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Optimization Research and E-commerce Design of Gastrointestinal Electron Microscopic Endoscopy Images Based on Convolutional Neural Networks

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Abstract. The research team backtracked the gastrointestinal electron microscopy manifestations of patients based on the pathological classification of clinical institutions. Through data backtracking, we obtained the diagnostic significance images of the patients. The diagnostic significance images were classified and implemented using convolutional neural networks, with Class A being benign lesions, Class C being malignant lesions, and Class B being non lesions. Based on existing data, we obtained a confusion matrix, and a report was made on the parameters of convolutional neural networks. This convolutional neural network has decent accuracy and can preliminarily meet the needs of clinical institutions, providing a powerful tool for clinical work.

Keywords: Architectural Science; Artificial Intelligence; Neural Networks; Internet of Things; Gastroenterology.

1. Introduction

A product neural network is a multi-layer neural network consisting of multiple independent neurons connected to each other to form a plane, and a complete network composed of multiple two-dimensional planes. Convolutional neural networks generally contain multiple convolutional layers and feature mapping layers, among which the convolutional layer is the most basic structure of a convolutional neural network. Generally speaking, a typical convolutional layer consists of data input, convolutional computation, activation, pooling, and other parts. Among them, the data input layer also includes selective processing of the original data, mainly image whitening processing such as normalization; The purpose of convolution calculation is to achieve feature extraction of images and obtain multiple feature maps by convolving the convolution kernel with input data; Activation improves the network's expressive power through non-linear activation function processing; The pooling layer reduces the size of parameters and lowers the complexity of the network through max pooling or average pooling.[1-5] The weights of all neurons on the feature mapping layer are the same, and the image features are mapped through logistic regression and ReLu activation. The last feature mapping layer outputs the results through softmax. Taking this study as an example, a total of 18 convolutional kernels were used in the convolutional layer, and maximum pooling was used to extract effective image features to prevent overfitting and improve the model's generalization ability; The feature mapping layer constrains the possible negative values in logistic regression through the ReLu function, and the final layer outputs the classification results through softmax..Therefore, interdisciplinary research is also necessary[6-9].The team reported on the application of this technology in gastroenterology.

2. Result

2.1. Judging patient sample typing through pathological reports

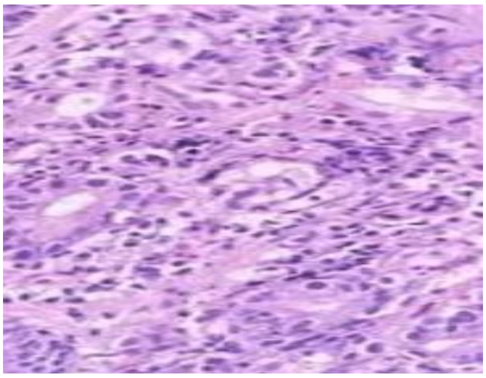

Figure 1. Examples of pathological samples

Pathological images are the beginning of the entire traceability process. We start by tracing the images of patients under electronic fiber endoscopy through pathology. This working mechanism depends on the information system of current hospitals in China, and we can complete this step through this information system.

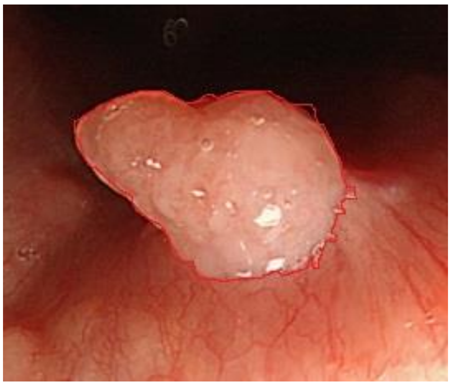

Figure 2. Morphological analysis through endoscopic lesion labeling in the digestive tract

Use QUPATH (https://qupath.readthedocs.io/en/0.5/)to mark and find target of disease tissue.

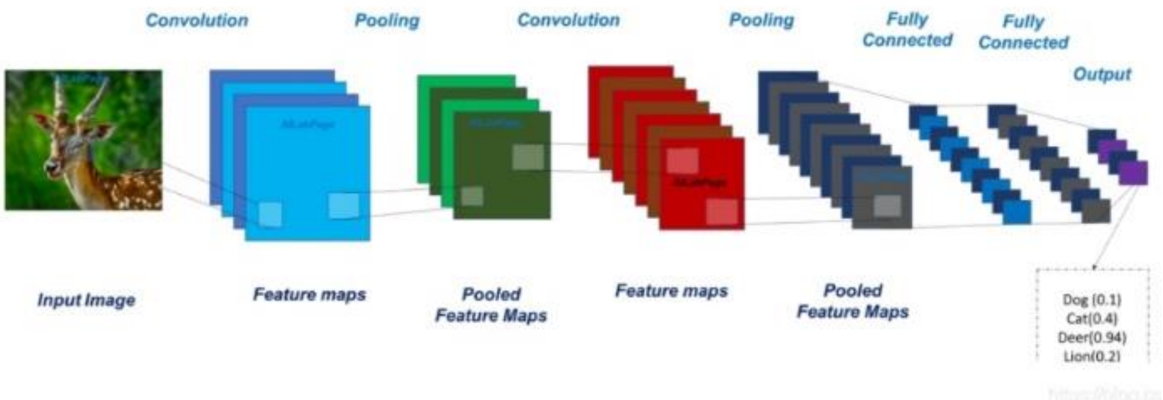

Figure 3. The working mechanism of convolutional neural networks

The relevant codes are as follows:

```
Options. solverName='sgdm‘; % Solver, sgdm (default) | rmsprop | adam

Options MaxEpochs=20; % Maximum number of iterations, default to 30

Options InitialLearnRate=0.03; % Initialize learning rate (default 0.005)

Options Plots='training progress'; % Whether to display the training process, 'none' is not displayed (default) | 'training progress' is displayed

Options Validation Frequency=10; % Verification frequency, which refers to the number of iterations between which validation is performed

Options LearnRateSchedule='piece news'; % Does the learning rate decrease after a certain number of iterations

Options LearnRateDropFactor=0.9; % Learning rate decline factor

Options LearnRateDropPeriod=100; % Iteration algebra when learning rate decreases

Options Plots='training progress'; % Display training process

Options GradientThreshold=1; % Gradient limit, default to Inf

%Network structure settings

ConLayer=[20, 20, 4, 1, 2;% Wave height is 5, width is 5, number of filters is 32, step size is 1, fill 2

20, 20, 8,1, 2; % Wave height 5, width 5, number of filters 128, step size 1, fill 2

20, 20, 16, 1, 2; % Wave height is 5, width is 5, number of filters is 256, step size is 1, fill 2

PoolingLayer={'maxPooling2dLayer ', 40, 40, 2, 0;% max pooling layer, size 3 * 3, step size 2, fill 0

'maxPooling2dLayer ', 40, 40, 2, 0; % Maximum pooling layer, size 3 * 3, step size 2, fill 0

'maxPooling2dLayer ', 40, 40, 2, 0}; % Maximum pooling layer, size 3 * 3, step size 2, fill 0

FcLayer=[]; % No additional fully connected layers will be set up
```

Figure 4. The Architecture of Convolutional Neural Networks

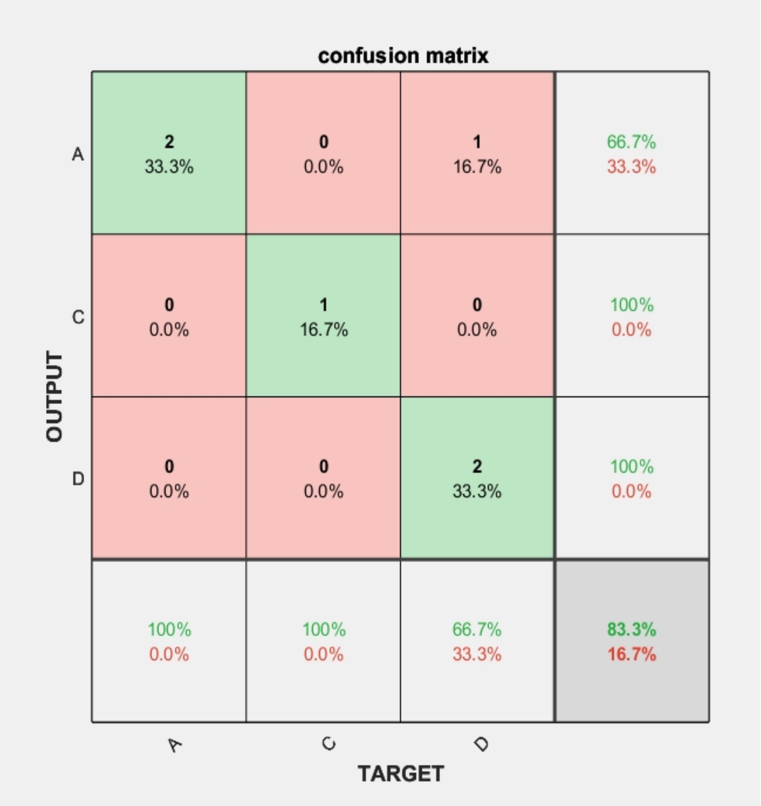

Figure 5. Confusion matrix after training

The parameters of a convolutional neural network are as follows.

16 with the following layers × 1 Layer array:

1 " Image Input 768 × seven hundred and sixty-eight × 3 images: 'zerocenter' normalization

2 " 2D Convolutional 4 20 × 20 convolutions: stride [1 1], padding [22 2 2]

3 " Batch Normalization Batch Normalization

4 " ReLU ReLU

5 " 2D max pooling 40 × 40 max pooling: stride [2 2], padding [0 0 0 0 0]

6 " 2D Convolutional 8 20 × 20 convolutions: stride [1 1], padding [22 2 2]

7 " Batch Normalization Batch Normalization

8 " ReLU ReLU

9 " 2D max pooling 40 × 40 max pooling: stride [2 2], padding [0 0 0 0 0]

10 " 2D Convolutional 16 20 × 20 convolutions: stride [1 1], padding [22 2 2]

11 " Batch Normalization Batch Normalization

12 " ReLU ReLU

13 " 2D max pooling 40 × 40 max pooling: stride [2 2], padding [0 0 0 0 0]

14 " fully connected 3 fully connected layers

15 " Softmax softmax

16 " classification output crossTropyex

Output size of each layer network.

1. Layer 1 (nnet. cnn. layer. ImageInputLayer): Output size=[768 768 3]
2. Layer 2 (nnet. cnn. layer. Convolution2DLayer): Output size=[753 753 4]
3. Layer 3 (nnet. cnn. layer. BatchNormalizationLayer): Output size=[753 753 4]
4. Layer 4 (nett. cnn. layer. ReLULayer): Output size=[753 753 4]
5. Layer 5 (nnet. cnn. layer. MaxPooling2DLayer): Output size=[357 357 4]
6. Layer 6 (nnet. cnn. layer. Convolution2DLayer): Output size=[342 342 8]
7. Layer 7 (nnet. cnn. layer. BatchNormalizationLayer): Output size=[342 342 8]
8. Layer 8 (nett. cnn. layer. ReLULayer): Output size=[342 342 8]
9. Layer 9 (nnet. cnn. layer. MaxPooling2DLayer): Output size=[152 152 8]
10. Layer 10 (nnet. cnn. layer. Convolution2DLayer): Output size=[137 137 16]
11. Layer 11 (nnet. cnn. layer. BatchNormalizationLayer): Output size=[137 137 16]
12. Layer 12 (nett. cnn. layer. ReLULayer): Output size=[137 137 16]
13. Layer 13 (nnet. cnn. layer. MaxPooling2DLayer): Output size=[49 49, 49, 16]
14. Layer 14 (nett. cnn. layer. FullyConnectiedLayer): Output size=[1 1 3]
15. Layer 15 (nett. cnn. layer. SoftmaxLayer): Output size=[1 1 3]
16. Layer 16 (nett. cnn. layer. ClassificationOutputLayer): Output size=[13]

The classification accuracy of the test set is 0.83333

As shown in Figure 3, we trained the convolutional neural network using the 25 images we collected. The code is analyzed in the following text, and we implemented the model for the initial design.

The confusion matrix shows the situation of incorrect recognition, which we believe is acceptable.

3. E-commerce Design

Figure 6. Principles of e-commerce systems for selling code

E-commerce is a way of conducting various business activities in an electronic network environment connected through certain protocols, utilizing existing computer hardware, software equipment, and network infrastructure. Generally speaking, the understanding of e-commerce can be approached from both broad and narrow perspectives. Broadly speaking, e-commerce refers to the entire process of using computer and network technology, modern information and communication technology, and electronic tools to achieve commercial exchanges and administrative operations, including electronic transactions, according to certain standards. Therefore, we believe that current online transactions and simplified processing are directions that can be optimized. Our code can be implemented through a simple programming language and then used as a cloud for other users to access, which can reduce the threshold for propagation.

4. Discussion

The main goal of medical image recognition is to efficiently and accurately extract useful pathological information from massive medical images, providing a solid foundation for medical research, clinical diagnosis, and disease treatment. At present, convolutional neural networks have become the preferred algorithm for medical image recognition. Convolutional neural networks are based on convolutional algorithms and pooling algorithms, gradually extracting pathological information from the target image, and collecting the extracted image features into higher-order features to complete the recognition and diagnosis of medical images. After learning a large number of sample images, deep learning algorithms may obtain feature information that exceeds the practical experience of doctors. They can make efficient judgments from the perspective of experts, reducing the burden on doctors and improving the efficiency and accuracy of diagnosis and treatment. This is of great significance for the development of modern medicine.

5. Conclusion

We have preliminarily achieved pathological classification through preliminary experiments, but due to the limited amount of data, we believe that exchanging ideas through meetings and collaborating with global peers can improve the efficiency of our convolutional neural network. We have verified the feasibility of the algorithm and proposed open discussions on data volume. We hope that relevant professionals from around the world can contact us for cooperation, Optimize the performance of this convolutional neural network.

Acknowledgments

This article did not conduct clinical trials, and the ethical approval for this experiment was based on Chifeng Cancer Hospital, with the code CNJYH23.

The data can be requested from the corresponding author at the end.

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