Incremental Learning For Fundus Image Segmentation

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Architecture

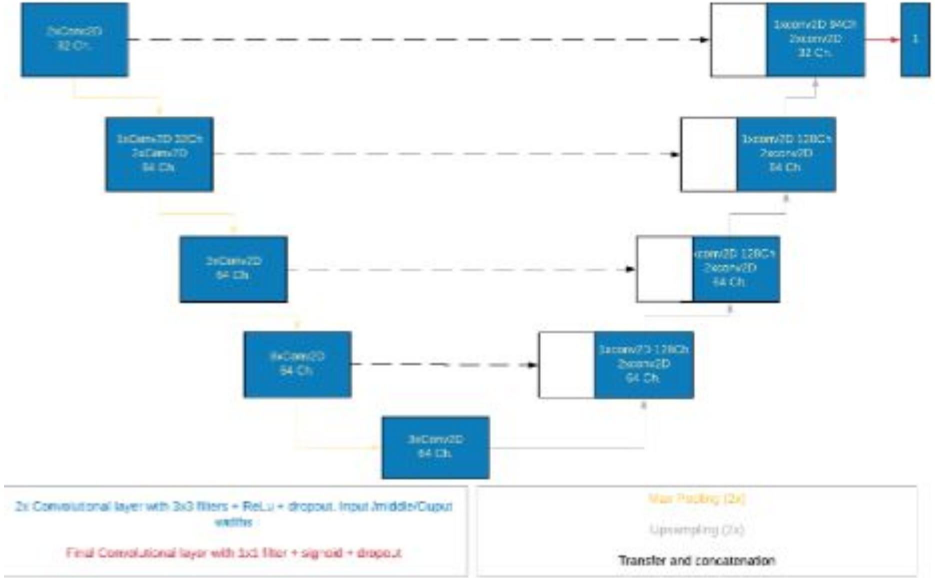

Fig. 1: U-Net Architecture

Eye Fundus & Datasets

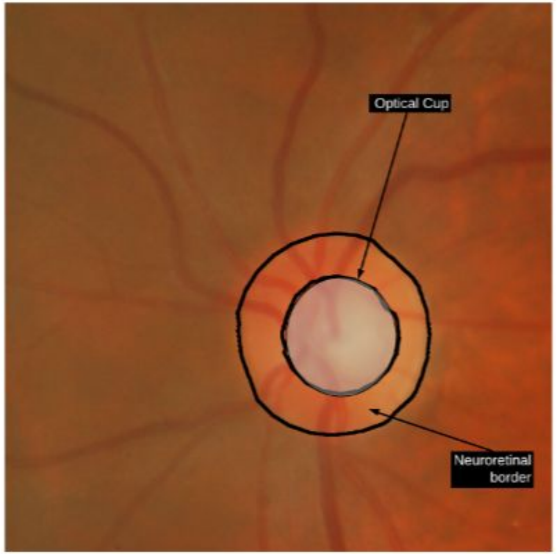

Fig. 2: Optic Disc and Cup

Fig. 3: Images from RIM ONE and DRISHTI datasets

Results

TABLE I. OD segmentation Dice (Mean/Best/Worst) and RRP

	Dice-DRI	Dice-RIM
DRI-Trained	0.98	0.64
RIM-retrained	0.89	0.80

TABLE II. OD segmentation RRP

	RRP-DRI	RRP-RIM
DRI-Trained	100%	23%
RIM-retrained	89%	80%

TABLE III. OD segmentation Dice comparison.

Author	DRI	RIM ONE
Zilly et al. [12]	0.97	-
Al-Bander [2]	0.95	0.90
Sevastopolsky [3]	-	0.94
Shankaranarayana et al. [11]	-	0.98
Drishti Trained	0.98	0.64
RIM Retrained	0.89	0.80

Conclusions

We have shown that by performing a fast retrain when adding data from a new dataset, and by preprocessing images and performing static and dynamic data augmentation, we can implement disc segmentation with an equivalent performance to that reported by researchers who use a single dataset both for evaluation and testing.

We also define a clinically significant parameter (Radii Ratio parameter- RRP) that can be useful to estimate the quality of the CDR estimations and thus, to give some confidence on the quality of the system for glaucoma prediction