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Parkinson's disease based on deep learning using MR images

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Abstract

Magnetic resonance imaging has become an indispensable aid in the Parkinson's disease. The traditional method of analysis is that the patient takes an MR image of the brain and then the doctor analyzes the MR image for diagnosis. However, due to the poor quality of MR images and the high noise, it is difficult for doctors to diagnose, and the professional requirements for doctors are relatively high when analyzing nuclear magnetic resonance images. This paper proposed a MR image classification algorithm based on deep learning. The algorithm is mainly divided into two phases. The first phase is to detect the diagnostic region of the MR image by the improved Faster RCNN network. The second phase is to classify the diagnostic areas detected in the previous phase through our custom CNN network. We tested the algorithm using MR images of Parkinson's disease. The experimental results show that the accuracy of MR image detection and classification can be greatly improved by algorithm improvement.

Keyword : Parkinson's Disease; Faster R-CNN; CNN; Deep Learning

1. Introduction

With the continuous advancement of technology, more and more medical images are used in modern medical diagnosis, such as X-ray, CT image, ultrasound image, nuclear magnetic resonance images(MR)[1]. Medical imaging technology provides us with a means to directly display and study the structure of the human body, making revolutionary changes in diagnosis and treatment. MR images play a major role in the diagnostic of the Parkinson's. However, in practical applications, due to the operation of the equipment and artifacts that occur during brain MR imaging, the image quality can sometimes be degraded. It often contains a large amount of noise and artifacts. This makes it difficult for doctors to analyze and diagnose MR images. In general, when a doctor obtains an MR image of a patient, the doctor needs to rely on his expertise in this area and long-term accumulated medical experience for diagnosis. For younger doctors who lack this experience in diagnosis, the interpretation of the images can be difficult. This kind of manual diagnosis by the doctor has a lot of potential for improvement. This is why the automatic classification of MR image analysis has become an important

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topic of research.

In recent years, with the development of image processing technology, the great success of deep learning[2] in the computer field has inspired many scholars to use this technology in the analysis of medical images, trying to give diagnostic advice through deep learning, thereby improving the accuracy of the doctor's diagnosis. The results indicate that the application of deep learning in medical imaging is becoming increasingly mature and its application in the classification of breast cancer and in the diagnosis of lung cancer is a good example.

This paper mainly studies in the use of deep learning methods to classify MR images. but due to in the rich content of MR images, the effect is poor when using the entire MR image for classification. Therefore, we propose an image classification algorithm using a specific region. The algorithm is mainly divided into two processes. The first process uses the Faster RCNN[3] to detect the defined area, and the second process uses the checked area to classify the image. The main innovations of this paper are as follows:

(1) We have improved the way Region Proposal Network (RPN) generates bounding-box in Faster RCNN.

(2) The number of hard negative images is increased when the training set is generated.

(3) After the RoIpooling layer, we added a classification network to classify objects or backgrounds.

(4) In the classification phase, we customized the classification network to classify the detected areas.

The structure of this paper is shown below. The first chapter is introduction. In this chapter, we introduce the purpose of the research and the innovation of this paper. Next is the related research, in which we introduce the basics of MR images and CNN and Faster RCNN. The third chapter is about the use of Faster RCNN and CNN to classify images, The final chapter is a summary.

2. Related Research

2.1 Convolutional neural network

A CNN (Convolutional Neural Networks) is a type of artificial neural network[4]. In 2012, the CNN model AlexNet[5] achieved remarkable results in the ImageNet competition[6]. The model reduced the classification error rate from 26% to 15%. Subsequently, CNNs have become an important research topic in the field of image recognition. CNN are very similar to ordinary back-propagation neural networks, they are made up of neurons that have learnable weights and biases. Each neuron receives some inputs and executes an inner product operation followed by a nonlinear activation function. The network as a whole still expresses a single differentiable score function. The network structure of a CNN has two characteristics, local connection and weight sharing. The weight-sharing network structure makes it similar to biological neural networks, thereby increasing the complexity of the network model and the number of weights. The advantage is evident when the input of the network is a multi-dimensional image. The image can be used directly as the input of the network, thus avoiding the complicated feature extraction and data reconstruction process in the traditional classification algorithm. A CNN is a multi-layer perceptron specially designed to recognize two-dimensional shapes. This network structure is highly invariant to translation, scaling, tilting, or common forms of deformation. The traditional CNN consists of four parts:

(1) Convolutional layer: The convolutional layer is composed of a feature map obtained by an inner product operation on the convolution kernel and the input image.

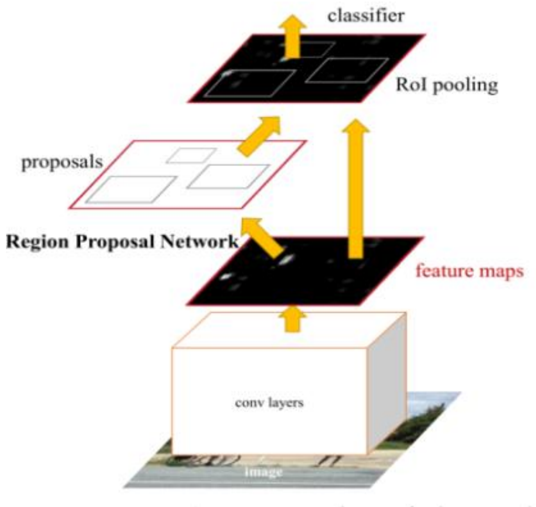
(2) Pooling layer: This layer is in the middle of a continuous convolution layer and is used to compress the quantity of data and parameters and to reduce overfitting to a certain extent.

(3) Activation layer: This layer performs a nonlinear mapping of the convolution output. Both the convolutional and pooling layers process the image through linear calculations, but as the classification is mostly linearly inseparable, we need to use an activation function for nonlinear processing.

(4) Fully connected layer: A fully connected layer plays the role of a "classifier" in the entire convolutional neural network, and it is often connected behind the convolution layer for classification.

2.2 Faster RCNN

Faster RCNN is an object detection algorithm proposed by Shaoqing Ren et al. The model concentrates the feature extraction classification regression problem into a network model. Compared with fast RCNN[7], Faster RCNN proposes to use RPN to generate candidate boxes. The region of interest is extracted by introducing an RPN network, so that it shares the convolution feature calculation with the target detection network. Target detection is divided into feature extraction, generation of regions of interest, classification, and regression. These four steps are unified into a deep network framework for end-to-end training. The flow chart of the Faster RCNN is shown in [Fig. 1]:



[Fig. 1] The structure of Faster RCNN

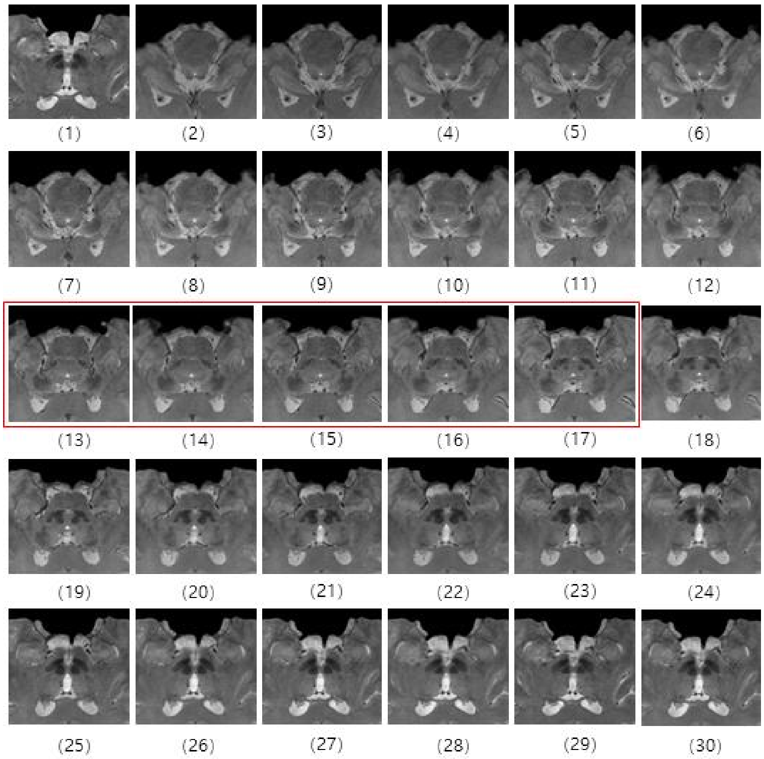
It can be seen from the figure that the Faster RCNN is composed of the RPN layer and the Fast RCNN.

The selective search algorithm was used to extract 2000 candidate frames from the image before using the Faster RCNN network structure. And in the training phase of the Fast RCNN network, the original image and the candidate bounding box are simultaneously input into the network model. The network first extract features from the image using a convolutional neural network, generates a feature map, and then finds the corresponding region on the feature map according to the size of each candidate bounding boxes. Since each area is different in size, each area is fixed to the same size using the ROI pooling layer.

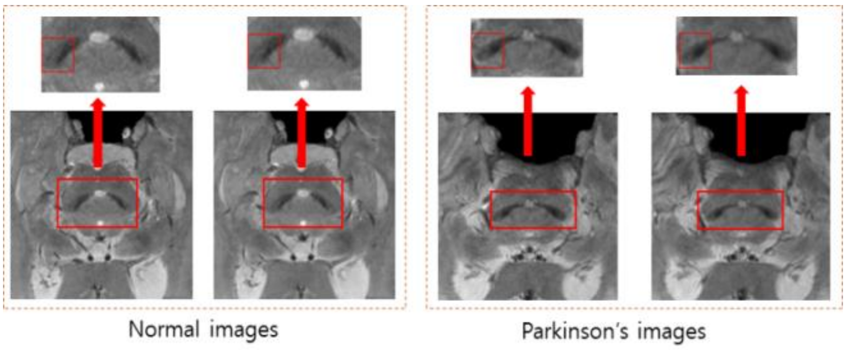
2.3 MR Image Dataset for Parkinson's Disease

The MR image of Parkinson's disease is a midbrain MR image taken to diagnose Parkinson's disease[8]. Each patient has recorded about 30 images. However, only five images in each patient's image were able to diagnose Parkinson's disease. For example, the MR images taken by Parkinson's patients are as follows:

The picture above shows MR images of the brain of a Parkinson patient. A total of 30 MR images were recorded, but only 13th to 17th images were able to diagnose patient with Parkinson's disease. The mark of the image in which Parkinson's disease can be identified and diagnosed is a sequence image when the substantia nigra area in the image appears to the fully. However, the position of these images in the sequence image are not fixed. The diagnosis of Parkinson's disease and normal images depends on the presence of a white area at the end of the substantia nigra area. If this white area is present the classification is normal, otherwise the person is classified Parkinson disease patient. The images of normal persons and those of Parkinson's patients are as follows:



[Fig. 2] MR images of one Parkinson patient

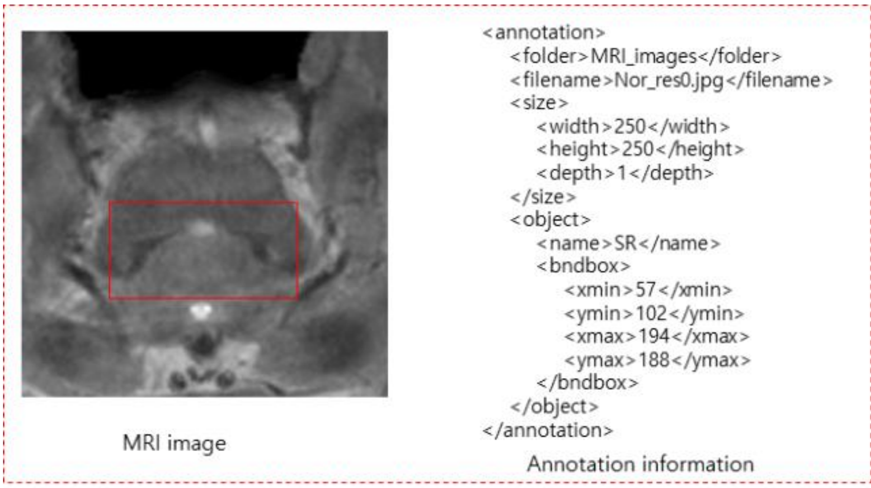


[Fig. 3] The images of normal and Parkinson's disease

In order to classify the Parkinson's disease image, the first step is to identify the substantia nigra area where Parkinson's disease can be diagnosed. This can be done using the Faster RCNN network. We call this specific area the SR area, and then the CNN network is used to classify the identified SR area. Through the above algorithm steps the purpose of diagnosing Parkinson's disease is achieved.

3. MR Image Classification with Improved Faster RCNN and CNN

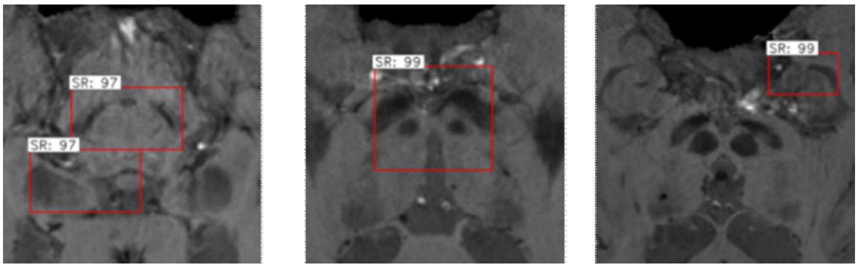
In order to train the Faster RCNN network, a training data set is required. 1,725 annotated images serve as the training data set. The original image size is 384×384 pixels in the data set. To reduce the amount of calculation, the image is reduced in size and cropped to 250×250 pixels from the point (67,67). The diagnostic area is manually marked on the image: the label of the image contains the image title, information of the starting point, and the size of each identified area. The diagnostic area SR is specified, and all annotated information is saved in an xml file. An example of a annotation and comments is shown in [Fig. 4].



[Fig. 4] MR images and annotation information

After the creation of this training data, this data set is used to train the Faster RCNN network. Here, ResNet51[9] is used as the feature extraction network. At the same time, the classification model is trained by the ImageNet dataset to obtain the weight of the network parameters. 1725 images are used for training and 100 images are used for testing. The test result showed that the accuracy of detection of MR images using faster RCNN is low. This happens for the following reasons. One is that the content of MR images is rich, and there are many similar contents in the images. As a result, the

Faster RCNN has many false detection areas when detecting the area of interest. Another reason is that the quality of the MR image is poor and contains noise. The following figure shows the misjudgment results when using the Faster RCNN to detect MR images:



[Fig. 5] Detection result. Left: Multiple regions detected in one image. Medium: The detected area does not match the ground truth size. Right: misdetection of the area.

As shown in the [Fig. 5], many different types of errors occur in this algorithm. In order to solve these problems, improvement are added to the algorithm. First, in the stage of using the Faster RCNN for area detection, the following three improvements are applied:

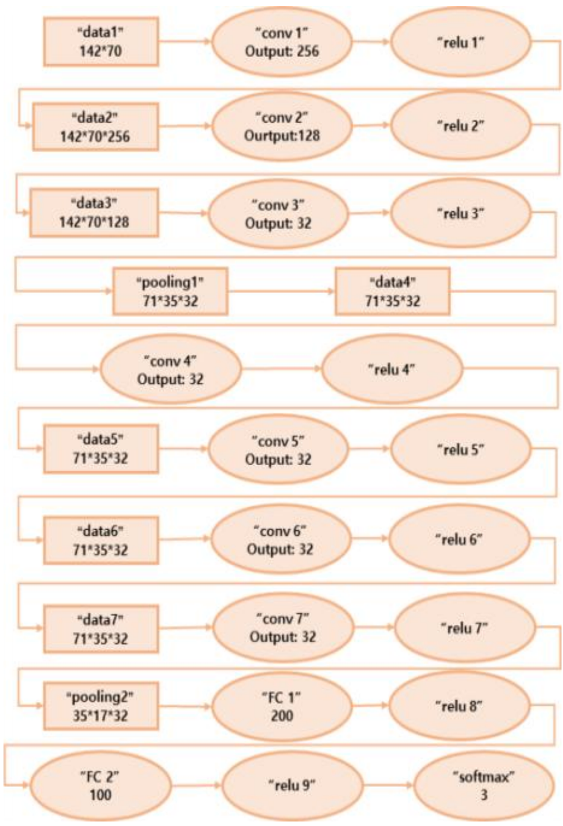
(1) In order to generate an anchor that matches ground truth more accurately, the scale and ratio of the RPN generation anchor is reset.

(2) The number of hard negative images in the training data set is generated in the RPN stage to improve the robustness of the RPN classification network.

(3) Due to the particularity of the MR image, the MR image region cannot be accurately classified in the final object classification phase of the Faster RCNN. A custom classification network has been added after the RoIPooling layer to reduce the probability of false detections in this phase.

As the substantia nigra area in each MR image is highly similar, three types of identified areas are obtained using the Faster R-CNN algorithm, i.e., normal, Parkinsonian, and non-diagnostic images. As the areas identified using the Faster R-CNN algorithm were not identical in size, we had to resize them. Most of the identified areas were approximately 142×70 in size, and hence, we decided to resize all the images to 142×70. we will define the convolutional neural network to train the data set. The defined network structure is as follows：

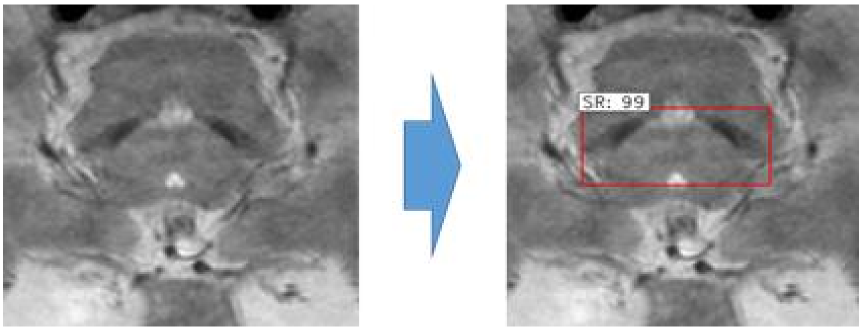
As shown in [Fig. 6]. A 10-layer CNN that includes seven convolutional layers and three fully-connected layers is defined. The network inputs were 142×70 grayscale images. In the first convolution layers, 256 3×3 filters were used to perform convolution, and we set the step length to 1 and the padding to 2, we used the ReLU function as an activation function. We obtained 256 feature maps with the size of 142×70×256. In the second and third layer, 128 3×3 filters and 32 3×3 filters were used to perform convolution, respectively. And after the third layer, we set a pooling layer, and used a 2×2 filter with a step size of 2. Owing to possible loss of image information during pooling, from the fourth to seventh layers of convolution, we used 32 3×3 convolution kernels for convolution, and hence, the output data at the seventh layer were of size 71×35×32 to reduce the amount of data to prevent overfitting. After the seventh convolution layer, we added a pooling layer, and used a 2×2 filter with a step size of 2. Owing to possible loss of image information during pooling, we used maximum pooling at this pooling layer. We used 200 neurons in the first fully connected layers and 100 neurons in second fully connected layers, still using the ReLU function as the activation function, and we used a dropout of 0.2 to prevent overfitting. In the last layer, we set up three elements, which are the output of the network. In this layer, we used the cross-entropy loss function for calculation.



[Fig. 6] Proposed CNN structure

4. Experimental results and Conclusion

To test the performance of our algorithm, we using Parkinson dataset for test. In the diagnostic area detection phase of Faster RCNN, the ratio of the diagnostic area detected by the algorithm to the actual diagnostic area is obtained by calculating the value of Mean IoU. the dataset consists of 1825 images of which1725 images are used for training, 100 images for testing. The input image and the detected image are as follows:



[Fig. 7] Input image and detection result image

In [Fig. 7], the left side shows the input image, and the right picture shows the SR area detected by the improved Faster RCNN. To test the performance of the improved Faster RCNN, 100 MR images were tested and then compared to the detection performance of the original Fster RCNN algorithm. In order to evaluate the accuracy of the detection frame position, the mean IoU was used as a performance comparison indicator, and the calculation formula for mean IoU is as follows:

$$IoU = \frac{1}{N}\sum_{i=1}^{N}\frac{(D \cap G)}{(D \cup G)}$$

Where D is the size of the detected object frame, G is the size of the ground truth, and the results of the Mean IoU tested using 100 images as shown in [Table 1]:

[Table 1] Compare of mean IoU value

	Faster RCNN	**Improved Faster RCNN**
Mean IoU	81.6%	86.4%

The above results show that the improved Faster RCNN detection algorithm has a Mean IoU value of 86.4% in the diagnostic area of the Parkinson image. This is 4.8% higher than the original Faster RCNN.

After the diagnosable area detection of the image, we will use CNN to classify the detected area. Our images have three categories, which are normal images, Parkinson images, and images that cannot be diagnosed. The size of our dataset is as following table:

[Table 2] The dataset for classification

	Number of images
Normal	2700
Parkinson	2775
Bad image	3300

80% of the data is used for training and then 20% of the data is used for testing. The results of the training and testing are as follows:

[Table 3] The classification result by CNN

	Number of training images	**Number of testing images**	**Accuracy**
Normal	2160	540	98.6%
Parkinson	2220	555	97.3%
Bad image	2640	660	94.5%

The main work of this paper was to study how to use a deep learning method to perform a series of analysis and processing on MR images, thus implementing the classification of MR images.The deep learning algorithm used in this paper is mainly based on the detection algorithm of Faster RCNN and the classification algorithm of CNN. However, there is a high degree of similarity between the MR images, and there is a lot of noise in MR images, which makes the effect detected by the Faster RCNN algorithm unsatisfactory. Therefore, the original algorithm needs to be improved.

In this paper we using the improved Faster RCNN algorithm to detect the MR image,then a custom CNN network for classification can be used. Test result show that the value of the Mean IoU obtained by the improved Faster RCNN by 4.8%, which higher than the original algorithm, reaching 86.4%. At the same time, the accuracy of the classification phase also increased by 3.7% to 96.8%. Future works, we will continue to focus on the diagnostic area detection of MR images. Due to the great similarity among the MR images, there are still several MR images that cannot be judged in test. This issue need further research and study. At the same time, the speed of the algorithm can also be improved. In this way, we help to diagnose more clearly Parkinson's disease and give doctors more time to improve health care.

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