. The health data and disease data are highly imbalanced; In addition, the data of more than 300 cases need to be divided into general lung cancer, non-small cell lung cancer, pneumonia, lung lymphoma, squamous cell lung cancer and other different types. So the imbalance of the data set is so strong that it seriously affects the correctness of the depth learning algorithm for medical assisted diagnosis; To improve the depth learning algorithm of medical assistant diagnosis, it is necessary to solve the problem of data set imbalance[4,5].

Therefore, how to expand the medical image data set in the simulated images through artificial intelligence has become an urgent problem in the field of computer aided diagnosis. A method to solve the problem is the generative adversarial network (GAN) proposed by GoodFellow et al. GAN and its variants (GANs) have been widely used in medical image synthesis due to their various advantages. Many studies have shown that using GANs for data enhancement can effectively improve the model effect[6,7].

This paper proposes an improved generative adversarial network and its improved model GAN to synthesize lung nodules images, balance the data volume of various lung nodules diseases, and help establish a more accurate computer aided medical diagnosis method.

2. Datasets and Preprocession

The datasets are the LUNA16 dataset includes data from low-dose lung CT images (mhd format), each containing multiple axial slices of a series of thoracic cavities. The number of slices included in each image varies with the scanning machine, scan layer thickness and patient.The original images are 3D images. Each image contains multiple axial slices of a series of thoracic cavities. This three-dimensional image consists of a varying number of two-dimensional images.

The LUNA16 dataset is a subset of the public lung nodule dataset, LIDC-IDRI(Lung Image Database Consortium-Image Database Resource Initiative). LIDC-IDRI consists of medical image files of the lung CT and corresponding diagnostic markers, which collected by the initiative of the National Cancer Institute (NCI). LUNA16 removed CT images with slice thickness greater than 3 mm and lung nodules smaller than 3 mm in LIDC-IDRI. The LUNA16 consists of 888 low-dose CT images of the lung.

The value obtained after the CT acquisition is the X-ray attenuation value in Hounsfield unit (HU). The HU value of water (μ_W) is 0, the HU value of air (μ_A) is -1000, and the HU value of other objects is calculated as:

$$HU=\frac{\mu_X-\mu_W}{\mu_W-\mu_A} \tag{1}$$

HU values are linearly transformed into pixel values in the image. The pixel values of the images obtained from different devices vary somewhat due to the different transformation standards. However, under the same ray, the HU values obtained from CT irradiation of the human body are the same, as shown in Table 1.

Table 1. HU values of human chemicals.

Chemicals	HU value
Air	-1000
Fat	-100
Water	0
Muscle	+40
Blood	+40
Bone	>+400

In the lung CT images, since the HU value of lung is about -500, the areas with HU values within [-1000,+ 400] (from air to bone) should be kept.

The CT file is in dot mhd format, which is a standard format for medical images. For each sample, it was a three-dimensional matrix D (Z-slicer *X-rows *Y-cols), X(rows) and Y(cols) represents the number of rows and columns of the image (default is 512), and Z(slicer) represents the number of slices.The images as training data input to the neural network are two-dimensional image format. It is necessary to convert to image format. All lung nodules exist lung parenchyma area. The images of lung parenchyma should be segmented form the original images.

The OTSU method be used to convert original images to binary images. The algorithm of threshold T is as follows.

1) The maximum gray value in the image is Tmax and the minimum gray value is Tmin.

$$T=(Tmax+Tmin)/2 \qquad (2)$$

2) Taking T as the threshold, the image is divided into (gray value greater than or equal to T) and background (gray value less than T). And the average value TF of foreground and the average gray value TB of background are calculated.

3) Update threshold T:

$$T = (TF + TB) / 2 \qquad (3)$$

4) Repeat steps 2 and 3 until T is unchanged.

Finally, the image is divided into foreground and background (binary images)with the final threshold T, and the image background be removed.

The erosion operation is performed using a disc with a radius of 2 pixels to separate the lung nodules, which attached to the vessels.The closure operation is performed using a disc with a radius of 5 pixels to let the nodules attach to the lung wall. By filling of small holes in the binary mask of the lung, and overlaying a binary mask on the images, lung parenchyma be segmented.The lung parenchyma segmentation, see Fig. 1.

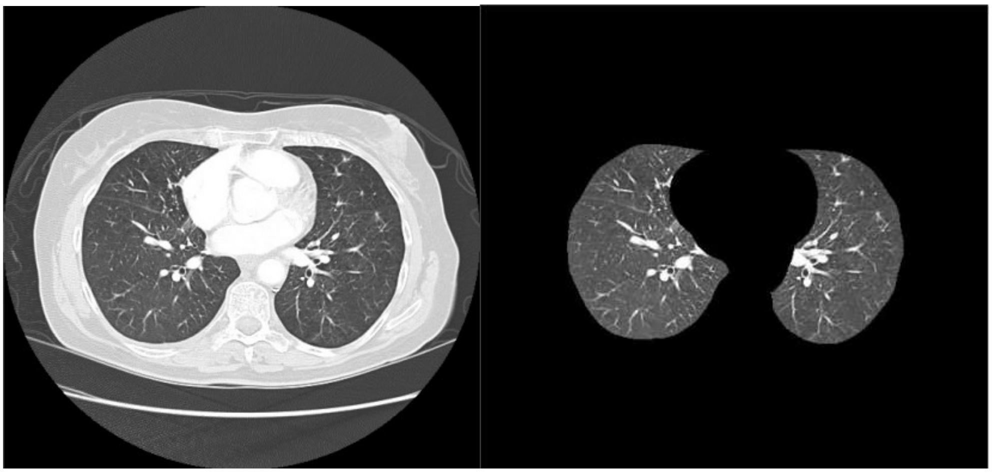
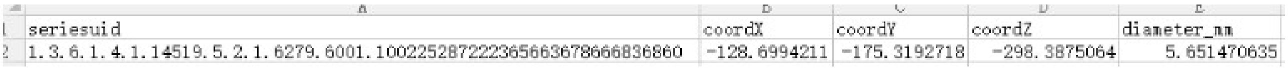


Fig. 1 Lung parenchyma segmentation

The label (annotations.csv) file contains 1186 lung nodule information, including position and diameter.With these information, the nodule images can be extracted. The label example, see Fig. 2. The Lung nodule in the lung parenchyma segmentation, see Fig. 3



	A	B	C	D	E
1	seriesuid	coordX	coordY	coordZ	diameter_mm
2	1.3.6.1.4.1.14519.5.2.1.6279.6001.100225287222365663678666836860	-128.6994211	-175.3192718	-298.3875064	5.651470635

Fig. 2 The label file

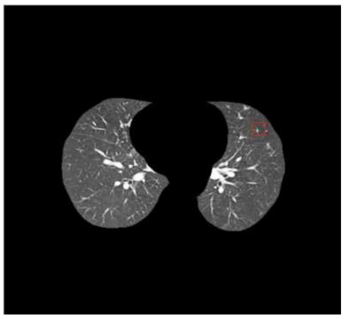


Fig. 3 Lung nodule in the parenchyma segmentation

The nodule as the image center, black pixels were filled into nodule section to normalize into 32 * 32 pixels. The labels show the levels of benign and malignant nodules (level 1-5, the most benign to the most malignant). Lung nodule sections were extracted with the levels of malignant. The lung nodule sections, see Fig. 4.

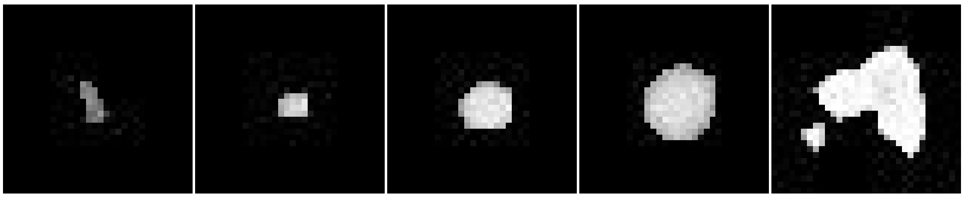


Fig. 4 Lung Nodules (From level 1 to level 5)

3. Image Generation of Lung Nodules based on W-CapsuleGAN

The lung nodules images were the gray image format in low resolution. Hence, the proposed GAN is not able to generate the variation as expected. The nodule data is similar to black-and-white hand-writings images as compared to coloured images like CIFAR-10. The Color Image Generator such as BigGAN , which works well on coloured images, does not well on low resolution gray nodule images. The reason may due to the mode collapse of GAN. Inappropriate loss function was be selected. The hinge loss function is not suitable for nodule generator.

The algorithms such as DCGAN, Wasserstein-GAN and CapsuleNets are suitable for handwriting. This paper propose a W-CapsuleGAN model to overcome the low classification performance on nodules datasets. The model uses capsuleNets to replace the deep convolutional network, and uses wasserstein distance as the loss function. The structure of networks, see Fig. 5 and Fig. 6.

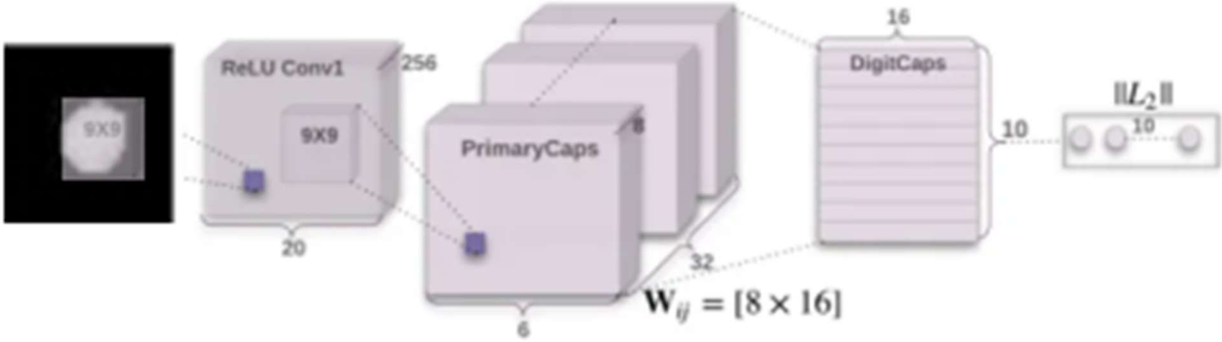


Fig. 5 The structure of CapsuleNets

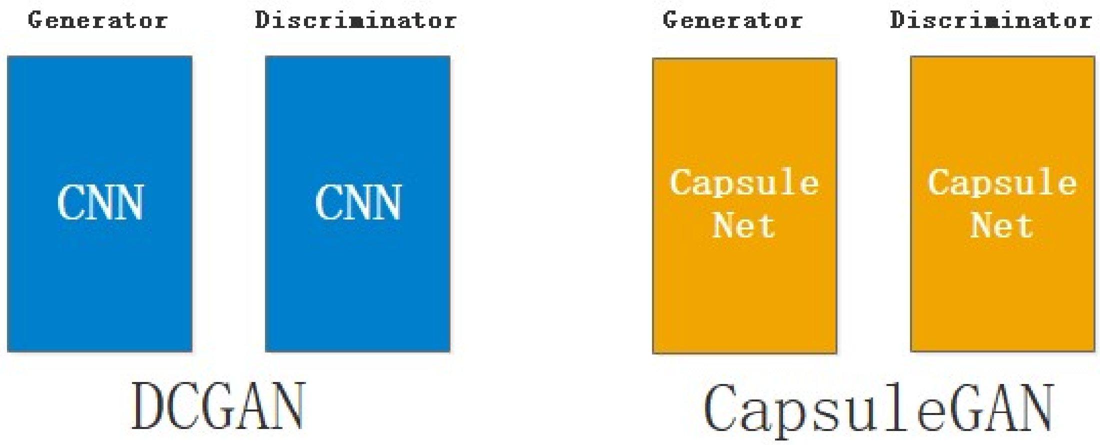


Fig. 6 The structure of CapsuleGAN

The loss function used by the original Capsule GAN is margin.The principle of margin function is similar to the Hinge loss function of BigGan, which is not applicable to gray images. The paper proposes wasserstein distance as the loss function. Wasserstein distance is defined as follows:

$$W(P_r, P_g) = \inf_{\gamma=\prod(P_r,P_g)} E_{(x,y)\sim\gamma}[||x - y||] \tag{4}$$

4. Experimental Testing

According to the pathological diagnosis in LUNA16 datasets, lung images were divided into 5 malignant nodules classes(level 1-5, the most benign to the most malignant), including 343 level 1(benign) nodule images, 254 level 2 nodule images, 207 level 3 nodule images, 199 level 4 nodule images and 183 level 5 nodule images. The experimental environment is shown in the Table 2.

Table 2. The experiment environment

Name	Value
CPU	1
RAM	16GB
GPU	Tesla v100
VRAM	8GB
Disk	100GB
CUDA	11.0
Python	python3.7
Framework	PaddlePaddle 1.8.0 (TensorFlow)
Calculation package	Paddorch (pytorch)

The experiment divide the nodule datasets into training set and testing set according to 4:1. The experiment used the methods to generate nodules, which were supplemented to 1000 in each category. The experimental result is shown in the Table 3, Fig. 7.

Table 3. The experimental result

Model	IS(Inception Score)	FID(Fréchet Inception Distance)
BigGAN	1.9	233
GAN	5.3	74.2
DCGAN	6.9	84.3
WGAN	7.2	54.5
CapsuleNets	7.5(best)	102.1
W-CapsuleGAN	7.3	30.2(best)

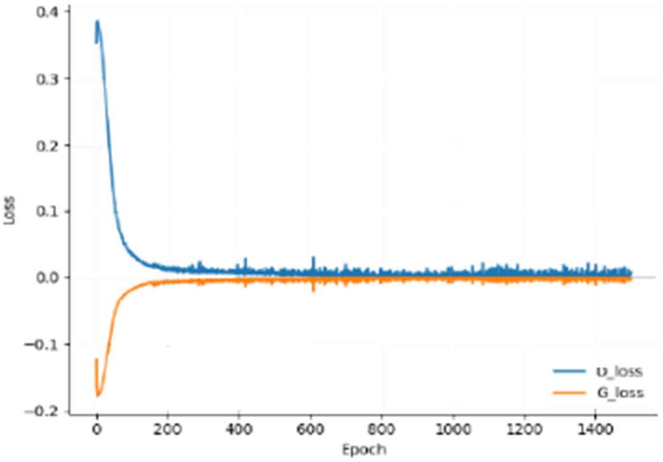


Fig. 7 The loss values of W-CapsuleGAN method

5. Conclusion

This paper proposes using Generative Adversarial Network to expand and balance the lung nodule image datasets, to improve the performance of lung disease prediction classifiers. The paper proposes a W-CapsuleGAN method to generate lung nodules images. In the LUNA16 datasets, the result of experiment shows that the algorithm of paper is more effective than other approaches.

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