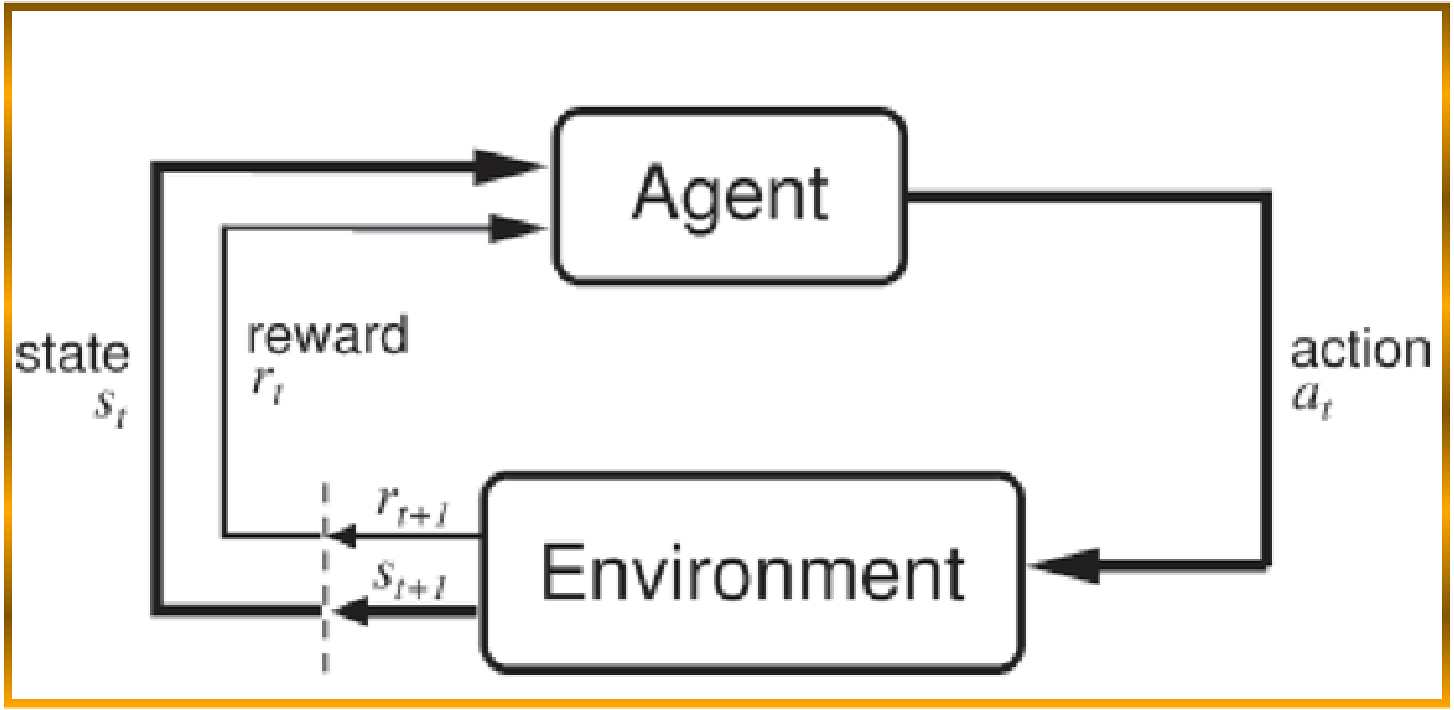
University of Cassino

Recent Work on Retinal Image Analysis

March/2018

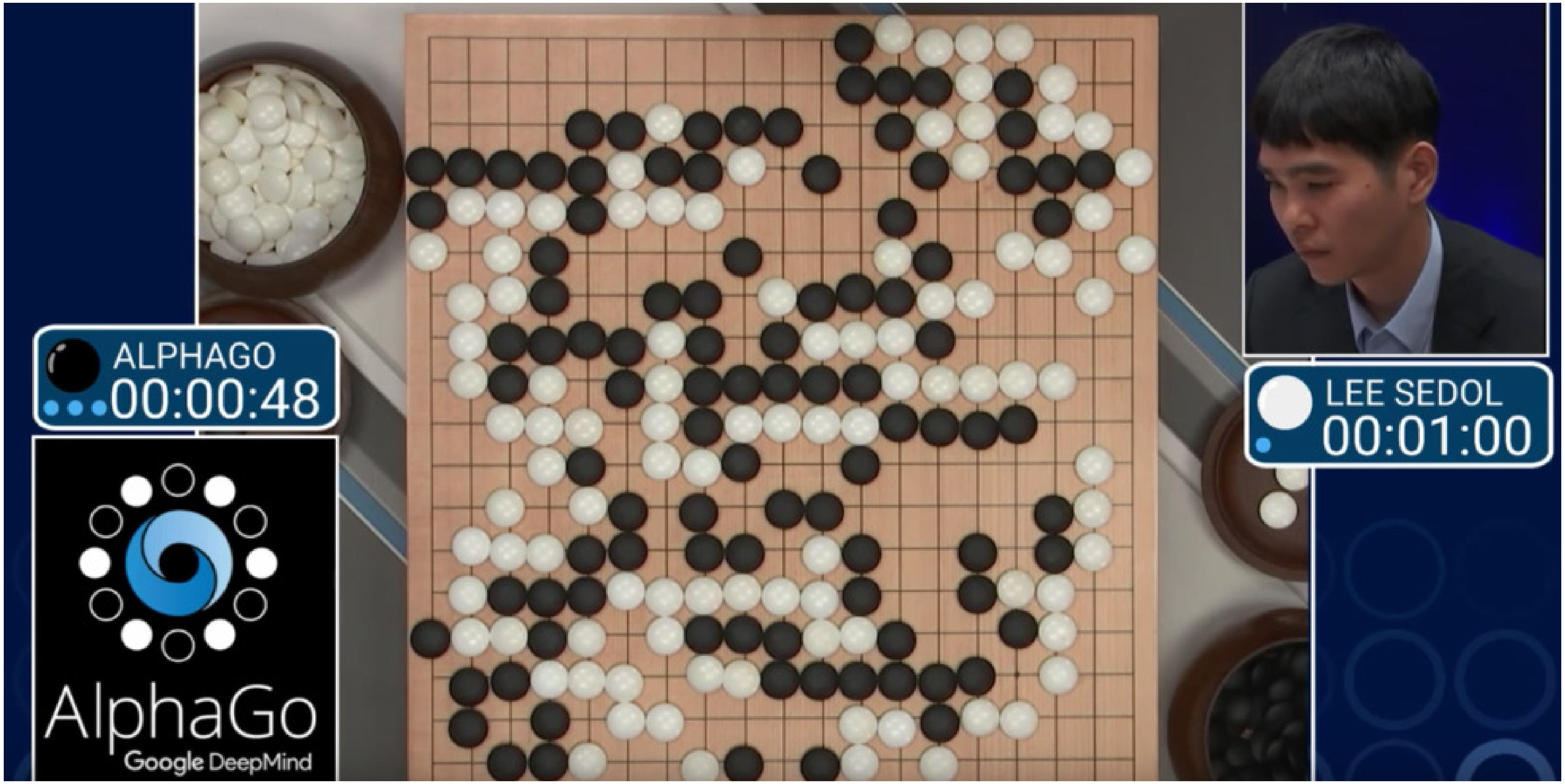
Adrian Galdran - Post-Doctoral Researcher
Biomedical Imaging Lab – INESC TEC Porto (Portugal)
http://bioimglab.inesctec.pt/

REINFORCEMENT LEARNING



LINK

REINFORCEMENT LEARNING



LINK

IMAGE COLORIZATION

LINK

VISUAL STYLE TRANSFER

Content

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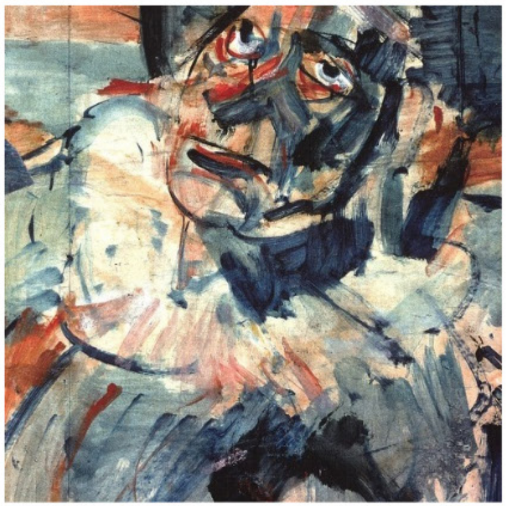

Style

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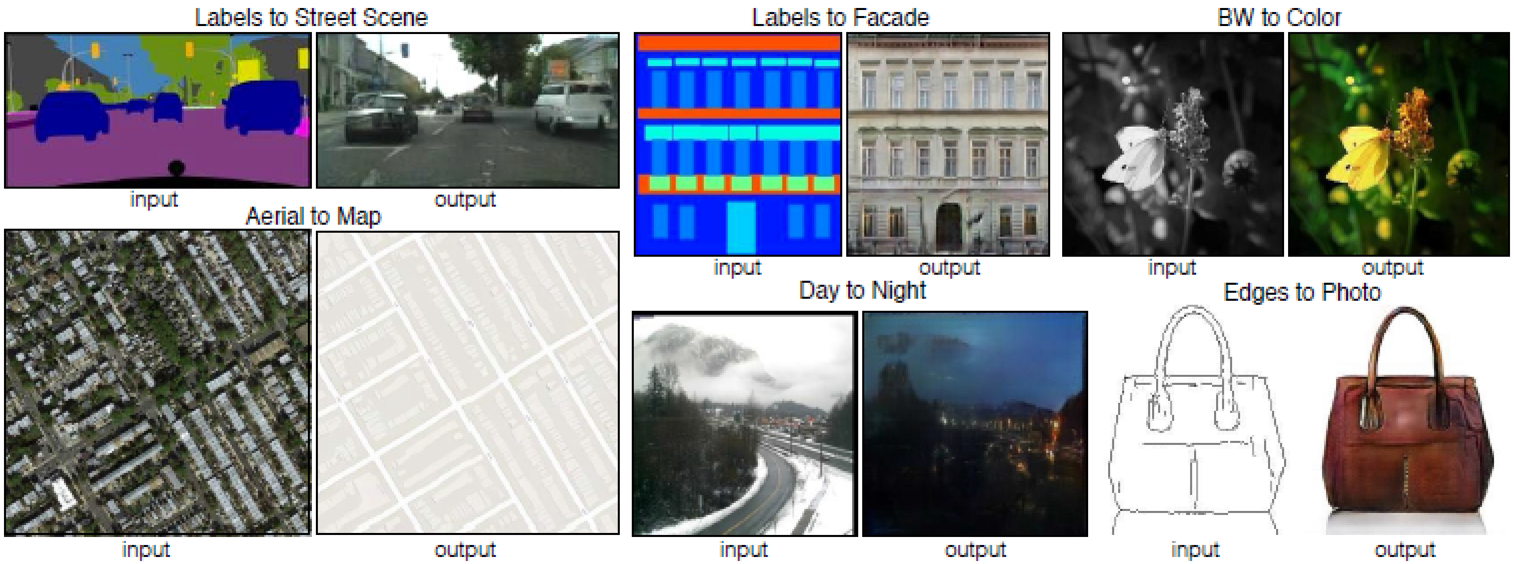
Pastiche

[LINK]

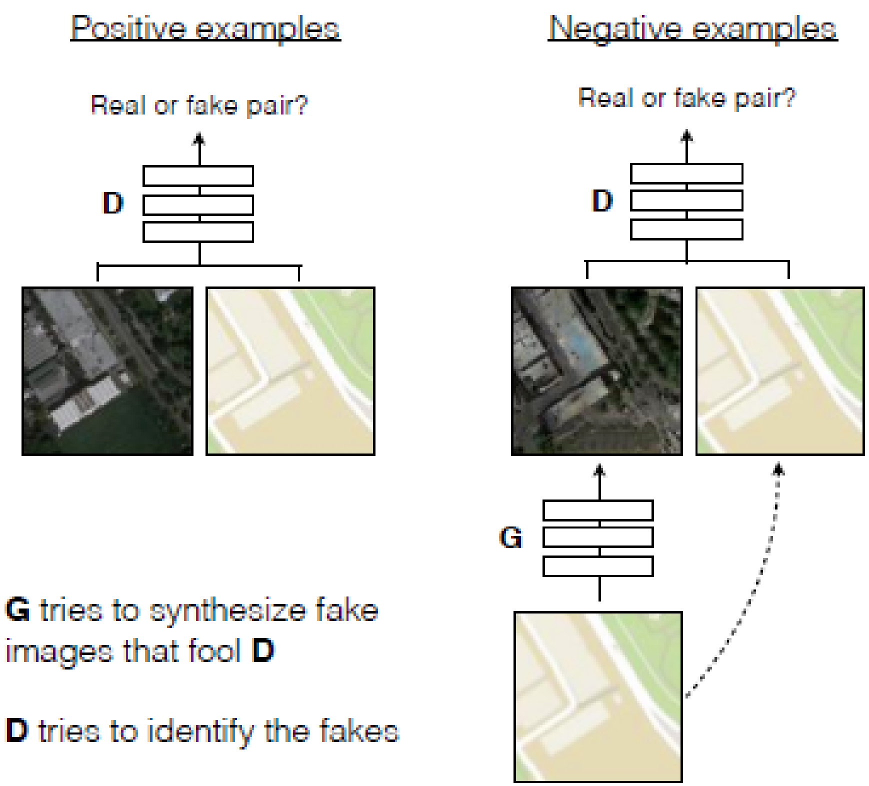
Image-to-Image Translation with Conditional Adversarial Networks

Phillip Isola Jun-Yan Zhu Tinghui Zhou Alexei A. Efros

Berkeley AI Research (BAIR) Laboratory
University of California, Berkeley
{isola, junyanz, tinghuiz, efros}@eecs.berkeley.edu



PIX2PIX: ADVERSARIAL IMAGE TRANSLATION



y: $G : z \rightarrow y$

$$G^* = \arg\min_G \max_D \mathcal{L}_{cGAN}(G, D) + \lambda \mathcal{L}_{L1}(G).$$

$$\mathcal{L}_{GAN}(G, D) = \mathbb{E}_{y \sim p_{data}(y)}[\log D(y)] + \mathbb{E}_{x \sim p_{data}(x), z \sim p_z(z)}[\log(1 - D(G(x, z))].$$

online demo

Towards Adversarial Retinal Image Synthesis

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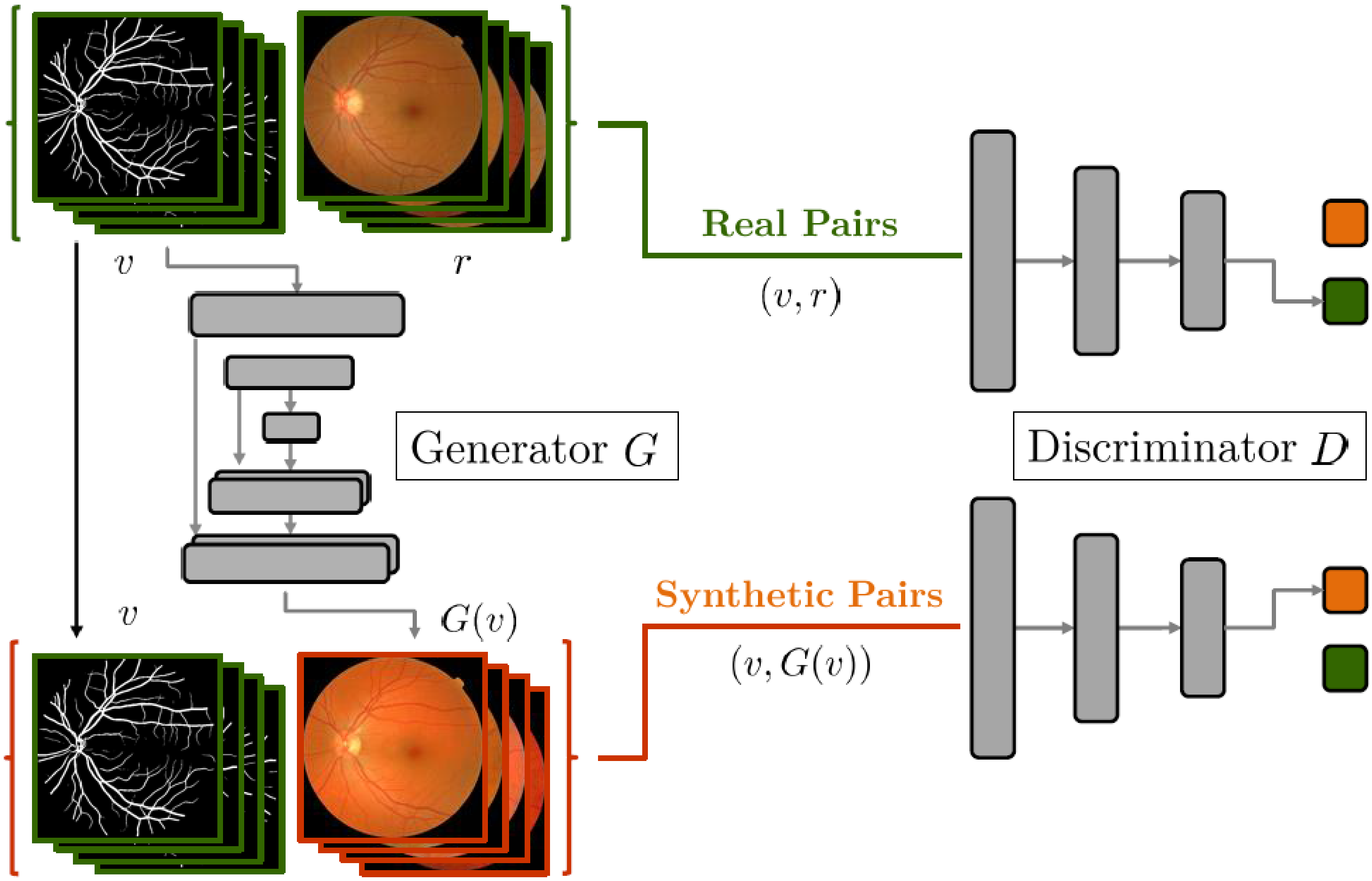
Faculty of Engineering, University of Porto
Porto, E-4200-464, Portugal
{amendon, campilho}@fe.up.pt

***FROM VESSELS TO RETINAS**



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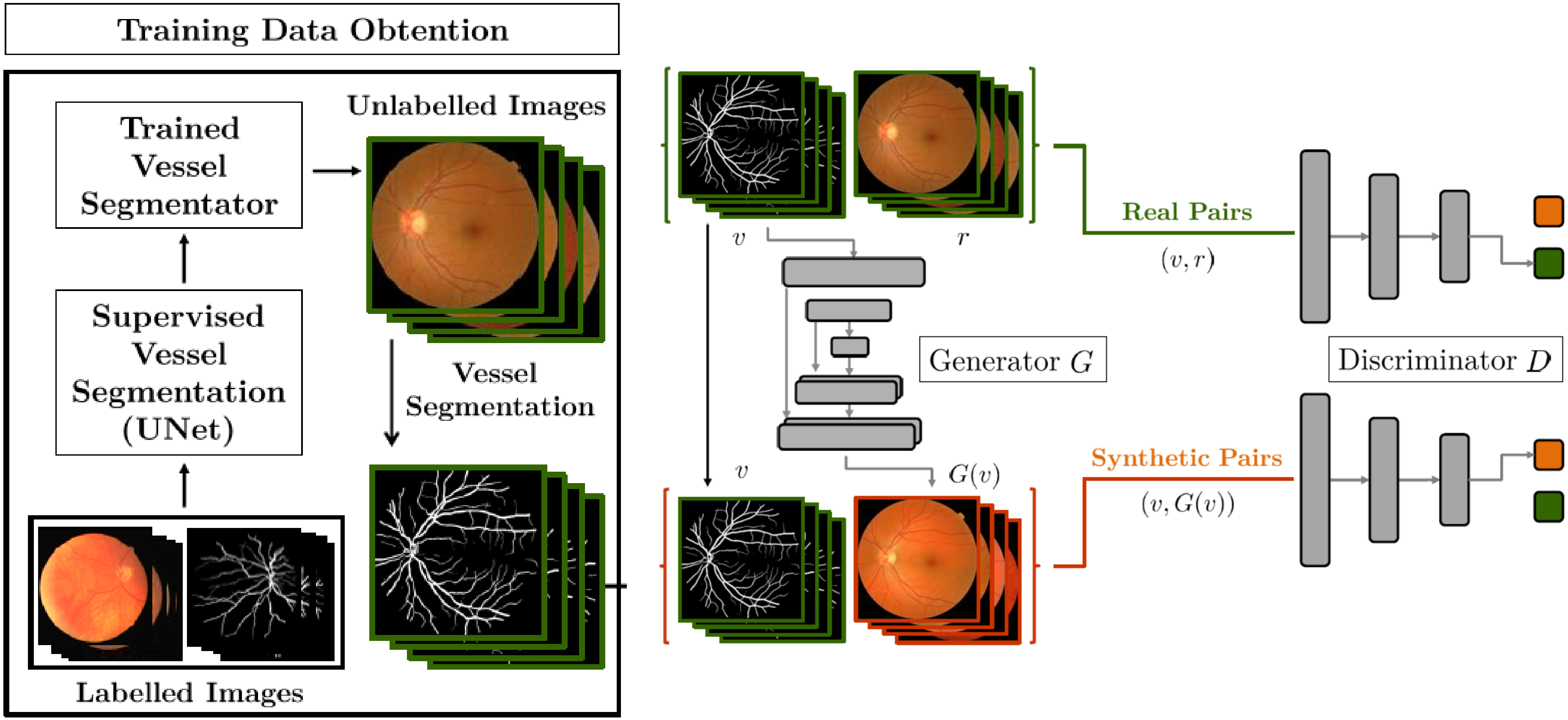
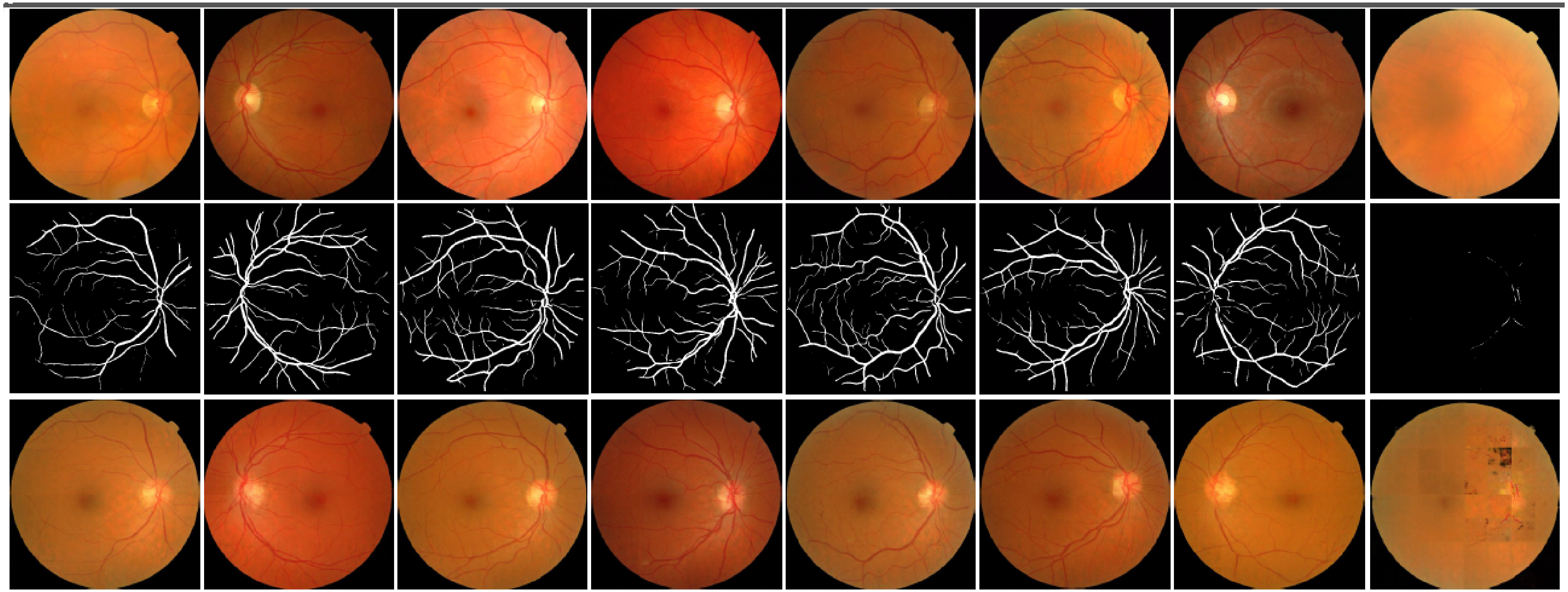


***FROM VESSELS TO RETINAS**

PIX2PIX: ADVERSARIAL RETINAL IMAGE TRANSLATION*



online demo

*FROM VESSELS TO RETINAS

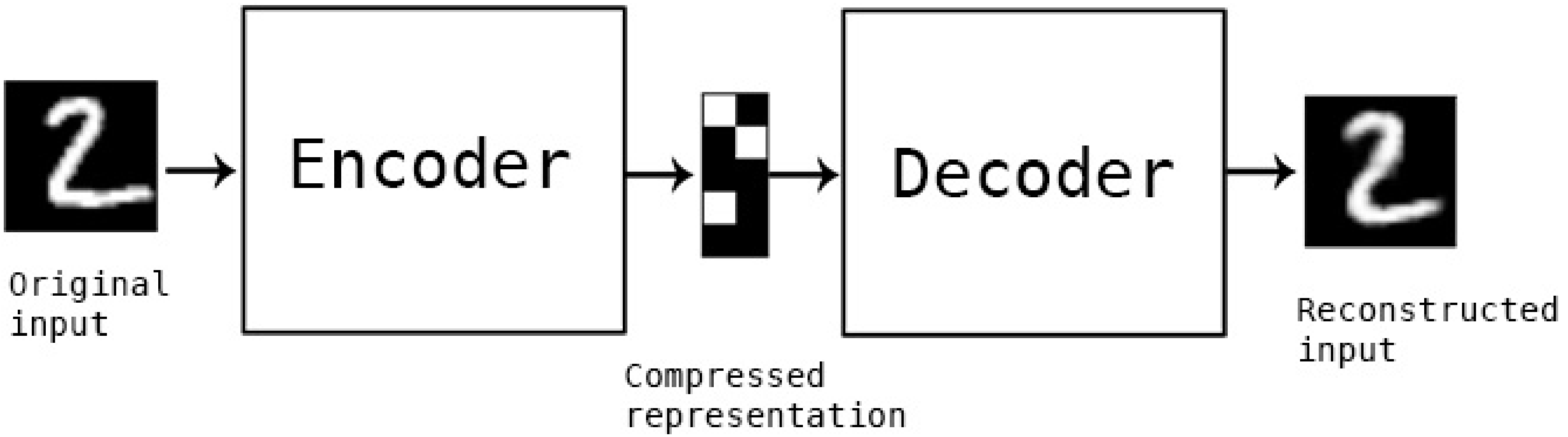
TRANSACTIONS ON MEDICAL IMAGING, VOL. XX, NO. X, JANUARY 2017

End-to-end Adversarial Retinal Image Synthesis

Pedro Costa*, Adrian Galdran, Maria Ines Meyer,
Meindert Niemeijer, Michael Abràmoff, Ana Maria Mendonça, and Aurélio Campilho

Adversarial Autoencoders for Vessel Trees Generation

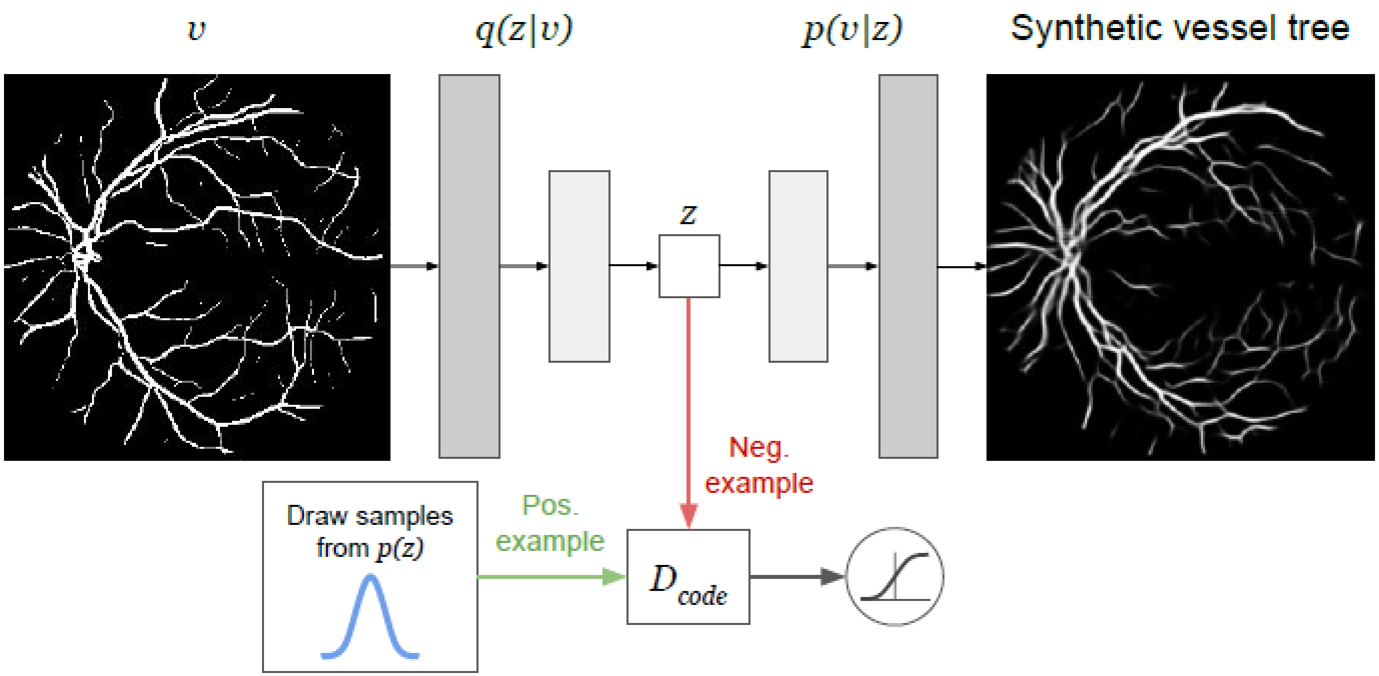
AUTOENCODERS:



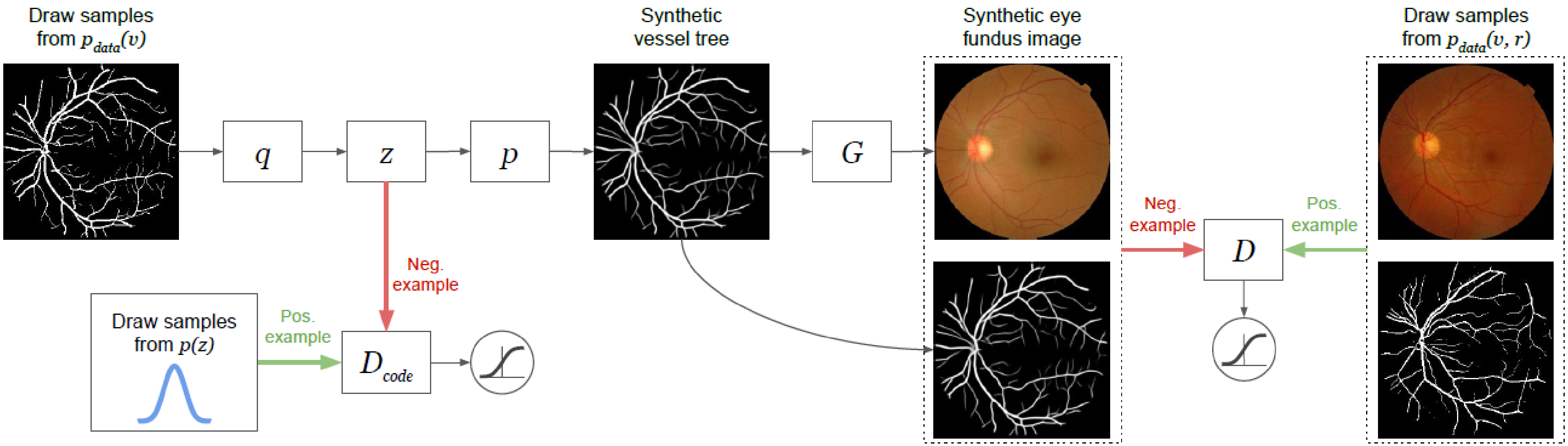
ADVERSARIAL AUTOENCODERS:

$$\mathcal{L}_{code}(D_{code}, q) = \mathbb{E}_{z\sim p(z)}[log(D_{code}(z))] + \mathbb{E}_{v\sim p_{data}(v)}[log(1 - D_{code}(q(z|v)))].$$

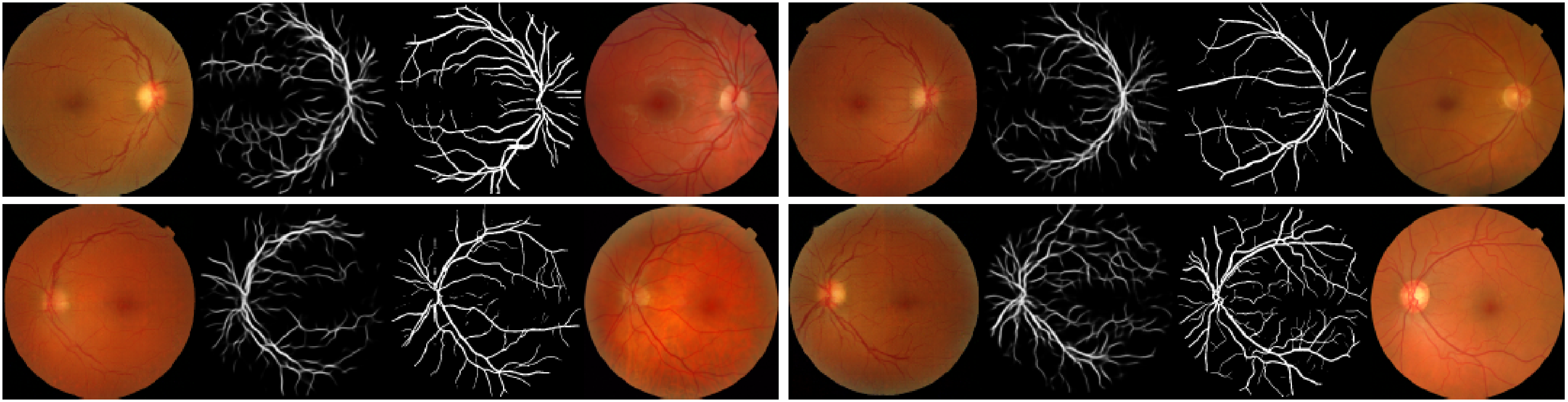
$$\mathcal{L}_{AAE}(D_{code}, q, p) = \mathcal{L}_{code}(D_{code}, q) + \gamma\mathcal{L}_{rec}(q, p)$$



FULL SYSTEM

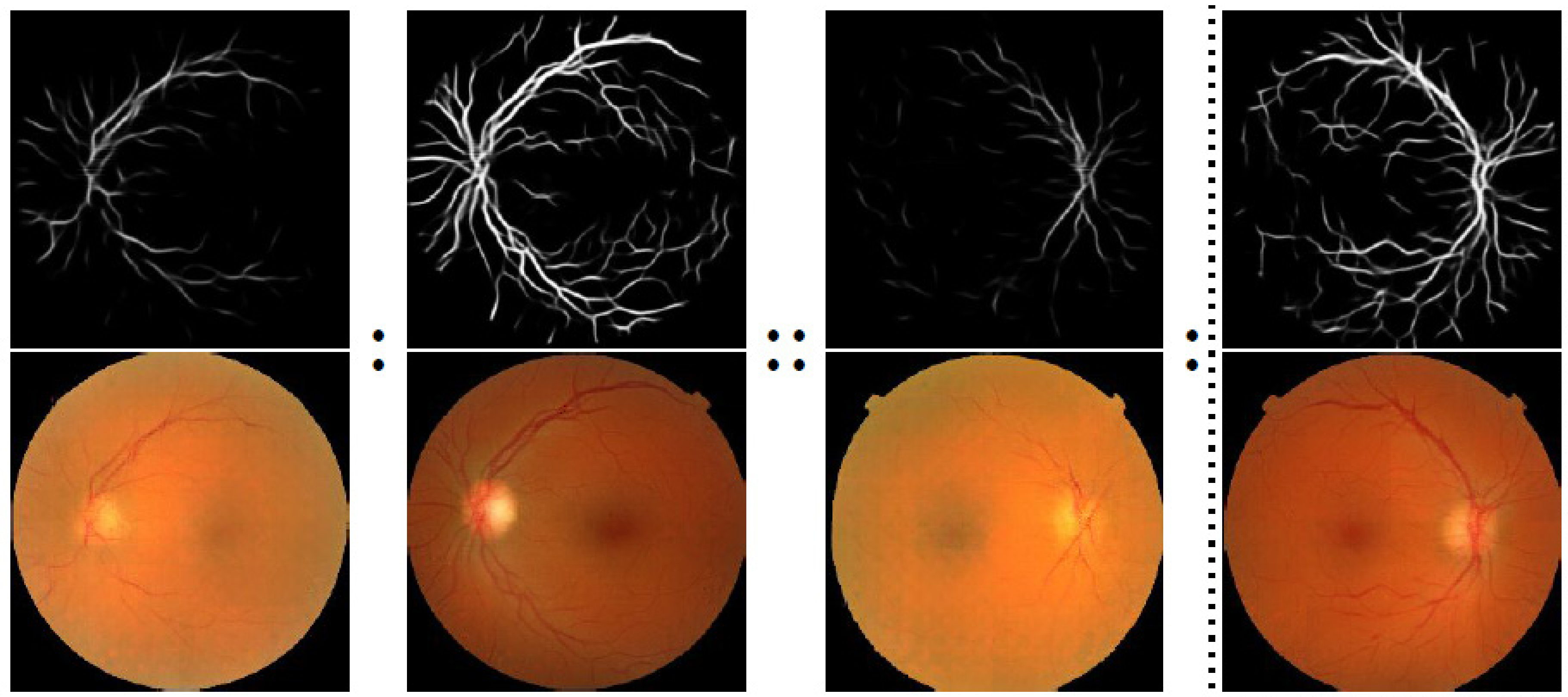

Draw samples
from $p_{data}(v)$
q
z
p
Synthetic
vessel tree
G
Synthetic eye
fundus image
Draw samples
from $p_{data}(v, r)$
Neg.
example
Pos.
example
D
Draw samples
from $p(z)$
Pos.
example
Neg.
example
D_{code}

RESULTS:



RESULTS:

CRAZY THINGS YOU CAN DO NOW:



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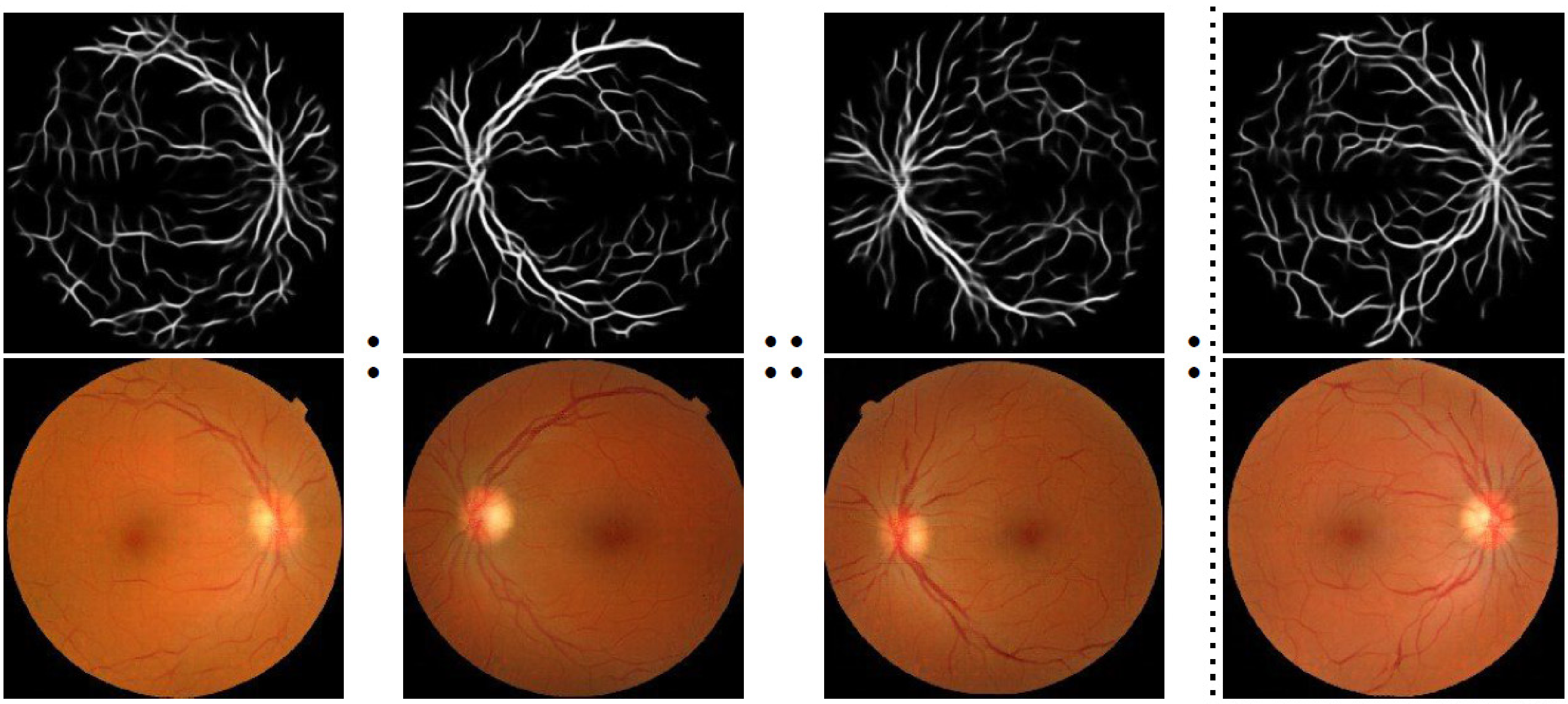

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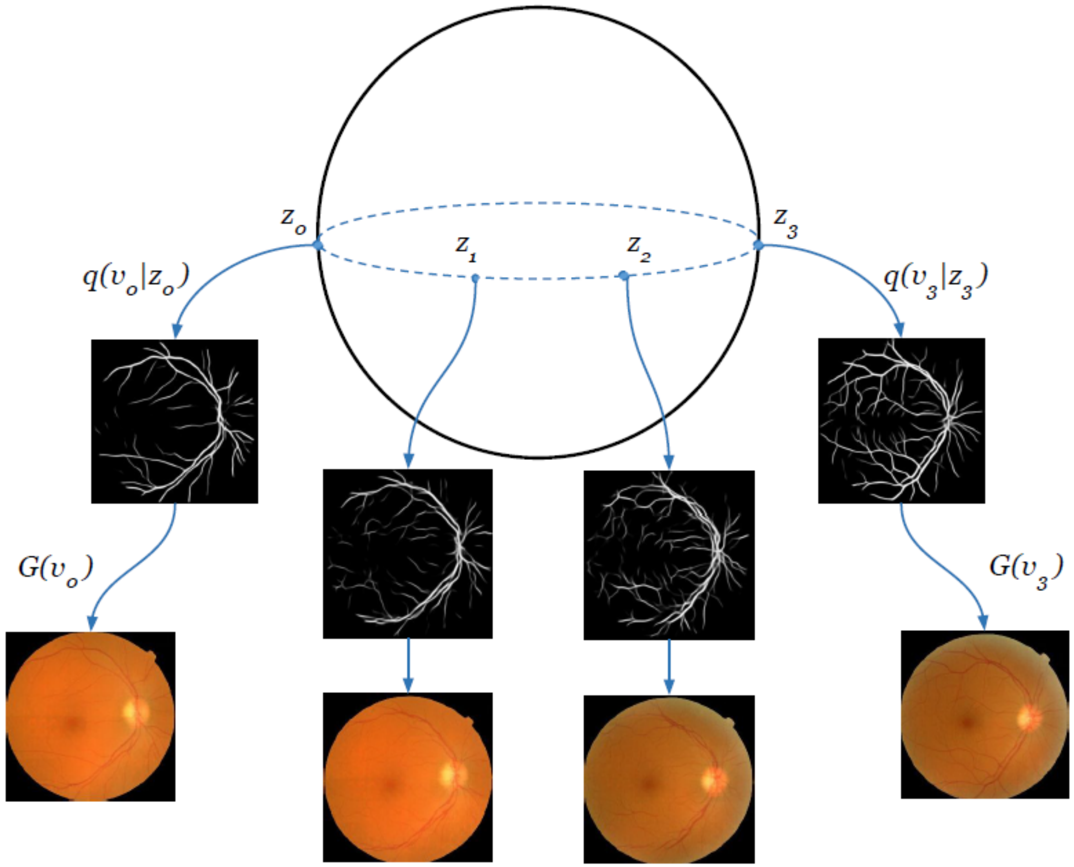

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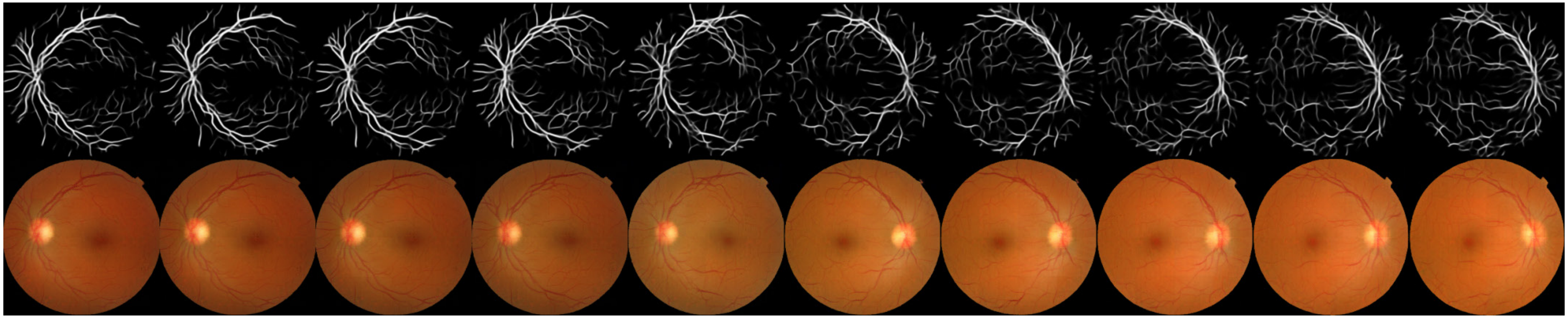

0. Overview

1. Introduction

2. Deep NNs for Artery/Vein Classification

3. Joint Optic Disc and Fovea Location

4. Retinal Vessel Map Quality Assessment

5. Conclusions, Q&A

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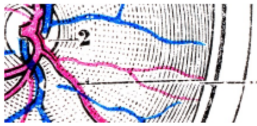

Diabetic Retinopathy Detection

Identify signs of diabetic retinopathy in eye images

$100,000 · 661 teams · 2 years ago

Overview Data Kernels Discussion Leaderboard Rules

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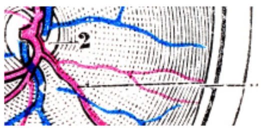

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December 13, 2016

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Varun Gulshan, PhD[1]; Lily Peng, MD, PhD[1]; Marc Coram, PhD[1]; Martin C. Stumpe, PhD[1]; Derek Wu, BS[1]; Arunachalam Narayanaswamy, PhD[1]; Subhashini Venugopalan, MS[1,2]; Kasumi Widner, MS[1]; Tom Madams, MEng[1]; Jorge Cuadros, OD, PhD[3,4]; Ramasamy Kim, OD, DNB[5]; Rajiv Raman, MS, DNB[6]; Philip C. Nelson, BS[1]; Jessica L. Mega, MD, MPH[7,8]; Dale R. Webster, PhD[1]

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[4]School of Optometry, Vision Science Graduate Group, University of California, Berkeley

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[6]Shri Bhagwan Mahavir Vitreoretinal Services, Sankara Nethralaya, Chennai, Tamil Nadu, India

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JAMA. 2016;316(22):2402-2410. doi:10.1001/jama.2016.17216

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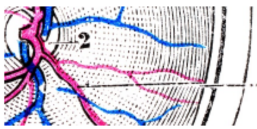

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Google's solution: spend millions of dollars, assemble a large-quality huge dataset, use pre-trained Inception V3

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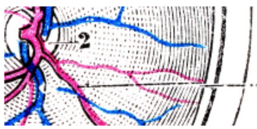

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Editorial Information. *JAMA*'s acceptance rate is 11% of the more than 7,000 major manuscripts it receives annually and 4% of the more than 4,400 research papers received. In 2016, the median time for an initial editorial decision for submitted manuscripts was 3 days; the median time from submission to acceptance for all articles was 18 days and 33 days from acceptance to publication (for additional information, see the *JAMA* Editorial). *JAMA*'s impact factor is 44.4. For more information on the types of articles published and editorial policies, see the journal's

1. Introduction

arXiv.org > cs > arXiv:1803.04337

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Computer Science > Computer Vision and Pattern Recognition

Replication study: Development and validation of deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs

Mike Voets, Kajsa Møllersen, Lars Ailo Bongo

(Submitted on 12 Mar 2018)

We have replicated some experiments in 'Development and validation of a deep learning algorithm for detection of diabetic retinopathy in retinal fundus photographs' that was published in JAMA 2016; 316(22). We re-implemented the methods since the source code is not available.
The original study used fundus images from EyePACS and three hospitals in India for training their detection algorithm. We used a different EyePACS data set that was made available in a Kaggle competition. For evaluating the algorithm's performance the benchmark data set Messidor-2 was used. We used the similar Messidor-Original data set to evaluate our algorithm's performance. In the original study licensed ophthalmologists re-graded all their obtained images for diabetic retinopathy, macular edema, and image gradability. Our challenge was to re-implement the methods with publicly available data sets and one diabetic retinopathy grade per image, find the hyper-parameter settings for training and validation that were not described in the original study, and make an assessment on the impact of training with ungradable images.

1. Introduction

arXiv.org > cs > arXiv:1803.04337

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$\boxed{\text{We were not able to reproduce the performance as reported in the original study.}}$ We believe our model did not learn to recognize lesions in fundus images, since we only had a singular grade for diabetic retinopathy per image, instead of multiple grades per images. Furthermore, the original study missed details regarding hyper-parameter settings for training and validation. The original study may also have used image quality grades as input for training the network.
We believe that deep learning algorithms should be easily replicated, and that ideally source code should be published so that other researchers can confirm the results of the experiments. Our source code and instructions for running the replication are available at: this https URL

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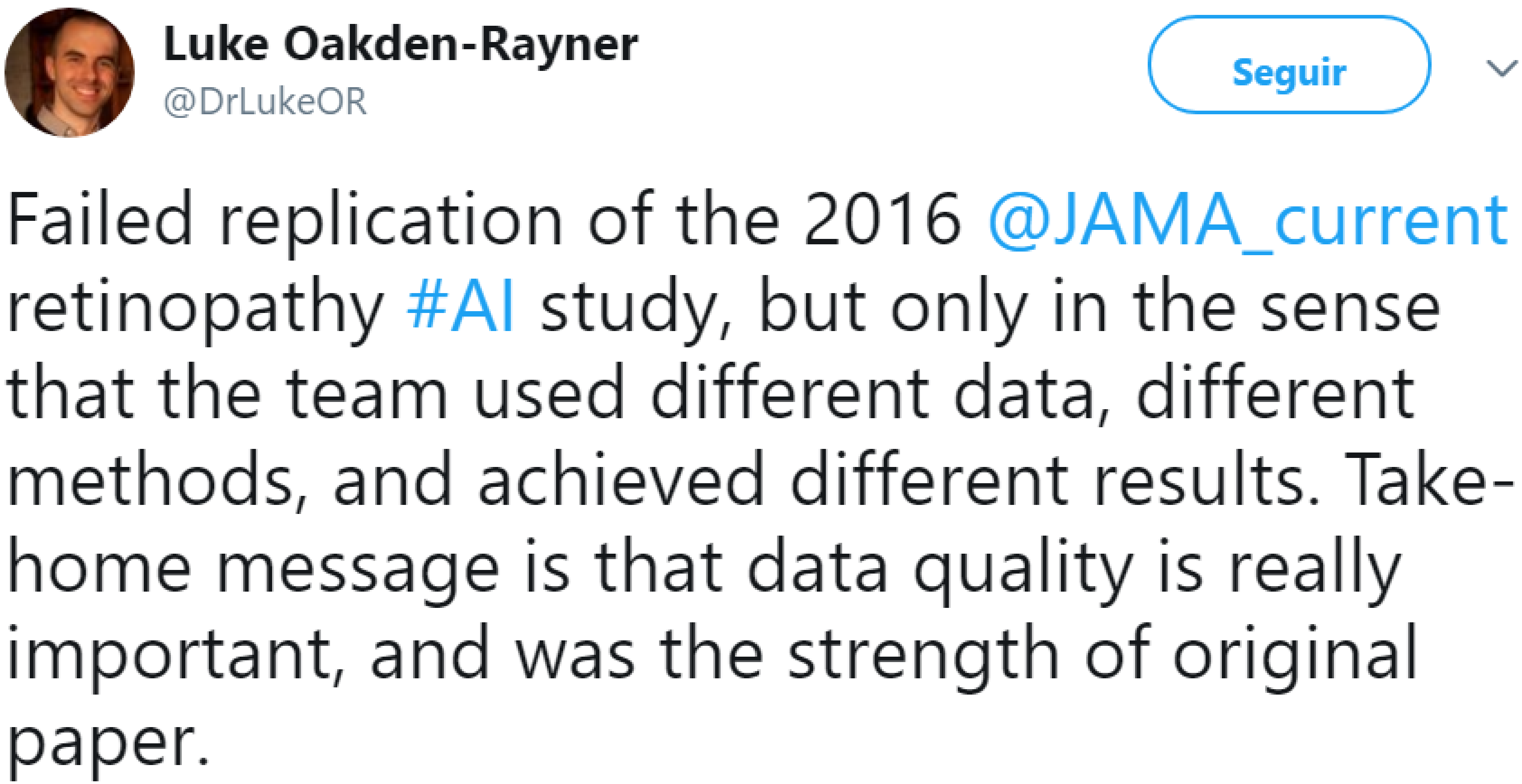

https://lukeoakdenrayner.wordpress.com/

1. **Introduction**
2. **Deep NNs for Artery/Vein Classification**
3. **Joint Optic Disc and Fovea Location**
4. **Retinal Vessel Map Quality Assessment**
5. **Conclusions, Q&A**

2. Deep NNs for Artery/Vein Classification

Motivation for the A/V problem:

Why do we want to solve this? Biomarkers associated to hypertension, heart stroke, diabetes, neural disorders, etc.

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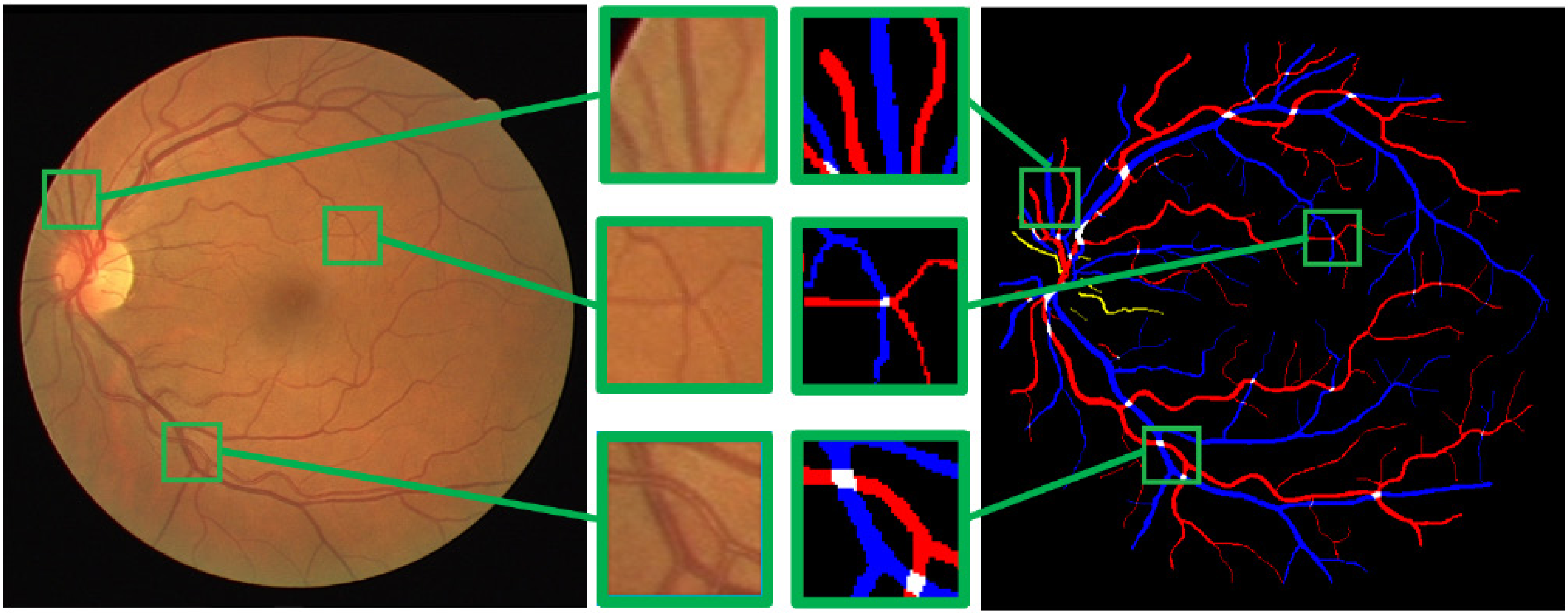
Why is this problem difficult?



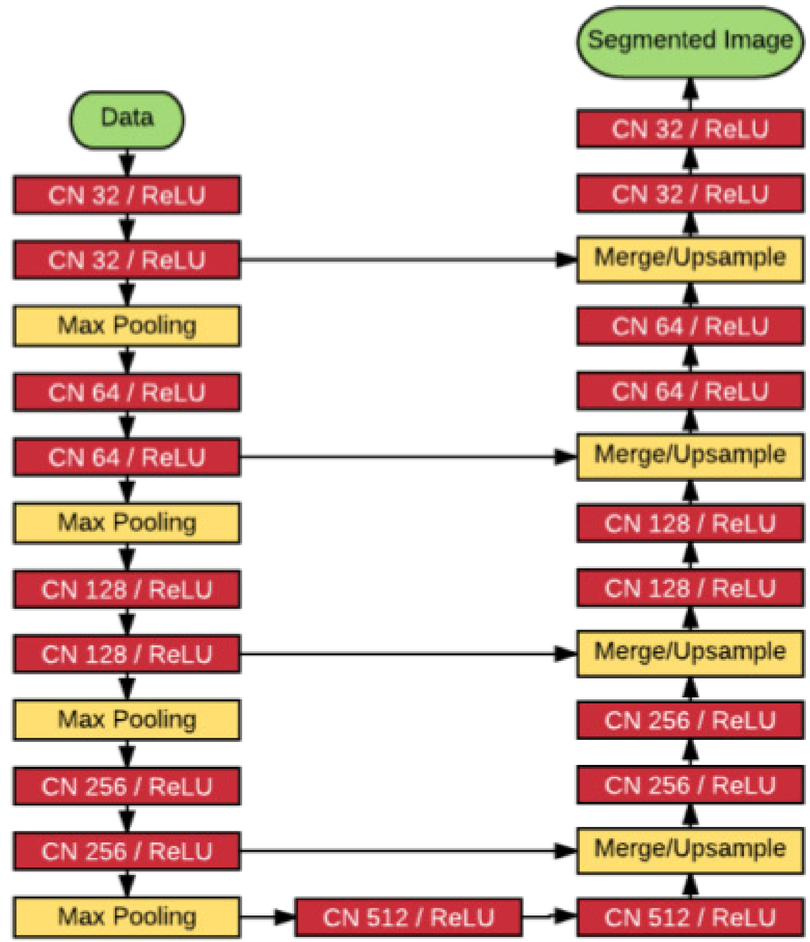
2. Deep NNs for Artery/Vein Classification

U-Net style architecture for A/V classification:

Simple change in the loss function to discard background info and we are good to go.

$$\mathcal{L}_i = \frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{3} w_j \; y_{ij} \log(\hat{y}_{ij}),$$

$$w_j = \begin{cases} 0, & j = 1 \\ 1, & j = 2 \\ 1, & j = 3, \end{cases}$$



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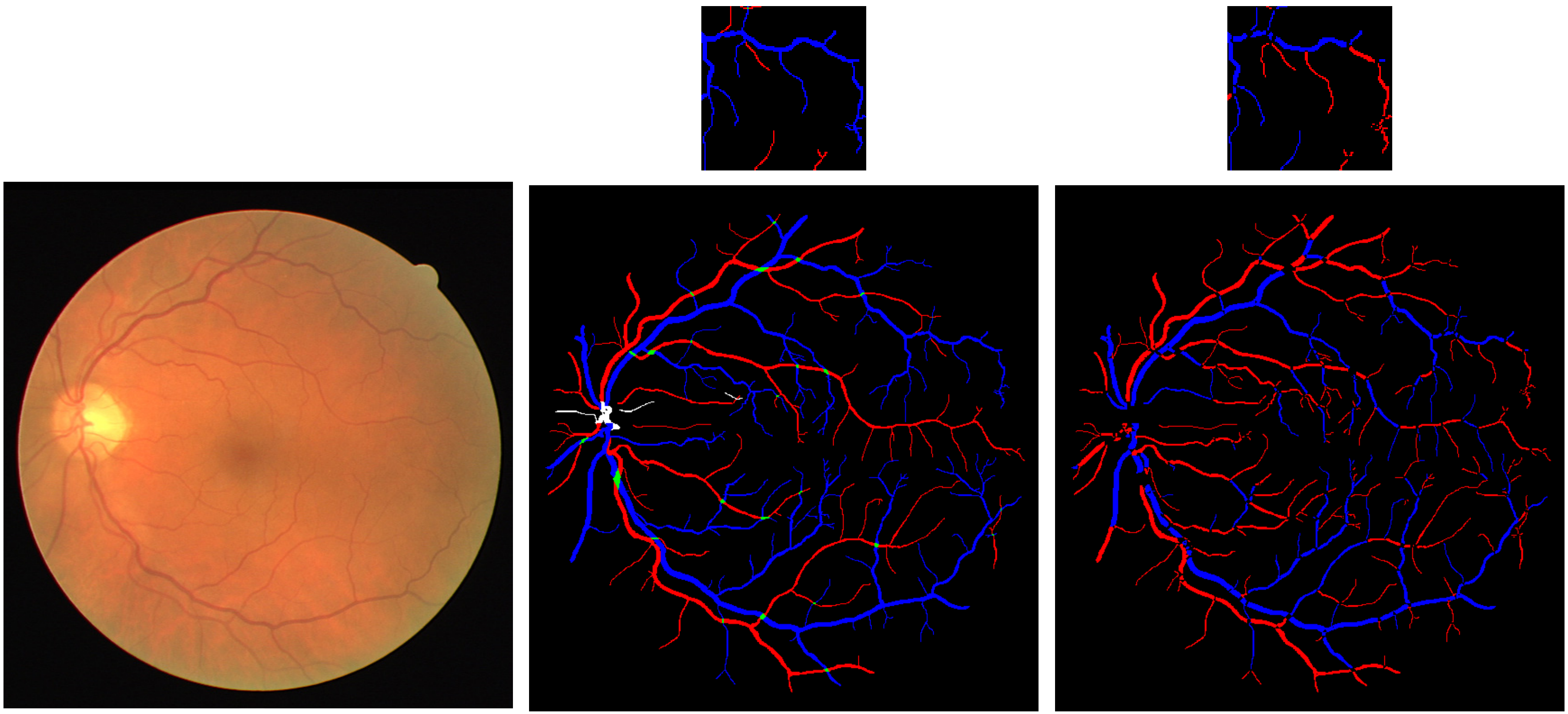
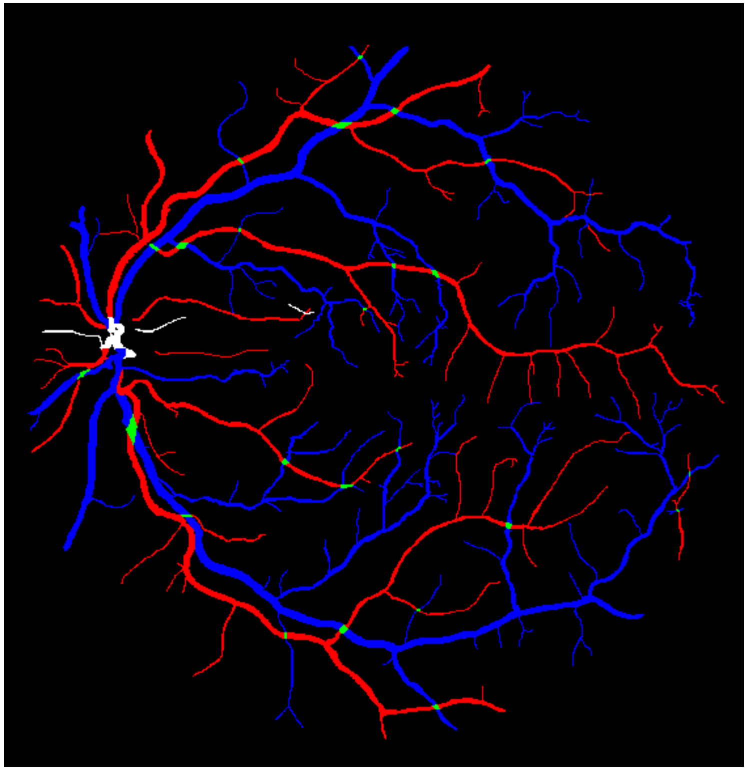
Results (not really good)



A Simple Incremental Learning Strategy

1) A bit of **domain knowledge** (arteries carry oxygen, they are brighter)

2) Curriculum Learning: start with a **simpler problem**, **add complexity**



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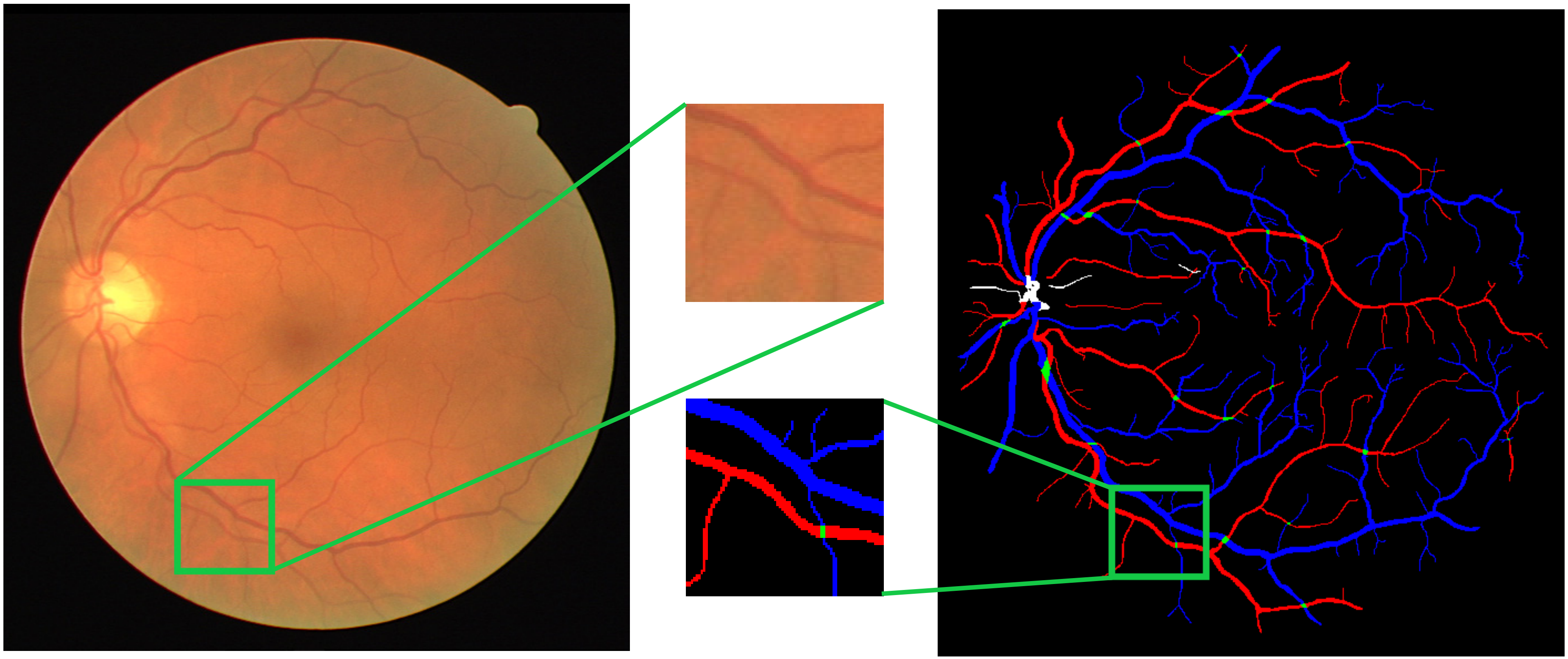

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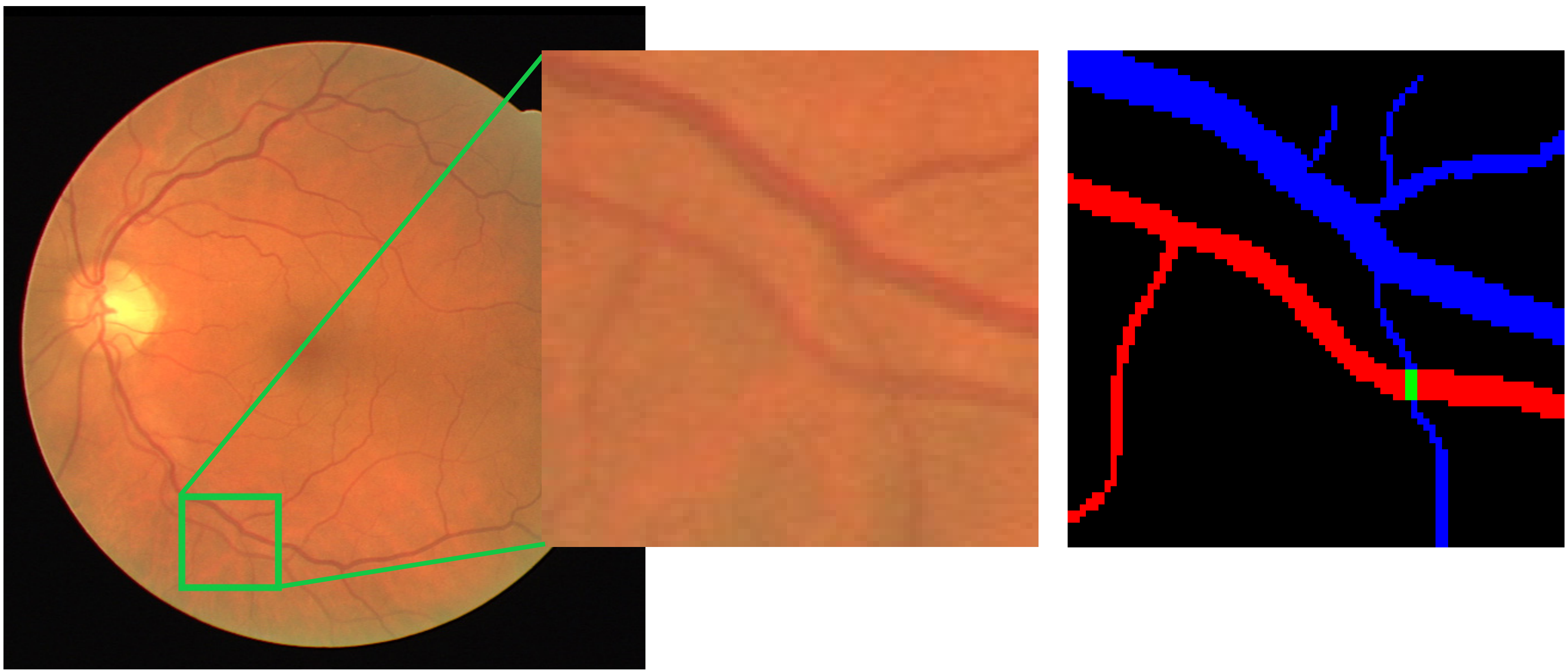

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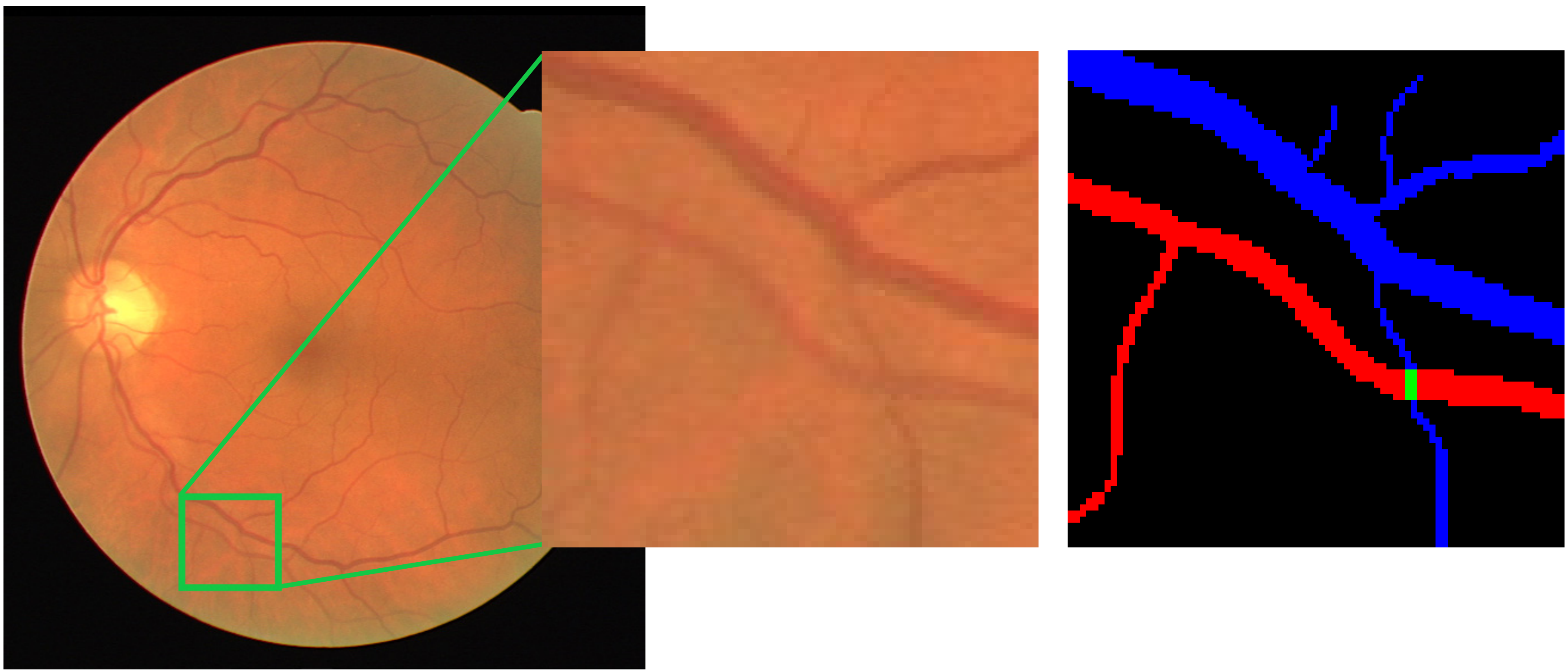

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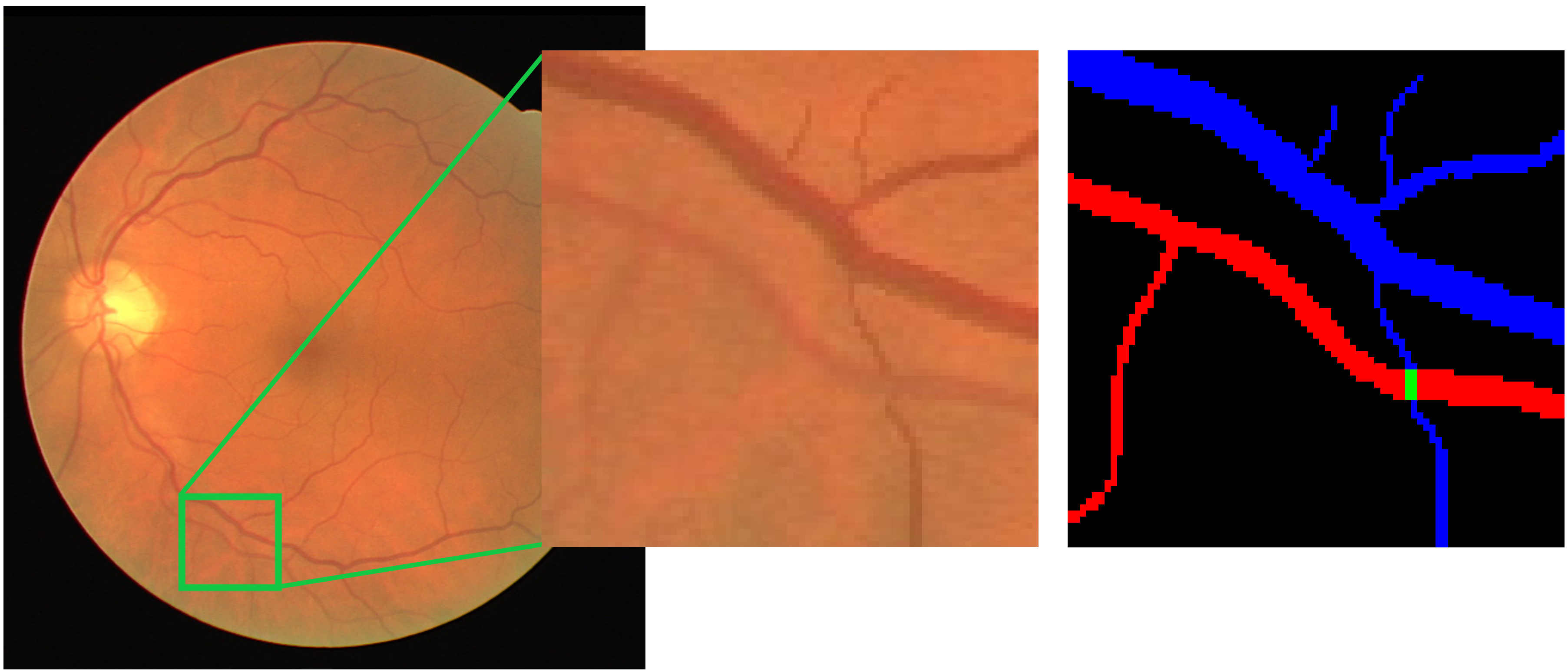
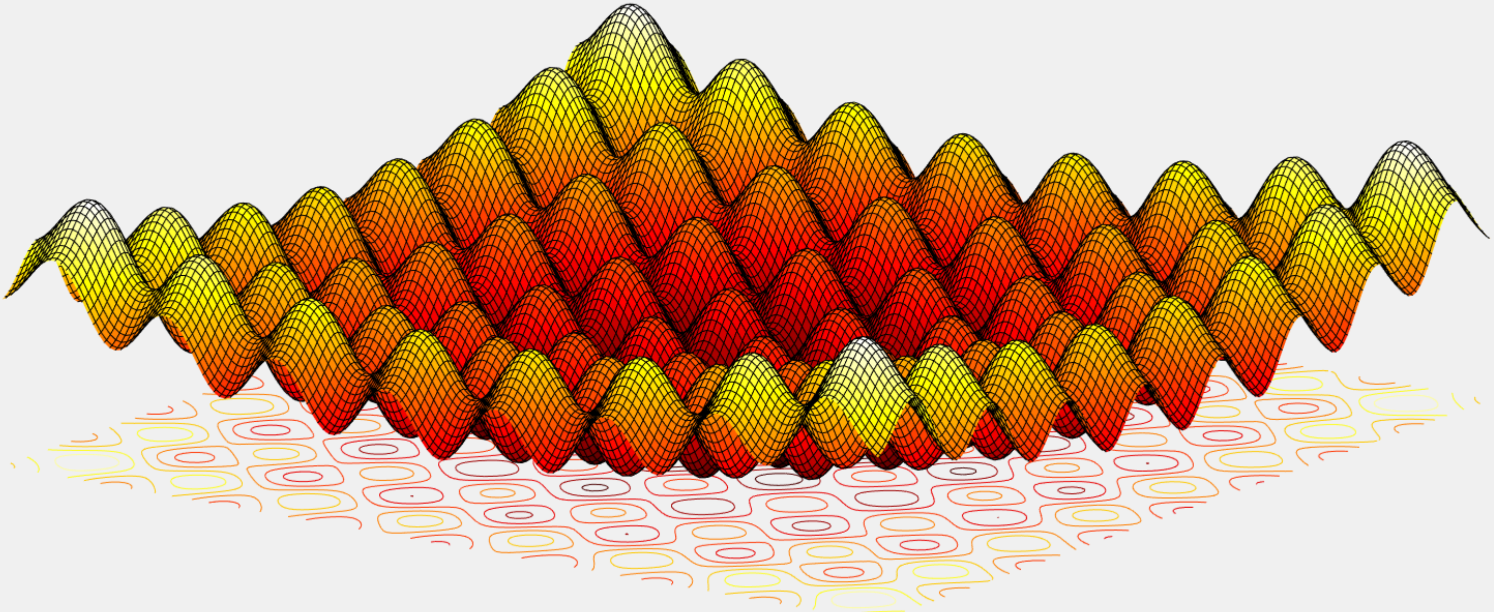


A Simple Incremental Learning Strategy - Interpretation

Deep neural networks have highly **non-convex** loss surfaces.



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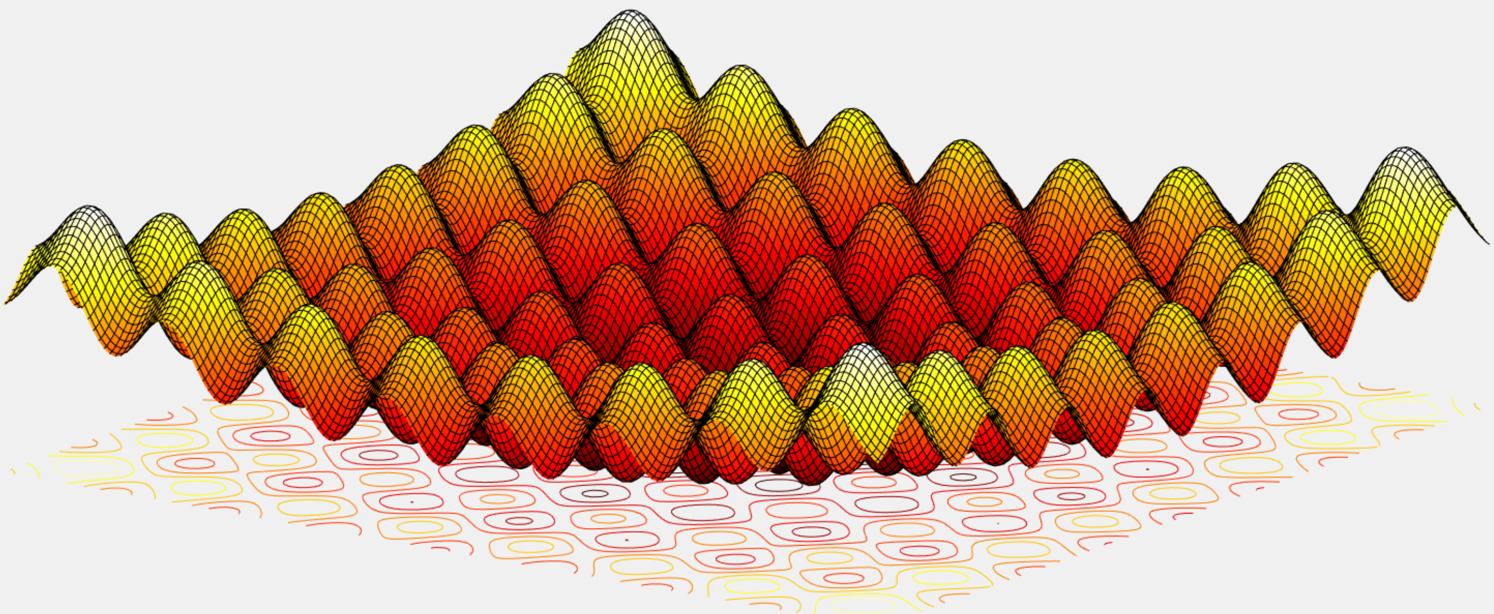
Gradient-based techniques tend to end stacked in **local minima**.



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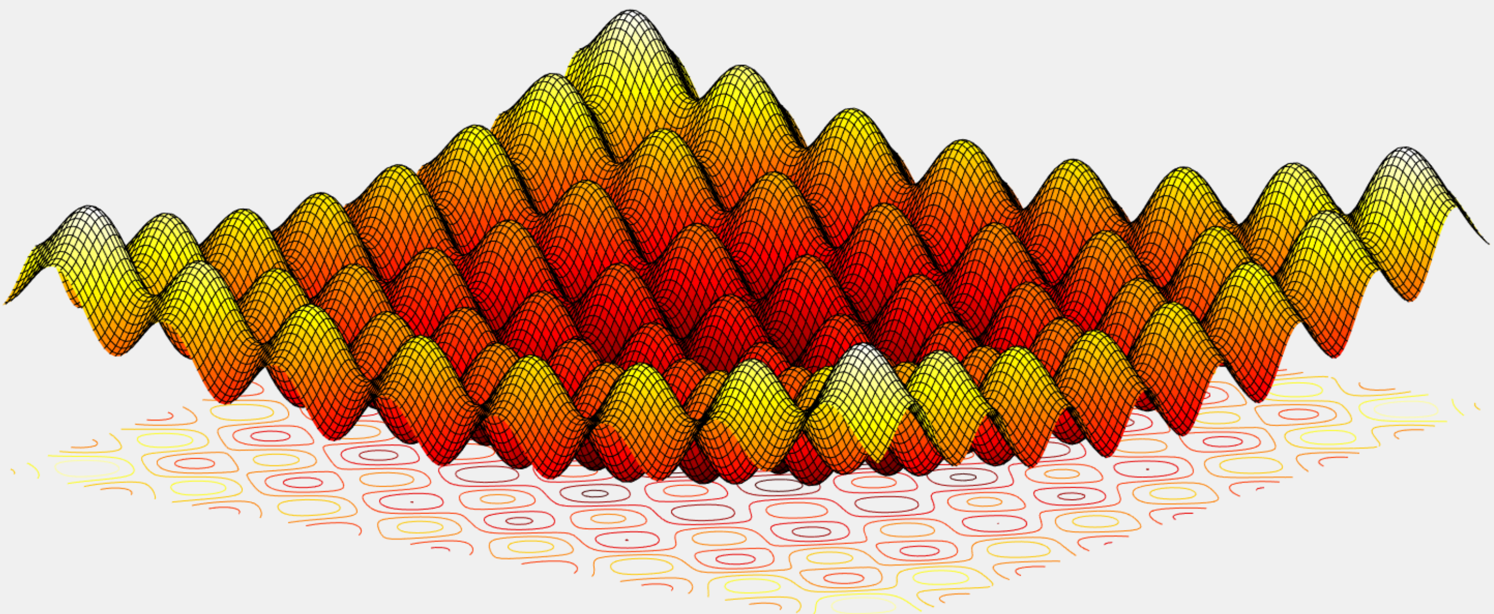

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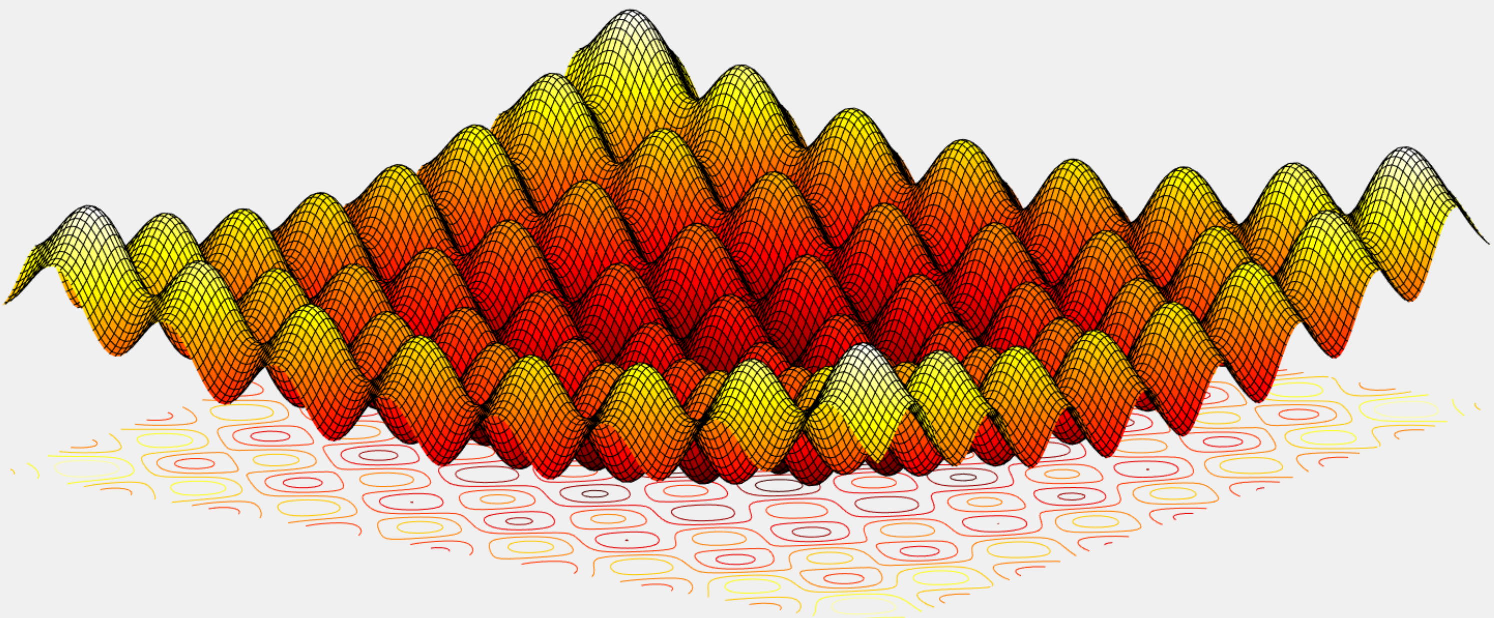
Deep neural networks have highly **non-convex** loss surfaces.
Gradient-based techniques tend to end stacked in **local minima**.
Local minima are solutions highly **sensitive** to noise on training data.
Simplifying data and **progressively adding back complexity** until we return to the original problem is a way to find good starting points.



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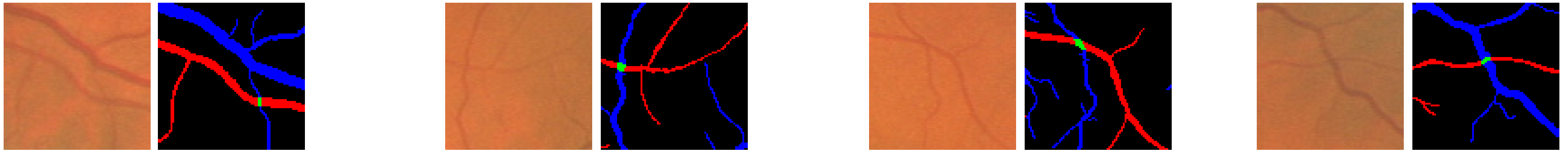

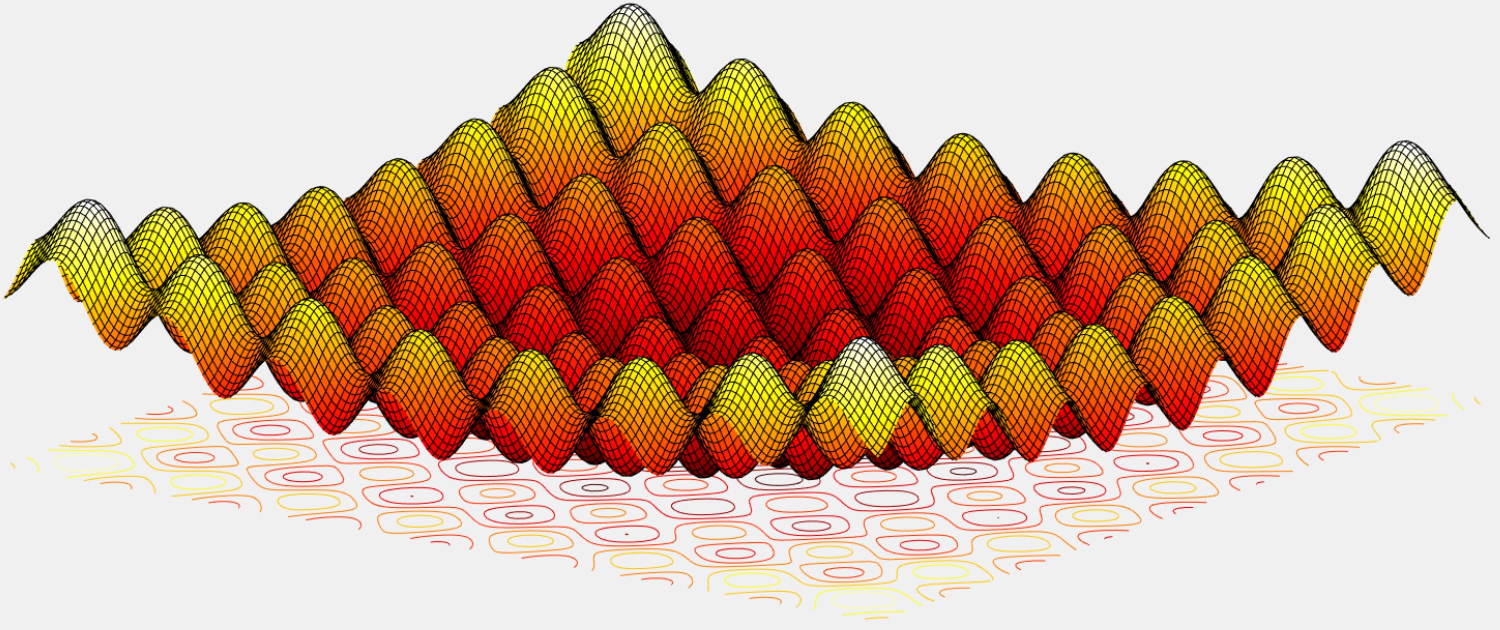

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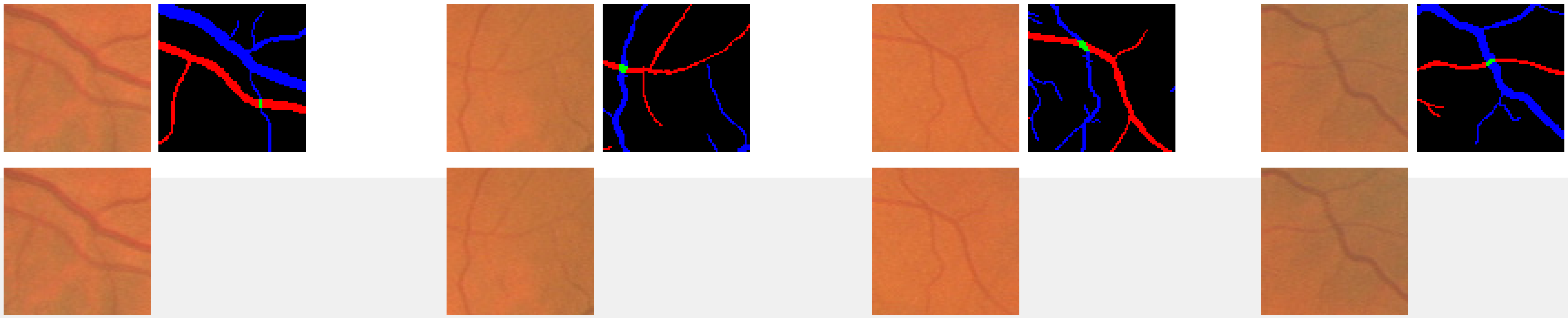

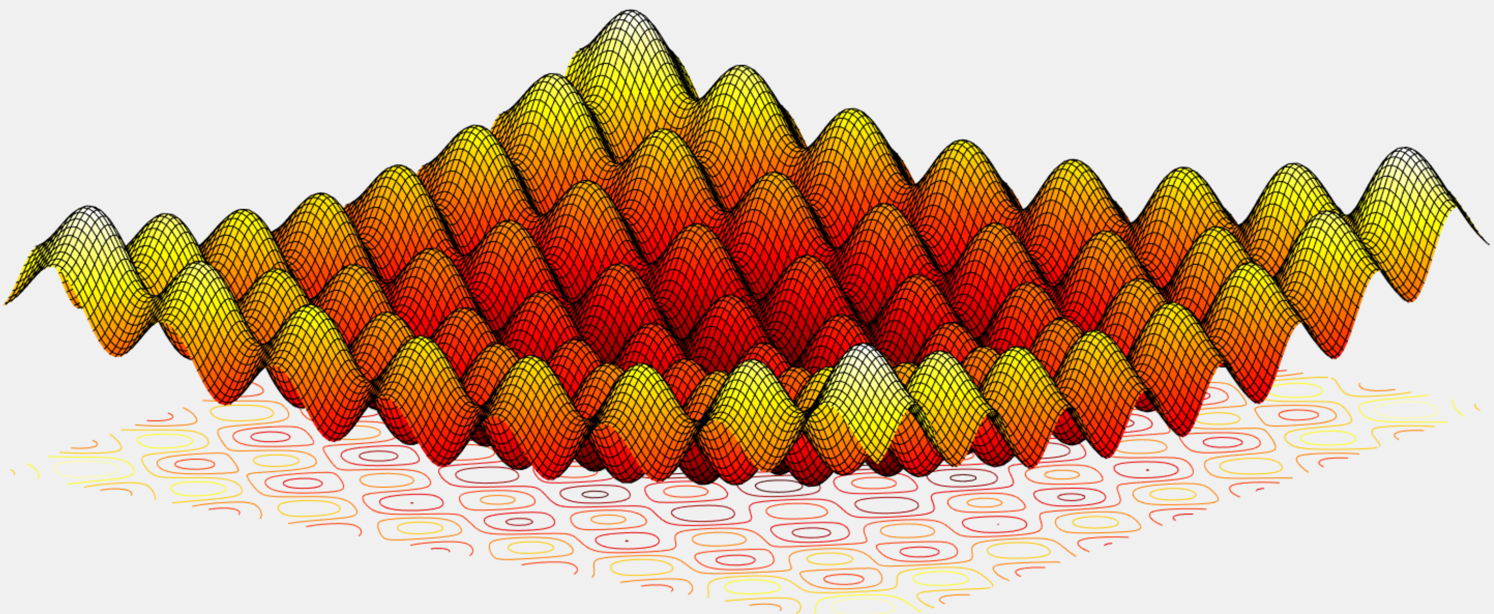

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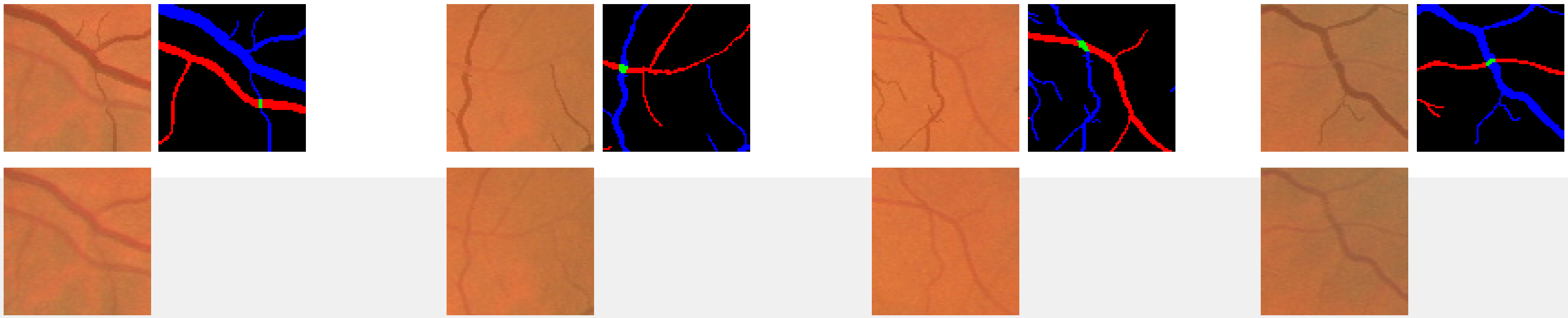

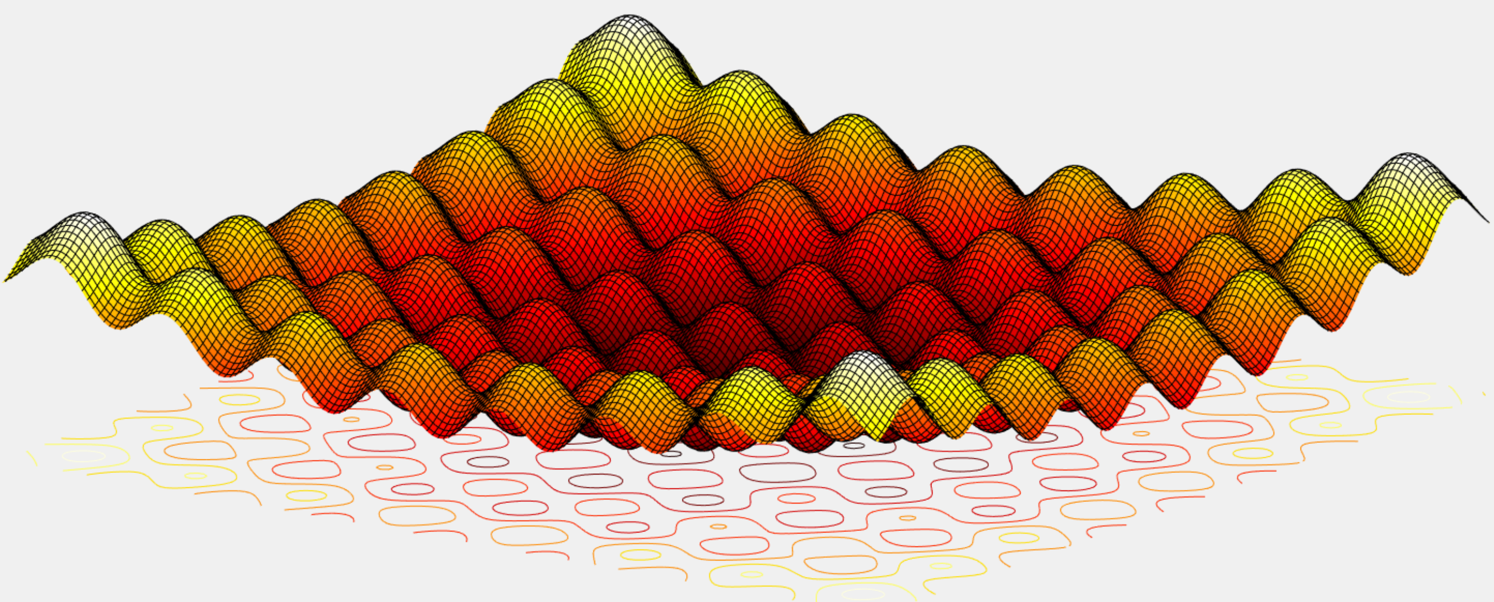

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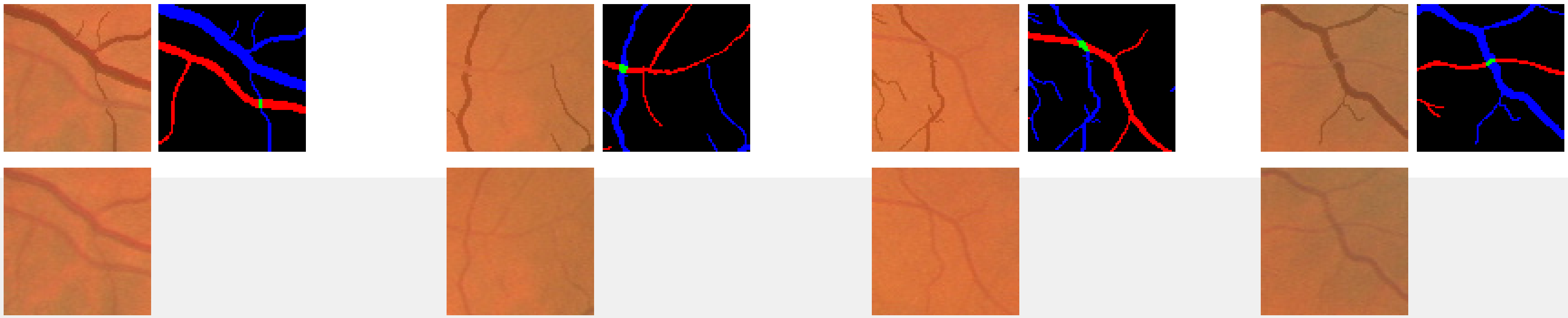
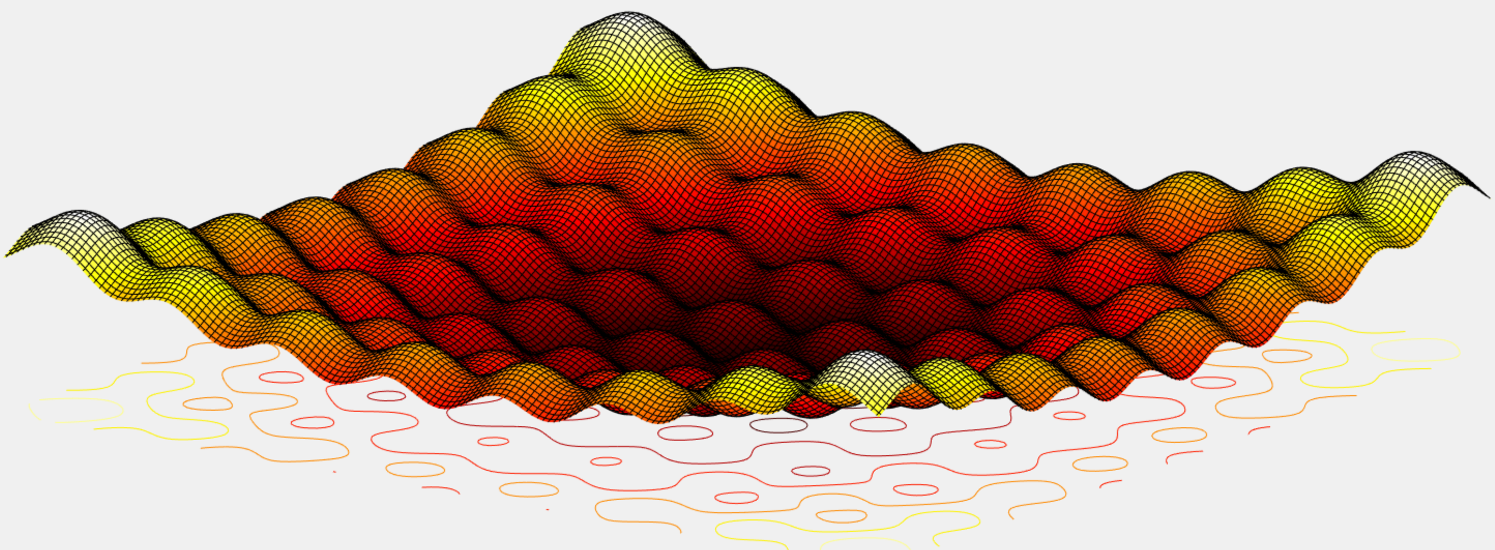
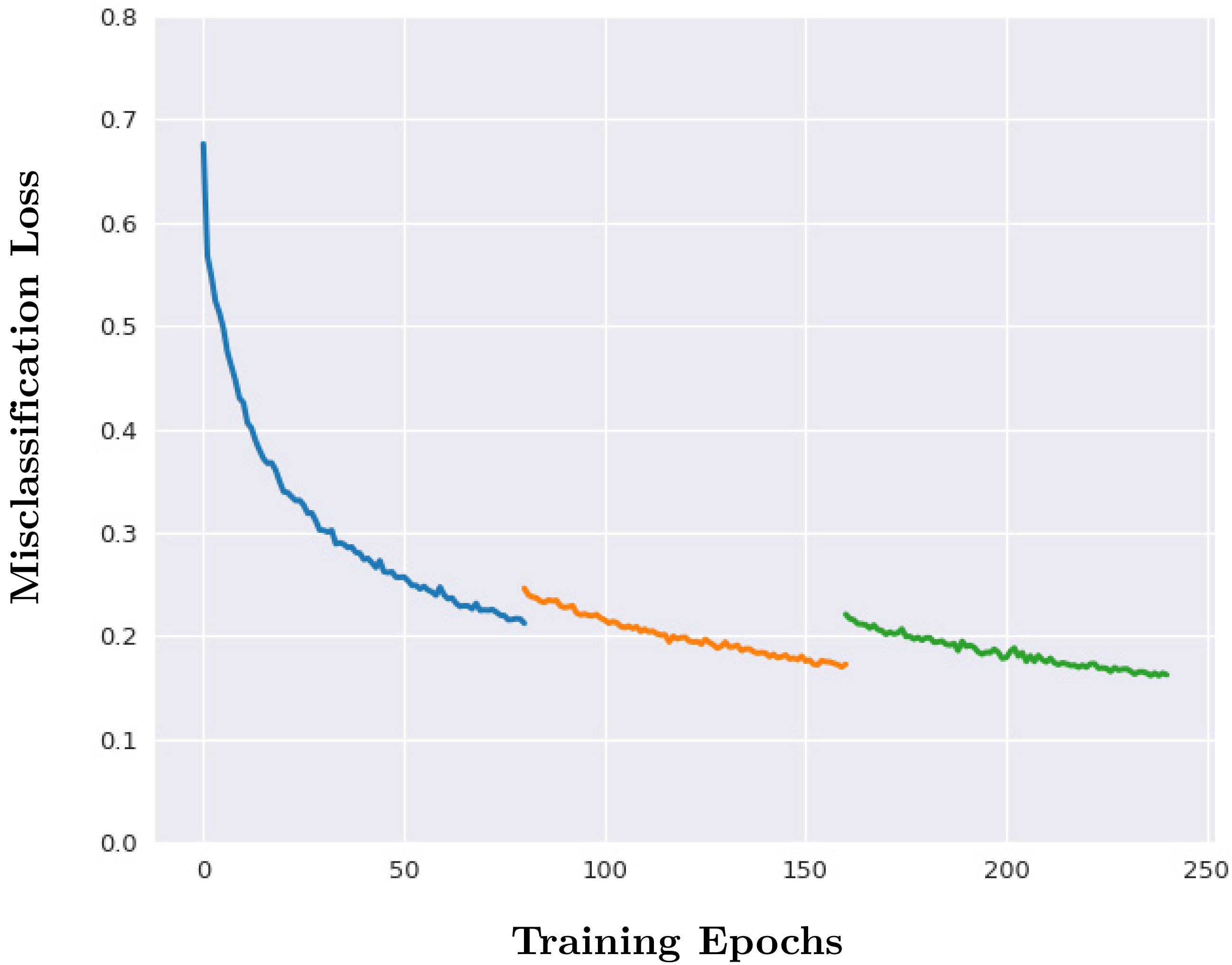


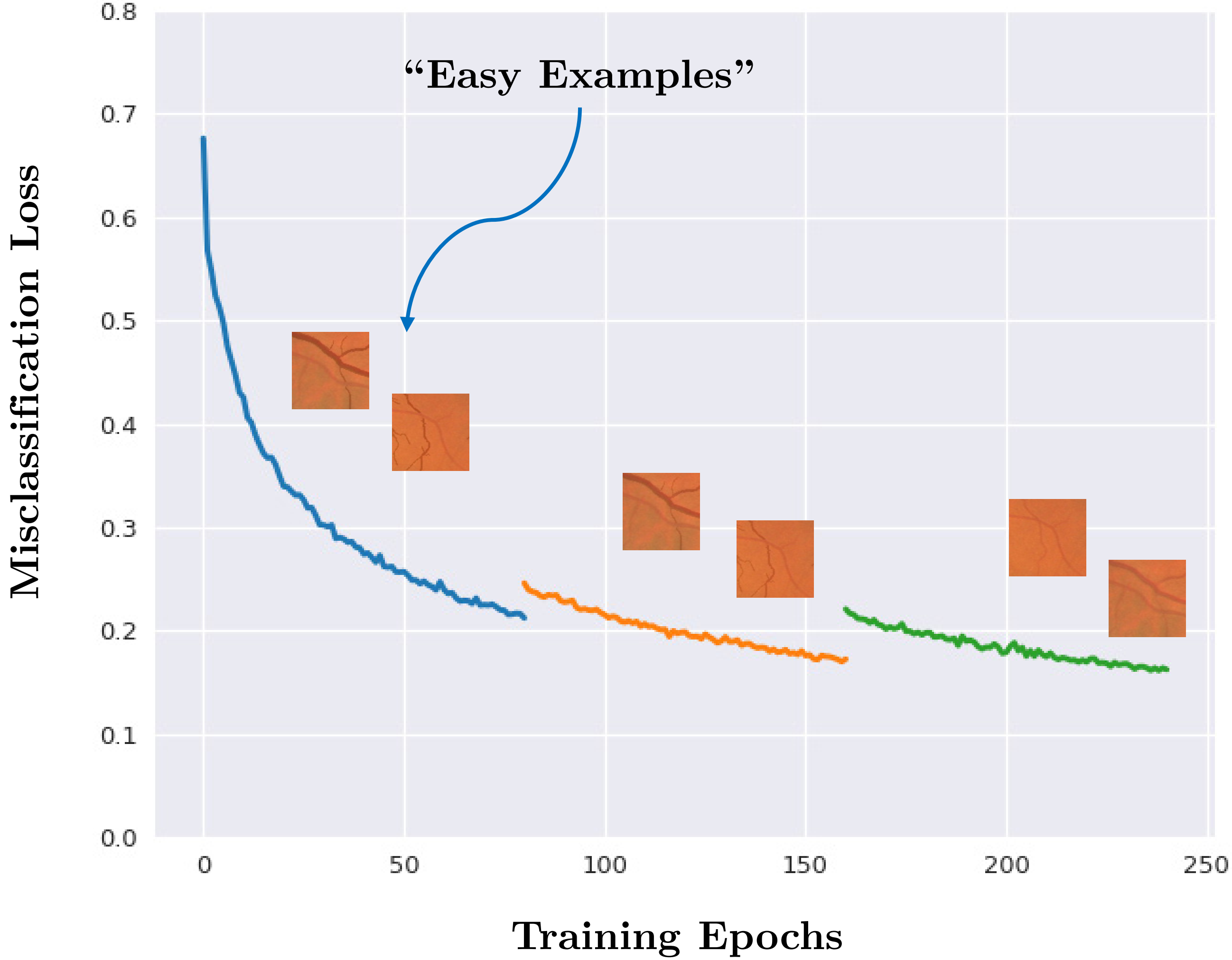


Training Dynamics:



2. Deep NNs for Artery/Vein Classification

Training Dynamics:



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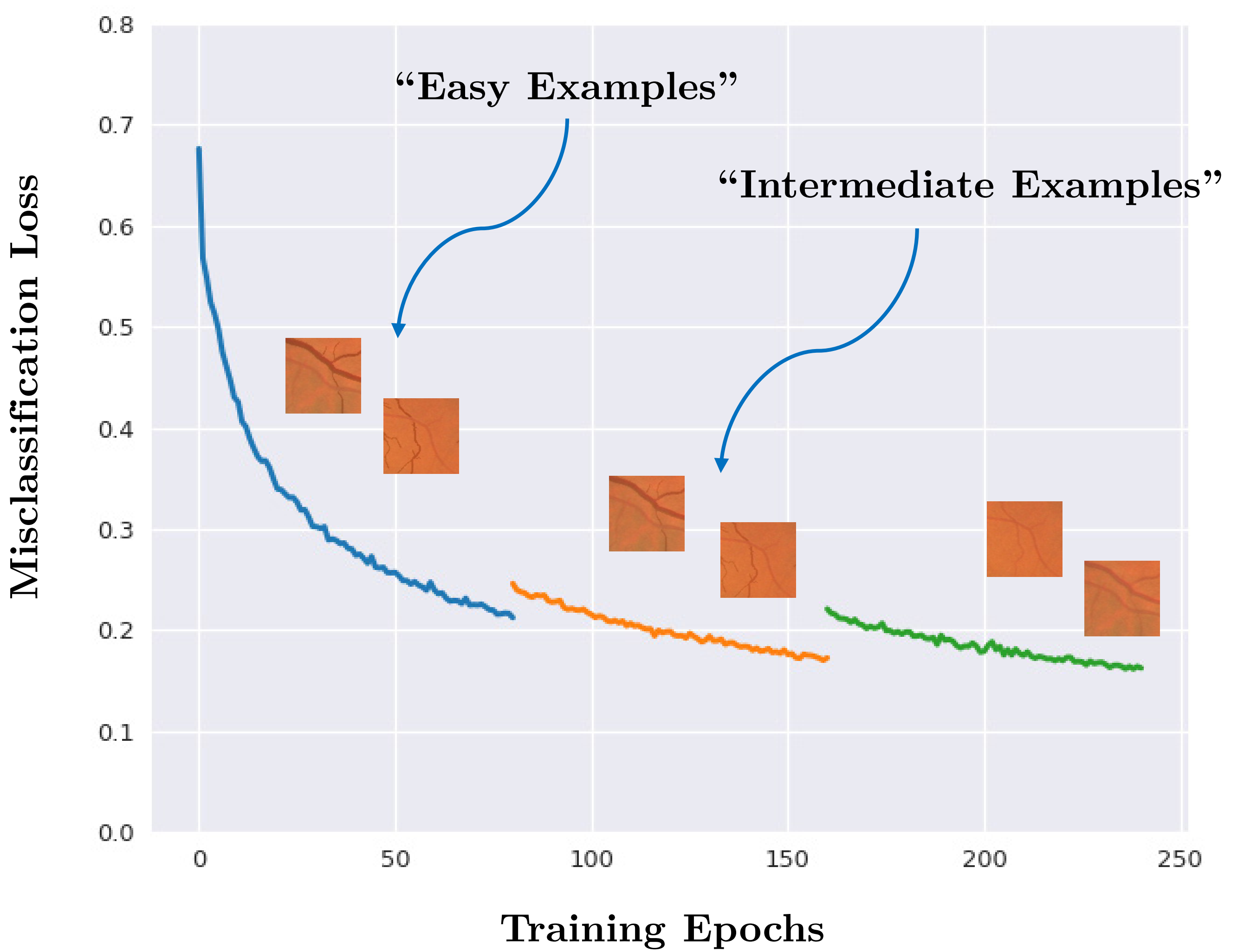

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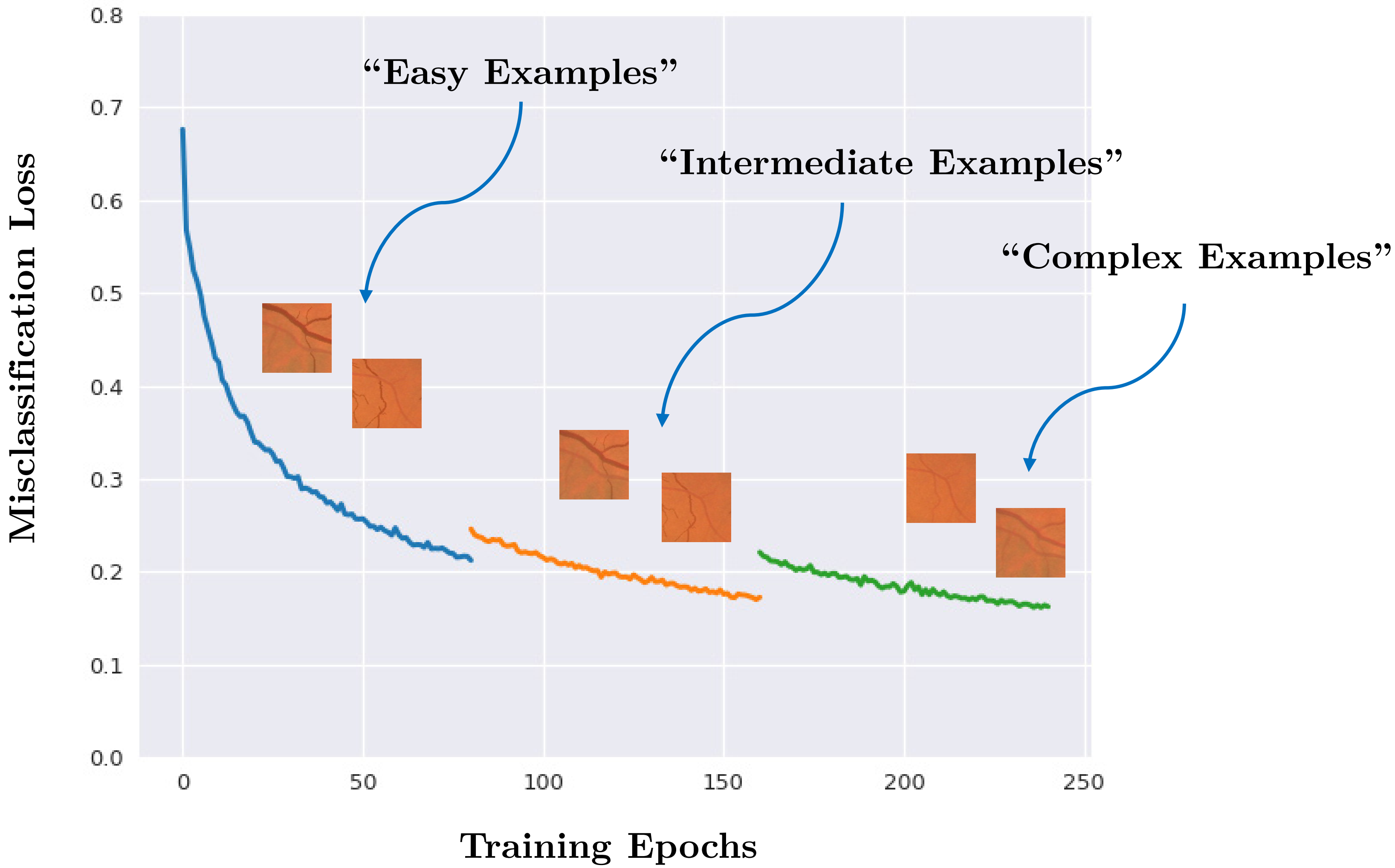
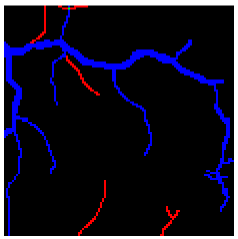
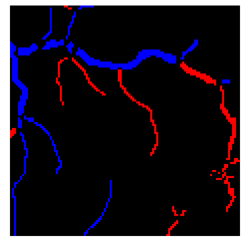
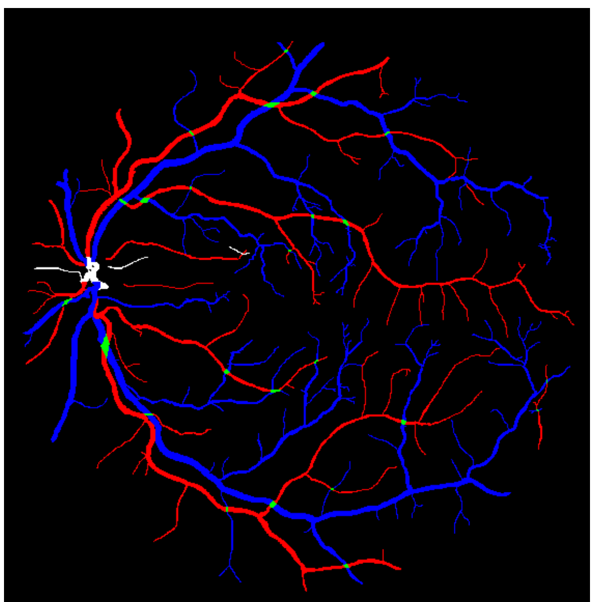


One Last Improvement

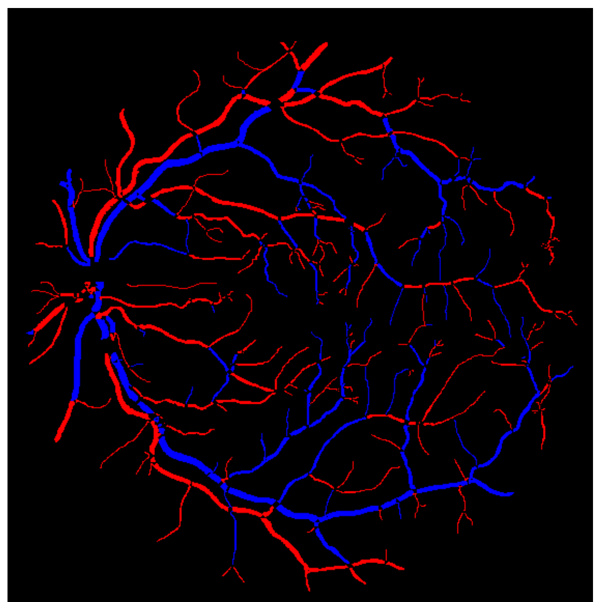
The model seems to be more confident on thick vessels, so we keep only those Predictions and use them as seeds for a 1NN propagation based on location.



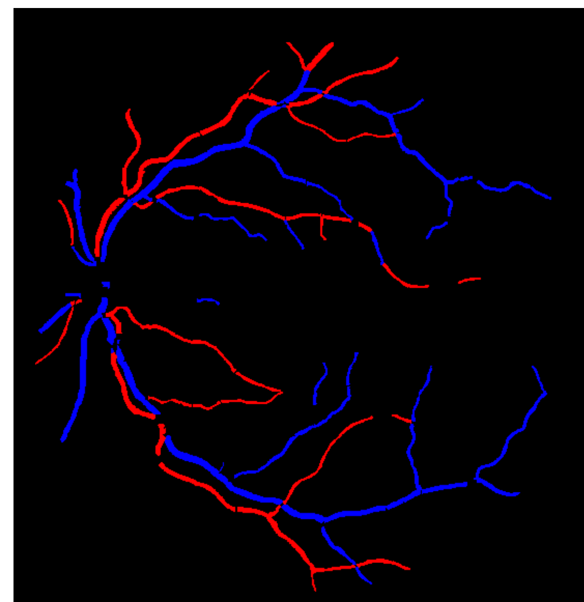




Ground-Truth



Old Result



Thick-Vessel Predictions

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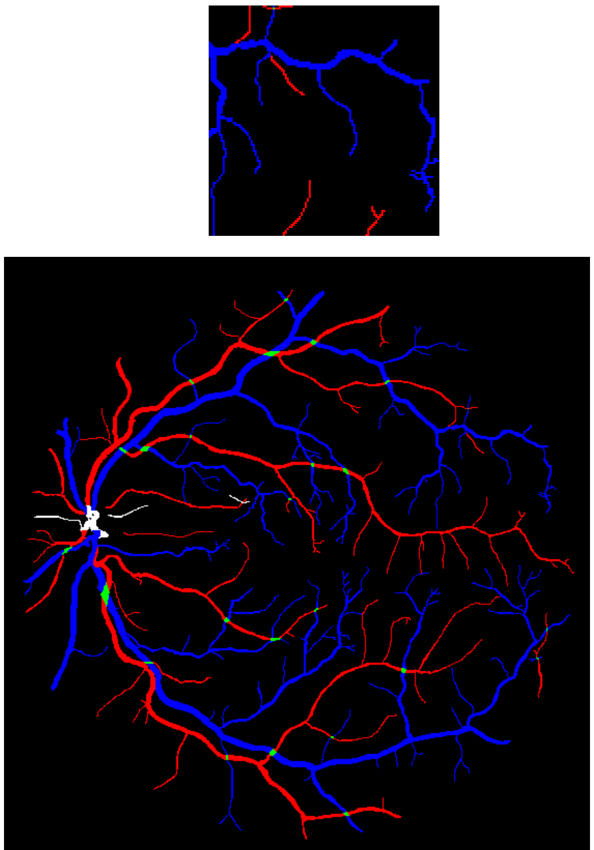
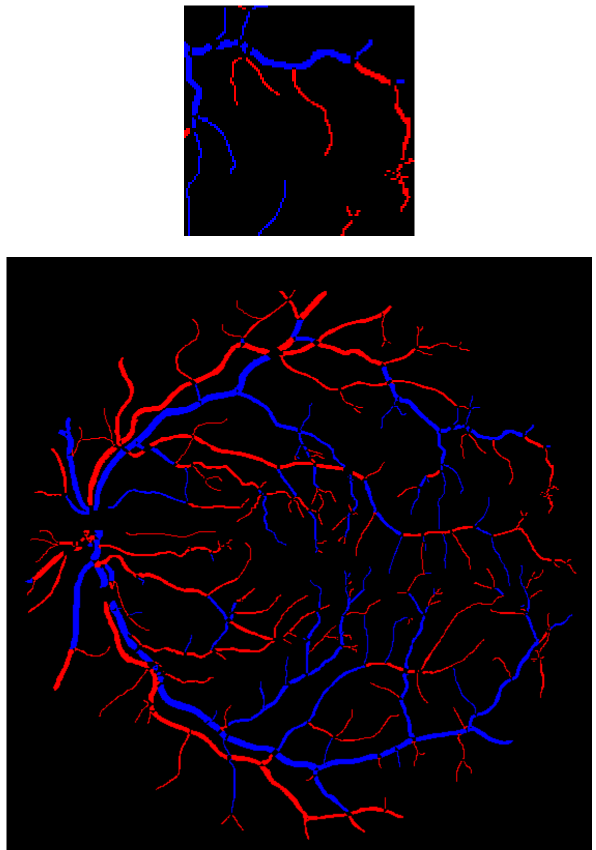
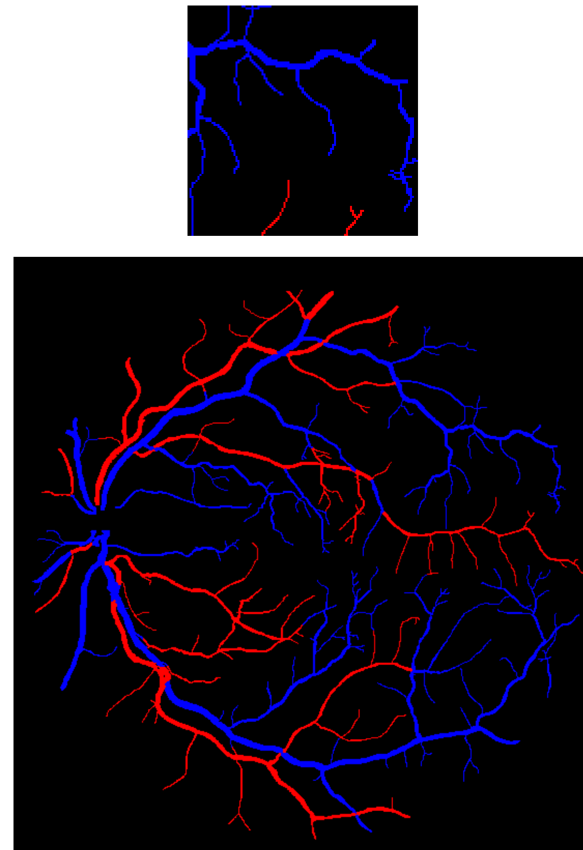


Ground-Truth



Old Result



1NN-Propagation

0. Overview

1. **Introduction**
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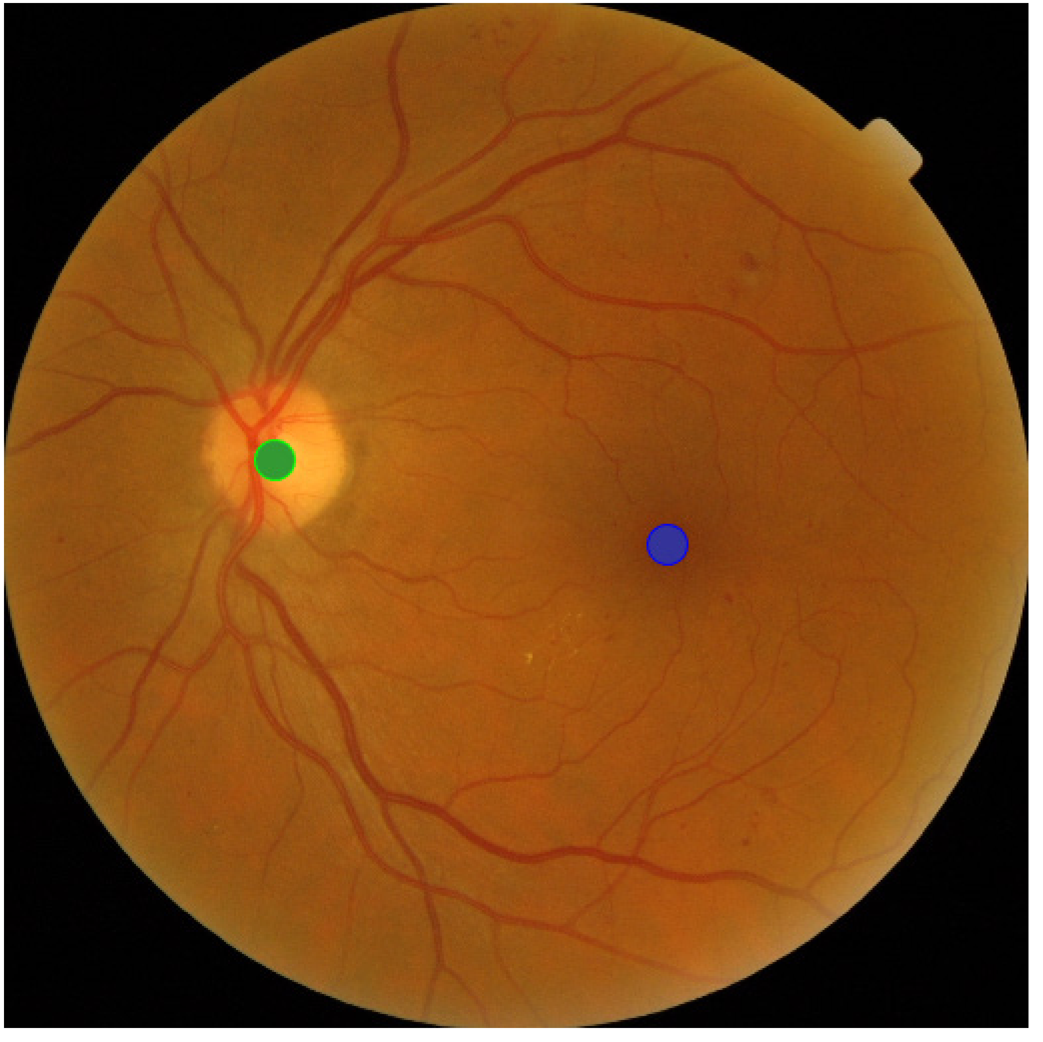
4. Retinal Vessel Map Quality Assessment
5. Conclusions, Q&A

3. Joint OD and Fovea Location

The problem of finding sparse locations:



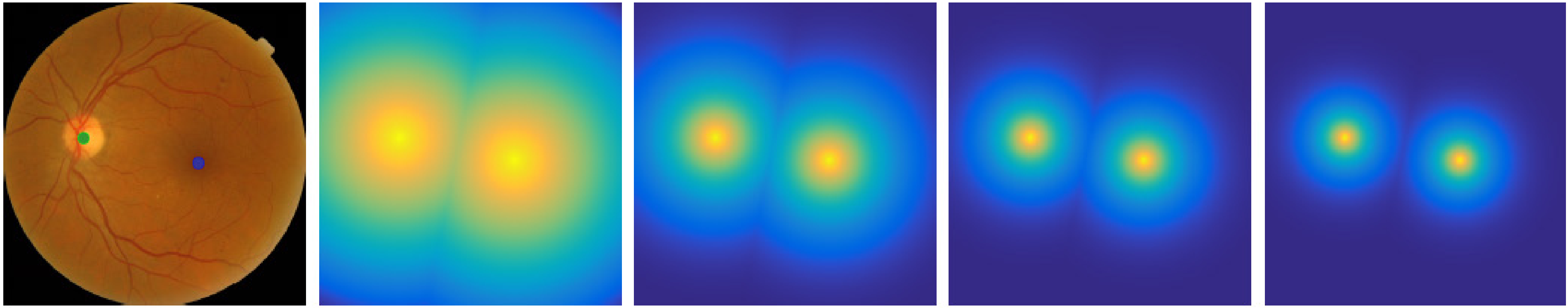
3. Joint OD and Fovea Location

This would be hard to solve with a classification/detection approach

But since we are looking for "**consistently located**" anatomical landarmks, we can turn the problem into a pixel-wise regression task:

$$\mathcal{B}(x,y) = \min\left(\sqrt{(x-x_{od})^2+(y-y_{od})^2}, \sqrt{(x-x_{fov})^2+(y-y_{fov})^2}\right)$$

$$\mathcal{B}^N(x,y) = \left(1 - \frac{\mathcal{B}(x,y)}{\max\limits_{\Omega} \mathcal{B}(x,y)}\right)^{\gamma}$$

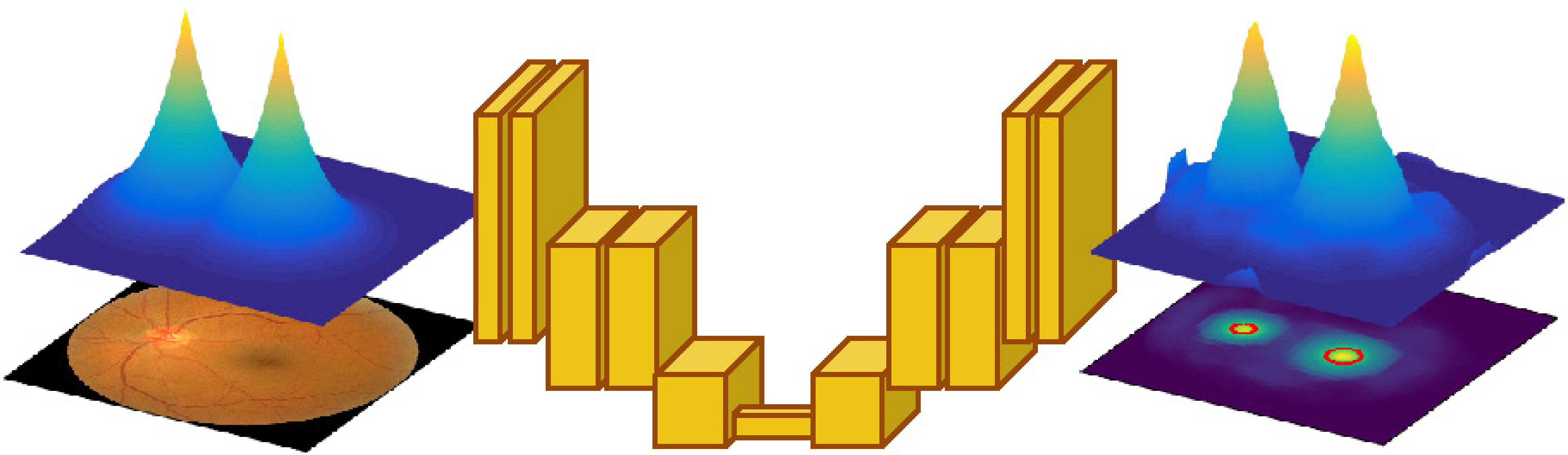


(a) (b) (c) (d) (e)

3. Joint OD and Fovea Location

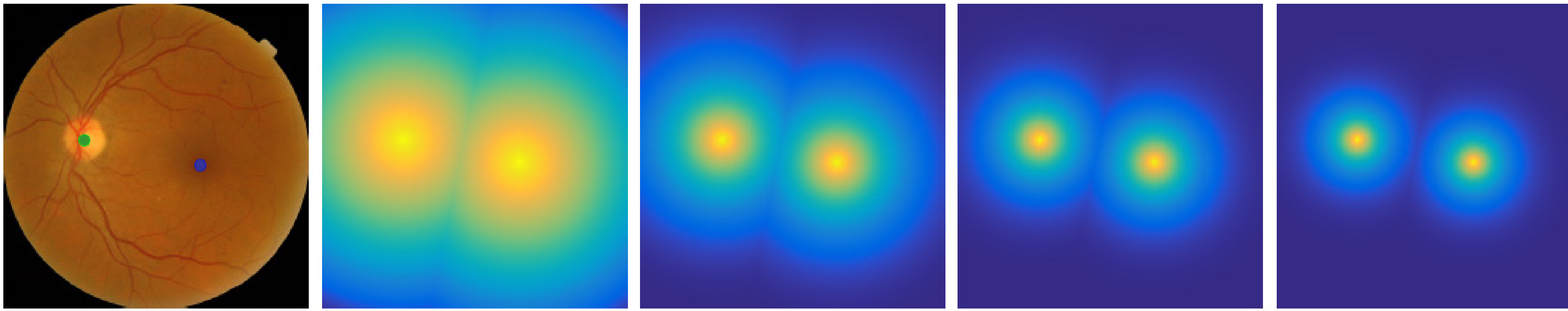
Now, each pixel contributes its bit of information to obtain a globally consistent result:

$$\mathcal{L}_{reg}(\theta) = \frac{1}{M} \sum_{x,y \in \Omega} ||\mathcal{U}_\theta(x,y) - \mathcal{B}^N(x,y)||^2$$



3. Joint OD and Fovea Location

The **optimal decay** is found via cross-validation in a separate dataset



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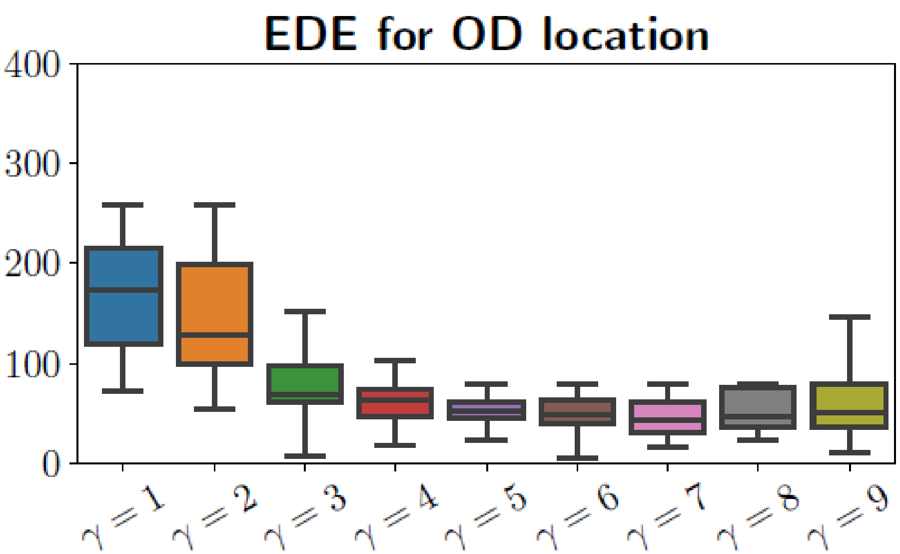

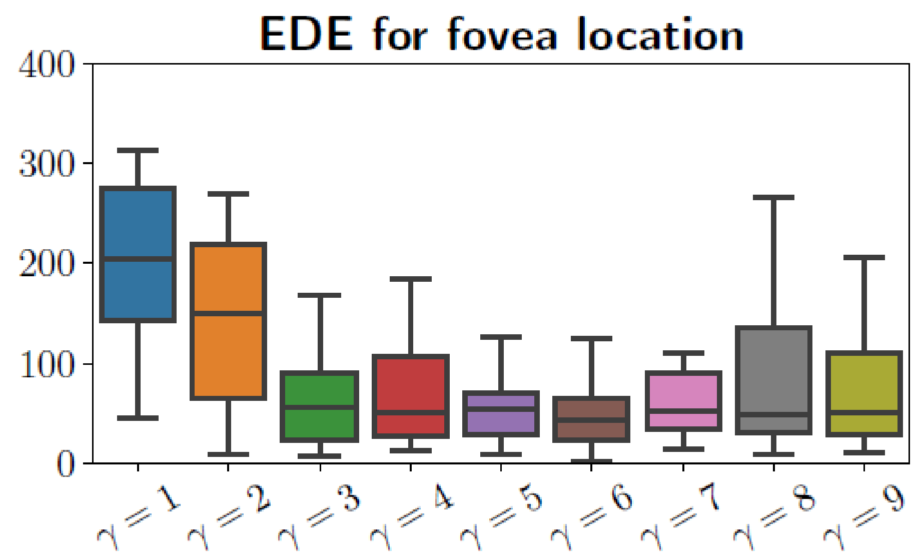

3. Joint OD and Fovea Location

It more or less works well ☺

Table 1. Performance comparison of the proposed model on OD and fovea detection.

Optic Disc Detection	No. Images	1/8R	1/4R	1/2R	1R	$\bar{D}_{FOV}$	$\bar{D}_R$
Al-Bander et al. [2]	1200	–	83.6	95.00	97.00	–	–
Yu et al. [16]	1200	–	–	99.08	98.24	–	–
Marin et al. [9]	1200	87.33	97.75	99.50	99.75	–	7.03
Proposed Approach	1136	68.84	94.01	97.18	98.94	1.17	15.70
Fovea Detection							
Gegundez-Arias et al. [6]	800	82.00	94.25	95.88	96.50	1.41	–
Yu et al. [16]	800	23.63	64.88	94.00	98.00	2.34	–
Niemeijer et al. [10]	800	76.88	93.25	96.00	97.38	1.87	–
Dashtbozorg et al. [3]	1200	–	66.50	93.75	98.87	–	–
Al-Bander et al. [2]	1200	–	66.80	91.40	96.60	–	–
Proposed Approach	1136	68.66	93.13	**96.65**	**99.30**	1.08	14.50
Human observer [6]	800	94.38	98.50	99.88	99.88	0.52	–

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4. Retinal Vessel Map Quality Assessment

Motivation for Predicting Vessel Maps Quality:

We can train a model to segment vessels, and val/test accuracy will be fine.

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We can train a model to segment vessels, and val/test accuracy will be fine.

However, when deploying our model, we are clueless about how it does.

The idea came to me from this paper:

IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 36, NO. 8, AUGUST 2017 1597

Reverse Classification Accuracy: Predicting Segmentation Performance in the Absence of Ground Truth

Vanya V. Valindria,* Ioannis Lavdas, Wenjia Bai, Konstantinos Kamnitsas, Eric O. Aboagye, Andrea G. Rockall, Daniel Rueckert, and Ben Glocker

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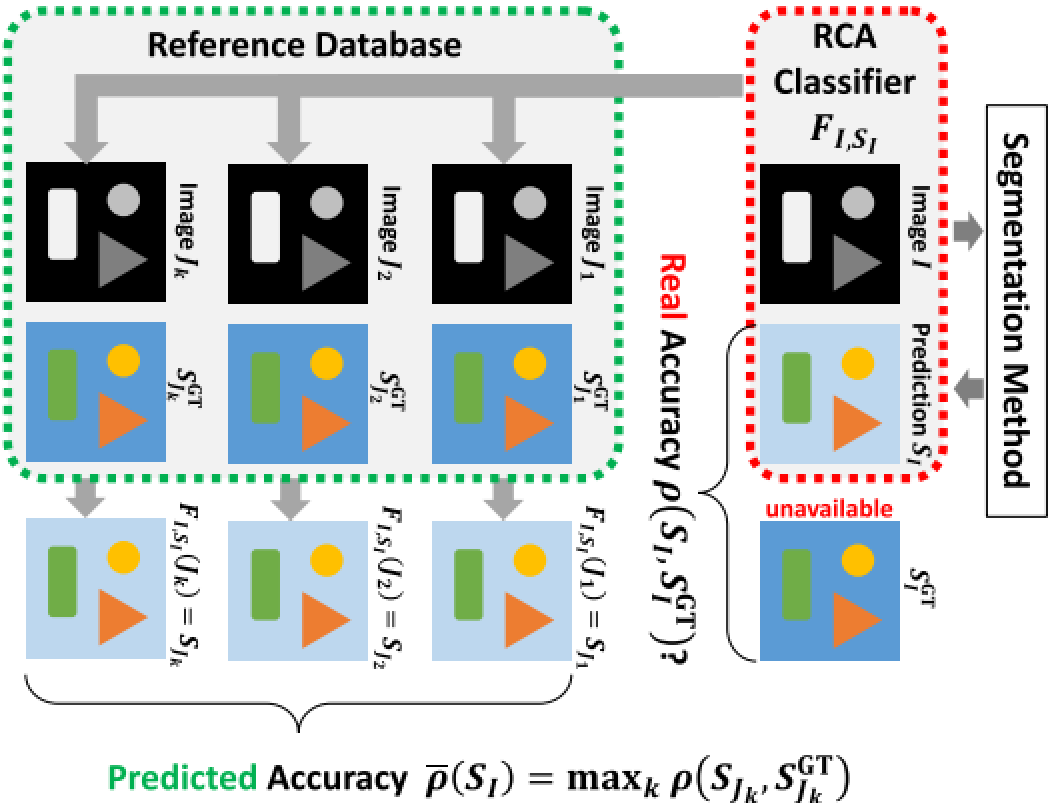

Fig. 1. Overview of the general framework for reverse classification accuracy. The accuracy of the predicted segmentation S_I of a new image I is estimated via a RCA classifier trained using S_I as pseudo ground truth, and applied to a set of reference images J_k for which ground truth reference segmentations $S_{J_k}^{GT}$ are available. The best segmentation score computed on the reference images is used as prediction of the real accuracy of segmentation S_I.

4. Retinal Vessel Map Quality Assessment

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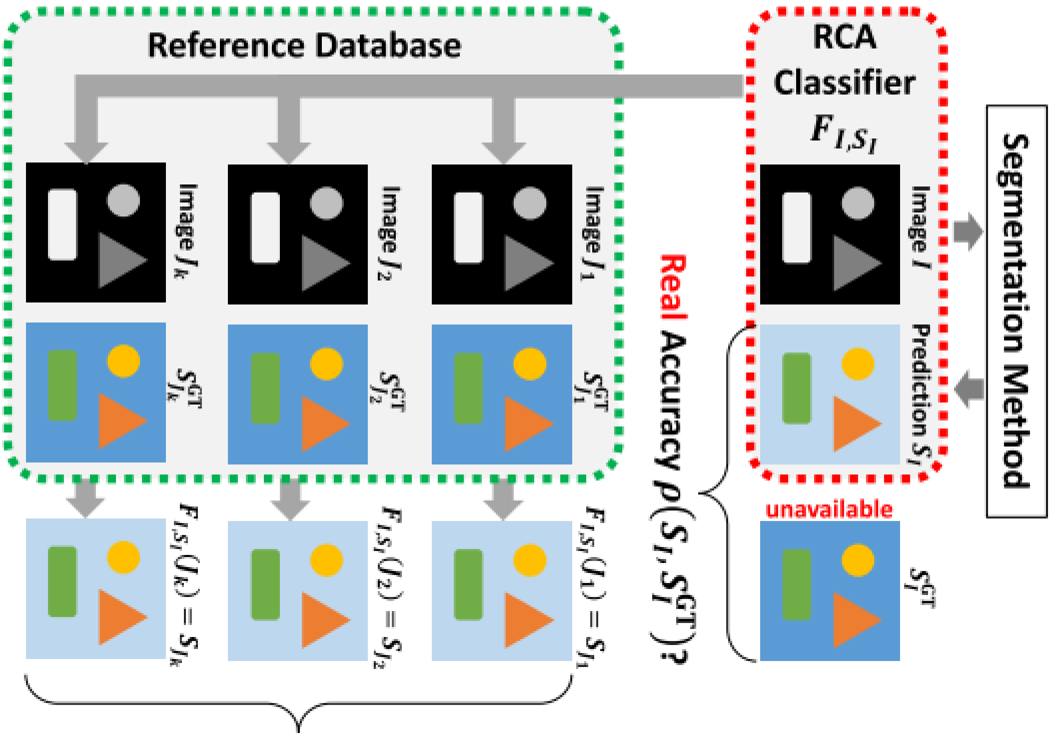

Predicted Accuracy $\bar{\rho}(S_I) = \max_k \rho(S_{J_k}, S_{J_k}^{GT})$

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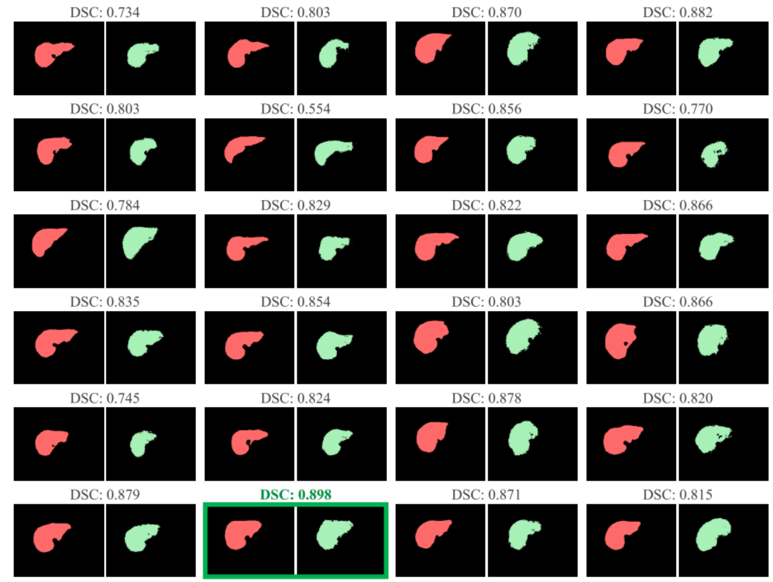

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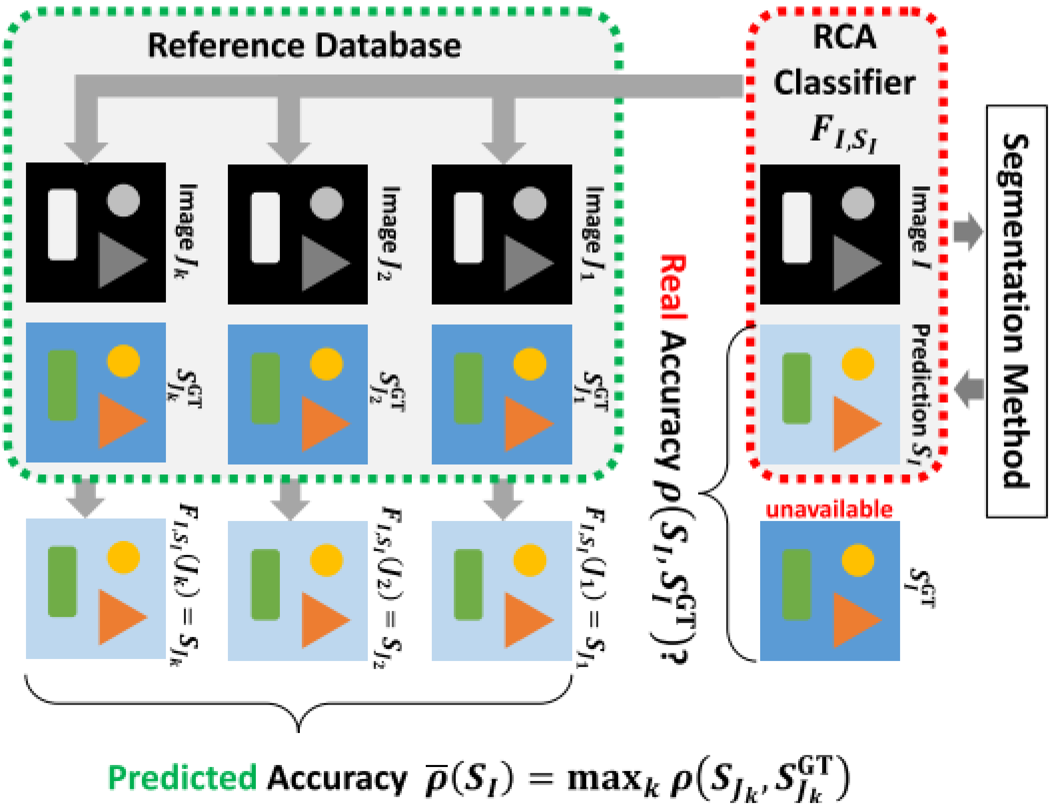

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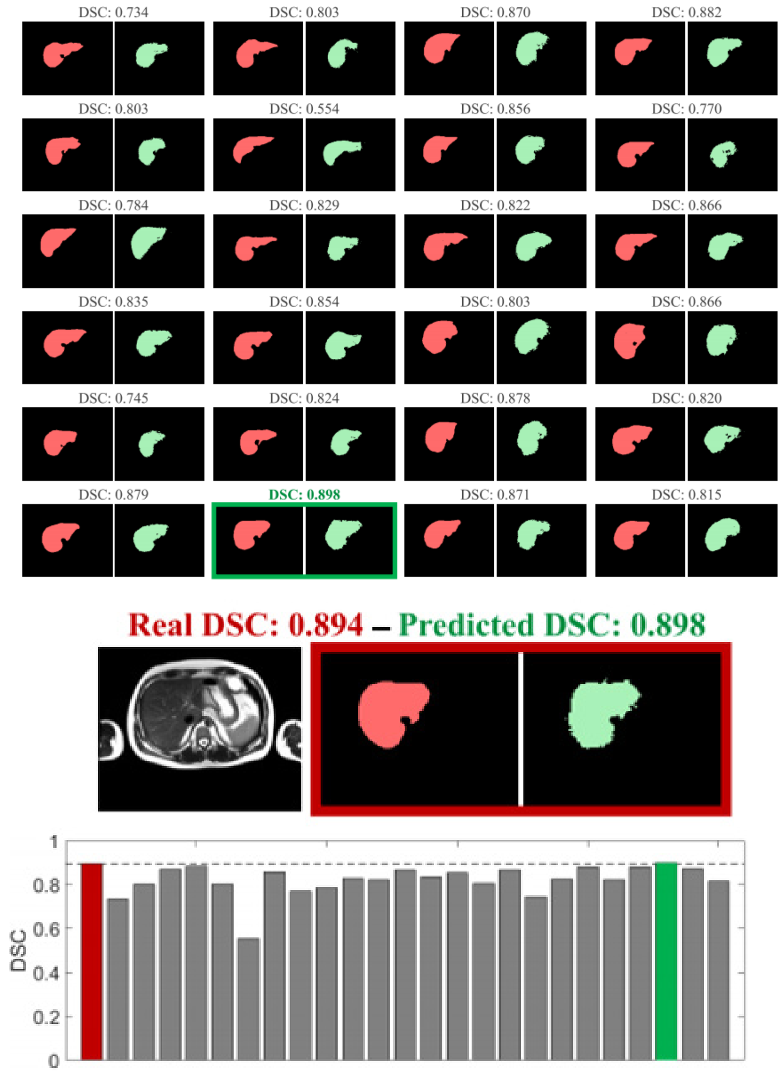
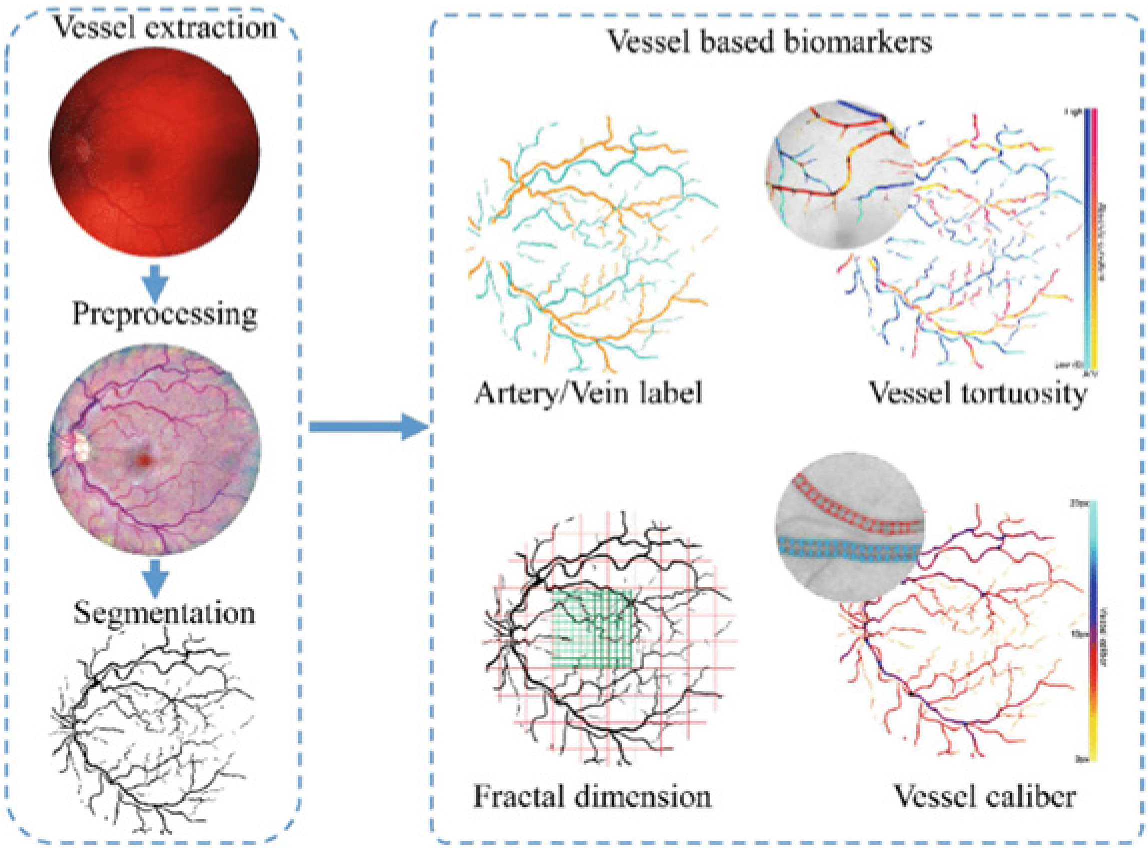


Motivation for Predicting Vessel Maps Quality:

In the case of retinal vessel trees, there is also lots of biomarkers that are **highly sensitive** to noisy under/over segmentations:



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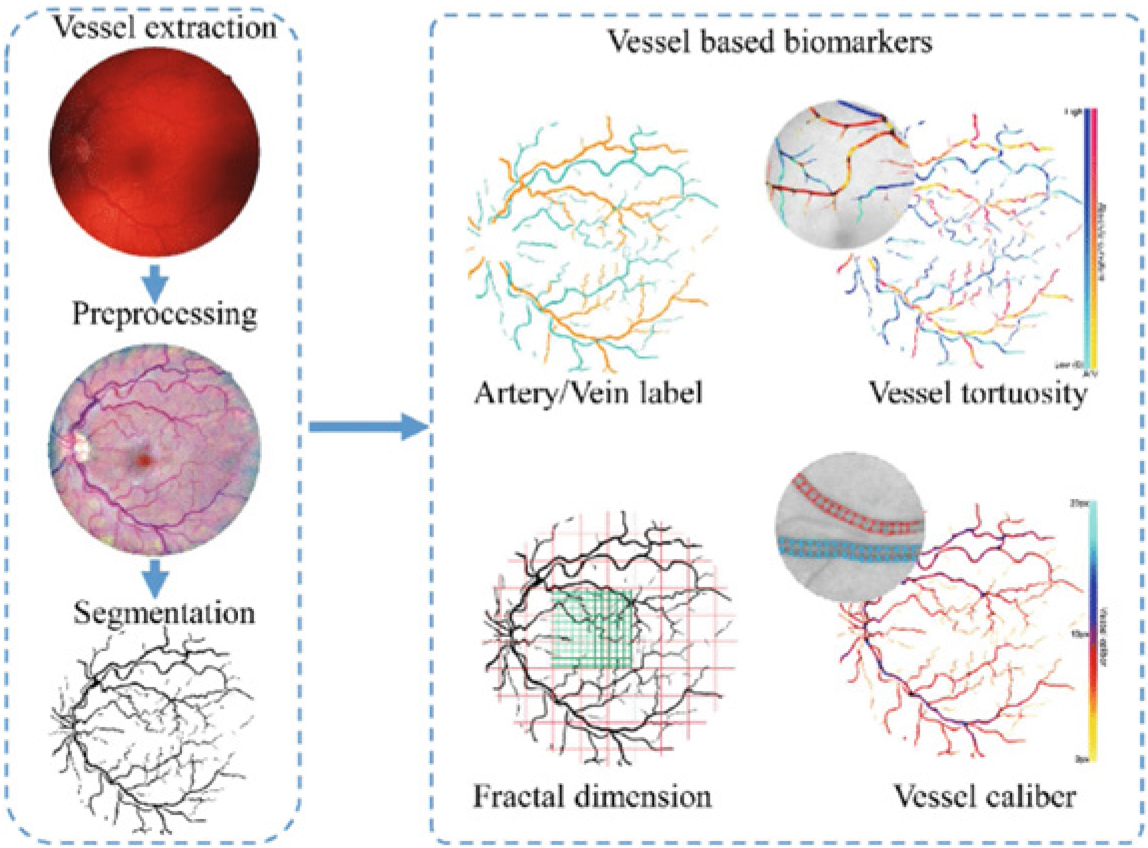
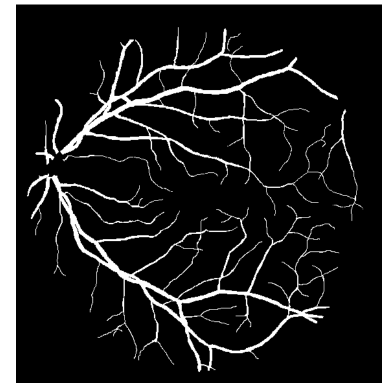
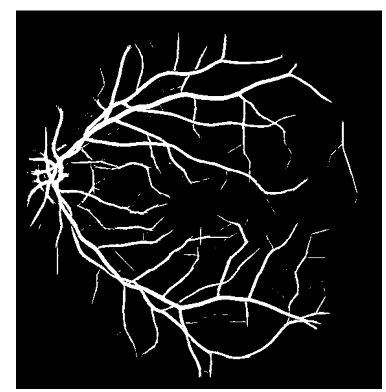




Manual



Automatic

A Simple Solution:

Given a manual (expert) vessel segmentation, we can generate realistic versions of it that resemble bad segmentations coming from our models.

A Simple Solution:

In addition, there is a straightforward way of measuring their quality: Simply compare degraded map against the manual vessel tree.

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$$\mathbf{MI}(\mathbf{v_1}, \mathbf{v_2}) = \sum_{\mathbf{x} \in \mathbf{v_1}} \sum_{\mathbf{y} \in \mathbf{v_2}} \mathbf{p}(\mathbf{x}, \mathbf{y}) \log \left(\frac{\mathbf{p}(\mathbf{x}, \mathbf{y})}{\mathbf{p}(\mathbf{x})\mathbf{p}(\mathbf{y})} \right)$$

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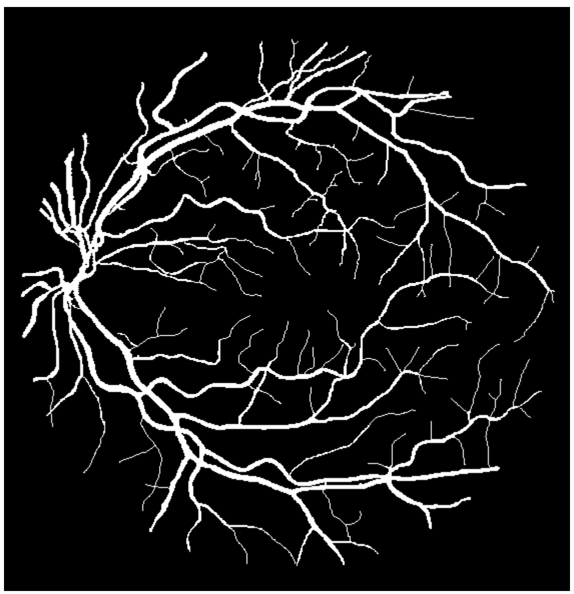
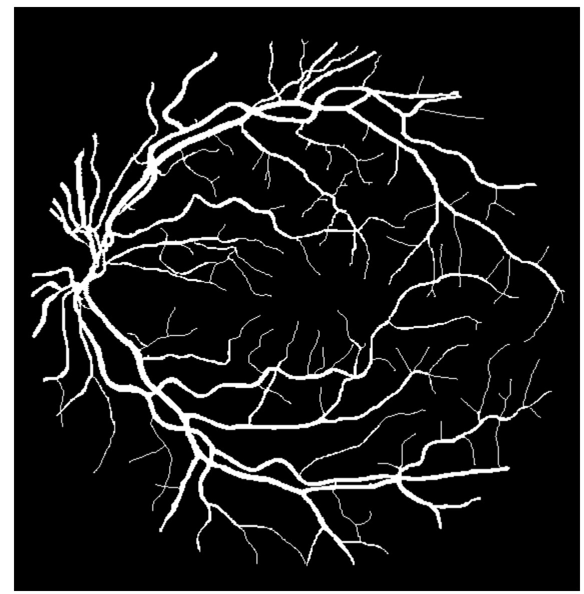


Do Nothing

$\mathbf{MI}(\mathbf{v_1}, \mathbf{v_2}) = \mathbf{1}$



4. Retinal Vessel Map Quality Assessment

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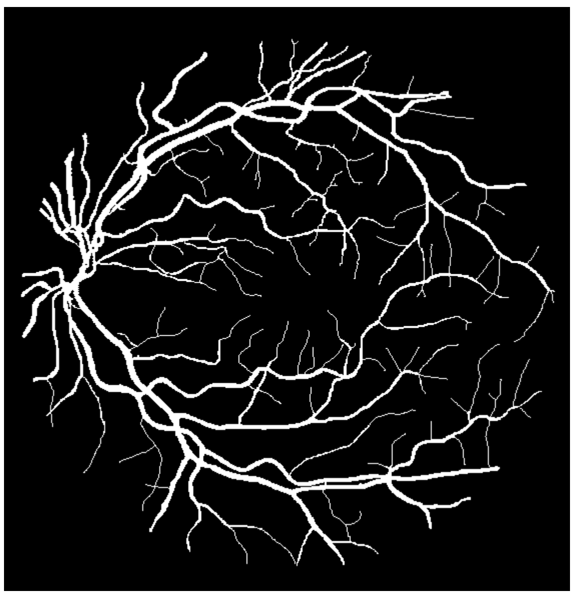
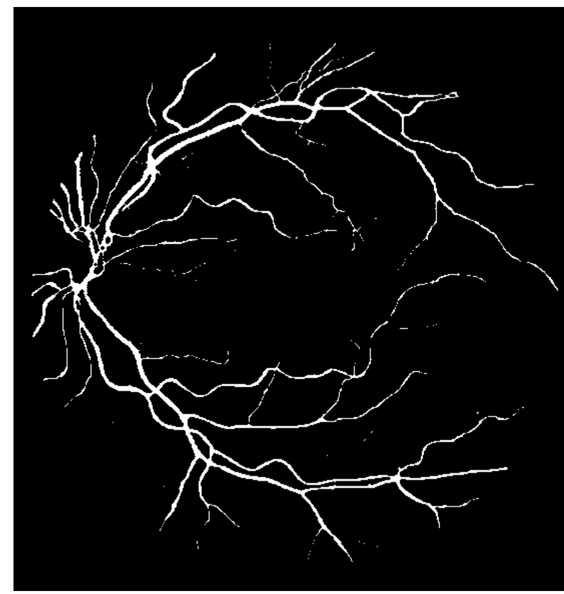


Disk(1) - erosion

$\mathbf{MI}(\mathbf{v_1}, \mathbf{v_2}) = \mathbf{0.493}$



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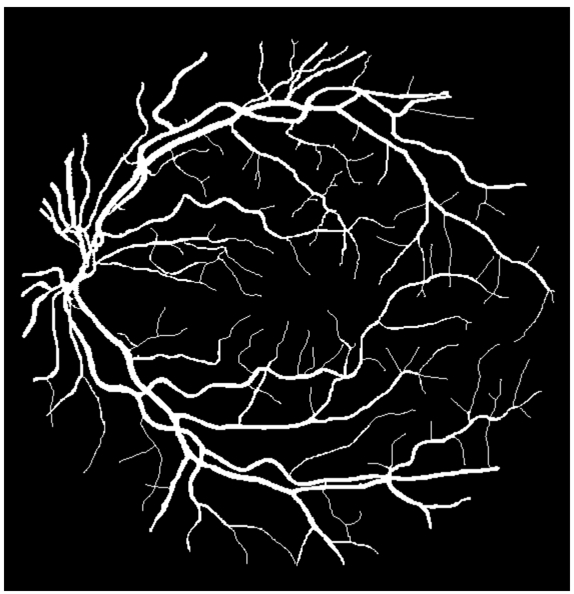
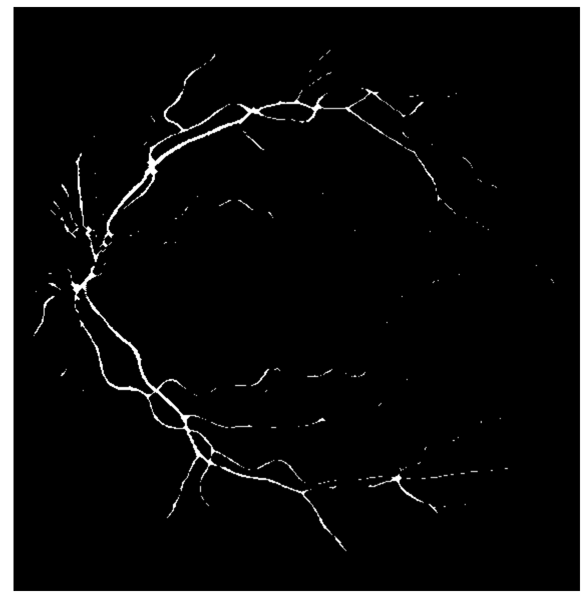


Disk(2) - erosion

$\mathbf{MI}(\mathbf{v_1}, \mathbf{v_2}) = \mathbf{0.194}$



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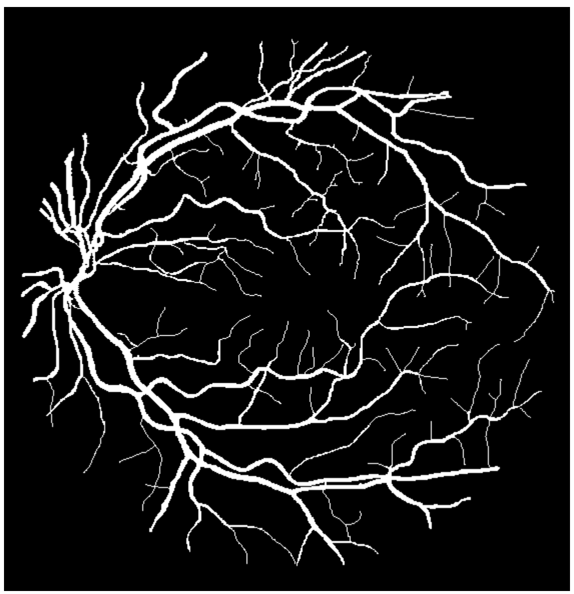
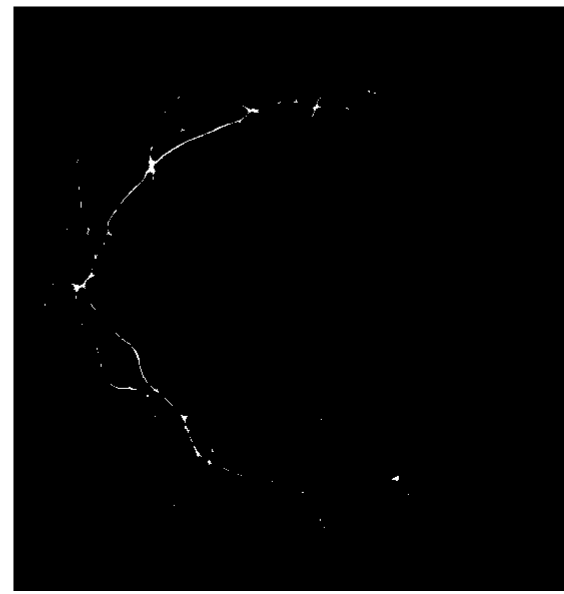


Disk(3) - erosion

$\mathbf{MI}(\mathbf{v_1}, \mathbf{v_2}) = \mathbf{0.035}$



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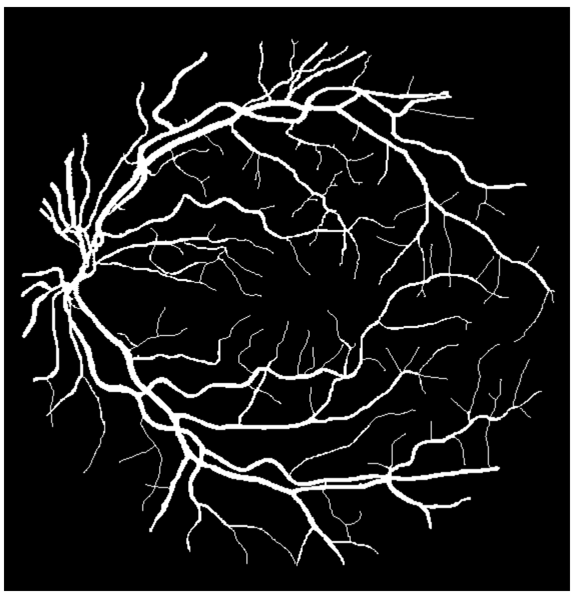
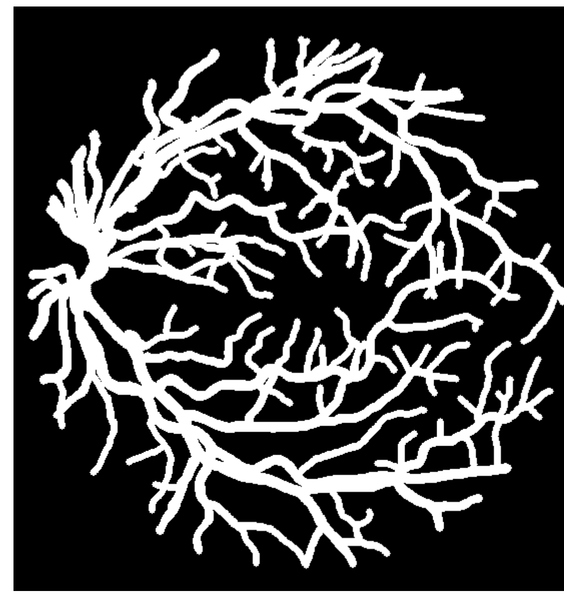


Disk(3) - dilation

$\mathbf{MI}(\mathbf{v_1}, \mathbf{v_2}) = \mathbf{0.315}$



4. Retinal Vessel Map Quality Assessment

The Data:

$$\mathbf{deg}(v) = \begin{cases} v, & \text{for } 0 \leq p < \frac{1}{5} \\ \mathcal{N}, & \text{for } \frac{1}{5} \leq p < \frac{2}{5} \\ \mathcal{M}(v), & \text{for } \frac{2}{5} \leq p \leq 1, \end{cases}$$

where $p \sim \mathcal{U}(0, 1)$, $\mathcal{N} \equiv$ impulse noise, and $\mathcal{M}$ is a stochastic morphological operator that performs a random number of local degradations.

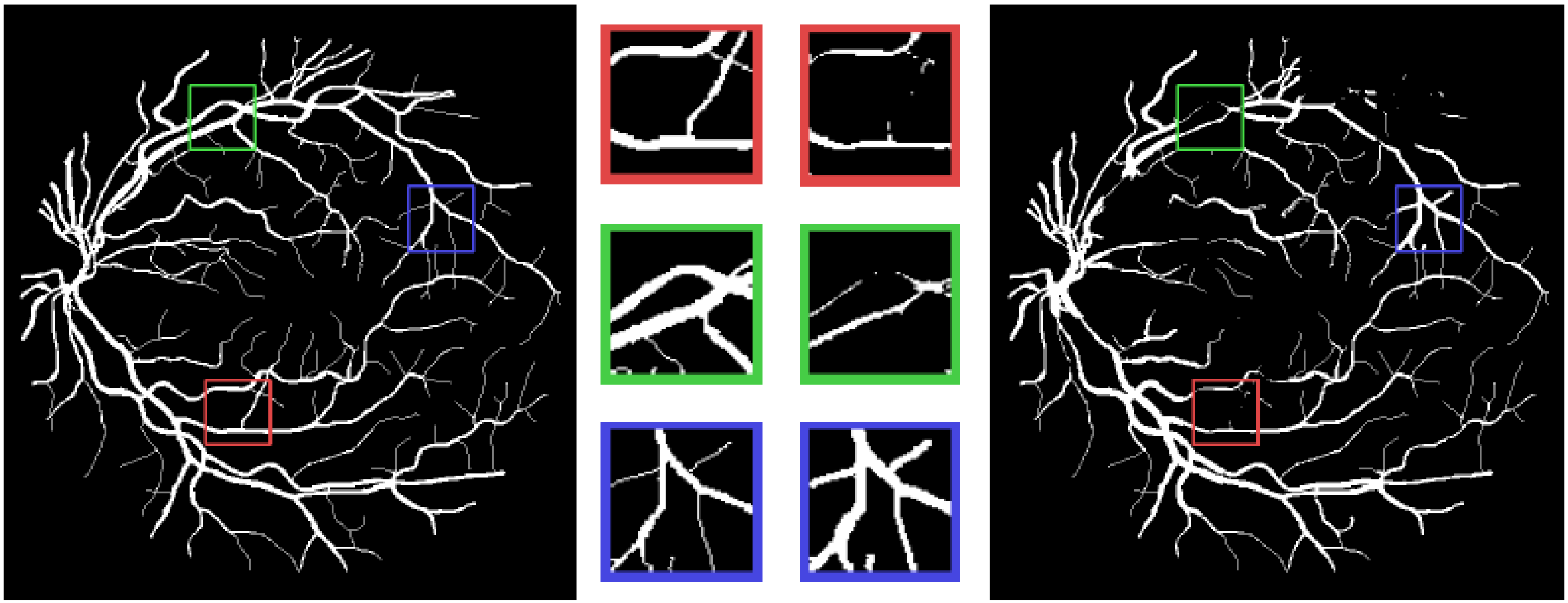
$$\mathcal{M}(\bar{v}) = \begin{cases} \mathcal{E}_s(\bar{v}), & \text{for } 0 \leq p < \frac{1}{2} \\ \mathcal{D}_s(\bar{v}), & \text{for } \frac{1}{2} < p \leq 1 \end{cases}$$

where $\mathcal{E}_s$ and $\mathcal{D}_s$ are morphological erosion and dilation operators, specified by a square structuring element s of a size of 3, 5, or 7 at each step.

The structuring element is itself randomly built according to a Bernoulli distribution with $p = 0.5$ at each pixel position. Once $\bar{v}$ has been artificially degraded, it is stored back at its original location in v.

4. Retinal Vessel Map Quality Assessment

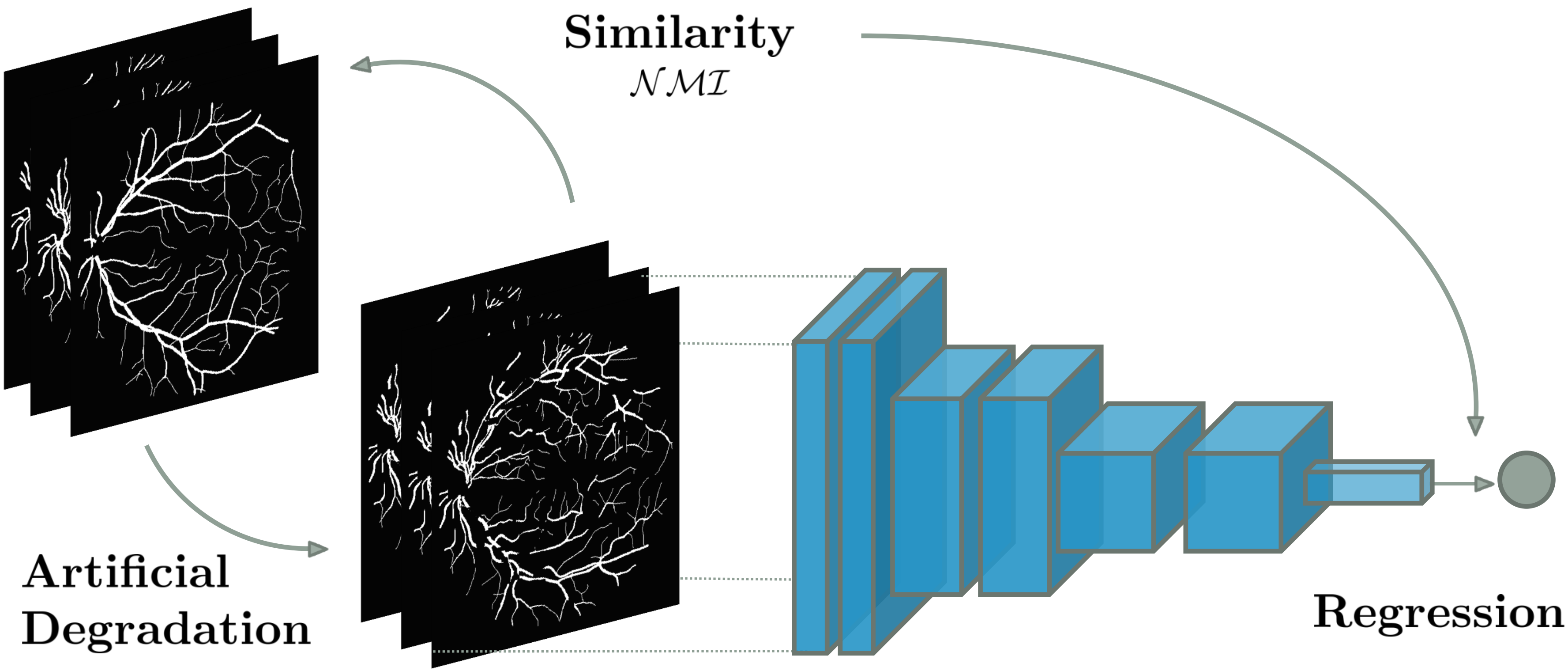
The Data:



Manual vessel tree delineations can be obtained from whichever dataset meant to train vessel segmentation models

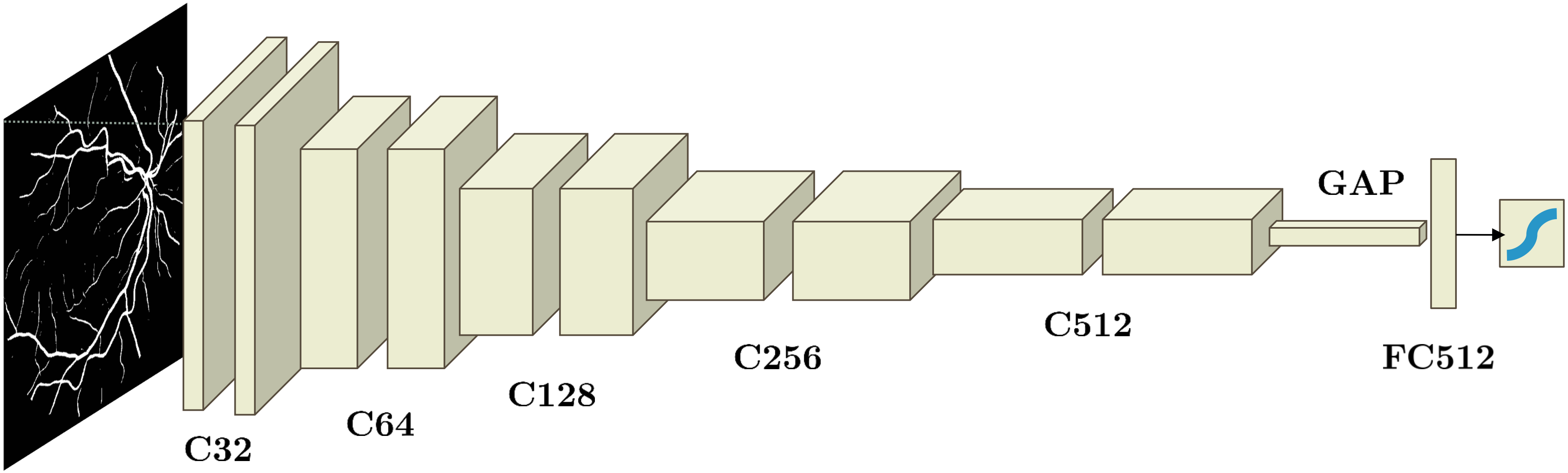
4. Retinal Vessel Map Quality Assessment

The Idea:

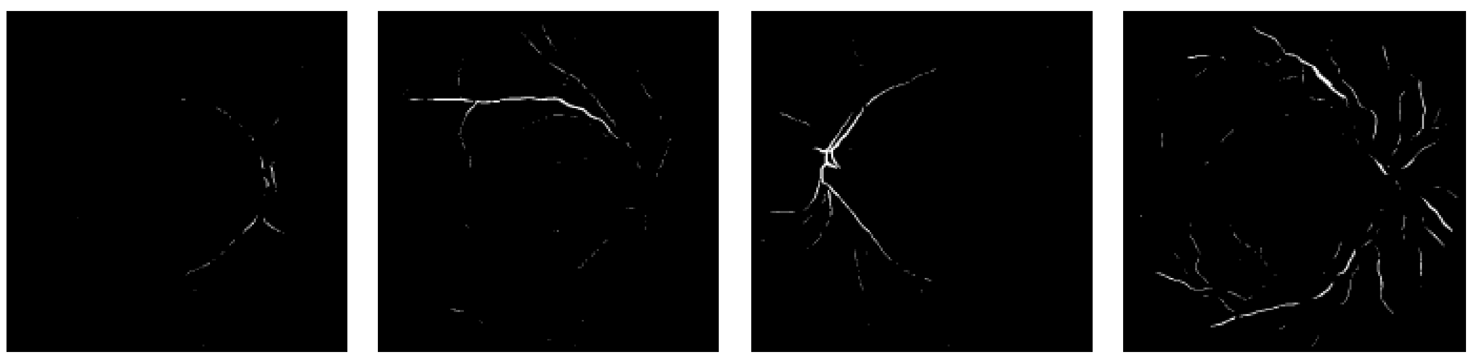


4. Retinal Vessel Map Quality Assessment

The Model:



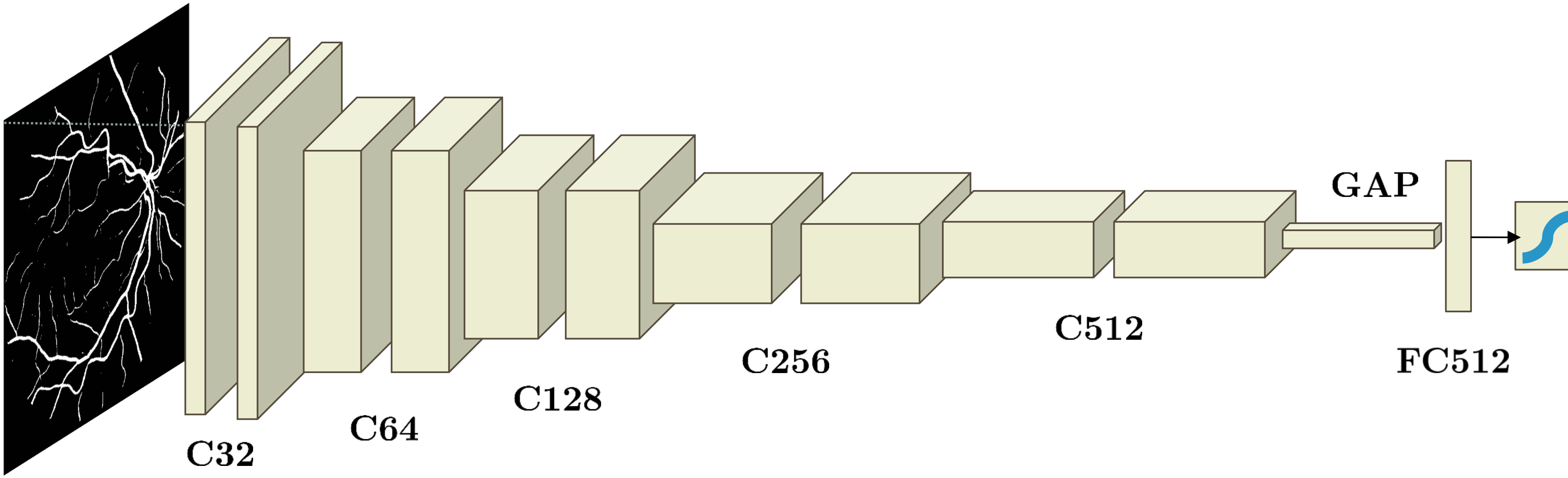
Qualitative Results:



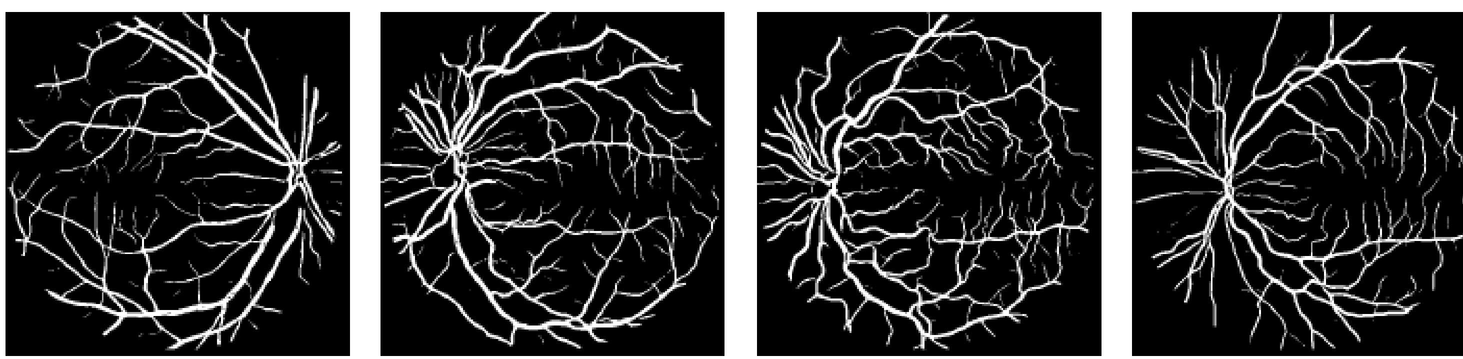
(a) (b) (c) (d)

4. Retinal Vessel Map Quality Assessment

The Model:



Qualitative Results:

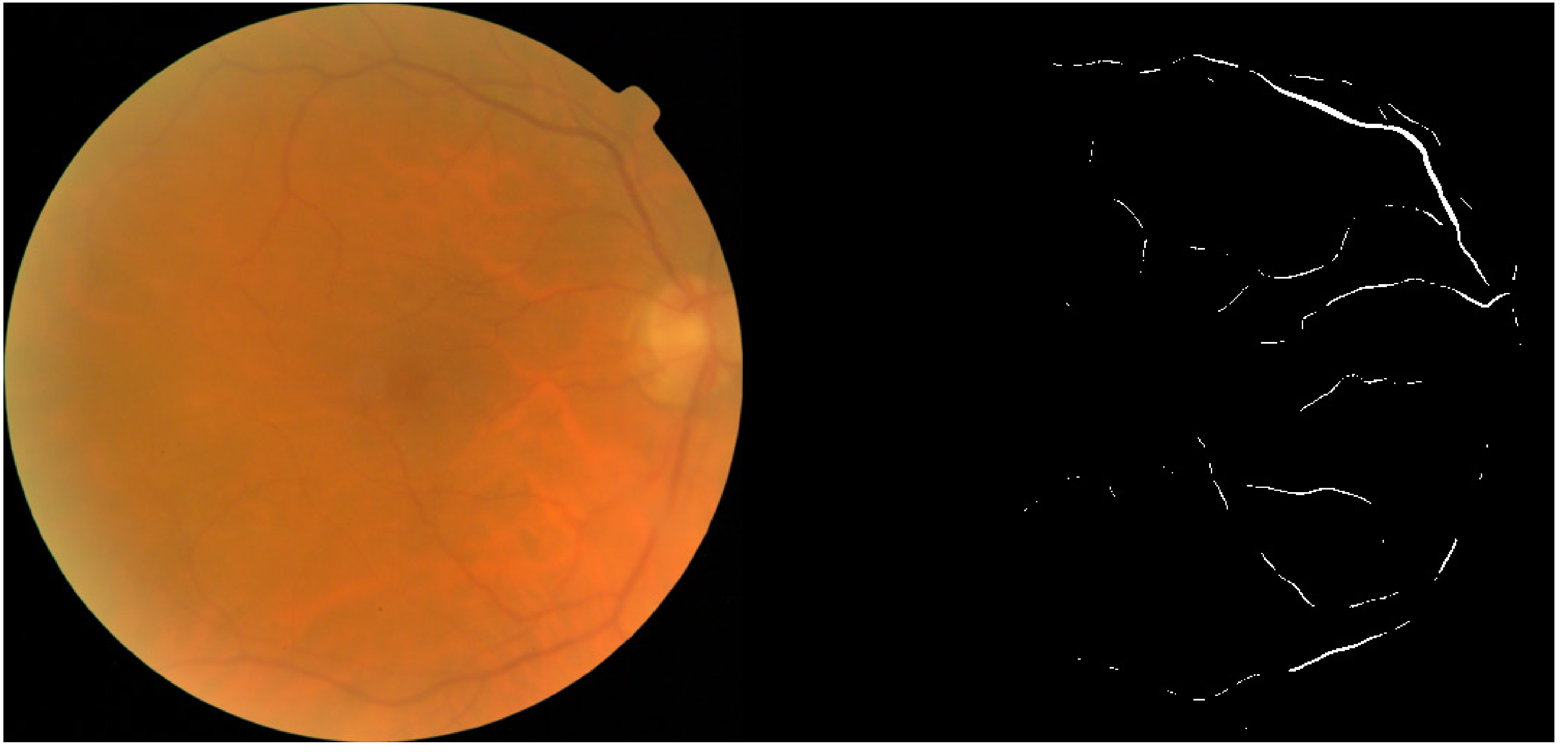


(e) (f) (g) (h)

4. Retinal Vessel Map Quality Assessment

Results (qualitative for now):

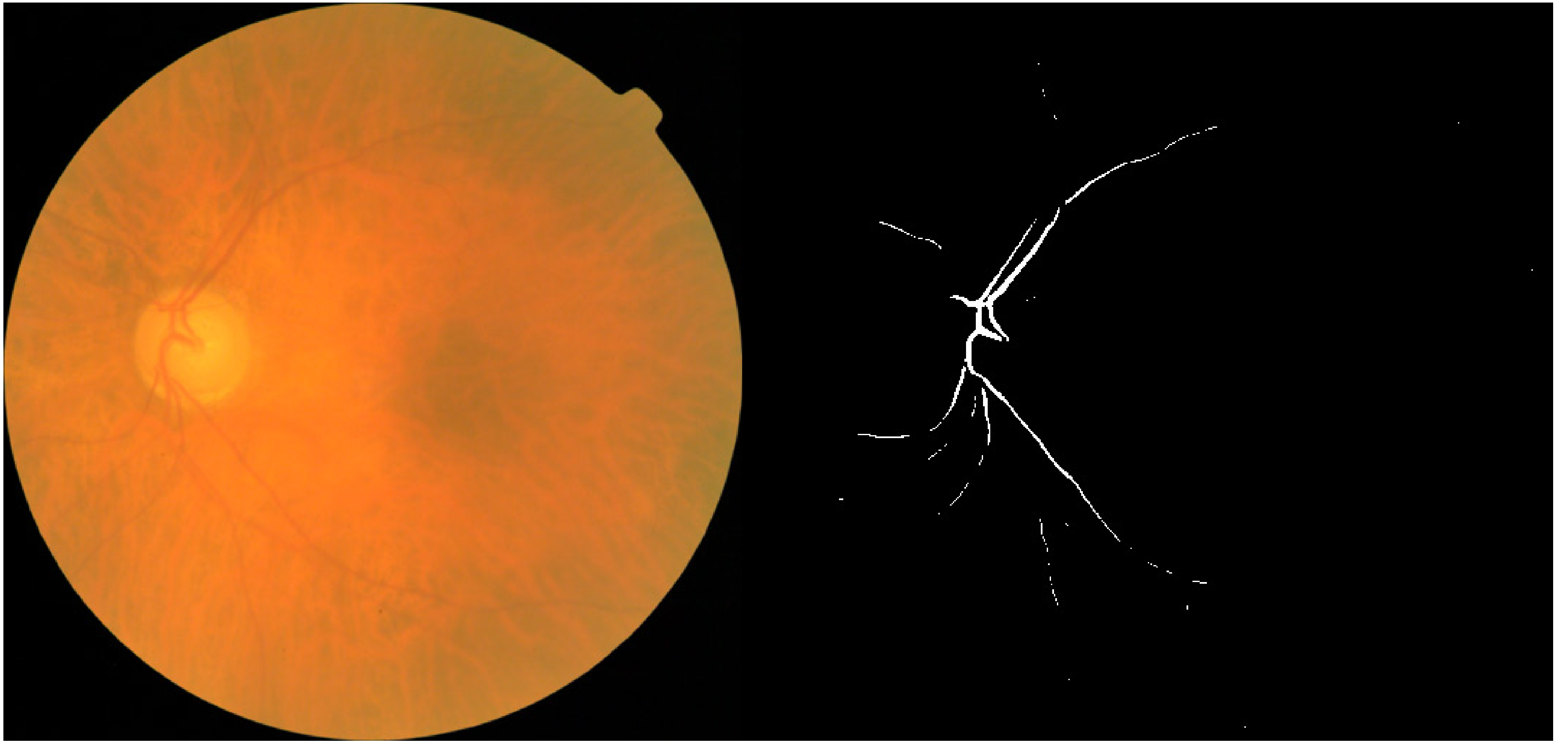
Worst Scores actually come from hard (low-quality) images



$\mathbf{s = 0.676}$

Results (qualitative for now):

Worst Scores actually come from hard (low-quality) images

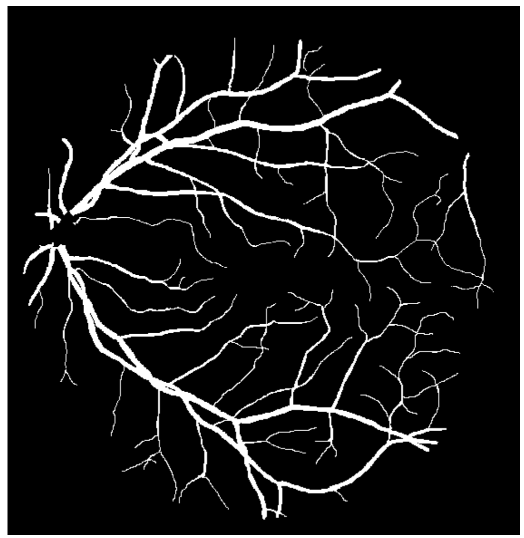


$\mathbf{s = 0.715}$

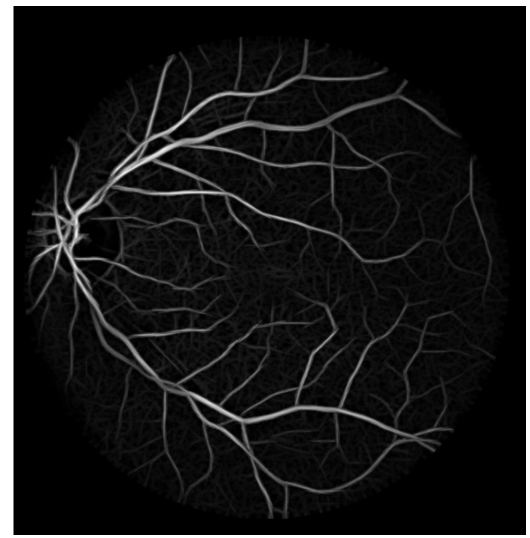
A straightforward application:

Find an optimal **per-image** threshold to build binary segmentations out of soft classifier predictions.

Input



Ground – Truth

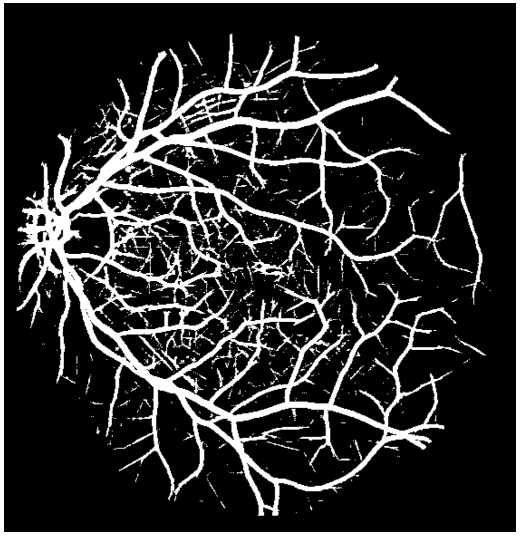


Probability Map

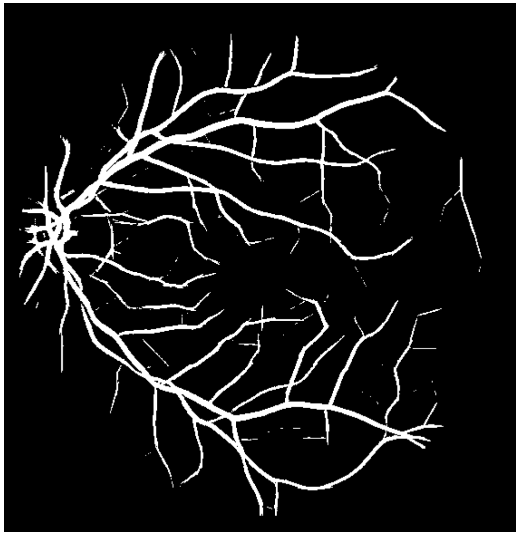
4. Retinal Vessel Map Quality Assessment

A straightforward application:

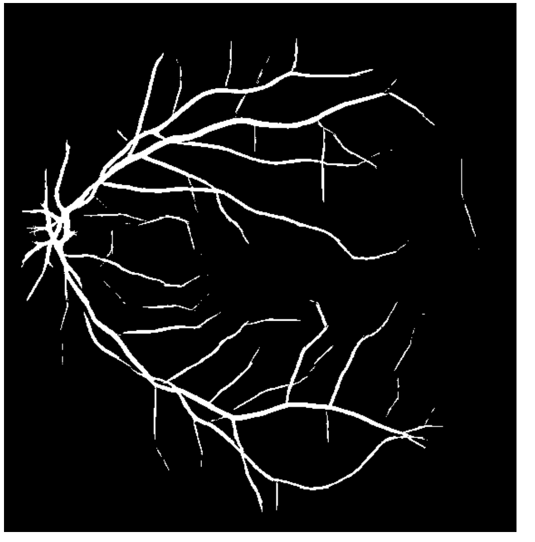
Find an optimal **per-image** threshold to build binary segmentations out of soft classifier predictions.



t > 20



t > 40

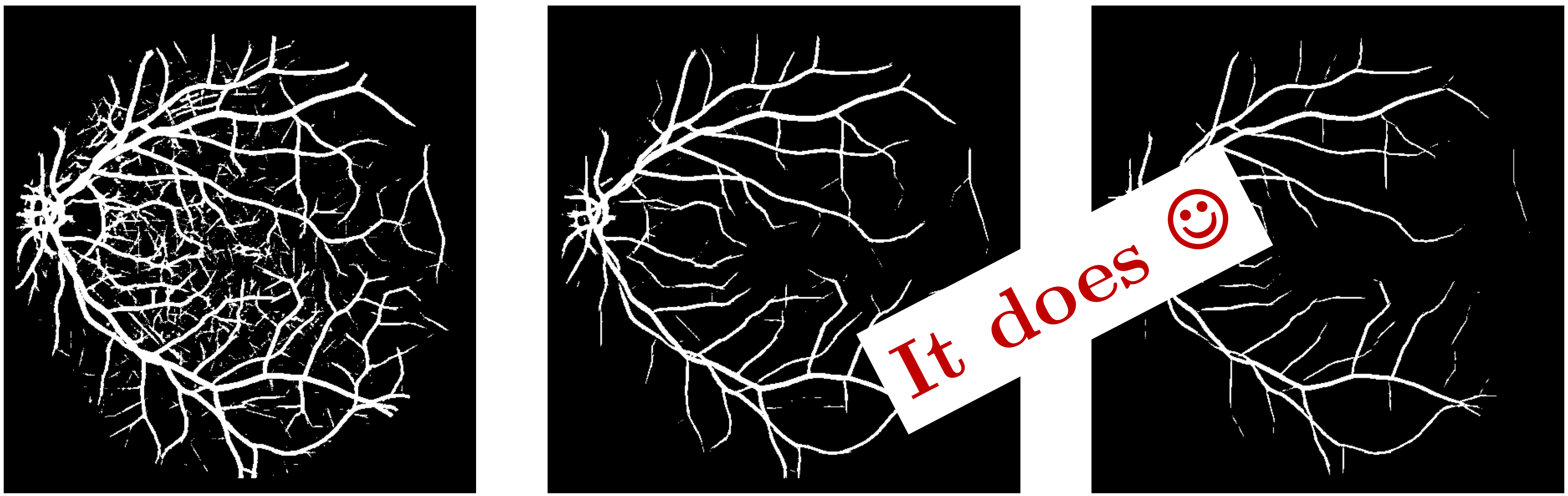


t > 60

4. Retinal Vessel Map Quality Assessment

A straightforward application:

Find an optimal **per-image** threshold to build binary segmentations out of soft classifier predictions.



t $>$ **20** **t** $>$ **40** **t** $>$ **60**

Evaluation:

Does the score **correlate** with F1/MCC whenever **GT available**?

4. Retinal Vessel Map Quality Assessment

In my opinion, this approach is not limited to a specific problem.

To me, the **key idea** here is:

Can you **simulate the kind of artifacts** that
you see in your specific class of images?
Then you can train a **quality score** by
regressing the similarity of synthetically
degraded images and original ones.

Next Natural Idea (extension):
Simulate color distortions and wrong illumination on
retinal images, inspect similarity in terms of SSIM
or any other full-reference metric.

0. Overview

1. **Introduction**
2. **Deep NNs for Artery/Vein Classification**
3. **Joint Optic Disc and Fovea Location**
4. **Retinal Vessel Map Quality Assessment**
5. **Conclusions, Q&A**