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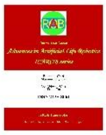

Research Article

Diagnostic Aid of Palm Image Relating to Asthma Based on Convolution Neural Network

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ABSTRACT

In the long history of TCM, it has been said that the shape and number of wrinkles, the depth of the wrinkles and the roughness of the matricular area of the palm are closely related to medical conditions such as asthma and allergic diseases. This study focuses on palmprint classification using deep learning based on TCM. This paper made the palm image dataset according to the characteristics of the wrinkles. In training, an inception V3 model using the Tensor Flow framework and Google Net was used to correctly classify the palmprint part of the thumbprint as negative or positive with a certain probability. This result expected to facilitate diagnosis to asthma and allergic diseases.

1. Introduction

Chinese medicine has long been widespread and widely developed in Asia. It differs significantly from Western medicine in its treatment policy, which is to look at the subject's overall systemic symptoms to determine the disease state. In 2017, the term Chinese medical was systematised and the name TCM was decided upon.

However, in recent years, engineering technology has been steadily making inroads in TCM, including the use of intelligent systems to systemise the parts of the treatment that have previously been judged by human eyes. For example, in the 1980s, Zou Yunxiang developed a system for the diagnosis and treatment of hepatitis B, focusing on diseases of the liver system, and expert systems have since been developed in TCM.

Expert systems have been used in a variety of fields, but the recent AI boom has seen AI technology make remarkable inroads into the medical field: AI technology using deep learning has improved dramatically, and today AI technology is used for a variety of medical systems [1],[2],[3],[4],[5]. For example, they are active in medical robotics, intelligent drug development, intelligent diagnostic and treatment systems and auxiliary diagnostic systems. In these fields, AI systems are mainly used to assist doctors in their diagnosis, rather than to completely replace them[6],[7],[8]. In this paper, too, the main focus is on the construction of a system that assists in the diagnosis of asthma based on the shape of palm print wrinkles in TCM.

In the long history of TCM, it has been said that the shape and number of wrinkles, the depth of the wrinkles and the roughness of the matricular area of the palm are closely related to medical conditions such as asthma and allergic diseases.

A good TCM practitioner can diagnose which allergic diseases a subject is suspected of having and whether he or she is at risk of asthma by looking at the wrinkles on the palm. However, this is made possible by years of experience of TCM practitioners and this diagnostic technique is very difficult to master.

If AI can assist TCM practitioners in this diagnosis, it can be used to improve the skills of young TCM

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practitioners and assist them in diagnosis, thereby contributing to the development of TCM. Therefore, this paper uses AI technology to extract allergic disease-related features from palm images and learn certain rules from them. If palm images can be successfully identified by this method, it will be useful for assisting diagnosis in TCM.

This paper focuses on palmprint classification using deep learning. Palm images were collected and a dataset was created based on the association between palmprints and allergic diseases such as asthma. The data images were subjected to pre-processing, i.e. palmprint cropping of the thumbprints. In training, an inception V3 model using the TensorFlow framework and GoogleNet was used to correctly classify the palmprint part of the thumbprint as negative or positive with a certain probability. This is expected to facilitate diagnosis. So the computer can be used as an objective reference when classifying in this case.

2. Classification System of Palm Print based on TCM

In this paper, the TensorFlow framework is used for numerical image calculation, and the inception V3 model is used for palm image classification and learning.

2.1. Pre-processing for Palm Print Classifications

In the long-term clinical practice of Chinese physicians, it has been found that the palm prints of the maternal phalanges can be divided into negative and positive according to their tactile characteristics.

Negative palm prints have small intervals. They present a small lattice pattern, with a fine mesh and shallow grooves. They are delicate to the touch.

Positive palm prints have large intervals. They are large lattice pattern, evenly distributed, deeply furrowed. They are characterized by well-defined lines and a coarse texture. Healthy people are said to have negative palm prints, while those with asthma have positive palm prints as shown in Figure 1.

A. A sample of the negative palm print

B. A sample of the positive palm print

Fig.1 Negative palm print(A) and positive palm print(B) based on TCM diagnosis

2.2. Positive and Negative classifications based on convolutional neural network

The network structure of convolutional neural network is divided into an input layer, a convolutional layer, a ReLU layer, a pooling layer and a total coupling layer. However, for practical purposes, the convolutional and ReLU layers are often collectively referred to as the convolutional layer.

2.2.1. Convolutional Neural Network Model

Convolutional neural networks are a commonly used network model in the field of image classification. A convolutional neural network consists of an input layer, convolutional layers, pooling layers, full connected layers and activation functions. The convolutional layer extracts the features of the image to be trained, while the pooling layer reduces the features to representative values. This makes it possible to create classifiers that are robust to changes in object resolution and movement.

2.2.2. Tensor Flow flame work

Tensor Flow is a framework for developing deep learning published by Google on 2015[9]. The Tensor Flow computing frame is very well suited for convolutional neural networks, recurrent neural networks, and special cases of RNNs. TensorFlow is also suited to long and short memory networks, which are a special case of RNNs. TensorFlow has the features that an effective framework should have.

2.2.3. Inception V3 model

Inception V3[10] has a unique structure that encompasses two connection layers: global average pooling and full connectivity.

This network model was initially called Inception V1, while Inception V2 adopted the idea of Batch Normalization to improve the convergence speed of the model. In Inception V3, the 2D convolutional layer is decomposed into two 1D convolutional layers. This reduces the number of parameters while mitigating overfitting. Several filters (and pooling) of different sizes are used for merging their results.

2.3. Chapter summary in palm classification

In this chapter, the flow and function of the convolutional neural network in the classification, pre-processing and deep learning of palm prints in the thumbprint region are described.

In this system, an inception V3 model using the TensorFlow framework and GoogleNet was used. The feature extraction was performed on the palmprint image of the thumbprint region in the learning process, Pooling was performed on the extracted feature map and the probability of being positive was calculated using the fully connected layer and activation function.

3. Palm data collection

In this paper, we collected the palm data for training and test. We erased the non-fine image, made palm data set classified in negative palm and positive palm. There are negative palm image and positive palm image in same ratio. we use the 800 pictures as training. Test image are 800 pictures too. Figure 2 shows the samples of the positive palm images and negative palm images.

A. Positive palm samples

B. Negative palm samples

Fig. 2 The sample of the collected palm image data set. A is the part of the positive palm image data set. B is the part of the negative palm image data set.

4. Simulation results and analysis

In this section, the simulation was worked as shown in section 2. In this result, test data are not used in training step. The test results are shown in Table 1.

Table 1. Simulation Results of Palm Print Recognition.

Class of the diagnosis	Accuracy of the recognition
Negative palm print	85. 7%
Positive palm print	86. 8%

The accuracy of the negative palm recognitions was 85.7%. The accuracy of the positive ones was 86.8%. From these results, it can be seen that using deep learning has a high accuracy in the palmprint classification of the large thenar area.

However, there were some mistakes in classifications. The reasons for this situation are, firstly, that the positive-negative differences are small for many palmprints. Secondly, the palmprint dichotomy is a classification based on human visual perception, which results in a dataset with a human error component. Third, the amount of training data is insufficient. Fourth, there are similarities between images of negative and positive palmprints in terms of groove depth. For example, if the palm print is very rough, even though it is clearly a negative palm print, the palm line may be deeper and judged positive.

4.1 Examples of classifications

Figure 3 shows the results of classifications. Above one is the negative palm sample, this palm can be detected as negative. The score was 0.910 points. This score shows the certainly of classification. Below one is the positive sample, this can be detected as positive. The score was 0.913 points. This system work as classifier of the negative palm and positive palm based on TCM.

A. Result of the negative palm image.
(Negative score is 0.910, positive score is 0.090.)

B. Result of the positive palm image.
(Positive score is 0.913, negative score is 0.087)

Fig. 3 Example of the results in a negative palm image(A) and a positive palm image(B)

5. Summary

In this paper, a palmprint dataset was collected. The dataset was classified into negative and positive types based on palmprint features in similar diseases such as asthma and used to train models. Deep learning was applied to the classification of the palmprints of the thumbprints and an accuracy of more than 85% was confirmed.

However, there are still shortcomings and areas for improvement due to the complexity of the palmprint images and the limitations of the existing conditions. First, in order to make the training results convincing, it is necessary to continuously enrich the dataset, collect more thumbprint data and build up the database. Second, we believe that the classification accuracy can be improved by selecting better models and algorithms.

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Authors Introduction

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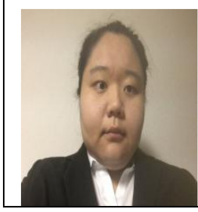

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