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A Novel Diabetic Retinopathy Detection Approach Based on Deep Symmetric Convolutional Neural Network

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ABSTRACT Diabetic Retinopathy (DR) may lead to blindness in diabetic patients, which is one of the most severe eye diseases. Therefore, using automatical technology to detect DR at the early phase has very vital clinical significance. In order to detect the microaneurysms (MAs) and hard exudates (HEs) of DR, a novel detection method based on deep symmetric convolutional neural network is proposed in this paper. The symmetric convolutional structure is used to improve the effectiveness of feature extraction. The proposed method also can overcome the imbalance of positive and negative samples to avoid overfitting by increasing the width and depth of the network. Furthermore, different network structures (convolution, pooling) are used to achieve different feature filtering in the stage of feature extractions. According to the experimental results, the proposed method is superior to the state-of-the-art approach on the public dataset DIARETDB1 (DB1). The detection accuracy of the objects is 92.0%, 93.2%, 93.6%, when using different filtering structures (convolution, max-pooling, ave-pooling) respectively. The detection of microaneurysms is much improved by using ave-pooling layer for feature filtering, and the max-pooling layer can improve the detection of hard exudates.

INDEX TERMS Diabetic retinopathy, hard exudates, microaneurysms, symmetric convolution neural network.

I. INTRODUCTION

At present, DR is one of the most serious causes of blinding eye diseases, which become the primary cause of blindness in adults between 20-74 in the world [1]. The detection of diabetic lesions as soon as possible is the most effective way to prevent blindness. The clinical diagnosis is mainly performed by ophthalmologists on the fundus images of patients now. With the development of automatical technology, more method based on machine learning and deep learning methods are used to detect DR which achieve good performance.

The methods based on machine learning generally extract the object's features manually by using machine learning methods, such as support vector machines (SVM),

k-nearest neighbors (K-NN), etc. The classification performance highly depends on feature extraction algorithms, which are complicated and difficult. The methods based on deep learning extract features automatically, which can better express the object features.

The number of fundus image samples is limited, and the number of positive and negative samples is very unbalanced. In order to solve the above problem, a deep learning network based on a symmetric convolutional structure was proposed in this paper to enhance the feature extraction capability, extract more complex features to improve the feature representation, which can better distinguish different kinds of lesions. Experimental results show that the ave-pooling for feature filtering can better improve the detection ability of microaneurysms, and the max-pooling can significantly improve the detection ability of hard exudates.

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II. RELATED WORK

The automatic detection of DR mainly uses traditional machine learning and deep learning techniques.

Traditional machine learning methods mainly include three stages: data pre-processing, manual feature extraction and classification. R. S. Biyani and B. M. Patre used a clustering approach for exudates detection in the screening of diabetic retinopathy. Ganjee *et al.* extracted the candidate regions of microaneurysms using the Markov Chain (MC) method and detected them based on Gaussian distribution, density and other characteristics [2]; In the study by Halloy *et al.*, the region of interest (ROI) is extracted from the hard exudate using Gaussian space and mathematical morphology, and then the Support Vector Machine (SVM) Classifier is used to classify hard exudates and soft exudates [3]. Mobeen *et al.* presented a method that preprocesses the images with the technique of histogram equalization of different objects from retina images, and then uses discrete wavelet transform (DWT) to transform the spatial domain data into coarse and data details. They found it more convenient to detect bleeding. After the feature extraction techniques are applied on the wavelet transform coefficients, Support Vector Machines (SVM) and k-Nearest Neighbour (K-NN) are used to further classify the image features extracted from the coefficient matrix [4]; Adal *et al.* proposed a technique for detecting red lesions in retinal images. This technique uses the characteristic that red lesions are the main cause of retinal changes and detects targets through small retinal features. The variants associated with diabetic retinopathy were further identified by SVM classifier, which uses the shape characteristics and intensity of diabetic retinopathy [5]. Because the early symptoms of diabetic retina mainly include microaneurysms and hard exudates, in order to detect the lesions more specifically, we use the ave-pooling operation for feature filtering when detecting microaneurysms, and the max-pooling operation for feature filtering when detecting hard exudates, so that the network model can better distinguish different lesion types.

In recent years, computer vision has widely used deep learning for object detection. Budak *et al.* firstly extracted the object of microaneurysms with Gaussian filtering and other technologies, and took the extracted regions as the input of the convolutional neural network (CNN) model to classify the microaneurysms [6]. Omar *et al.* used the Local Binary Pattern (LBP) method to extract the texture features of the hard exudates, and used these features as the input of the artificial neural network (ANN) model to detect the hard exudates [7]; Tan *et al.* built a ten-layer fully CNN model to detect microaneurysms, hemorrhages, and hard exudates for each pixel of the fundus image [8]. Sudha *et al.* worked on a VGG-19 deep neural network that was trained using a feature set derived from the KAGGLE fundus image dataset. In their researchs, segmentation methods have been proposed to detect the retina defects such as hard exudates, microaneurysms and bleeding from digital images of the fundus and then divided into four grades. Subsequently, a rectified linear unit (ReLU) layer and

a max pooling layer are added to each stacked convolutional layer [9]. Kwasigroch *et al.* introduced a method to automatically detect diabetic retinopathy based on deep learning. This method presented integrates a special class coding method during the training phase of convolutional neural networks. Quadratic weighted kappa kernel was calculated between the score of the dataset and the predicted scores expected to analyze the performance of the designed model. However, in this paper, symmetric convolutional structure is adopted to improve the feature extraction ability of the model. It is used to increase the width and depth of the network to overcome the problem of positive and negative samples imbalance and avoid overfitting of the model.

III. THE PROPOSED METHOD

A. SYMMETRIC CONVOLUTION STRUCTURE

Different kinds of lesions in the fundus images detected in this paper have great differences in shape, color, size and other characteristics. The microaneurysms are small in size, more regular in shape, showing small red dots, while hard exudates have different sizes, mainly showing highlighted irregular shape, as shown in Figure 1. In order to extract more complex and higher-dimensional feature information, the proposed method uses a symmetric convolutional structure to enhance the model's ability to locate and classify the targets. The symmetric convolutional structure increases the depth and width of the network in order to overcome the imbalance of the number of positive and negative samples and avoid the overfitting of the model. Therefore, 1×1 convolutional kernel is selected for this structure in order to introduce more nonlinearity and reducing parameters, which can improve the generalization performance of this model [10], as shown in Figure 2. Rectified Linear Unit (ReLU) function is selected in the network in this paper.

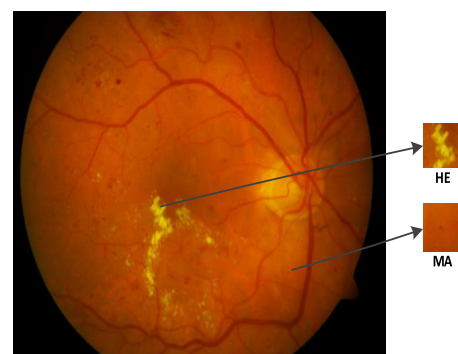


FIGURE 1. Different kinds of lesions in fundus image.

B. FEATURE FILTERING

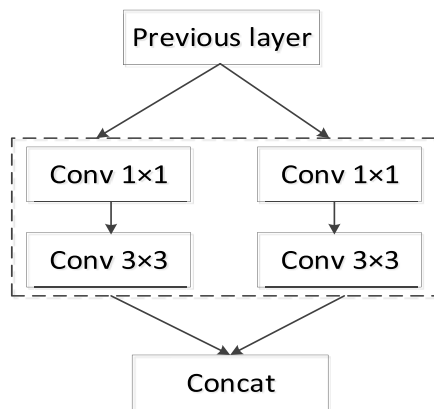
Since not all the features in the fundus images can represent the lesions, such as the background, noise and other useless information in the image. To detect the two kinds of lesions more accurately and efficiently, the proposed method uses different network structures to filter the information

TABLE 1. The parameters of convolutional layer in the network.

Order	Layer	Size of filter	Number of channels	Step size	Output
0	Input	—	—	—	—
1	Conv	3×3	8	1	$25 \times 25 \times 8$
2	Conv	3×3	16	1	$23 \times 23 \times 16$
3	Parallel Structure1	—	—	—	$21 \times 21 \times 24$
4	Parallel Structure2	—	—	—	$17 \times 17 \times 8$
5	Conv	3×3	—	8	$15 \times 15 \times 8$
6	FC	24	—	—	24
7	FC	3	—	—	3

TABLE 2. The parameters of the pooling layer in the network.

Order	Layer	Size of filter	Number of channels	Step size	Output
0	Input	—	—	—	—
1	Conv	3×3	8	1	$25 \times 25 \times 8$
2	Max-pooling/Ave-pooling	2×2	—	2	$13 \times 13 \times 8$
3	Parallel Structure1	—	—	—	$11 \times 11 \times 24$
4	Parallel Structure2	—	—	—	$7 \times 7 \times 8$
5	Conv	3×3	—	8	$5 \times 5 \times 8$
6	FC	24	—	—	24
7	FC	3	—	—	3

**FIGURE 2.** Symmetric convolutional structure.

of the samples at the stage of feature extraction. Different structures can extract and filter different features, which produce different effects on the detection of lesions. The pooling layers are to extract the main information of the targets. The shape of the microaneurysms is relatively regular, and its location is mainly concentrated in the center of the sample. In addition, the average pooling operation can retain more characteristics of the local center information of samples. In order to improve the detection performance of microaneurysms, the ave-pooling operation was used in the network to filter the target features during the detection of microaneurysms. The hard exudates occupy a large area in the sample and have irregular shapes. With the max-pooling operation, more parts of the sample containing hard exudates can be retained. Therefore, in the detection of hard exudates, the max-pooling operation is used to filter out some useless features.

C. THE PROPOSED NETWORK

The method proposed in this study mainly consists of three stages, which are the pre-processing stage, feature filtering and feature extraction, and classification stage, respectively. Figure 3 shows the framework of the method proposed in this paper. In the pre-processing stage, the fundus image is separated into red, green and blue channels, respectively. Compared with the red and blue channels, the green channel includes much more image information and can better represent different kinds of lesions in fundus images [11]. Therefore, the green channel is selected as the input of the network in this paper. In the feature filtering module, the convolutional layer, the max-pooling layer, and the ave-pooling layer are selected to filter and extract the features of the lesion, respectively. Table 1 and Table 2 are the parameters for selecting the corresponding network layer. In the classification stage, the SoftMax classifier is used to classify targets.

IV. EXPERIMENTAL RESULTS AND ANALYSIS

A. DATASET

In order to evaluate the detection performance of the proposed method, this paper performed the method in a public database named DIARETDB1. DIARETDB1 is used to compare digital images of diabetic retinopathy. This public database was used to evaluate the performance of detection for diabetic retinopathy. And the database contains digital images of the fundus with exudates, fragile exudates microaneurysms and hemorrhages, and these lesions were marked by experts.

B. EXPERIMENTAL SETTINGS

The experiment in this paper was carried out on a PC with an Intel Core I7-6700 CPU and a working frequency of 3.40Ghz. Pre-processing and sample set construction are realized by

Algorithm 1: Proposed Algorithm

Input: Fundus Images(X, Y); where $Y = y/y \in \text{Normal, ProliferativeDiabeticRetinopathy}$

Output: The trained model classifying the fundus images $x \in X$

Import a set of pretrained models $H \in \text{Inception}$;

foreach $h \in H$ **do**

 Learning rate $\alpha = 0.00390625$;

for $\text{epochs} = 1$ to 2000 **do**

foreach mini batch X_i, Y_i **do**

 Update the parameters of the related model.

end

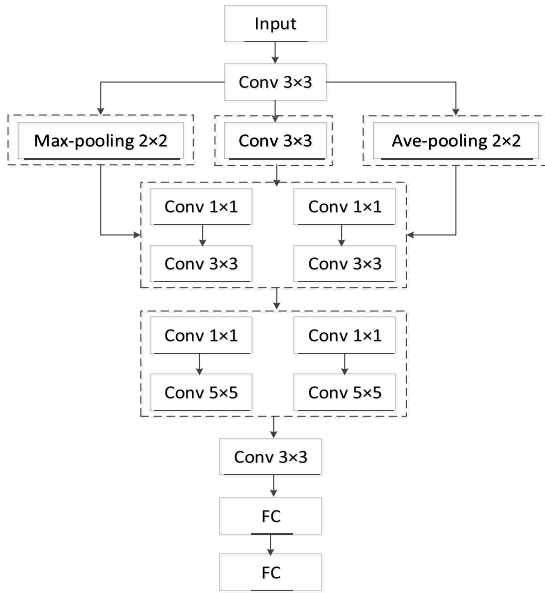
end

end

foreach $x \in X_{\text{test}}$ **do**

 Ensemble the result from all models.

end

**FIGURE 3.** The proposed network.

MATLAB2016b. This experiment uses the deep learning framework Caffe [12] to design the network model.

This method is trained and tested on the public database DIARETDB1 (DB1) [13] which contains 89 color fundus images, all images are taken by fundus cameras, and the image size is 1500×1152 . In this database, different lesion types and their positions in the fundus images are annotated by an ophthalmologist. In the pre-processing stage, the center of microaneurysms and hard exudates in the fundus image is taken as the sample center for sampling with a size of 27×27 . The sample set consists of three different types of sample patches, which are microaneurysms, hard exudates and backgrounds. In this paper, the areas excluding the microaneurysms and hard exudates in the fundus images

TABLE 3. Sample set construction.

	Background	MAs	HEs	Sum
Training set	1000	337	796	2133
Testing set	8000	144	340	8484

are called the background. Table 3 shows the construction of training and testing sample sets.

C. EVALUATION

To evaluate the detection performance of the proposed method on different types of lesions in fundus images, accuracy, sensitivity and specificity are used in this paper to quantify the detection performance of different targets. The calculation method is as follows.

$$\text{Sensitivity} = \frac{TP}{TP + FN}$$

$$\text{Specificity} = \frac{TN}{TN + FP}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FN + TN + FP}$$

where, TP (true positive) is the number of correctly predicted positive samples, TN (true negative) is the number of correctly predicted negative samples, FP (false positive) is the number of false prediction negative samples, and FN (false negative) is the number of false prediction positive samples.

D. EXPERIMENTAL RESULTS

First of all, this paper carried out detection experiments on the green channel, red channel, and blue channel of diabetic images respectively, which used the proposed network with convolutional layer, and the detection results are shown in the table 4. It can be seen from the results that the green channel has the best detection accuracy. Therefore, the green channel is used for detection experiments in this paper. To compare the influence of different feature filtering operations, this paper sets up three groups of experiments, which select the convolutional layer, the max-pooling layer, and the ave-pooling layer to filter and extract sample features, respectively. The detection sensitivity, specificity, and accuracy of three groups of experiments are shown in Tables 5, 6, and 7, respectively. The experimental results show that the accuracy of the network model using the pooling layer is better than the model

TABLE 4. The detection results of different channels of diabetic images.

Channel	Accuracy	Iteration times
Green	0.920	2000
Red	0.871	2000
Blue	0.788	2000

TABLE 5. The sensitivity of different feature filtering operation.

	Background	MAs	HEs	Iteration times
Conv	0.919	0.889	0.965	2000
Max-pooling	0.931	0.903	0.971	2000
Ave-pooling	0.937	0.910	0.929	2000

TABLE 6. The specificity of different feature filtering operation.

	Background	MAs	HEs	Iteration times
Conv	0.952	0.957	0.960	2000
Max-pooling	0.954	0.962	0.968	2000
Ave-pooling	0.925	0.963	0.974	2000

TABLE 7. The accuracy of different feature filtering operation.

	Accuracy	Iteration times
Conv	0.920	2000
Max-pooling	0.932	2000
Ave-pooling	0.936	2000

TABLE 8. Comparison of microaneurysms detection results.

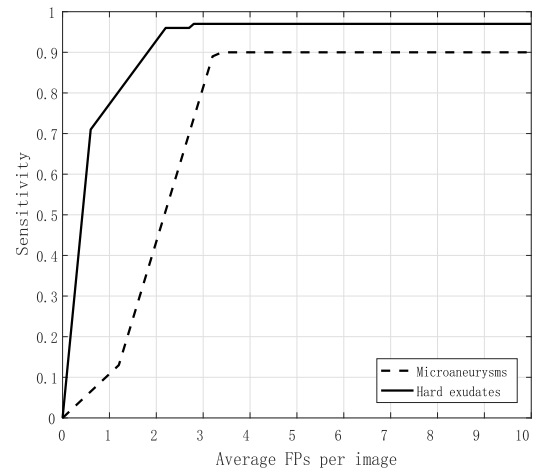
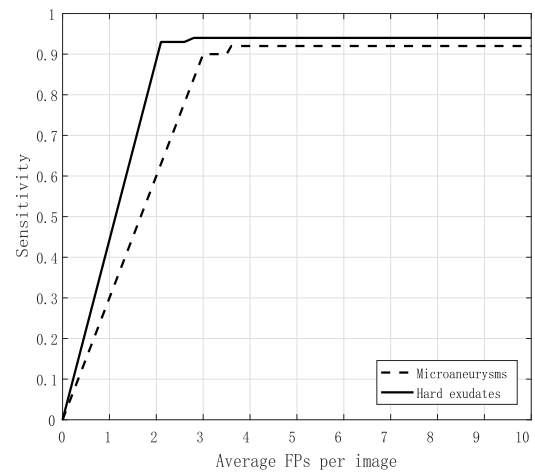
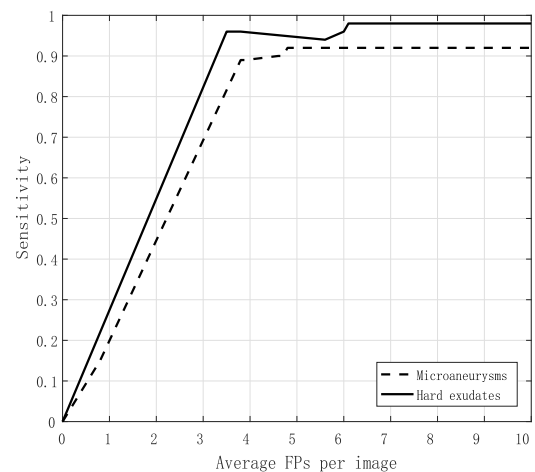
Method	Sensitivity	Specificity	Accuracy
proposed method(using Ave-pooling)	0.910	0.963	0.963
Patil et al.(2020) [14]	0.72	—	—
Manjaramkar et al.(2016) [15]	0.801	0.975	—
Ram et al.(2011) [16]	0.885	—	—
Kumar et al.(2018) [17]	0.960	0.920	—

TABLE 9. Comparison of hard exudates detection results.

Method	Sensitivity	Specificity	Accuracy
proposed method(using Max-pooling)	0.971	0.968	0.932
Khajasteh et al.(2019) [18]	0.990	—	0.982
Biyani et al.(2016) [19]	0.883	0.993	—
Lokuarachchi et al.(2019) [20]	0.946	0.885	—
Qomariah et al.(2017) [21]	0.851	0.996	0.995

using the convolutional layer, and the detection sensitivity of hard exudates in the experiment with the max-pooling layer is significantly higher than the model with the ave-pooling layer. The detection sensitivity of microaneurysms in the ave-pooling model is slightly higher than that of the max-pooling.

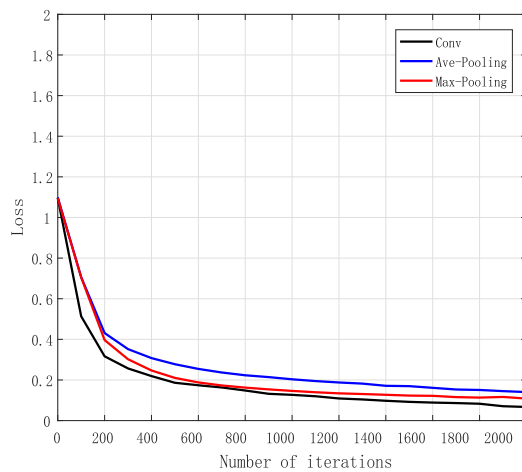
Table 8 lists the comparison of the detection results of microaneurysms in the DB1 database between the proposed methods using ave-pooling to filter and extract features in this paper and some existing methods. Table 9 lists the comparison of the detection results of hard exudates in the DB1 database between the proposed method using max-pooling in this paper and some existing methods. Table 10 lists the comparison between the results of the algorithm proposed in this research and the results of different methods that simultaneously detect multiple types of lesions. Furthermore, the methods listed in the table include both traditional machine learning methods and deep learning methods. The results

**FIGURE 4.** FROC with max-pooling layer.**FIGURE 5.** FROC with ave-pooling layer.**FIGURE 6.** FROC with convolutional layer.

show that the accuracy, sensitivity and specificity of the proposed method in this paper are better than those of most comparative methods.

TABLE 10. Comparison of multi-class detection results.

Method	Sensitivity			Specificity			Accuracy
	MA _s	HE _s	Background	MA _s	HE _s	Background	
proposed method (using max-pooling)	0.903	0.971	0.931	0.962	0.968	0.954	0.932
proposed method (using ave-pooling)	0.910	0.929	0.937	0.963	0.974	0.925	0.936
Samah et al.(2019) [22]	0.849	0.974	–	–	–	–	0.928
Khojasteh et al.(2018) [23]	0.850	0.960	0.950	0.960	0.980	0.970	–
Khojasteh et al.(2018) [24]	0.840	0.910	0.980	0.970	0.940	0.990	–
Tan et al.(2017) [8]	0.460	0.870	–	0.970	0.980	–	–

**FIGURE 7.** Loss curve.

This paper also uses FROC [14] to evaluate the performance of this method model, which describes the relationship between the sensitivity of different kinds of lesions and the average number of false positives on each image, as shown in Figures 4, 5, and 6, which are FROC of the three groups of experiments in this paper. The number of training iterations of the proposed method is set 2000 in this paper. Figure 7 shows the change of the loss value with the increase of the number of iterations.

V. CONCLUSION

A deep convolutional network proposed in this research is based on a symmetric convolutional structure to detect different kinds of lesions in diabetic retinal images. The symmetrical convolutional structure can extract more complex lesion features and significantly improve detection performance. In this paper, convolution, max pooling and average pooling layers are selected in the feature filtering module for the experiment, and the experimental results of the three groups are compared. The experimental results show that the overall accuracy of the pooling operation is higher than that of the convolutional operation. Moreover, when the max-pooling operation is selected, the detection performance of hard exudates is better, with sensitivity is 97.1% and specificity is 96.8%. When the average pooling operation is selected, the detection performance of microaneurysms is better, with

sensitivity and specificity of 91.0% and 96.3%. In future work, we will further modify the model to detect more objects simultaneously and accurately in diabetic retinopathy images.

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