Journal of Artificial Intelligence Practice (2020) Vol. 3: 22-30
Clausius Scientific Press, Canada

DOI: 10.23977/jaip.2020.030105
ISSN 2371-8412

Complexion Classification Based on Convolutional Neural Network

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Keywords: Inspection of TCM, Complexion recognition, Convolutional Neural Network, Classification

Abstract: Traditional Chinese medicine (TCM) has proved that the complexion of the human body is closely related to the health of each organ, and some visual features of the face can provide valuable clues for the diagnosis of diseases. This paper makes an attempt to develop an automated facial complexion classification model for objective TCM facial diagnosis based on convolutional neural network, and compared it with the existing and traditional machine learning facial classification methods, which has certain reference significance for the future development of deep learning algorithm in the field of TCM.

1. Introduction

Traditional Chinese Medicine (TCM), as one of the representatives of Traditional Medicine in the world, has a complete theoretical system and rich clinical practice experience, which benefits people all over the world [1]. TCM believes that facial features and tongue features are closely related to human health, which can accurately reflect the pathological changes of the patient's whole body, and are easy to observe. So, tongue diagnosis and facial diagnosis become the two most core diagnostic methods in inspection of TCM [2]. Although inspection is the first of the four diagnoses in TCM, traditional inspection, affected by external conditions such as doctors' cognition level, light and temperature, restricts the formation of industry consensus and standard of inspection technology and seriously hinders the popularization, promotion and development of TCM. The modernization of TCM diagnosis has become one of the common concerns and efforts of medical and related researchers [3]. This paper is put forward under the background of the modernization of TCM.

In TCM's inspection, doctors generally select the parts with less occlusion and obvious exposure for observation, especially the parts of cheek and forehead, which are usually used as the basis for judging the patient's facial color. This paper is based on the classification theory of TCM complexion. Traditional Chinese medicine person's face can be divided into “cyan, red, sallow, pallid and dark”, commonly known as the "five colors". But the cyan face case is relatively rare in the actual situation, clinical samples is difficult, so temporary not consider, which has shown in figure 1.

(a) (b) (c) (d)

Figure 1. Four typical facial complexions of TCM: (a) Red; (b) Sallow; (c) Pallid; (d) Dark.

Due to the rapid development of computer image processing and machine learning in recent years, the application of computer in clinically-assisted diagnosis and treatment has not only objectified and standardized, but also has certain advantages in practical operation and certain feasibility and practical application value. Deep learning is a new research direction emerging in the field of machine learning in recent years. Through the construction of network, machines can imitate the generation of vision and hearing, and even the learning and thinking process of human beings. Among them, with its excellent classification and recognition accuracy and efficient performance, convolutional neural network has made great breakthroughs in data mining, image processing, natural language processing and other fields. Convolutional neural network model-based TCM auxiliary diagnosis and treatment methods are also attracting the attention of relevant researchers.

However, the deep learning method has not been widely accepted in the field of TCM, and the traditional machine learning method is still the mainstream method in the field of TCM diagnosis and treatment and TCM facial diagnosis. In view of the good classification and recognition performance of convolutional neural network in other fields and traditional Chinese medicine diagnosis fields, we make an attempt to develop an automated facial complexion recognition method for objective and quantitative facial diagnosis based on convolutional neural network, and compared it with the existing and traditional machine learning facial classification methods

Under the guidance of the related TCM experts, we complete image acquisition of the consultation. We also achieve face detection and feature extraction using machine learning and deep learning techniques. At last, the method proposed in this paper is proved to be accurate and it is feasible, simple and fast in operation.

2. Related work

The precise location of face image and the segmentation of the region of interest are important prerequisites for the automatic detection of facial diagnosis in TCM. In recent years, due to the rapid development of the subject of image recognition, computer image processing technology has also been widely used in the objectifying study of TCM facial diagnosis. In the existing research results, the thresholding segmentation method, morphology-based segmentation method and region-based segmentation method are mainly used.

For the acquired images, facial feature point location, regional segmentation and feature recognition can only be studied after accurate face detection and location are realized. The research on face detection and location has been quite mature at home and abroad, but the research on face detection and segmentation in the objectification of Chinese facial diagnosis has just begun.

Due to the attention of doctors and scholars to TCM, some progress has been made in the objectification of TCM facial diagnosis [4-8]. For a long time, because the traditional machine learning algorithm can also achieve more accurate classification effect on small data sets by selecting appropriate characteristic values, the research based on traditional machine learning algorithm has been widely reported in the field of TCM diagnosis and treatment [9]. These studies make great contribution in exploring the classification rules and promoting the standardization and objectification of TCM. Jayanti et al. [10] proposed a fast segmentation algorithm by using skin model of elliptic clustering of Subban et al. [11] and designed a face detection &segmentation system. Li et al. [12] according to the color space based on human visual system proposed a method to measure and distinguish facial complexion. The experimental results show the complexion feature can achieve the better performance.

Up to now, there are many researches on complexion and gloss of facial diagnosis information extraction, and the researches on expression of eyes, skin texture, facial spot and lip color are still in the initial stage, which is an indispensable part of TCM's inspection. Li et al. [13] designed a computer-assisted classification method is and applied for syndrome diagnosis based on the lip images. The extracted 84 features contain the lip color space component, texture and moment features. Yang et al. [14] proposed a cheek region extraction method for face diagnosis, rotated face region image according to the eye positions to put straight the image. Finally, the skin block center is determined to extract the cheek region automatically based on the geometric structure of the face. Miyamot et al. [15] developed a digital image analysis system which can quantitatively analyse the pigmentation points and accurately measure their area and average skin tone. Spectral reflectivity also be used to accurately describe the complexion, Wang et al. [16] based on the characteristics of facial skin color, determined the optimal sample set and the combination of basis function for facial spectral reflectance restoration in order to reconstruct the facial spectral reflectance. Li et al. [17] collected 5330 face images from three Chinese medicine clinic, built a convolution neural network constructed by seven convolution layer, three pooling layer, and two fully connected layer to extract the face image feature extraction and fusion of color characteristics. This CNN method achieves 65.29% classification accuracy, proves the feasibility of convolutional neural network in the field of automation level diagnosis of TCM. At the same time, TCM automatic intelligent auxiliary diagnosis and treatment system based on traditional machine learning algorithm [18] has also been put into use.

Not only in the field of facial diagnosis, computer vision technology is also widely used in other Chinese medicine diagnosis techniques. Tongue features are important objective basis for clinical diagnosis, Hu et al. [19] used color difference between the paired images to estimate the lighting condition based on the Support Vector Machine (SVM) and developed an automatic tongue diagnosis system based on built-in sensors of smartphones for continuous monitoring of health conditions. A new scheme was presented by Yan et al. [20] for analyzing the Auscultation Signals consisted of qi-deficient, yin-deficient and normal people. Liu et al. [21] argued that deep learning is clearly more in line with human brain and can use high-dimensional abstract features to represent some of the original low-dimensional features. It is a good way to find the relationship between the symptoms and syndromes. This idea is consistent with the diagnosis of traditional Chinese medicine. So, they use the deep learning and multilabel learning methods to build one model used to diagnose the chronic gastritis in TCM. Based on the data mining algorithm, a novel method called TCMSP (traditional Chinese medicine syndrome prediction) is proposed by Wang et al. [22]. They filtered the critical features from the based on an improved information gain method in multi-view, 20 critical features are selected from original 105 features and the corresponding syndromes of 138 new cases are identified respectively.

While the convolutional neural network model is widely used in speech recognition, image recognition, natural language processing and other fields, deep learning algorithms are gradually emerging in the medical field, and more and more researchers are also involved in the field of deep learning [41]. With its excellent feature extraction performance and classification effect, CNN has great application potential in auxiliary medical treatment, medical imaging, drug mining and health management [42].With the development of TCM informatization, sharing data centers and networks have been established in the field of TCM, and most TCM hospitals have also established hospital information systems and electronic case systems. Therefore, deep learning has great development potential and application value in the field of TCM diagnosis. Huan [55] built a convolution neural network consists of seven convolution layer, three pooling layer, one starting layer and two full connection layer, respectively from three Chinese medicine clinic collected 5330 face images, use the network to extract the face image feature extraction and fusion of color characteristics, classifying patients constitution, reaching 65.29% classification accuracy, proves the convolutional neural network in the field of automation level diagnosis in traditional Chinese medicine diagnosis feasibility.

3. The Proposed method

3.1 Image preprocessing

Before the images are put into the convolutional neural network (CNN) model training, we need to preprocess the existing photo sets. Uniform picture size and picture type can make network training easier. The preprocessing consists of two steps. The first step is to crop and transform the image data, and the second step is to expand the existing data to get a model with better classification effect.

In order to unify the format of the input image when training the network, we first cut and scale the 575 original face image data collected, which can make the training of convolutional neural network more efficient. The size of our face data is 5568*3712. It is unrealistic to use the original image for network training and parameter adjustment. For this reason, this paper first cuts out the center of these images, so that only the middle face area is retained and the unnecessary background part is removed. Then carry out resize operation to reduce it to the resolution size of 227*227 and 224*224, 227*227 corresponds to the input size of AlexNet network, 224*224 corresponds to the input size of VGGNet and ResNet. Images after cropping and scaling can be directly used as input parameters for network model training.

Due to the particularity of images, insufficient medical image data is an inevitable problem. Many cases of diseases are special in nature. In addition, patients' privacy is involved. For the small sample problem, the usual approach is to use some methods to expand the existing data set. When the input is an image format, the commonly used data expansion methods include translation, flip, rotation, random cropping, and color adjustment of image brightness. As for the image data in this experiment, due to the particularity of the face, the method of rotation and random cropping is not suitable for processing the face image. If the existing amount of data is increased by changing the chroma, it will actually change the real facial skin color, which is not consistent with the actual diagnostic status and will seriously affect the final facial complexion classification result. Therefore, the method of adjusting image chroma is not applicable to the problem dealt with in this experiment.

Taking the above considerations into account, this paper adopts the Gamma correction method to adjust the existing face image brightness for a small sample database. The Gamma correction principle can be expressed by the following formula:

$$f(I) = I^{\gamma} \tag{1}$$

Where, I represents the input image and f represents the Gamma correction function. When

γ<1, the contrast of the image is enhanced, and the corrected image will be brighter than the image in terms of visual effect. When γ>1, the dynamic range of the low gray value area becomes smaller, thus reducing the contrast of the image of the ground gray value area, thus reducing the gray value of the whole image. In this experiment, γ values were increased from 0.5 to 0.1, and the final range of γ was between [0.5,1.5], which allowed the small sample data to be expanded tenfold. By changing the method of image brightness data set to expand, not only can effectively expand the number of data sets, solve the problem of large deep learning sample size requirements, and can simulate real life different light and Angle of face caused by the shadow effect, from the constraints of the single environment light source, make training model has better generalization ability, and has more practical reference value.

3.2 Construction of CNN models

With the hot development of deep learning, neural network model is no longer out of reach. The proposal of deep learning framework enables ordinary people to process and apply deep network model. At present, mainstream deep learning frameworks include TensorFlow, Caffe, Keras, Pytorch, etc. In this paper, network construction and training are carried out on the most commonly used model framework TensorFlow.

The structure of convolutional neural network has strong characteristics. In 2012 ImageNet image recognition, AlexNet was born and with excellent classification accuracy become champion of the contest of the image recognition. It also caused the convolution of the neural network application boom, become the frontier in the field of image processing, target recognition algorithm, make deep study on the forefront of the development of artificial intelligence. Take AlexNet as an example. Its network structure is shown in Figure 2. It consists of eight layers. The first five layers are convolutional layers, and only the first, second and fifth convolutional layers have sampling layer. As shown in the figure, the final AlexNet result is 1000 classes, so after the full connection layer processing, the final classification result can be obtained.

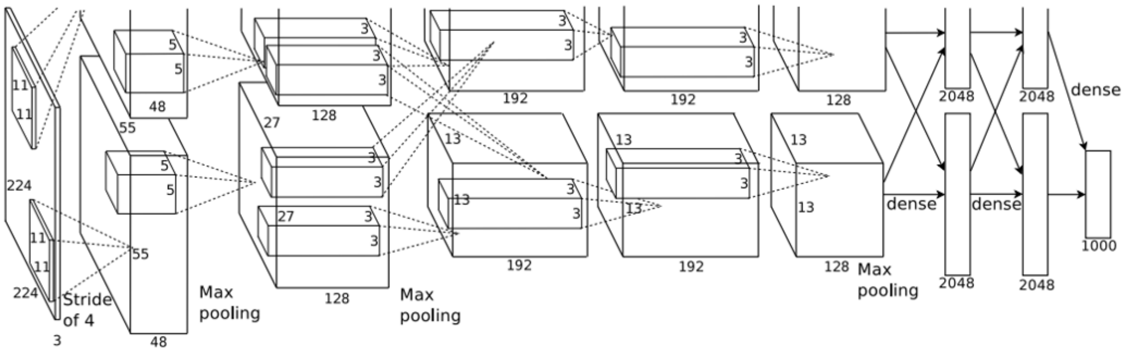


Figure 2. AlexNet and its network structure

VGGNet network is proposed based on the structure of AlexNet network. Their network is very similar, consisting of 5 convolutional layers. The difference is that each convolutional layer of VGG has sampling operation, and it has made exploration improvements in the depth and width of the network. The residual network is actually a deeper VGG network, but ResNet replaces the full connection layer of VGG with the global average pooling layer, which can greatly reduce the training parameters of the network and avoid the occurrence of overfitting to some extent.

In this experiment, two GPUs are used to accelerate the training of the convolutional neural network model. For many scientific calculations, performance is largely determined by the Floating-point capabilities of the GPU. Especially for deep learning tasks, which are mainly single-precision floating point operations, the GPU has a great impact on the model training speed. Other factors, such as CPU speed, memory size, communication bandwidth, etc. are not very important for training the neural network. The hardware environment and configuration used to train the neural network model in this experiment are shown in Table.1 below.

Table.1. Experimental hardware environment configuration

Hardware	Parameter
CPU	Inter Core i7
RAM	32G
GPU	Nvidia GeForce GTX 1080Ti * 2
Hard disk	2T
VRAM	16g

4. Results

For the collected face image data, after the preprocessing operation of cropping, downsizing and data amplification, it was put into the model for training, and the accuracy of different convolutional network models was calculated by using the method of ten-fold cross validation. Table. 2 shows the comparison of six convolutional neural network models and two traditional machine learning approach with the whole image as input. The accuracy rate and recall rate are used as the evaluation indexes of the classification effect of the model. The accuracy rate and recall rate are shown in formula (2) and (3).

$$Precision = PPV = \frac{TP}{TP+FP} \times 100\% \tag{2}$$

$$Recall = TPR = \frac{TP}{TP+FN} \times 100\% \tag{3}$$

Table.2. Classification accuracy of different models (%)

Classification model	Accuracy	Recall
RF	55.16	54.64
SVM	58.37	56.98
AlexNet	76.07	73.85
VGG16	71.29	78.57
VGG19	81.96	80.22
ResNet18	78.54	76.60
ResNet34	83.96	81.11
ResNet50	80.58	77.85

It can be seen from Table 2 that:

(1) These selected six convolution neural network models have achieved a better classification result on the automatic classification problem face diagnosis in traditional Chinese medicine, accuracy is above 70%, the best classification effect of ResNet34 reached the highest classification accuracy rate of 83.94%. It proves that deep learning can solve the problem of TCM complexion, and using convolution neural network model for medical image classification still has a big

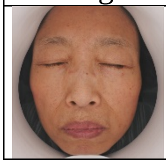
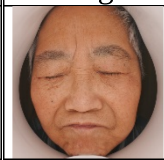
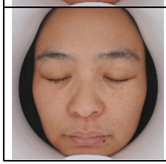
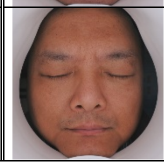
advantage.

(2) For the same network model, with the deepening of network layers, the effect of convolutional neural network will be improved to some extent. However, by observing the experimental results, it can be found that the deeper the layers, not the better the convolutional neural network model. For example, the classification effect of ResNet with 34 layers is better than that with 50 layers. It also reminds us that we need to design the number of network layers for specific problems instead of blindly pursuing the depth of the network.

(3) The advantage of deep learning is that it can simultaneously extract multiple dominant and invisible features of human face, while the classification method based on traditional machine learning and often focuses on the features of certain information of human face. Therefore, the convolutional neural network method can find some features that are difficult to be found by human eyes, and its results are better than the traditional machine learning method that only focuses on one feature.

Take once experiment as an example. Some classification results are selected in the prediction of test samples, and these results are shown Table.3.

Table.3. Part of the prediction results of the proposed method

Original Image	Judgement of TCM experts	Model prediction classification	Original Image	Judgement of TCM experts	Model prediction classification
	Sallow	Sallow		Sallow	Sallow
	Dark	Red		Red	Red
	Pallid	Pallid		Red	Dark

5. Conclusion

Deep learning is a new research direction emerging in the field of machine learning in recent years. Through the construction of network, machines can imitate the generation of vision and hearing, and even the learning and thinking process of human beings. Among them, with its excellent classification and recognition accuracy and efficient performance, convolutional neural network has made great breakthroughs in data mining, image processing, natural language processing and other fields. Convolutional neural network based TCM auxiliary diagnosis and treatment methods are also attracting more and more researchers.

This paper for the first time make the convolutional neural network model applied to objective surface diagnosis in TCM's inspection study, using the method of random forests, support vector machine (SVM) from the training models and in AlexNet, VGGNet, ResNet such classic network on the basis of using the migration study, comparing the model trained by found deep learning approach on the face classification problem of traditional Chinese medicine has a good performance. Compared with the feature fusion method based on traditional machine learning in the previous chapter, it is found that the two methods can effectively solve the problem of complexion classification and each has its own advantages.

Although convolutional neural network is rarely used in the research field of objectification of traditional Chinese medicine, this paper has made some attempts in this field, which has certain reference significance for the future development of deep learning algorithm in the field of Traditional Chinese medicine.

Acknowledgements

The author gratefully acknowledges the financial support from Postgraduate Research & Practice Innovation Program of Jiangsu Province (Grant No. KYCX18_1441).

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