Transfer Learning Through Weighted Loss Function and Group Normalization for Vessel Segmentation from Retinal Images

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Introduction

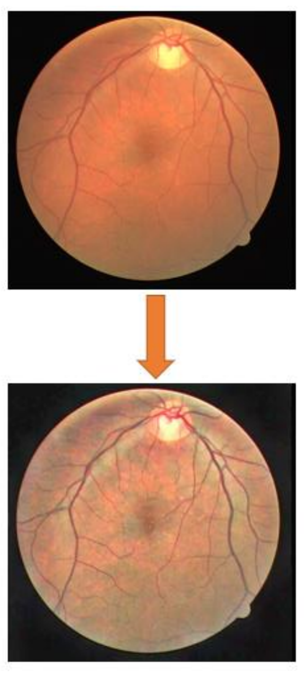
- Your sense of sight is one of the most important senses you have.
- Retinal condition leading to irreversible vision loss, such as glaucoma and diabetic retinopathy, threatens our vision.
- Retinal vessels can help specialists when diagnosing for these retinal conditions.
- In this paper we focus on properly segmenting the vessels from retinal images along with contributing with new dataset (ORVS)

Challenges

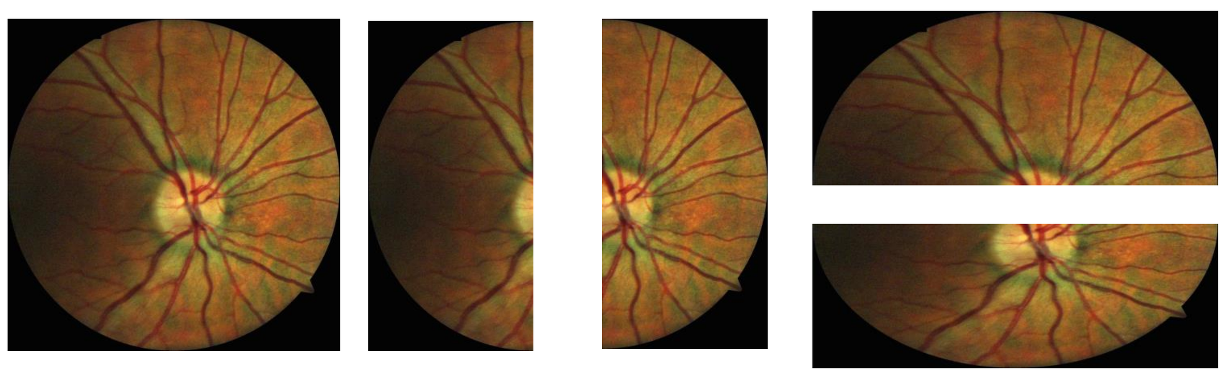
- Diversity
  - Retinal images can be very diverse
- Class Imbalance
  - More than 90% of a given image should be classified as background, while only 10% or less belongs to the segmented region
- Shortage of Retinal Images
  - 381 retinal images available only

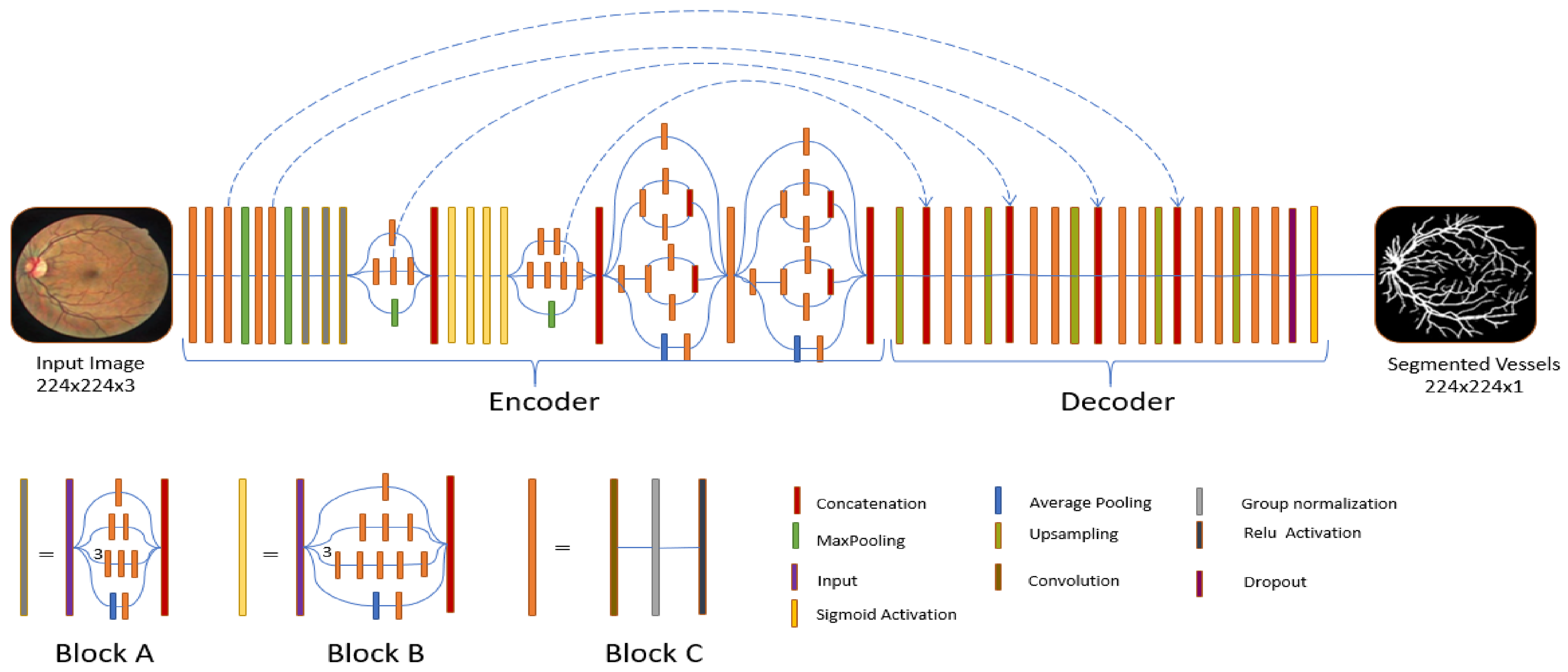
ORVS Dataset

49 publicly available Images annotated by an expert who works in the field of retinal-image analysis and went through training



Approach





$$L_f = \beta_1 \times BCE + \beta_2 \times L_j$$

Results

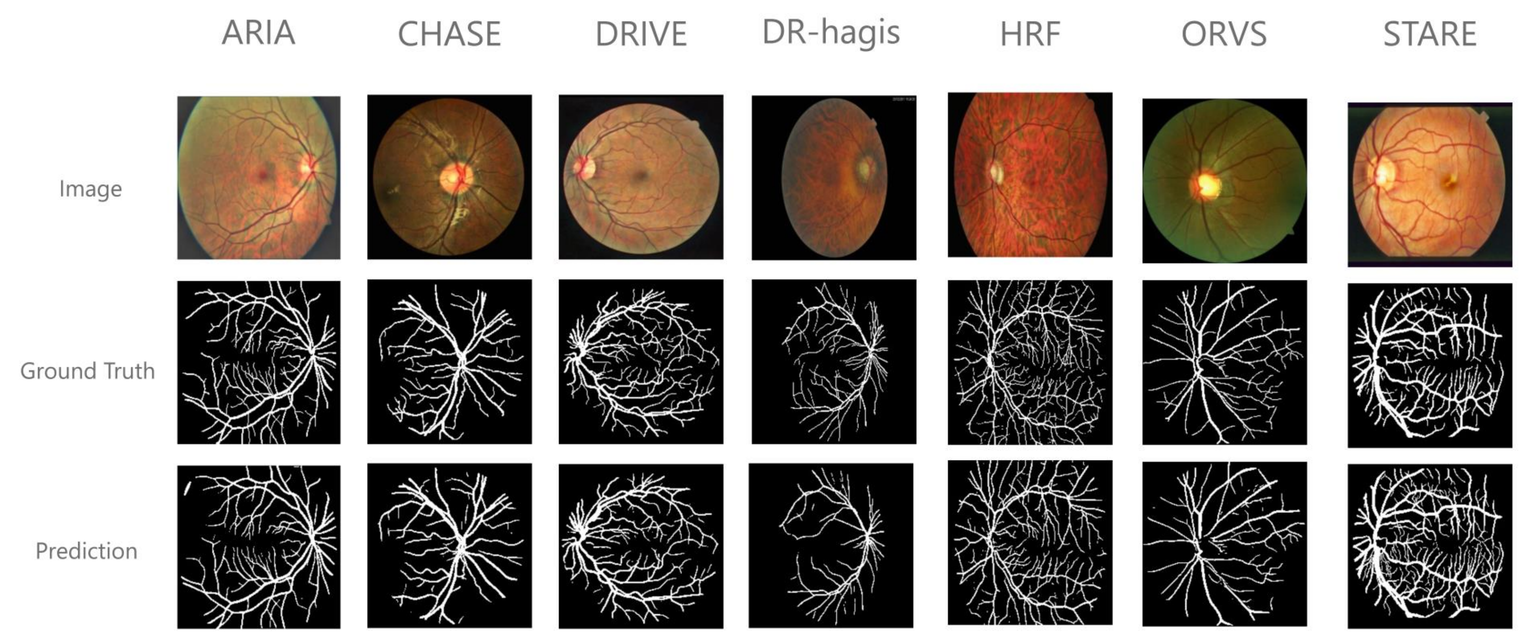


TABLE IV
APPROACHES FOR RETINAL VESSELS SEGMENTATION ON THE DRIVE AND STARE DATASETS.

Method	DRIVE				STARE			
	Acc	Sen	Spec	DC	ACC	Sen	Spec	DC
Unsupervised								
Nguyen et al.[9]	94.07	-	98.58	72.98	93.24	-	98.63	77.74
Roychowdhury, Sohini, et al. [10]	94.9	73.9	97.8		95.6	73.2	98.4	
Memari et al. [12]	96.1	76.1	98.1	-	95.1	78.2	96.5	-
Zhao et al. [11]	94.7	73.54	97.89	-	95.09	71.87	97.67	-
Khan et al. [7]	95.1	73.4	96.7	-	95	73.6	97.1	-
Zhang et al. [29]	94.7	74.3	97.6	-	95.4	76.7	97.6	-
Bankhead et al. [8]	93.7	70.3	97.1	-	93.2	75.8	95.0	-
Supervised								
Wang et al.[27]	95.41	76.48	98.17	80.93	96.40	75.23	98.85	81.25
Hu et al. [16]	95.33	77.72	97.93	-	96.32	75.43	98.14	-
Oliveira et al. [15]	95.76	80.39	98.04	-	96.94	83.15	98.58	-
Xia et al. [14]	96.55	77.15	-	-	96.93	74.69	-	-
Fu, Xu, Wong, et al. [30]	95.20	76.00	-	-	95.80	74.10	-	-
Yan et al. [26]	95.40	76.50	98.10	-	96.10	75.80	97.50	-
Brancati et al. [31]	94.90	78.20	97.60	-	-	-	-	-
Orlando et al. [28]	-	78.97	96.84	78.41	-	76.80	97.38	76.44
Jin et al. [32]	95.66	79.63	98.00	82.37	96.41	75.95	98.78	81.43
Proposed Method	95.61	**82.67**	97.27	**82.45**	95.26	**85.61**	96.57	**84.06**

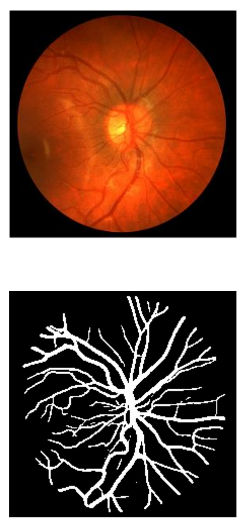


TABLE V
APPROACHES FOR RETINAL VESSELS SEGMENTATION ON CHASE DATASET.

Method	Acc	Sen	Spec	DC
Oliveira et al.[15]	96.53	77.79	98.64	-
Wang et al. [27]	96.03	77.30	97.92	78.09
Memari et al. [12]	93.90	73.80	96.80	-
Yan et al. [26]	96.10	76.33	98.09	-
Orlando et al. [28]	-	72.77	97.12	73.32
Jin et al. [32]	96.10	81.55	97.52	78.83
Proposed Method	**96.83**	**90.21**	97.34	**85.46**

TABLE VII
PERFORMANCE OF OUR APPROACH ON THE DR-HAGIS, ARIA, AND ORVS DATASETS

Dataset	Acc	Sen	Spec	DC
DR-Hagis	96.87	67.13	98.57	71.49
ARIA	95.31	81.94	96.40	77.59
ORVS	96.52	84.32	97.19	78.11

TABLE VI
PPROACHES FOR RETINAL VESSELS SEGMENTATION ON HRF DATASET.

Method	Acc	Sen	Spec	DC
Orlando et al. [28]	-	78.74	95.84	71.58
Jin et al. [32]	96.51	74.64	98.74	-
Proposed Method	95.07	**91.56**	95.09	**81.90**

Conclusion

- Proposed a deep-learning approach for vessel segmentation, using a U-Net based model and a InceptionV3 as encoder with group normalization instead of batch normalization.
- Contributed with a new dataset, ORVS, for retinal vessel segmentation
- Utilized a weighted loss function
- Our model is more precised in segmenting the vessels then other approaches with average accuracy of 95.60% and a Dice coefficient of 80.98%

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