Diabetic Retinopathy Detection Based on Deep Convolutional Neural Networks

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Introduction

Diabetic retinopathy (DR) is an eye disease associated with long-standing diabetes. Early works on DR detection rely on the design of handcrafted features, which tends to be complicated [1]. Recently, CNN-based methods have significantly improved the DR detection accuracy [2][3]. Fig. 1 shows the proposed DR detection system.

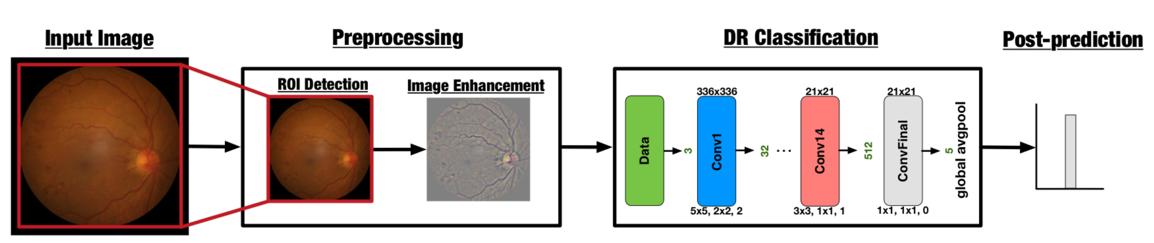

Figure 1: System overview of our proposed DR recognition pipeline based on deep convolutional neural networks.

Table 1: SI2DRNet-v1

Type	Filters	Size/Stride	Output
Convolution	32	5x5/2	336x336
Convolution	32	3x3	336x336
Max Pooling		3x3/2	168x168
Convolution	64	5x5	168x168
Convolution	64	3x3	168x168
Convolution	64	3x3	168x168
Max Pooling		3x3/2	84x84
Convolution	128	5x5	84x84
Convolution	128	3x3	84x84
Convolution	128	3x3	84x84
Max Pooling		3x3/2	42x42
Convolution	256	5x5	42x42
Convolution	256	3x3	42x42
Convolution	256	3x3	42x42
Max Pooling		3x3/2	21x21
Convolution	512	5x5	21x21
Convolution	512	3x3	21x21
Convolution	512	3x3	21x21
Convolution	5	1x1	21x21
Global Avg. Pooling		21x21	1x1

Table 2: Five major evaluation metrics

Measure	Formula
Specificity (TNR)	$\frac{TN}{TN+FP}$
Sensitivity (TPR)	$\frac{TP}{TP+FN}$
Accuracy	$\frac{TP+TN}{TP+FN+TN+FP}$
AUC	$\int_{-\infty}^{\infty} TPR(T)FPR'(T)dT$
κ	$1-\frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,j}O_{i,j}}{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{i,j}E_{i,j}}$

*FPR = 1 - Specificity, T = threshold
*N = number of classes, $w_{i,j}$ = weight matrices
*$E_{i,j}$ = expected matrices, $O_{i,j}$ = observed matrices

Proposed Framework

Image Enhancement The formulation of the classic linear unsharp masking (UM) is given by:

$$y(n,m) = x(n,m) + \lambda g(n,m) \quad (1)$$

We implement $g(n,m)$ as:

$$g(n,m) = 4[G(n,m,\sigma) * x(n,m) - x(n,m)] \quad (2)$$

where $G(n,m,\sigma)$ is a Gaussian filter with σ equals to $\frac{30}{r}$, r is the radius of ROI of the fundus image, $*$ denotes the convolution operator, and λ is set to 4.

The DR Classification Network: Table 1 shows the detailed architecture of SI2DRNet-v1.

- To reduce the number of parameters and regularize the model, we use global average pooling and 1 x 1 filters to replace fully connected layers.
- We also found that scaling the kernel size of convolutional layer after each pooling layer from 3 x 3 to 5 x 5 increases the performance.

Post-prediction: Five probability values are extracted from the softmax layer, and summed up according to the following formula:

$$y_{pp} = 0 \cdot p_0 + 1 \cdot p_1 + 2 \cdot p_2 + 3 \cdot p_3 + 4 \cdot p_4 \quad (3)$$

where y_{pp} is the post-prediction value, p_0, p_1, p_2, p_3, and p_4 are the probabilities of normal, mild, moderate, severe, and proliferative DR. Then, we can decide new thresholds according to our objective function, such as quadratic weighted kappa which is more flexible than fine-tuning.

Experiment

We evaluate the proposed framework on two public datasets: EyePACS and Messidor and utilize five metrics as listed in Table 2 to evaluate the performance of our proposed framework.

- Table 3 shows the results of six methods to further boost the recognition accuracy
- Table 4 compares the results of our method with previous works on the Messidor dataset.
- Table 5 shows the comparison results of model complexity.

Table 4: Performance comparison on the Messidor dataset

Method	DR		RDR	
	Acc.	AUC	Acc.	AUC
Fisher Vector [1]	-	-	-	0.863
VNXK [2]	0.871	0.870	0.893	0.887
CKML Net [2]	0.857	0.862	0.897	0.891
Comprehensive CAD [4]	-	0.876	-	0.91
Expert A [4]	-	0.922	-	0.94
Expert B [4]	-	0.865	-	0.92
Zoom-in-Net [3]	0.905	0.921	0.911	0.957
SI2DRNet-v1	**0.905**	**0.959**	**0.912**	**0.965**

Table 5: Model complexity comparison

Network	Input size	Params	FLOPs
CKML Net [2]	451x451	71.5M	19.2G
VNXK [2]	449x449	507.4M	63.4G
Zoom-in-Net [3]	492x492	55.8M	38.2G
SI2DRNet-v1	672x672	**10.6M**	**15.4G**

Table 3: Ablation study of the proposed recognition pipeline on the EyesPACS dataset

	Baseline								SI2DRNet-v1
Use pre-train model		√	√	√	√	√	√	√	√
Image enhancement			√	√	√	√	√	√	√
More data augmentation				√	√	√	√	√	√
L1 norm					√	√	√	√	√
Post-prediction						√	√	√	√
Scale input resolution (2x)							√		
Scale input resolution (3x)								√	√
10 crops for testing									√
EyesPACS validation set (κ)	0.466	0.611	0.671	0.707	0.723	0.754	0.801	0.808	0.808
EyesPACS test set (κ)	0.471	0.601	0.654	0.704	0.709	0.742	0.796	0.802	0.804

Conclusion

We present a framework based on DCNN for the DR detection. Along with six useful methods, the proposed framework achieves 0.959 and 0.965 AUC for DR and RDR cases on the Messidor dataset which outperform state of the art (0.921 and 0.957) [3]. Furthermore, we are able to achieve this performance with a lightweight model. Compared with CKML Net [2], VNXK [2], and Zoom-in-Net [3], SI2DRNet-v1 is more memory efficient with at least 5.26x fewer in total parameters and requires lower computation cost with at least 1.24x fewer in total FLOPs.

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