MICCAI 2019
Ocular Disease Related Work

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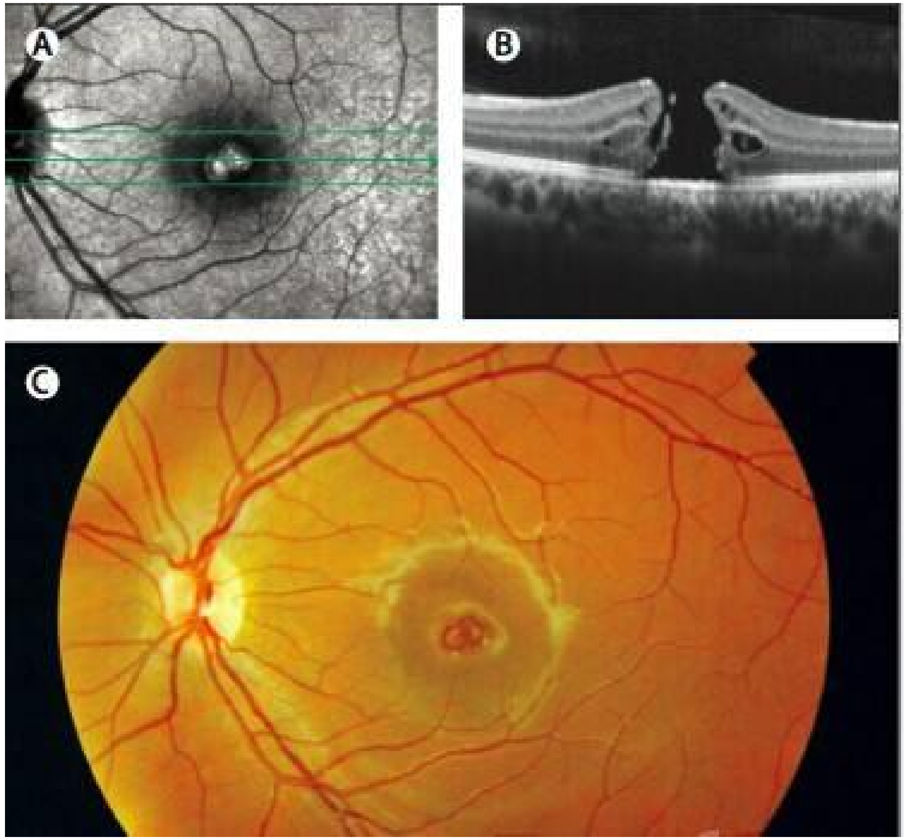
Images of Ocular Disease Dtection:

- 彩色眼底照相：可快速获得不同视野范围的彩色眼底图，包含活体信息和特征，能较全面反映后极部视网膜损害；（公开数据集多）
- FFA0(荧光眼底血管造影)：从血管循环生理角度反应视网膜屏障损坏状态，动态捕捉毛细血管循环状态，可连续采集动态影像；
- OCT（光学相干断层扫描）：以显微级别分辨率直接测量视网膜神经纤维层厚度变化，能发现眼底照相和FFA不易检测的DR引起的轻微黄斑水肿，但不能确定微血管瘤存在与否。



Tasks in Ocular Disease Images:

- Classification:
  - Single disease grading (DR, glaucoma, cataract grading)
  - Diverse disease classification
- Segmentation:
  - Retinal Vessel Segmentation
  - Microaneurysms Segmentation
  - Optic Disc Segmentation
  - etc.…
- others:
  - Optic Disc Localization
  - Enhancement of Blurry Retinal Images

Challenges in Ocular Disease Classification:

- Lack of Labeled Images:
  - Semi-supervised, weakly supervised…
  - Data augmentation
- Imbalanced Dataset:
  - Data augmentation
- Mciro-lesions and diverse:
  - global-local
  - segmentation

Paper List

- **Retinal Abnormalities Recognition Using Regional Multitask Learning**, MICCAI 2019
- **Retinopathy Diagnosis Using Semi-supervised Multi-channel Generative Adversarial Network**, OMIA 2019
- **DME-Net: Diabetic Macular Edema Grading by Auxiliary Task Learning**, MICCAI 2019

Retinal Abnormalities Recognition Using Regional Multitask Learning

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Overview of the Framework

- Regions of the retina with three sub-networks
  - optic-disc
  - macula
  - entire retina

- Two Principal Components：
  - macular and optic-disc region detection； **joint CNN detector**
  - semantic multitask learning for retinal disease classification.

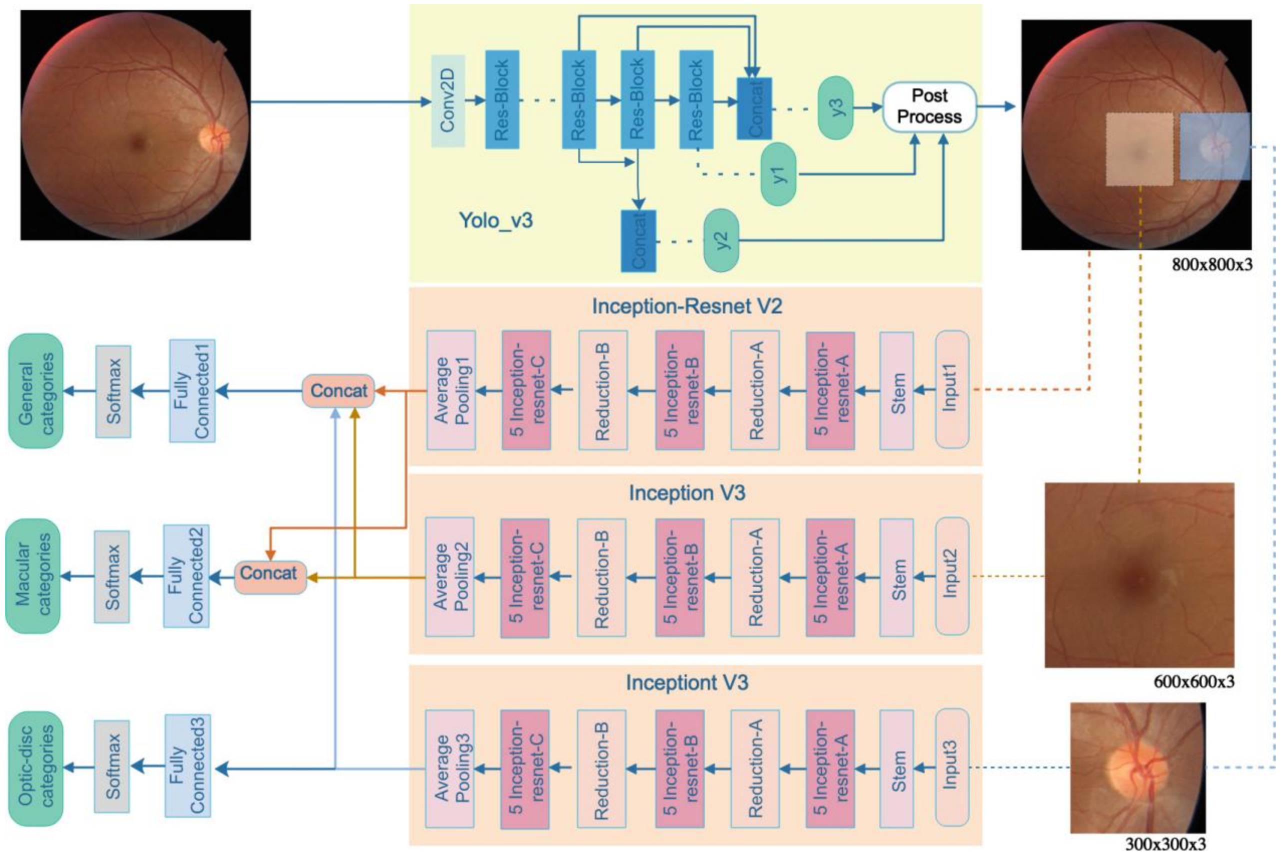
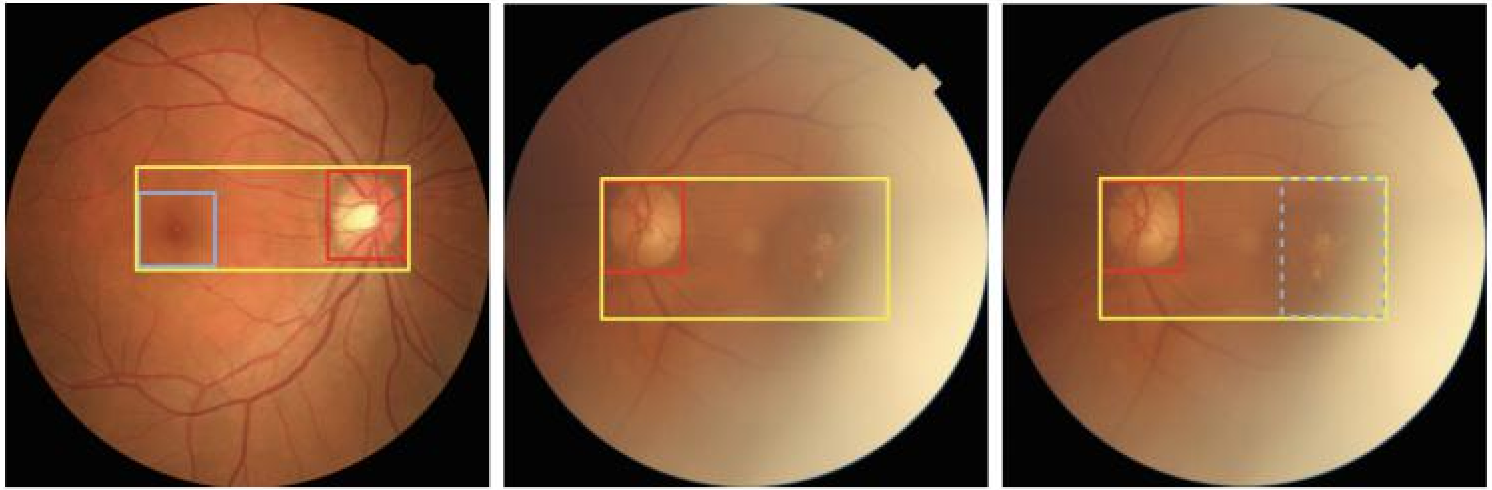


Fig. 1. The multi-label classification network has been split into three sub-networks and trained for three mutual exclusive tasks: a general task to detect diseases affect the whole retina (DR, CRVO/BRVO etc.), a **macular** sub-network to identify macular diseases (drusen, macular edema etc.) and a **optic-disc** network component to detect optic-disc related diseases (glaucoma, optic atrophy etc.). Because the features representing each of these region tasks are relevant, we design a hierarchical fusion strategy to combine late semantic representations.

1. Macular and Optic-Disc Region Detection

- Geometric Constraints



(a) (b) (c)

Fig. 2. Illustration of auxiliary bounding box AUX. (a) annotations of optic-disc bounding box OD in red, macular box MA in blue and the auxiliary bounding box AUX of joint region in yellow; (b) the detection result with missing macula MA because of low quality/blurry region; (c) localisation of macula MA in dash blue from (b) through AUX post-processing described in Sect. 3.1 (Color figure online)

- the centre distance between optic-disc and macula is approximately equivalent to two and half times as the diameter of the optic disc

2. Semantic Multitask Learning for Retinal Disease Classification

- Macular Diseases: age-related macular degeneration (AMD) 年龄相关性黄斑变性, macular edema黄斑水肿 and macular hole黄斑裂孔;
- Optic-disc Diseases: glaucoma青光眼, optic-disc edema视盘水肿, optic atrophy视神经萎缩;
- Entire Retina Diseases: DR糖尿病, hypertensive retinopathy高血压性视网膜病 and CRVO/BRVO视网膜动脉/静脉阻塞 etc.

2. Semantic Multitask Learning for Retinal Disease Classification

Collaborative Multi-Task Learning Framework With Three Streams:

General task stream: features from **optic-disc, macular regions** and **the whole fundus image**;

Macular task stream: features from macular region and entire retina (some sub-type macular edema diseases are closely correlated to general retinal disease such as DR)

Optic-disc task stream: relatively **independent task** (its categories are self-contained and the regionally independent compared to other region).

Results

Table 1. Results on task based classification

Methods	Average recall	Average precision
MA-One-Stream (single task)	68.8%	61.3%
MA-Two-Stream (single task)	**73.6%**	67.6%
MA-Two-Stream (multitask)	73.1%	**68.6%**
GC-One-Stream (single task)	65.2%	60.8%
GC-Three-Stream (single task)	67.5%	61.5%
GC-Three-Stream (multitask)	**67.8%**	**62.2%**

Table 2. Results on 36 category classification on different disease regions

Methods	Regions	Average recall	Average precision
One-Stream	Macula	60.9%	61.1%
Three-Stream	Macula	**62.6%**	**63.0%**
One-Stream	Disc	57.5%	69.7%
Three-Stream	Disc	**62.4%**	**70.0%**
One-Stream	General	69.2%	60.5%
Three-Stream	General	**70.6%**	**61.4%**

Visualization

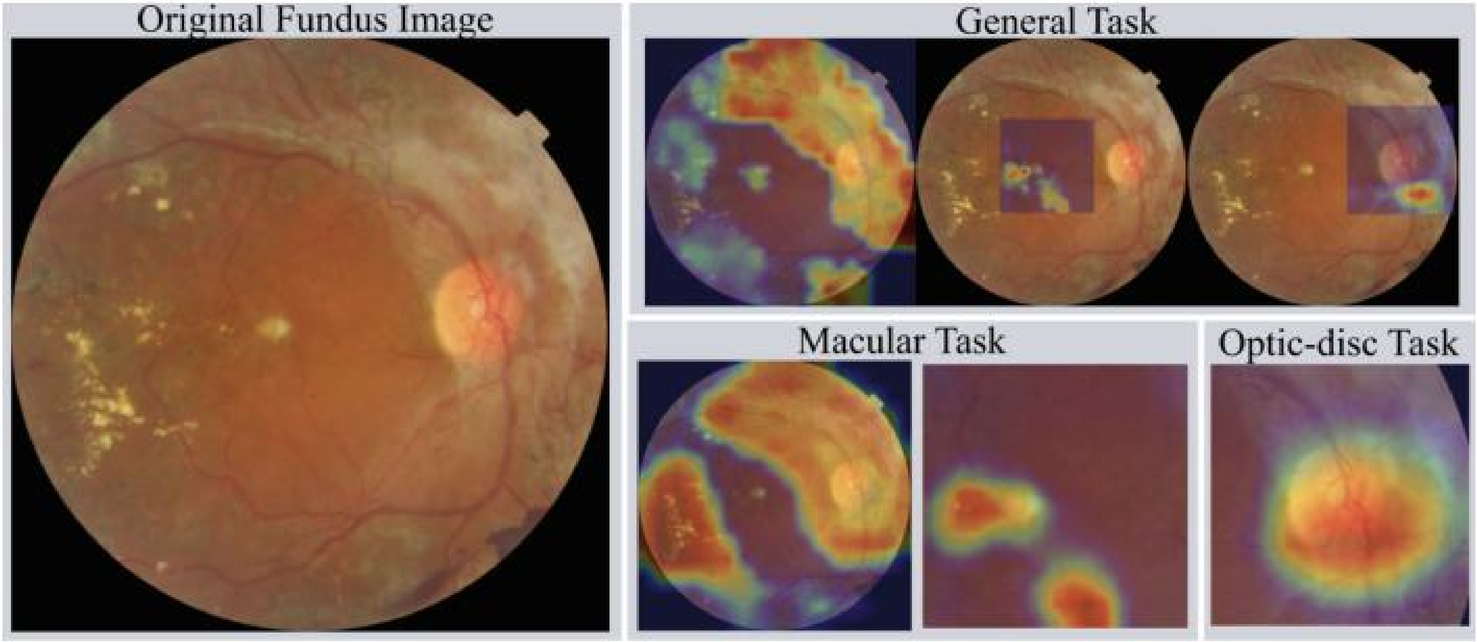


Fig. 3. Class activation maps (CAM) of a challenging multi-label sample, CAM generated for each task from a fundus image with PDR, macular edema and other optic-disc disease.

Retinopathy Diagnosis Using Semi-supervised Multi-channel Generative Adversarial Network

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Semi-supervised Multi-channel Generative Adversarial Network

- Highlights：
  - Feature Extractor: compress the input images with low distortion, alleviating the dispersion problem of tiny lesions information；
  - Semi-supervised learning in GAN: learn extra effective information in unlabeled images;
  - Multi-channel generator: cooperatively generate new samples, increase the diversity of the training set.

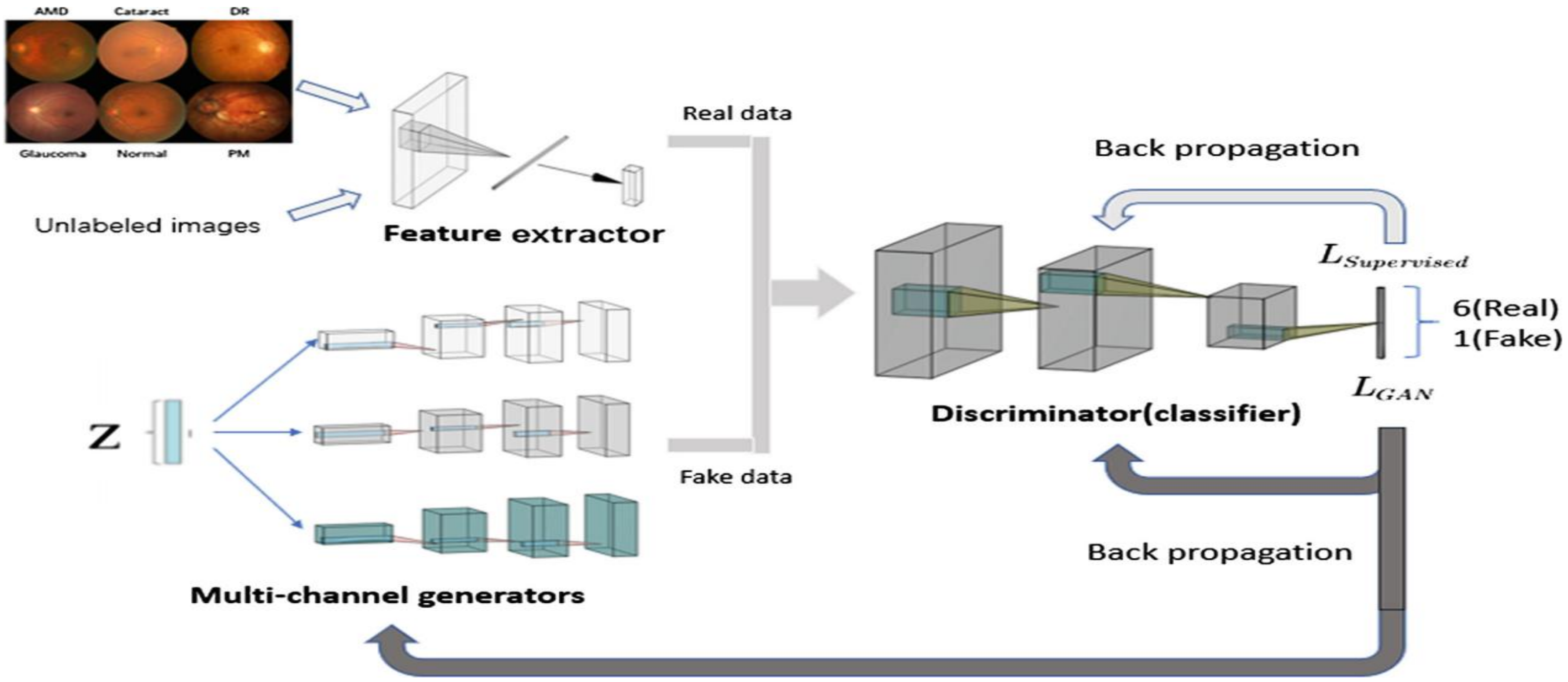

Fig. 1. Multi-channel semi-supervised generative adversarial network

Semi-supervised Multi-channel Generative Adversarial Network

Loss Function. Based on the analysis on the theoretical basis, the loss function of our network is divided into two parts: the cross entropy loss of the supervised network and the unsupervised game loss of the GAN [15].

$$L = L_{\text{ Supervised }} + L_{\text{ GAN}} \tag{3}$$

where:

$$\begin{aligned}
L_{\text{ Supervised }} &= -\mathbb{E}_{\boldsymbol{x}\sim p_{\text{data}}} \log p_{\text{model}}(y|\boldsymbol{x}, y < K+1) \\
L_{\text{ GAN}} &= \mathrm{L}_{\text{ Classifier }} + \mathrm{L}_{\text{ Generator}} \\
&= -\{\mathbb{E}_{\boldsymbol{x}\sim p_{data}} \log[D(\boldsymbol{x})] \\
&\quad + \mathbb{E}_{z\sim noise} \log[(1 - D(G(\boldsymbol{z})))]\} \\
&\quad - \mathbb{E}_{z\sim noise} \log[D(G(z))]
\end{aligned}$$

Details & Results

- **Details：**
- Feature Extractor: train Inception Resnet V2 on ImageNets (resize…normalize…)
- Use labeled images: fine-tune Inception Resnet V2

Table 1. Datasets

Classification	DataSource	Amount
Normal	ISBI 2019 Palm(184) + HRF(15)[2] + iChallenge-AMD(195) + Diaretdbv0(20)[8]	414
PM	ISBI 2019 Palm	213
Glaucoma	MICCAI 2018 REFUGE(40) + HRF(15) + Share(97)	152
Cataract	Share	75
AMD	iChallenge-AMD	87
DR	Diaretdbv0(110) + HEI-MED(169)[5] + HRF(15)	294
Unlabeled	Diaretdbv1(89)[7] + ISBI 2019 Palm(400) + Share(276) + MICCAI 2018 REFUGE(1153)	1918

Table 2. Quantitative analysis on test set

Method	Accuracy/%
Fine-tuning (RAW + No unlabeled)	78.4
Fine-tuning (AUG + No unlabeled)	80.2
Our method (RAW + No unlabeled)	86.7
Our method (AUG + No unlabeled)	87.5
Our method (RAW + Unlabeled)	87.8
Our method (AUG + Unlabeled)	88.9

DME-Net: Diabetic Macular Edema Grading by Auxiliary Task Learning

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DME-Net: Diabetic Macular Edema Grading by Auxiliary Task Learning

- 检测黄斑和硬渗出物
- **Highlights：**
  - Mask Segmentation Model（based on U-Net）
  - Multi-scale Feature Integration Model
  - XGBoost（a scalable tree boosting system; classifier）

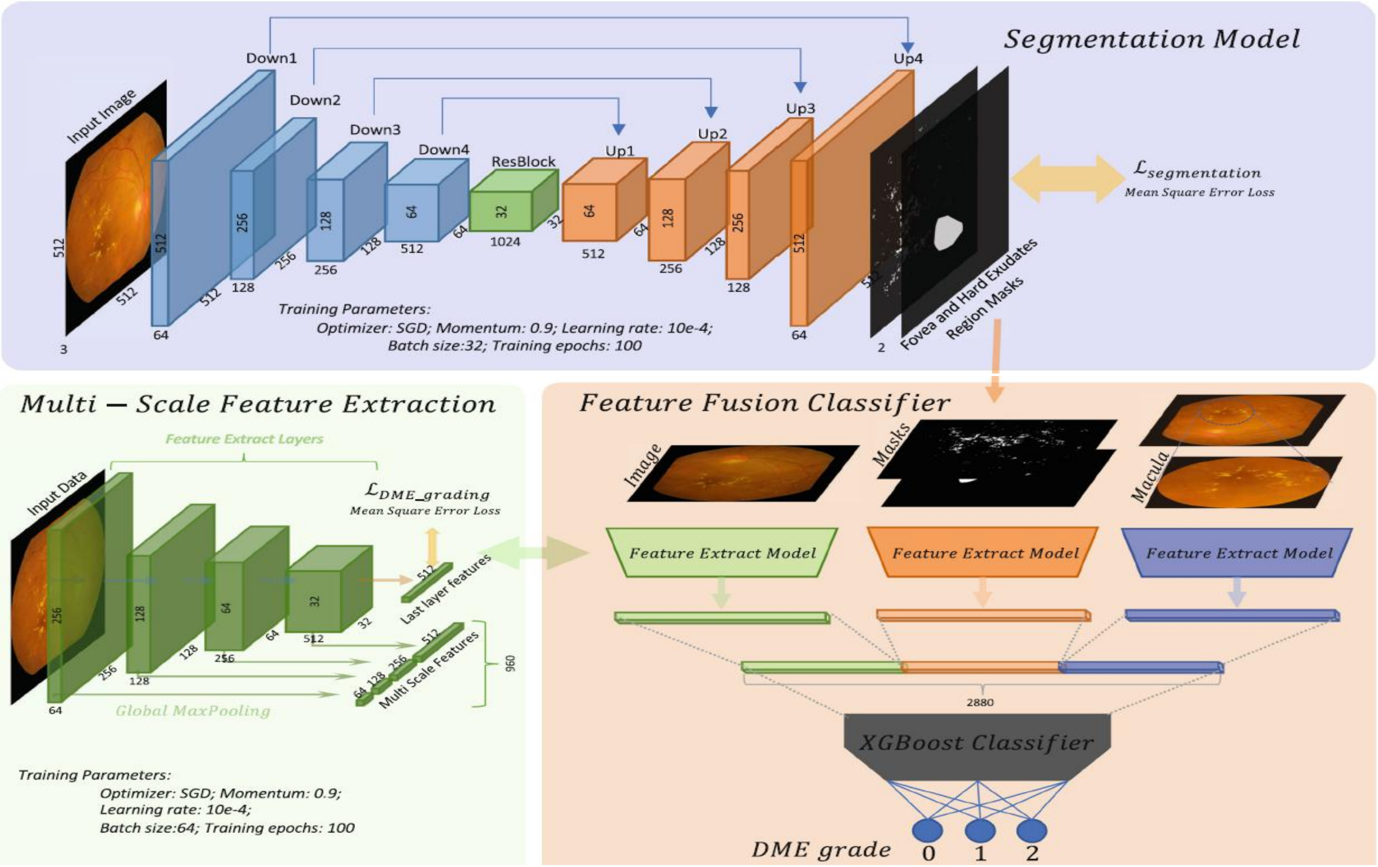
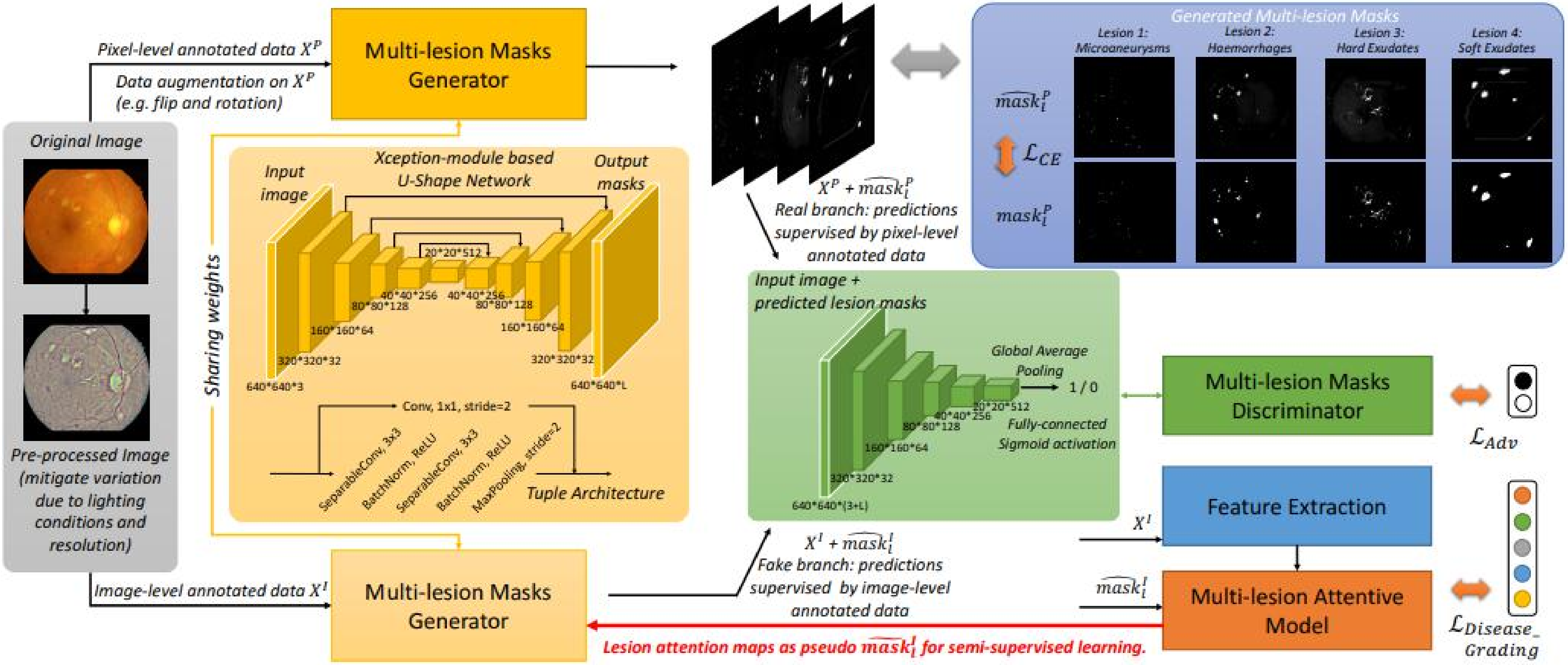


Fig. 1. The pipeline of the proposed method. The input data consists of pixel-level annotated lesion images and DME grading images. The segmentation model is proposed for learning the hard exudate and macular masks.

compared with one paper in CVPR



Results

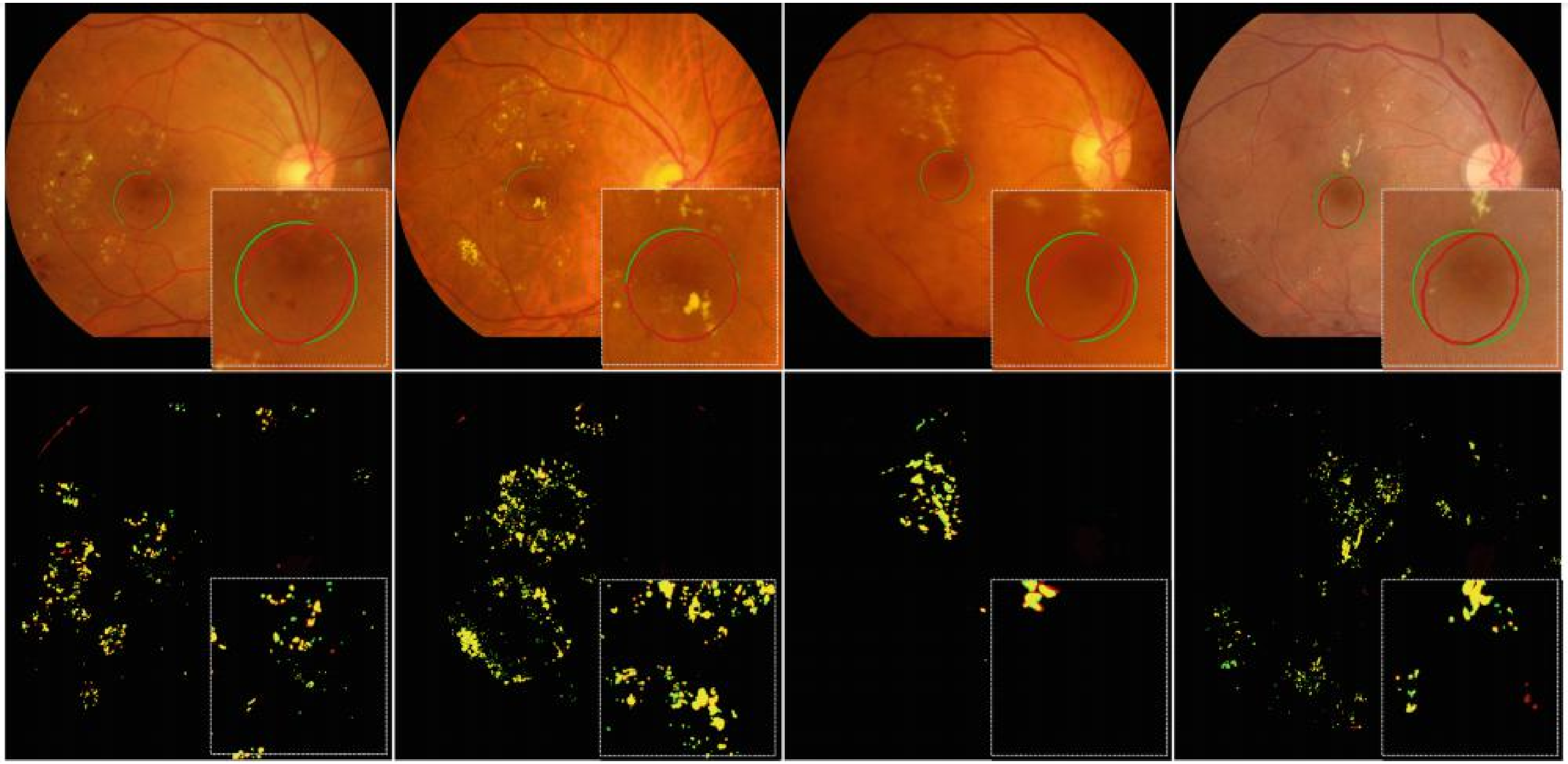


Fig. 2. Segmentation mask of the macula and hard exudates. Red contours in the images of the first row are macula predictions, green contours are ground-truths. The masks in the second row are ground-truths and hard exudate predictions, yellow areas show overlap between prediction and ground-truth, green areas are ground-truths, red areas are predictions (Color figure online)

Results

Table 2. The DME grading accuracy of different models.

Model	Image(test/train)	Masks(test/train)	Macular(test/train)
VGG13	0.7859/0.7915	0.7968/0.8159	0.6564/0.6865
VGG16	**0.7904**/0.8202	**0.8294**/0.8502	**0.6758**/0.6859
ResNet18	0.7857/0.9027	0.7970/0.8560	0.6692/0.7590
ResNet34	0.7764/0.9198	0.7954/0.9383	0.6487/0.6724
ResNet50	0.7442/0.9187	0.7512/0.9357	0.6162/0.7423
DenseNet121	0.7231/**0.9709**	0.7447/**0.9430**	0.6011/**0.7642**

Table 3. The DME grading Accuracy of IDRiD testing set.

Input feature	Fully-connected	SVM	XGBoost
Last feature of image	**0.8058**	0.8058	0.7961
Last feature of masks	0.8349	**0.8543**	0.8447
Last feature of macula	**0.6796**	0.6796	0.6796
Multi-Scale (MS) features of image	0.8155	0.8349	**0.8447**
MS features of masks	0.8447	0.8543	**0.8741**
MS features of macula	0.6990	0.7282	**0.7379**
Last feature of image, masks & macula	0.8543	0.8640	**0.9080**
MS feature of image, masks & macula	0.8543	0.8741	**0.9417**

Results

Table 4. Comparision with State-of-the-arts.

Model & dataSet	Specificity	Sensitivity	AUC	Accuracy
Mammoth [1] in IDRiD	-	-	-	**0.9322**
SDNU [1] in IDRiD	-	-	-	0.8789
HarangiM1 [1] in IDRiD	-	-	-	0.8741
Fundus Image (Ours) in IDRiD	0.8352	0.8568	0.8715	0.8447
All Features (Ours) in IDRiD	0.9384	0.9553	0.9637	**0.9417**
Deepak et al. in Messidor	-	-	0.96	**-**
Akram et al. in Messidor	0.9730	0.9590	-	**0.9680**
All Features (Ours) in Messidor	0.9591	0.9712	0.9824	**0.9633**

Summary

- Fundus image classification trends:
  - Semi-supervise (combined with GAN)
  - multi-label (more than two lables in the same image)
  - multi-catergories (covering most of the possible diseases)
  - multi-scale (global, local; according to pathological structure)
  - multi-task (combined with segmentation, location)
  - Multi-modal (combined with FFA, OCT....maybe..)
  - 视网膜眼底图像预测心脏病风险....

Thanks!