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# Low Quality Retinal Image Recognition Based on Convolutional Neural Network

***Ge Yangzu**, *Zhang Guicang* and *Wang Jing***

School of Mathematics & Statistics, Northwest Normal University
Gansu Lanzhou, 730000, China
*Corresponding author. Email: 2019211696@nwnu.edu.cn

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***Abstract*.** In order to solve the problem of low accuracy of traditional image recognition methods for low quality retinal images, a low quality retinal image recognition Algorithm based on convolutional neural network was proposed. Firstly, a nonlinear transform image enhancement algorithm based on logarithmic transform is proposed to restore image details and improve image quality. Secondly, the L2 regularization method is introduced to optimize the over-fitting problem by using convolutional neural network to extract image features. Finally, the Support vector machine is used for convolutional neural network output recognition to achieve low quality image recognition. The study found that the proposed image enhancement algorithm can effectively improve the image quality of the retina, and the combination of convolutional neural network and Support vector machine can effectively realize the recognition of the enhanced image, it can solve the problem of low quality retinal image recognition. Experimental results show that the algorithm can effectively solve the problem of low-quality retinal image recognition accuracy.

***Keywords:*** Retinal Image Recognition; Convolutional Neural Network; Support Vector Machine; Image Enhancement; L2 Regularization

***AMS Mathematics Subject Classification (2010):*** 92B20

## 1. Introduction

As a powerful means to realize artificial intelligence, deep learning has many successful applications in image recognition. It is of great practical significance to carry out research on image recognition technology to promote the development of artificial intelligence. With the development of deep learning algorithms, convolutional neural network has achieved great success in image recognition, and researchers have gradually applied it to other fields, such as medicine, industry and so on. Compared with traditional machine learning algorithm, CNN has the advantage that it can automatically learn image feature information. Lee et al. [1] trained a U-net convoluted neural model using 1,289 labeled OCT images to segment the fluid regions of the diseased retina. Awais et al. [2] used pre-trained convolutional neural network VGG-16 to classify DME and NORMAL OCT images. The final accuracy was 87.5% , spin echo SE and oxygen SP were 93.5% and 81% respectively. Karri et al[3] used a pre-trained GoogleNet model to classify the Dataset, with 99% , 89% and 86% accuracy for NORMAL, age-related macular degeneration AMD and DME, respectively. Kermany et al. [4] used convolutional Neural Network v 3 to classify choroidal neovascularization CNV, DME, Drusen, and NORMAL retinal images with an accuracy of 96.6% .Combining with the open-source U-net convolution neural model, Wu et al. [5] classified the DME symptoms with an accuracy rate of 96.31% .

Medical Image plays an important role in disease treatment and is an important information carrier. However, aiming at the low accuracy of the traditional image recognition methods for low-quality retinal images, this paper proposes a nonlinear transformation of logarithmic transformation to enhance some low-quality retinal images, to restore the details of the image for the realization of retinal image recognition. As the main method of depth learning, CNN is applied to retinal image recognition, which improves the efficiency and accuracy of retinal image recognition. Because Soft max is used as the convolutional neural network classifier in CNN, the generalization ability of the pattern recognition model is insufficient, and the image classification cannot be well applied. Therefore, this paper combines Support vector machine with CNN to identify the anterior segment of the retina. In feature extraction, CNN is used to extract image features, and SVM is used to classify and recognize images. Experimental results show that the proposed image enhancement method can effectively enhance the details of low-quality retinal images, and the combination of CNN and SVM can effectively achieve image classification and obtain good recognition results.

In order to solve the problem of low accuracy of low quality retinal image recognition, this paper presents a low quality retinal image recognition Algorithm based on convolutional neural network combining image enhancement, convolutional neural network feature extraction and Support vector machine. The advantages of this paper are as follows: firstly, in the process of low quality retinal image recognition, the combination of CNN and SVM achieves a good recognition effect; a nonlinear transformation based on logarithmic transformation is proposed to enhance the retinal image. Thirdly, in the feature extraction of CNN, L2 regularization is used to prevent over fitting.

## 2. Algorithm research

### 2.1. Nonlinear transform image enhancement algorithm based on logarithmic transform

In order to eliminate the influence of light and other factors on retinal image recognition, a nonlinear transformation image enhancement algorithm based on logarithmic transformation is proposed in this paper. The detail of image is restored and the accuracy of image recognition is improved. The specific process is as follows:

The first step is to input image I, grayscale processing, and combine median filter image denoise;

The second step is to calculate the maximum value of the image Pixel, and write the

$$\max = \max S(x, y), \min = \min S(x, y) \tag{1}$$

The third step is to adopt the following nonlinear transformation

$$S_1(x, y)=\text{min-(max-min)}\times(\frac{S(x, y)-\min}{\max-\min})^{\gamma} \tag{2}$$

The nonlinear transformation is based on the gamma transformation. When $\gamma=1$ is used, the transform does not transform the image, that is, the output of the transform is still the input image. When $\gamma<1$ is used, the transform can stretch the range of low pixel values and suppress the range of high pixel values.In this case, the transformation increases the local contrast of the dark area of the image, which can improve the influence of the dark light on the image to some extent, and the image information of the dark area can be well improved. When $\gamma>1$ is used, the transformation can stretch the range of high pixel values to suppress low pixel values. In this case, the local contrast of the brighter area of the image can be increased, which can improve the influence of the brighter light on the image to some extent, and the image information of the brighter area can be well improved. $\gamma=0.8$ is adopted in this article. Although this transformation can eliminate the influence of other factors such as light on the quality of retinal image to some extent, it cannot improve the contrast of the whole image effectively.

The fourth step is to use the following logarithmic transformation

$$S_2(x, y)=\log_{10}(S_1(x, y)+m) \tag{3}$$

The transformation can further expand the scope of low image pixel values, enhance image darker area and a bright region contrast, better restore image information, the darker area and more applicable to the dim light conditions. However, logarithmic transform to suppress the high pixel values and lowered the brightness of the image. In order to improve the situation, the constant value added to the image in front of the logarithm transformation, can improve the brightness of the image. $m=10$ is adopted in this article.

The fifth step is to normalize the image so that its pixel value is between 0 and 255.

$$S_3(x,y)=\frac{(S_2(x,y)-\min)\times 255}{\max-\min} \tag{4}$$

### 2.2. Feature extraction of convolutional neural network

As a special multilayer perceptron, convolutional neural network (CNN) [6] is suitable for models with and without supervised learning and has great advantages in image processing. Convolution neural network after preprocessing the image input to the network, through convolution pooling operation, to extract the characteristics of the images, finally will complete the image of image features into the support vector machine (SVM) classification. By convolution and pooling a series of operations, convolution complex network can be found in the two-dimensional data model, and the two-dimensional image data are expressed as more abstract, more advanced features.

#### 2.2.1. Convolution layer

The main function of the convolutional layer is to generate image characteristic data, and the operation mainly includes window sliding and local association. Local correlation means that each neuron only perceives the surrounding local area and integrates the local feature information to obtain the global feature. After convolution operation, Relu excitation function is adopted in this paper to carry out nonlinear mapping of the convolution result, so as to ensure the non-linear network model.

#### 2.2.2. Pooling layer

Pooling layer on the characteristics of the input data, and combined with the characteristics of activation, reduce the dimension of the feature mapping, reduce excessive fitting. The pool of commonly used method for maximum pool and average pool, according to detect the target content to select the pooling method. The biggest is the main purpose of pooling to retain image texture feature extraction, and the average pooling is mainly on the background of the image features extraction. Pooling average method is adopted in this paper, in order to make the study to the data characteristics of a more global, the data will be convolution pooling operation through many layers, and enter into all links.

#### 2.2.3. Relu activation Function

Activation function [7] plays a very important role in learning very complex and nonlinear functions of the convolutional neural network model and is an important part of the neural network. The common activation functions include Sigmoid activation function, Tanh activation function and Relu activation function [8]. This article uses the Relu activation function, defined as follows:

$$relu(x) = \max(x, 0) = \begin{cases} x, x \geq 0 \\ 0, x < 0 \end{cases} \tag{5}$$

where the derivative is defined as

$$relu'(x) = \begin{cases} 1, x \geq 0 \\ 0, x < 0 \end{cases} \tag{6}$$

### 2.4. L2 Regularization

Regularization is a form of regression, in which all parameters are squared element by element to suppress the weight of the largest number, and the weight vector tends to be smaller and more dispersed. In order to reduce the complexity and instability of the model, regularization is adopted to avoid the risk of overfitting. The regularization definition of L2 is as follows:

$$L = L_0 + \lambda \sum_j w_j^2 \tag{7}$$

where $L_0$ is the training sample error, $\lambda$ controls the size of the regular term and determines the complexity of the constraint model.

### 2.4. Support vector machine

Support vector machine (SVM) is a quadratic optimization problem to find the best data classification algorithm of boundary. The SVM by using kernel functions increase model of the nonlinear and flexibility. The kernel function is aimed at an integral data samples. Through the sample vector is mapped to high-dimensional space, after the mapping of data samples can be separated in high dimensional space, improve the performance of SVM classification and recognition.

SVM is a kernel-dependent machine learning classification and recognition algorithm. In this paper, radial basis function (RBF) kernel function was used to achieve better image recognition performance [9]. Define it as follows:

$$K(x, x_i) = e^{\frac{\|x-x_i\|^2}{2}} \tag{8}$$

The kernel function can be used to solve the new plane model of feature space classification.

$$f(x) = w^T(x) + b = \sum_{i=1}^{m} y_i (x_i)^T (x) + b = \sum_{i=1}^{m} y_i K(x, x_i) + b ,$$

where $b$ is the offset term.

## 3. Low quality retinal image recognition algorithm flow

The algorithm flow of low-quality retinal image recognition is shown in Figure 1.

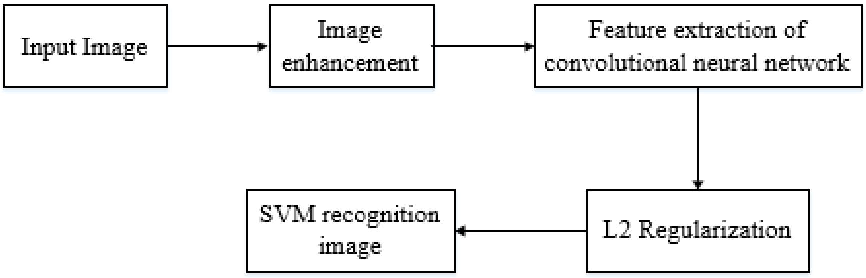


**Figure 1:** Algorithm flowchart

The specific algorithm flow is described as follows:

**Step 1:** The three low-quality retinal images were enhanced by 2.1 algorithm, and the enhanced images were analyzed by PSNR evaluation index.

**Step 2:** The features of the three enhanced images were extracted by 2.2 algorithm.

**Step 3:** The image after feature extraction is optimized by 2.3 method to avoid over fitting.

**Step 4:** The obtained data were classified and recognized by using SVM. Meanwhile, other algorithms were tested and analyzed to obtain accuracy.

## 4. Experimental results and analysis

In order to verify the feasibility of the algorithm in this paper, three retinal images, NORMAL retinal image, DRUSEN image and EXUDATES image, were selected as the study images to conduct recognition research respectively.

The experimental hardware device is: The processor is Intel Core(TM) I5-4 210U CPU@ 1.70ghz 2.40ghz memory 4.00GB; The system is 64-bit Windows 10 operating system. The operating environment is MATLAB(2018A) and Visual Studio(2017).

In order to better evaluate the quality of retinal image processing and the recognition effect of this algorithm, the signal-to-noise ratio (PSNR) and the recognition accuracy are taken as evaluation indexes. For the original image I with a given size and the processed image K, PSNR(dB) is defined as follows:

$$PSNR = 10 \times \log_{10}\left(\frac{\max^2}{MSE}\right) \tag{10}$$

where max refers to the maximum value of image pixels, and MSE refers to the mean square error, which is defined as follows:

$$MSE = \frac{1}{mn}\sum_{i}^{m-1}\sum_{j}^{n-1}\left[I(i,j) - K(i,j)\right]^2 \tag{11}$$

In order to evaluate the effect of image enhancement algorithm, this paper compares and analyzes many algorithms, such as guided image filtering (GIF)[10], multi-scale Retinex (MSR)[11] and , multi-scale Retinex with Color Restoration-on algorithm (MSRCR)[12]. The research results are shown in Table 1:

**Table 1:** Image enhancement PSNR values of different algorithms

| Algorithm | PSNR(dB) |
|---|---|
| GIF | 22.16 |
| MSR | 18.78 |
| MSRCR | 23.62 |
| This paper | 27.02 |

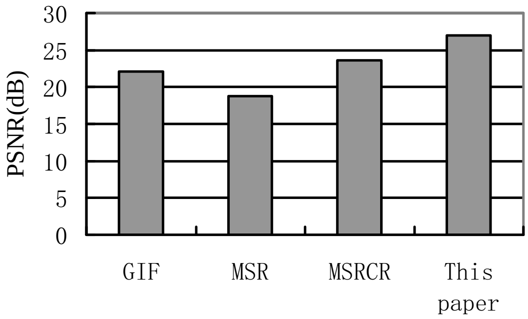


**Figure 2:** Different algorithms for image enhancement compare graphs

It is found in Table 1 that THE PSNR value of MSR is the smallest and the image enhancement effect is the worst, with a value of 18.78(dB). GIF and MSRCR have slightly better enhancement effect than MSR, with a PSNR value of 22.16 (dB) and 23.62 (dB), respectively. PSNR value of the image enhancement algorithm in this paper is 27.02(dB).Table 1 is plotted as a bar graph in Figure 2. Combining Table 1 and Figure 2, it can be seen that the PSNR value of the image enhancement algorithm in this paper is the highest and the image enhancement effect is the best.

In order to evaluate the performance of the retinal image recognition algorithm, BP neural network, SVM and CNN were compared for performance analysis in this paper. The results are shown in Table 2.

**Table 2:** Image recognition accuracy of different methods

| Algorithm | Accuracy (%) |
|---|---|
| BP | 86.12 |
| SVM | 83.69 |
| CNN | 88.37 |
| This paper | 94.27 |

Table 2 of the study showed that the SVM method of image recognition, the worst rate was 83.69%. The image recognition based on BP neural network is better than the SVM, the accuracy is 86.12%. Used alone CNN image recognition method is superior to the use of BP neural network and SVM image recognition method, its accuracy is 88.37%. The recognition algorithm in this paper the accuracy of 94.27%.

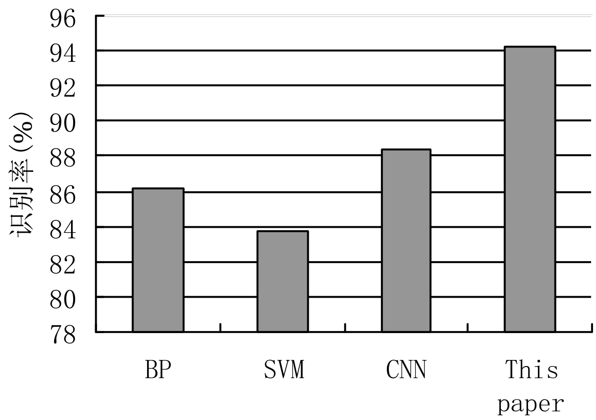


**Figure 3:** Image recognition comparison of different algorithms

Table 2 is drawn into the bar chart shown in Figure 3. Combining table 2 and Figure 3, it can be seen that the recognition algorithm in this paper has the highest accuracy and the best recognition effect.

## 5. Conclusion

Image processing plays a more and more important in our life, the role of image recognition is effectively extract the key means of image required from many of the images. Because of its low image quality, low quality images of the traditional image recognition method to it is difficult to identify, so how to effectively identify the low-quality images become a new problem, in order to solve this problem. Using the advantage of deep learning convolution neural network, this paper will combine image enhancement, feature extraction and optimization, put forward a kind of low quality of retinal image recognition based on convolutional neural network algorithm. First of all, using a new kind of low quality image enhancement algorithms, improve the effect of the retinal image preprocessing. Second, L2 regularization method is used to optimize the convolution neural network and the extracted features. Finally, in order to improve the accuracy of recognition, using support vector machine (SVM) for image recognition. The study found that, in this paper, the image enhancement algorithm can effectively improve the effect of low quality of retinal image preprocessing, image quality is improved. L2 regularization optimization can avoid excessive fitting to the greatest extent, and feature extraction in combination with the SVM recognition than used alone CNN has better identification precision. Therefore, in this paper, the image recognition algorithm can achieve good effect and higher identification accuracy.

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