Research of Classification of Palmprint Based on Deep Learning

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Abstract

After many years of clinical research in traditional Chinese medicine, it was found that the large thenar part of the palm was related to allergic reactions such as the asthma. This paper classifies the thenar part of the palm according to the characteristics of the wrinkles through the transfer learning in the depth learning, so as to play an assistant role in the diagnosis.

Keywords: Deep Learning, Inception V3, Great thenar palmprint, CNN.

1. Introduction

Traditional Chinese medicine has a long history in Asia. With the development of modern science and technology, the intelligentization of Chinese medicine has gradually become a boom. As early as the 1980s, Sun Tongjiao developed a diagnosis and treatment system for hepatitis B experts based on research on hepatitis B. Zou Yunxiang After conducting in-depth research on diseases of the kidney system in Chinese medicine, a computerized diagnosis and treatment and nursing system was developed. Over 140 Chinese medicine diagnosis expert systems have been developed nationwide during this period. Nowadays, with the rapid development of AI technology, the development of artificial intelligence in medicine can be seen everywhere. For example, some sub-healthy physical condition detectors can quickly detect whether the human body is in the sub-health stage and the coefficients of various physical indicators in just a few minutes, and give a test result and intimate reminders. Not only these aspects, AI also has certain achievements in medical treatment: such as medical robots, intelligent drug development, intelligent diagnosis and treatment systems, and auxiliary diagnosis systems. The upsurge of intelligent informatization of Chinese medicine diagnosis is rapidly developing, which has further promoted the modernization of Chinese medicine and provided many conveniences for people's daily life.

In Chinese medicine, after years of diagnostic experience, Chinese medicine experts have discovered that the thenar part of human palm prints can be found to be related to asthma and other allergic diseases in terms of its lines and roughness. Traditional Chinese medicine can provide diagnostic evidence for some allergic diseases through the characteristics of palm prints in the thenar area. However, TCM judges the condition through observation, pulse diagnosis, inquiry and research, which is subjective. If it is possible to identify and classify the collected large thenar palm print pictures through a computer, according to certain quantification rules, extract the characteristics of the yin and yang large thenar palm prints, and then classify them. Because computer recognition has a certain degree of objectivity, it can play a certain auxiliary diagnostic role in TCM diagnosis and provide convenience for TCM diagnosis.

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This article mainly uses deep learning to classify palm prints in the thenar area. According to the relationship between the palm prints of the thenar and asthma and other allergic diseases and their characteristics, collect data sets, preprocess the data images, intercept and segment the thenar regions, and use the TensorFlow framework and GoogleNet's inception V3 model to compare the large thenar part of the palm is classified, so that the model can correctly classify the negative and positive large thenar palm prints under a certain high probability, so as to assist in the diagnosis. However, due to the small difference in characteristics between the two types of thenar palm prints, especially for some pictures of thenar palm prints on both sides of the yin and yang big thenar palm prints, it is also difficult to distinguish between the two types of thenar palm prints by human eyes., So the computer can be used as an objective reference when classifying in this case.

2. Design of Thenar Palmprint Classifier

In this paper, the TensorFlow framework is used for image numerical calculation, and the inception V3 model is used to classify and train large thenar palm prints.

2.1. Pretreatment for classification of thenar palm prints

In the long-term clinical practice of Chinese physicians, it is found that the palm prints of the big thenar can be divided into negative (level I, II) and positive (level III and IV) according to their texture characteristics. Among them, the feminine thenar palm prints are smaller in spacing, presenting a small lattice pattern, with fine mesh, shallow grooves, and more delicate touch; the positive thenar palm prints are larger in spacing, presenting a large lattice pattern, and are distributed Uniform, deep grooves, clear lines, rough touch.



Fig.1 Negative palmprint and Positive palmprint

2.2. Design of classifier based on convolutional neural network

The network structure of convolutional neural network is divided into input layer, convolutional layer, ReLU layer, pooling layer and fully connected layer. The network structure of convolutional neural network is divided into input layer, convolution layer, ReLU layer, pooling layer, fully connected layer and output layer. However, in practical applications, the convolutional layer and the ReLU layer are often collectively referred to as the convolutional layer.

2.2.1. Convolutional layer

In the convolutional layer, the feature map of the previous layer is convolved by a learnable convolution kernel, and then through an activation function, the output feature map can be obtained. Each output feature map can be combined to convolve multiple feature maps value.

 u_{j}^{\prime} The net activation of the jth channel of the convolutional layer l.

 x_i^{l-1} Output feature map of the previous layer.

 $x_{j}^{'}$ Is the output of the jth channel of the convolutional layer l.

*Is the convolution symbol.

 \mathbf{k}_{ij}^{l} Is the convolution kernel matrix

 b_j^l Is the bias of the feature map after convolution.

 M_{j} Is a subset of the calculated input feature map.

2.2.2. Pooling layer

After the original data image of the thenar palmprints is calculated by convolution, it is necessary to perform the pooling operation on the feature map of the thenar palmprints obtained by the convolution to perform spatial size compression. Commonly used pooling operation methods are average pooling and maximum pooling. The pooling layer of the thenar palmprint classification in this paper selects the maximum pooling.

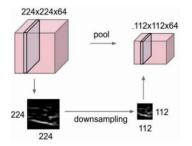


Fig.2 Pooling layer processing effect

2.2.3. Fully connected layer

Through convolution and pooling, the local features of the big thenar palm print image are extracted. Full connection uses the weight matrix to combine the local features of the previous big thenar palm print image into a complete image.

$$\begin{aligned} x^{l} &= f(u^{l}) \\ u^{l} &= w^{l} x^{l-1} + b^{l} \end{aligned} \tag{2}$$

u' The net activation of the fully connected layer 1.

 W^{l} Is the weight coefficient of the fully connected network.

 $b^{'}$ Is the bias term of the fully connected layer 1.

2.2.4. Activation function

In the training process, a function is needed to convert the input large thenar palm print image into an output value to facilitate more intuitive classification. This function is called an activation function. The function of the activation function is to add some non-linear factors to solve the difficulties that cannot be solved by the linear model. The activation function used in this article is the ReLU function.

$$h(x) = \begin{cases} x \ (x > 0) \\ 0 \ (x \le 0) \end{cases}$$
(3)

2.2.5. Softmax classifier

In the output layer, the activation function corresponding to the output layer needs to be selected according to the corresponding goal to be achieved. Generally speaking, if it is a regression problem, use the identity function; if it is applied to image classification research, use the softmax function.

For the study of palmprint classification in this article, the SoftMax function, also known as the normalized exponential function, is used, and the result is a real number between 0.0 and 1.0. The distance between the two probability distributions obtained from the cross entropy function is processed by the Softmax classifier, and the probability distribution of each mutually exclusive output class is returned, so that the range of each element is between (0,1) and the sum of all elements The time is 1.

$$Softmax(z_i) = \frac{e^{z_i}}{\sum_{c=1}^{C} e^{z_c}}$$
(4)

 z_i Is the output value of the i-th node.

C Is the number of output nodes, that is, the number of categories.

2.3. Chapter summary

This chapter mainly describes the data collection, classification and processing of palmprints in the thenar region, the levels of convolutional neural networks in deep learning, and the functions and functions of each level. In actual operation, feature extraction is performed on palmprint images of the thenar area during the training process, and then the size of the extracted feature maps is compressed, and the category of a certain thenar palmprint image is output through the objective function in the fully connected layer. The probability value of the trend.

3. Results and analysis

Create a new test folder and use the data pictures in the test file to test the accuracy of the model. The test results are as follows.

Table1 .Model Test Re	esult.
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Classification of palmprint	Recognition accuracy
Negative	88.2%
Positive	85.7%

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From the results, it can be seen that using inception V3 has a high accuracy in the palmprint classification of the large thenar area, and it is an effective model.

3.1 Analysis

When the test set pictures are used for verification, the recognition of the more obvious thenar negative palmprints and positive palmprints can reach more than 90%.



negative (score = 0.91046) positive (score = 0.08954)

positive (score = 0.91335) negative (score = 0.08665)

Fig. 3 Test result

4. Summary and Reflection

This article mainly applies deep learning to the classification of palm prints of the big thenar, preprocessing the collected data, and intercepting the big thenar area of the palm. According to the characteristics of palm prints in the large thenar area of asthma and other similar diseases, the data set is divided into two types, negative and positive, for training the model.

However, due to the complexity of the thenar palmprint image and the limitations of existing conditions, there are still some shortcomings and areas for improvement. First of all, it is necessary to continuously enrich the data set, collect more data of large thenar palm prints, and establish a database to make the training results more convincing. Second, choose a better model or algorithm, which can improve the classification accuracy.

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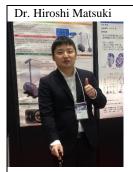
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Authors Introduction



She is graduated from Ludong University in China in 2014, and went to Japan to study in the same year. Currently studying for a master's degree at Ashikaga University in Japan



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