

# Diabetic Retinopathy Prediction using Convolutional Neural Networks

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# What is DR?

- Diabetic Retinopathy can be termed as any damage caused to the retina of an eye due to abnormal blood flow.

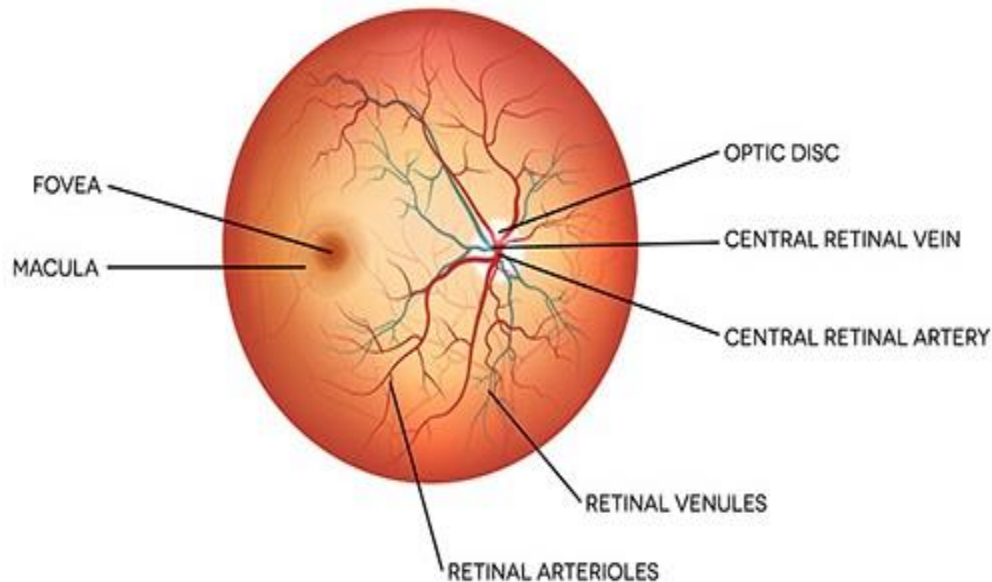


Fig. 1: Normal Eye

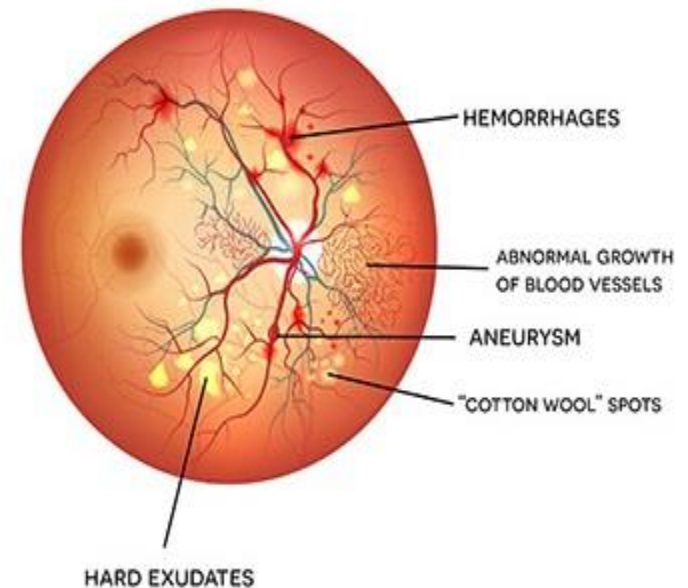


Fig. 2: Abnormal Eye

# Abnormalities stages in DR:



a. Mild DR



b. Moderate DR



c. Severe DR



a. Proliferative DR

Fig. 3: DR abnormalities  
(related abnormalities are circled)

# Literature Survey:

Table 1: Literature Survey

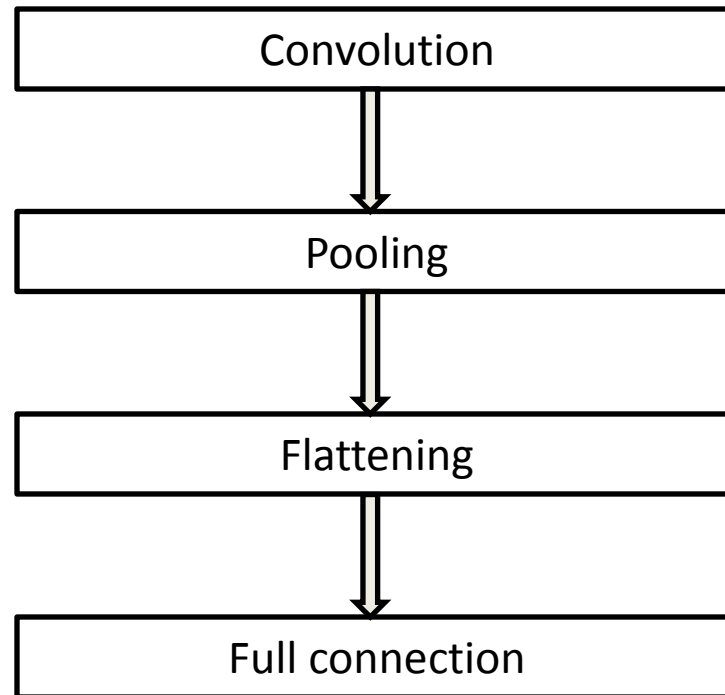
<u>No.</u>	<u>Published Paper</u>	<u>Year</u>	<u>Classification Type</u>	<u>Techniques Used</u>	<u>Accuracy</u>
1	Automatic detection of diabetic retinopathy using an artificial neural network: A screening Tool. [Authors: G G Gardner, D Keating, T H Williamson, A T Elliott]	1996	Binary	Neural Network	88.4%
2	Automated identification of diabetic retinopathy stages using digital fundus images. [Authors: Nayak J, Bhat PS, Acharya R, Lim CM, Kagathi M]	2008	Three-class	Neural Network	93.0%
3	Application of higher order spectra for the identification of diabetes retinopathy stages. [Authors: Acharya UR, Chua CK, Ng EY, Yu W, Chee C]	2008	Five-class	SVM	82.0%
4	Computer-based detection of diabetes retinopathy stages using digital fundus images. [Authors: Acharya UR, Lim CM, Ng EY, Chee C, Tamura T]	2009	Five-class	SVM	85.9%
5	Multiclass SVM-based automated diagnosis of diabetic retinopathy. [Authors: P. Adarsh, D. Jeyakumari]	2013	Five-class	SVM	96.0%

## Problem Statement:

*“The aim of this study is to explore how we can automate the process of correctly classifying and predicting an eye image as abnormal or normal”.*

# Methodology:

Steps for building CNN:



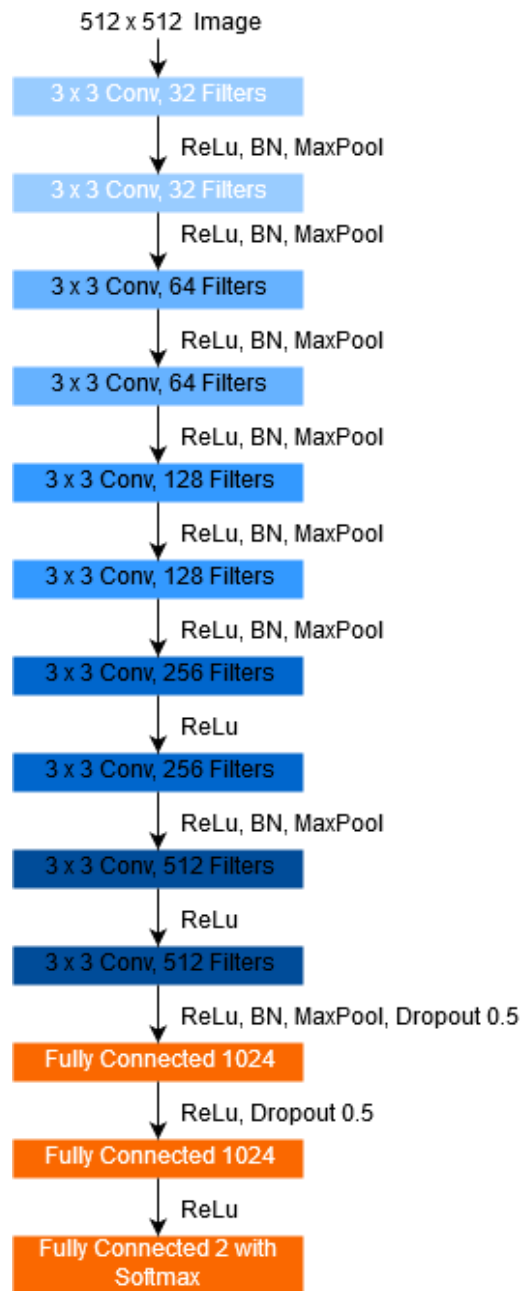


Fig. 4: Network Architecture

Table 2: Hyper-parameters & other settings

No.	Attributes Used	Values
1	training_batch	32
2	test_batch	32
3	learning_rate	0.0001
4	epochs	50
5	drop_out	0.5
6	class_mode	category
7	input_size	512 x 512
8	kernel_size	3 x 3
9	pool_size	3 x 3
10	strides	2 x 2
11	padding	same
12	color_mode	Grayscale

Table 3: CNN architecture

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 (BatchNormalization)	(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 (BatchNormalization)	(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 (BatchNormalization)	(None, 64, 128, 128)	512
max_pooling2d_3 (MaxPooling2)	(None, 64, 64, 64)	0
conv2d_4 (Conv2D)	(None, 64, 64, 64)	36928
leaky_re_lu_5 (LeakyReLU)	(None, 64, 64, 64)	0
batch_normalization_4 (BatchNormalization)	(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 (BatchNormalization)	(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 (BatchNormalization)	(None, 128, 16, 16)	64
max_pooling2d_6 (MaxPooling2)	(None, 128, 8, 8)	0
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 (BatchNormalization)	(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 (BatchNormalization)	(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
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: 7,865,554		
Trainable params: 7,863,514		
Non-trainable params: 2,040		



# Dataset:

Source: <https://kaggle.com/c/diabetic-retinopathy-detection/data>

Table 4: Training dataset

Cat.	DR TYPE	COUNT
0	Normal	25810
1	Mild DR	2443
2	Moderate DR	5292
3	Severe DR	873
4	Proliferative DR	708
	Total	35126

Normal  
4000  
Train:3600  
Test:400

Abnormal  
4000  
Train:3600  
Test:400

Table 5: Testing dataset

Cat.	DR TYPE	COUNT
0	Normal	39533
1	Mild DR	3762
2	Moderate DR	7861
3	Severe DR	1214
4	Proliferative DR	1206
	Total	53576

# Pre-processing:

## Noise

Corrupted image

Blurred image

Poorly focused

Lighting variation

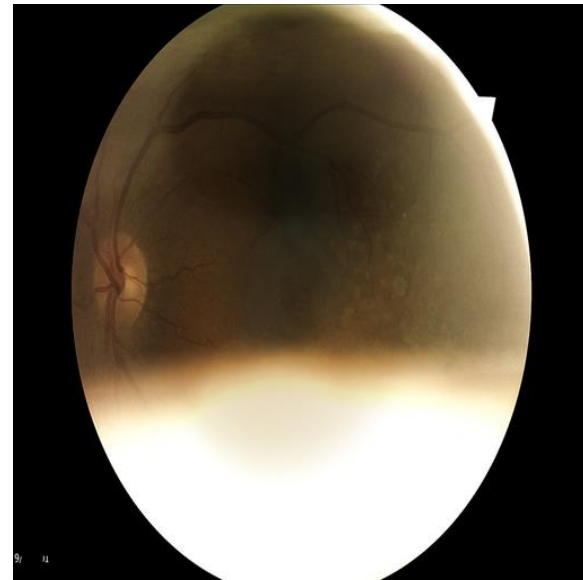


Fig. 4: Example of noisy image



Fig. 5: Preprocessed image

## Remedy

Cropping

Resizing 512 x 512

Normalization (GaussianBlur)

# Augmentation:

- Done when batches are formed.
- Randomly rescaled by  $\pm 10\%$ .
- Randomly rotated 0-90 degree.
- Random horizontal and vertical flip.
- Performed on training data only (except rescaling).

# Experiment 1:

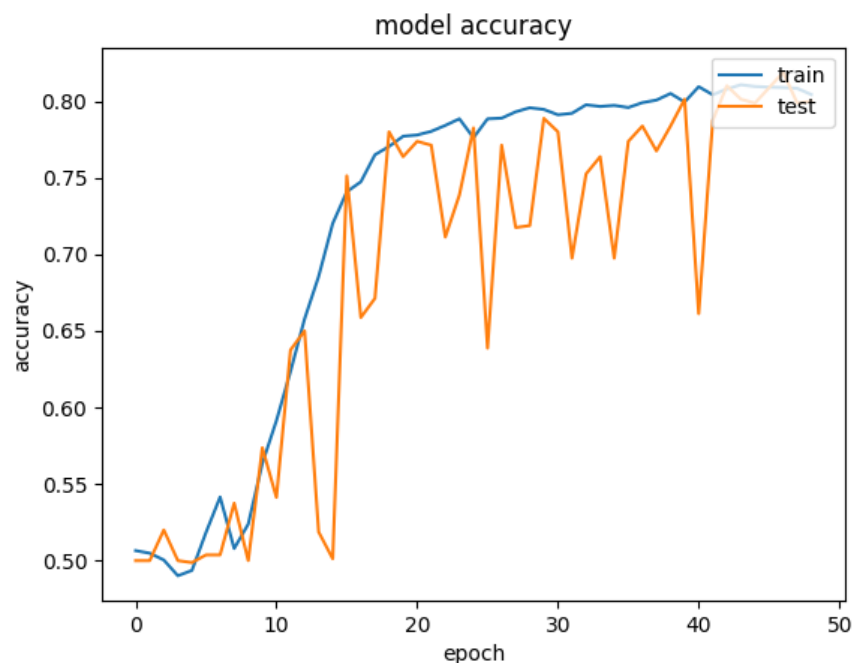


Fig 6: Accuracy graph

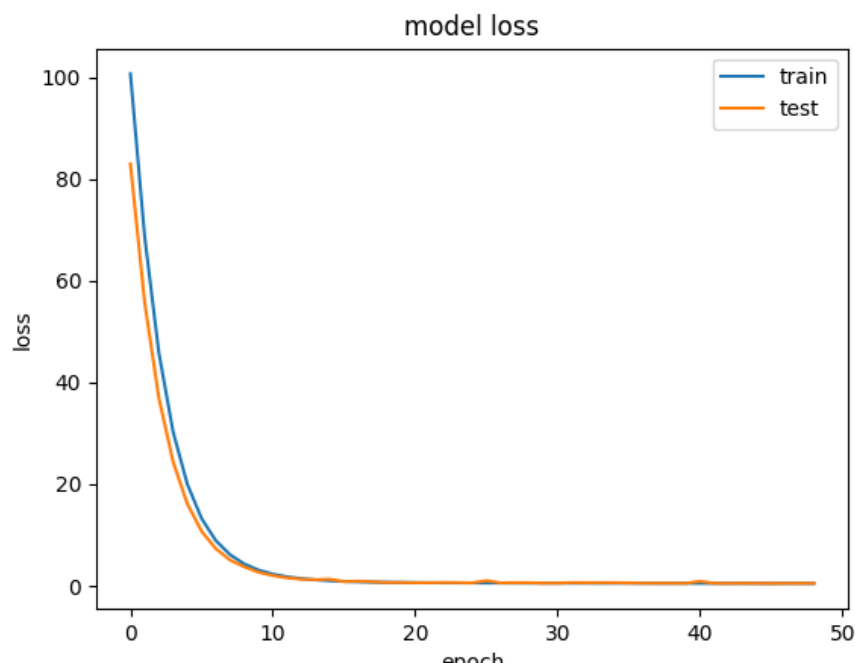


Fig 7: Loss graph

<u>batch_size</u>	<u>learning_rate</u>	<u>epochs</u>	<u>drop-out</u>
32	0.0001	50	0.5

	0	1
0	303	97
1	92	308

Fig 8: Confusion Matrix

	Precision	Recall	F1-score	Support
0(abnormal)	0.74	0.87	0.80	400
1(normal)	0.84	0.69	0.76	400
Total/Avg	0.79	0.78	0.78	800

Table 6: Classification Report

# Experiment 2:

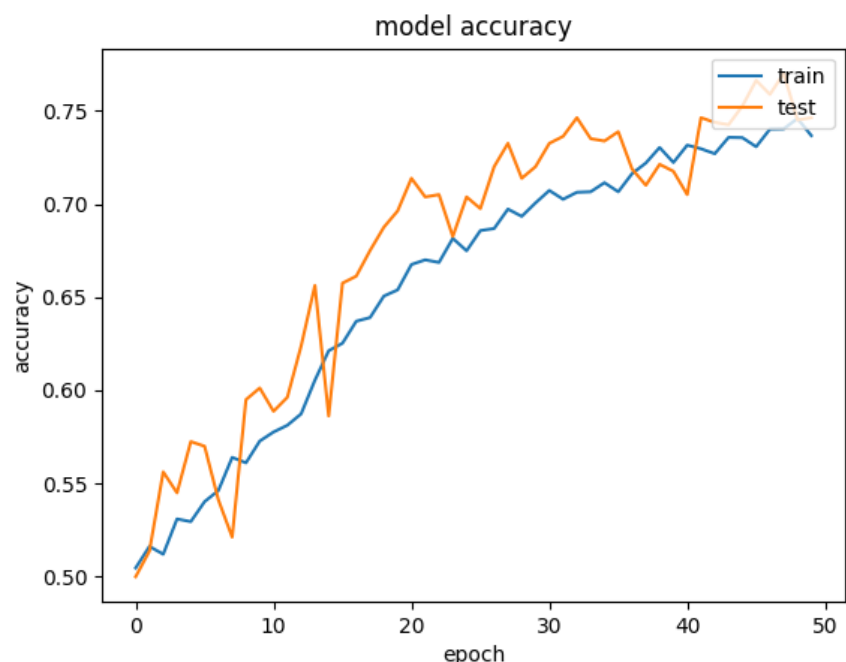


Fig 9: Accuracy graph

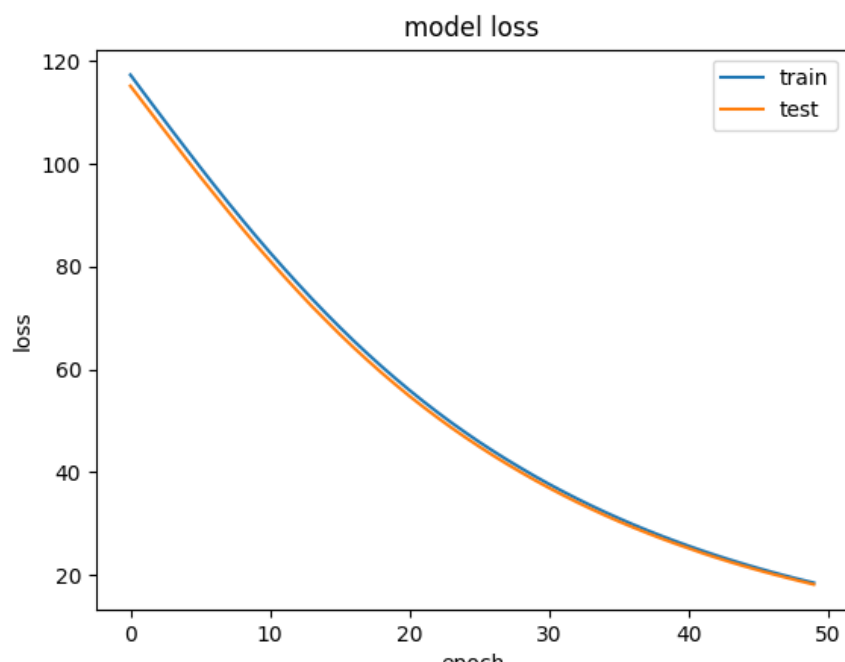


Fig 10: Loss graph

<u>batch_size</u>	<u>learning_rate</u>	<u>epochs</u>	<u>drop-out</u>
32	0.00001	50	0.5

	0	1
0	305	95
1	55	345

Fig 11: Confusion Matrix

	Precision	Recall	F1-score	Support
0(abnormal)	0.77	0.76	0.76	400
1(normal)	0.76	0.77	0.77	400
Total/Avg	0.76	0.76	0.76	800

Table 7: Classification Report

# Experiment 3:

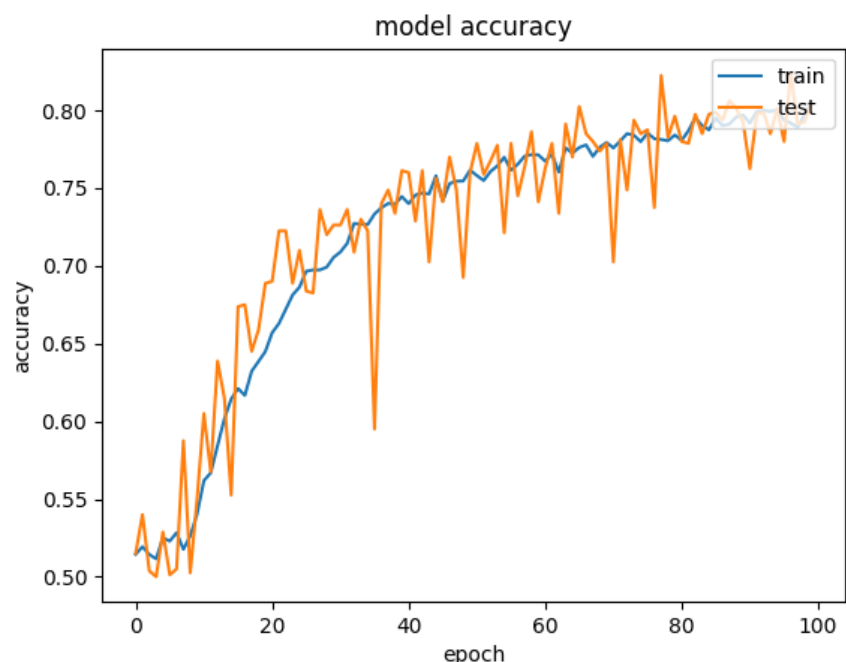


Fig 12: Accuracy graph

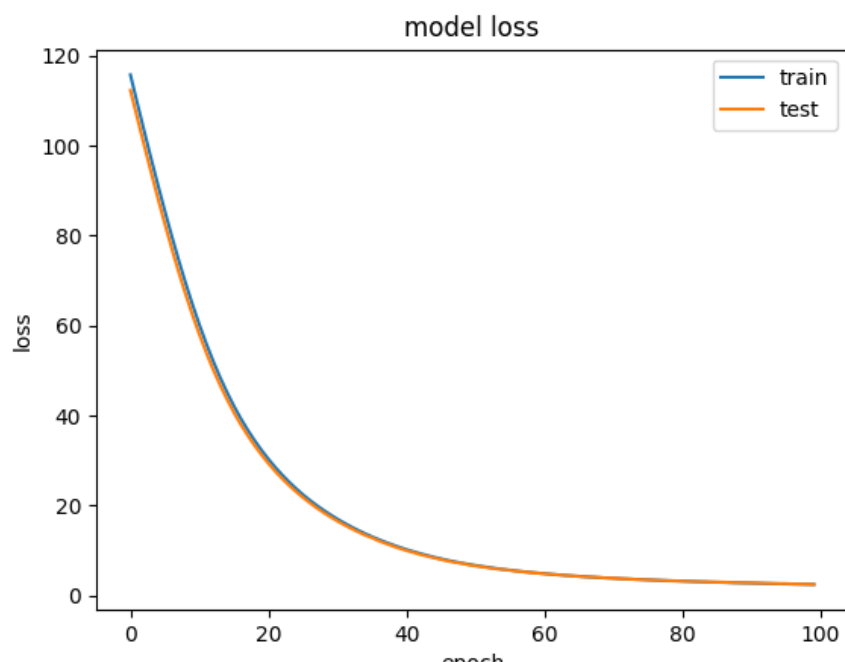


Fig 13: Loss graph

<u>batch_size</u>	<u>learning_rate</u>	<u>epochs</u>	<u>drop-out</u>
16	0.00001	100	0.5

	0	1
0	348	52
1	123	277

Fig 14: 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 8: Classification Report

## Future Work:

- add more training images
- use adversarialization process
- more complex architecture such as VGGNet, ResNet, Inception, Xception and other architectures
- five-class classification

# References:

- [1] G. G. Gardner, D. Keating, T. H. Williamson, A. T. Elliott.. Automatic detection of diabetic retinopathy using an artificial neural network: a screening tool. *British Journal Ophthalmology* 1996;**80**(11):940-944.
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# Thank You

Special thanks

Karthik Thiagarajan [Ms Scholar]

Saurabh Desai [Project Associate, RBCDSAI LAB]