

Deep convolutional neural networks for diabetic retinopathy detection by image classification[☆]

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ABSTRACT

Diabetic retinopathy (DR) is a common complication of diabetes and one of the major causes of blindness in the active population. Many of the complications of DR can be prevented by blood glucose control and timely treatment. Since the varieties and the complexities of DR, it is really difficult for DR detection in the time-consuming manual diagnosis. This paper is to attempt towards finding an automatic way to classify a given set of fundus images. We bring convolutional neural networks (CNNs) power to DR detection, which includes 3 major difficult challenges: classification, segmentation and detection. Coupled with transfer learning and hyper-parameter tuning, we adopt AlexNet, VggNet, GoogleNet, ResNet, and analyze how well these models do with the DR image classification. We employ publicly available Kaggle platform for training these models. The best classification accuracy is 95.68% and the results have demonstrated the better accuracy of CNNs and transfer learning on DR image classification.

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1. Introduction

Diabetic retinopathy(DR), one of the most common retinal diseases, is a common complication of diabetes and one of the major causes of blindness in humans. Since the disease is a progressive process, medical experts suggest that diabetic patients need to be detected not less than twice a year in order to timely diagnose signs of illness. In the current clinical diagnosis, the detection mainly relies on the ophthalmologist examining the color fundus image and then evaluates the patient's condition. This detection is arduous and time-consuming, which results in more error. Furthermore, due to the large number of diabetic patients and the lack of medical resources in some areas, many patients with DR can not timely diagnosed and treated, thus lose the best treatment opportunities and eventually lead to irreversible visual loss, as well as even the consequences of blindness. Especially for those patients in early phase, if DR can be found and treated immediately, the deteriorated process can be well controlled and delayed. At the same time, the effect of manual interpretation is extremely dependent on the clinician's experience. Misdiagnosis often occurs due to the lack of experience of medical doctors. In the last ten years, deep CNNs have made the remarkable achievements in a large amount of computer vision and image classification, substantially surpassing all previous image analysis methodologies. Computer-aided diagnosis is desired because it allows for mass screening of the disease. Therefore, in order to achieve fast, reliable computer-aided diagnosis

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Table 1
Classification dataset.

Class name	The degree of DR	Numbers
Class 0	Normal	25810
Class 1	Mild	2443
Class 2	Moderate	5292
Class 3	Severe	873
Class 4	Proliferative	708

and treatment, the application of CNNs to automatically and accurately process and analyze DR fundus images is still a very necessary and urgent task.

The motivation of this paper is to implement an automatic diagnosis of DR using fundus images classification. We work on classifying the fundus images by the severity of DR, so that an end-to-end real-time classification from fundus image to the condition of patients can be achieved. Instead of the doctors' manual operation with experience, it relieves their pressure on the diagnosis and treatment for DR in an automatic and high-accuracy way. For this task, we are employing various image preprocessing methods to extract many important features and then classify to their respective classes. We adopt CNNs architecture to detect the DR in 5 data sets. We evaluate the sensitivity, specificity, accuracy, Receiver Operating Characteristic (ROC) and Area Under Curve (AUC) of the models. The contributions of this paper are summarized as follows:

- In order to get the finest mass image dataset to train with for our models, we take preprocessing steps, like data augmentation will increase the number of training examples, and data normalization will denoise to precisely predict classification.
- We could train the latest CNNs model (AlexNet, VggNet, GoogleNet and ResNet) to recognize the slight differences between the image classes for DR Detection.
- Transfer learning and hyper-parameter tuning are adopted and the experimental results have demonstrated the better accuracy than non-transferring learning methodology on DR image classification.

The remainder of this article is organized as follows. [Section 2](#) presents related work of Convolutional Network Architectures on DR image classification. [Section 3](#) introduces Kaggle data sets and describes the image preprocessing methods. [Section 4](#) overviews the CNNs models, AlexNet, VggNet, GoogleNet and ResNet. [Section 5](#) presents experimental analysis and evaluation metrics. Finally, we conclude this article in [Section 6](#)

2. Related work

Automated detection of DR images has such benefits that DR can be diagnosed at early levels efficiently. Early detection and treatment are really important for delaying or preventing visual degradation. For an overview of such methods referred [\[1,2\]](#). More recently, deep learning techniques have extraordinary revolutionized the computer vision field. Especially leveraging CNNs to perform image classification has attracted many researchers. Research in this field include segmentation of these features, as well as blood vessels [\[3,4\]](#). Deep CNNs structures were originally presented for the solution of natural image classification, and recent research has made rapid progress in working on DR fundus images classification. Wang et al. [\[5\]](#) adopt a CNN (LeNet-5) model to extract image features for addressing blood vessel segmentation. These methods has some limitations. Firstly, because of the features of dataset are extracted manually and empirically, their accuracy can't be guaranteed. Secondly, the data sets are small in size and low in quality, usually only a few hundred or even dozens of fundus images with relatively single collection environment, bringing difficulties to compare the performance of algorithms in the experiment. Since Alex et al. [\[6,7\]](#) presented AlexNet architecture for remarkable performance improvements at the 2012 ILSVRC competition, the widespread applications of deep CNNs in computer vision have formally mushroomed. After a number of excellent CNNs architectures have been proposed, such as VggNet [\[8,9\]](#), GoogleNet [\[10\]](#). As one of the most important network models, ResNet [\[11\]](#) was proposed in 2015, which further enhances the performance of CNNs in image classification. Since it is arduous and time-consuming to build a model from zero, transfer learning and hyperparameter tuning are used in this paper. These architectures can be proposed in [\[12–24\]](#). We employ transferring learning to expedite the learning time and compare the performance with AlexNet, VggNet, GoogleNet and ResNet, which finally provides an automatic and accurate detection so that visual damage could be minimized to the minimum degree. Compared to the previous methods, our work has the following improvements over the convergence time for the large scale experimental datasets and a better performance on classification.

3. Dataset and preprocessing

Our dataset is from an publicly Kaggle [\[25\]](#) website, which tries to develop a model for DR detection. Data set consists of high resolution eye images and graded by trained professionals in 5 classes(0–4) which is according to below [Table 1](#) and [Fig. 1](#). The data set contains 35,126 high resolution RGB images with a resolution of about 3500x3000 in multiple varieties of imaging situations. The labels are provided by professionals who rank the presence of DR in each image by a scale of 0, 1, 2,

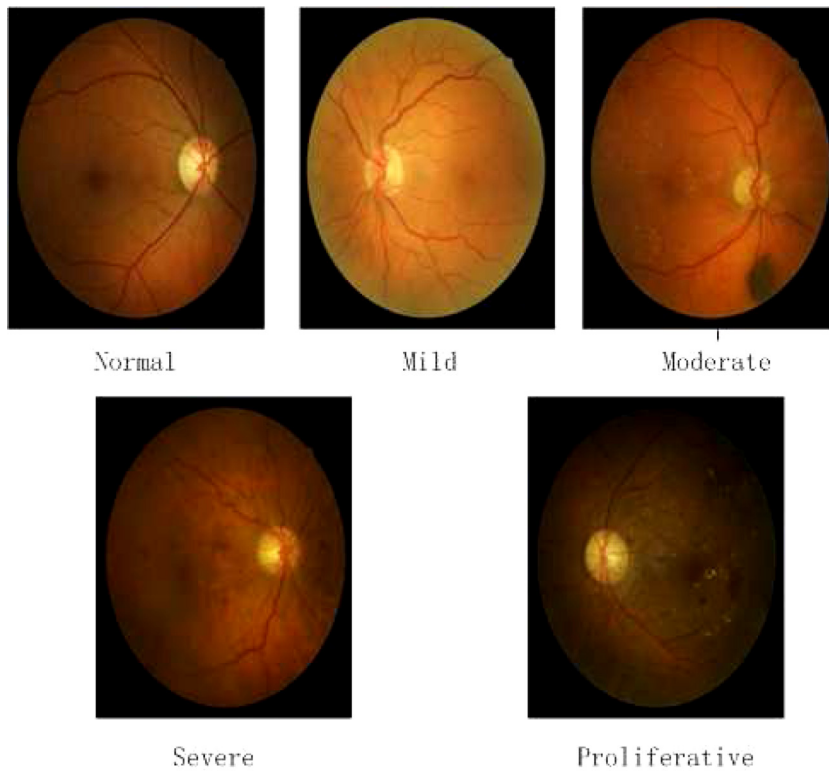


Fig. 1. Classification dataset.

3, 4, which stand for no DR, mild, moderate, severe, proliferative DR respectively. Obviously, the distribution of experimental data is highly imbalanced, and the number of label “0” is almost 36 times as much as that of label “4”.

Since the image of low quality will produce inaccurate results, preprocessing is an important operation to improve image quality, whose results are viewed as the original input for training data which will classify the images into their 5 classes. Due to the noisy data and the limited number of data sets, normalization schemes and data augmentation are adopted to preprocess. Also, the fundus images are cropped to a smaller size in order to eliminate the extra areas. NonLocal Means Denoising (NLMD) presented by Buades et al. [26], is employed to remove noise. On channel i at pixel j , the denoising image x can be computed as:

$$\hat{x}_i(j) = \frac{1}{C(j)} \sum_{k \in \beta(j,r)} x_i(j)w(j,k), C(j) = \sum_{k \in \beta(j,r)} w(j,k) \quad (1)$$

Additionally, as a baseline normalization scheme, we need to subtract the mean and then divide the variance from the train image datasets. The training images are rotated, randomly stretched and flipped to increase multiple fundus images examples.

4. Methods

CNNs have made great achievements for their good performance on image classification. Coupled with transfer learning and hyper-parameter tuning, we have used AlexNet, VggNet, GoogleNet, ResNet, which are the latest Deep CNNs, and do transfer learning and discuss how well these models classify with the DR image dataset. Comparative discussion for retinopathy detection research is provided on the performance of models. Transfer learning is the method which the last fully connected layer of a previous trained CNNs is deleted and viewed as a feature extractor. As long as we have successfully extracted all the features for all the medical images, we train a classifier on the new dataset. The parameters of hyperparameter-tuning method are not initialized by the network itself, it is necessary to tune and optimize these parameters according to the results of training the DR image in enhancing the performance. The pipeline of the proposed DR detection using CNNs can be shown in Fig. 2.

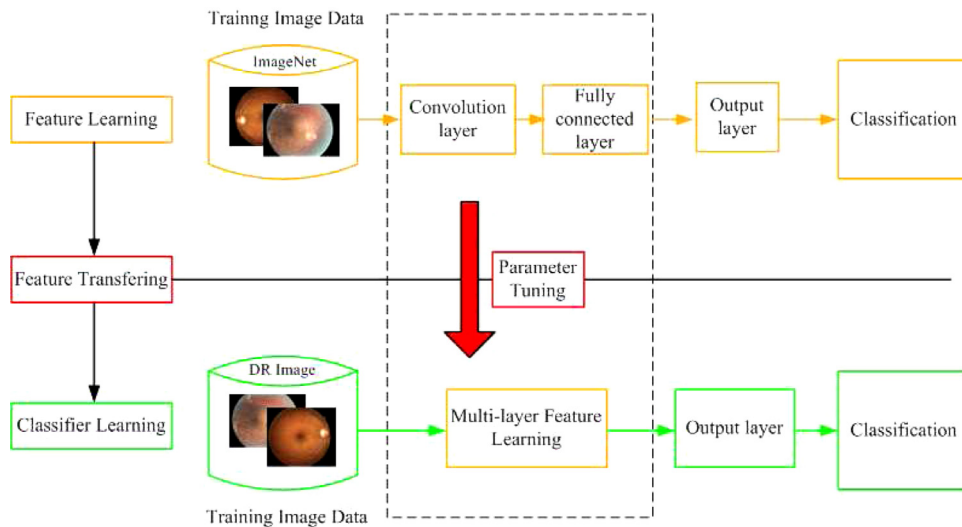


Fig. 2. The pipeline of the proposed method using CNNs.



Fig. 3. AlexNet model.

4.1. Alexnet

Alex Krizhevsky [6], proposed a deep CNN called AlexNet in 2012, which could be deeper and wider than LeNet. Compared to traditional methods, The architecture of AlexNet is one of the first deep CNN model to promote ImageNet Classification accuracy significantly. Several relatively new technology points are presented and AlexNet firstly utilized Trick successfully, such as ReLU, Dropout, and LRN to CNN. It is the foundation of the modern deep CNN for its profound historical significance. While AlexNet also uses GPUs for computational acceleration, the authors open source their CUDA code for training CNNs on the GPU.

AlexNet contains 630 million connections, 60 million parameters, and 650,000 neurons, with 5 convolutional layers, of 3 which are followed by the max pooling layer, and finally with 3 fully connected layers. AlexNet won the highly competitive ILSVRC 2012 with a significant advantage, with the top-5 error rate down to 16.4%, a huge improvement over the 26.2% error rate from the second place. It is composed of 5 convolutional layers followed by 3 fully connected layers as seen in Fig. 3, with an input image size of 227x227 and an image of 1000 natural color. The first convolutional layer includes conv1 and pool1, conv1 layer uses 96 11x11 filters (11x11x3)*96 convolution kernel to operate the input images at stride 4; in pool1 layer, 3x3 filters are applied at stride 2. The second convolutional layer includes conv2 and pool2, which is similar to the previous layer, resulting in 256 feature maps. Full connectivity layer, fc6 and fc7 have 4096 neurons node, as well as output layer fc8 layer using softmax classifier initiates 1000 neurons according to the class scores.

4.2. Vggnet

VGGNet [8,9] is a deep CNN developed by researchers at the University of Oxford Vision Geometry Group and Google's DeepMind, working on the connection between the depth and performance of a CNN. It succeeds in constructing a convolution of 16 to 19 deep layers Neural Networks by stacking 3 * 3 small convolution kernels and 2 * 2 maximum pooling layers repeatedly. Compared to the previous state of the art network architecture, VGGNet gains a significant error rate drop, achieves second place in the ILSVRC 2014 competition category and first place in the positioning project. The 3 * 3 convolution kernels and 2 * 2 pooling cores are applied in all of the papers of VGGNet to improve performance by continuously deepening network structure. The following Fig. 4 shows the VGGNet network structure at all levels, as well as the amount of parameters for each level, with detailed performance testing from 11th layer of the network up to 19th layer of the network.

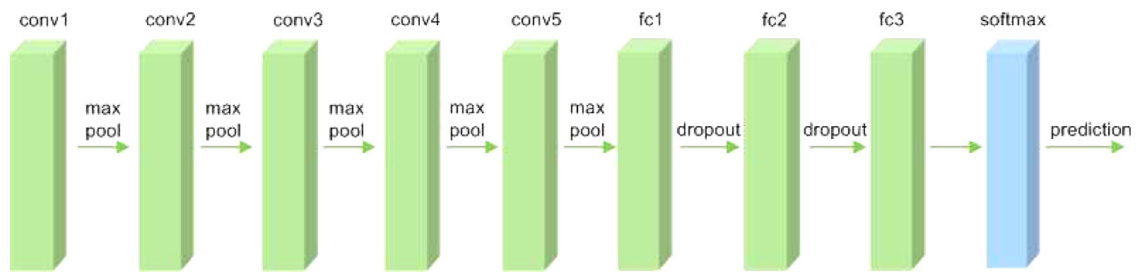


Fig. 4. VggNet model.

Although the network at each level gradually gets darker, the amount of network parameters does not increase much because it is mostly consumed in the last three fully connected layers. Though deep in front of the Convolution, parameters are not consumed largely. However, training is more time-consuming part of the convolution for its computational complexity. VGGNet has 5 sections of convolution, each section has 2–3 convolution layers, each section will be connected to the end of a maximum pool to reduce the size of the picture. Each segment has the same number of convolution kernels, and the more contiguous segments have more convolution kernels: 64 - 128 - 256 - 512 - 512. A very useful design usually contains multiple identical 3×3 convolutions stacked together. The effect of two 3×3 convolution layers in series is equivalent to one 5×5 convolution layers, that is, one pixel is associated with the surrounding 5×5 pixels, and the receptive field size is 5×5 . Three 3×3 convolution layers in series have the same effect with a 7×7 convolution layers, but the former has fewer parameters (55%) and more nonlinear transformations than the latter so that CNN is more capable of learning features. The former can use a ReLU activation function three times while the latter can only use one time.

4.3. GoogleNet

GoogleNet InceptionNet V1 introduces the inception structure, which maintains computational performance with dense matrices as well as intensifies the sparsity of CNNs structure. The way to better the accuracy of the model is to increase the complexity of the model. The most direct way to enhance the performance of the network is to increase the depth and width of the network, which means a huge increasing amount of parameters. However, the large number of parameters eliciting over-fitting will greatly increase the amount of computation. The fundamental way to solve these two shortcomings is to convert all connected or even convolution into sparse connections. On the one hand, connections of real biological nervous systems are also sparse. On the other hand, He et al. [11] shows that for large-scale sparse neural networks, an optimal network can be constructed layer by layer by analyzing the statistical properties of activation values and the clustering of highly correlated outputs which shows that overstaffing sparse networks may be simplified without performance loss. So, the question now is whether there is a way to keep the network structure sparser and to exploit the high computational performance of dense matrices. A large number of documents show that sparse matrices can be clustered into more dense sub-matrices to improve computing performance. Therefore, Fig. 5, Fig. 6 proposed a structure called Inception to achieve this goal.

GoogleNet used a 22 layers deep CNN in the 2014 ILSVRC competition, which is smaller and more speedily than VggNet, and smaller and more precise than AlexNet on the original ILSVRC images. For top-5 classification tasks, the error rate is 5.5%. The network structure is more complex than VggNet, adding 'Inception' layers to the network structure. Each an 'Inception' layer contains six convolutional and one pooling operation, which decreases the thickness of fusion feature image. We apply parallel filter operations on the input data from the previous layer and many receptive field image sizes for convolution are respectively, 1×1 , 3×3 , 5×5 and pooling operation is 3×3 .

4.4. ResNet

Residual Neural Network (ResNet) is put forward by Kaiming [11]. By means of using the Residual Unit, it successfully trains 152 deep neural network to win the ILSVRC 2015 championship and get a 3.57% error rate classification for top 5 classes, which is quite prominent though the number of parameters is less than VGGNet. The core of ResNet, Highway Nets, uses the skip connection to let some input into(skip) the layer indiscriminately in order to integrate the information flow which can avoid the loss of information transferring in the layer and gradient vanishing problem (which also suppresses the generation of some noise). In addition, suppressing noise means averaging the model, and the model still balances between training accuracy and generalization. The most effective way is still to increase more label data, to achieve a higher training accuracy and the approximate level of traversal. The ResNet structure is decent that can greatly accelerate the training of ultra-deep neural networks and improve the accuracy of the model. The ResNet notion stems from what the depth of CNN increases, a degradation problem arises. The accuracy rises at first and then hits the limitation, while increasing the depth, decreases the accuracy. This is not a matter of over-fitting, because the error increases not only in the test examples but also in the training examples itself. If a moderately shallow network that meets the accuracy of saturation and contains

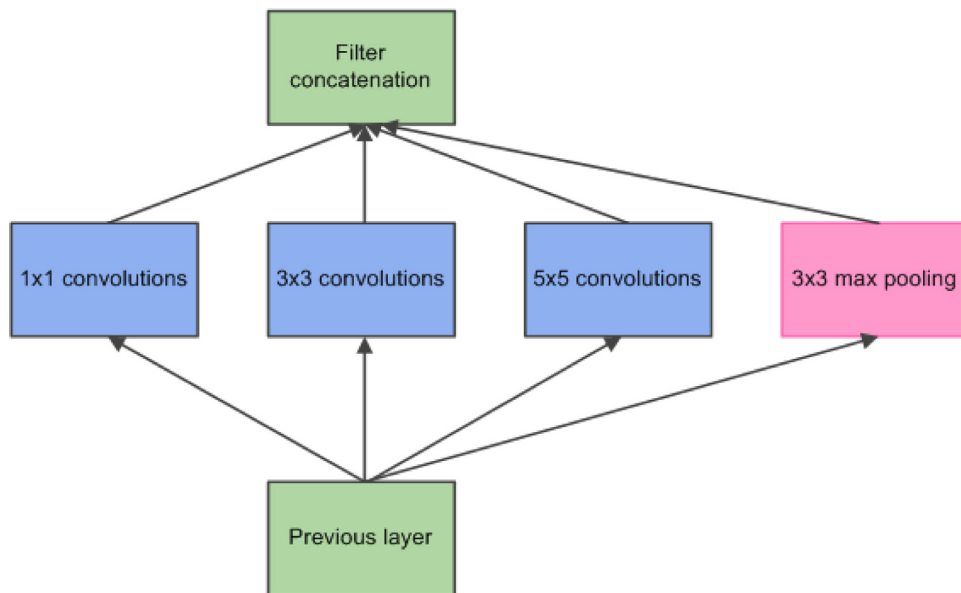


Fig. 5. Inception model with naive version.

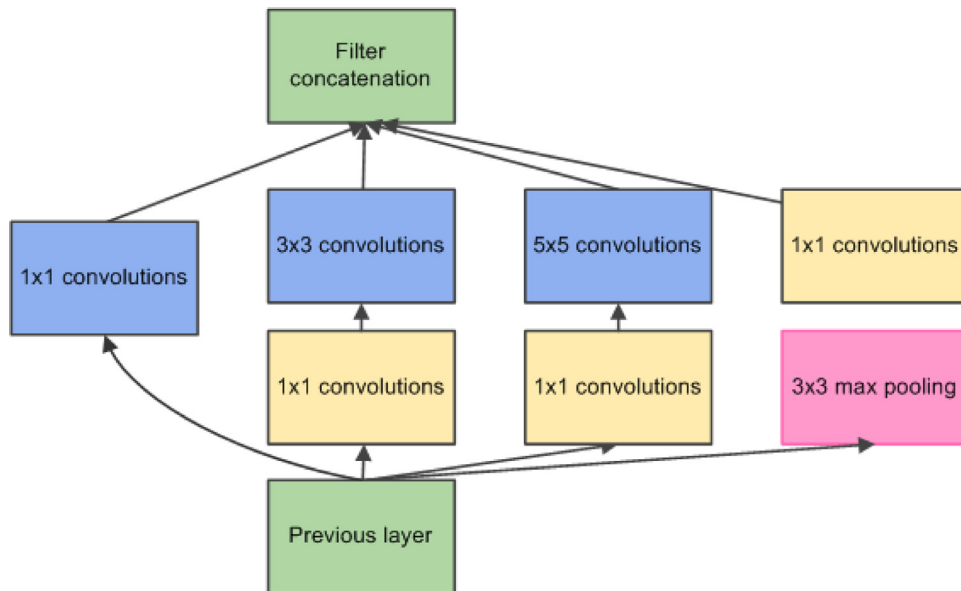


Fig. 6. Inception model with dimensionality reduction.

a few of the congruent mapping layers, then to the minimum, the error will not add up, that is, the deeper the network should not result in more training examples error. The idea to pass the previous output directly to the next layer by using congruent mapping inspires ResNet. Assuming that the input to a certain CNN is x and the anticipated output is $H(x)$, then our learning goal is $F(x) = H(x) - x$ when directly transfer the input x to the output as the initial result, shown in Fig. 7.

5. Experiments and results

5.1. Performance metrics

The metrics for performance evaluation which are well known used to assess the performance of classification algorithms are accuracy, sensitivity, specificity, and AUC. It is acknowledged that accuracy is the ratio of accurately classified examples

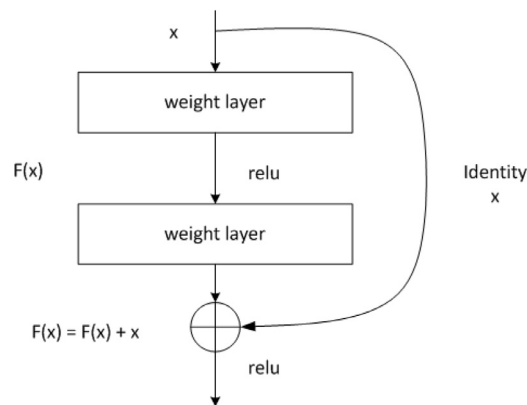


Fig. 7. ResNet Architecture.

Table 2

Classification results with randomly initialized parameters of CNNs model.

Model	SP	SE	AUC	ACC
AlexNet	90.07%	39.12%	0.7968	73.04%
VggNet-s	93.98%	33.43%	0.7901	73.66%
VggNet-16	29.09%	86.37%	0.5512	48.13%
VggNet-19	96.05%	54.51%	0.7938	82.17%
GoogleNet	86.84%	64.83%	0.7756	86.35%
ResNet	90.53%	73.77%	0.8266	0.7868%

Table 3

Classification results with hyperparameter-tuning.

Model	SP	SE	AUC	ACC
AlexNet	94.07%	81.27%	0.9342	89.75%
VggNet-s	97.43%	86.47%	0.9786	95.68%
VggNet-16	94.32%	90.78%	0.9616	93.17%
VggNet-19	96.49%	89.31%	0.9684	93.73%
GoogleNet	93.45%	77.66%	0.9272	93.36%
ResNet	95.56%	88.78%	0.93.65	90.40%

to the whole examples, which is a good measure to evaluate models performance.

$$ACC = \frac{TP + TN}{TP + FP + TN + FN} \quad (2)$$

$$SE = \frac{TP}{TP + FN} \quad (3)$$

$$SP = \frac{TN}{TN + FP} \quad (4)$$

5.2. Experimental validation

As shows in Table 2, different CNNs architectures have different classification performance and the overall classification performances are poor. At the same time, in the process of training, we found that there existed over-fitting phenomenon, in order to work out the over-fitting problem, we use transfer learning and hyperparameter-tuning methods to more accurately classify the fundus images.

Transfer learning experimental settings are as follows: the fundus images data was increased to 20 times of the original, with 30 training iterations, the learning rate is linear variation between [0.0001-0.1], as well as the stochastic gradient descent optimized method is used to update the weights values. Five times the cross-validation is to compute the results. The accuracy of VggNet-s model classification in the experiment is 95.68% in Table 3. The other have poor classification accuracy. This may be due to the fact that the other architectures have larger and more complicate structure and more training parameters than VggNet-s. More tracing parameters and less training data would produce over-fitting phenomenon, which may yield the less inaccurate classification performance.

6. Conclusions and future work

Diabetic Retinopathy is one of the complications of diabetes and is an important blinding disease. Effective and automated diagnosis to the degree of Diabetic Retinopathy lesions have an important clinical significance. Early diagnosis allows for early treatment, which is crucial because early detection can effectively prevent visual impairment. Diabetic Retinopathy automatic classification of fundus images can effectively assist doctors in Diabetic Retinopathy diagnosis, which can improve the diagnostic efficiency. In this paper, precisely Convolutional Neural Networks for detecting Diabetic Retinopathy and transfer learning are presented to classify Diabetic Retinopathy fundus images and automatic feature learning reduces the process of extracting the feature of fundus images. At the same time, data normalization and augmentation make up for the lack of fundus image defects, as well as the model selection and parameter training which are discussed. The best experimental classification accuracy is 95.68% and our results yield better accuracy on Diabetic Retinopathy image classification.

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Supplementary material

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