

# Automatic Detection of Hard Exudates in Retinal Fundus Images

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## Abstract

Among the early clinical symptoms of Diabetic Retinopathy (DR), the hard exudates (HE) on the retina are the most obvious. The automatic detection of hard exudates through deep learning technology is of great significance for the early diagnosis and treatment of DR. Therefore, this paper mainly proposes a method for detecting hard exudates of retinal fundus images based on convolutional neural networks. In the preprocessing process, due to the problems of low brightness and contrast in the fundus image, the brightness adjustment algorithm based on the HSV color space is used to correct the brightness of the fundus image by adjusting the V attribute in this paper. Besides, after brightness adjustment, the green channel image with the strongest contrast of hard exudates is extracted from the fundus image for patch generation. Under the condition that the number of training samples is limited, this paper proposes a convolutional neural network based on patches, which converts the detection problem of hard exudates into a pixel two-class classification problem. Finally, all output labels are reshaped into predicted images. In addition, the network also uses techniques such as dropout, weight initialization, and batch normalization to avoid overfitting the network and speed up network training. Finally, the proposed method is tested on the public dataset IDRiD. At the lesion level, the sensitivity, specificity and accuracy of this method for hard exudate are 70.27%, 96.71%, and 96.11%. Compared with other methods that also use IDRiD dataset, the sensitivity is increased by 28.71%.

Keywords: Diabetic retinopathy, Hard exudates, HSV, Patch generation, Deep learning

## 1 Introduction

Diabetic retinopathy (DR) is caused by long-term diabetes, and it is also an important factor that causes blindness among working people all over the world. DR patients are more difficult to realize the visual impairment at the early onset, which is easier to miss the best period of diagnosis and treatment. The early symptoms of DR are generally characterized by slight changes in capillaries. Common symptoms include microaneurysms, intraretinal hem-

orrhage, soft exudates, and hard exudates, as shown in Figure 1. Among them, the hard exudates on the retina are more prominent than other pathological features. Exudates are formed by the leakage of macromolecular substances in the blood after the blood vessel wall is damaged, which is mainly characterized by sharp edges and relatively clear bright spots. So, the research on the detection of hard exudates is very significant for the early screening of DR.

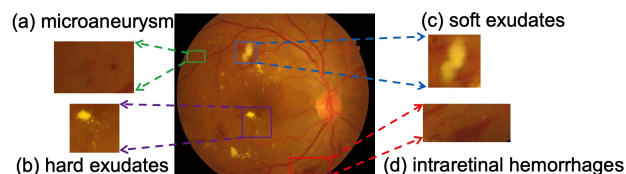


Figure 1: Color fundus images, including common conditions of diabetic retinopathy (Microaneurysm, Hemorrhages, Hard exudates and Soft exudates)

In clinical diagnosis, the collected fundus images are often limited by the physiological structure and non-ideal imaging conditions, which makes it difficult for doctors to directly use the images for efficient analysis. Besides, fundus images are usually affected by different lighting conditions, collection angles and equipment conditions, resulting in differences in inspection results and the inability to screening comprehensively. Therefore, the use of computers can effectively improve the screening efficiency and accuracy of lesions in fundus images, and it is very urgent and necessary to develop an automatic detection technology based on color fundus images.

Many scientists adopted a variety of machine learning methods to detect the lesions on the fundus image, including K-means algorithm, Random forests (Fraz et al. 2017), Support vector machine (Long et al. 2019), etc. However, these approaches were highly dependent on hand-crafted features and not adaptive to multi-modality missions. In order to overcome these defects, researchers turned to use deep learning, which has powerful feature extraction capabilities and can extract low-level features into abstract high-level features. Some commonly used deep learning methods in recent years are U-net (Ye 2018), transfer learning (Li et al. 2017), CNN (Avula and Chakraborty 2018), etc.

Considering the problems of different brightness, low

contrast and a small number of fundus images, this paper proposes an automated detection method for hard exudates based on deep learning as a solution to address this problem. The performance of the proposed method is verified on the public dataset named IDRiD, and then the experimental results are compared with other methods.

## 2 Related Work

Automatic detection of exudates is a challenging problem because the retinal fundus images often have uneven illumination and poor contrast. Under these complicated conditions, several related exudates' detection methods have been proposed, which can be divided into the following four categories: Threshold-based (Pereira, Gonçalves, and Ferreira 2015), Region-based growth (Li and Chutatape 2004), Morphological-based (Harangi and Hajdu 2014; Zhang et al. 2014), Pixel-based (Akram et al. 2012) classification. The above-mentioned exudation detection methods all regard the image pixels as the result of the discrete representation of the image, rather than the result of the natural entity, which may adversely affect the interpretation and representation of the image, for example, the representation of structural defects caused by complex imaging mechanisms and noise.

Achanta et al. proposed a new method of generating superpixels, called Simple Linear Iterative Clustering (SLIC), which is faster than existing superpixel generation methods (Achanta et al. 2012). This method can control the size and regularity of superpixels, it has good accuracy and boundary recall characteristics, which improves the performance of the segmentation algorithm.

With the development of deep learning in recent years, more and more scholars try to use deep learning and other methods to analyze fundus images. Xianyi Ye proposed a detection method of hard exudates based on principal component analysis (PCA) network and U-net (Ye 2018). Luhui Wu proposed an image labeling model based on deep learning, it used a generative adversarial network (GAN) to generate fundus images and developed an automatic detection algorithm of DR fundus images using loss-weighted method (Wu 2019).

With the technical support of big data and distributed computing, the calculation speed and detection accuracy of medical images processed by deep learning methods have

been effectively improved.

## 3 Method

In this section, we introduce the framework of our project firstly. Then, we introduce the CNN model used to realize hard exudates' classification. Finally, we will introduce the metric how we evaluate our model's performance.

### 3.1 Framework

In order to solve the problem of the limited number of training samples, we design and train an 8-layer convolutional neural network on image patches. The network essentially learns patches and then predicts the category of its central pixel. Therefore, this is a mapping process from the image patches to the predicted value of the pixel. Figure 2 shows the framework of our method.

During the training process, image patches are used for training the CNN. The output of the network is compared with the annotated images of the lesion through the network model to assess the performance of the network model for hard exudates.

During the evaluating process, after preprocessing and image augmentation on the test dataset, image patches directly use the learned convolution kernels to perform the convolution operation. The network will predict whether the center pixel of each image patch is a hard exudate or a background. Finally, the output is reshaped into an image to represent the prediction, and the label image is an image the same size as the original fundus image.

### 3.2 CNN model for exudates classification.

In this section, the CNN model will be illustrated in detail. After preprocessing the original dataset to get the classification dataset required for training, we design a convolutional neural network model for hard exudates. It's necessary to continuously adjust the model's structure according to the experimental results until the model reaches the best performance.

Given that the distribution of the hard exudate is uncertain, that the overall distribution is clustered, and that the context between the hard exudate pixels is related, the input size of the CNN model is set to  $32 \times 32$ . Figure 3 shows the structure of our CNN model.

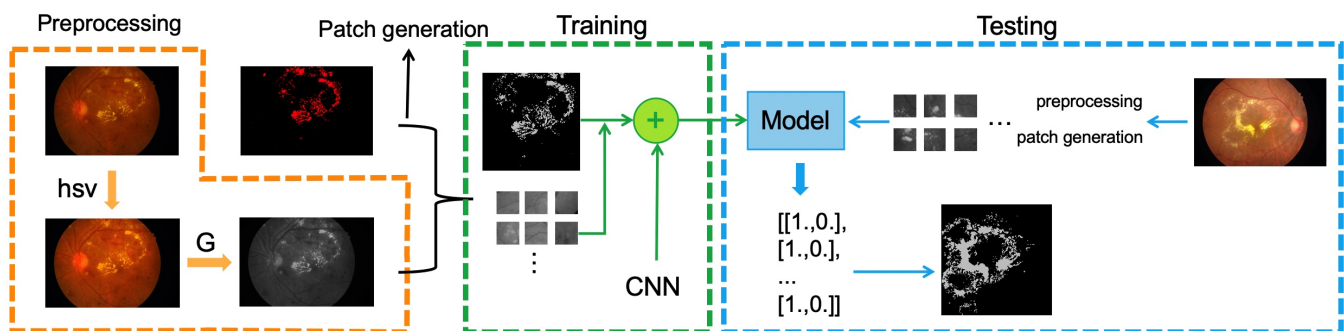


Figure 2: The framework of our method. Before we train our model, we need to adjust the channel performance of the dataset. The middle is the training process, and the right is the testing process.

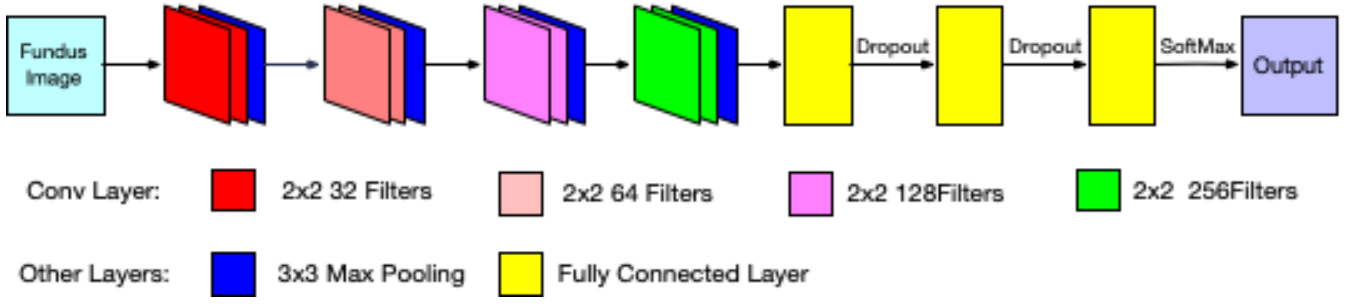


Figure 3: The structure of the hard exudates’ CNN. In our model, we use multi-scale convolutional layers to extract features from the image patches firstly. We use BN-ReLu between the same scale convolution layers. Then we use fully connected layers to calculate the final label, and we use ReLu and DropOut to avoid overfitting between fully connected layers. Finally, softmax function predicts the label of images.

The initial weights of the CNN follow a truncated normal distribution with a mean of 0 and a standard deviation of 0.1, and the initial deviation is 0.1. The optimizer uses Adam with learning rate of 0.0001, and the loss function uses cross entropy.

### 3.3 Metric

The standard based on the lesion is to evaluate the performance of the model by judging whether the detection area in each fundus image is a hard exudate.

For each retinal fundus image, we use the corresponding annotated image provided by the database as standard, compare the pixel value and the annotated value detected by the detection method, count the number and draw the confusion matrix as shown in Table 1.

Ground-truth	Prediction	
	Hard Exudate	Background
Hard Exudate	True Positive	False Negative
BackGround	False Positive	True Negative

Table 1: The metrics of Our method. True positive means that a pixel is actually a hard exudate, and it’s also a hard exudate in prediction; FP means that a certain pixel is actually a background, but it is a hard exudate in prediction; TN means that a certain pixel is actually a background and is also a background in prediction; FN means that a certain pixel is actually a hard exudate, but it is a background in prediction.

According to the statistical value, three evaluation indicators can be calculated:

$$SE = \frac{TP}{TP + FN}$$

$$SP = \frac{TN}{TN + FP}$$

$$ACC = \frac{TP + FP}{TN + TP + FN + FP}$$

SE represents the accuracy of extracting hard exudates; SP represents the accuracy of extracting background; and the

accuracy of ACC refers to the ratio of the correct results of the method, which represents the method’s efficiency. Pixel-level detection is mainly to determine whether each pixel is a hard exudate. SE, SP and ACC are usually used to evaluate the performance of the detection.

## 4 Experiment

### 4.1 Dataset

This paper mainly uses IDRiD dataset to evaluate the performance of hard exudates’ detection methods. The retinal fundus images in the IDRiD dataset were taken using a Kowa VX-10 alpha digital fundus camera with a 50-degree field of view (FOV) by experts from an Indian eye clinic. The resolution size of each fundus image is 4288×2848. Each pixel of these annotated images is marked as a part of the hard exudate or background).

The fundus images in the dataset have the problems of uneven brightness and low contrast. If we use traditional methods, a large number of false detections will be caused. It is also difficult to efficiently and accurately detect hard exudates.

### 4.2 Preprocessing

In the process of obtaining fundus images, due to the uneven brightness and eye movement during shooting, the fundus images often suffer from low image quality, uneven brightness and poor contrast. To solve this problem, the retinal fundus image is preprocessed before model training. This paper mainly uses HSV-based brightness adjustment and extracts the green channel gray-scale image with the highest contrast of hard exudates for the next image patch extraction.

#### I Brightness adjustment based on HSV

The brightness adjustment algorithm based on the HSV color space mainly adjusts the brightness V attribute of the HSV color space. We use experiments to select different adjustment coefficients ”α” for the brightness average range of the original fundus image, and then adjust the brightness value to expand the brightness difference. The specific flow chart is shown in Figure 4.

The contrast of fundus images before and after brightness adjustment is shown in Figure 5.

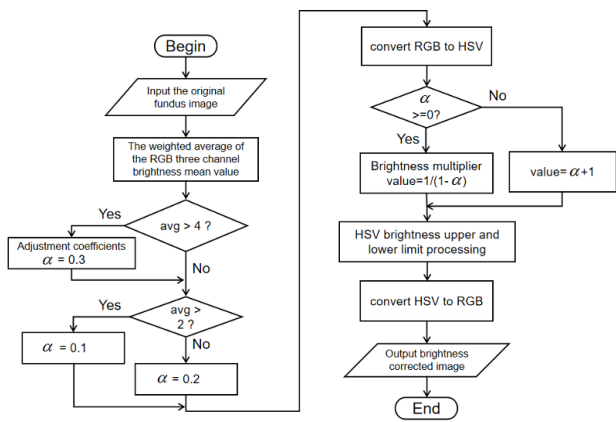


Figure 4: Flow chart of brightness adjustment algorithm based on HSV color space

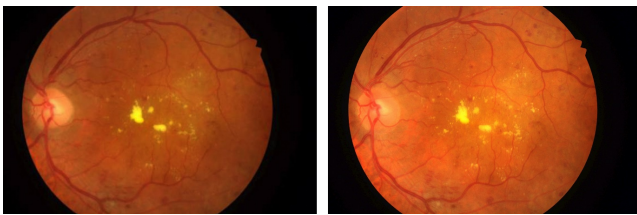


Figure 5: Comparison of fundus images before and after brightness correction

## II Extract green channel grayscale image

After the brightness adjustment of the fundus image, the image still has the problem of poor contrast, including the contrast between exudates' structure and other parts. Therefore, for the adjusted color fundus image, we extract the corresponding images of the R, G, and B channels, as shown in Figure 6, and select the channel with the highest contrast of hard exudates' lesions. Therefore, the green channel grayscale image is used for the next image patch's generation

## III Generation of image patches

By performing a series of operations on each training sample, such as random cropping, rotation, flipping and so on to generate copies of the training sample to expand the training set, which can enhance the generalization ability of the network. Therefore, this paper will use a random cutting method based on the ground truth image to generate patches for each fundus image, so as to better adapt to the requirements of network training and serve as training samples for the network. Specific steps of the random cutting method based on annotated images:

(1) Adjust the resolution of the image and its corresponding lesion annotation image to  $256 \times 256$ , and convert them to a float32 type array;

(2) Randomly select a pixel from the fundus image, that is, randomly select a coordinate  $(i, j)$ . Then, crop out a  $32 \times 32$  square image patch centered on the pixel;

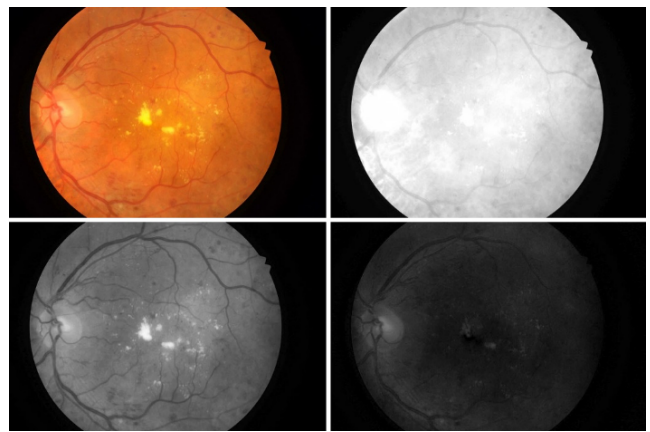


Figure 6: Comparison of fundus images(top-left) and Images of R(top-right), G(bottom-left), B(bottom-right) three channels

(3) In the extracted image patch with a size of  $32 \times 32$ , we take the corresponding hard exudates labeled image as a reference. If the pixel at the center of the image patch  $(17, 17)$  is a hard exudate, it is marked as 1, or it belongs to the background, then it is marked as 0. Each label uses one-hot encoding;

(4) Repeat the two steps of (2) and (3), extract 2000 hard exudates' image patches and 2000 background image patches for each fundus image.

The above processing is performed on each fundus image in the dataset. The generated hard exudates and background patches are shown in Figure 7. Since no padding is used during the patch generation, all pixels cannot be predicted.

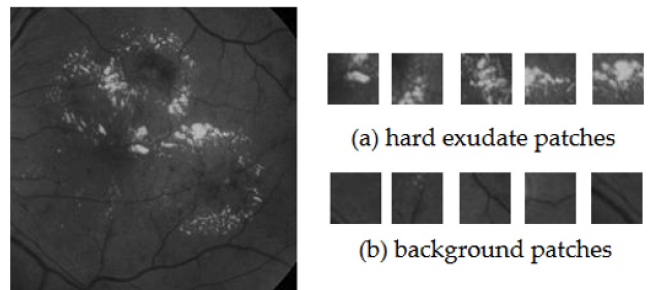


Figure 7: Image Patches

## 4.3 Experimental Setting

In this paper, the CNN model of hard exudates is developed on Tensorflow. The maximum number of iterations is 200. In each iteration, 216,000 images are divided into six groups for training, each containing 36,000 images. During the training process, a small batch of 100 training images were trained each time.

After training the network, the fundus images of each test set are decomposed into 50,176 image patches. The network predicts whether the central pixel of each  $32 \times 32$  image patch belongs to background or hard exudate. The predicted

values of all image patches are reconstructed to  $224 \times 224$  images to represent the prediction results. The size of the lesion annotation image provided by the dataset was adjusted to  $256 \times 256$  and crop annotation image from coordinates (16, 16) to (240, 240) for evaluating the accuracy of the prediction image output from the network.

In the prediction, we only predict the pixels of interest in the  $32 \times 32$  image patch, that is, the pixels at the center position (17,17). Each pixel in the predicted image is predicted through the network. However, by selecting a series of  $32 \times 32$  image patches to classify each pixel, this method can not predict the edge pixels of the original fundus image.

#### 4.4 Results

After training, we get the optimal CNN model. The accuracy of the model on the training dataset is 99.01%. The prediction image in the IDRiD test dataset is shown in Figure 8 and the confusion matrix is obtained according to the number of statistics, as shown in Table 2.

Prediction	Ground-truth		
	Hard Exudate	Background	Total
Hard Exudate	21407	43583	64990
BackGround	9058	1280704	1289672
Total	30465	1324287	1354752

Table 2: For each retinal fundus image in the test dataset, the corresponding labeled image provided by the dataset is taken as the reference standard, and the pixel value detected by CNN model is compared with the labeled value statistics to get the confusion matrix.

The detection method in this paper is compared with other literature methods that also use the IDRiD dataset, and the results are shown in Table 3. Among them, Ben’s method (Avula and Chakraborty 2018) also detects hard exudate lesions based on CNN. Since the definitions of TP and TN in Ben’s method are different from those in this paper, the confusion matrix in Ben’s method is used to calculate the sensitivity and specificity according to the definition in this paper for comparison. In order to further test the generalization ability of the CNN model of hard exudate, the hard exudate detection method proposed in this paper was evaluated on the e-optha-EX dataset.

By analyzing the data in Table 3, it can be found that the accuracy rate of the hard exudates’ detection method proposed in this paper reaches 96.11% on idrid test dataset, and the sensitivity is 28.71% higher than that in Ben’s method. On the e-optha-EX test dataset, the model showed high accuracy and specificity, but low sensitivity, and there was still room for improvement. In addition, as can be seen from Fig-

Dataset	Detect Method	Sensitivity	Specificity	Accuracy
IDRiD	ours	<b>70.27</b>	96.71	96.11
	Ben’s method	41.56	<b>98.29</b>	<b>96.60</b>
e-optha-ex	ours	44.25	97.48	97.35

Table 3: comparison of evaluation indexes between this method and detection methods used in other literatures (%)

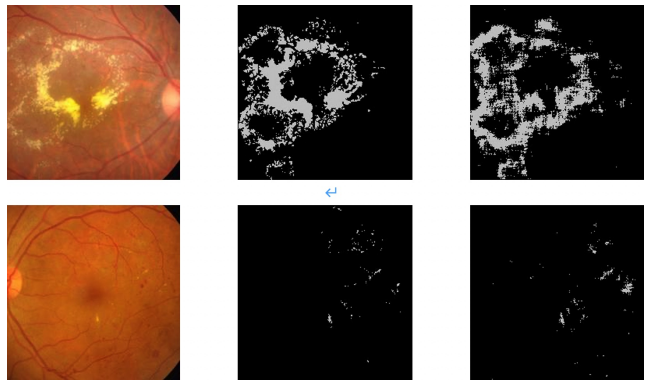


Figure 8: Comparison of fundus image, lesion labeling image and prediction image on IDRiD test dataset.

ure 8, the bright part of the fundus image after brightness correction includes hard exudates and optic discs, which has a certain impact on the detection of hard exudates. To sum up, the automatic detection method for hard exudates proposed in this paper achieves high accuracy and high sensitivity at the image level and also achieves good results at the lesion level. Although there are some false detections, they are all within the tolerance.

## 5 Conclusion

In this paper, a detection method about hard exudates based on deep learning is proposed. In order to overcome the uneven brightness and poor contrast of fundus images, the method adopts the brightness adjustment algorithm based on Hsvand extracts the green channel image for patch generation. Finally, a CNN model is built to detect hard exudates. The experimental results show that the sensitivity, specificity and accuracy of the proposed method are 70.27%, 96.71%, 96.11% in the pixel-based criterion. Compared with other methods that also use the IDRiD dataset, the sensitivity increased by 28.71%.

However, due to the difficulty of detecting DR lesions and the limited research time, the method still has some limitations and needs further improvement. The future research work to improve are:

- 1.This method performs poorly in edge detection of hard exudates. In future work, we will try to use contrast enhancement methods, such as multi-scale top hat transformation, to enhance the edge information of hard exudates.

- 2.The brightness and color of the optic disc affects the detection of hard exudates and cause a small number of false detections. In future work, the disc disk removal operation will be performed before patch generation.

- 3.Since padding is not used when generating patches, the pixels at the edge of the fundus image are not predicted, the future work will fill the original image before patch generation so that each pixel has an image patch centered on it.

## References

- Achanta, R.; Shaji, A.; Smith, K.; Lucchi, A.; Fua, P.; and Süsstrunk, S. 2012. SLIC Superpixels Compared to State-of-the-Art Superpixel Methods. *IEEE Transactions on Pattern Analysis & Machine Intelligence* 34(11): 2274–2282.
- Akram, M. U.; Tariq, A.; Anjum, M. A.; and Javed, M. Y. 2012. Automated detection of exudates in colored retinal images for diagnosis of diabetic retinopathy. *Appl Opt* 51(20): 4858–4866.
- Avula, B.; and Chakraborty, C. 2018. Detection of Hard Exudates in Retinal Fundus Images Using Deep Learning. 465–469. doi:10.1109/ICIEV.2018.8641016.
- Fraz, M.; Jahangir, W.; Zahid, S.; Hamayun, M.; and Barman, S. 2017. Multiscale segmentation of exudates in retinal images using contextual cues and ensemble classification. *Biomedical Signal Processing and Control* 35: 50–62. doi:10.1016/j.bspc.2017.02.012.
- Harangi, B.; and Hajdu, A. 2014. Automatic Exudate Detection by Fusing Multiple Active Contours and Regionwise Classification. *Comput. Biol. Med.* 54(C): 156–171.
- Li, H.; and Chutatape, O. 2004. Automated feature extraction in color retinal images by a model based approach. *Biomedical Engineering IEEE Transactions on* 51(2): 246–254.
- Li, X.; Pang, T.; Xiong, B.; Liu, W.; Liang, P.; and Wang, T. 2017. Convolutional neural networks based transfer learning for diabetic retinopathy fundus image classification. 1–11. doi:10.1109/CISP-BMEI.2017.8301998.
- Long, S.; Huang, X.; Chen, Z.; Pardhan, S.; and Zheng, D. 2019. Automatic Detection of Hard Exudates in Color Retinal Images Using Dynamic Threshold and SVM Classification: Algorithm Development and Evaluation. *BioMed Research International* 2019: 1–13. doi:10.1155/2019/3926930.
- Pereira, C.; Gonçalves, L.; and Ferreira, M. 2015. Exudate segmentation in fundus images using an ant colony optimization approach. *Information ences* 296: 14–24.
- Wu, L. 2019. *Diagnosis of diabetic retinopathy based on deep learning[D]*. Nanjing University of Aeronautics and Astronautics. Ph.D. thesis.
- Ye, X. 2018. *Research on the detection of exudates in diabetic retinal images based on deep learning*. Ph.D. thesis.
- Zhang, X.; Thibault, G.; Decencière, E.; Marcotegui, B.; Lay, B.; Danno, R.; Cazuguel, G.; Quéllec, G.; Lamard, M.; and Massin, P. a. 2014. Exudate detection in color retinal images for mass screening of diabetic retinopathy. *Medical Image Analysis* .