



Improvement of Image Recognition by Depth Neural Network

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Abstract—Based on the existing research at home and abroad, this paper studies the improvement of image recognition by depth neural network. By using MATLAB and other software to process the data, we get more realistic results, which will play an important role in the future research of image recognition.

Keywords— Image Recognition, Intelligent Detection, Depth Neural Network.

I. INTRODUCTION

At present, many countries have applied intelligent systems in medical images, so as to achieve accurate processing of medical results. The application of computer as a new technology in medical image processing has become an inevitable trend of development. Many people have studied the application of computer in medical image processing and achieved some results. For example, some scholars used computer vision system to recognize and analyze the fundus image, and used genetic neural network to classify the fundus color, and applied the chroma matrix to identify the fundus lesions. With the continuous deepening of researchers, in order to get a clear outline of the fundus, the overlapping fundus method of mathematical morphology is used to calculate the position of the fundus and improve the clarity of the image. Although there are some achievements in the research of intelligent recognition in image processing, there is still a certain distance from practicability, so further research is needed.

II. OPTIMAL DESIGN OF DEEP LEARNING NETWORK

Pathological images show obvious features in geometric structure. Under the same conditions, pathology can usually show common features, and the features of lesions are similar to each other in varying degrees. According to this characteristic, it provides theoretical support for solving the lesion.

In order to achieve the purpose of automatic image recognition, the automatic lesion recognition machine should first have the ability to automatically extract the geometric characteristics of pathological images. At the same time, in the process of image recognition processing, image distortion, translation and rotation will occur due to environmental factors, which will affect the accuracy of image transmission. In order to eliminate the interference of this phenomenon, a graph is adopted. Image recognition system. In addition, in the target of helpless machine learning with non-feature information in diseased image, it must be filtered, otherwise it will provide obstacles to the operation of the network.

In combination with the above process, the network introduces sampling components and convolution components, which can meet the need of removing redundancy in the process of image extraction, and convolution components are used to extract geometric features of lesion images. Through multi-level convolution sampling process, the network can extract image features.

Network Structural Parameter Design

In the process of learning network operation, the nodes or components in the same column are named "layer", and the weight of connecting the output node and the input node is named

"connection". Information flows from the output node to the input node in one direction. Layers and layers are bridged by links. Two adjacent links are separated by layers. Multilayers in turn form a learning network structure, which is stored in the structure of connection parameters defined in the input layer.

Analysis of Network Model

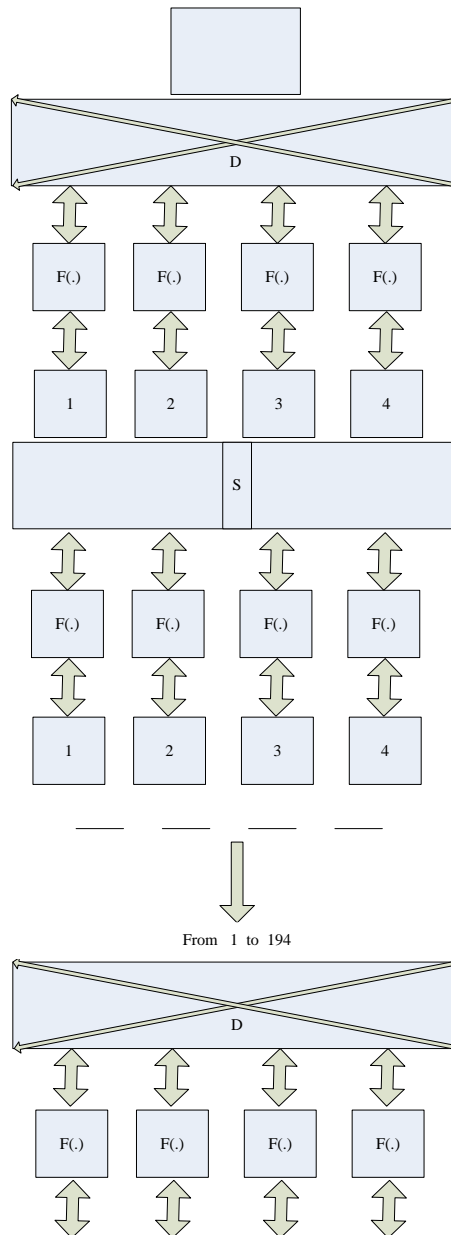


Figure 1. Convolutional Neural Network Logic Structure

As can be seen from the figure, the lesion feature map constitutes a frame sequence, which can be represented by a cube. In the graph, the convolutional full connection is represented by a D-marked rectangle with diagonal lines. The convolution operator between input and output is represented by "connection". Layer input and output are used at both ends. It is shown that the excitation function is represented by a box of intermediate $f(.)$ and that the neuron components constitute a combination, while the peer components are composed of layers. Convolutional through connection is a rectangle with double vertical lines labeled by "S". Usually the operator is a constant, connecting the same

number of frames. In view of the loss of information in the sparse network structure, the sparse convolution connection structure of the five-level deep neural network is neglected, and 194 corresponding eigenvalues are obtained by full connection and recursion at one time, which is used as the input of the neural network. Then, for the middle of the non-alphabetical diagonal marking to represent the form of full connection, after the excitation function, the maximum voting value is obtained as the output of the component.

Layer parameters and connection parameters constitute the training parameters of the network, and the convolution network simplifies the algorithm flow.

III. TRAINING RESULTS

Four common subsets of image data of lesions are selected and trained by network. 400 samples are tested to get the corresponding confusion matrix graph, as shown in Figure 2.

96.8%	0	4	0	120
3.2%	0.0%	0.8%	0.0%	24.0%
99.3%	1	0	133	0
0.7%	0.2%	0.0%	26.6%	0.0%
99.1%	1	112	0	0
0.9%	0.2%	22.4%	0.0%	0.0%
98.4%	127	2	0	0
1.6%	25.4%	0.4%	0.0%	0.0%
98.4%	98.4%	94.9%	100%	100%
1.6%	1.6%	5.1%	0.0%	0.0%

Figure 2. Target output obfuscation matrix

As can be seen from the figure above, 120 output classes (5,5) in the grid are shown as I, accounting for 24% of the total, and four output classes (3,1) in the grid are shown as I, accounting for 0.8%. Generally speaking, the recall rate is about 98%. For the data of lesion image, the recall rate of this method is relatively high and the effect is relatively good.

Fig.3 shows the comparison between the true average speed and predicted average speed over the next 45 minutes. Table 5 shows the comparison of the specific forecasting accuracy indexes in different forecasting periods. The Equality Coefficient (EC) reflects the fit between the predicted value and the true value. Generally, it is considered to be a better fit when EC is bigger than 0.9. Its expression is as follows:

$$EC = 1 - \frac{\sqrt{\sum_{i=1}^n (x_i - \hat{x}_i)^2}}{\sqrt{\sum_{i=1}^n x_i^2} + \sqrt{\sum_{i=1}^n \hat{x}_i^2}} \quad (1)$$

In the formula, n is the predicted number of samples, \hat{x}_i is the predicted value, x_i is the true value.

Table 5 Comparison of prediction accuracy indicators in different prediction periods

Prediction period	MRE (%)	Accuracy (%)	EC
15min	1.63	99.25	0.986
30min	2.29	95.86	0.982
45min	5.77	83.73	0.961

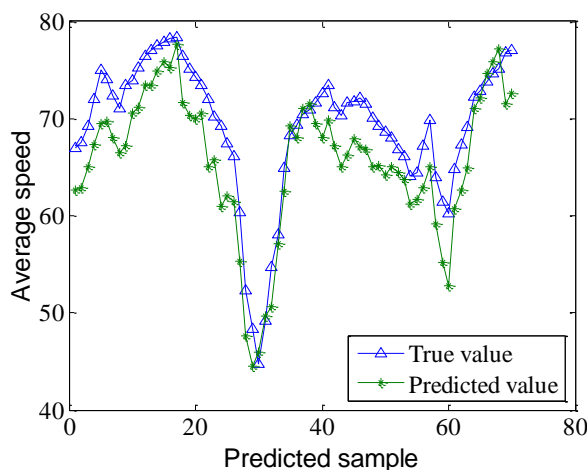


Figure 3. Comparison of traffic speed prediction in the future 45 minutes

Simulation results show that with the prolongation of the prediction time, the prediction accuracy will also decrease, but the accuracy of the various prediction periods can be maintained at a relatively high level. In the first part, the predicted MRE is less than 2%, accuracy and EC are higher than 95% and 0.98. In the second part, although the prediction accuracy decreases, but the MRE can still be maintained at less than 6%, accuracy and EC are higher than 83% and 0.96. The simulation results show that the optimized deep BP neural network based on the improved genetic algorithm has higher prediction accuracy and lower error level, it can be used for medium-term traffic flow prediction.

IV. CONCLUSION

In this paper, an image recognition method based on depth neural network is proposed for medical image recognition. The final recall rate is 98% by applying this method to the diagnosis of common diseases in focus image recognition. In addition, the training and comparison between this method and traditional image recognition methods show that the accuracy of this method is improved by 2.1% on average.

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