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Original Article

Ischemic Stroke Detection System Based on GAN Model

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Stroke is a leading cause of death and disability worldwide, with ischemic stroke most common. Brain CT images of patients who have suffered ischemic stroke show obvious features. Hence, brain CT images are often used to determine whether a patient has suffered an ischemic stroke. In recent years, there has been rapid development of software, hardware, and artificial intelligence (AI) applications. To speed up the diagnostic process, medical images can be labeled using AI technology. As medical images are difficult to acquire, we applied Generative Adversarial Network (GAN) deep learning algorithm. Through the network of generators and discriminators in the GAN model, there is continuous learning with improved parameters from a small amount of data. With this model, the best parameters are determined to generate labeled brain CT images that closely match those manually labeled by physicians. The method proposed in this paper can be used to precisely label the regions of ischemic stroke. In addition, we provide a platform for doctors to label brain CT images. We hope that the proposed method can effectively assist physicians in studying brain CT images, thereby shortening the diagnostic time, accelerating the treatment process, and providing an understanding of a patient's condition in the shortest amount of time.

Keywords: CT image, Ischemic Stroke, GAN, Auto segmentation, CycleGAN

Introduction

Strokes are categorized as ischemic or hemorrhagic, with ischemic stroke the most common, accounting for about 87%. Ischemic stroke is defined as a blood flow deficiency due to blockage of blood vessels, which causes brain tissue to die or lose competence. Hemorrhagic strokes are divided equally into intracerebral hemorrhage and atraumatic subarachnoid hemorrhage, accounting for about 13% of all strokes[1]. If a patient has experienced a stroke, there will be obvious features on CT image of the brain. Therefore, CT images are often used in clinical practice to confirm the diagnosis of stroke. The aim of this study is to develop a method to assist physicians in interpreting ischemic stroke images as quickly as possible.

On CT images of the brain, ischemic stroke presents as area of black edema. Ischemic stroke is mainly gray matter edema, which differs from the mainly white matter edema of malignant tumors[2-3]. As medical imaging can be used to diagnose strokes[4], many methods for detecting ischemic stroke have been proposed, including traditional image processing methods and more recent methods based on deep learning algorithms. In terms of the former, Mirajkar et al.[5] combined CT and MRI images to produce composite images to perform cutting of stroke lesions and detect acute ischemic stroke. Yahiaoui et al.[6] developed

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an ischemic detection method based on CT brain image, which recognizes the low attenuation of acute stroke by enhancing the contrast of brain CT images and extracting ischemic regions from normal tissues. Wu et al.[7] proposed a novel multi-scale symmetry image patch classification model designed to detect stroke regions. Acharya et al.[8] proposed a system based on the extraction of higher order bispectrum entropy and its phase features from brain MRI images, and used support vector machine (SVM) to classify the severity of ischemic stroke.

At present, there are many methods for identifying regions of ischemic stroke on images using deep learning algorithms. Chen et al.[9] proposed a novel framework, which combines EDD and MUSCLE (multi-scale convolutional label evaluation) nets, to automatically segment stroke lesions via diffusion-weighted MR imaging (DWI). Liu et al.[10] developed an end-to-end ischemic stroke disease cutting network, known as the medical knowledge-infused deep convolutional neural network (MK-DCNN). MK-DCNN's deep network, multi-core strategy, and dropout method effectively improve the cutting of ischemic stroke lesions. Guerrero et al.[11] introduced a CNN architecture, uResNet, which distinguishes white matter-hyperintensities (WMH) caused by different pathologies and stroke lesions caused by cortical, large, or small cortical infarctions.

In recent years, more and more scholars have reported on the cutting and diagnosis of medical images based on training via deep learning algorithms[12-13]. The Generative Adversarial Network (GAN) model has gained in popularity in the field of image processing due to its good results[14]. Some scholars have proposed using GAN deep learning algorithm to train, compare, and correct with a small amount of data[15-18]. Previous studies have demonstrated that after continuous training, more and more similarities to real samples are produced to construct the best predictive model.

From a review of the literature, current deep learning technologies can be used to automatically recognize problem areas on images and help doctors to explain them. In the field of medical imaging interpretation, physicians often use red dots to indicate such areas on images[19]. It is expected that the GAN deep learning algorithm can immediately identify abnormal areas associated with ischemic stroke on CT images of the brain and clearly label them. This can help physicians to quickly determine whether a patient has suffered an ischemic stroke.

There is currently no system in hospitals that enables drawing on images stored in Digital Imaging and Communications in Medicine (DICOM) files. In addition to automatic labeling of the region of ischemic stroke, the physician can label the image himself/herself using this system. This information is then entered into the dataset for training to improve learning and accuracy of automatic markers.

The main features of this paper are listed below:

A. We developed a "manual labeling program" to allow physicians to label ischemic stroke areas on brain CT images, based on personal experience and expertise.
B. By reducing the need for a physician or radiologist to label a CT image manually, there are savings in terms of labor costs and time.
C. Using the GAN model, the location of black edema area on brain CT image is automatically labeled, which can speed up interpretation of images by physicians and help diagnose patients with ischemic stroke.
D. We adjusted the deep learning network architecture and parameters to improve overall identification accuracy and processing speed.

This paper is divided into four sections. The first section is the introduction. Section two is materials and methods, which introduces our method of marking images and the GAN architecture. The third section includes the results, through fine-tuning of parameters and other methods for evaluating the GAN structure proposed in this paper. The last section is the discussion.

Materials and Methods

In this section, we describe our dataset and preprocessing and image marking methods. Data acquisition methods are detailed in the dataset introduction. Preprocessing involved denoising brain CT images. Next, brain CT images were used for training the GAN architecture and algorithms presented in this paper to indicate ischemic stroke regions. In addition, the system provides a platform for physicians to label ischemic stroke regions on brain CT images. Section 2.1 is an introduction to the dataset. Tagging capabilities of the system are described in section 2.2, pre-processing methods in section 2.3, and GAN framework in section 2.4.

2.1. Dataset

The dataset used in this paper was comprised of brain CT images provided by a physician in the Department of Medical Imaging at Chung Shan Medical University Hospital. These images are from healthy and ischemic stroke patients. They were labeled by this physician according to diagnoses.

Physicians use the "manual label program" developed in this paper to label areas of ischemic stroke on brain CT images. Physicians can select colors for labeling. Labeled images are automatically stored in the training dataset and input into the GAN network to improve overall accuracy.

2.2. AI Image Labeling Platform

After obtaining CT images of the brain, physicians can open them through the program and use the brush function to label occurrences of ischemic stroke. The program also provides image enhancement technology that allows physicians to adjust image color, contrast, and brightness, etc. This prevents misidentification due to unclear images or insufficient contrast and enables problem areas to be quickly identified and labeled. Physicians can then save the labeled images in the DICOM file. The method proposed in this paper can be improved by physicians identifying possible areas of ischemic stroke and determining the corresponding diagnosis. The system automatically saves the images to the training dataset and inputs them into the GAN network for training to improve overall accuracy. Figure 1 shows the manual label program we developed to help physicians label brain CT images more quickly.

Fig. 1 「Manual label program」system interface

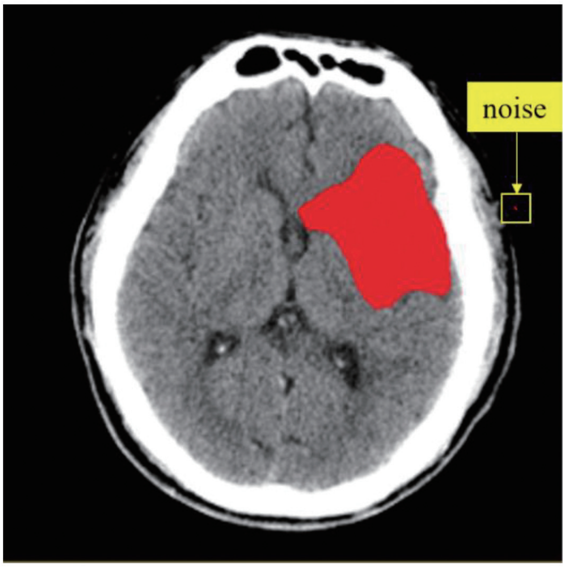

Fig. 2 The CT image contains noise

2.3. Preprocessing

Before entering images into the model, they are preprocessed to improve the success rate of system identification. The system outputs 150×150 images for training and testing in deep learning networks. Reasons and methods for preprocessing are briefly explained to improve the quality of the input images.

Preprocessing mainly involves application of denoising method. Some images have noise, which may be inadvertently labeled by a physician through the system's labeling function. Even if such noise is not visible to the naked eye, the generation of anti-network learning will result in the learning of this data and the inability to improve accuracy. Noise from manmade source, the contours of which appear similar to a point on the image, is classified as clutter. Figure 2 shows accidental point on CT image of patient with ischemic stroke.

Therefore, image preprocessing is first performed to remove noise. Then, the program masks and deletes these special values, effectively avoiding misidentification of noise in the training of the deep learning network.

2.4. Generative Adversarial Network

Medical imaging data is not abundant and medical images labeled by physicians are rare. Therefore, we conducted deep learning with a small number of medical images labeled by physician and created an auxiliary system for automatic labeling of medical images to assist physicians. GAN, proposed by Goodfellow in 2014[14], served as the model. GAN can generate results with a small dataset.

GAN model is composed of a generator and a discriminator. The main task of a network is to generate an image similar to the target image. The output needs to mimic the image in the training set such that the authentication network cannot distinguish it. The generated fake image and the real image in the dataset are the ultimate goal. The two networks achieve this by constantly confronting each other and adjusting the loss function. For better results, we used the GAN deep learning architecture proposed by Ignatov et al.[20] with some minor adjustments to generate images that have a high level of similarity with those labeled by physician.

2.4.1. GAN architecture

In this paper, the model is defined as a generator, with vector inputs and labeled CT images of the brain as outputs. The generator used in this paper contains 12 convolutional layers starting with 9×9 layers followed by four residual blocks, with each residual block composed of two 3×3 layers, alternating with the batch normalization layer. Next is the convolution layer with kernel sizes of 3×3 and 9×9. The last layer is applied to the output using the hyperbolic excitation function, while the remaining convolutional layers use the ReLU excitation function.

A classifier, also called a discriminator, is defined to determine whether the image is true or false, that is, whether the image is in the dataset or generated. The input is a brain CT image and the output is true or false. The discriminator used in this paper is composed of five convolution layers. Each convolution layer has a leaky ReLU excitation function, four of which have a batch normalization layer, and the third discriminator is the first fully connected layer.

Results

This experimental results section is divided into six parts. In the first part is explained the experimental environment. This is followed by a comparison of the results by fine-tuning parameters. In the third part, we show the results of this study. In the fourth part, we asked physicians to assess the labeled images. In the fifth part we compare our method with CycleGAN model. In the last part, we use image quality assessment mean squared error (MSE) and structural similarity index (SSIM) to evaluate the images generated by GAN model.

3.1. Experimental environment

This study was run with Windows 10 operating system, 8GB RAM, Intel i7-8750 CPU, and NVIDIA GTX 1060 GPU. We used Anaconda 3 to construct the Tensorflow learning framework and run the CNN model with Python. We also used CUDA 9.0 and cuDNN 7.3.1 with NVIDIA integration technology, which enabled parallel computing on NVIDIA graphics processors to

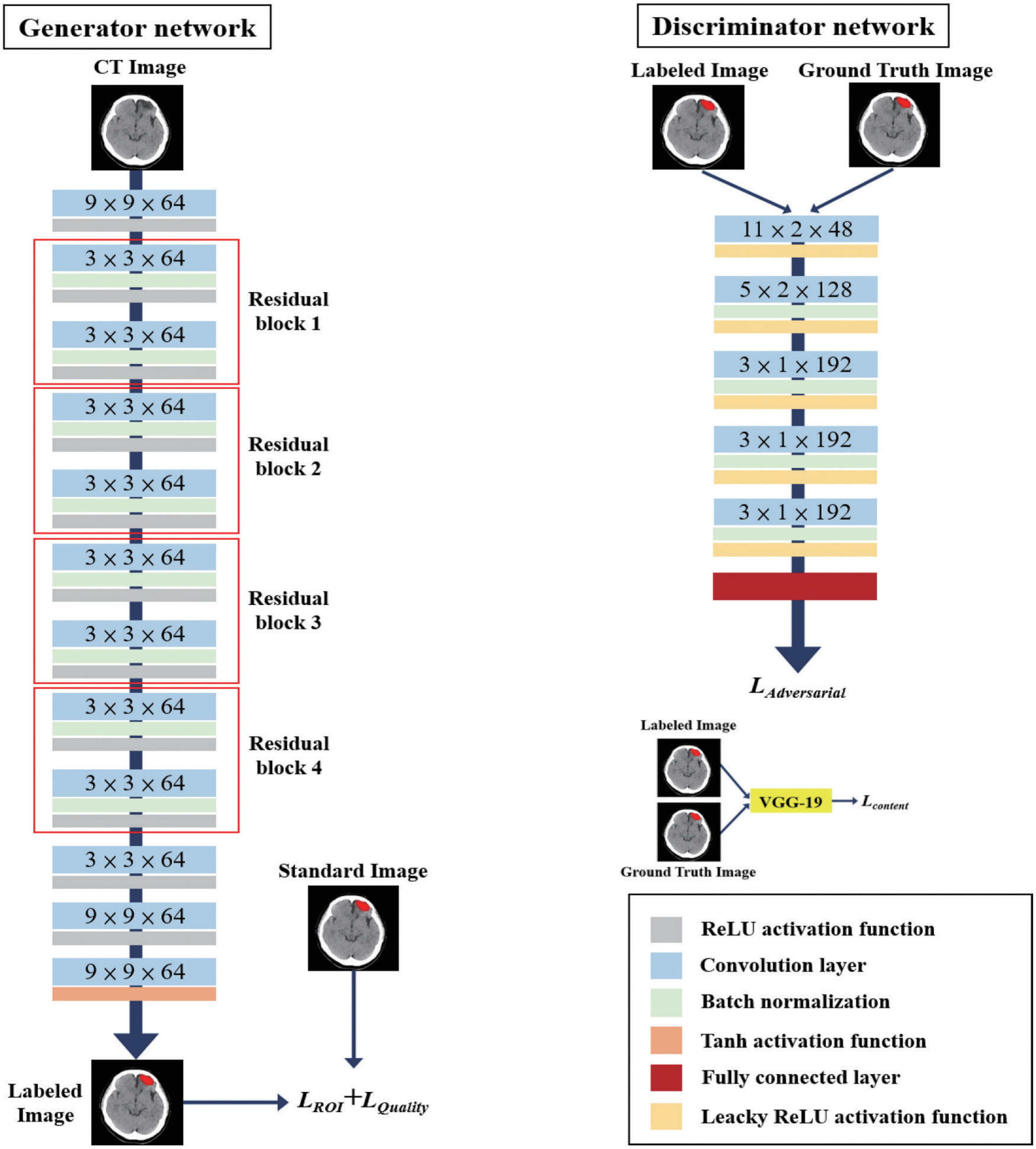

Fig. 3 The architecture of GAN

speed up training time. In addition, the user interface was created with Python's GUI library Tkinter, which increased the fluency of the system.

3.2. Comparisons by fine-tuning of parameters

We trained the GAN model to label the brain CT images and tested the settings of the environment and the parameters that GAN uses to generate labeled images that are close to those labeled by physician. We constantly adjusted the parameter settings of the GAN model to test it. Since the color loss function forces the generated images to have the same color distribution as physician labeled images, we adjusted the initial weight of color loss.

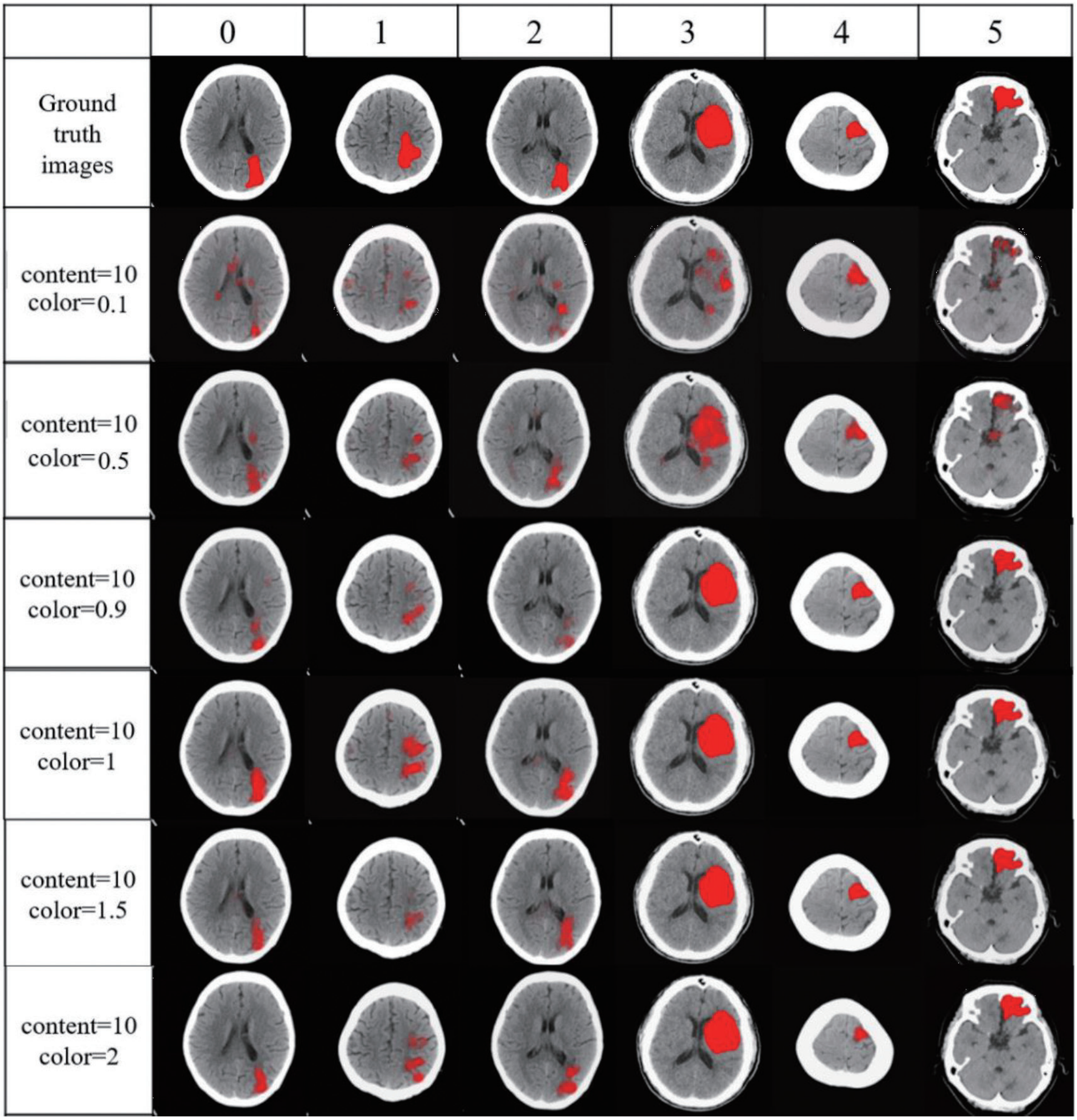

Fig. 4 Comparisons of Fine-tuning parameters

First, we fixed the initial weight of the content loss to 10 and adjusted the initial weight of the color loss for comparison. As shown in Fig. 4, the images generated by GAN model performed better than those with other parameters when the initial weight of the color loss was set at 1. However, when the initial weight of the color loss was set at 1.5, test image 2 in column 3 performed better. Therefore, the color loss function affected the color distribution of GAN-generated images.

3.3. Results of our method

Fig. 5 shows the results of the proposed method after continuous training and testing, followed by convergence to the optimal value of loss function. Fig. 5 shows that the images generated by GAN are similar to the images labeled by physician in terms of the positions and distributions of the labeled areas. This demonstrated that the proposed GAN model learns from physicians to carry out labeling of the regions of ischemic stroke lesions on brain

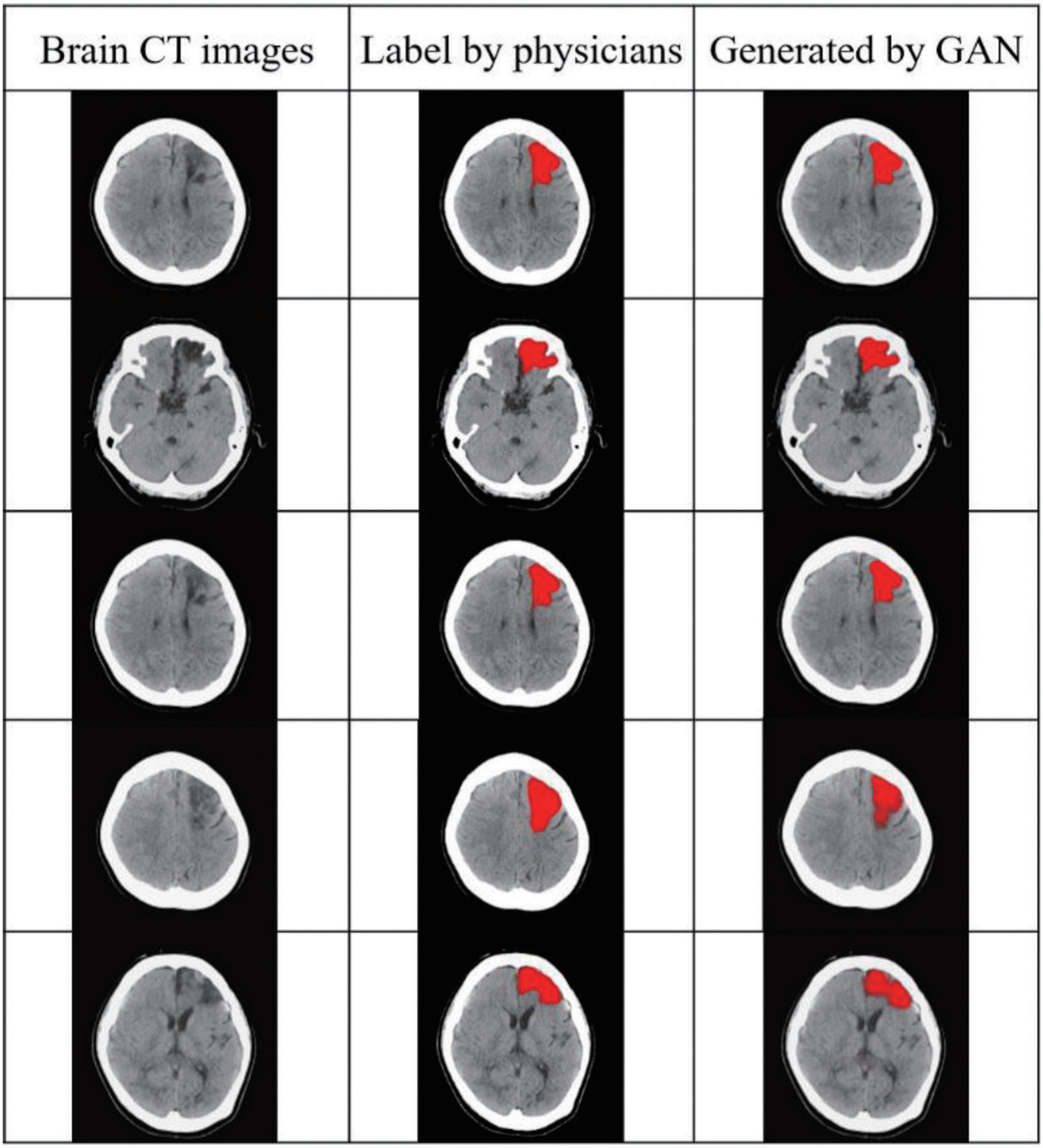

Fig. 5 Comparison of the original image, physicians label and the label image generated by GAN. This figure shows that the label ability of the system could label the area as same as the physicians' label.

CT images.

Although labeled areas were consistent on some CT images of the brain, the edges and distributions of the labels were incomplete. Furthermore, the brain CT images were not clear enough, such that the labeled areas of the brain CT images in the fourth and fifth rows did not match the brain CT images labeled by physician and the colors were bleaker. These are areas in need of improvement. Fig. 6 shows the automatic label system interface. When physicians open a brain CT image, the system inputs the image to GAN model and generates a labeled brain CT image. This can assist physicians in recognizing problem areas on CT

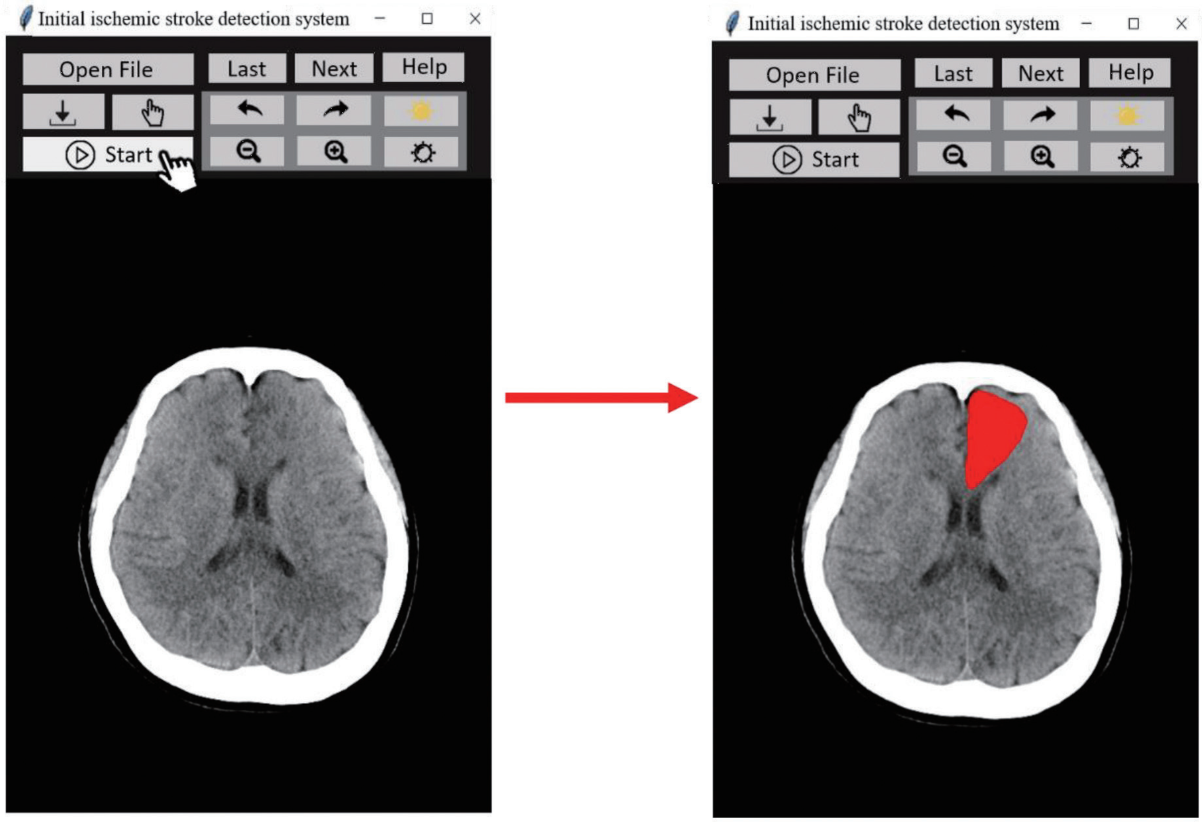

Fig. 6 Comparisons of Fine-tuning parameters

images and speeding up the diagnostic process.

3.4. Physician assessment

In this study, two key points were examined, namely whether the CT images generated by GAN include labeled areas of ischemic stroke lesions in line with physician standards and whether this labeling is similar to that of physicians. To demonstrate that the methods proposed in this study are effective in improving the efficiency and accuracy of physician identification, two physicians assisted with the assessment of 250 labeled images. Half of the images were generated by GAN model and the other half were labeled by physician. The first task was to judge the accuracy and integrity of the labeled area of each image. The second task was to distinguish the images generated by the system from the images labeled by physician. We used the results of the physician evaluations as the standard for comparison. Table 1 is a summary of the results.

In terms of labeling accuracy, Physician 1 and Physician 2 identified 92% and 94% of the images generated by GAN, respectively. They confirmed that the labeled areas met physician standards. This showed that the labeled images generated by GAN accurately map the area of ischemic stroke on brain CT images and are similar to the images labeled by

Table 1. Professional assessment of physicians

	Correct classification of the label images	Label accuracy	
		Images generated by GAN (%)	Label by physicians (%)
Physician 1	132/250=52.8%	92%	97%
Physician 2	148/250=59.2%	94%	98%

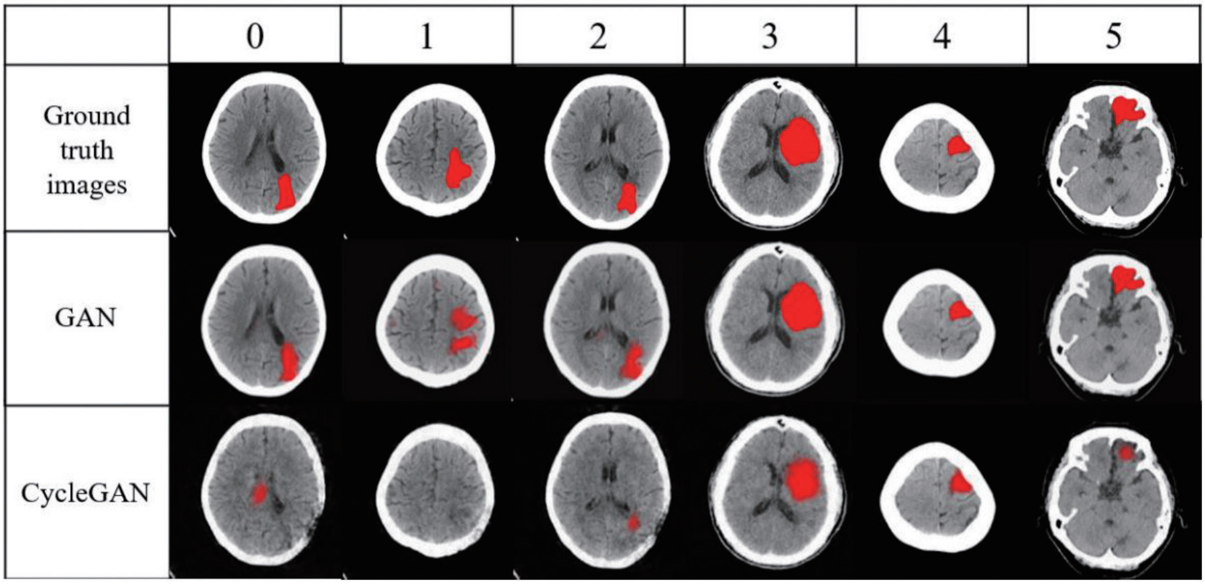

Fig. 7 The architecture of GAN

a physician, with a difference of about 4%.

In terms of discernment of images generated by GAN from those labeled by physician, Physician 1 and Physician 2 showed 52.8% and 59.2% accuracies, respectively. This demonstrated that the performance of the images generated by GAN is similar to the performance of the images labeled by a physician. Finally, both experts achieved similar results for the two tasks, indicating that the images generated by GAN are meaningful.

3.5. Comparison with CycleGAN model

We also compared our proposed method with CycleGAN model, to understand which deep learning model is more accurate and generates images that are more similar to those labeled by physician. Fig. 7 shows the brain CT images generated by GAN and CycleGAN models. Some brain CT images generated by CycleGAN model were incomplete due to insufficient training images and coloring of labels. With our method, complete brain CT images were obtained with coloring of labels that was similar to that of images labeled by physician. Table 2 shows the accuracies of training and testing. GAN and CycleGAN model used the same dataset and parameter settings. From our results, the method based on GAN deep learning algorithm proposed in this study performed better than the method based on CycleGAN in terms of training and testing.

3.6. MSE and SSIM assessments

Finally, we used MSE and SSIM as proposed by Wang et al.[21] to compare the images generated by GAN and CycleGAN models with the images labeled by physician. Both MSE and SSIM measure image quality. MSE calculates a large distance between pixels, which does not necessarily mean that the content of the image is significantly different. Compared with traditional assessment methods, SSIM is more in line with manual judgment of image quality. Table 3 shows better performance for our proposed method based on MSE and SSIM assessments. This indicates that

Table 2. Methods comparing

Method	Training Accuracy (%)	Testing Accuracy (%)
Our method (GAN)	98.7%	85.4%
CycleGAN	95.5%	79.5%

Table 3. Quantitative index of label brain CT images

Method	MSE	SSIM
Our method (GAN)	13.73	0.94
CycleGAN	15.12	0.78

the labeled images generated by GAN model are more similar to the images labeled by physician.

Discussion

In this study, a GAN-based algorithm was developed that effectively helps physicians to mark lesions indicative of an ischemic stroke on CT images of the brain. With GAN, it is possible to use a smaller number of training sets to generate images that are close to the physician labeling standard and to calculate the return error using three different loss functions to improve the quality of the resulting images. In addition, the model increased level of similarity during training by comparing the generated images and physician marked images and accuracy of the system reached 85.4%. This means that this system is effective in judging CT images of the brain and generating images that closely match those marked by physicians. In the future, we will increase the number of brain images and marked brain images in the training set to enable the model to learn more to achieve better identification. In addition, it is hoped that the volume of the region where ischemic stroke occurs can be added to the marker in the network model and trained to provide physicians with faster and more accurate CT image information to improve the quality and efficiency of medical services.

Acknowledgements

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