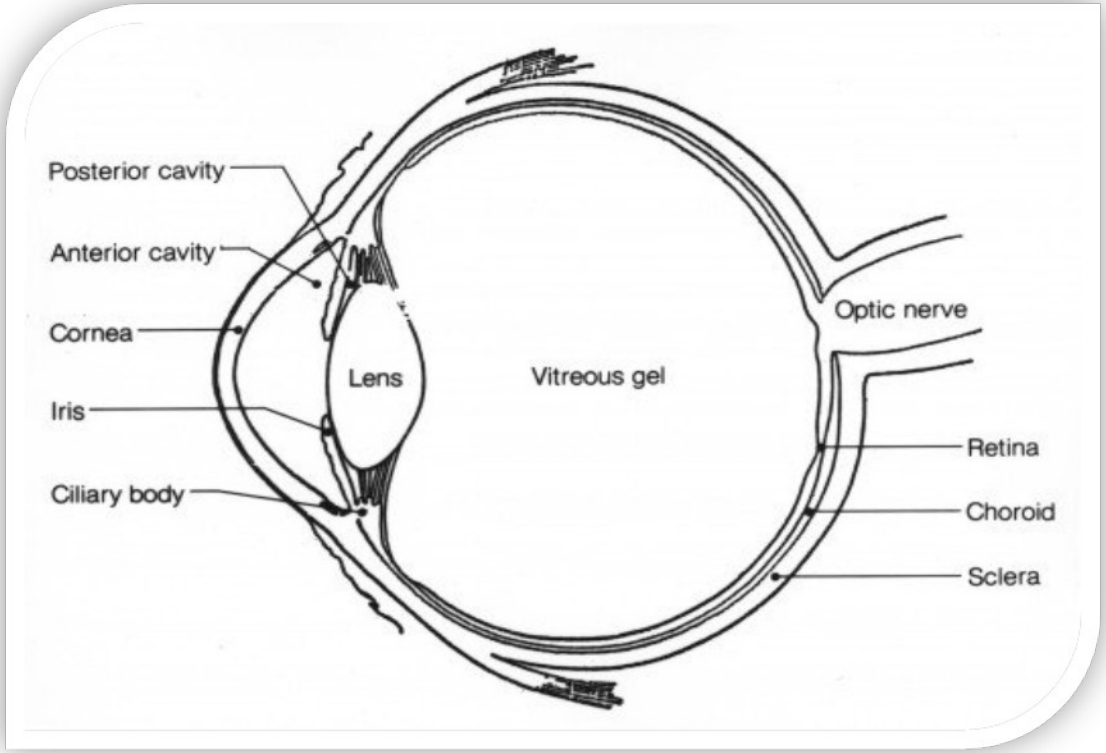
Retinal Layer segmentation

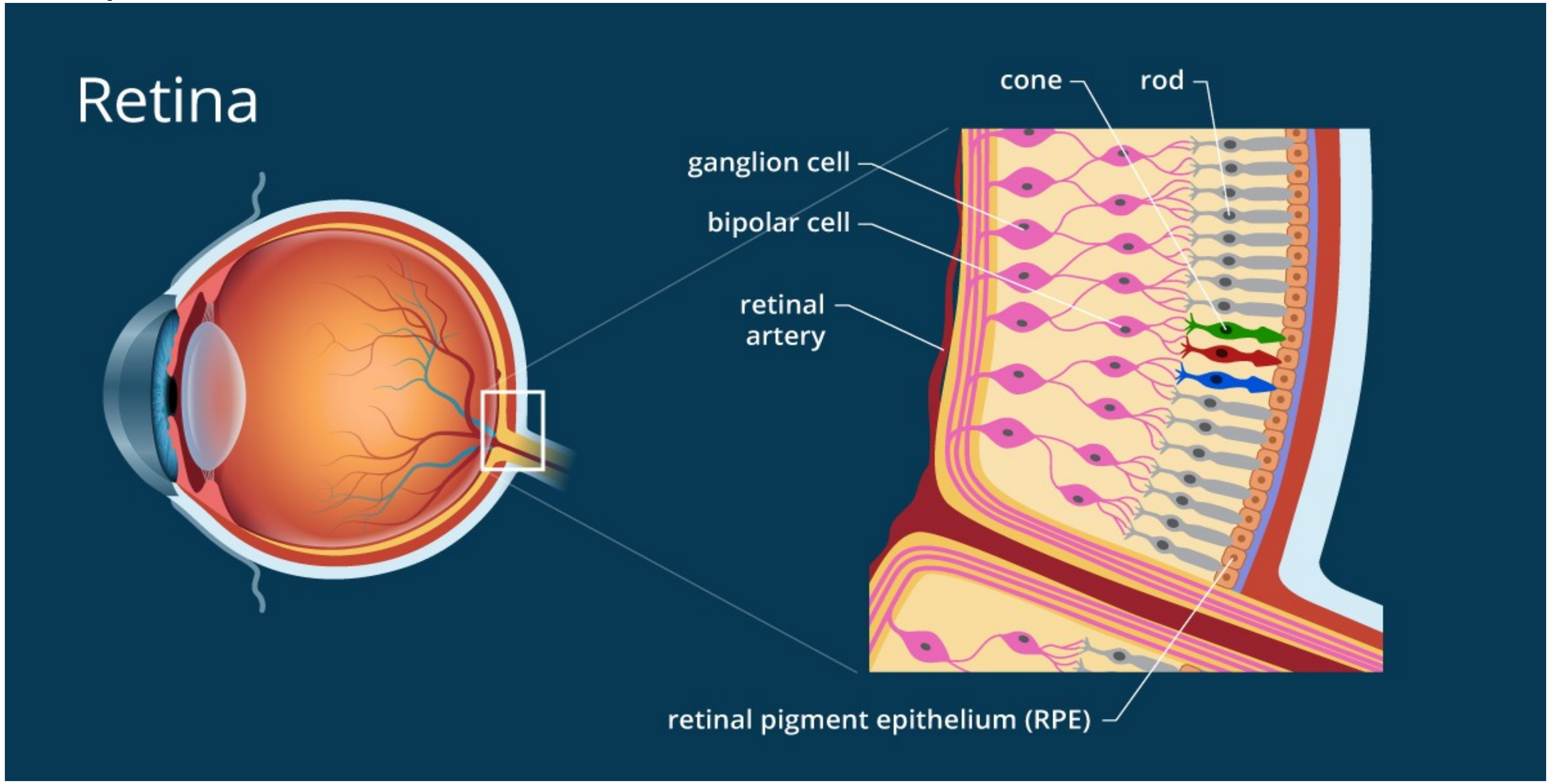
Human Eye

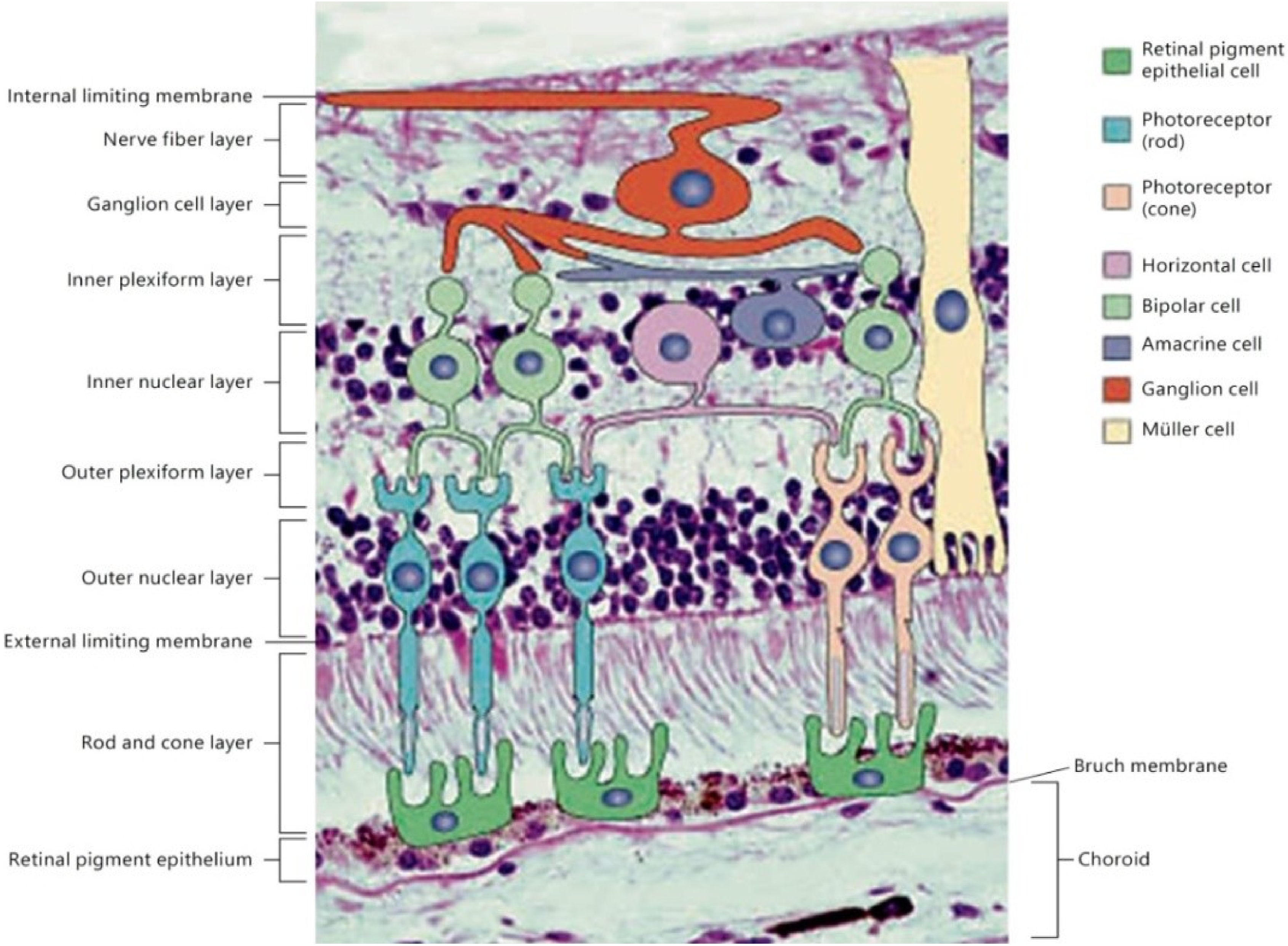
The anatomy of human eye



Retina

The retina is a thin layer of tissue at the back of the eye and it is located near the optic nerve



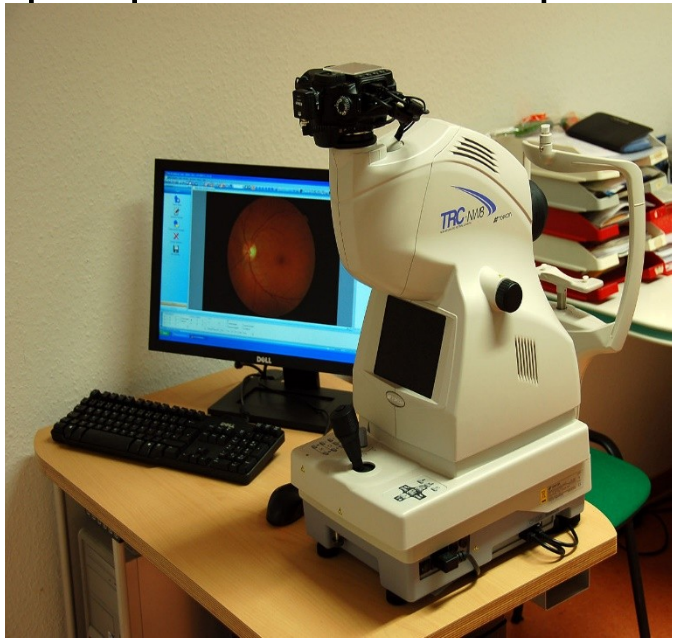


The layered structure of human retina

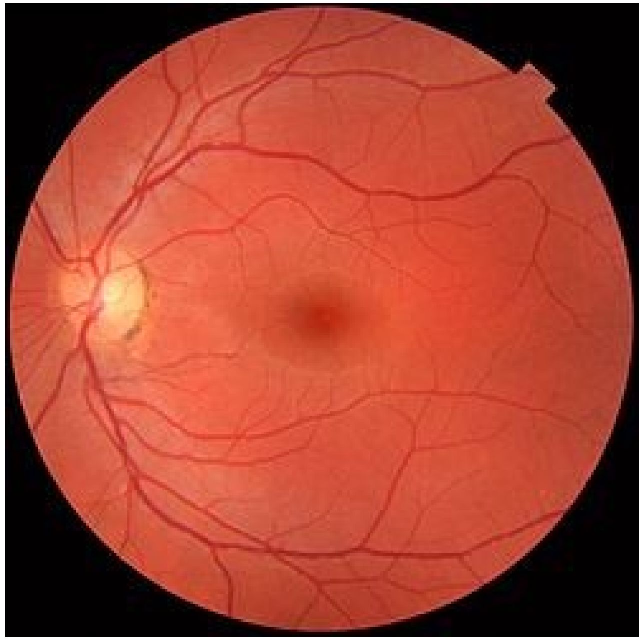
Due to the retina's vital role in vision, damage to it can cause permanent blindness.

How to visualize Human eye?

1. Fundus photography involves capturing a photograph of the back of the eye i.e. fundus. Specialized fundus cameras that consist of an intricate microscope attached to a flash enabled camera are used in fundus photography. The main structures that can be visualized on a fundus photo are the central and peripheral retina, optic disc and macula.

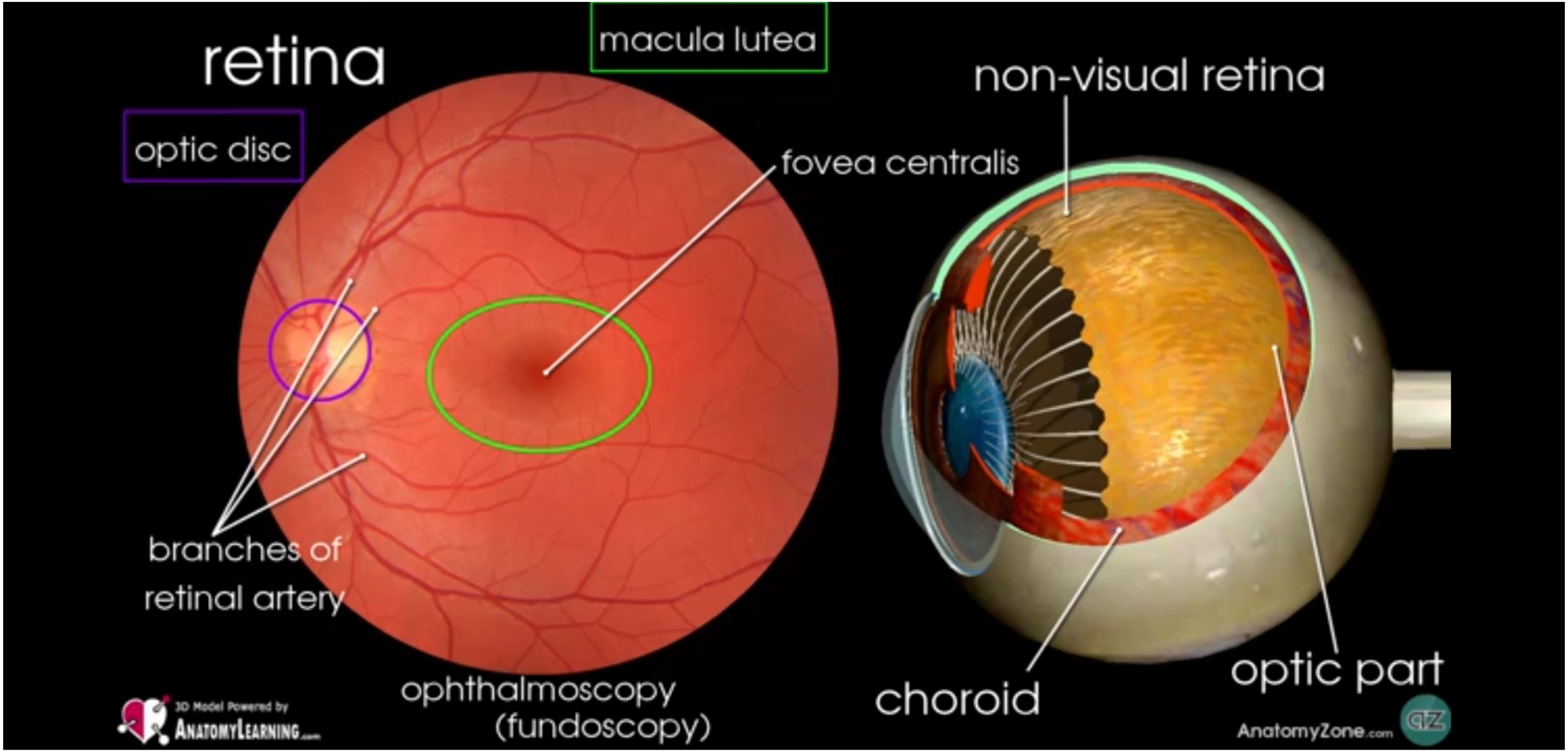


Fundus camera



Normal Eye

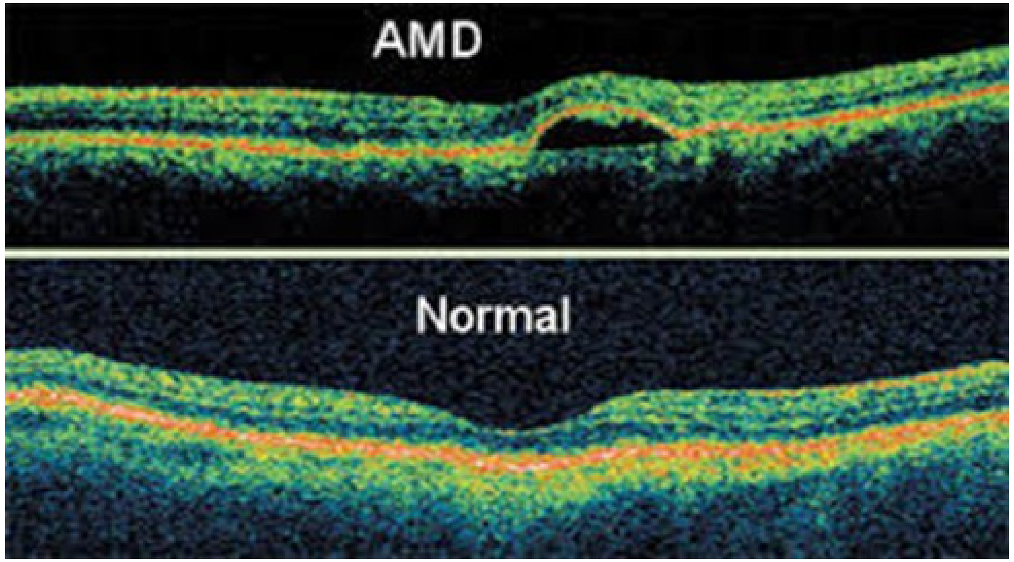
Retinal_artery_Occlusion



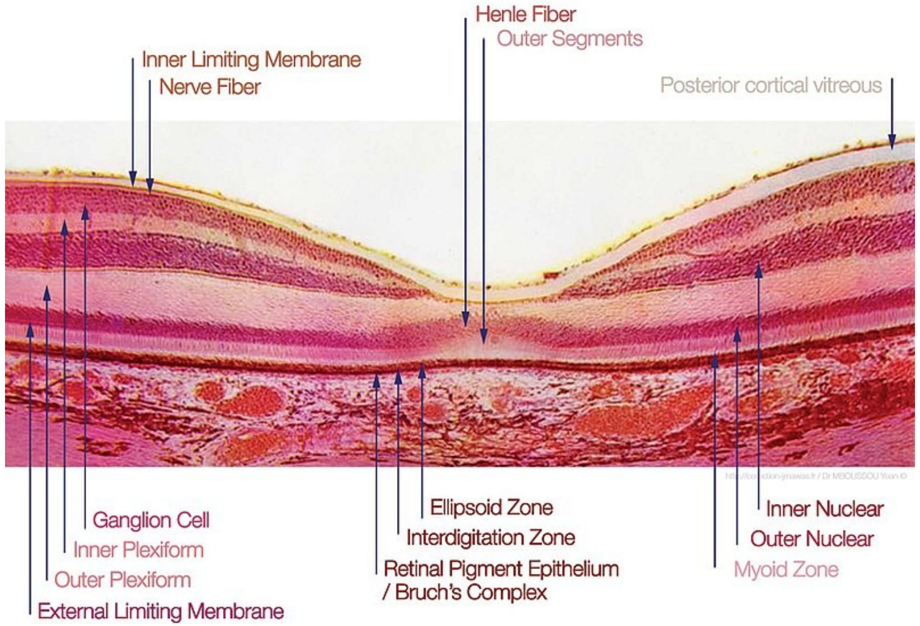
retina
macula lutea
optic disc
fovea centralis
non-visual retina
branches of
retinal artery
ophthalmoscopy
(fundoscopy)
choroid
optic part
3D Model Powered by
AnatomyLearning.com
AnatomyZone.com

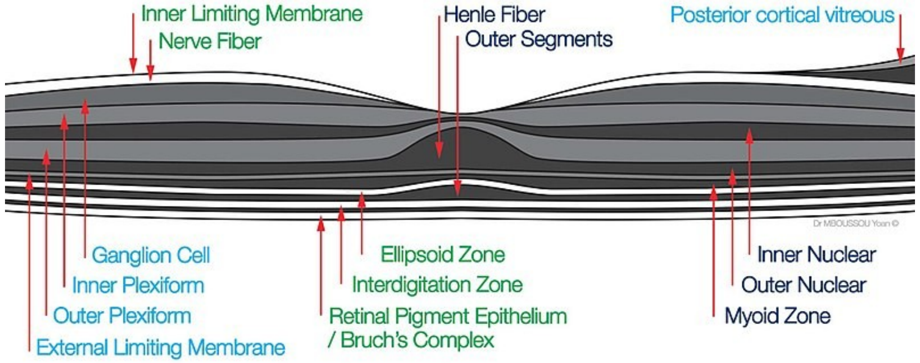
2 Optical Coherence tomography(OCT)

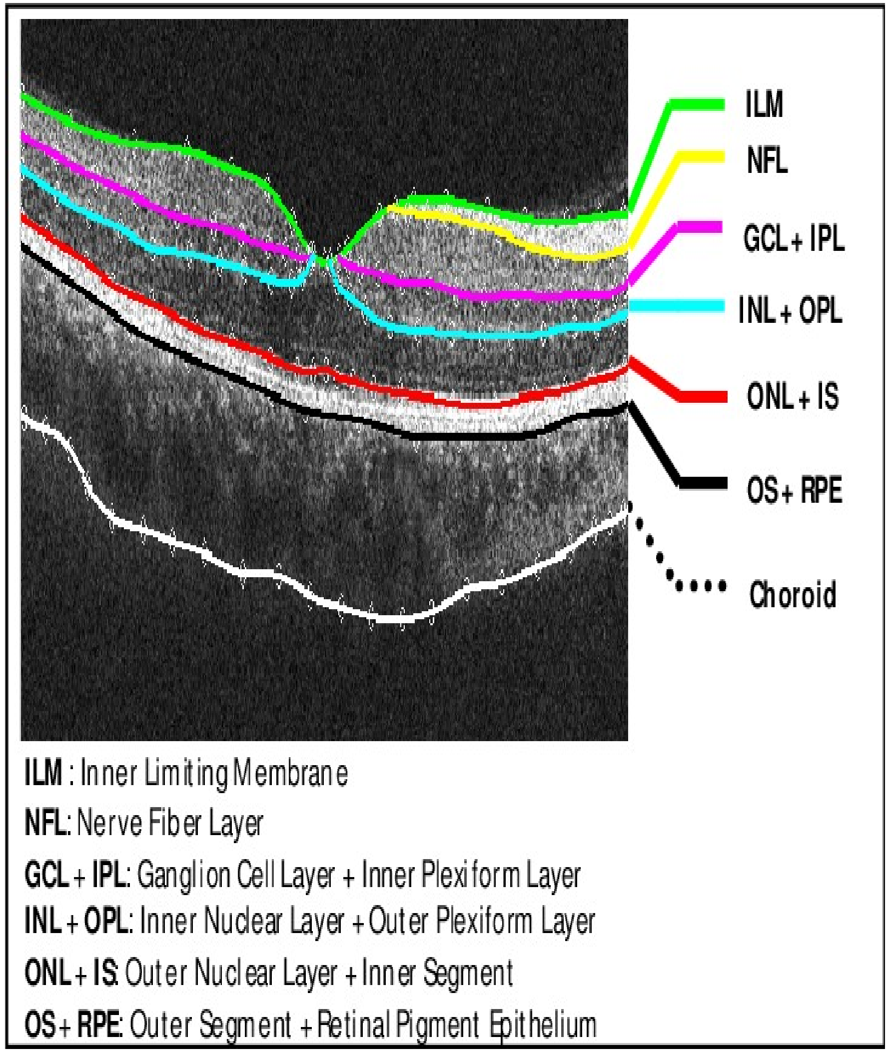
- Optical Coherence Tomography (OCT) is a non-invasive imaging technology, widely used in ophthalmology for the diagnosis of chronic retinal diseases. Includes,
    - Macular degeneration
    - Glaucoma
    - Retinal detachment



Retinal layer segmentation







- Retinal layer segmentation plays a vital role in the proper detection and quantification of retinal disorders.

Literature survey

SI.No	Author	Method
1.	Kugelman (2018)	RNN as the feature extractor and Graph search for classification
2.	Guo(2018)	Bidirectional graph search based segmentation
3.	Duan(2018)	Group wise curve alignment
4.	Xiang(2018)	A random forest classifier
5.	Shi(2015)	B-scan alignment and multi-resolution graph search
6.	Yin(2014)	A user-guided segmentation method using likelihood estimation
7.	Srinivasan(2014)	support vector machines, graph theory, and dynamic programming
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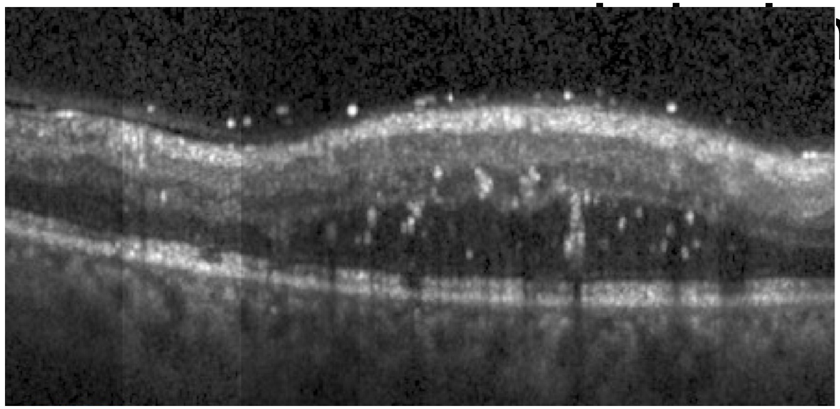
10.	Vermeer (2012)	SVM
11.	Yang (2011)	Gradient-based shortest path algorithm
12.	Yazdanpanah (2011),	active contours
13.	Chiu(2010)	graph theory and dynamic programming
14.	Ghorbel (2010)	active contour method and random markov fields
15.	Lu(2010)	gradient based approach, segmentation using optimal graph search
16.	Fernandez(2005)	retinal layers can be automatically and/or interactively located with good accuracy with the aid of local coherence information of the retinal structure

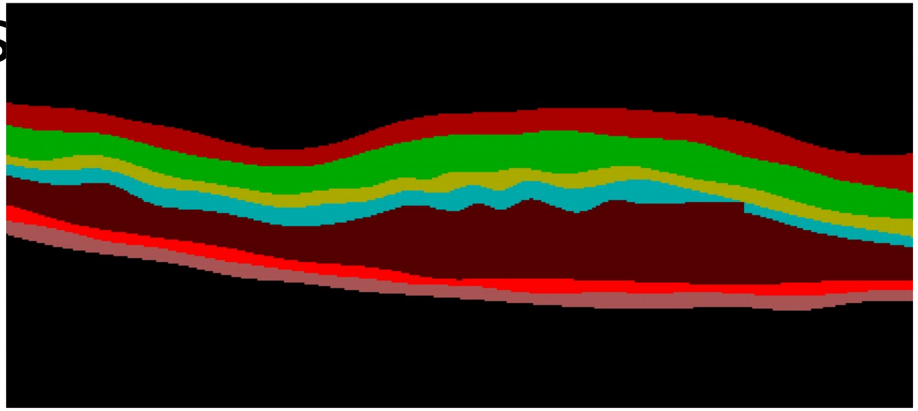
CNN based Methods

SI.No	Author	Method
1.	Shah(2018)	convolutional neural network (CNN) [unet]
2.	Hamwood(2018)	combination of CNN and graph search based segmentation algorithm
3.	Kiaee(2018)	3D fully convolutional encoder-decoder structure
4.	Roy(2017)	fully convolutional deep architecture, termed ReLayNet
5.	Fang(2017)	Convolutional neural networks and graph search method

Dataset

- Duke DME SD-OCT dataset.
- The scans of the dataset were obtained from 10 subjects with DME.
- The dataset consists of a total of 110 annotated images (11 B-scans per subject) with a resolution of 496×768.
- All these scans were annotated for the retinal layers by
nologis





ILM: Inner Limiting Membrane

NFL-IFL: Nerve Fiber Layer to Inner Plexiform Layer

INL: Inner Nuclear Layer

OPL: Outer Plexiform Layer

ONL-ISM: Outer Nuclear layer to Inner segment myeloid

ISE: Inner segment ellipsoid

OS-RPE: Outer segment to Retinal pigment epithelium

Our Method:

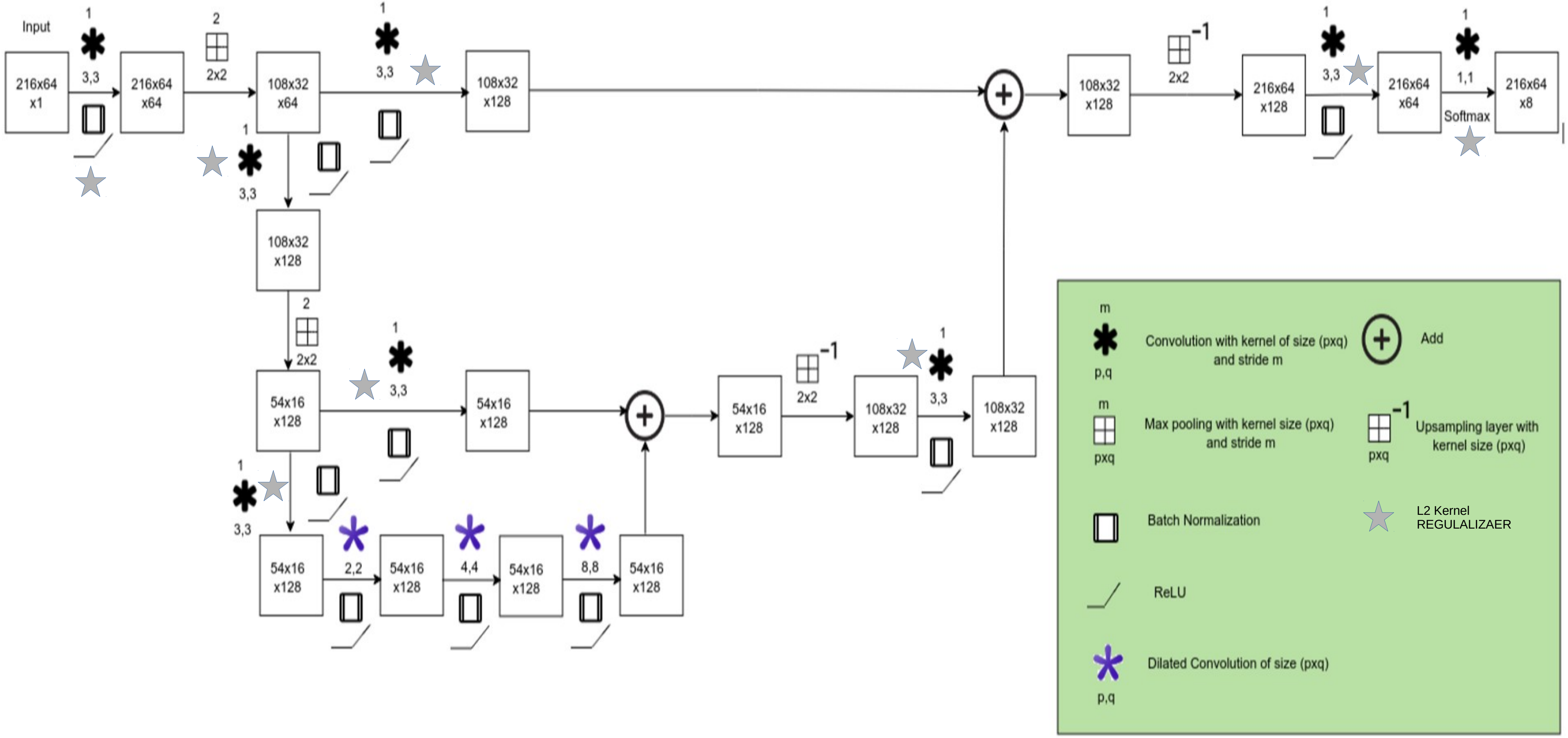
Our method is using 4 parallel ensembled models for one-vs-all segmentation (pixel-wise one-vs-all classification)

Ensemble methods is a machine learning technique that combines several base models in order to produce one optimal predictive model

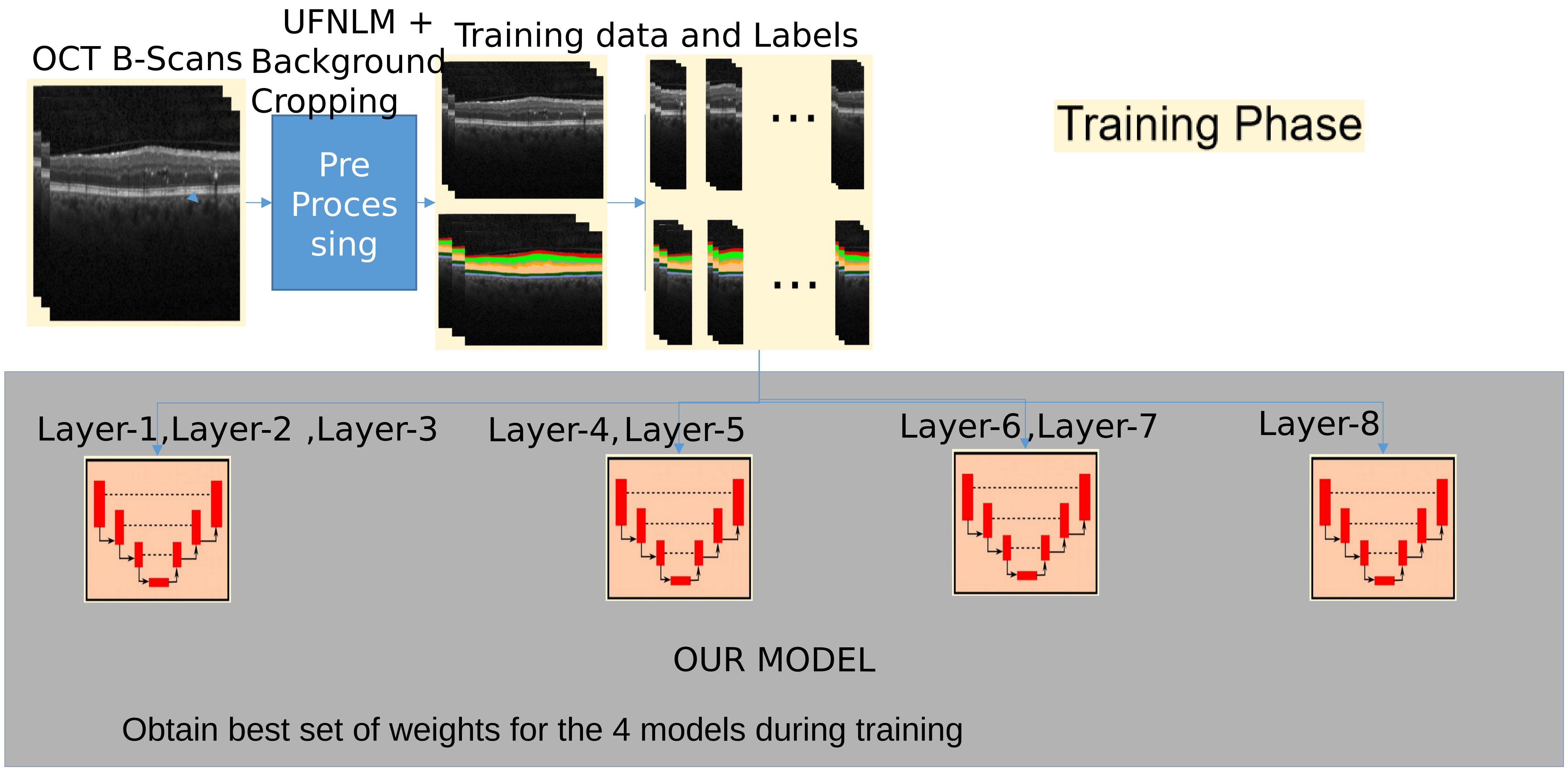
Ensemble methods are meta-algorithms that combine several machine learning techniques into one predictive model in order to decrease variance (bagging), bias (boosting), or improve predictions (stacking)

ensemble methods use multiple learning algorithms to obtain better predictive performance than could be obtained from any of the constituent learning algorithms alone. Unlike a statistical ensemble in statistical mechanics, which is usually infinite, a machine learning ensemble consists of only a concrete finite set of alternative models, but typically allows for much more flexible structure to exist among those alternatives

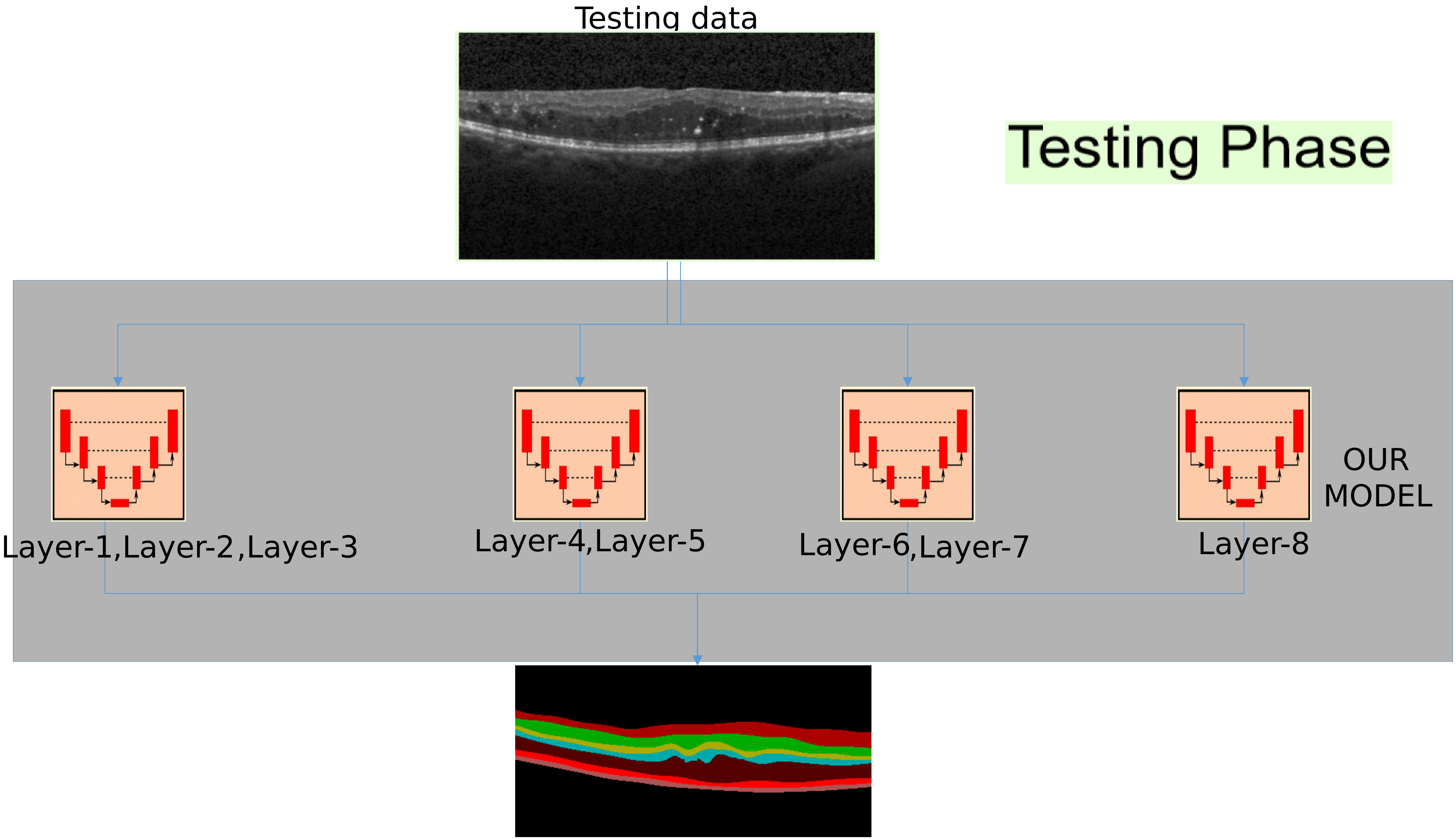
One-vs.-rest (or one-vs.-all, OvA or OvR, one-against-all, OAA) strategy provides a way to leverage binary classification. Given a classification problem with N possible solutions, a one-vs.-all solution consists of N separate binary classifiers—one binary classifier for each possible outcome. During training, the model runs through a sequence of binary classifiers, training each to answer a separate classification question



Input
216x64 x1
216x64 x64
108x32 x64
108x32 x128
108x32 x128
54x16 x128
54x16 x128
54x16 x128
54x16 x128
54x16 x128
54x16 x128
54x16 x128
108x32 x128
108x32 x128
108x32 x128
216x64 x128
216x64 x64
216x64 x8
1
3,3
2
2x2
2,2
4,4
8,8
-1
1,1
Softmax
m
p,q
Convolution with kernel of size (pxq) and stride m
Add
pxq
Max pooling with kernel size (pxq) and stride m
Upsampling layer with kernel size (pxq)
Batch Normalization
L2 Kernel REGULALIZAER
ReLU
Dilated Convolution of size (pxq)



OCT B-Scans
UFNLM + Background Cropping
Pre Processing
Training data and Labels
Training Phase
Layer-1,Layer-2 ,Layer-3
Layer-4,Layer-5
Layer-6,Layer-7
Layer-8
OUR MODEL
Obtain best set of weights for the 4 models during training


Testing data
Testing Phase
OUR MODEL
Layer-1,Layer-2,Layer-3
Layer-4,Layer-5
Layer-6,Layer-7
Layer-8

Results

QUANTITATIVE ANALYSIS

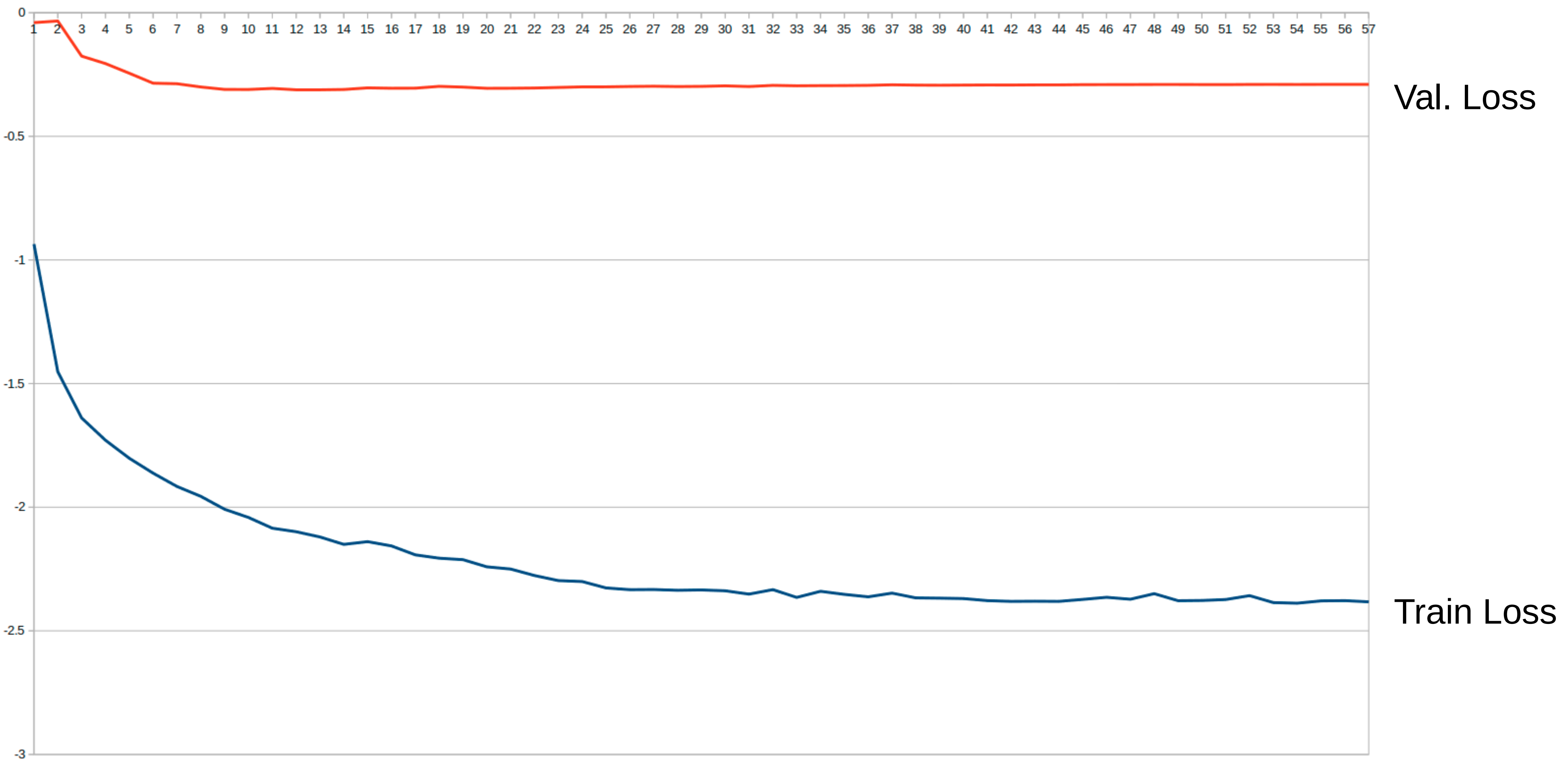
COMPARISON WITH EXISTING METHODS :

Layers	Background	ILM	NFL-IPL	INL	OPL	ONL-ISM	ISE	OS-RPE
RELAYNET	0.99	0.9	0.94	0.87	0.84	0.93	0.92	0.9
DILATED RELAYNET	0.99	0.89	0.94	0.88	0.87	0.96	0.94	0.9
OUR METHOD with denoised images	**0.99**	**0.91**	**0.96**	**0.92**	**0.91**	**0.97**	**0.95**	**0.91**
OUR METHOD with noisy images	0.99	0.87	0.91	0.81	0.78	0.93	0.9	0.87

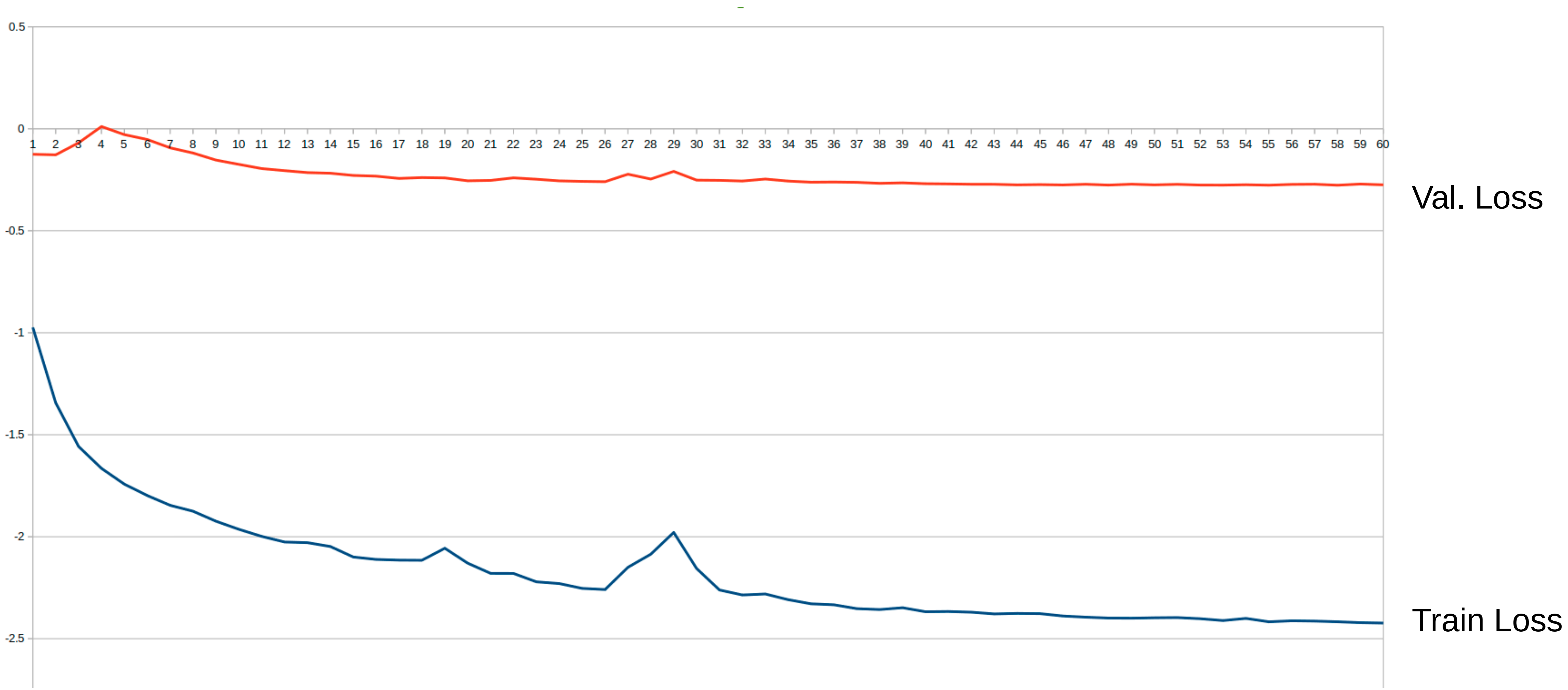
Cross Validation	Background	ILM	NFL-IPL	INL	OPL	ONL-ISM	ISE	OS-RPE
1	0.99132559	0.90746096	0.95343075	0.91308224	0.90096243	0.97095823	0.94231485	0.90928823
2	0.99005486	0.90503702	0.95815344	0.92081797	0.89495132	0.96953409	0.94811721	0.91443499
3	0.98987067	0.89352292	0.9488487	0.90422138	0.88186577	0.9657164	0.93848193	0.90258286
4	0.99122596	0.90934723	0.95973808	0.92211156	0.9046884	0.97258456	0.94842372	0.91207372
5	0.99125638	0.90890387	0.96017008	0.92395955	0.90763748	0.97406542	0.94977268	0.91429293
6	0.9909732	0.9031841	0.95739056	0.91624944	0.89731385	0.97245676	0.94392633	0.90625209
7	0.99139253	0.90502272	0.96143553	0.92290046	0.8991738	0.97230372	0.94977654	0.91304178
8	0.99072672	0.89261299	0.95244996	0.90420042	0.88124888	0.96601441	0.93922002	0.90302897
9	0.99138641	0.90649538	0.96129704	0.92320272	0.90381945	0.97270281	0.94937027	0.91266622
10	0.99211976	0.91251173	0.96585714	0.93417871	0.91796355	0.97774154	0.95605596	0.92129836
11	0.99149335	0.90391546	0.96110376	0.91959429	0.90173673	0.9739308	0.94620916	0.90905065
AVERAGE	0.99107503	0.90436494	0.95817045	0.91859261	0.89921469	0.97163715	0.94651533	0.91072825

Metric	Recall		Precision		F1 Score	
Layer	Noisy	**Denoised**	Noisy	**Denoised**	Noisy	**Denoised**
Background	0.97477437	**0.98484217**	0.99696847	**0.99869595**	0.98558724	**0.99168828**
ILM	0.92449108	**0.96440937**	0.82785477	**0.87021875**	0.86725146	**0.91284572**
NFL-IPL	0.9180609	**0.95507853**	0.89510901	**0.95168423**	0.90218245	**0.95337835**
INL	0.83944339	**0.91900103**	0.78345561	**0.94706099**	0.79971674	**0.93139859**
OPL	0.80143462	**0.94067318**	0.72686159	**0.90320257**	0.75398658	**0.91965186**
ONL-ISM	0.91392398	**0.95665112**	0.9364954	**0.95968558**	0.92204451	**0.95816594**
ISE	0.90706797	**0.95250429**	0.89217584	**0.9418199**	0.89594684	**0.9471319**
OS-RPE	0.92140311	**0.94633072**	0.81303174	**0.87480252**	0.86003594	**0.90916192**

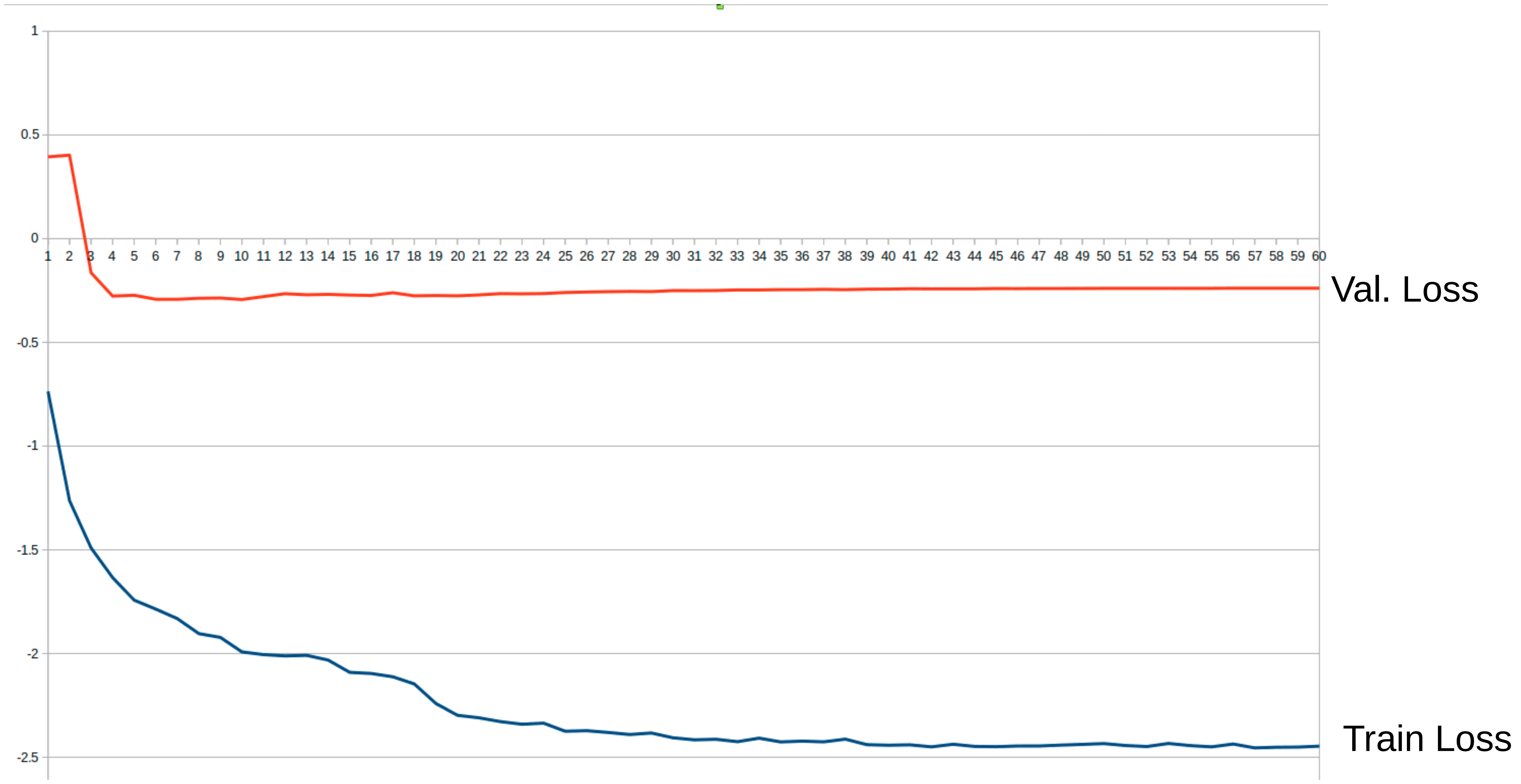
Model DRY : Plot of Train loss vs Validation Loss



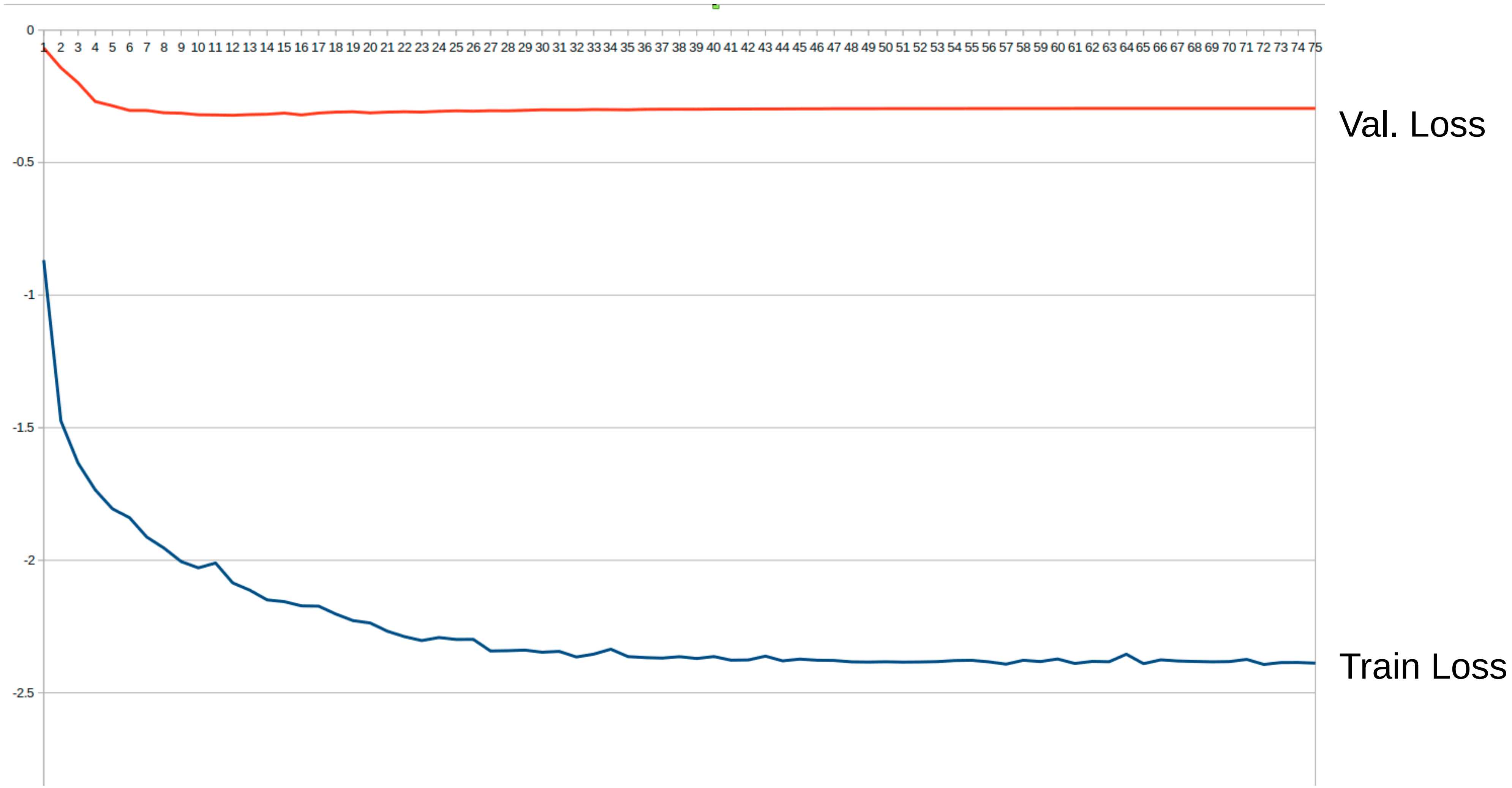
Model OSRP : Plot of Train loss vs Validation Loss



Model DLRO1 : Plot of Train loss vs Validation Loss

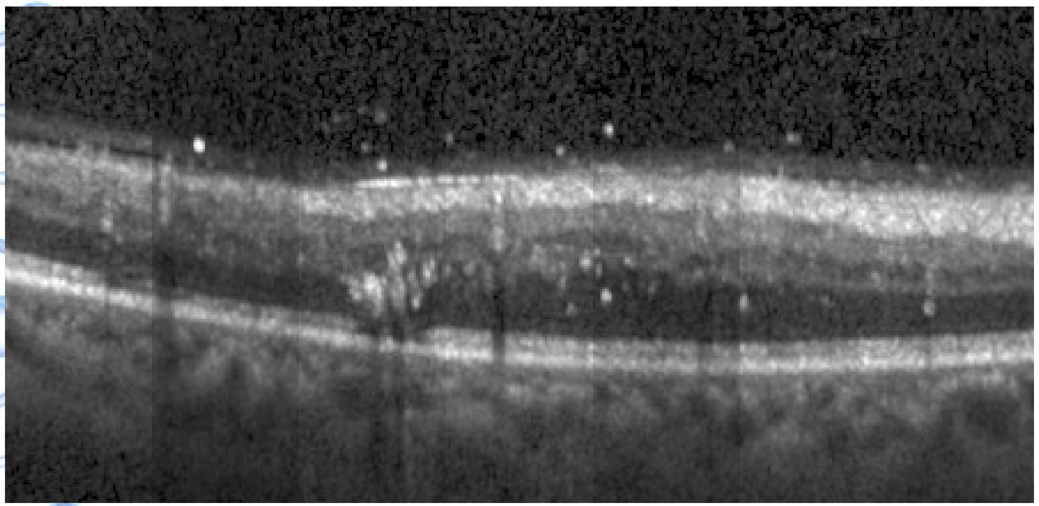


Model RLO1 : Plot of Train loss vs Validation Loss

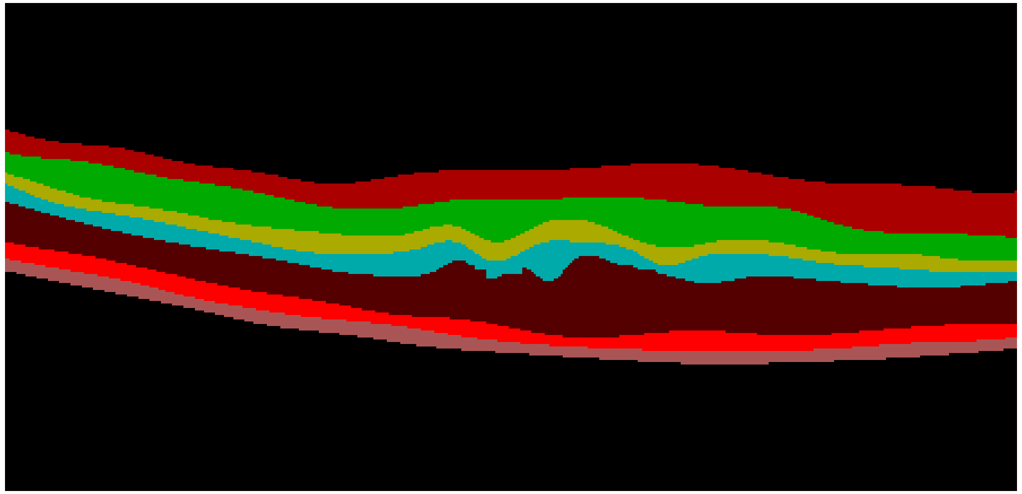


Qualitative Analysis :

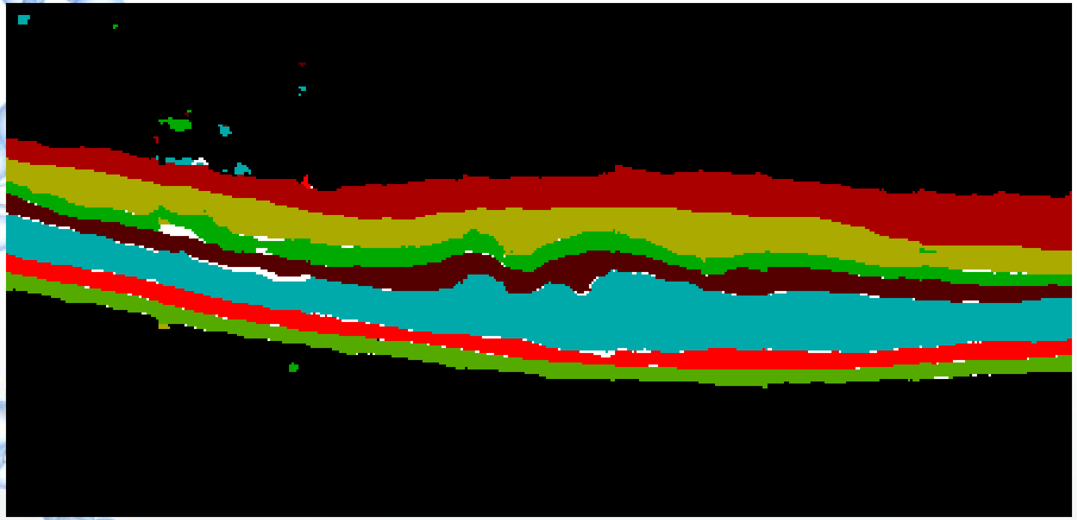
Input Image :



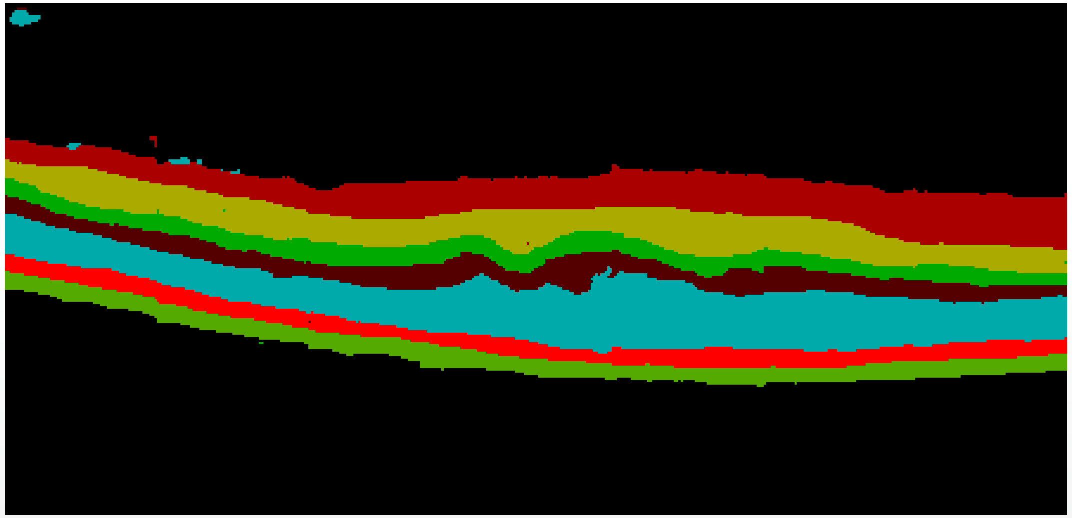
Ground Truth :



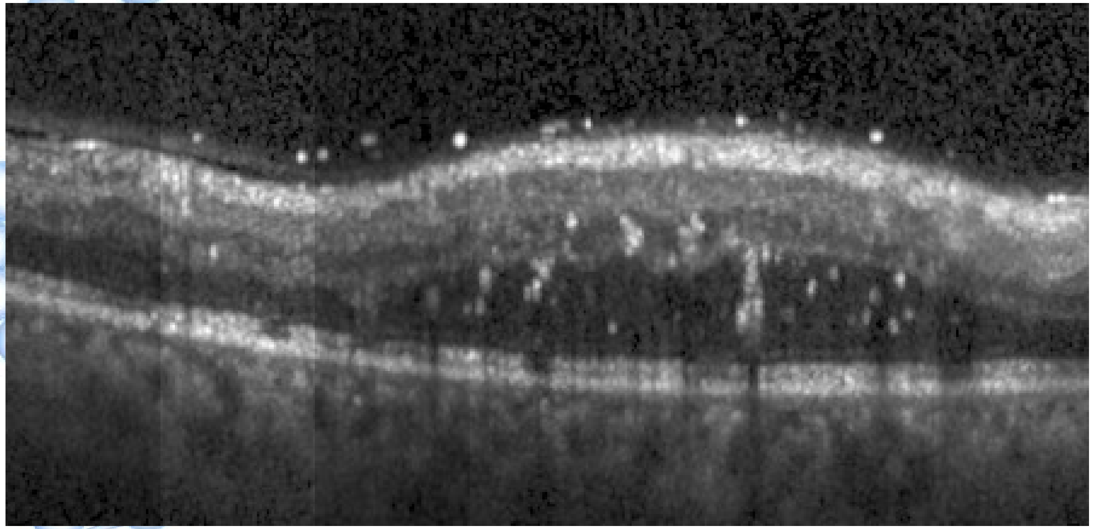
Output- Combined



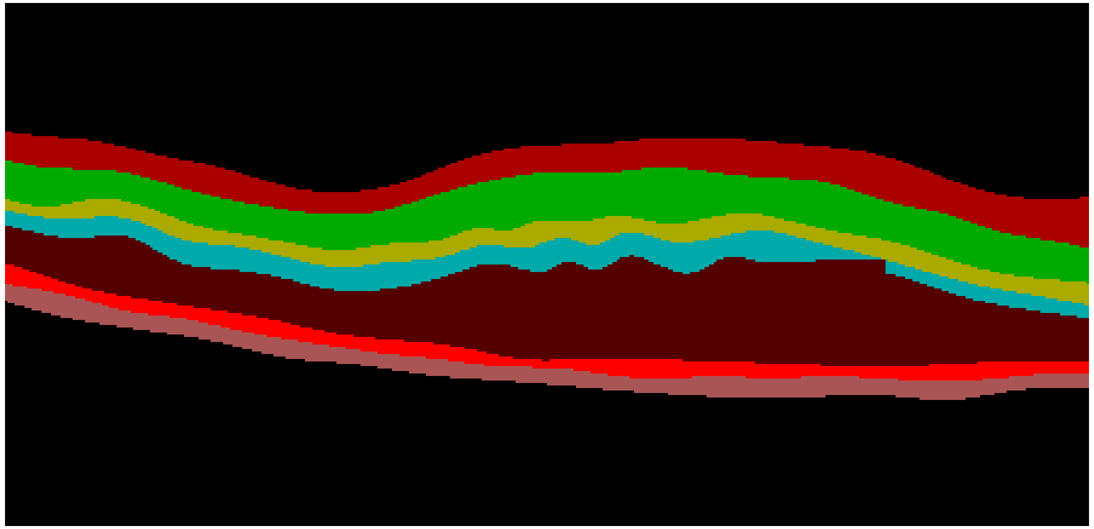
Output- Single



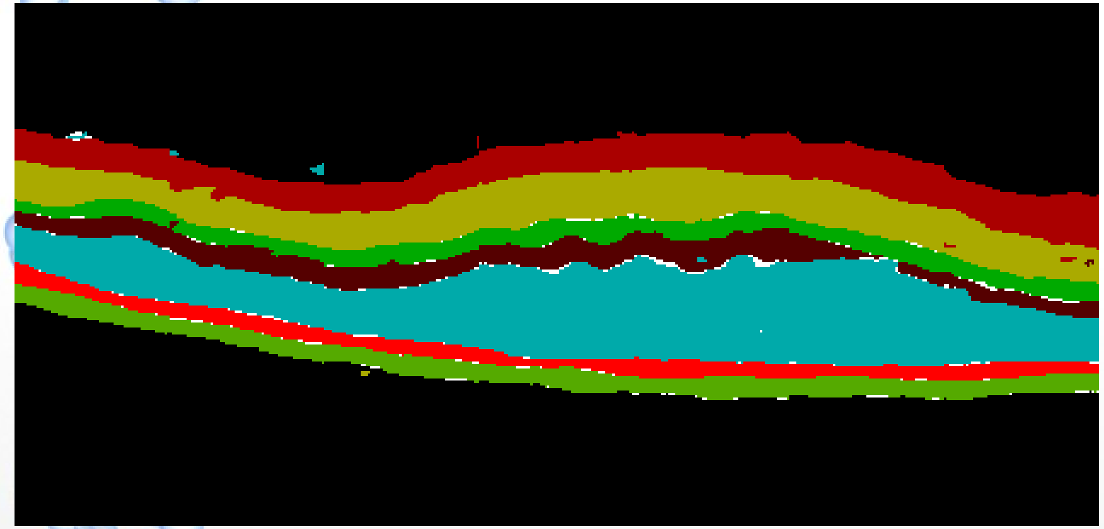
Input



Ground Truth :



Output- Combined



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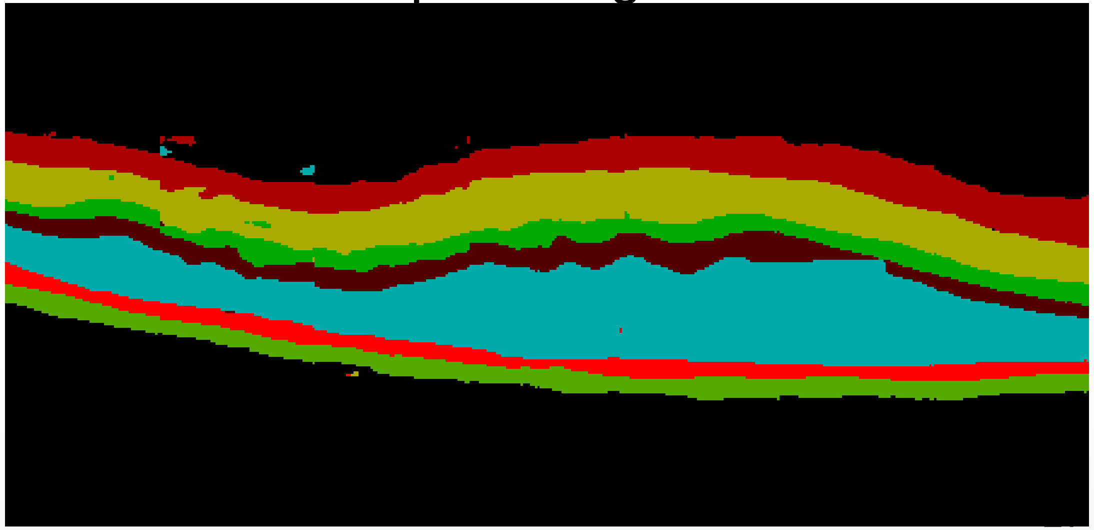

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