

DiabeticRetinopathy Review and Attempt

Goole Approach

Intro to DiabeticRetinopathy

Pathological symptoms

Material

Grade quality control

pre-processing

Algorithm

Department Ophthalmology, Jichi Medical University

Material

Grading

Model

ICLR2018 Interpretable Computer Aided Diagnosis of Diabetic Retinopathy

Material

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HighLight

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My Approach For DiabeticRetinopathy Detection Problem

Material

Grading

Exploration

Image Preprocessing

crop the extra black edge

Enhance the image

Resize to (299,299) (512,512)

Subtract local mean color

Remove 10% of the outer circle

Place the processed image in the center of image

Abandon the Image with std lower than 16(too dark or too bright)

DataAgumentation

BatchNormalization

Preprocessing Parralelismly Using MultiProcessor

Balanced Sampling via Label Shuffling

Label Smooth

Model Architecture

Training Environment

Accuracy

PartResult

Bad Attempts

Summary

Diabetic Retinopathy Review and Attempt

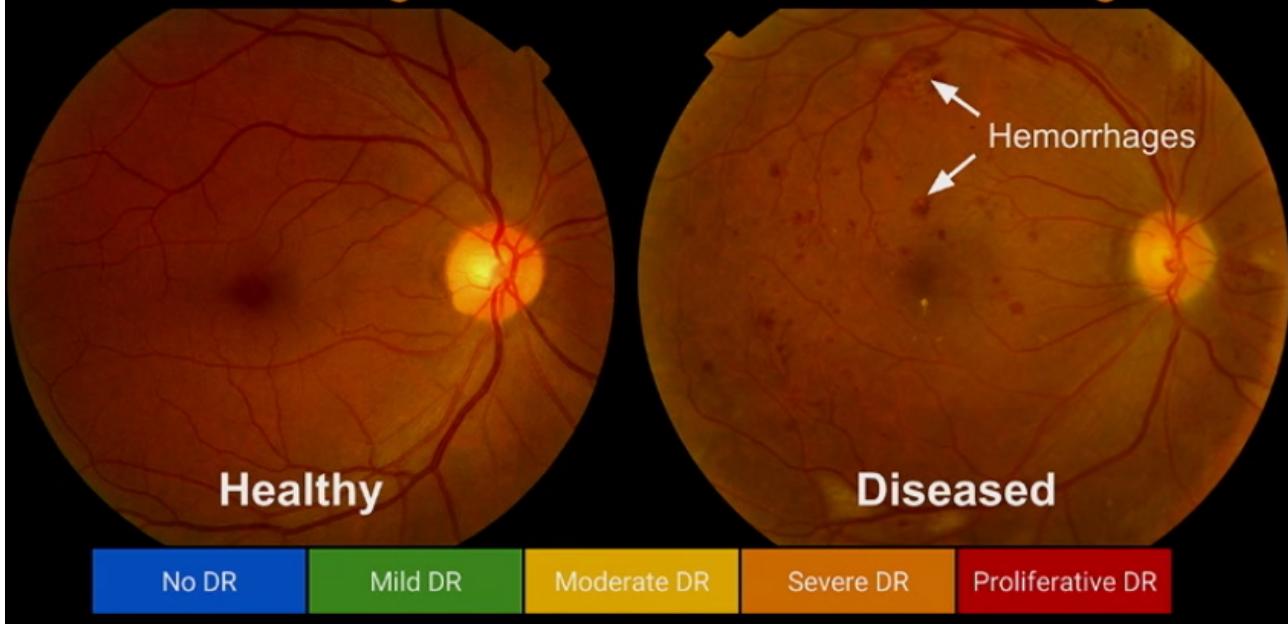
Google Approach

Intro to Diabetic Retinopathy

TensorFlow 在医疗领域的应用 - 视网膜图像 (2017年TensorFlow开发者大会)

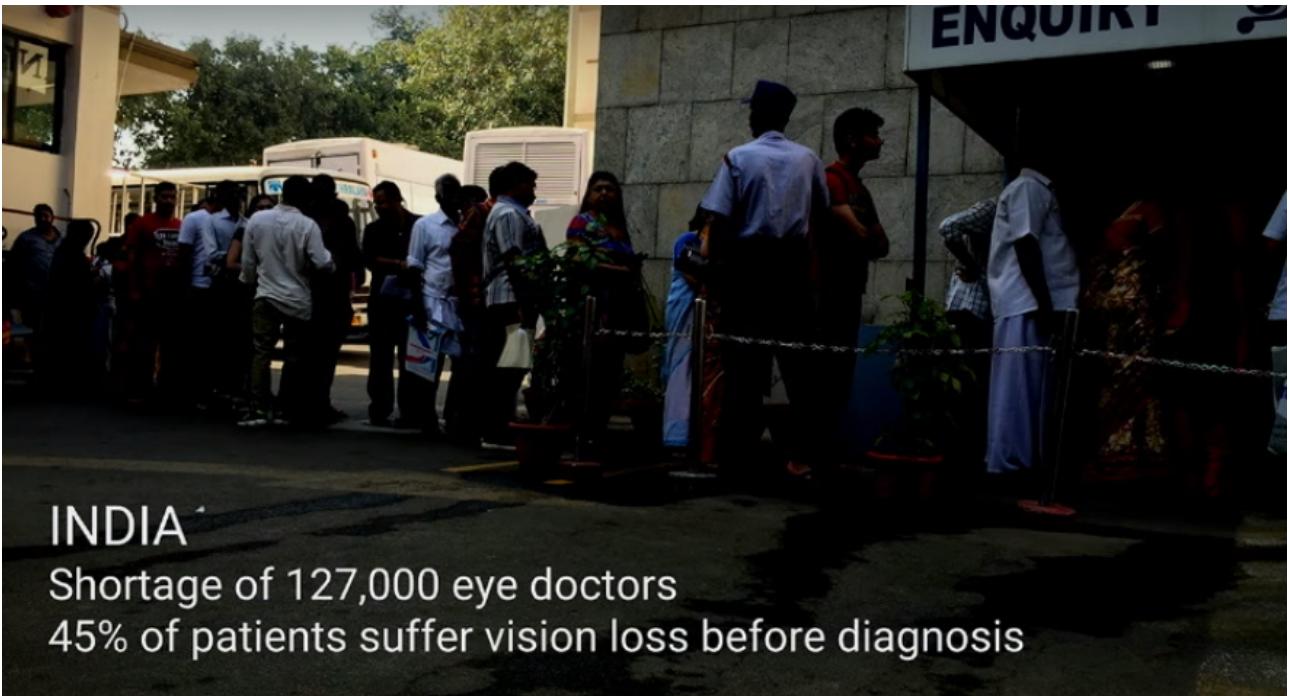


How DR is Diagnosed: Retinal Fundus Images



Regular screening is key to preventing blindness





INDIA

Shortage of 127,000 eye doctors

45% of patients suffer vision loss before diagnosis

Pathological symptoms

- 糖尿病损害视网膜主要是由于血糖增高，小血管管壁增厚，渗透性增大，使小血管更易变形和渗漏。糖尿病视网膜病变的严重性和视力下降的程度与血糖水平控制情况以及患糖尿病时间的长短有关。患病时间长短尤为重要，一般患糖尿病至少10年后才出现糖尿病性视网膜病变
- 在非增殖性（单纯型）视网膜病变，视网膜小毛细血管发生破裂和渗漏。在每一膨大的毛细血管破裂之处，形成一有血蛋白沉淀的小囊。医生根据眼底检查可发现这些改变
- 血管渗漏和闭塞。黄斑部水肿或局部缺血是导致视力减退的主要原因。增殖性是由单纯性进一步发展的结果。
- 由于血管变化，毛细血管内皮细胞开始增殖，缺氧的网膜组织释放出血管增殖物质，促使形成新生血管，进而导致出血、机化，而发生增殖性病变，并造成极其严重的不良后果。

Material

- Macula-centered retinal fundus images were retrospectively obtained from EyePACS in the United States and 3 eye hospitals in India (Aravind Eye Hospital, Sankara Nethralaya, and Narayana Nethralaya) among patients presenting for diabetic retinopathy screening. All images were deidentified according to Health Insurance Portability and Accountability Act Safe Harbor prior to transfer to study investigators. Ethics review and institutional

review board exemption was obtained using Quorum Review IRB.

- large data sets of images ($n = 128\ 175$) to first “train” an algorithm, then using 2 separate data sets ($n = 9963$ images and $n = 1748$ images) to “test” this algorithm

Grade quality control

X ✓ C S  Submitted Answers: 0

CONTRAST ⌂

MAGNIFIER shift ⌂

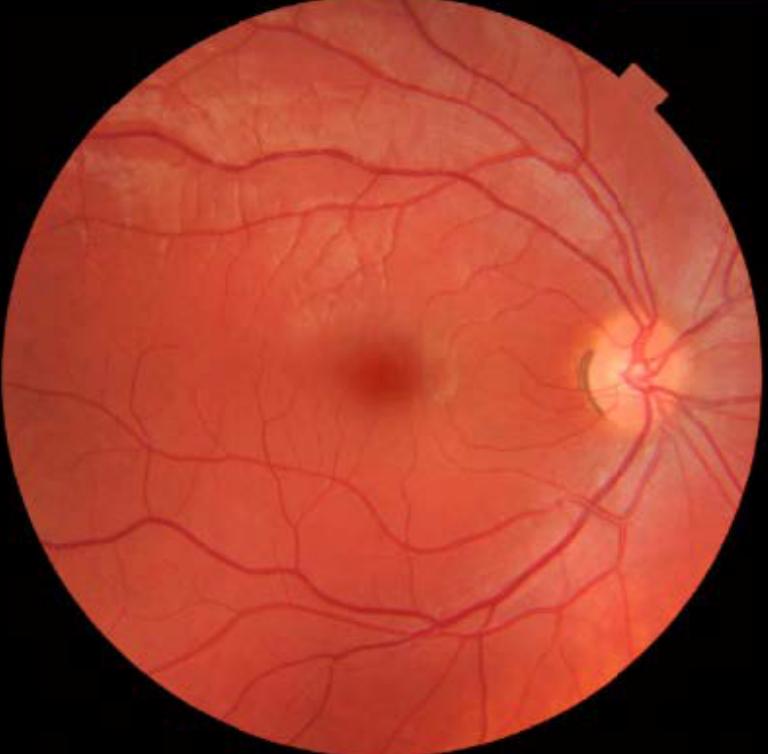
IMAGE QUALITY

1 EXCELLENT
2 GOOD
3 ADEQUATE
4 INSUFF. FOR FULL INTERP.
5 INSUFF. FOR ANY INTERP.
6 OTHER IMAGE PROBLEM
7 NO IMAGE / TECHNICAL PROB

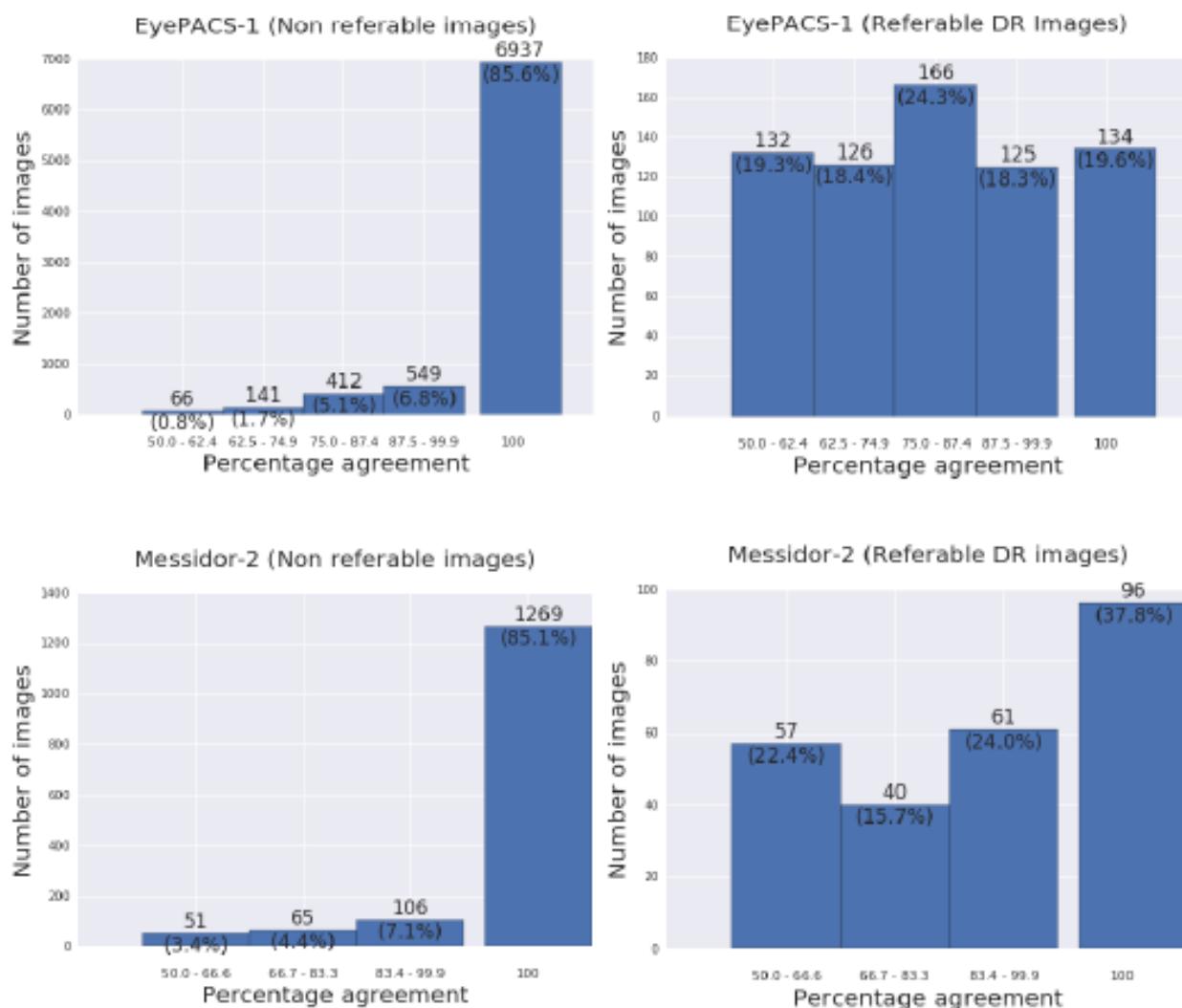
NEXT

QUALITY COMMENTS

E.g. why is this image unsuitable for grading?



eFigure 3. Distribution of Agreement Amongst Ophthalmologists on EyePACS-1 (8 Ophthalmologists) and Messidor-2 (7 Ophthalmologists)

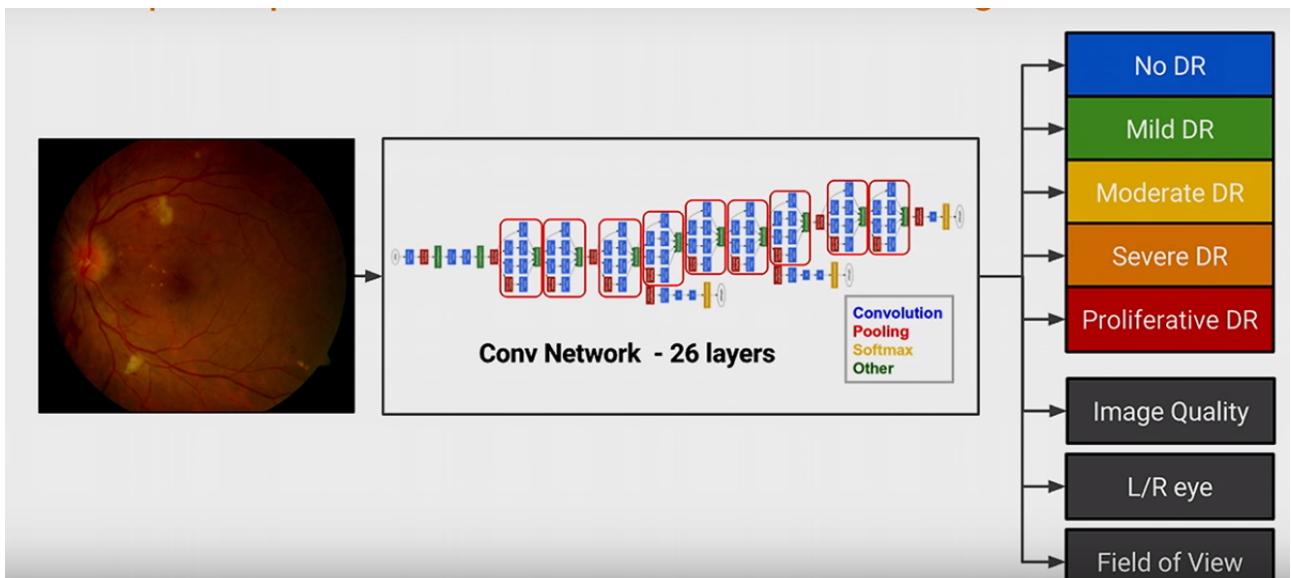


Considered fully gradable by the majority

pre-processing

For algorithm training¹, input images were **scale normalized** by detecting the circular mask of the fundus image and resizing the diameter of the fundus to be 299 pixels wide. Images for which **the circular mask** could not be detected were **excluded** from the development and the clinical validation sets

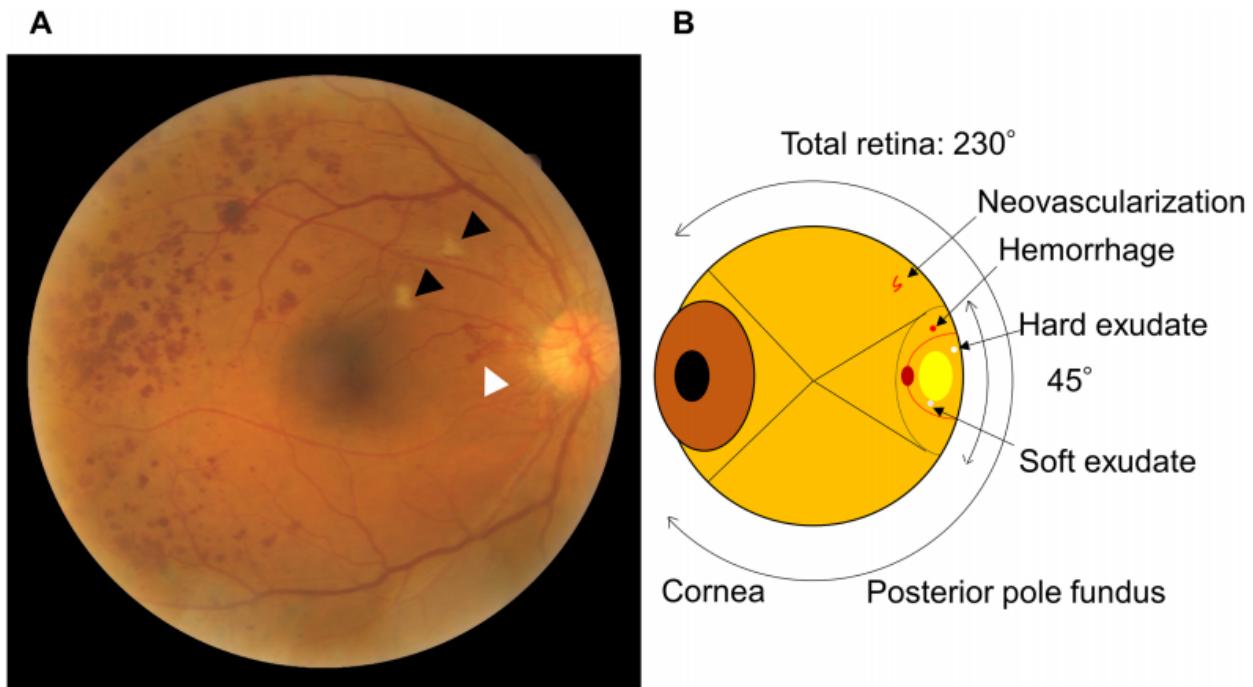
Algorithm



- The optimization algorithm used to train the network weights was a **distributed stochastic gradient descent** implementation by Dean et al.¹⁶. To speed up the training, **batch normalization**² as well as **preinitialization** using weights from the same network trained to classify objects in the ImageNet data set¹⁷ were used. Preinitialization also improved performance.
- training: 80% of the data was used to optimize the network weights and (2) tuning: 20% of the data was used to optimize hyperparameters (such as early stopping for training, image preprocessing options). An **ensemble** of 10 networks trained on the same data was used, and the final prediction was computed by a linear average over the predictions of the ensemble.

Department Ophthalmology, Jichi Medical University

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A fundus photograph and schema of an eye ball

Material

- 9,939 posterior pole photographs from 2,740 patients with diabetes at Jichi Medical University between May 2011 and June 2015³
- The original photographs were $2,720 \times 2,720$ pixels. The outlying 88 pixels of the margin were deleted and the photographs shrunken by 50% to $1,272 \times 1,272$ pixels

Grading

- Modified Davis grading

Grading	
SDR	Microaneurysm, retinal hemorrhage, hard exudate, retinal edema, and more than 3 small soft exudates
PPDR	Soft exudate, varicose veins, intraretinal microvascular abnormality, and non-perfusion area over one disc area
PDR	Neovascularization, pre-retinal hemorrhage, vitreous hemorrhage, fibrovascular proliferative membrane, and tractional retinal detachment

SDR, simple diabetic retinopathy; PPDR, pre-proliferative diabetic retinopathy; PDR, proliferative diabetic retinopathy.

- Grading by actual prognosis.

Grading	Needed treatments	When	Prognosis	No. of 4709	NDR	SDR	PPDR	PDR	
0	None	Next visit	All	4445	2479	1289	333	344	
1	DME treatments		12	0	5	1	6		
2	PRP		Improve	20	1	2	14	3	
3			Stable	6	1	1	0	4	
4			Worsen	0	0	0	0	0	
5	Vitrectomy		Improve	2	0	0	0	2	
6			Stable	4	0	0	0	4	
7			Worsen	2	0	0	0	2	
8	DME treatments	Current visit	All	16	0	0	7	9	
9	PRP		Improve	108	0	0	40	68	
10			Stable	31	0	1	5	25	
11			Worsen	29	0	0	9	20	
12	Vitrectomy		Improve	10	3	0	0	7	
13			Stable	16	0	0	1	15	
14			Worsen	8	0	0	0	8	

Model

- Modified GoogLeNet ResNet Used
- 4 GPU Used Simultaneously si(12 GB, GeForce GTX TITAN X; NVIDIA)
- Open framework for deep learning (Caffe, Berkeley Vision and Learning Center, Berkeley, CA, USA).

ICLR2018 Interpretable Computer Aided Diagnosis of Diabetic Retinopathy

published:10/20/2017

Material

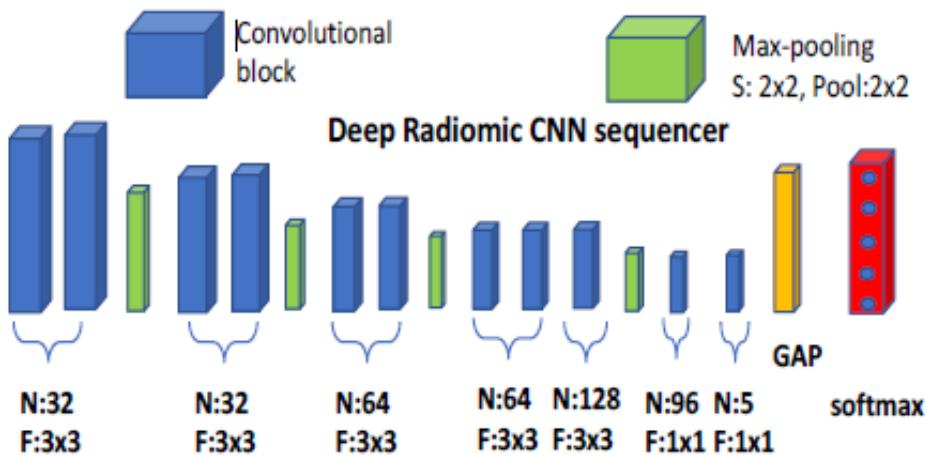
Kaggle diabetic retinopathy dataset five grades of diabetic retinopathy are as follows:
0: Negative, 1: Mild, 2: Moderate, 3: Severe, and 4: Proliferative.

Approach

- Select retinal fundus images for one eye (right) only and performed an automatic selective cropping to remove the background information. The use of a single eye led to 53,354 images in total.
- Divide the dataset into 90% and 10% of the dataset for training and testing respectively.
- Perform horizontal and vertical flipping along with channel-wise normalization for the whole dataset as data augmentation

Model

- Deep Radiomic CNN sequencer



Accuracy

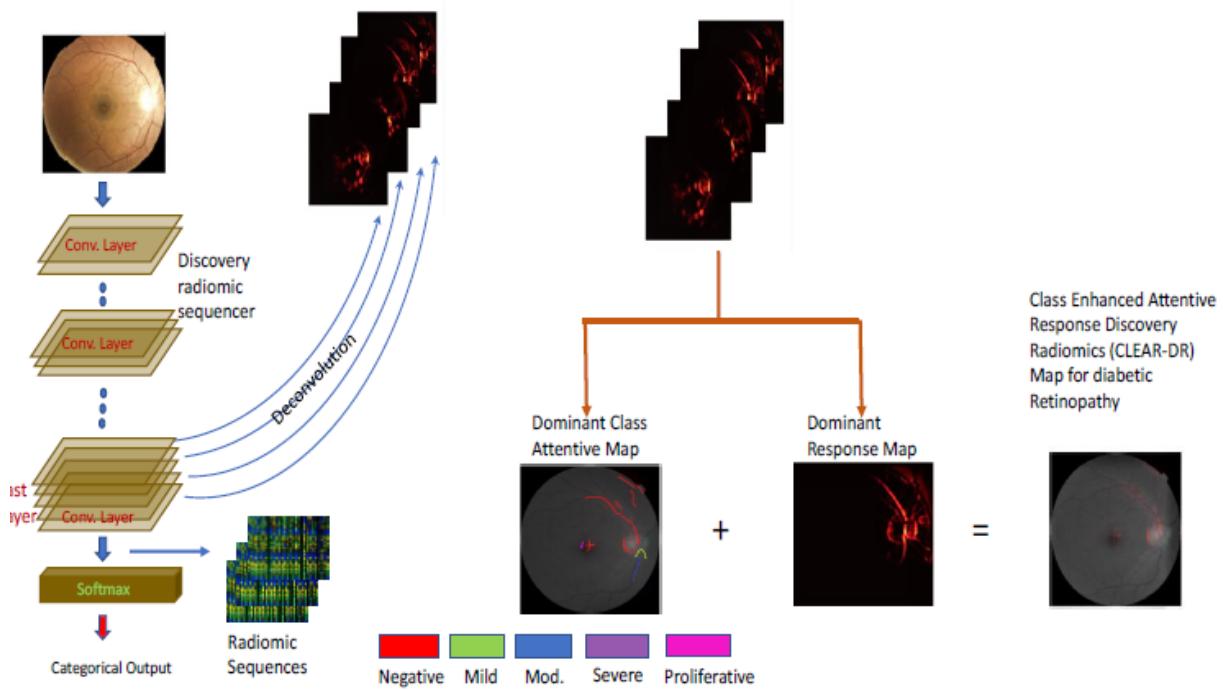
73.2% overall

HighLight

Not only generates discriminating radiomic sequences for diabetic retinopathy grading **but also** provides a mechanism to **visually interpret its decision making process**

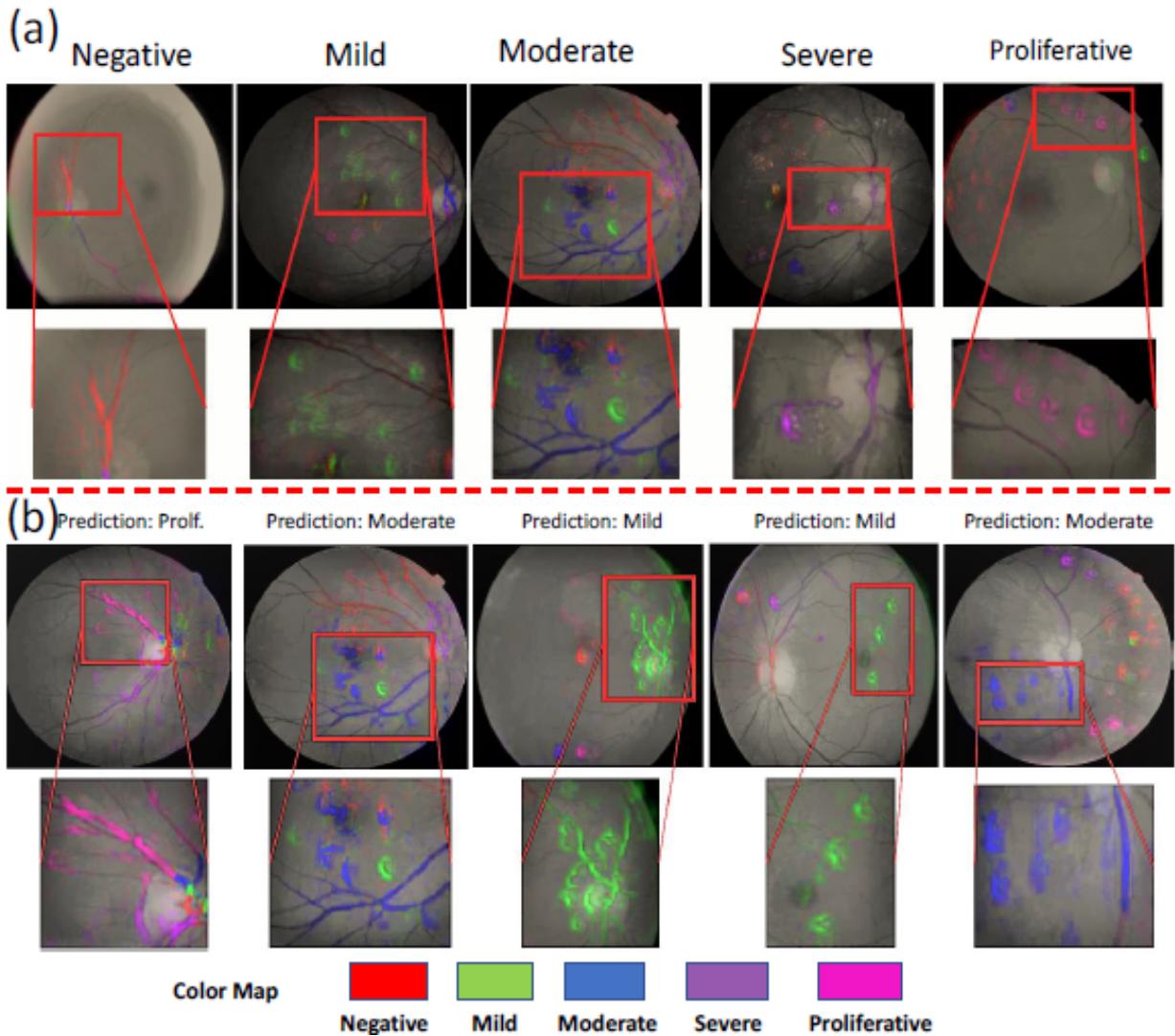
* individual attentive response maps are computed for each kernel associated with a grade by back-projecting activations from the output layer

- Compute two different types of maps
 - a. A dominant attentive response map, which shows the dominant attentive level for each location in the image;
 - b. A dominant grade involved in the decision-making process at each location
 - c. the dominant attentive response map and the dominant attentive grade map are combined visually by using color and intensity to produce the final CLEAR-DR map



Experiment

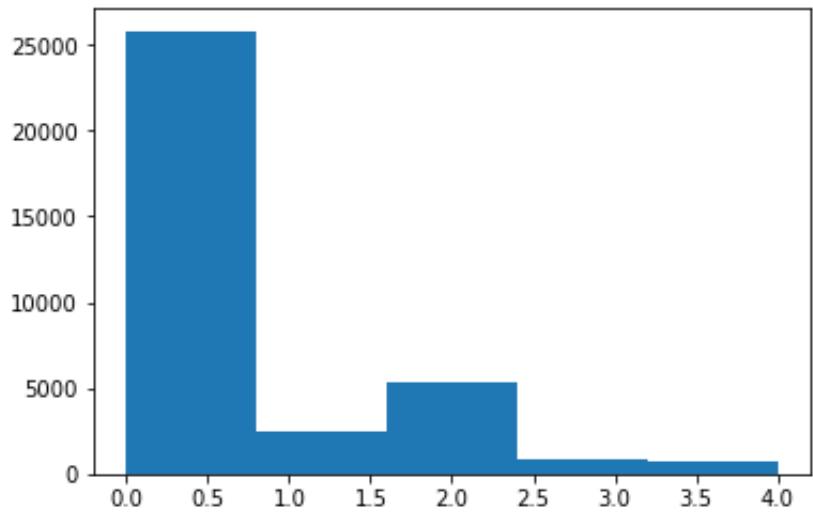
Correctly (a) and Mis-classified (b) examples for all diabetic retinopathy grades. Each color represents a single grade, as identified by the color map at the bottom of the figure. As well, the red box indicates the most attentive region used for grade prediction. It can be observed that the attentive regions used by the deep radiomic sequencer for **making correct decisions corresponds to medically relevant landmarks**, thus providing additional evidence for the proposed prediction. Best viewed in color and zoomed in.



My Approach For Diabetic Retinopathy Detection Problem

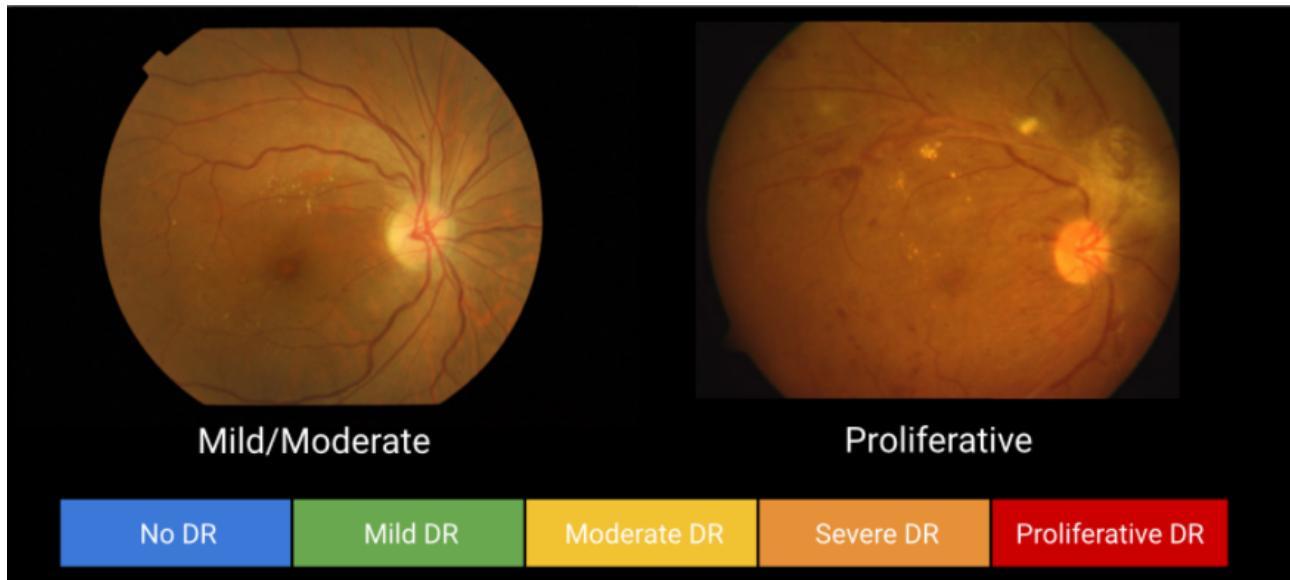
Material

- The data set comes from **Kaggle** which is sponsored by the **California Healthcare Foundation** and Retinal images were provided by **EyePACS**, a free platform for retinopathy screening.
- it consists of high-resolution retinal fundus images with varying degrees of illumination conditions captured using different types of cameras. The retinal fundus images in the dataset were clinically annotated with five different grades related to the presence of diabetic retinopathy.
- fairly unbalanced classed



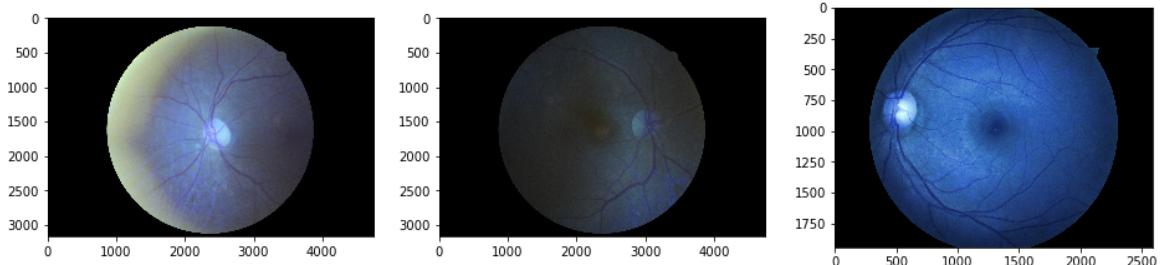
Class	Name	Number of images	Percentage
0	Normal	25810	73.48%
1	Mild NPDR	2443	6.96%
2	Moderate NPDR	5292	15.07%
3	Severe NPDR	873	2.48%
4	PDR	708	2.01%

Grading

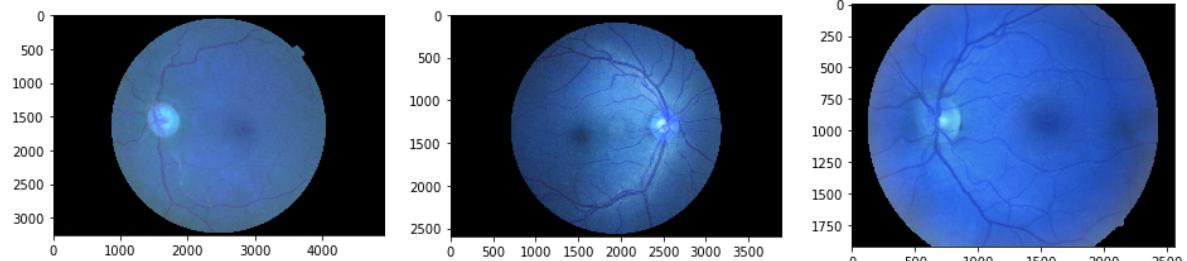


Exploration

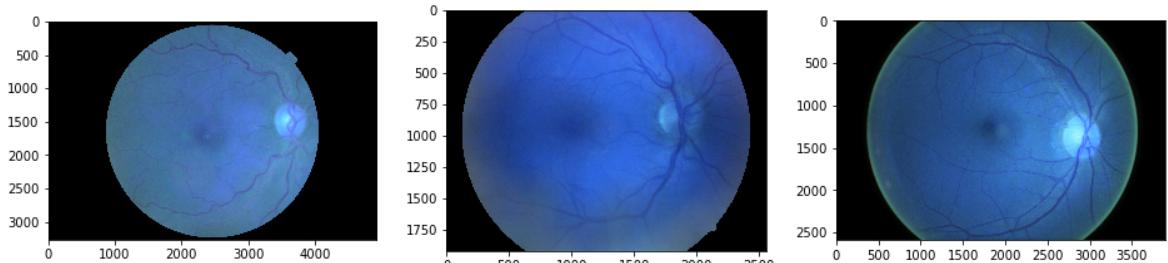
- No DR



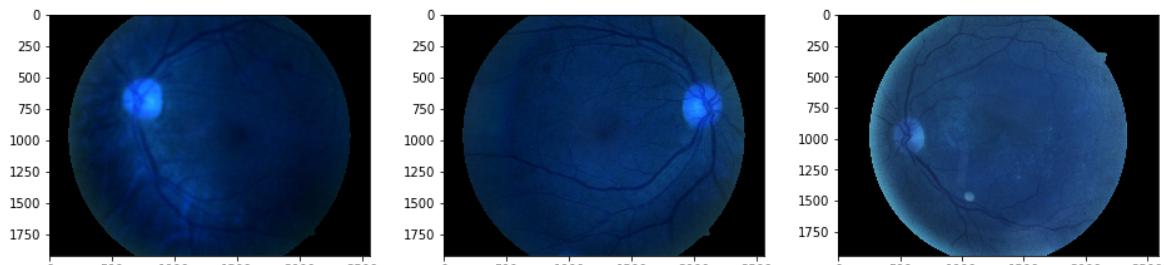
- Mild DR



- Moderate DR



- Severe DR



- Proliferative DR

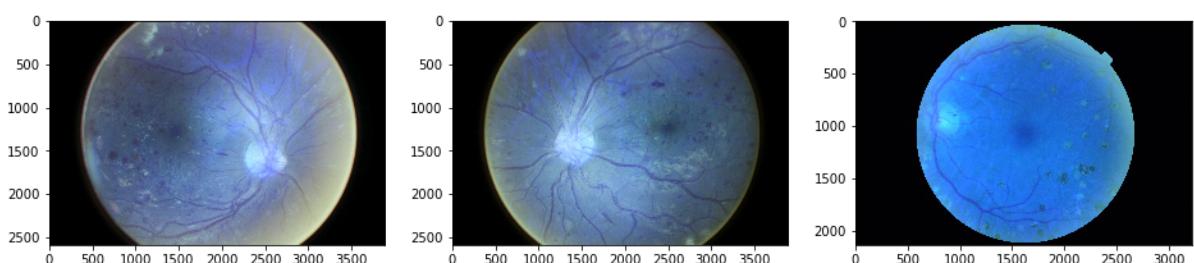
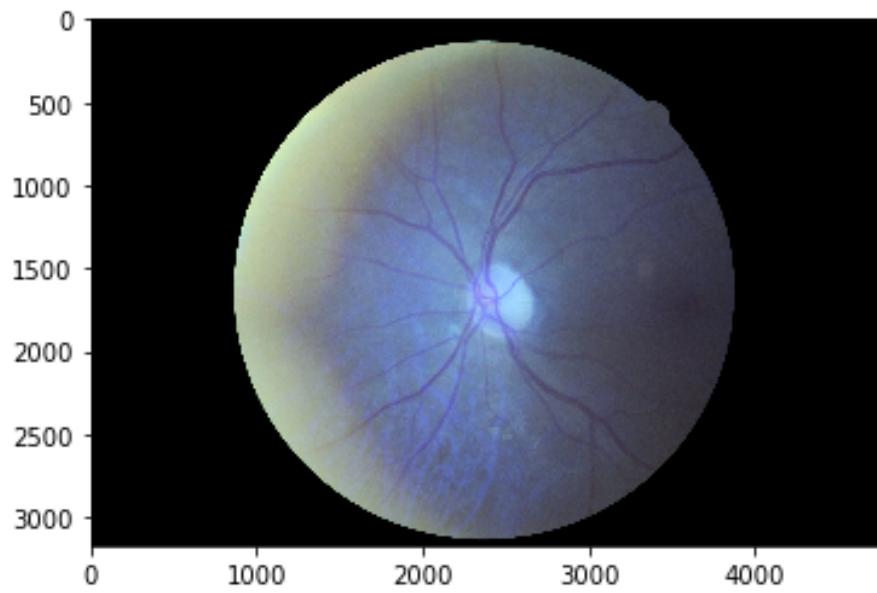


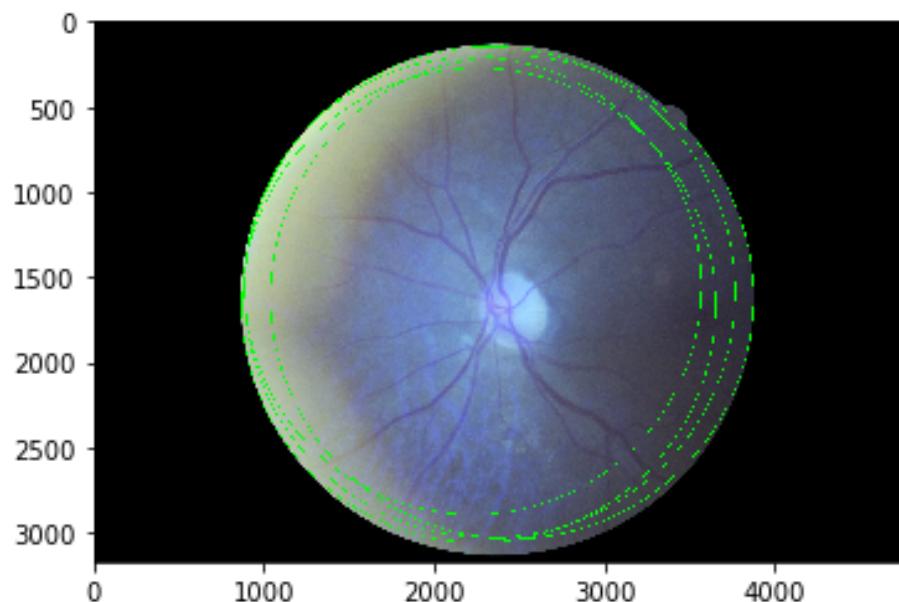
Image Preprocessing

- original image

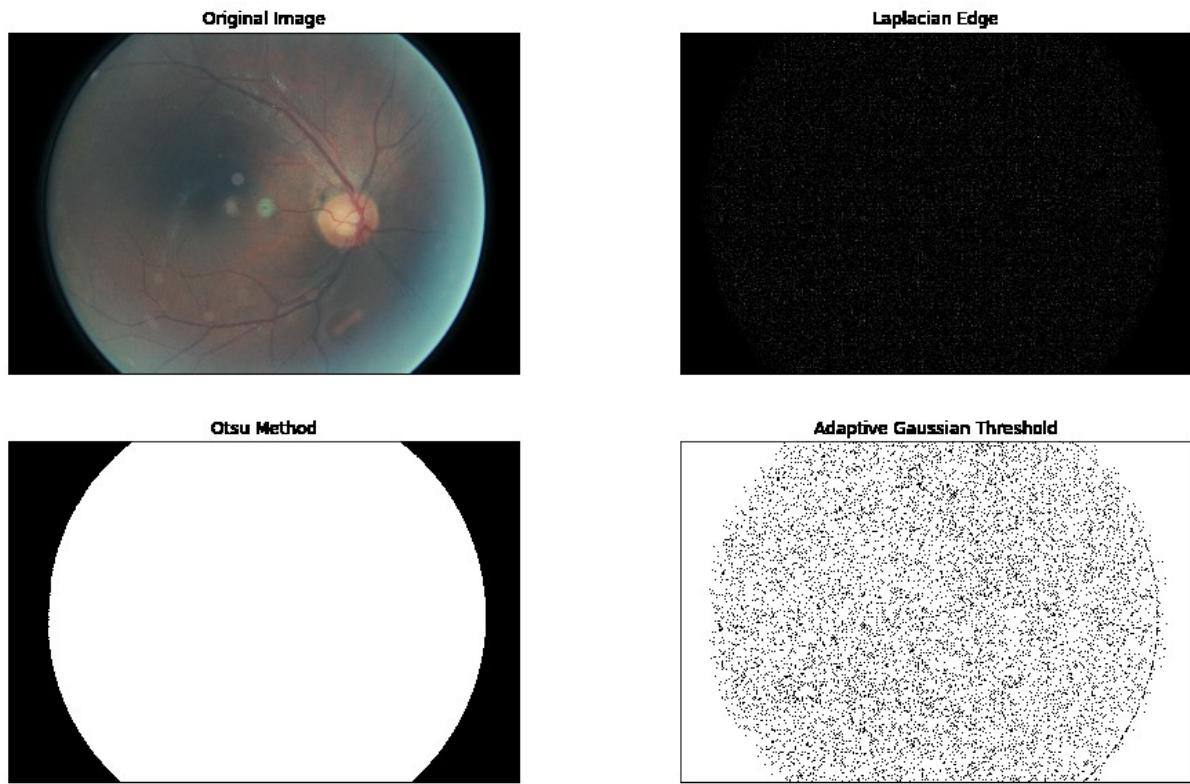


crop the extra black edge

1. detect the circle and crop



2. Use filter to detect the edge (implement opencv library)

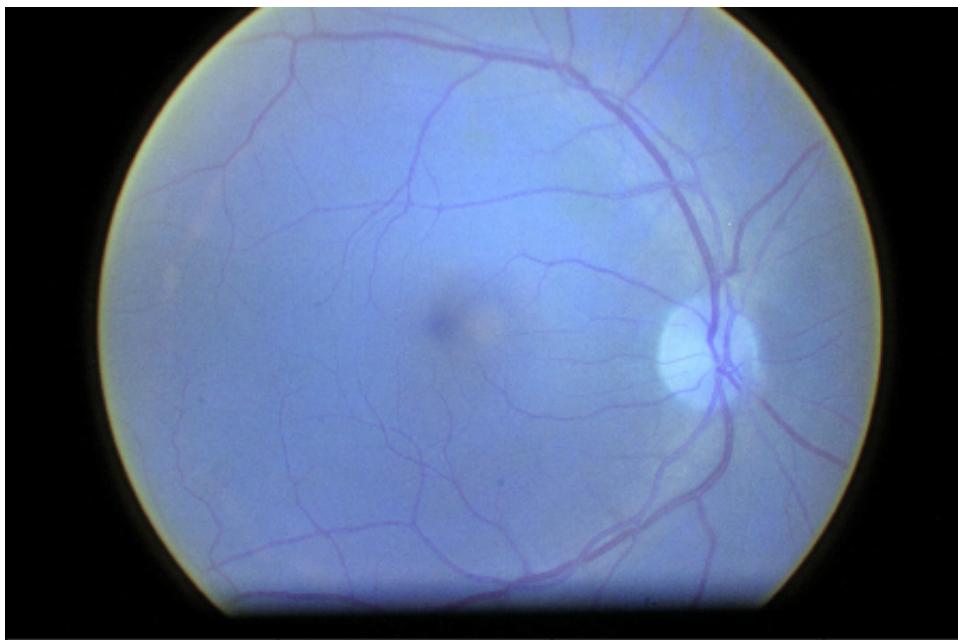


3. Finally It looks like this below

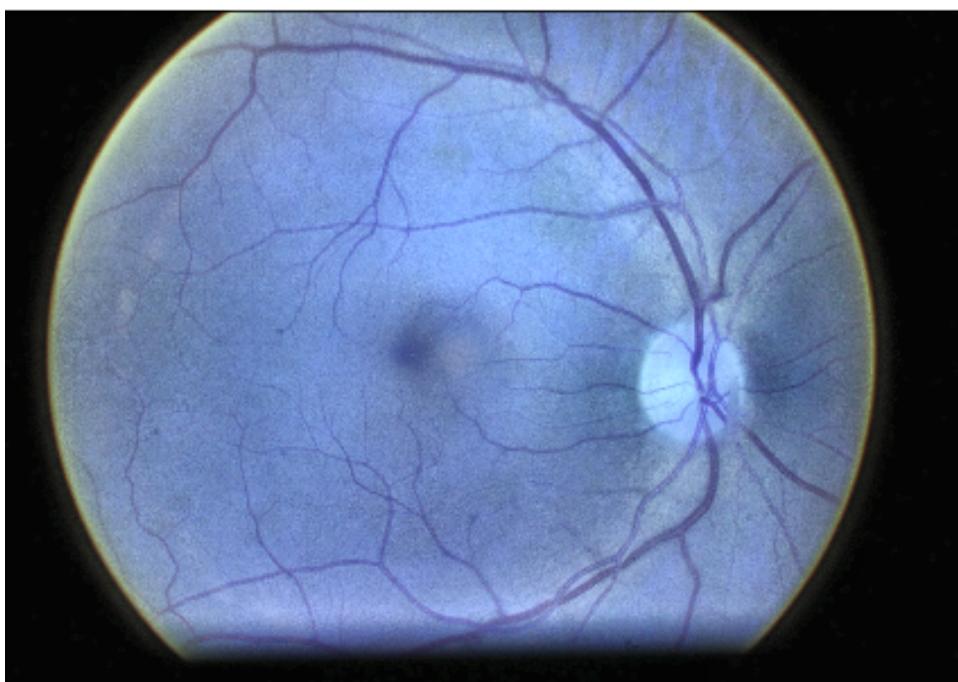


Enhance the image

- before



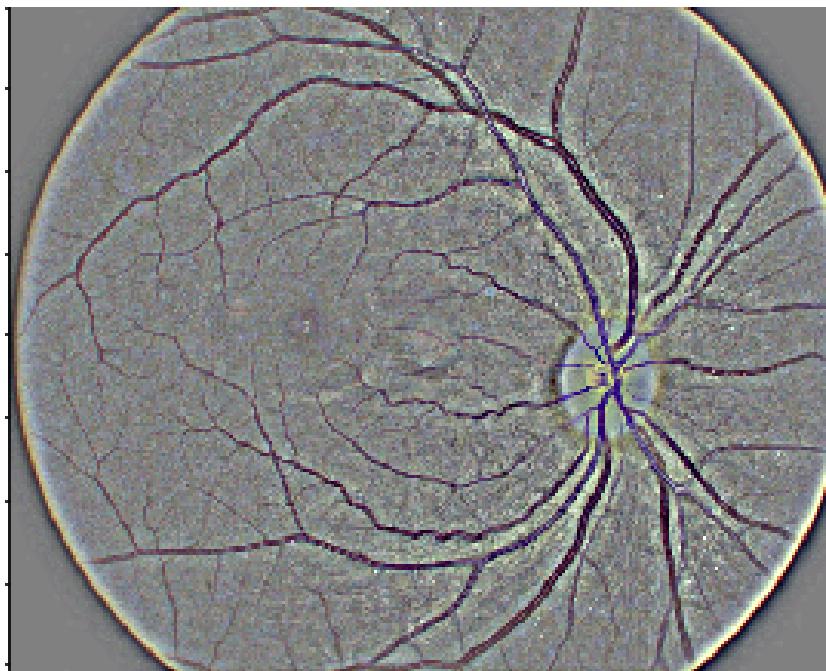
- After Enhance



openCV createCLAH method implemented

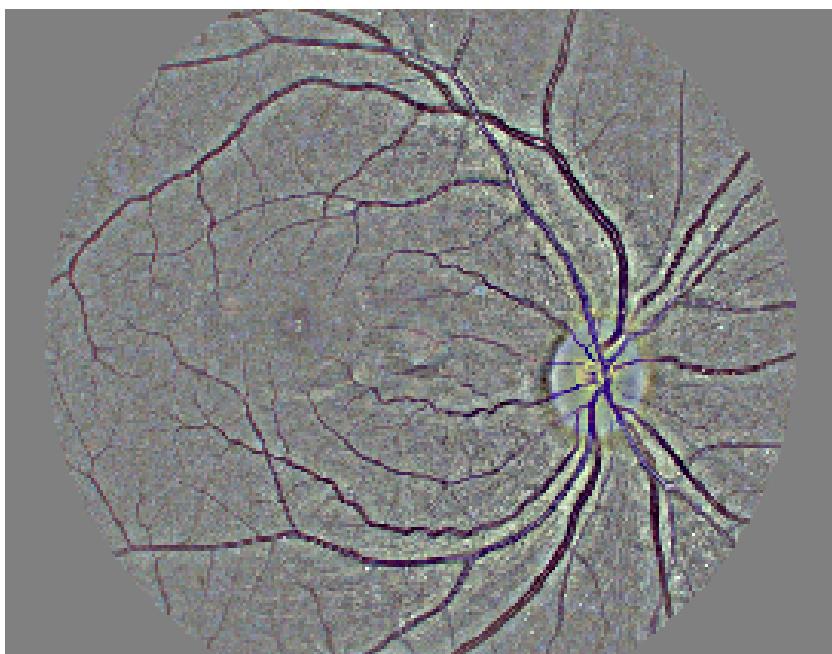
Resize to (299,299) (512,512)

Subtract local mean color

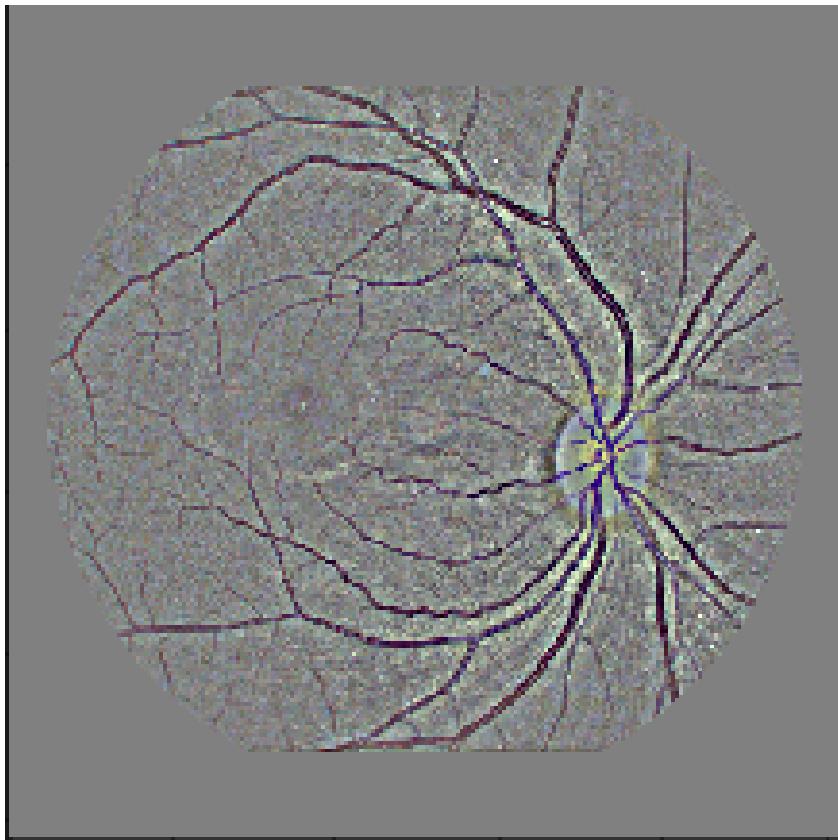


```
1 def subtract_gaussian_blur(img):
2     #
3     # http://docs.opencv.org/trunk/d0/d86/tutorial_py_image_arithmetics.html
4     # http://docs.opencv.org/3.1.0/d4/d13/tutorial_py_filtering.html
5     gb_img = cv2.GaussianBlur(img, (0, 0), 5)
6
7     return cv2.addWeighted(img, 4, gb_img, -4, 128)
8
9 img_gbs = subtract_gaussian_blur(img_crop.copy())
10 plt.imshow(img_gbs)
```

Remove 10% of the outer circle



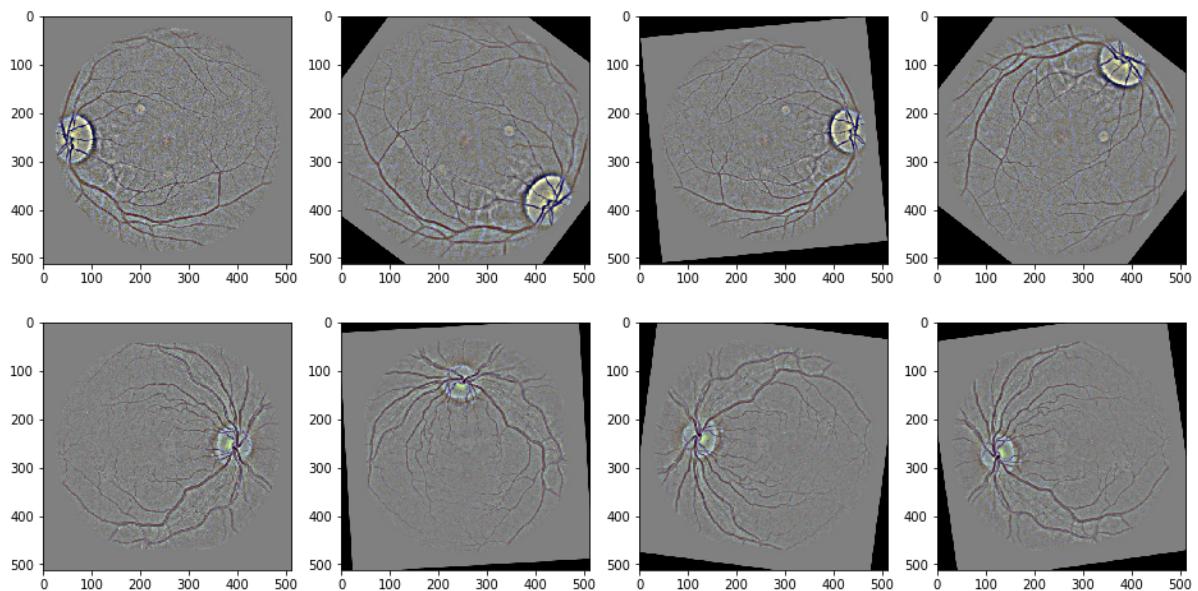
Place the processed image in the center of image

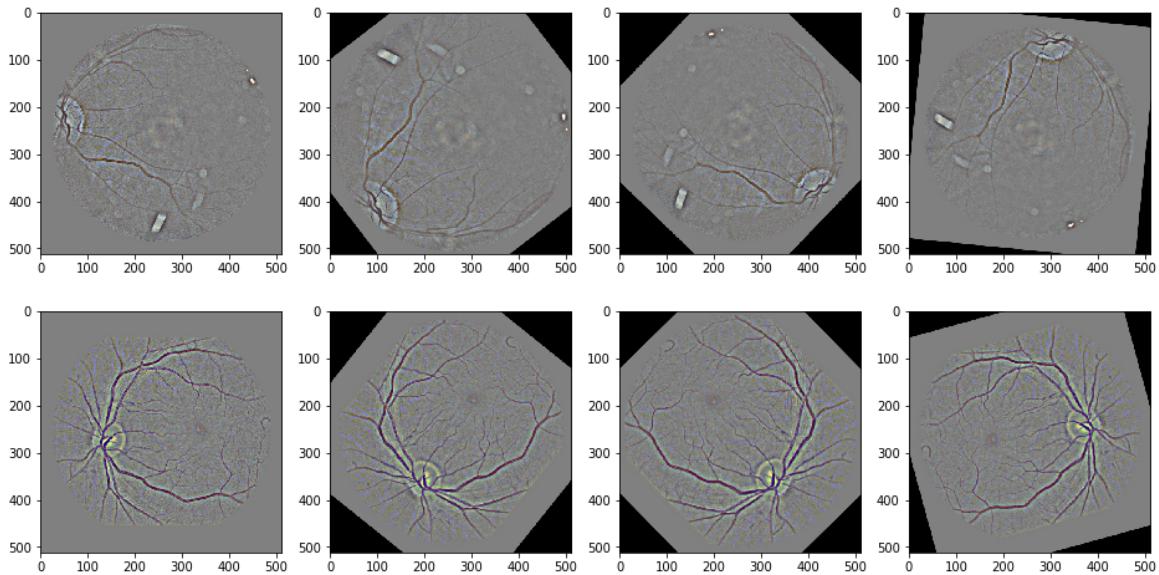


Abandon the Image with std lower than 16(too dark or too bright)

DataAugmentation

- Flip
- Scale
- Rotate





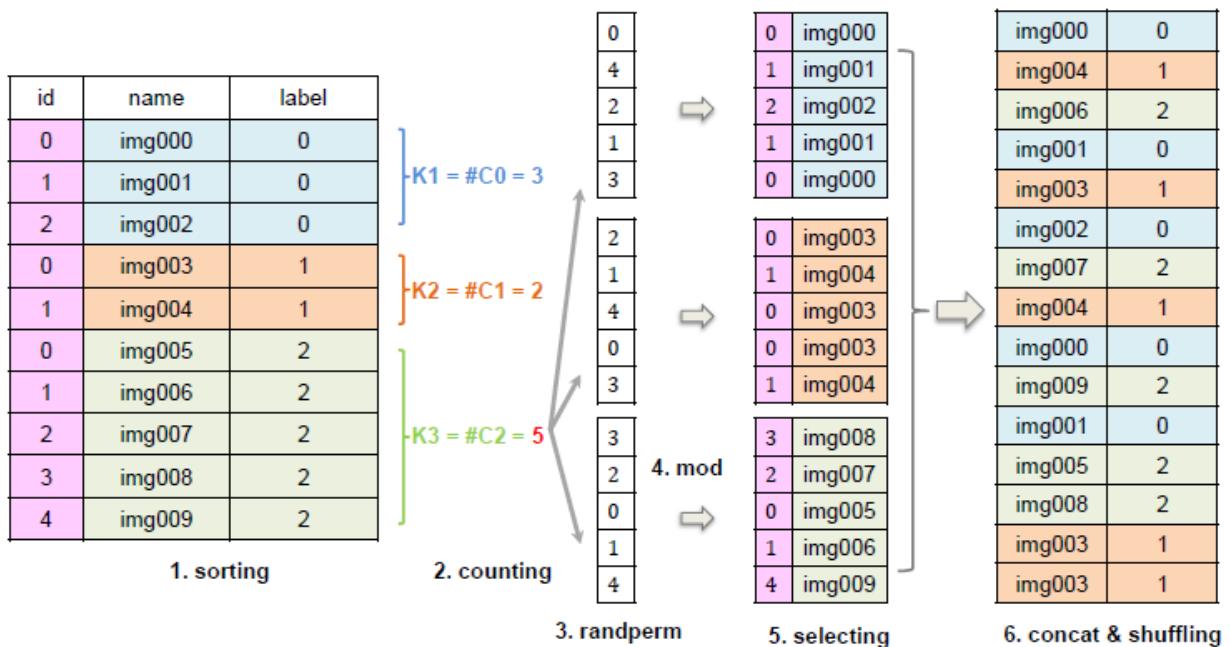
BatchNormalization

Preprocessing Parralelismly Using MultiProcessor

```
top - 14:38:40 up 3 days, 16:54, 9 users, load average: 6.57, 2.72, 1.62
Tasks: 825 total, 38 running, 787 sleeping, 0 stopped, 0 zombie
%Cpu(s): 87.3 us, 3.1 sy, 2.4 ni, 7.0 id, 0.1 wa, 0.0 hi, 0.0 si, 0.0 st
KiB Mem : 13175270+total, 43812444 free, 26394320 used, 61545944 buff/cache
KiB Swap: 4194300 total, 4194300 free, 0 used. 10319016+avail Mem
```

PID	USER	PR	NI	VIRT	RES	SHR	S	%CPU	%MEM	TIME+	COMMAND
85452	zhangst	20	0	3419220	111588	4176	R	101.0	0.1	0:04.71	python
85422	zhangst	20	0	3400788	73096	4192	R	100.7	0.1	0:04.72	python
85435	zhangst	20	0	3415372	87868	4200	R	100.7	0.1	0:04.71	python
85443	zhangst	20	0	3417920	110736	4196	R	100.7	0.1	0:04.69	python
85419	zhangst	20	0	3400788	68756	4176	R	100.3	0.1	0:04.70	python
85421	zhangst	20	0	3419224	111764	4180	R	100.3	0.1	0:04.71	python
85418	zhangst	20	0	3419224	111456	4196	R	100.0	0.1	0:04.70	python
85432	zhangst	20	0	3419220	111752	4184	R	100.0	0.1	0:04.68	python
85433	zhangst	20	0	3400788	77748	4192	R	100.0	0.1	0:04.68	python
85438	zhangst	20	0	3406508	98752	4196	R	100.0	0.1	0:04.70	python
85440	zhangst	20	0	3400788	63696	4196	R	100.0	0.0	0:04.70	python
85450	zhangst	20	0	3371260	66284	4180	R	100.0	0.1	0:04.68	python
85420	zhangst	20	0	3400788	92684	4196	R	99.7	0.1	0:04.68	python
85424	zhangst	20	0	3395244	85808	4192	R	99.7	0.1	0:04.66	python
85425	zhangst	20	0	3400788	92532	4196	R	99.7	0.1	0:04.69	python
85446	zhangst	20	0	3379696	72124	4196	R	99.7	0.1	0:04.69	python
85447	zhangst	20	0	3402284	94708	4196	R	99.7	0.1	0:04.65	python
85448	zhangst	20	0	3419224	111004	4176	R	99.7	0.1	0:04.66	python
85449	zhangst	20	0	3419224	112400	4196	R	99.7	0.1	0:04.67	python
85423	zhangst	20	0	3467920	128176	4196	R	99.3	0.1	0:04.68	python
85428	zhangst	20	0	3444172	132948	4184	R	99.3	0.1	0:04.67	python
85429	zhangst	20	0	3419224	111748	4188	R	99.3	0.1	0:04.67	python
85437	zhangst	20	0	3400788	71380	4196	R	99.3	0.1	0:04.68	python
85444	zhangst	20	0	3419224	110964	4196	R	99.3	0.1	0:04.64	python
85431	zhangst	20	0	3400788	63976	4196	R	99.0	0.0	0:04.65	python

Balanced Sampling via Label Shuffling



Label Smooth

Model Architechce

Modified InceptionV3

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 299, 299, 3)	0
batch_normalization_95 (Batch Normalization)	(None, 299, 299, 3)	12
inception_v3 (Model)	(None, 8, 8, 2048)	21802784
global_average_pooling2d_1 (Global Average Pooling 2D)	(None, 2048)	0
dropout_1 (Dropout)	(None, 2048)	0
dense_1 (Dense)	(None, 5)	10245

Total params: 21,813,041

Trainable params: 21,778,603

Non-trainable params: 34,438

Modified Xception

Layer (type)	Output Shape	Param #
input_8 (InputLayer)	(None, 299, 299, 3)	0
batch_normalization_104 (BatchNormalization)	(None, 299, 299, 3)	12
xception (Model)	(None, 10, 10, 2048)	20861480
global_average_pooling2d_2 (GlobalAveragePooling2D)	(None, 2048)	0
dropout_2 (Dropout)	(None, 2048)	0
dense_2 (Dense)	(None, 5)	10245

Total params: 20,871,737

Trainable params: 20,817,203

Non-trainable params: 54,534

Basic CNN model

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 510, 510, 32)	896
conv2d_2 (Conv2D)	(None, 508, 508, 32)	9248
max_pooling2d_1 (MaxPooling2D)	(None, 254, 254, 32)	0
conv2d_3 (Conv2D)	(None, 252, 252, 64)	18496
conv2d_4 (Conv2D)	(None, 250, 250, 64)	36928
max_pooling2d_2 (MaxPooling2D)	(None, 125, 125, 64)	0
conv2d_5 (Conv2D)	(None, 123, 123, 96)	55392
conv2d_6 (Conv2D)	(None, 121, 121, 96)	83040
max_pooling2d_3 (MaxPooling2D)	(None, 60, 60, 96)	0
conv2d_7 (Conv2D)	(None, 58, 58, 128)	110720
conv2d_8 (Conv2D)	(None, 56, 56, 128)	147584
max_pooling2d_4 (MaxPooling2D)	(None, 28, 28, 128)	0
conv2d_9 (Conv2D)	(None, 26, 26, 192)	221376
conv2d_10 (Conv2D)	(None, 24, 24, 192)	331968

conv2d_6 (Conv2D)	(None, 121, 121, 96)	83040
max_pooling2d_3 (MaxPooling2D)	(None, 60, 60, 96)	0
conv2d_7 (Conv2D)	(None, 58, 58, 128)	110720
conv2d_8 (Conv2D)	(None, 56, 56, 128)	147584
max_pooling2d_4 (MaxPooling2D)	(None, 28, 28, 128)	0
conv2d_9 (Conv2D)	(None, 26, 26, 192)	221376
conv2d_10 (Conv2D)	(None, 24, 24, 192)	331968
max_pooling2d_5 (MaxPooling2D)	(None, 12, 12, 192)	0
conv2d_11 (Conv2D)	(None, 10, 10, 256)	442624
conv2d_12 (Conv2D)	(None, 8, 8, 256)	590080
max_pooling2d_6 (MaxPooling2D)	(None, 4, 4, 256)	0
conv2d_13 (Conv2D)	(None, 2, 2, 256)	590080
max_pooling2d_7 (MaxPooling2D)	(None, 1, 1, 256)	0
flatten_1 (Flatten)	(None, 256)	0
dense_1 (Dense)	(None, 256)	65792
dense_2 (Dense)	(None, 5)	1285

Total params: 2,705,509

Trainable params: 2,705,509

Non-trainable params: 0

Ensemble Of Them

Training Environment

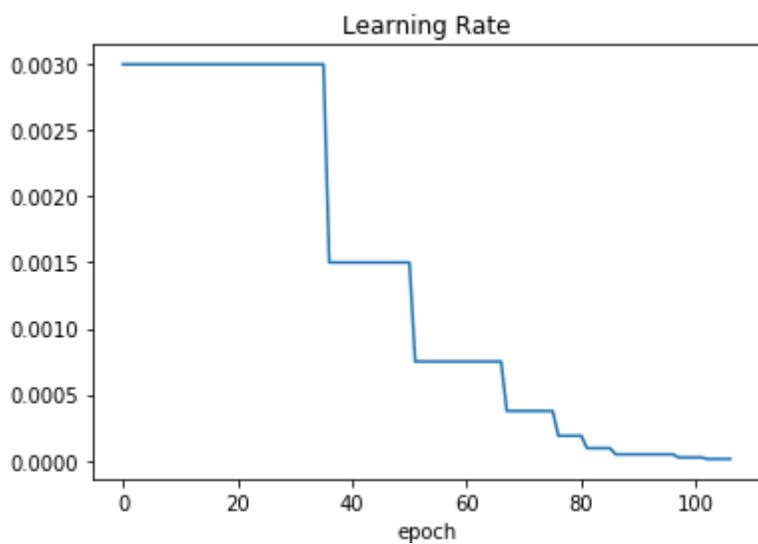
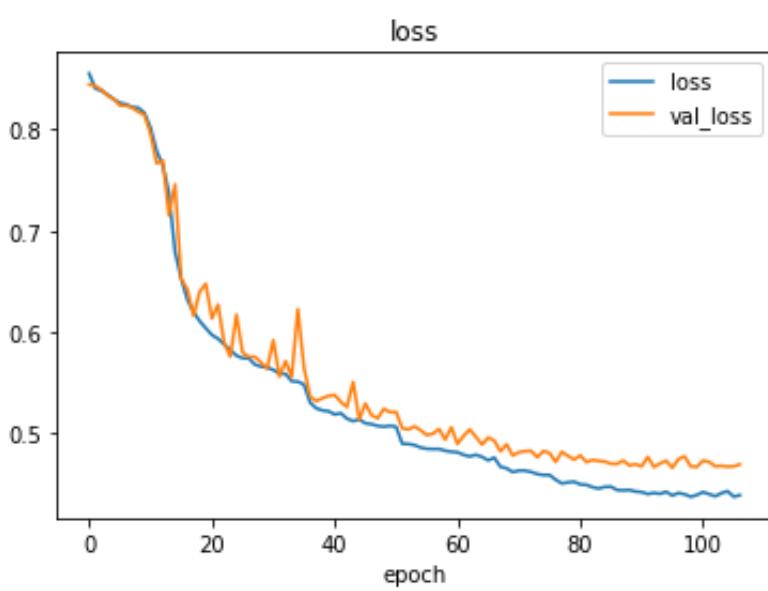
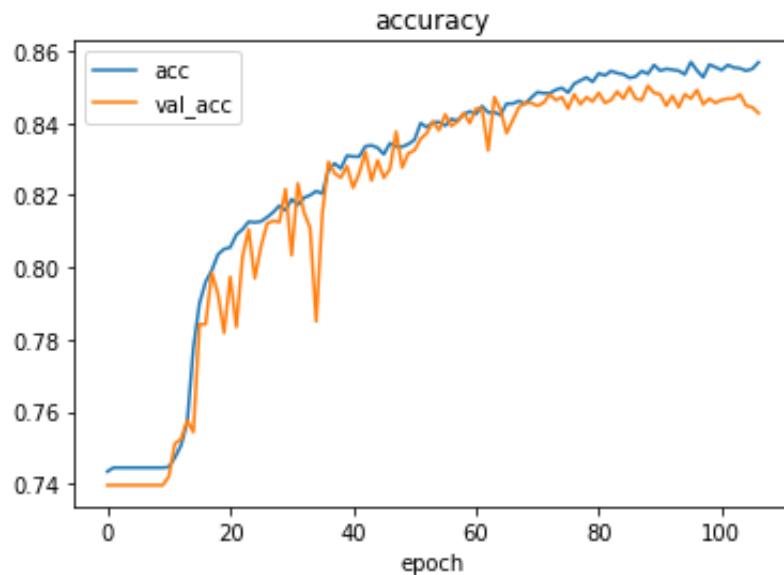
- CUDA8.0 CuDnn5.1
- Open framework for deep learning (Tensorflow-Gpu ,Keras)
- 8 GPUS (12 GB, GeForce GTX TITAN X; NVIDIA) Training Parralelismly

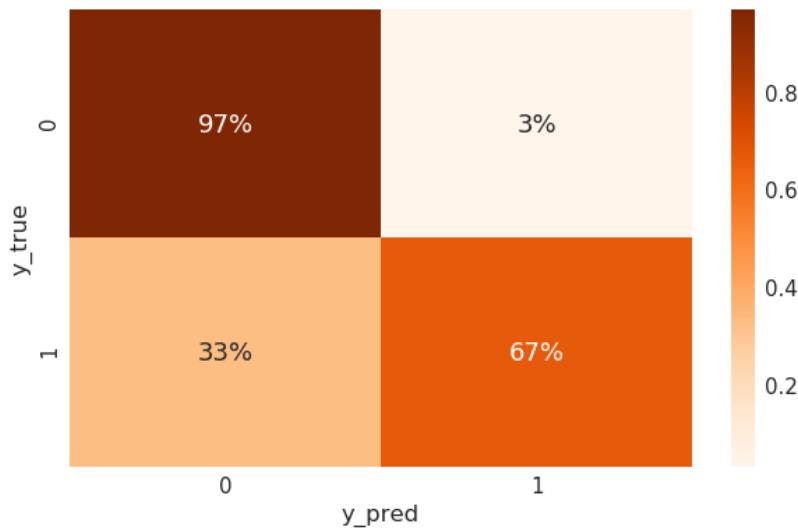
NVIDIA-SMI 381.22					Driver Version: 381.22			
GPU	Name	Persistence-M	Bus-Id	Disp.A	Volatile	Uncorr.	ECC	
Fan	Temp	Perf	Pwr:Usage/Cap		Memory-Usage	GPU-Util	Compute M.	
0	TITAN Xp	Off	0000:04:00.0	Off			N/A	
23%	45C	P2	80W / 250W	12019MiB / 12189MiB		46%	Default	
1	TITAN Xp	Off	0000:05:00.0	Off			N/A	
23%	34C	P2	60W / 250W	11713MiB / 12189MiB		16%	Default	
2	TITAN Xp	Off	0000:08:00.0	Off			N/A	
23%	40C	P2	60W / 250W	11713MiB / 12189MiB		25%	Default	
3	TITAN Xp	Off	0000:09:00.0	Off			N/A	
23%	36C	P2	61W / 250W	11713MiB / 12189MiB		18%	Default	
4	TITAN Xp	Off	0000:84:00.0	Off			N/A	
23%	40C	P2	59W / 250W	11713MiB / 12189MiB		9%	Default	
5	TITAN Xp	Off	0000:85:00.0	Off			N/A	
23%	34C	P2	60W / 250W	11713MiB / 12189MiB		3%	Default	
6	TITAN Xp	Off	0000:88:00.0	Off			N/A	
23%	37C	P2	60W / 250W	11713MiB / 12189MiB		21%	Default	
7	TITAN Xp	Off	0000:89:00.0	Off			N/A	
23%	35C	P2	60W / 250W	11713MiB / 12189MiB		4%	Default	

Acuracy

- Divide the dataset into 90% and 10% of the dataset for training and testing respectively.
- 85.5%** overall for 5 classification (0,1,2,3,4,5)
90.1% overall for 2 classification(0 vs 1,2,3,4)

PartResult





Bad Attempts

Too many to say

Summary

1. The model can get Top 10 result when resubmitting in Kaggle
2. There also leaves somewhere to improve but the time is limited
3. Many idea comes from papers and imageClassification matches
4. **Visually interpreting** its decision making process and **Deconvolution of the cnn** to help Doctors to Find the new features to judge the DiabeticRetinopathy is **Promising** rather than the higher Accuracy.

To be Continued...

1. Artificial IntelligenceWith Deep Learning Technology Looks Into Diabetic Retinopathy Screening ↵
2. Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift ↵
3. Applying artificial intelligence to disease staging: Deep learning for improved staging of diabetic retinopathy ↵
4. Discovery Radiomics with CLEAR-DR: Interpretable Computer Aided Diagnosis of Diabetic Retinopathy ↵