Diabetic Retinopathy Prediction using Convolutional Neural Networks

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Introduction

- Any damage caused to the retina of an eye due to abnormal blood flow or even presence of exudates and lesions is termed as Diabetic Retinopathy.

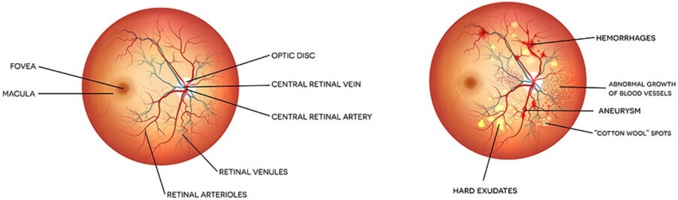


Figure 1: Eye and related abnormalities.

Data: Normal

- Normal eye do not have any of the abnormality symptoms.

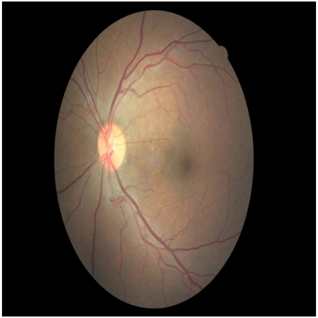


Figure 2: 7_Left_Eye

Figure 3: 7_Right_Eye

Data: Mild DR

- Symptom: Tiny dot-like aneurysm.

Figure 4: 5187_Left_Eye

Figure 5: 5187_Right_Eye

Data: Moderate DR

- Symptom: White cotton-wool like (soft exudates).

Figure 6: 1320_Left_Eye

Figure 7: 1320_Right_Eye

Data: Severe DR

- Symptom: Irregular exudates (Hard exudates).

Figure 8: 10840_Left_Eye

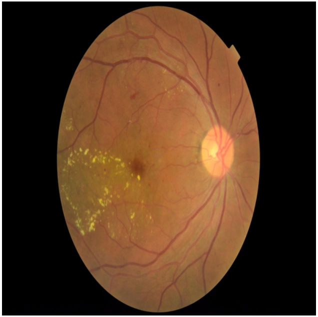


Figure 9: 10840_Right_Eye

Data: Proliferative DR

- Symptom: Hemorrhage and neovascularization with hard exudates too.

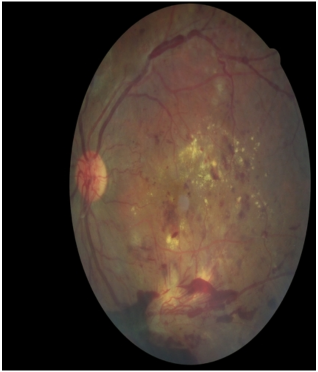


Figure 10: 36847_Left_Eye

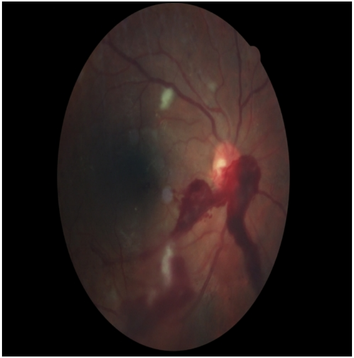


Figure 11: 36847_Right_Eye

Problem Statement

- “The aim of this study is to explore how we can automate the process of correctly classifying the eye images into different stages of Diabetic Retinopathy”.

Data Distribution

- Dataset (unbalanced):

Category	Train	Test
0	25810	39533
1	2443	3762
2	5292	7861
3	873	1214
4	708	1206
Total	35126	53576

Table 1: Dataset as provided by Kaggle.

Binary Classification

- Dataset (unbalanced) [Table 1].
- 800 images per class for testing, with 90:10 percent split.

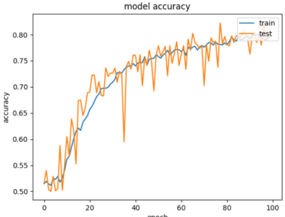


Fig : Accuracy graph

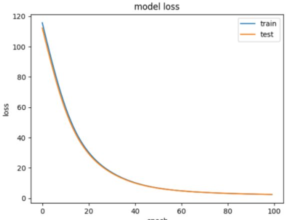


Fig : Loss graph

batch_size	learning_rate	epochs	drop-out
16	0.00001	100	0.5

	0	1
0	**348**	52
1	123	**277**

Fig : Confusion Matrix

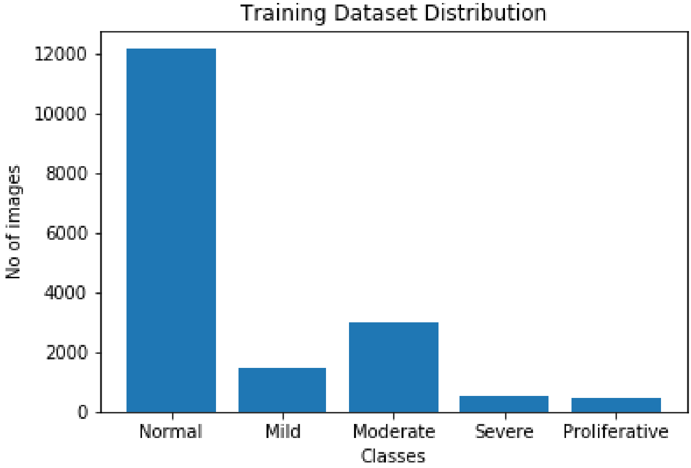
	Precision	Recall	F1-score	Support
0(abnormal)	0.85	0.76	0.80	400
1(normal)	0.78	0.86	0.82	400
Total/Avg	0.82	0.81	0.81	800

Table : Classification Report

Figure 12: Binary classification result (previously obtained).

Related Issues ...

- Imbalanced dataset.



Related Issues ...

- Noisy dataset.

Figure 13: Miscategorized

Figure 14: Corrupted

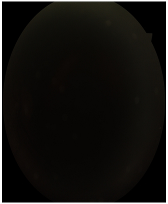


Figure 15: Dim light

Figure 16: Blurred

Related Issues ...

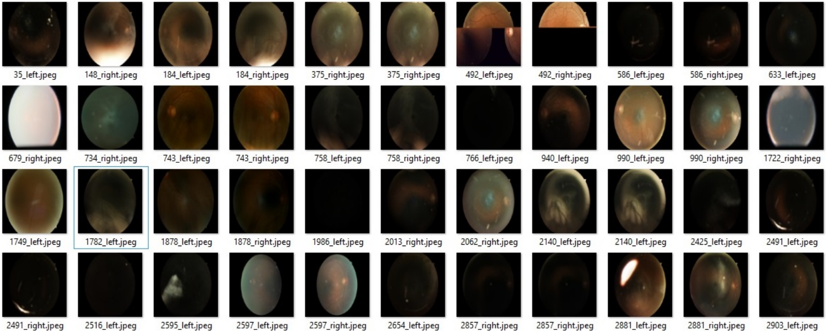


Figure 17: Noisy images [manually removed]

Augmented Dataset

- Re-scaled to 512 X 512.
- Randomly re-scaled by ± 10 %.
- Randomly rotated 0-90 degree.
- Random horizontal and vertical flip.
- Zoom range 0.2 %.
- Width/height shift range 0.2 %.

Pre-processing

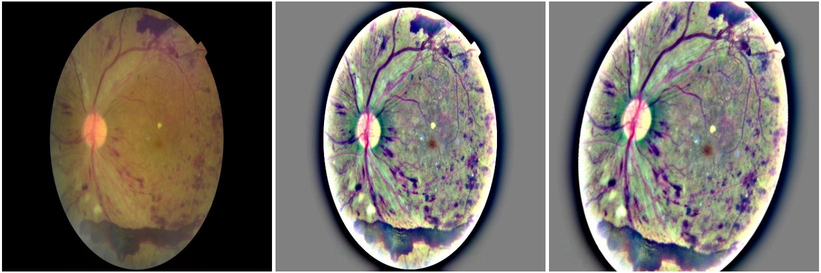


Figure 18: Before and after applying gaussian function & augmentation.

CNN Model

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 32, 512, 512)	320
leaky_re_lu_2 (LeakyReLU)	(None, 32, 512, 512)	0
batch_normalization_1 (BN)	(None, 32, 512, 512)	2048
max_pooling2d_1 (MaxPooling2)	(None, 32, 256, 256)	0
conv2d_2 (Conv2D)	(None, 32, 256, 256)	9248
leaky_re_lu_3 (LeakyReLU)	(None, 32, 256, 256)	0
batch_normalization_2 (BN)	(None, 32, 256, 256)	1024
max_pooling2d_2 (MaxPooling2)	(None, 32, 128, 128)	0
conv2d_3 (Conv2D)	(None, 64, 128, 128)	18496
leaky_re_lu_4 (LeakyReLU)	(None, 64, 128, 128)	0
batch_normalization_3 (BN)	(None, 64, 128, 128)	512
max_pooling2d_3 (MaxPooling2)	(None, 64, 64, 64)	0

CNN Model continued ...

Layer (type)	Output Shape	Param #
conv2d_4 (Conv2D)	(None, 64, 64, 64)	36928
leaky_re_lu_5 (LeakyReLU)	(None, 64, 64, 64)	0
batch_normalization_4 (BN)	(None, 64, 64, 64)	256
max_pooling2d_4 (MaxPooling2)	(None, 64, 32, 32)	0
conv2d_5 (Conv2D)	(None, 128, 32, 32)	73856
leaky_re_lu_6 (LeakyReLU)	(None, 128, 32, 32)	0
batch_normalization_5 (BN)	(None, 128, 32, 32)	128
max_pooling2d_5 (MaxPooling2)	(None, 128, 16, 16)	0
conv2d_6 (Conv2D)	(None, 128, 16, 16)	147584
leaky_re_lu_7 (LeakyReLU)	(None, 128, 16, 16)	0
batch_normalization_6 (BN)	(None, 128, 16, 16)	64
max_pooling2d_6 (MaxPooling2)	(None, 128, 8, 8)	0

CNN Model continued ...

Layer (type)	Output Shape	Param #
conv2d_7 (Conv2D)	(None, 256, 8, 8)	295168
leaky_re_lu_8 (LeakyReLU)	(None, 256, 8, 8)	0
conv2d_8 (Conv2D)	(None, 256, 8, 8)	590080
leaky_re_lu_9 (LeakyReLU)	(None, 256, 8, 8)	0
batch_normalization_7 (BN)	(None, 256, 8, 8)	32
max_pooling2d_7 (MaxPooling2)	(None, 256, 4, 4)	0
conv2d_9 (Conv2D)	(None, 512, 4, 4)	1180160
leaky_re_lu_10 (LeakyReLU)	(None, 512, 4, 4)	0
conv2d_10 (Conv2D)	(None, 512, 4, 4)	2359808
leaky_re_lu_11 (LeakyReLU)	(None, 512, 4, 4)	0
batch_normalization_8 (BN)	(None, 512, 2, 4)	16
max_pooling2d_8 (MaxPooling2)	(None, 512, 2, 2)	0
dropout_1 (Dropout)	(None, 512, 2, 2)	0
flatten_1 (Flatten)	(None, 2048)	0

CNN Model continued ...

Layer (type)	Output Shape	Param #
dense_1 (Dense)	(None, 1024)	2098176
leaky_re_lu_12 (LeakyReLU)	(None, 1024)	0
dropout_2 (Dropout)	(None, 1024)	0
dense_2 (Dense)	(None, 1024)	1049600
leaky_re_lu_13 (LeakyReLU)	(None, 1024)	0
dense_3 (Dense)	(None, 2)	2050
Total params: 7,869,205 Trainable params: 7,867,165 Non-trainable params: 2,040		

Table 2: Convolutional Neural Network Architecture

Tuning up

Attributes	exp1	exp2	exp3	exp4
preprocessing	gaussian	gaussian	gaussian	gaussian
batch_size	32	32	32	32
learning_rate	0.001	0.000003	0.0003	0.0003
epochs	16	48	98	56
drop_out	0.5	0.5	0.5	0.5
class_mode	categorical	categorical	categorical	categorical
input_size	256 X 256	512 X 512	512 X 512	512 X 512
kernel_size	3 X 3	3 X 3	3 X 3	3 X 3
pool_size	3 X 3	3 X 3	3 X 3	3 X 3
strides	2 X 2	2 X 2	2 X 2	2 X 2
padding	same	same	same	same
color_mode	rgb	rgb	rgb	rgb

Table 3: Hyper-parameters & other settings.

- Augmented dataset used for experiment (90:10 % split).

	0	**1**	**2**	**3**	**4**	**Total**
Original (Train)	25610	2403	5262	863	688	34826
Augmented	25610	25610	25610	25610	25610	128450

Result (Experiment 1) ...

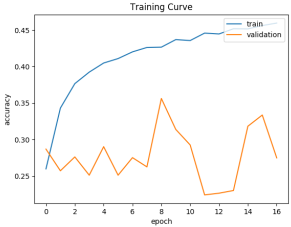


Figure 19: Training Accuracy

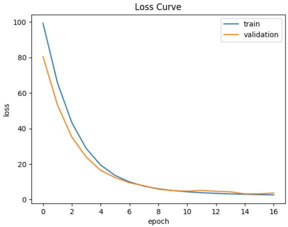


Figure 20: Loss Accuracy

	0	**1**	**2**	**3**	**4**
0	29219	8867	1173	29	245
1	2325	1287	140	4	6
2	3245	2478	1883	123	131
3	179	251	594	160	30
4	247	116	489	81	273

Figure 21: Confusion Matrix

	Precision	Recall	F1-score	Support
0	0.83	0.74	0.78	39533
1	0.10	0.34	0.15	3762
2	0.44	0.24	0.31	7860
3	0.40	0.13	0.20	1214
4	0.40	0.23	0.29	1206
Total/Avg	0.70	0.61	0.64	53575

Table 4: Classification Report

- Accuracy: 69.36%

Result (Experiment 2)

- Augmented dataset used for experiment (90:10 % split).

	0	**1**	**2**	**3**	**4**	**Total**
Original (Train)	25610	2403	5262	863	688	34826
Augmented	10000	10000	10000	10000	10000	50000

Result (Experiment 2) ...

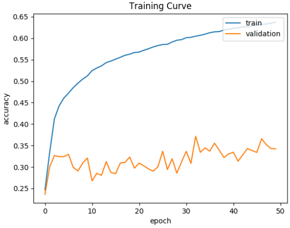


Figure 22: Training Accuracy

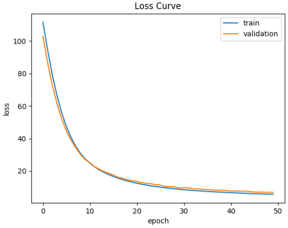


Figure 23: Loss Accuracy

	0	**1**	**2**	**3**	**4**
0	35244	78	3997	14	17
1	3369	4	381	2	0
2	5564	8	2232	10	5
3	553	2	631	16	3
4	469	2	709	7	5

Figure 24: Confusion Matrix

	Precision	**Recall**	**F1-score**	**Support**
0	0.78	0.90	0.83	39340
1	0.04	0.00	0.00	3756
2	0.28	0.29	0.28	7819
3	0.33	0.01	0.03	1205
4	0.25	0.00	0.01	1192
Total/Avg	0.63	0.70	0.66	53312

Table 5: Classification Report

- Accuracy: 70.34%

Result (Experiment 3)

- Augmented dataset used for experiment (80:20 % split).

	0	**1**	**2**	**3**	**4**	**Total**
Original (Train)	25610	2403	5262	863	688	34826
Augmented	10000	10000	10000	10000	100000	50000

Result (Experiment 3) ...

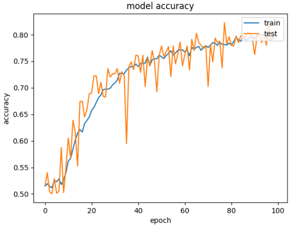


Figure 25: Training Accuracy

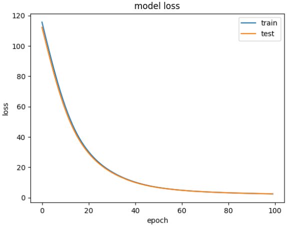


Figure 26: Loss Accuracy

	0	**1**	**2**	**3**	**4**
0	38385	303	533	1	118
1	2912	434	400	0	10
2	3108	376	3855	227	253
3	112	10	611	307	165
4	192	3	355	75	567

Figure 27: Confusion Matrix

Result (Experiment 3) ...

	Precision	**Recall**	**F1-score**	**Support**
0	0.86	0.98	0.91	39340
1	0.39	0.12	0.18	3756
2	0.67	0.49	0.57	7819
3	0.50	0.25	0.34	1205
4	0.51	0.48	0.49	1192
Total/Avg	0.78	0.82	0.79	53312

Table 6: Classification Report

- Accuracy: 81.00%

Result (Experiment 4)

- Augmented dataset used for experiment (90:10 % split).

	0	**1**	**2**	**3**	**4**	**Total**
Original (Train)	25610	2403	5262	863	688	34826
Augmented	12000	12000	12000	12000	12000	60000

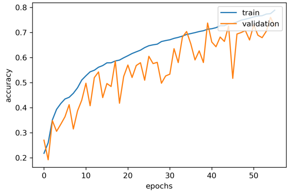


Figure 28: Training Accuracy

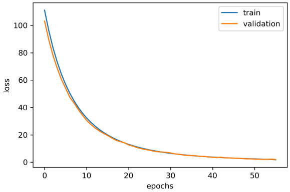


Figure 29: Loss Accuracy

	0	1	2	3	4
0	36041	1178	1729	10	382
1	1318	1867	528	4	39
2	1141	313	5472	465	428
3	552	2	268	663	220
4	105	2	167	31	887

Figure 30: Confusion Matrix

Result (Experiment 4) ...

	Precision	**Recall**	**F1-score**	**Support**
0	0.93	0.91	0.92	39340
1	0.55	0.49	0.52	3756
2	0.67	0.70	0.69	7819
3	0.56	0.55	0.56	1205
4	0.45	0.74	0.55	1192
Total/Avg	0.84	0.83	0.84	53312

Table 7: Classification Report

- Accuracy: 84.23%

Conclusion

- DR classification screening with respect to binary and multi-class can be performed with much higher accuracy than the actual result found.
- For certain cases, where the images were out of focus, the algorithm fails to identify some of the DR highlights, cause of the camera artifacts.
- Consequently, in the near future, the algorithm will be improved to handle the impact of an unfocused images.

References

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Thanks