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Preliminary diagnosis of Parkinson’s disease based on convolutional neural network

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Abstract. The mainstream examination for Parkinson’s disease is still to determine the Unified Parkinson’s Disease Rating Scale (UPDRS), it can be inaccurate due to doctors’ or patients’ subjectivity. But recent studies have shown that patients of Parkinson’s disease will represent a certain extent of dysgraphia in the early stage. Based on this feature, we proposed a method to realize the preliminary diagnosis for Parkinson’s disease based on patients’ hand-drawings. In this paper, after the images that we used are pre-processed based on Threshold Segmentation, we set a 4-layer network for Convolutional Neural Networks (CNNs). First, we design a convolutional layer to learn the local features of hand-drawing, then the image is passed to then Maxpooling to go through the maximum pooling operation to preserve the contour features and to remove extraneous information. We set up two fully connected layers to capture more nonlinear relationships between images and labels. In the last, an accuracy calculation formula is adopted to diagnose Parkinson’s disease. Overall, this diagnosis scheme that only requires patients’ hand-drawing can be completely automatic and more convenient than the traditional examination, the accuracy of result can be further improved if more details in the hand-drawing can be gathered.

Keywords: Parkinson’s disease, Convolutional neural network, Deep learning, Hand-drawing.

1. Introduction

Parkinson's disease remains a problem for researchers because it is difficult to treat. This disease has great harm. First, patients with this disease are prone to balance disorders, unstable walking and easy to fall. Once a fall occurs, it is very easy to lead to fractures, craniocerebral trauma and other serious complications [1]. Secondly, many patients with Parkinson's disease are accompanied by depression and anxiety, which will seriously threaten their mental health and have a great impact on their social communication function [2]. Third, Parkinson's disease patients to the late once bedridden, very easy to appear lung infection, bedsores and other complications after research found that patients in the early stage of Parkinson's disease will appear muscle tremor paralysis symptoms [3].

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According to statistics, in 2018, more than 6 million people worldwide were living with Parkinson's syndrome and 1.03 million died of Parkinson's disease. The annual rate of new cases has reached 0.00018 percent. About 2.6 million people in developed countries in Europe and the United States suffer from the disease. There are 120,000 new cases a year. The number of patients is rising annually as a result of an aging society. This places a significant cost on society as well as placing great financial strain on the relatives of the sufferers. Currently, the number of Parkinson's disease patients in China is nearly 3 million, half of the world's Parkinson's disease patients are in China. Experts predict that the number of Parkinson's disease patients in China will reach 5 million by 2030 [4]. Data show that the proportion of people over 60 years old with Parkinson's disease is more than 1%, and the rate of people over 70 years old with Parkinson's disease is 3%-5% [5]. Therefore, the probability of Parkinson's disease increases with age.

As information science and technology progress, biological signals can be analyzed digitally to a greater extent. Increasing degrees of convenience are now available to doctors because to advancements in information processing technologies and declining hardware costs. Among them, hand-drawn signal analysis is frequently used in non-invasive disease diagnosis and treatment because it can not only assist medical professionals in identifying various stages of neurological disease but also assist both medical professionals and patients in determining the efficacy of the prior treatment strategy. Particularly in the early stages of Parkinson's disease diagnosis, this technique is employed [6]. The fingers, wrist, and elbow move in unison to create the hand-drawn signal. We can significantly aid in the early detection and treatment of Parkinson's disease by the study of these signals [7]. The traditional diagnosis method of Parkinson's disease based on hand-painted pictures is to extract relevant features from hand-painted pictures, and then use machine learning classification algorithm to achieve early diagnosis of Parkinson's disease. Due to the relatively few features extracted from the hand-painted map, the accuracy of the training model in diagnosing patients is very low, which leads to the poor diagnostic performance of traditional Parkinson's disease diagnosis methods. Therefore, this paper builds a convolutional neural network model to achieve early diagnosis of Parkinson's disease. Hand-drawn drawings of Parkinson's patients and normal people are used as data to analyze through convolutional neural network. After a series of debugging, the final pre-diagnosis results are basically consistent with the actual results, which proves that the neural network has the ability of pre-diagnosis for Parkinson's disease patients.

2. Method based on deep learning

2.1. PD hand-drawn dataset

In this study, we adopt the dataset “Parkinson’s Drawings” from Kaggle [8]. This dataset consists of 204 hand-drawn samples (with 256*256 resolution) that are divided into spiral and waveform drawings of the healthy and Parkinson’s patients. And they are further classified into training set and testing set respectively to compare the experimental results. Each test was divided into 30 images, and the training set was divided into 72 images. The number of samples from the healthy and Parkinson’s patients was the same. In order to make the results of this study more accurate, the sample are also preprocessed.

2.2. Image processing method

2.2.1. Image threshold segmentation. It is observed that the color in the picture is relatively single, and the black and white information of the line and the background is more obvious. Therefore, the image threshold segmentation method is used to remove the color information unrelated to the hand-painted image. The idea is to divide the image into a mixture of two types of regions with different gray levels by using the difference in gray level between the target and the background to be retrieved in the image. The associated binary picture is formed by choosing an appropriate threshold to decide whether each pixel in the image should belong to the target region or the background area. It can be seen from the data that the gray difference between the target image and the background is significant. Threshold segmentation can better extract the information of the target image, reduce the interference of irrelevant disturbances, and improve the computational efficiency of the neural network. Figure 1 presents the sample images of the original and preprocessed images.

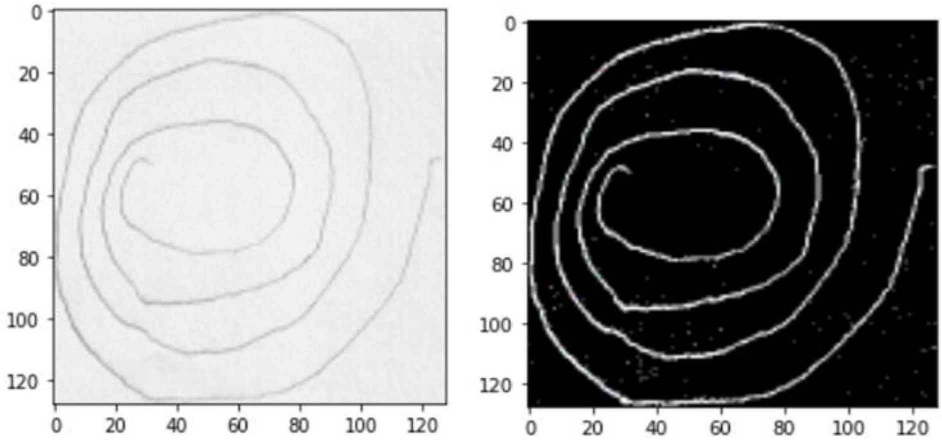

Figure 1. In Original and corresponding processed sample image.

2.2.2. Median filter. In From the above processing results, it can be found that there are many white random noise in the image background, we use median filtering to remove the noise. Median filtering is a kind of nonlinear smoothing filter. The basic idea is to rearrange the pixels from small to large in a filter template, and replace the pixel value to be processed with the middle position value of all pixels in the filter window region. Let g (x, y) be the central pixel value, S (x, y) be the m * n filter window of the central point in (x, y), and g (x, y) be the median filter. The output is as follows:

$$G(x,y)=\text{median}\{g(s,t)\}\ (s,t)\in Sxy \tag{1}$$

Processing the image with a size of 3*3median filter, the sample output can be found in Figure 2.

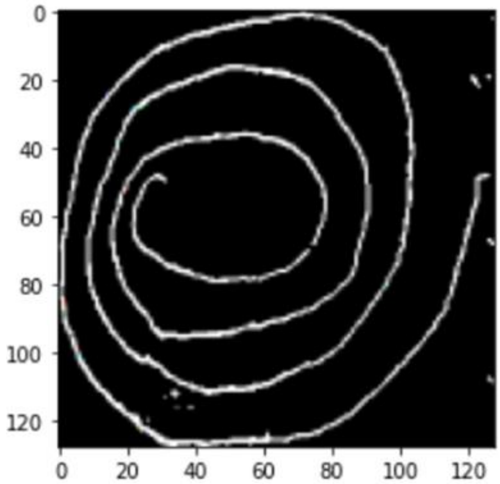

Figure 2. The sample image that has been processed by 3×3 median filter.

2.3. Building convolutional neural networks

Convolutional neural network is a kind of forward feedback neural network which contains convolution operation and has a deep structure, which is widely used in many fields [9, 10]. Compared with the traditional neural network, CNN can recognize the automatic convolution of the feature

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domain of interest in the image with a local receptive field. Then, the model can realize fast learning of similar features based on weight sharing. Finally, CNN pools the image to preserve contour or background information. Its main structure includes input layer, convolutional layer, pooling layer, fully connected layer and output layer.

The convolutional layer is mainly responsible for image feature acquisition, which is used to initially extract features from the hand-drawn image array. Setting each convolution kernel can be used to extract a feature in the hand-drawn image information. The number of convolution kernels determines the number of features output by the convolution layer. By setting the appropriate convolution layer values, it can ensure that the image features are not lost and can be accurately identified.

The pooling layer is mainly responsible for image feature mapping. The main method to improve the generalization ability of hand-drawn images is to complete the mapping of hand-drawn image convolutional neural network features. The array processed by mapping should be more characteristic and easier to be recognized by neural network. This project uses the maxpooling2D function in the keras structure for feature mapping, which retains the input features while reducing the parameters to be processed and reducing the amount of comprehensive computation, effectively preventing feature overfitting and improving the adaptability to new samples.

The fully connected layer is mainly responsible for the recognition and classification of features. The fully connected layer plays the role of mapping the learned sample features to the sample label space. This project uses the fully connected layer for feature recognition. The most important thing is to set the number of neuron nodes and activation function, choose the appropriate way to fully connected layer training. If the activation function is not set to the current dataset, gradient explosion may occur. Whether the activation function is selected or not will affect the accuracy of the neural network for feature recognition and the correctness of the activation function for image classification.

The Dropout layer prevents overfitting. The model becomes more generalized and less reliant on specific local properties when we allow the activation value of a neuron to stop operating with a given probability p in accordance with the Bernoulli distribution during forward propagation.

We set up a 4-layer network for CNN. First, we design a convolutional layer with 32 5 * 5 2D convolution kernels to learn the local features of the hand drawing. The activation function is relu. Since the hand drawing used is a color map, the channel set is 3. It is worth noting that the classified images contain a large amount of background, so we pass the image to Maxpooling for maximum pooling operation to preserve the contour features of the image. In order to better preserve the jitter features of the lines in the hand-drawn image information, the poolsize is set to 2 * 2. Further, in order to acquire more nonlinear relationships between images and labels, we set up two fully connected layers to capture this relationship. The activation function of the first fully connected layer is Relu, and the second fully connected layer is used for classification. Select the softmax activation function. In between, the Flatten layer is set up to join convolution and full join operations. Due to the small sample size, after the two fully connected layers, we set the dropout layer to prevent overfitting, and set the probability of neurons not participating in training in each round of training to 0.5.

During model training, epochs are set to 20, and the number of samples per iteration is set to 64. The model optimizer selects adam, the loss function in the model adopts the cross entropy loss function, and the evaluation function selects accuracy.

3. Results and discussion

3.1. The performance of the model

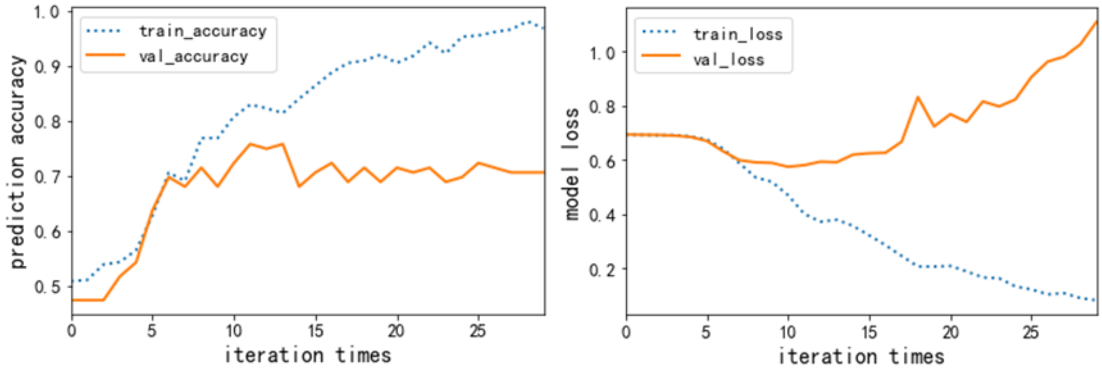

Figure 3. The prediction accuracy and the corresponding loss based on the model.

It can be seen from the Figure 3 that the accuracy of the training set increases with the number of iterations, but the accuracy of the validation set is more unstable in 0-10 iterations, and tends to remain unchanged in subsequent iterations. In the model loss, as the number of iterations increases, the training loss decreases, and the loss of the validation set decreases first and then increases. Obviously, the model has overfitting during the training process.

Table 1. The validation loss and accuracy of regularization methods.

Regularization method	Validation loss	Validation accuracy
Non regularization	0.512	0.6917
L2punishment	0.4929	0.7124
Drop out	0.4892	0.7182

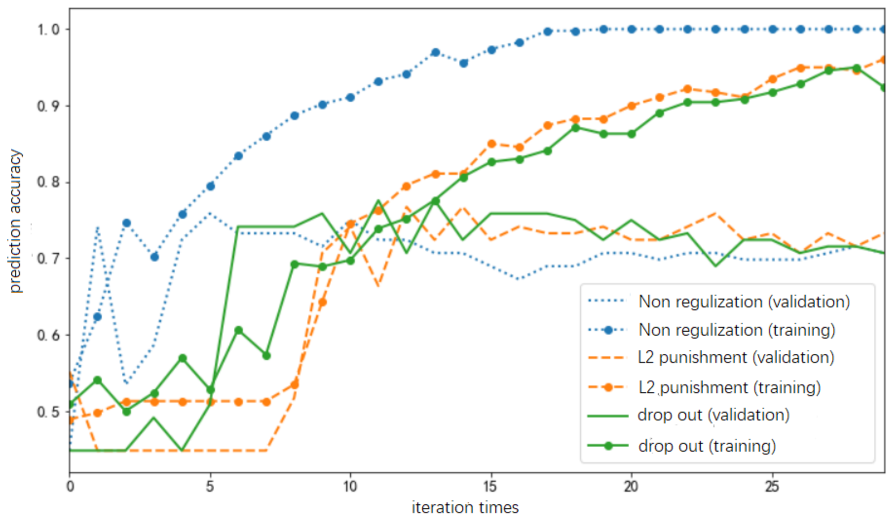

Figure 4. Accuracy based on three methods in training set and testing set.

For the over-fitting phenomenon, we use the L2 regularization method and the discard method for processing. The results are shown in Table 1 and Figure 4 Compared with the model without regularization, the loss of the validation set of the model after regularization is reduced, while the accuracy of the validation set is increased. Compared with L2 regularization method, discarding method works better. The verification set loss is reduced to 0.4892 and the verification set accuracy is

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increased to 0.7182. It can be seen from the prediction accuracy of Figure 4 that the accuracy of the validation set of the three methods is significantly improved in the 5-10 rounds of iterations, and tends to converge in the 10-30 rounds of iterations.

From the results of Figure 4 it is not difficult to see that although the regularization method improves the accuracy of the model, the model is still overfitting. Observing the data set, we find found that although image threshold segmentation enhances the feature information of hand-drawn graphics, the data is still not sufficient. Image rotation and other processing do not really solve this problem, resulting in insufficient learning of hand-drawn graphics features. In the process of image data processing, some information is deleted. For example, in the process of image threshold segmentation, the information of line depth in the original image is lost. Because Parkinson 's patients exhibit tremor-like symptoms early on, the depth and thickness of the lines in some hand-drawn images are not regularly distributed compared to healthy people. If this information is extracted, it can also be of great help to model recognition. Simultaneous PD diagnosis based on deep learning improves model recognition as data is collected.

4. Conclusion

In this work, we proposed the preliminary diagnosis Parkinson's disease based on hand drawing to avoid inaccuracy caused by human subjectivity. We first set a 4-layer network for convolutional neural networks to let computers to learn the features of images, then an accuracy calculation formula is adopted to diagnose Parkinson's disease. We conducted a large number of experiments to evaluate the effectiveness of this method. Experimental results represent that this model has relatively high accuracy, but it is still overfitting. In the future, we will try to extract more features from the images to further improve the ability of model recognition.

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