THE HONG KONG POLYTECHNIC UNIVERSITY
香港理工大學

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Robust Localization of Retinal Lesions via Weakly-supervised Learning

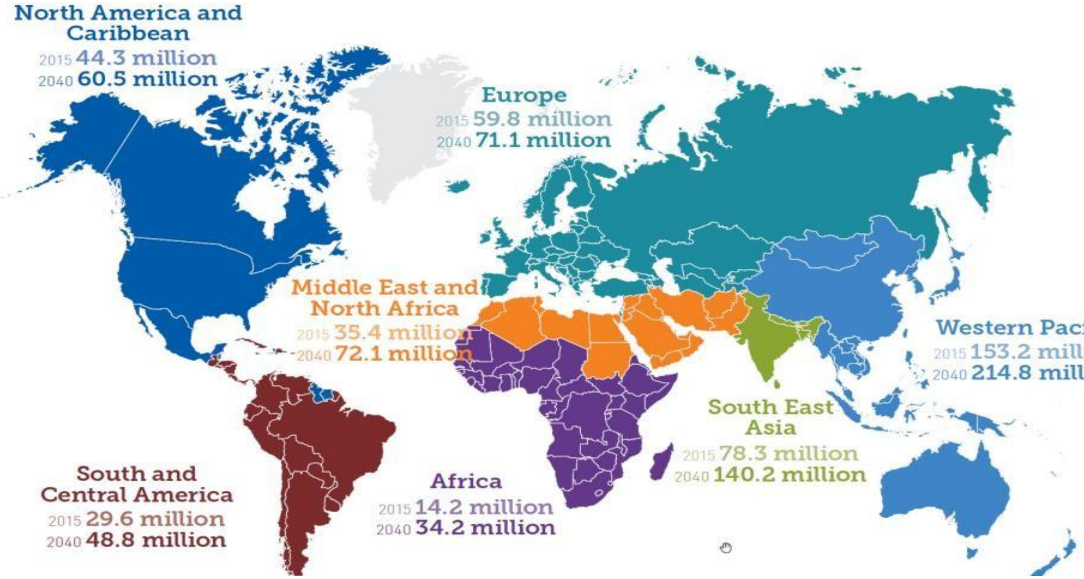
Ruohan Zhao, Qin Li, Jane You

Contact: csrzhao@comp.polyu.edu.hk

Diabetic Retinopathy(DR) - Disease

➲ In 2014 there have been 415m adults living with diabetes. About 145m (35%) had some form of diabetic retinopathy (DR). Among these 45m (11%) had vision-threatening DR. In 2040 about 642m adults will have diabetes.

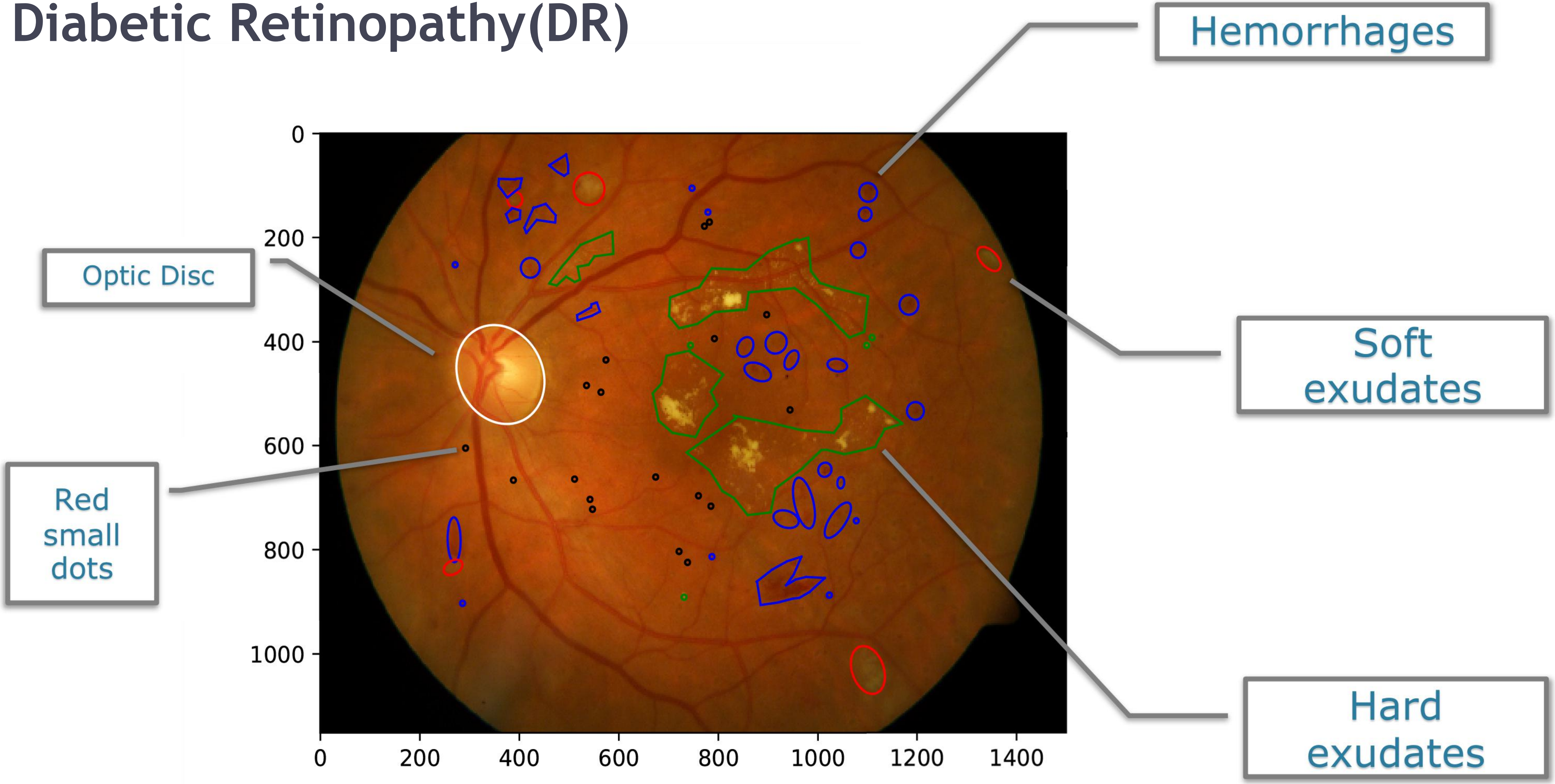
➲ About 7m of people with diabetes are *blind* due to DR.



➲ Low- and middle-income countries account for about 75% of the global diabetes cases. But medical infrastructure is lacking to identify and treat this disease.

➲ There are no early symptoms, but early detection and treatment can reduce the risk of vision loss by *95%.*

Diabetic Retinopathy(DR)



Motivation

- Traditional diabetic eye screening lasts about *30 minutes*.
- Within *six weeks*, they will receive results.
- requires a *well-trained* clinician to manually evaluate color fundus photographs of the retina
- *Equipment* are highly demanded in rural areas

Fundus camera

mobile model

Retinal image

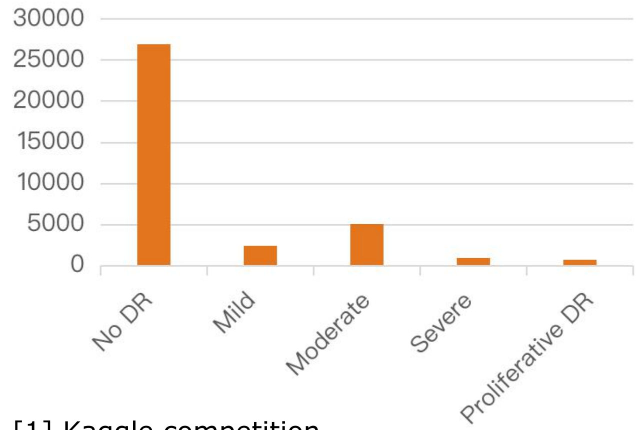
Only image-level label

Classification

Healthy

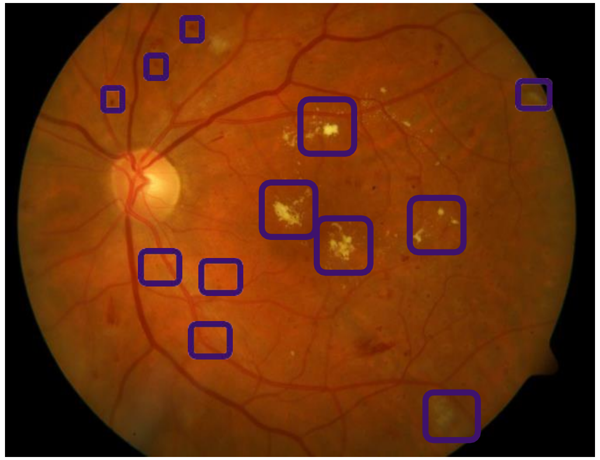
Unhealthy

How?



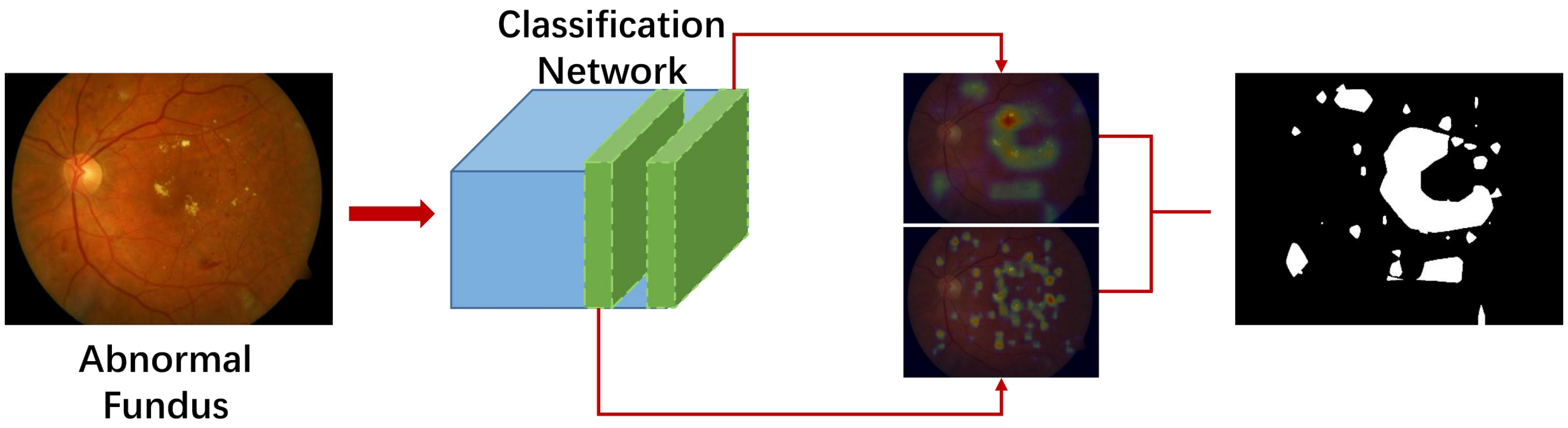
[1] Kaggle competition

Lesions localization

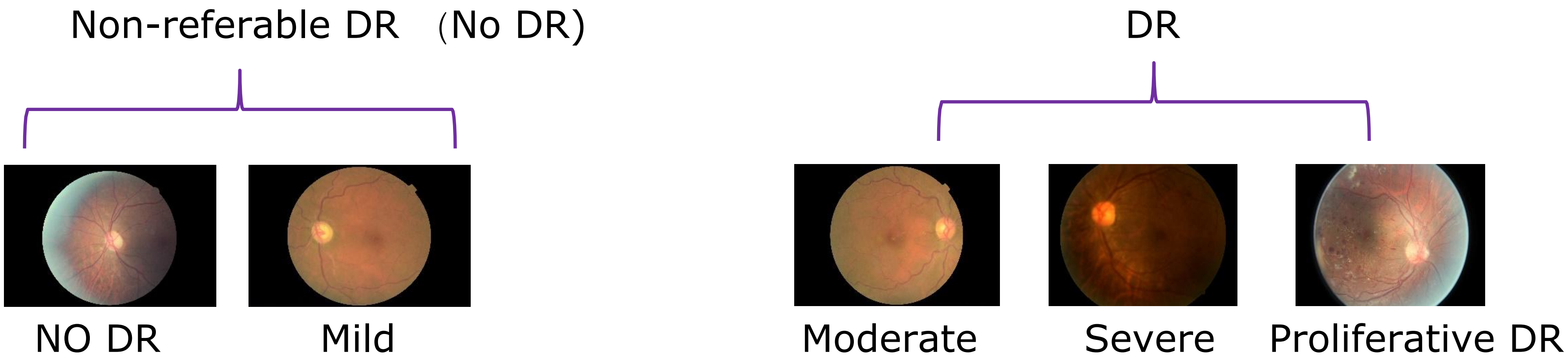


[1]"Diabetic Retinopathy Detection | Kaggle." [Online]. Available: https://www.kaggle.com/c/diabetic-retinopathy-detection.

Method



1. Classficaition: The network is trained in *only labels* on image level (No DR, Referabel DR).



Method

2. Proposed Framework

Algorithm 1: Training and localizing procedure

Training procedure:

Input: Training Data $I = \{(I_i, c_i)\}_{i=1}^{N}$

Output: Network parameters θ

While training is not convergent:

Use mix-training $\hat{I}_2, \hat{c} \leftarrow$ Mix-Training(I_1, I_2, c_1, c_2);

Get classification score $Y \leftarrow$ Classifier$(\hat{I}_2)$;

Update $\theta \leftarrow$ BinaryCrossEntropy$(Y, \hat{c})$;

Localization procedure:

Input: The inference image I_t

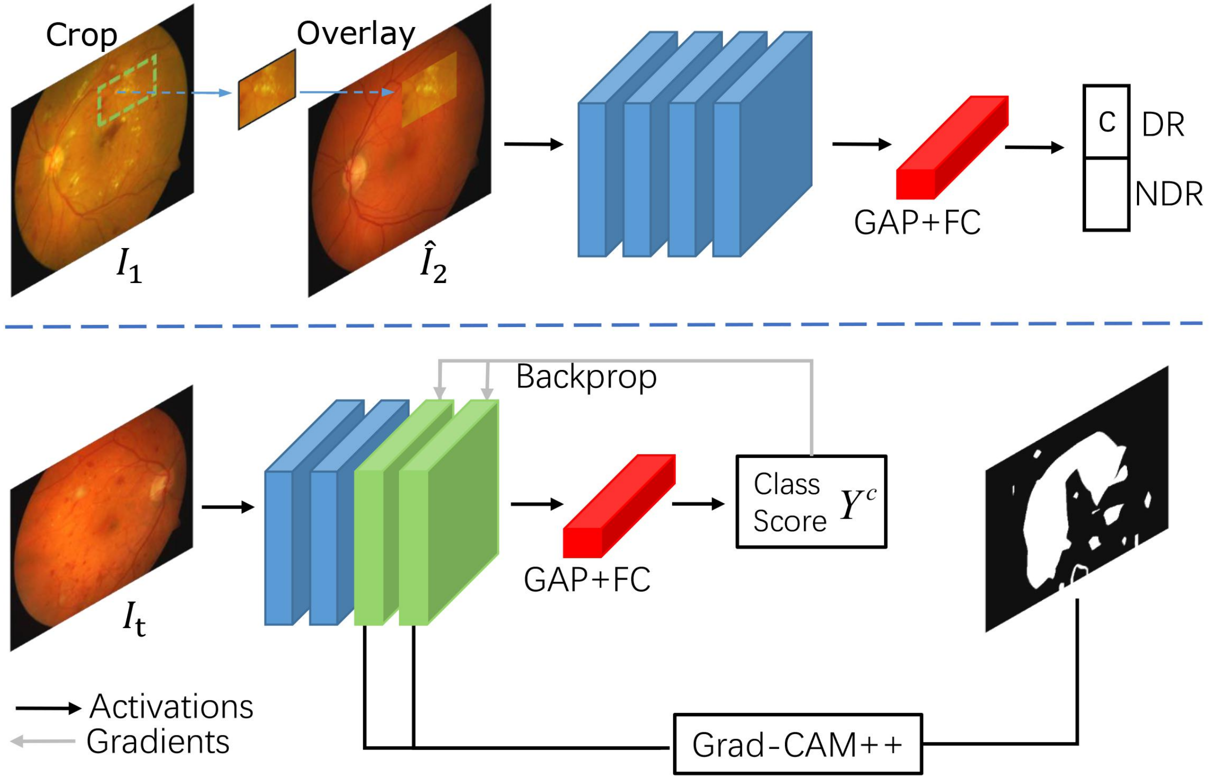
Output: localization map L

$A_n^k, Y \leftarrow$ Feed-forward(I_t);

For different layers n:

$L_n \leftarrow$ Grad-CAM$^{++}(A_n^k, Y)$;

$L \leftarrow$ Aggregation(L_n)



Method

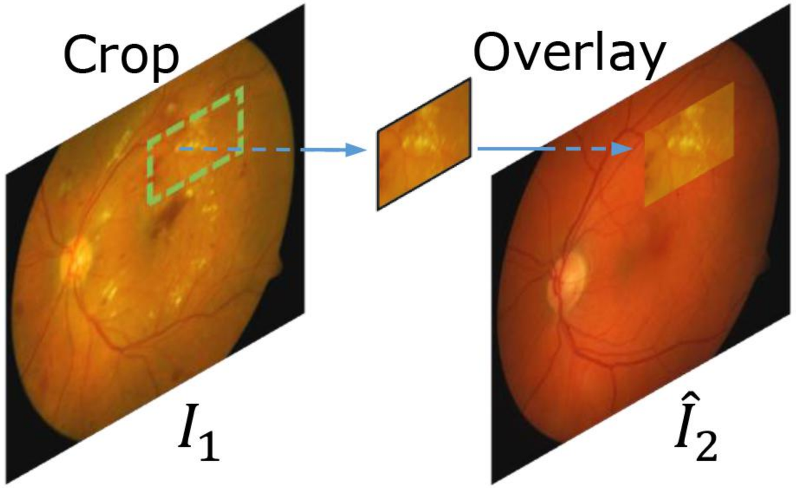
3. Mix-training stragety. Promote the capacity of capturing diversified lesions.

We choose two random training samples, denoted as $\{I_1, I_2\} \in \mathbb{R}^{W \times H \times 3}$ with their corresponding image labels $\{c_1, c_2\}$. We then crop a random patch from I_1 and overlaid the cropped patch to the corresponding region of I_2, to synthesize a new training sample $\hat{I}_2$.

$$\hat{I}_2 = \mathbf{M} \odot I_1 + (\mathbf{1} - \mathbf{M}) \odot I_2$$

$$r_x \sim U(0, W), \quad r_y \sim U(0, H),$$
$$r_w = \lambda \cdot W, \quad r_h = \lambda \cdot H,$$

$$\hat{c} = \begin{cases} \lambda c_1 + (1-\lambda) c_2 & c_1 \in \mathrm{DR}, c_2 \in \mathrm{NDR} \\ c_2 & others \end{cases}$$



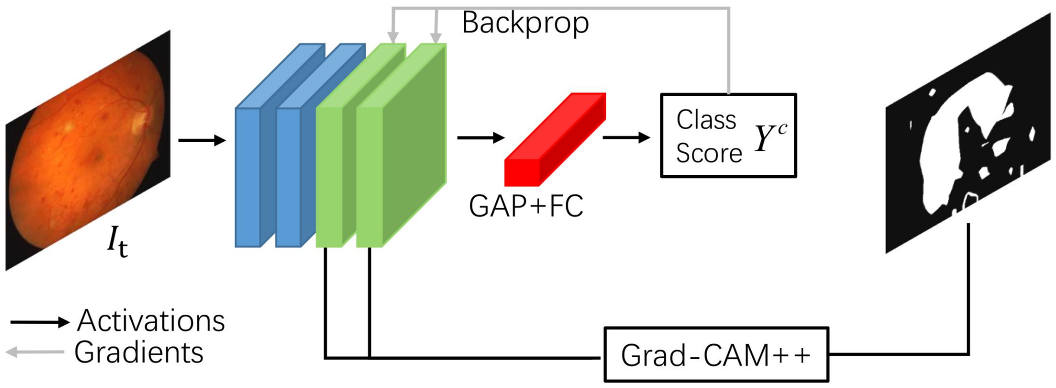
Method

4. Inference method

The feature map extracted by the classifier reflects the parts of the fundus that are investigated by the classification network for assigning a label. To leverage feature maps from multi-layers and classification score, Grad-CAM^{++} can then be used to derive the localization map. We firstly feed the image I_t into the network and obtain classification score Y of referable fundus. Denote the feature map at the n^{th} convolution layer of unit k as A_n^k.

$$L_n = \mathrm{ReLU}\left(\sum_k w_k \cdot A_n^k\right)$$

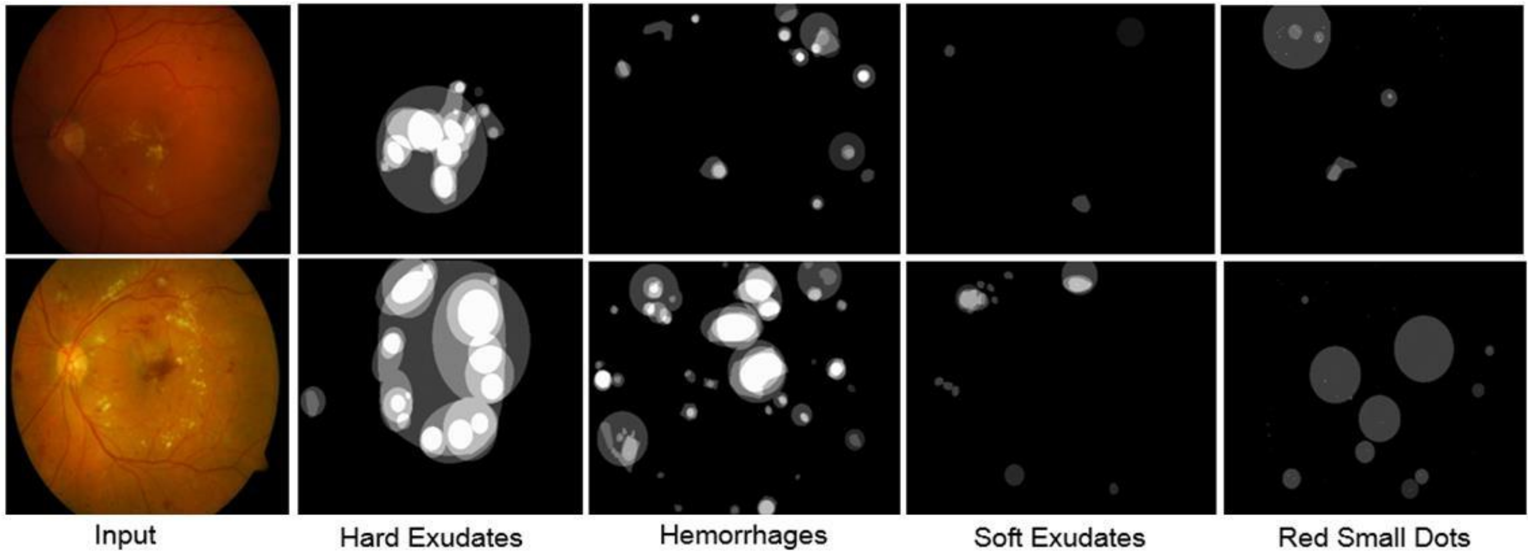
$$w_k = \sum_i \sum_j \alpha_{ij}^k \cdot \mathrm{ReLU}\left(\frac{\partial Y}{\partial A_{ij}^k}\right)$$



[2] A. Chattopadhay, A. Sarkar, P. Howlader, and V. N. Balasubramanian,"Grad-cam++: Generalized gradient-based visual explanations for deepconvolutional networks," in2018 IEEE Winter Conference on Applica-tions of Computer Vision (WACV). IEEE, 2018, pp. 839–847.

Result

Test data set: DiaretDB1 dataset [3]



- High resolution images used for testing
- Lesions marked by four experts
- Regions with more than 75% confidence among the experts are considered as acceptable.

[3] T. Kauppi et al., “the DIARETDB1 diabetic retinopathy database and evaluation protocol,” Procedings Br. Mach. Vis. Conf. 2007, p. 15.1-15.10, 2007.

Result

TABLE I: Performance evaluation at lesion-level with other methods on DIARETDB1.

Method	Red lesion				Bright lesion			
	Microaneurysm		Hemorrhages		Hard Exudates		Soft Exudates	
	Sen%	FPI	Sen%	FPI	Sen%	FPI	Sen%	FPI
Chudzik *et al.*	64.1	8	-	-	-	-	-	-
Seoud *et al.*	63.9	8	-	-	-	-	-	-
Quellec *et al.*	61	10	71	10	80	10	90	10
Gondal *et al.*	52	1.5	91	1.5	87	1.5	89	1.5
Ours	63.4	4.2	95.9	2.6	94.2	3.0	93.1	2.3

[4] Chudzik, S. Majumdar, F. Caliv á, B. Al–Diri, and A. Hunter, “Microa–neurysm detection using fully convolutional neural networks,” Computer methods and programs in biomedicine, vol. 158, pp. 185—192, 2018.
[5] L. Seoud, T. Hurtut, J. Chelbi, F. Cheriet, and J. P. Langlois, “Redlesion detection using dynamic shape features for diabetic retinopathy screening,” IEEE transactions on medical imaging, vol. 35, no. 4, pp.1116—1126, 2016.
[6] G. Quellec, K. Charri`ere, Y. Boudi, B. Cochener, and M. Lamard, “Deep image mining for diabetic retinopathy screening,” Medical Image Analysis, vol. 39, pp. 178—193, 2017.
[7] W. M. Gondal, J. M. K öhler, R. Grzeszick, G. A. Fink, and M. Hirsch, “Weakly–supervised localization of diabetic retinopathy lesions in retinal fundus images,” arXiv preprint arXiv:1706.09634, 2017.

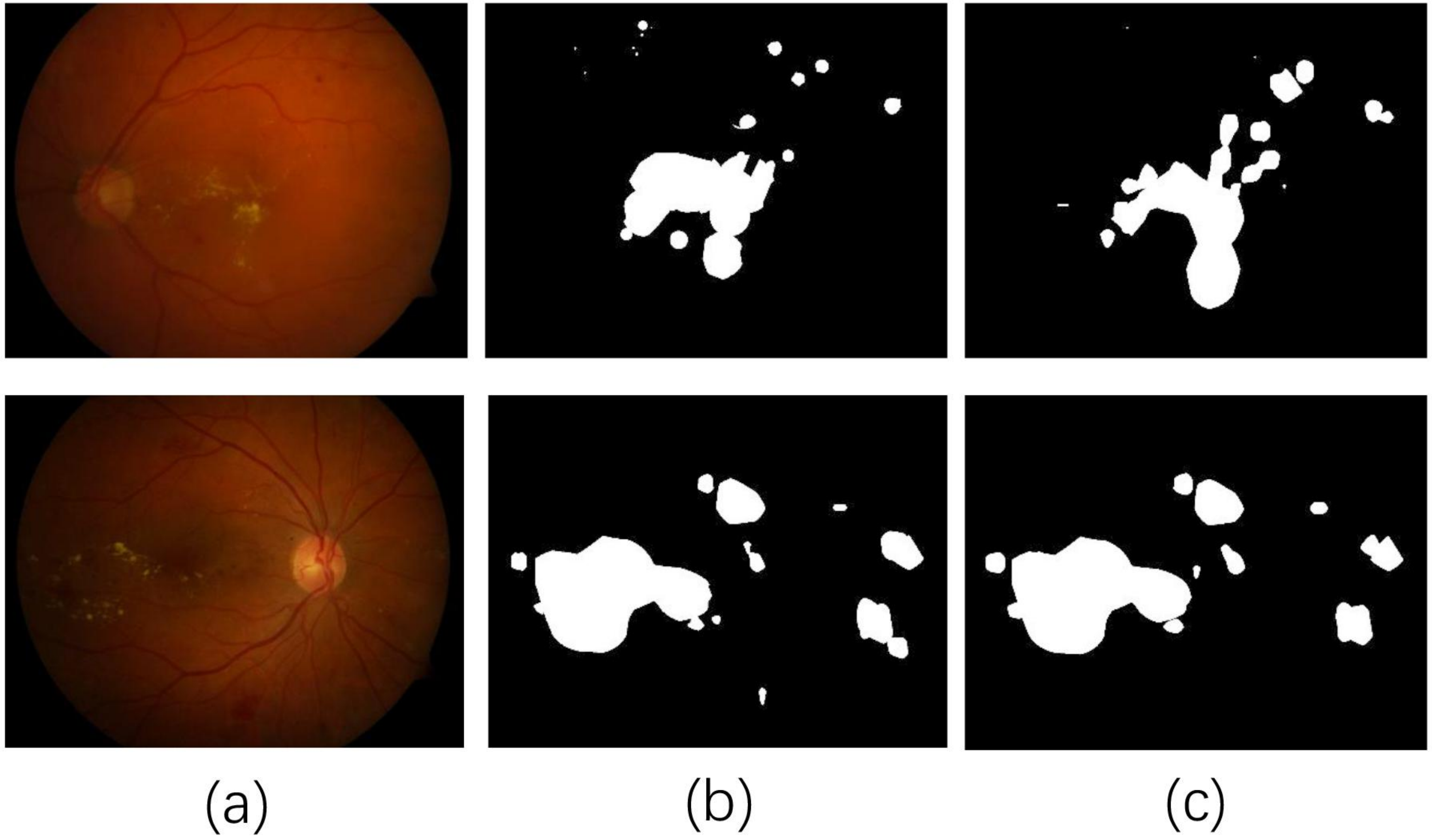
Result

TABLE II: Sensitivity% at image-level on the DIARETDB1 dataset. The best is shown in bold.

Method	MAs	HEs	Soft Exudates	Hard Exudates
Liu *et al.*	-	-	83.0	83.0
Zhou *et al.*	-	94.4	-	
Zhao *et al.*	-	**98.1**	-	-
Quellec *et al.*	-	94.7	-	-
Gondal *et al.*	50	97.2	90.9	**100**
Ours	**68.9**	97.5	**92.2**	98.5

[8] Liu, B. Zou, J. Chen, W. Ke, K. Yue, Z. Chen, and G. Zhao, "Alocation-to-segmentation strategy for automatic exudate segmentationin colour retinal fundus images," Computerized medical imaging andgraphics, vol. 55, pp. 78—86, 2017.
[9] L. Zhou, P. Li, Q. Yu, Y. Qiao, and J. Yang, "Automatic hemorrhagedetection in color fundus images based on gradual removal of vascular branches," inImage Processing (ICIP), 2016 IEEE International Con-ference on. IEEE, 2016, pp. 399—403.
[10] Y. Zhao, Y. Zheng, Y. Zhao, Y. Liu, Z. Chen, P. Liu, and J. Liu, "Uniqueness-driven saliency analysis for automated lesion detection with applications to retinal diseases," inInternational Conferenceon Medical Image Computing and Computer-Assisted Intervention.Springer, 2018, pp. 109—118.

Result



(a) Fundus images (b) Ground-truth (c) Segmented results