Adversarial Learning for Diabetic Retinopathy

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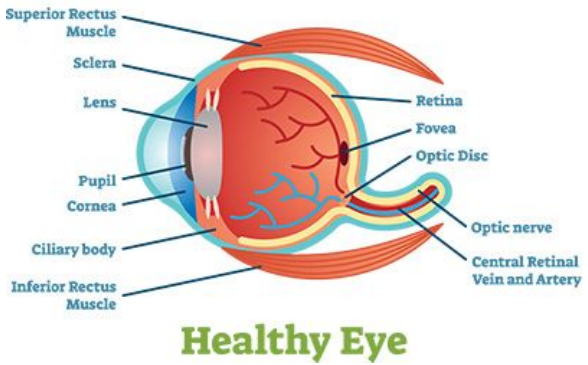
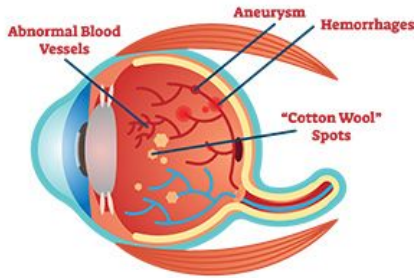
Outline

- **Motivation for Diabetic Retinopathy Problem**
- **Diabetic Retinopathy Lesion Detection**
  - Problem Definition
  - Detection Methods
  - Detection Performance
- **Diabetic Retinopathy Lesion Segmentation**
  - Problem Definition
  - Segmentation Framework
    - Conditional GAN Based.
    - Generator: HedNet
  - Segmentation Performance
- **Conclusion**

Motivation: Diabetic Retinopathy



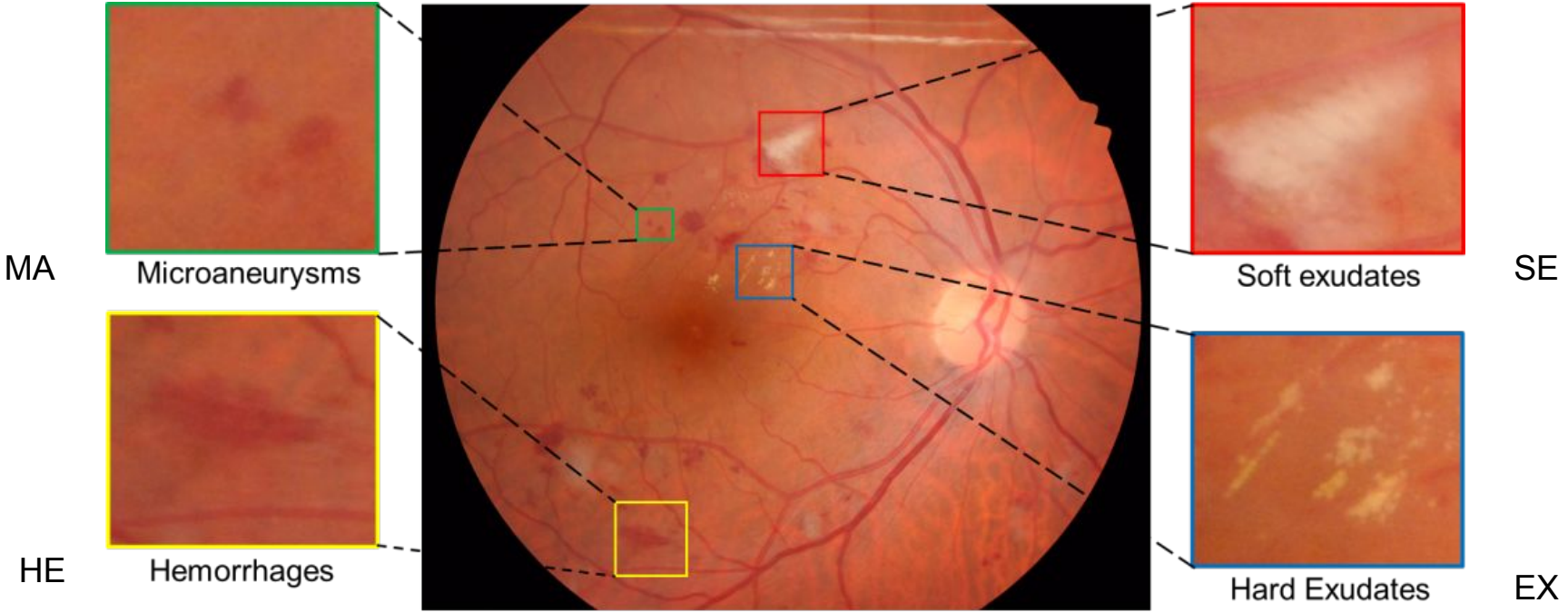
Healthy Eye



Diabetic Eye

- **What:**
  - Diabetes complication
  - Caused by damage to the blood vessels
  - Cause of preventable blindness.
- **Why:**
  - Early detect diseases
  - Hard, time consuming
  - Make it automatic.

Diabetic Retinopathy Lesions



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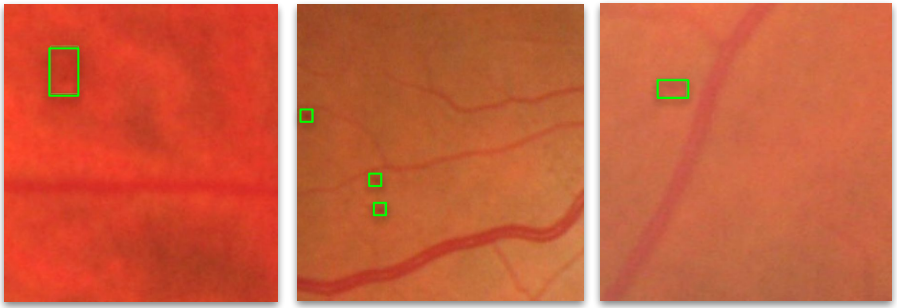
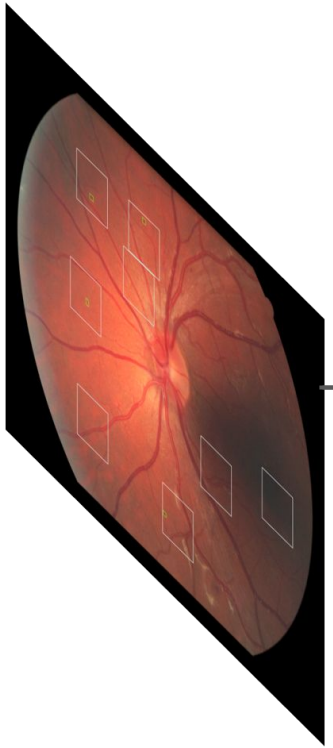
Definition: Diabetic Retinopathy Lesion Detection

- **Training:**
  - **train** the model **given** several retinal images, with labels of microaneurysms.
- **Testing:**
  - **detect** the locations of microaneurysms on new images.



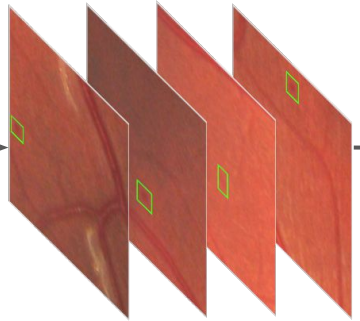
Example microaneurysms in 200×200 patches with bounding box labels(noted in green)

Detection Framework

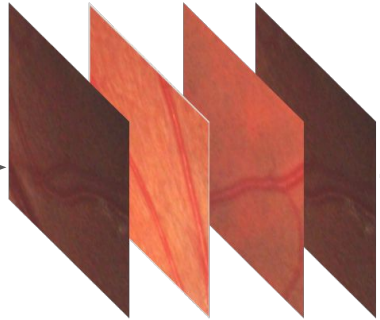


generate bboxes

data augmentation:
random crop



positive samples,
ratio = 0.5



negative samples,
ratio = 0.5

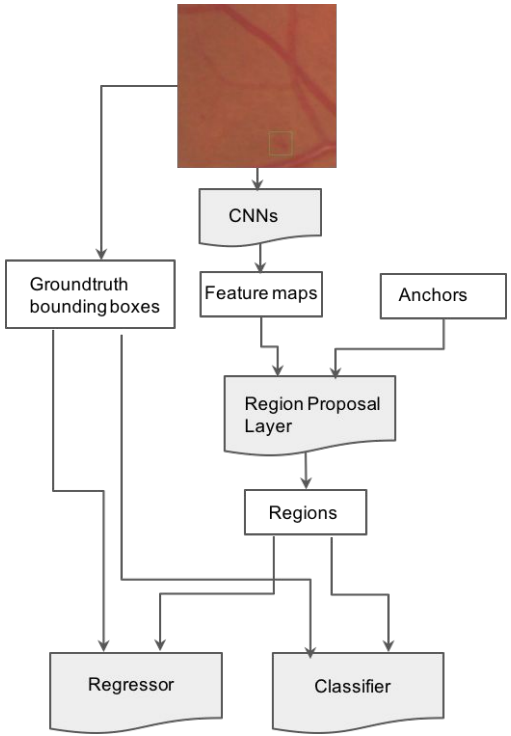
Faster RCNN

Modified
Faster RCNN

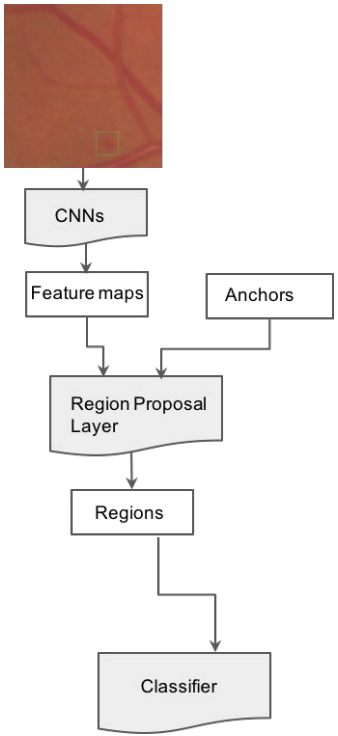
Methods: inclusion of negative samples

Inclusion of negative samples

- *positive samples:* patches containing at least one microaneurysm;
- *negative samples:* patches without microaneurysms;

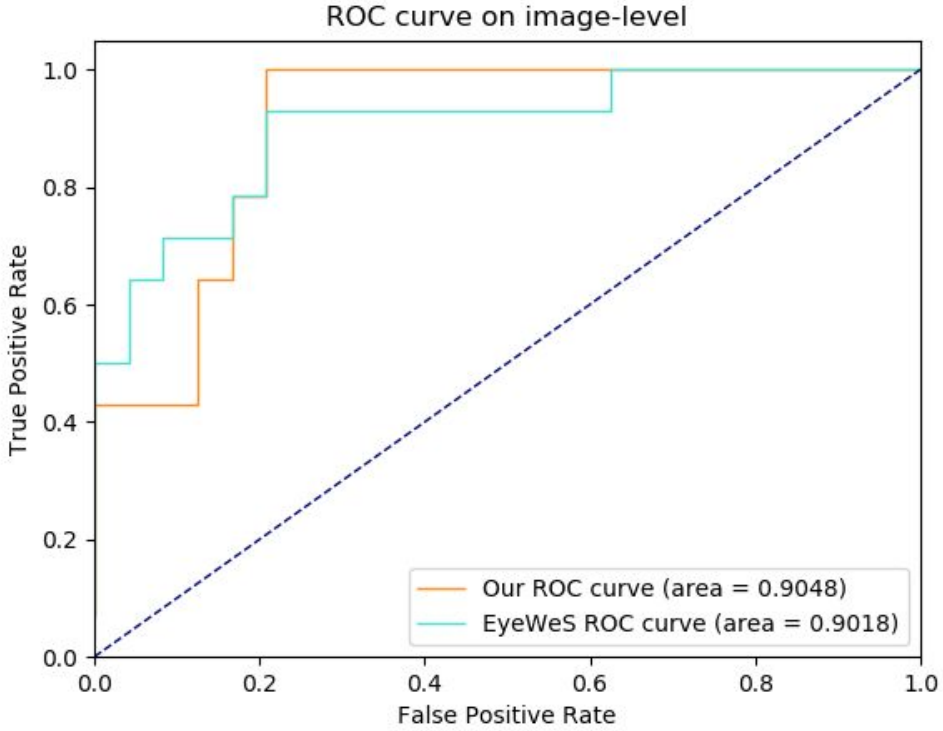


Faster RCNN, can only train on positive samples



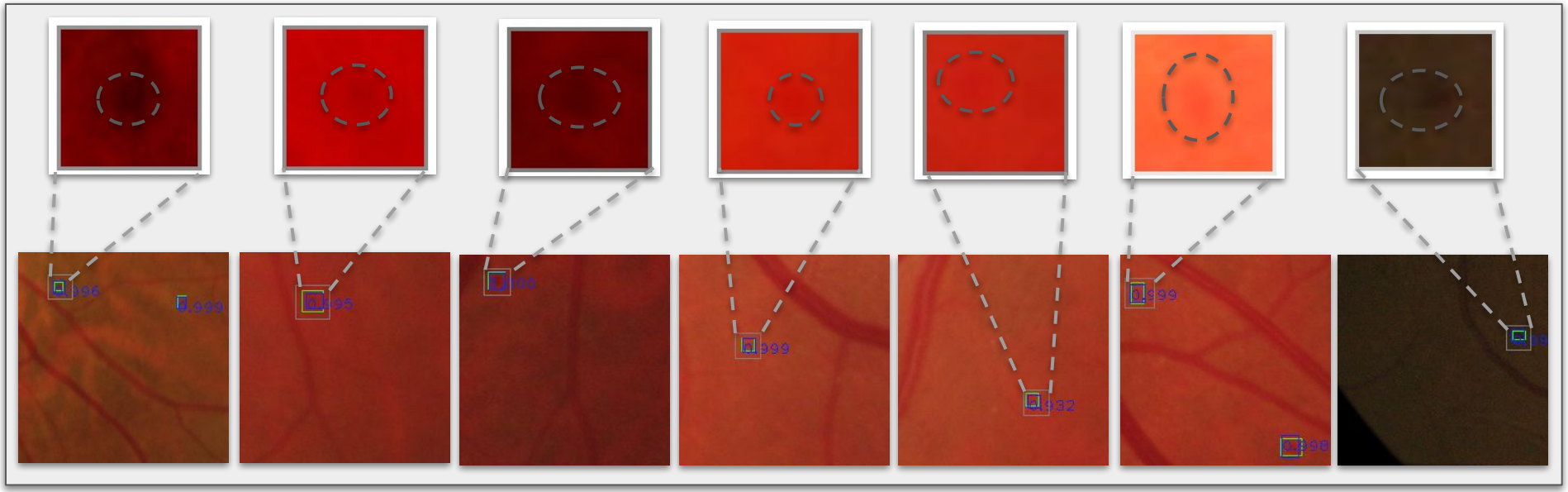
Modified Faster RCNN, allow training on negative samples

Comparison with other image-level work



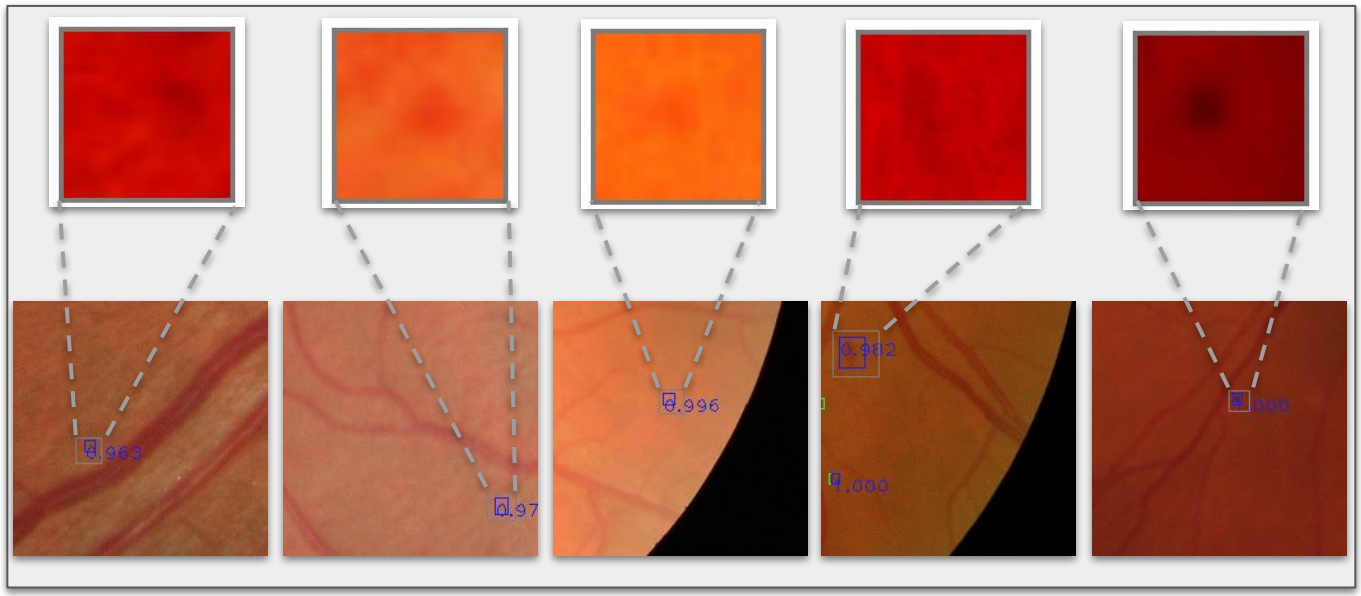
- Both with VGG16;
- Our method can simply transform the bounding box results into image scores(by summing up all the bounding-box scores, and then normalize all the scores to [0, 1]);
- Our method does not directly train for image-level classification.

Detection result examples(correct)

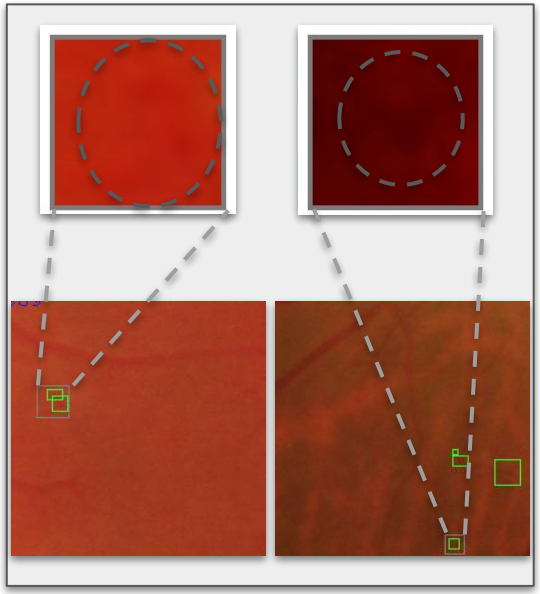


True Positive Examples(detected bounding boxes noted in blue and ground truth noted in green, the bottom part means the detected patch, the top part in grey is a zoomed region corresponding to the grey box in the bottom. There is a microaneurysm in the grey box marked in dotted circle.

Detection result examples(incorrect)



False Positive Examples



False Negative Examples

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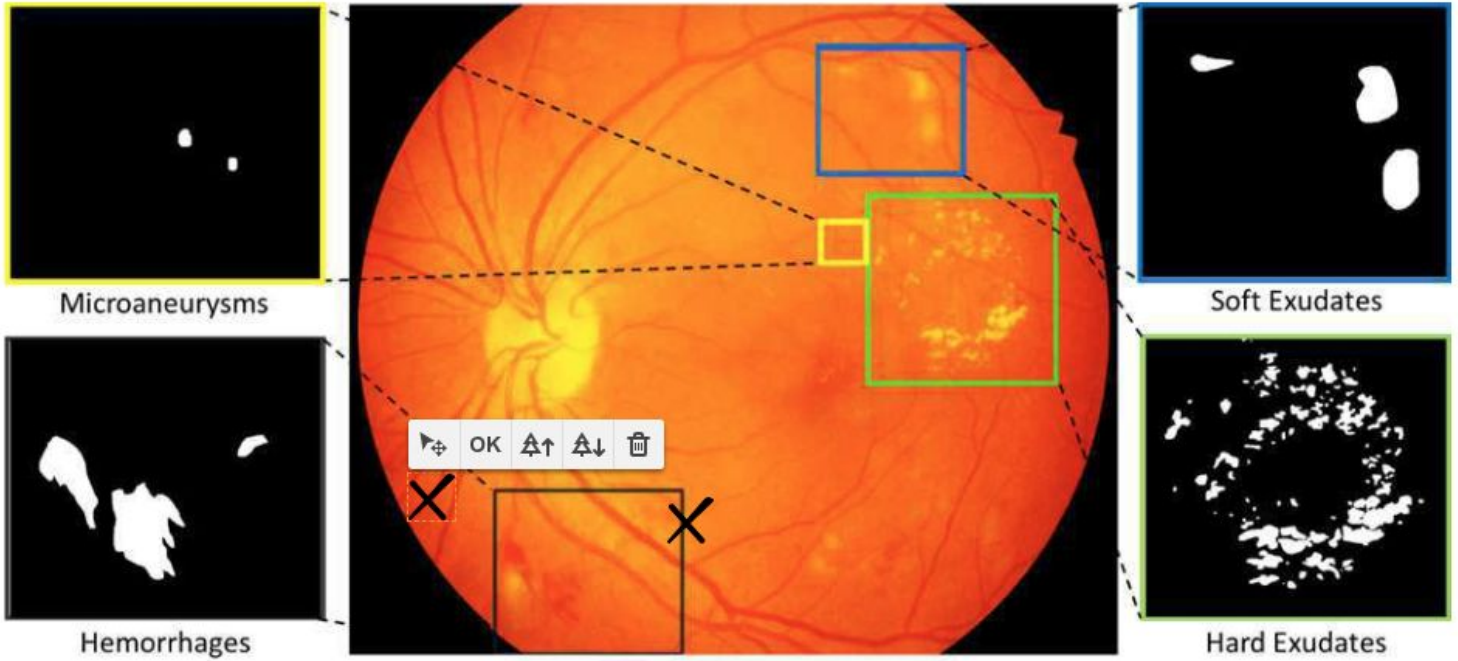
Definition: DR Lesion Semantic Segmentation



DR Lesion Segmentation Dataset

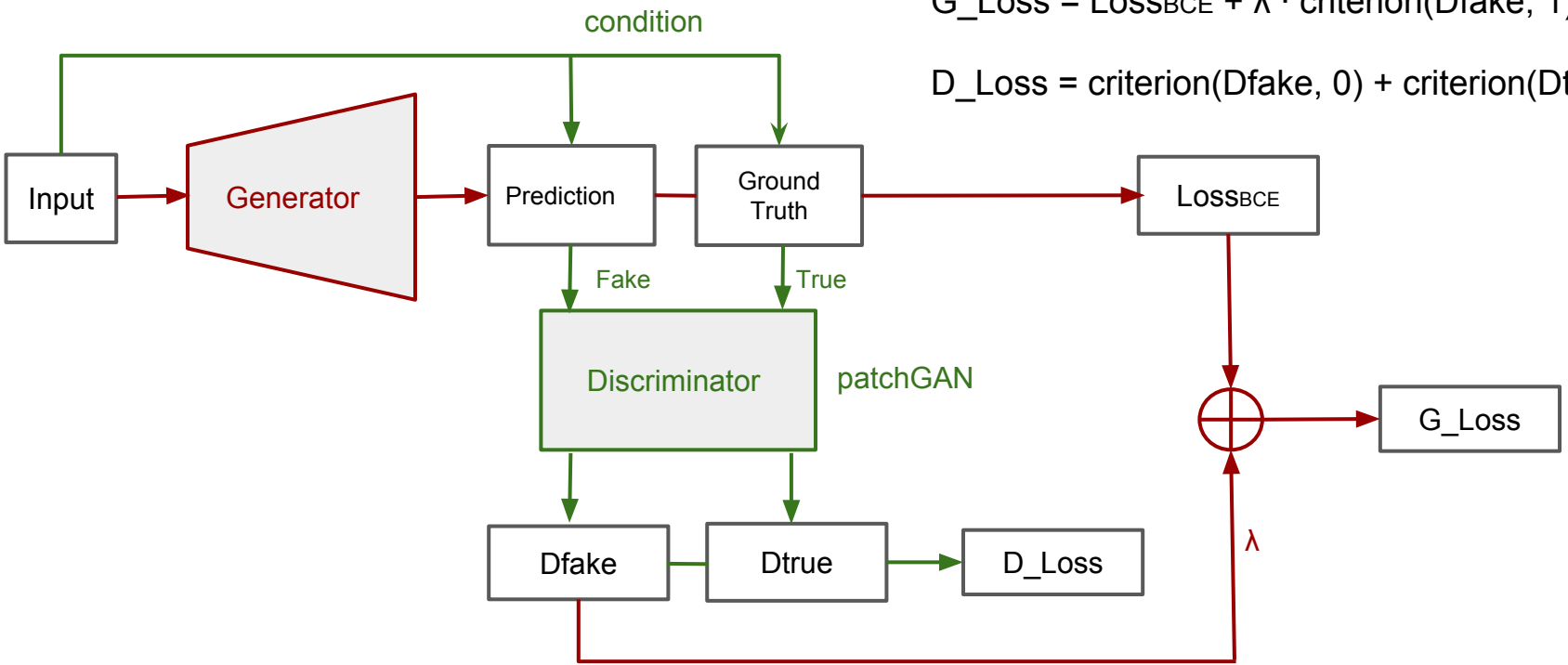
- Indian Diabetic Retinopathy Image Dataset (IDRiD)

	TRAINING SET	TESTING SET
microaneurysms (MA)	54	27
soft exudates (SE)	26	14
hard exudates (EX)	54	27
hemorrhages (HE)	53	27

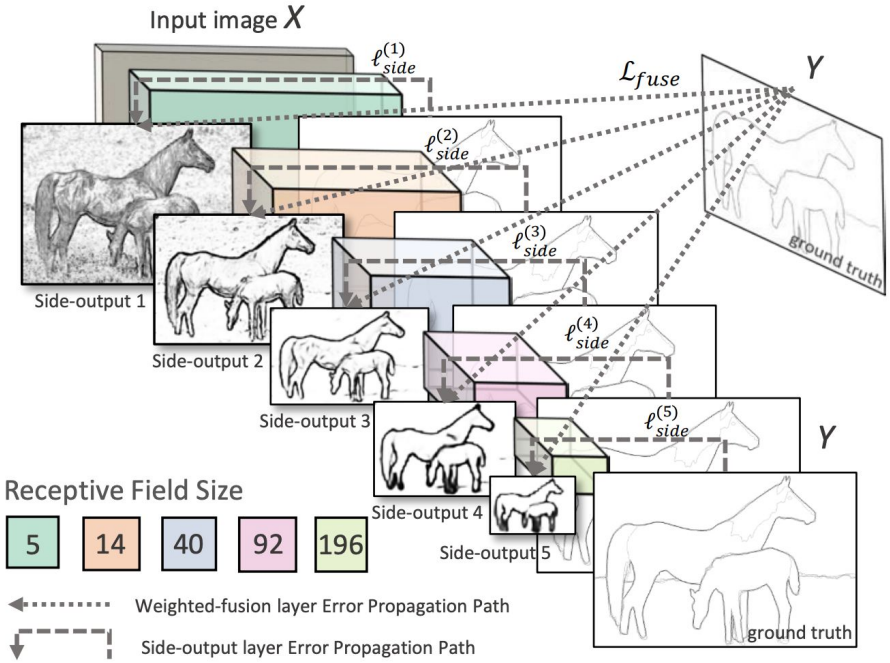
Segmentation Framework

$$G\_Loss = Loss_{BCE} + \lambda \cdot criterion(Dfake, 1)$$

$$D\_Loss = criterion(Dfake, 0) + criterion(Dtrue, 1)$$



Generator: HedNet Based



- Advantages:
  - Different Scales.
  - Converge quickly.
- Loss function:
  Pixel-wise binary cross-entropy loss
- Loss weights:
  Positive:Negative = 10:1

- Xie, Saining, and Zhuowen Tu. "Holistically-nested edge detection." *Proceedings of the IEEE international conference on computer vision*. 2015.

Quantitative Results(Average Precision)

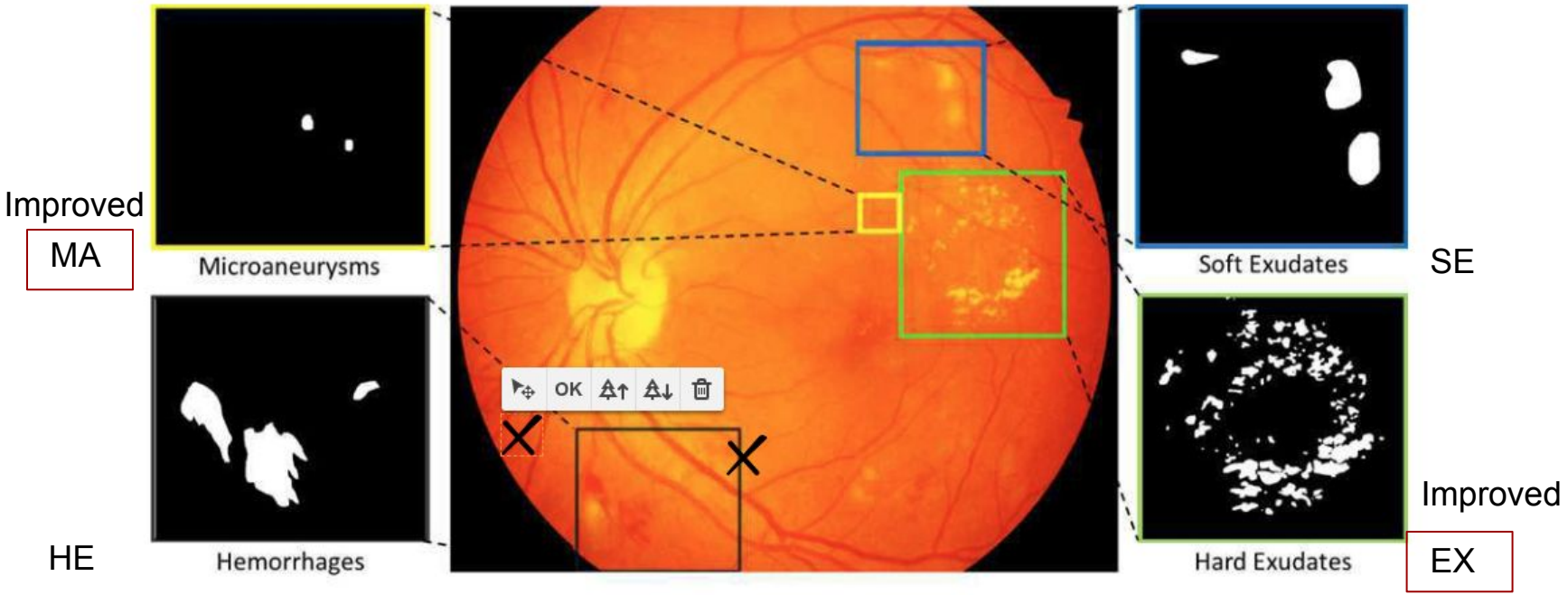
Our Results

	MA	HE	SE	EX
Hednet	0.4270	0.4302	0.5215	0.7935
Our method (λ = 0.01)	0.4468	0.4330	0.5158	0.8183

LeaderBoard Results

Team Name	MA Score	RANK	HE Score	RANK	SE Score	RANK	EX Score	RANK
VRT	0.4951	2	0.6804	1	0.6995	1	0.7127	11
PATech	0.474	3	0.649	2	-		0.885	1
iFLYTEK-MIG	0.5017	1	0.5588	3	0.6588	3	0.8741	2
SOONER	0.4003	5	0.5395	4	0.5369	7	0.739	10
SAIHST	-		-		-		0.8582	3
lzyuncc_fusion	-		-		0.6259	4	0.8202	4
SDNU	0.4111	4	0.4572	7	0.5374	6	0.5018	17
CIL	0.392	6	0.4886	5	0.5024	8	0.7554	8
MedLabs	0.3397	8	0.3705	8	0.2637	10	0.7863	5
AIMIA	0.3792	7	0.3283	10	0.2733	9	0.7662	6

Possible Reasons



Conclusion

- We introduced a feasible method based on Faster RCNN to perform lesion-level DR detection from eye fundus images. Our method can accurately detect microaneurysms.
- We applied a new GAN based framework on DR lesion segmentation task. Our method can further improve the performance of the segmentation for MA and EX.