UNIVERSITY OF CALGARY

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

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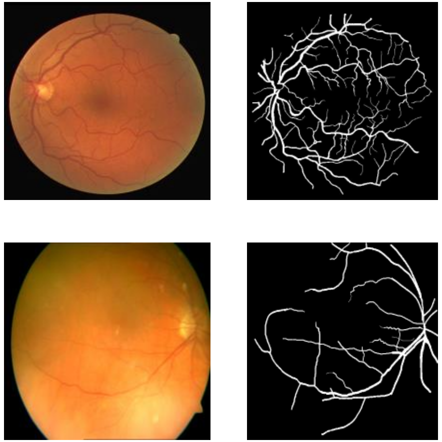
Introduction

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 or visions sense

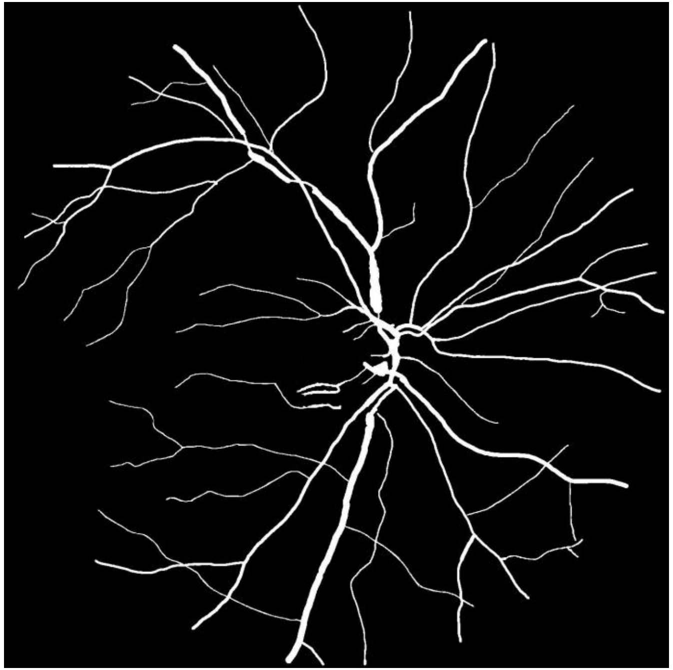
The structure of blood vessels may help when detecting these retinal conditions such as using the ISNT rule for glaucoma [1,2].

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
  - Six public datasets and our dataset (ORVS) → total is 381 retinal images

ORVS Dataset – New Dataset



ORVS - 49 publicly available Images annotated by an expert who a has been working in the field of retinal-image analysis and went through training

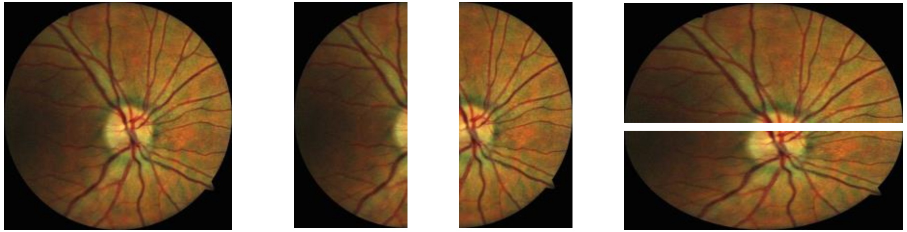
Approach: Adjustment

Before

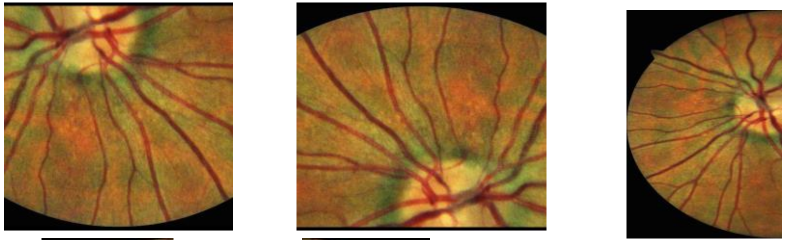
After

Approach: Augmentation

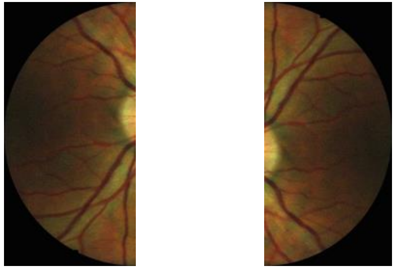
Each Image is split both vertically and Horizontally



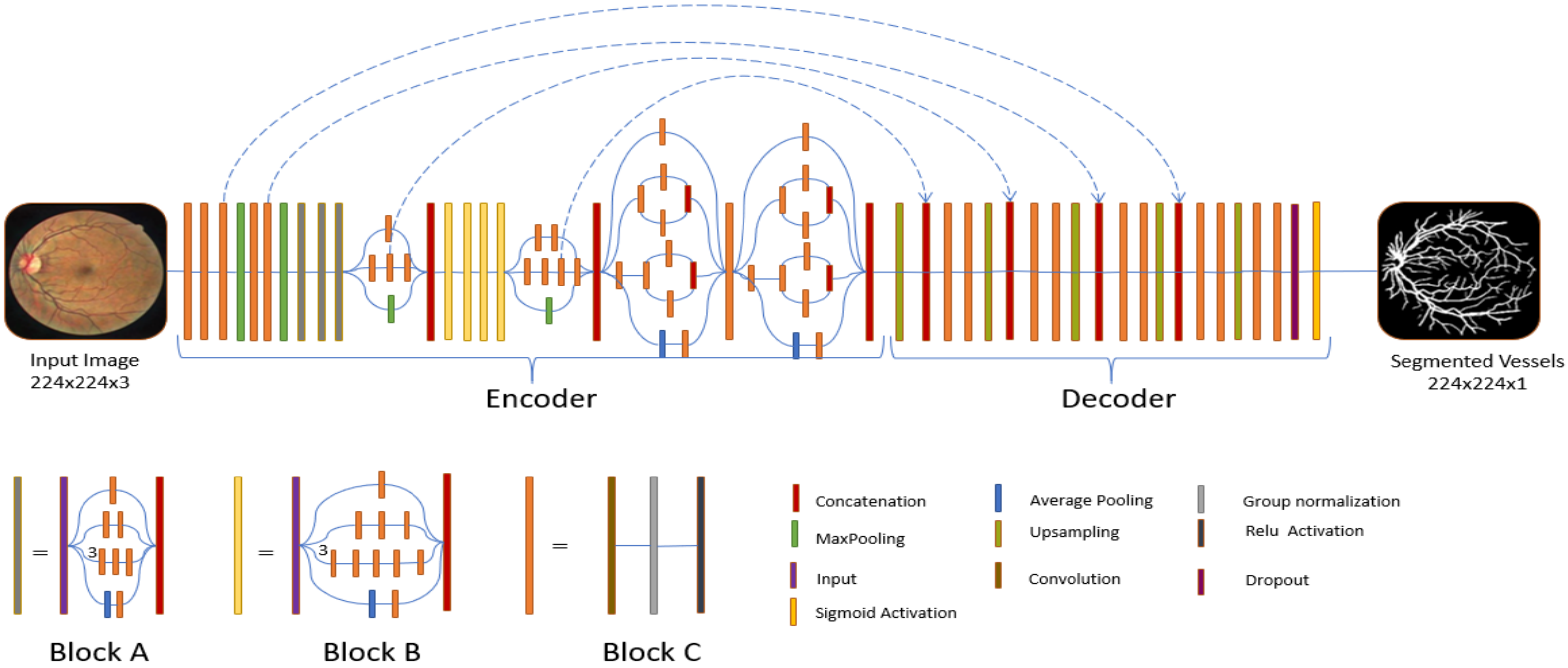
Then each image rotated by 90, 180, and 270 degrees



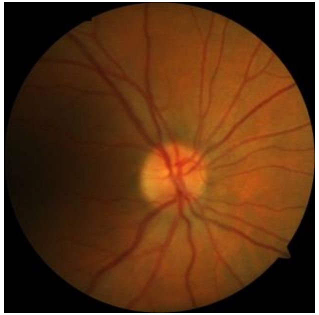
Then each image flipped vertically and horizontally



Approach: Model



Approach: Loss Function



More than 90% of the image area is background

Binary Cross entropy:

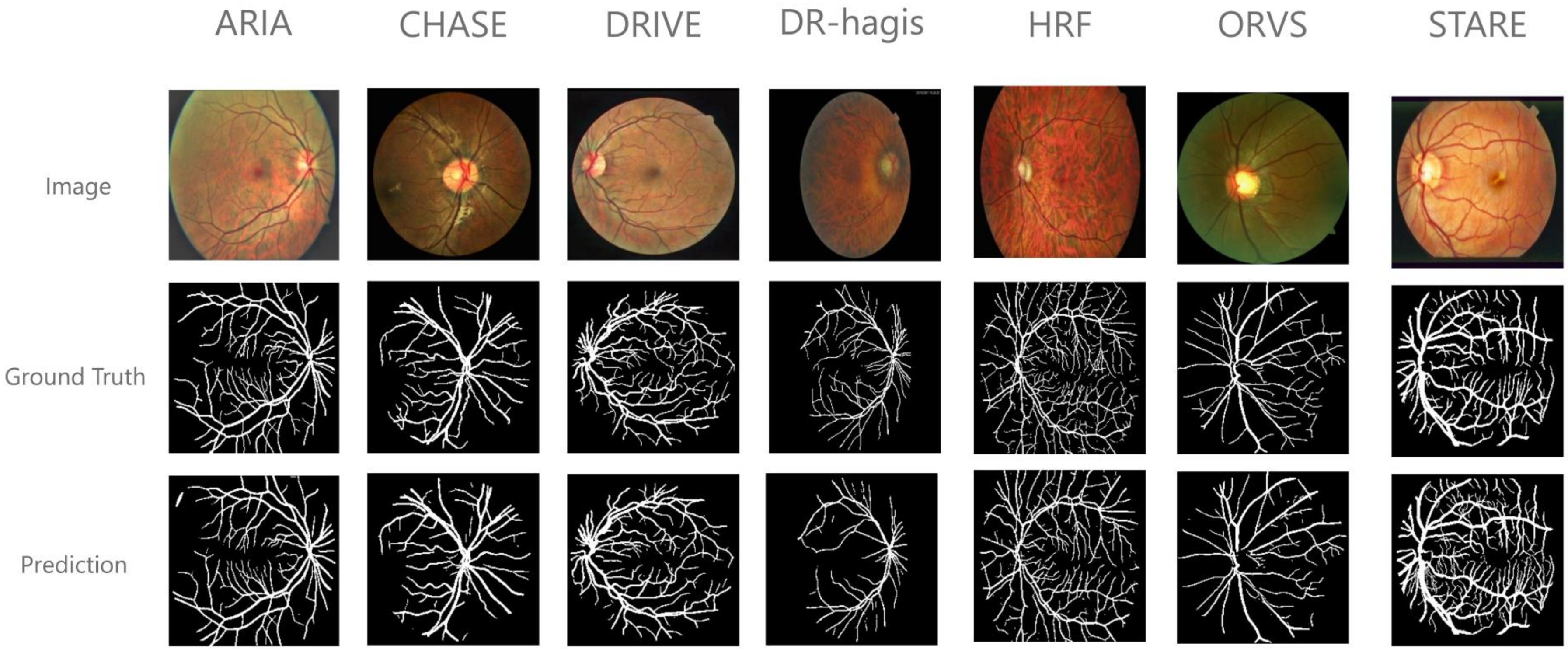
$$-\frac{1}{N}\sum_{i=1}^{N} y_i . \log(p(y_i)) + (1 - y_i) . \log(1 - (p(y_i)))$$

Jaccard Loss:

$$1 - \frac{|Y_d \cap \hat{Y}_d|}{|Y_d \cup \hat{Y}_d|}$$

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

Model Output - Test Images



Ablation Study

TABLE II

PERFORMANCE COMPARISON OF PROPOSED METHOD WITH AND WITHOUT USING TRANSFER LEARNING (TL) AND/OR IMAGE AUGMENTATION (IA).

Experiment	Acc	Sen	Spec	DC
Rotated+Flipped	93.98	56.45	98.98	68.14
TL+RotatedOnly	95.58	84.57	96.60	80.88
TL+Rotated+Flipped	95.60	85.18	96.51	80.98

TABLE III

PERFORMANCE OF THE MODEL ACROSS DIFFERENT LOSS FUNCTIONS.

Loss Function	Acc	Sen	Spec	DC
BCE	95.25	86.58	95.92	80.23
Jaccard Distance	95.21	85.24	96.12	79.82
Jaccard Distance+BCE	95.60	85.18	96.51	80.98

Overall Performance 1/4

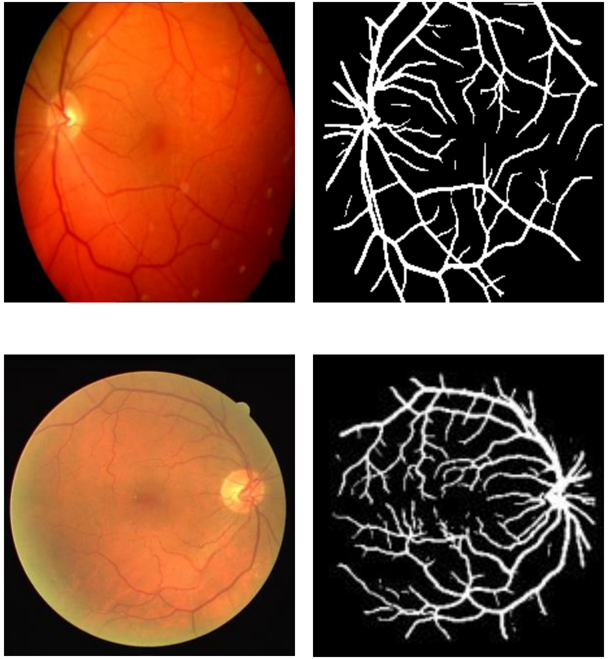
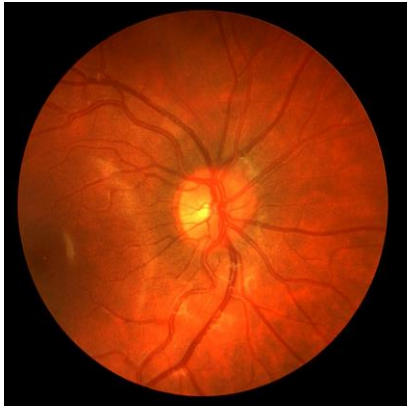


TABLE IV
APPROACHES FOR RETINAL VESSELS SEGMENTATION ON THE DRIVE AND STARE DATASETS.

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**

Overall Performance 2/4



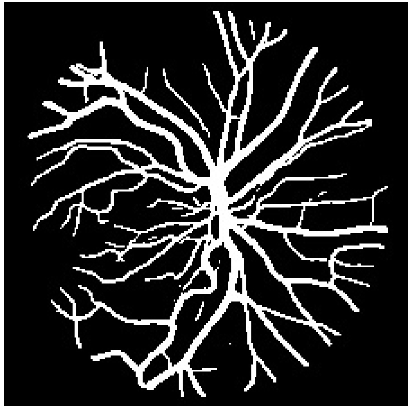
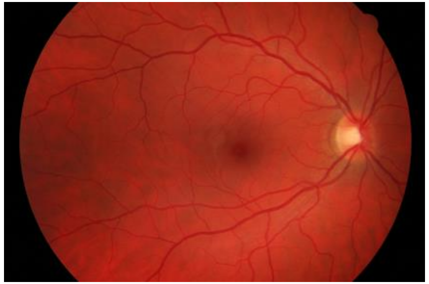


TABLE V
APPROACHES FOR RETINAL VESSELS SEGMENTATION ON CHASE DATASET.

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**

Overall Performance 3/4



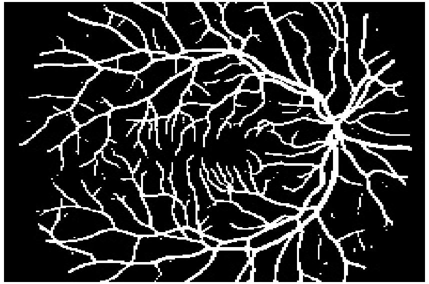


TABLE VI
APPROACHES FOR RETINAL VESSELS SEGMENTATION ON HRF DATASET.

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**

Overall Performance 4/4

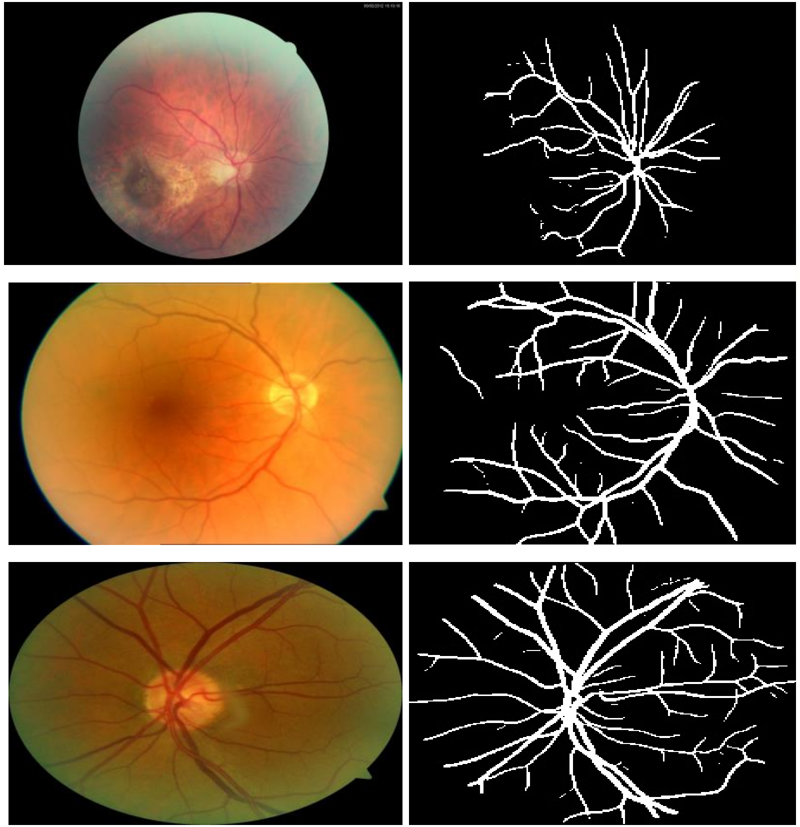


TABLE VII
PERFORMANCE OF OUR APPROACH ON THE DR-HAGIS, ARIA, AND ORVS DATASETS

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

Conclusion

- In this paper, we propose 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.
- We utilized a weighted loss function
- Showed effectiveness of:
  - Transfer learning & Image augmentation
  - loss function
- Contributed with a new dataset, ORVS, for retinal vessel segmentation
- Our model was more precised in segmenting the vessels then other approaches

Thank You

Any Questions?

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