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An Efficient Deep Learning Network for Automatic Detection of Neovascularization in Color Fundus Images*

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***Abstract*— Retinopathy screening is a non-invasive method to collect retinal images and neovascularization detection from retinal images plays a significant role on the identification and classification of diabetes retinopathy. In this paper, an efficient deep learning network for automatic detection of neovascularization in color fundus images is proposed. The network employs Feature Pyramid Network and Vovnet as the backbone to detect neovascularization. The network is evaluated with color fundus images from practice. Experimental results show the network has less training and test time than Mask R-CNN while with a high accuracy of 98.6%.**

I. Introduction

Diabetic Retinopathy (*DR*) is an eye disease consisting on retina damage due to diabetes mellitus, a chronic degenerative disease with a worldwide prevalence of 2-6% [1]. Retinopathy screening is a non-invasive method to collect retinal images. Read from these images, early diagnosis of *DR* can be applied by ophthalmologists.

The formation of neovascularization is an important basis for the staging and classification of diabetic retinopathy, and is the only golden standard for diabetic retinopathy to enter the proliferative stage. The number and duration of neovascularization are the most important indicators to determine the treatment plan of diabetic retinopathy, which is of great significance to evaluate the treatment results and determine the prognosis [2].

Detection of neovascularization regions in color fundus images is very important as it can act as a pre-emptive strategy for getting immediate attention and treatment, help ophthalmologists in identifying hard-to-see features of neovascularization, and indirectly lower the cases of very serious retinal damage. However, detection of neovascularization regions is a difficult task for the following reasons: First, neovascularization is very similar to normal blood vessels, thus it is challenging to distinguish neovascularization with normal blood vessels. Second, neovascularization can appear anywhere in retinal images, thus there is no very accurate location distribution of the neovascularization in color fundus images. Third, The thickness of the blood vessel which constructs neovascularization is usually as thin as 1 pixel, and neovascularization can present itself in several patterns, such as umbrella, flower, sea coral, or other complicated structures, so it is very difficult to design an operator to detect it.

Neovascularization detection using color fundus images is an area which has not been fully explored. To the best of our knowledge, there recently published several works related to neovascularization detection. In the year of 2017 [3], a deep learning system is proposed to classify retinal images in to diabetic retinopathy, possible glaucoma, and age-related macular degeneration. Varun Gulshan *et al.* presents a deep learning algorithm for referable diabetic retinopathy [4]. Another deep learning framework [5] for the detection of blood vessels is proposed to detect exudates, microaneurysms, hemorrhages and neovascularization. The Deep-learning-based CAD system [6] uses AlexNet to extract features and uses SVM to classify retinal images into five stages, namely normal, mild NPDR, Moderate NPDR, Severe NPDR and PDR. An automated detection employing GoogLeNet and AlexNet, VGG16 for the recognition task of diabetic retinopathy staging is presented [7]. However, the works above focus on classification of the images rather than detect neovascularization regions in images.

Object detection using deep learning has has rapidly developed with the help of GPU accelerations. Fast R-CNN [8] employs Convolutional Neural Networks (CNN) to extract features and uses fully connected layers (FCs) to estimate classes and ROI(region of interest) bounding box(bbox) of objects. SPP-net in [9] can extract features in images in multi-scale and remove the fixed-size constraint of the network. Faster R-CNN [10] introduces Region Proposal Networks (RPNs) which can estimate region proposals using GPUs. In [11], RetinaNet implements a One-stage detector which consists of Feature Pyramid Network (FPN) backbone and classification subnet and box regression subnet. Mask R-CNN [12] uses ROI Align technique to determine the position and category of various objects in an image and give pixel-level prediction.

In this paper, we hope to apply the object detection using deep learning to the detection neovascularization in color fundus images. The main contributions of this paper are summarized as follows.

1) We have established a deep learning network which can detect neovascularization in retina images. The deep learning network can detect whether there is neovascularization in color fundus images, at the same time, it can detect the regions of neovascularization. This will help doctors diagnose color fundus images from screening.

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2) An efficient deep learning network for neovascularization detection from color fundus images is proposed. Experimental results show that this network can has less training and testing time, but has a high accuracy.
3) The network can detect neovascularization automatically without human intervention, and this will assist ophthalmologists in identifying hard-to-see features of neovascularization.

The remainder of this paper is organized as follows. Section II proposes the design of neovascularization detection network. Section III evaluates the automatic neovascularization detection network with real data. Section IV concludes the paper and points out some future work.

II. Neovascularization Detection Network Architecture

A. Architecture overview

Neovascularization detection in color fundus images is a difficult task which cannot be easily solved by simple networks, so we propose a deep learning architecture consists of three stages as shown in Fig. 1. Stage I extracts basic features from color fundus images; Stage II collect the basic features and generate intermediate feature maps; Stage III generate proposal region bounding boxes and masks. The above three steps are essential for the detection of neovascularization, and the three stages can work together efficiently.

B. Stage I

In Stage I, color fundus images are transferred to a Feature Pyramid Network (FPN) to extract the features in multi-scale. This stage is designed for the following reasons: First, neovascularization are often very thin and curved, and neovascularization may appear different patterns, thus small scale features can represent them. Second, normal areas on color fundus images often present smooth, and large scale features can describe them. Multi-scale features will help to distinguish neovascularization from normal areas. In practice, we choose p_2, p_3, p_4, p_5 and p_6 features where p_L has the $1/L$ resolution of the original color fundus image. These features are enough to describe objects in various scales, and thus can help to describe neovascularization. However these multi-scale features are in their each own scales separately without connections, and should be future analyzed in State II.

C. Stage II

In Stage II, the features extracted from Stage 1 are delivered to backbone to generate intermediate feature maps. The features directly extracted from color fundus images in Stage I should be interpreted and processed for estimation the regions of neovascularization. So a backbone of several deep learning blocks are constructed to generate intermediate feature maps for the detection of regions of neovascularization in Stage III. In practice, we use Vovnet [13] instead of ResNet as the backbone as it is more efficient while preserving the benefit from concatenative aggregation for object detection task. As shown in Fig. 2, ResNet arrange several residual blocks connected in series, and each block sums the feature from the previous block. As explained in [14], the information extracted from early feature maps may be vanished by summing with others. As neovascularization detection requires features in various scales, keeping information from various layers is extremely important. However, in Vovnet backbone as shown in Fig. 1, several blocks are connected without activation functions, and feature maps are aggregated using one activation function, and this operation will keep the primitive features, and make it easy to be trained. Plus, Vovnet is optimized for GPU acceleration, thus it can work more efficient than ResNet, which can be validated in Section III

D. Stage III

In Stage III, the intermediate feature maps are processed to estimate the bounding box and mask for neovascularization regions. Neovascularization regions can appear anywhere in color fundus images, so we need an object detector with translation-variant properties. RoI Align technique introduced by Mask R-CNN [12] just meets the demand. In this stage, the intermediate feature maps produced by Stage II are swallowed to two fully-connected networks (FCs) to estimate bounding box and the mask separately. The activation functions in Mask R-CNN are removed in this stage as the activation has been calculated in Stage II.

The designated neovascularization detection network can work automatically without human intervention. The network should work efficient and effectively once it has been trained by practical color fundus images. In section III, the network will be evaluated and examined with real data.

III. Experimental Evaluation

A. Experimental setup

The experimental procedures involving human subjects described in this paper were approved by the Institutional Review Board. A dataset of 330 practical color fundus images and was built up. Expert ophthalmologists are asked to make the annotations for neovascularization areas on these images. Among the fundus images, 230 pictures are randomly selected for training and the rest 100 images are for testing.

For fair speed comparison, we measure the inference time of all models in on the same GPU workstation with NVIDIA GeForce RTX 1060, CUDA v 10.01, Intel(R)Core(TM)i7-8700 CPU, 64G DDR4 memory. The experimental environment was configured under Ubuntu 18.04.

B. Performance evaluation

In order to evaluate the effectiveness of the model, we compare our proposed method with some existing state-of-art models, such as Faster R-CNN and Mask R-CNN. For the performance evaluation, for fair comparison, without any bells-and-whistles, we keep hyper-parameters such as learning rate and the number of iterations same. COCO standard Average Precision (AP) was calculated using Intersection

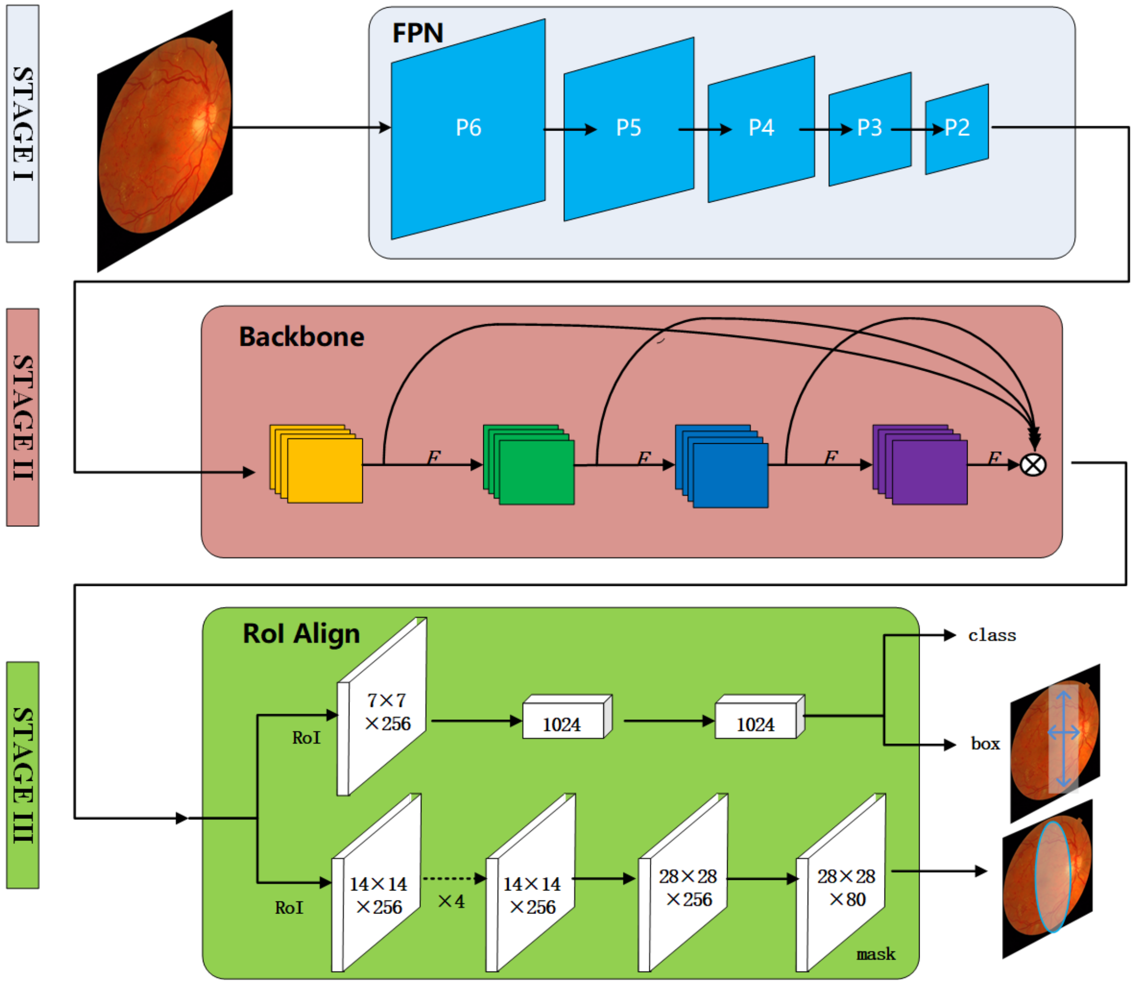

Fig. 1. Efficient Deep Learning Network for Detection of Neovascularization in Color Fundus Images.

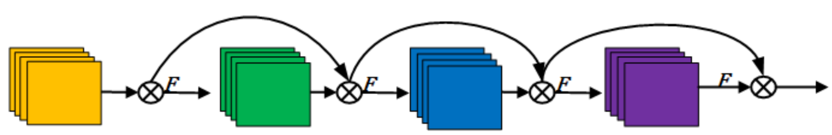

Fig. 2. ResNet Backbone.

over Union (IoU), and AP_50 (AP at IoU=0.5) and AP_75 (AP at IoU=0.75) for the evaluation of models. Bounding boxs (marked as bbox) evaluation was compared with Faster R-CNN and Mask R-CNN while Segmentation mask(marked as seg) was compared with Mask R-CNN for Faster R-CNN did not produce mask estimations. The comparison results are shown in Table I. We can find that our work achieve high accuracies with bbox detection accuracy 98.6% and segmentation accuracy 98.6% with IoU $>$ 0.5. As expected, our works has the same level of accuracy with Mask R-CNN, but the training time and test time are much less than Mask R-CNN. Faster R-CNN uses the least test time for it only estimates the bounding boxs (bbox) while Mask R-CNN and our works estimates bboxs and segmentations.

C. Accuracy Evaluation

To show the efficacy of the proposed method as compared to the different existing techniques, we compare our method with the methods proposed by Akram et al. [15], Kar et al. [16]. The comparison results shown in Table I demonstrates that our proposed method can achieve a high accuracy of 0.986 for neovascularization detections, which outperforms the existing methods.

We also display qualitative results on mini-testing dataset. Table III lists several typical images and ground truth as well as the results of Faster R-CNN , Mask R-CNN and our work. The boxes and segmentations in the figure have confidence scores over 0.7. As is seen from Table III, our proposed method can detect neovascularization regions most accurately while Faster R-CNN and Mask R-CNN sometimes

TABLE I

PERFORMANCE EVALUATION

Network	AP^{bbox}	AP^{bbox}_{50}	AP^{bbox}_{75}	AP^{seg}	AP^{seg}_{50}	AP^{seg}_{75}	**Training Time(s)**	**Testing Time(s)**
Faster R-CNN	41.2	76.3	41.9	–	–	–	4823.0	13.0
Mask R-CNN	28.7	54.0	28.6	27.0	52.8	22.7	5063.4	66.4
Proposed method	72.7	98.6	88.9	83.7	98.6	93.7	1071.7	31.6

can generate wrong bbox or masks, such as the results in Sample Image 2 and 3. We can also find that our method can find some small regions of neovascularization such as Region D in Sample Image 2. The comparison results were submitted to for evaluation, and ophthalmology experts admitted that our work had shown very impressive results.

TABLE II

COMPARISON OF NEOVASCULARIZATION DETECTION METHODS

No.	Method	Accuracy
1	Akram et al. [15]	0.95
2	Kar et al. [16]	0.9506
3	Proposed method	0.986

IV. CONCLUSION

In this paper, an efficient deep learning network for automatic detection of neovascularization in color fundus images is introduced. Experiments shows the network has less training and test time while with a high accuracy of 98.6%. In the future, we hope to apply it in practice to assist ophthalmologists to make neovascularization diagnosis.

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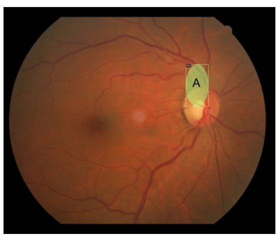
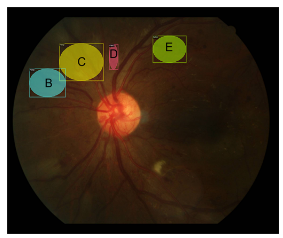
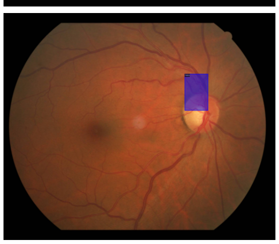
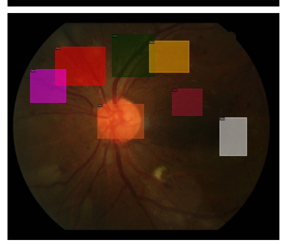
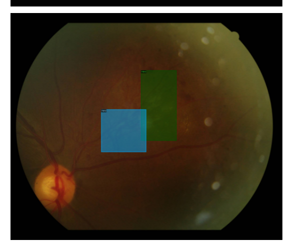
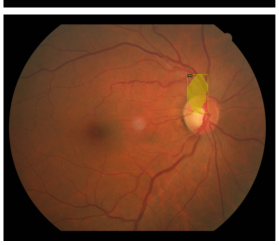
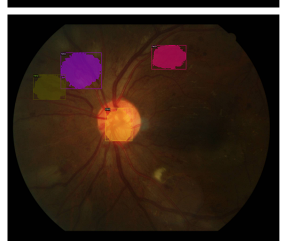
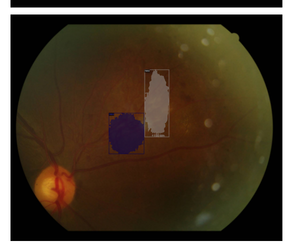
TABLE III

COMPARISON OF QUALITATIVE DETECTION RESULTS.

	Sample Image 1	Sample Image 2	Sample Image 3
Original Image			
Ground Truth			
Faster R-CNN			
Mask R-CNN			
Proposed Method