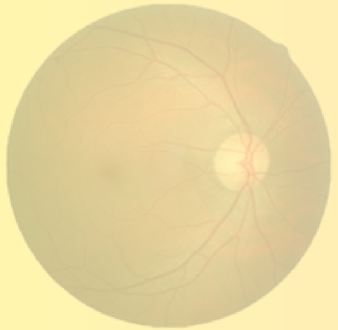

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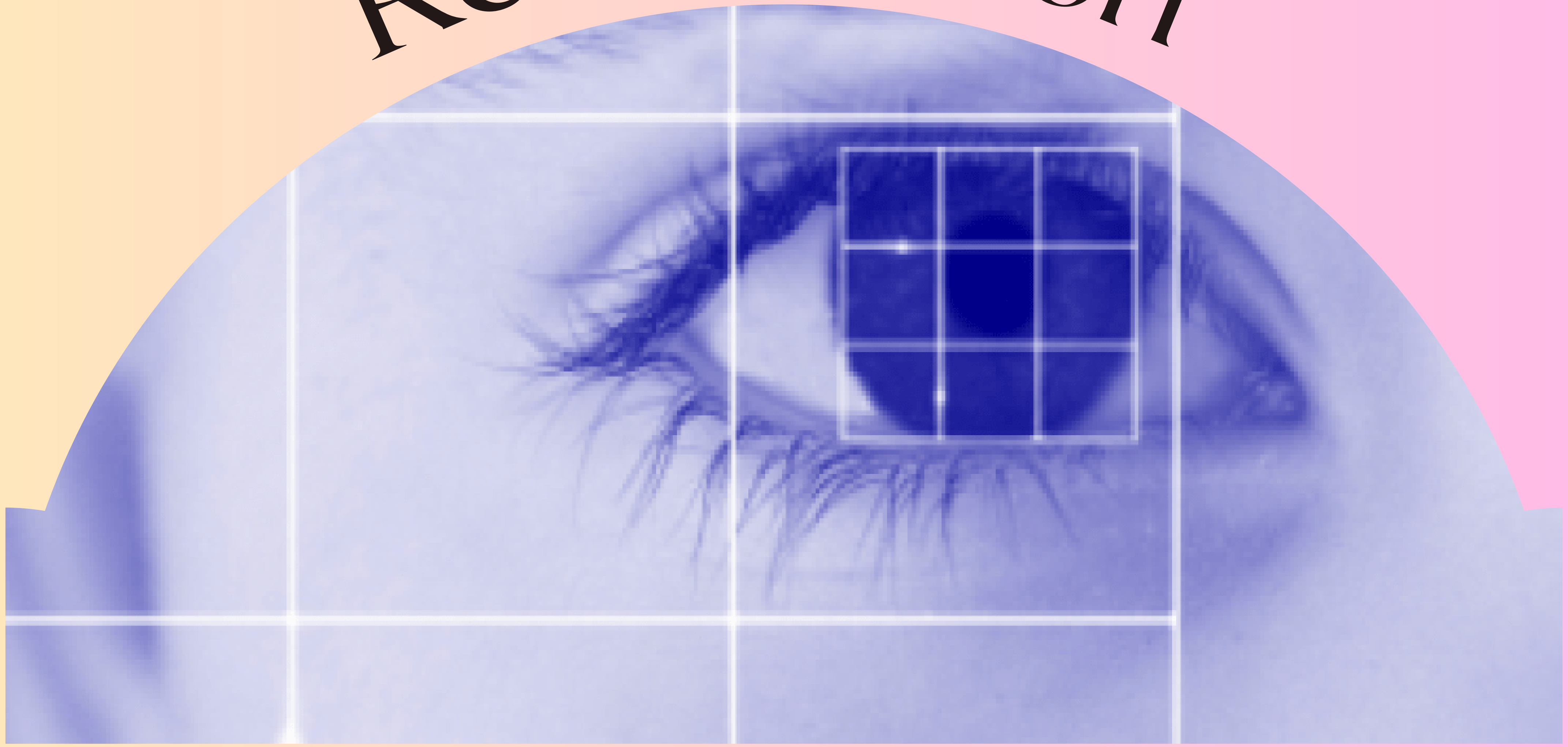
RetinaVision



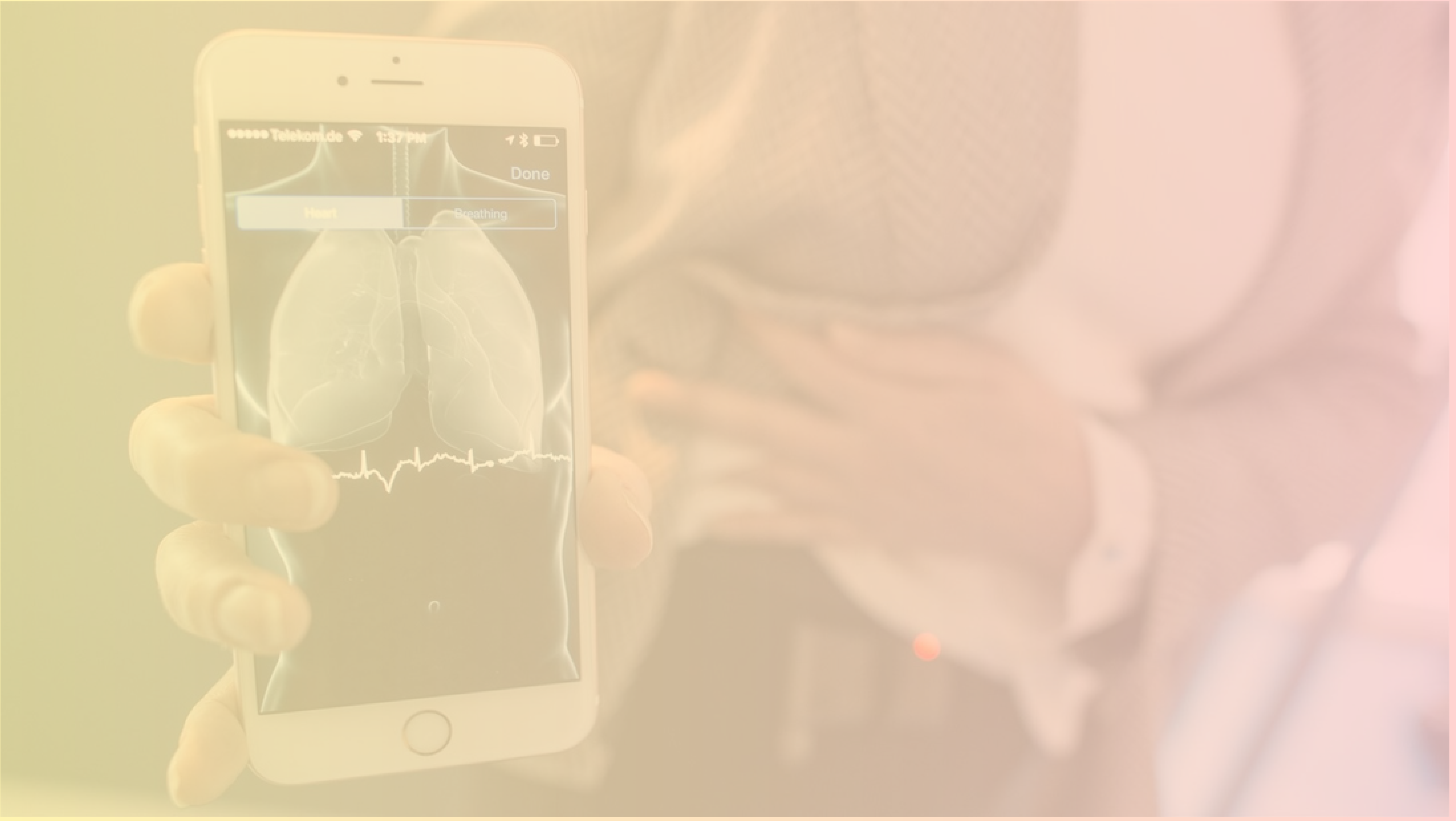
Tracing Retinal Vessels for Deeper Insights

Md Abuzar | Harbour.space University | 2023

Artificial Intelligence in Healthcare

"AI is not just changing healthcare; it's redefining it by enabling us to predict, prevent, and personalize treatment like never before." — Dr. Ziad Obermeyer

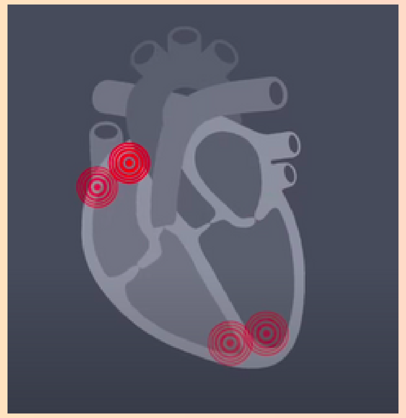
Can you guess any diagnostic tool that is AI-enabled?

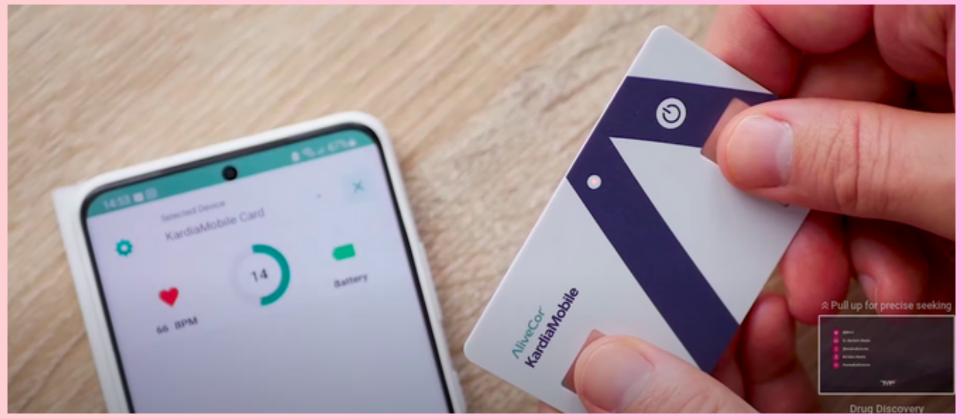


Artificial Intelligence in Healthcare

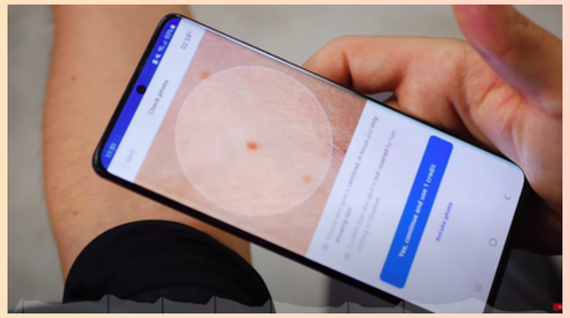
Can you guess any diagnostic tool that is AI-enabled?

1. Detecting Arrhythmias:





2. Skin checking Apps



3. Stroke Detection

4. Breast Cancer, Seizure detection smart bracelets, etc.,

Retina-Vision

"In the intricate canvas of the eye, retinal vessel segmentation paints the path to early disease detection."

Global Prevalence of Retinal Diseases:

Did you know that retinal diseases affect approximately **196 million** people worldwide, making them a significant global health concern?

Leading Cause of Blindness:

Retinal diseases are a leading cause of blindness, with conditions like diabetic retinopathy affecting more than **93 million** individuals globally.

Age-Related Vision Changes:

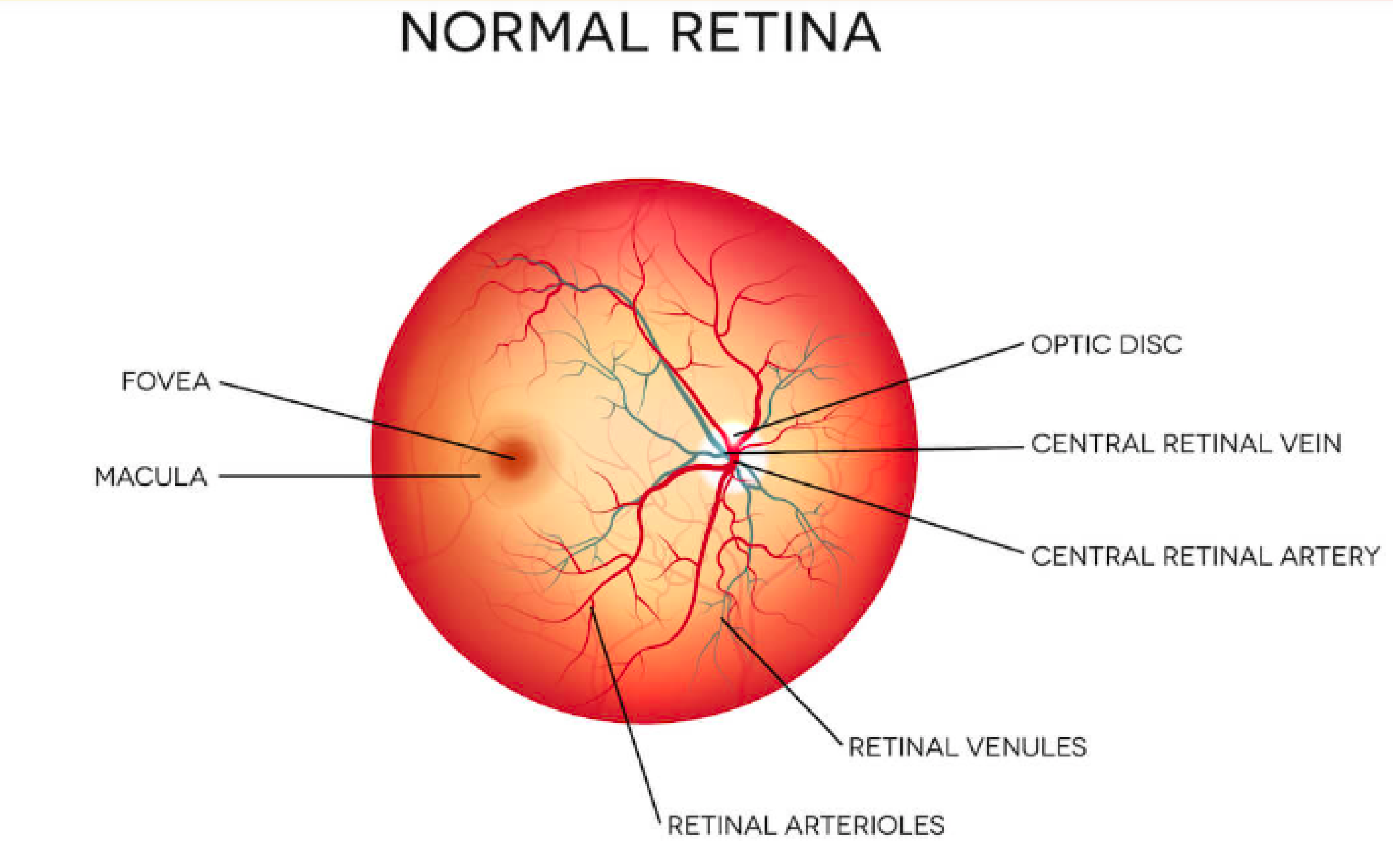
As the world's population ages, age-related retinal diseases are becoming more prevalent, highlighting the urgency of improved segmentation technique

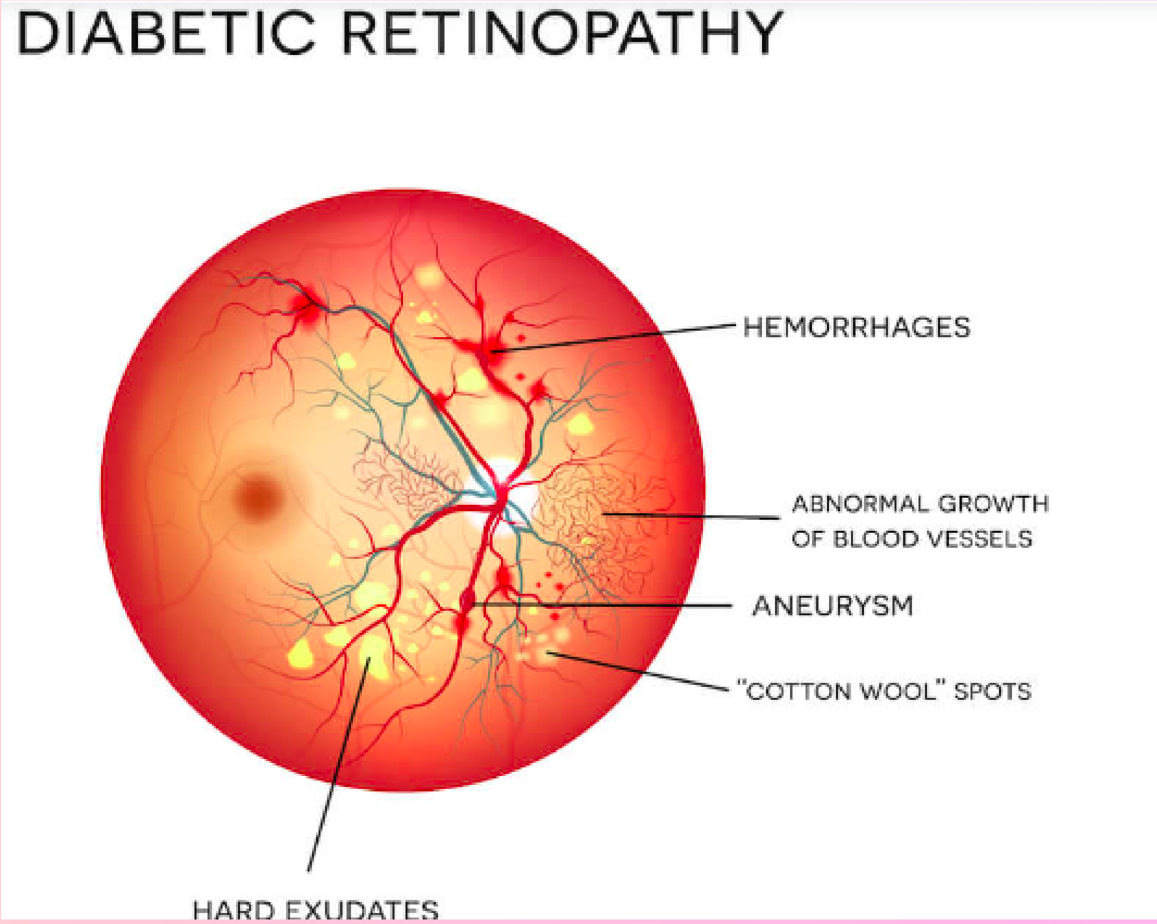
Gender Disparities:

Interestingly, studies have shown that certain retinal diseases, such as age-related macular degeneration, affect women more frequently than men, underscoring the need for gender-specific research in this field.

Retina-Vision

Have you ever wondered how a simple image of your eye can reveal the intricate secrets of your overall health?



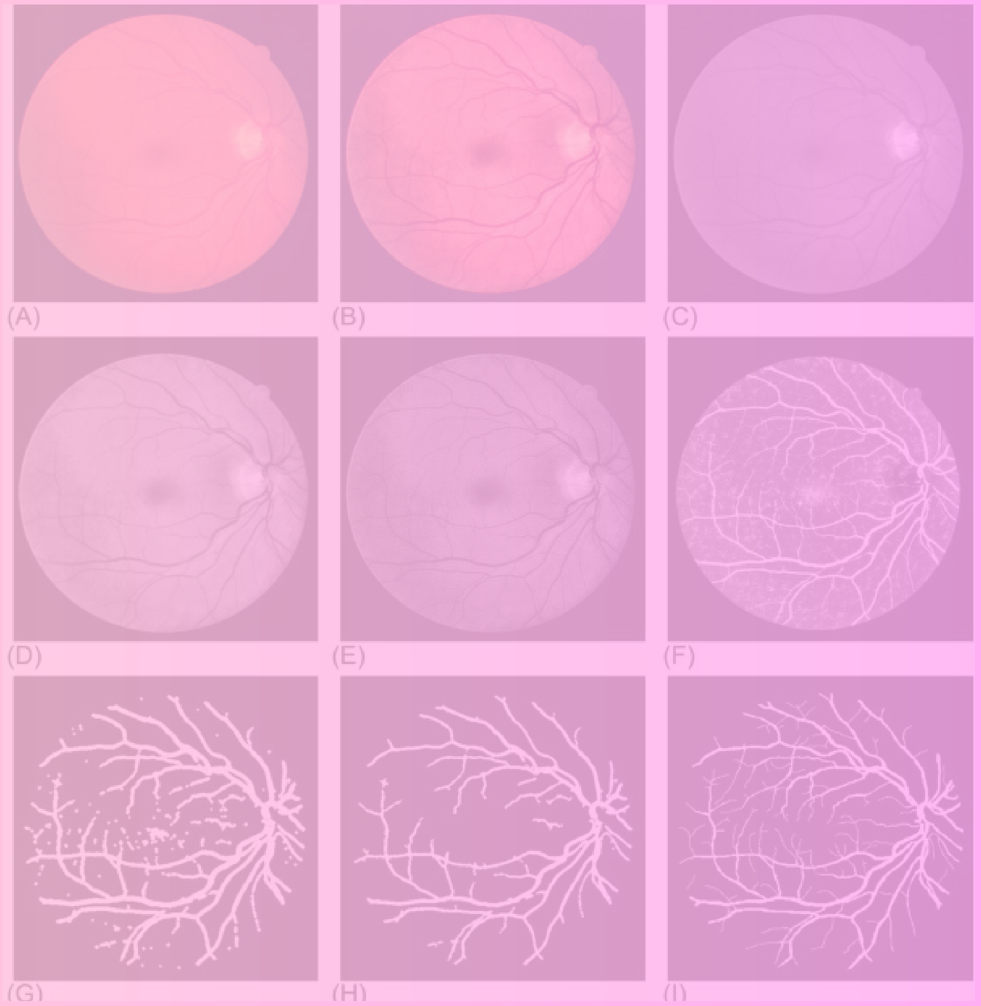


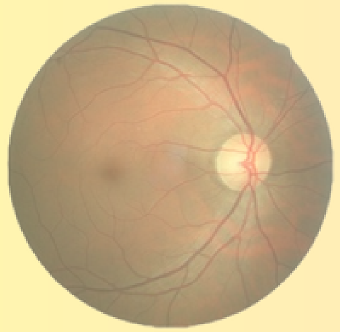
Could you find the difference? How difficult it could be to analyse in pathology !!

Retina-Vision

Today, we will explore the principles behind retinal vessel segmentation, its applications in the field of ophthalmology, and the cutting-edge technologies driving its development.

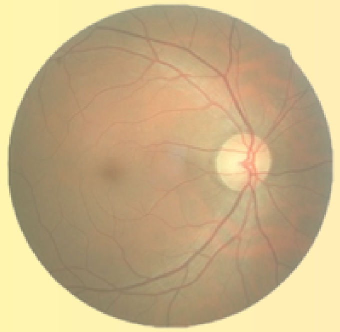
Are you overwhelmed to see the tech behind this solution and how it looks like?





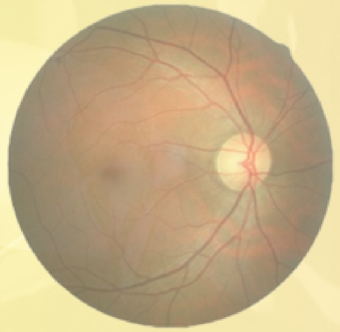
Abstract

- Blood vessels play a crucial role in maintaining overall health and serve as diagnostic indicators for various diseases.
- Diseases like diabetic retinopathy, macular edema, and arteriosclerosis are diagnosed based on vessel morphology, guiding treatment decisions.
- Geometric characteristics of retinal vessels, including vessel diameter, branch angle, and branch length, aid in the early diagnosis and monitoring of retinal conditions.
- Initial vessel images from medical equipment may lack clarity, leading to manual vessel outlining by specialists, which is time-consuming.
- Automated vessel segmentation, powered by technology, automates the process of vessel outlining, saving time and improving accuracy.
- Traditional methods used mathematics and filters, but deep learning, particularly with models like U-Net, has significantly enhanced the precision of vessel segmentation.



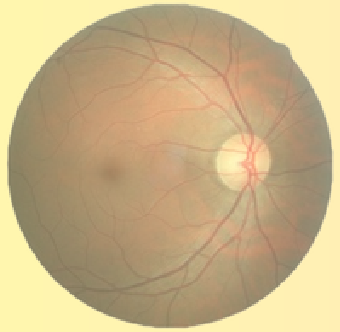
Overview

- Introduction
- Dataset
- Problem With Dataset
- Literature Review
- Experiment Introduction
- Architecture
- Experiment set up
- Results
- Web interface
- Conclusion
- References
- Code
- Thank You



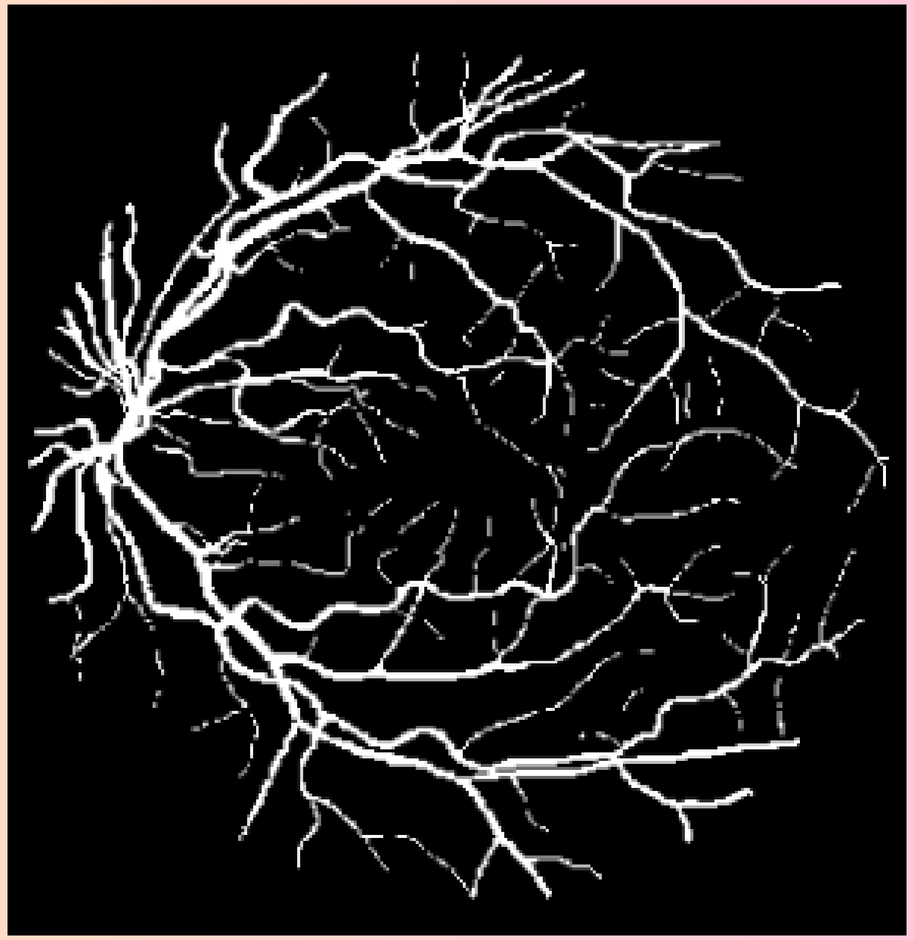
Introduction

- Analysis of retinal vessel networks yields valuable insights into eye conditions.
- Morphological attributes of retinal vessels, including length, width, tortuosity, and branching patterns, are crucial for diagnosis, screening, and treatment.
- Segmenting blood vessels from fundoscopic images is a challenging task due to thin vessel edges, poor image quality, noise, and potential detail loss.
- Errors in vessel segmentation can lead to incorrect diagnoses, either falsely identifying a disease or missing one.
- Image quality can be influenced by factors like lighting, camera issues, angles, and filters.
- Medical Image Segmentation often relies on the U-Net architecture.
- The study uses the DRIVE dataset, which presents challenges such as limited annotated data and variations in disease representation.
- Experiments involve the application of the U-Net Architecture with Data Augmentation to analyze the results.
- Finally, we are introducing a web-based application to perform the segmentation.

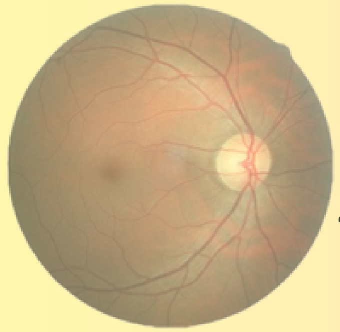


DataSet

- Retinal Vessel Segmentation.
- Utilizing the DRIVE dataset from Kaggle.
- 20 train and 20 test images.
- Each image represents a different disease.
- Challenging due to limited annotated data.
- Addressing input data quality issues.
- Emphasizing the constraint of limited annotated data.

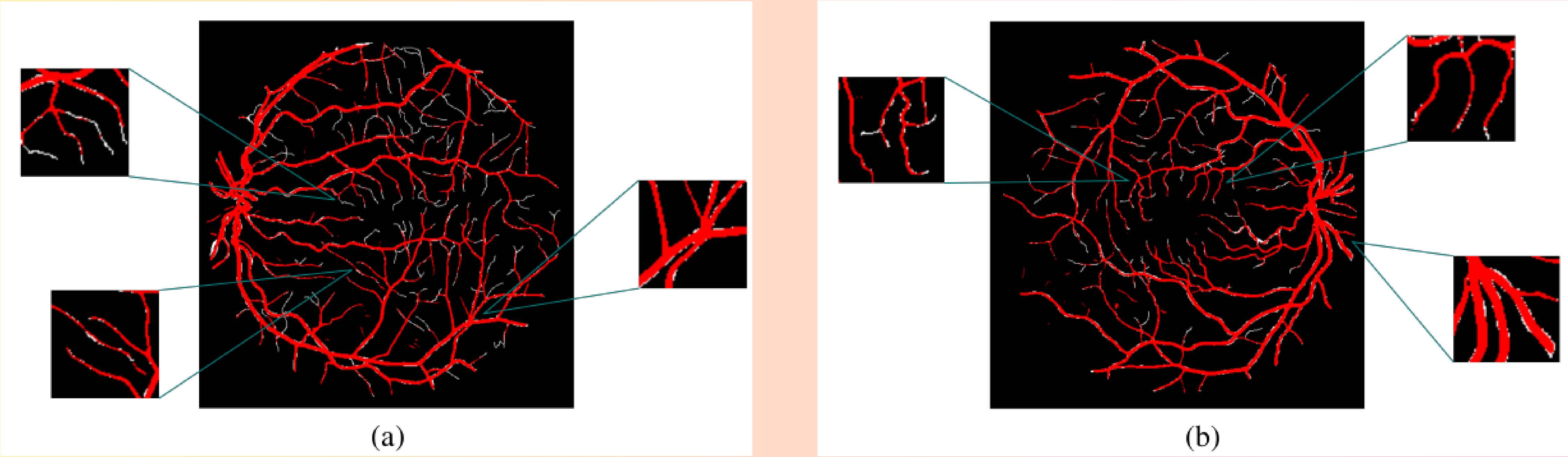


Training sample from DRIVE dataset

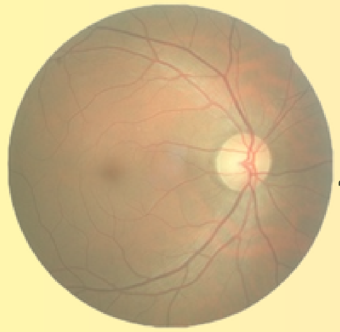


Problem with DataSet

The actual problem with the dataset is the segmentation of the minor vessels. Minor vessels are one of the hardest regions to segment. The below Figure shows the predicted and ground truth vessels together. It can be seen that the majority of the incorrect segmentations occur at the minor vessels.



Two examples for a combination of predictions and ground truths. Red pixels are predicted vessels, white pixels are ground truth pixels. By (a), it is observed that the model errors due to the minor vessels. The model performs well in segmenting thick vessels as it is pointed in the right hand side of (a). The model performs better at segmenting the vessels in (b). Minor vessels are segmented better than (a) in this example.



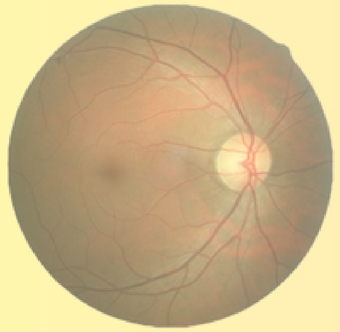
Literature Review

The convolutional networks have already existed for a long time, their success is limited due to the size of the available training sets and the size of the considered networks. The typical use of convolutional networks is on classification tasks, where the output to an image is a single class label. However, in many visual tasks, especially in biomedical image processing, the desired output should include localization, i.e., a class label is supposed to be assigned to each pixel. There is a general perception that successful training of deep networks requires many thousand annotated training samples. Thousands of training images are usually beyond reach in biomedical tasks.

The paper[1] presents a network and training strategy that relies on the strong use of data augmentation to use the available annotated samples more efficiently.

The paper[2] presents different kinds of Augmentation. Some of them are listed below:

1. Gamma Correction/Random Crop/Grid and Optical Distortion
2. White Noise/Elastic Deformations/Shift
3. Blurring/Dropout/Eq. Histogram
4. Rotation And Flipping



Experiment

Introduction

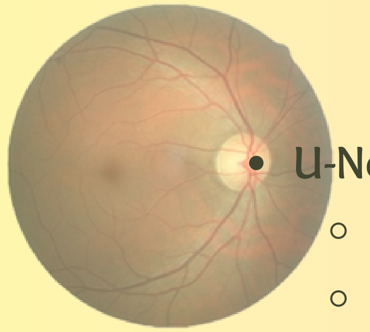
In this Experiment, We propose that optimal data augmentation can be successful for Retinal Vessel Segmentation, using simple U-Net architecture[3].

Data augmentation techniques are helpful for three reasons:

1. It is helpful because the input data is very scarce. Data augmentation techniques increase the input image size and provide the model with some extra information to learn.
2. Through data augmentation, we can recover some performance loss that occurred in the models due to the image quality.
3. Data augmentation will help with the segmentation model we used, which is the U-Net architecture that makes use of pooling operations. The model learns relatively lower from the corner and side parts of the input image.

Techniques used:

- Adding noise from a normal distribution (mean 0, std. deviation).
- Augmentations with various epsilon values ($\geqslant 1$).
- Incorporating zoomed and randomly cropped images.
- Applying shifting and flipping for edge information capture.



Architecture

- U-Net Overview:
  - A specialized computer model for image processing.
  - Resembles the letter "U."
  - Excellent at tasks like image segmentation (outlining important parts).
- U-Net's Operation:
  - Two main parts: Contracting Path (Left) and Expanding Path (Right).
  - Contracting Path breaks the input image into smaller details using convolutional layers.
  - Bottleneck combines and understands these details.
  - Expanding Path assembles a new image with outlined important parts using deconvolutional layers.
- Applications of U-Net:
  - Valuable in medical imaging (e.g., detecting blood vessels or tumors).
  - Learns from examples to make accurate diagnoses.
  - Saves time and aids doctors in treatment decisions.
- In Simple Terms:
  - U-Net is like a skilled artist that outlines important things in pictures, aiding doctors in understanding what's happening inside the body.

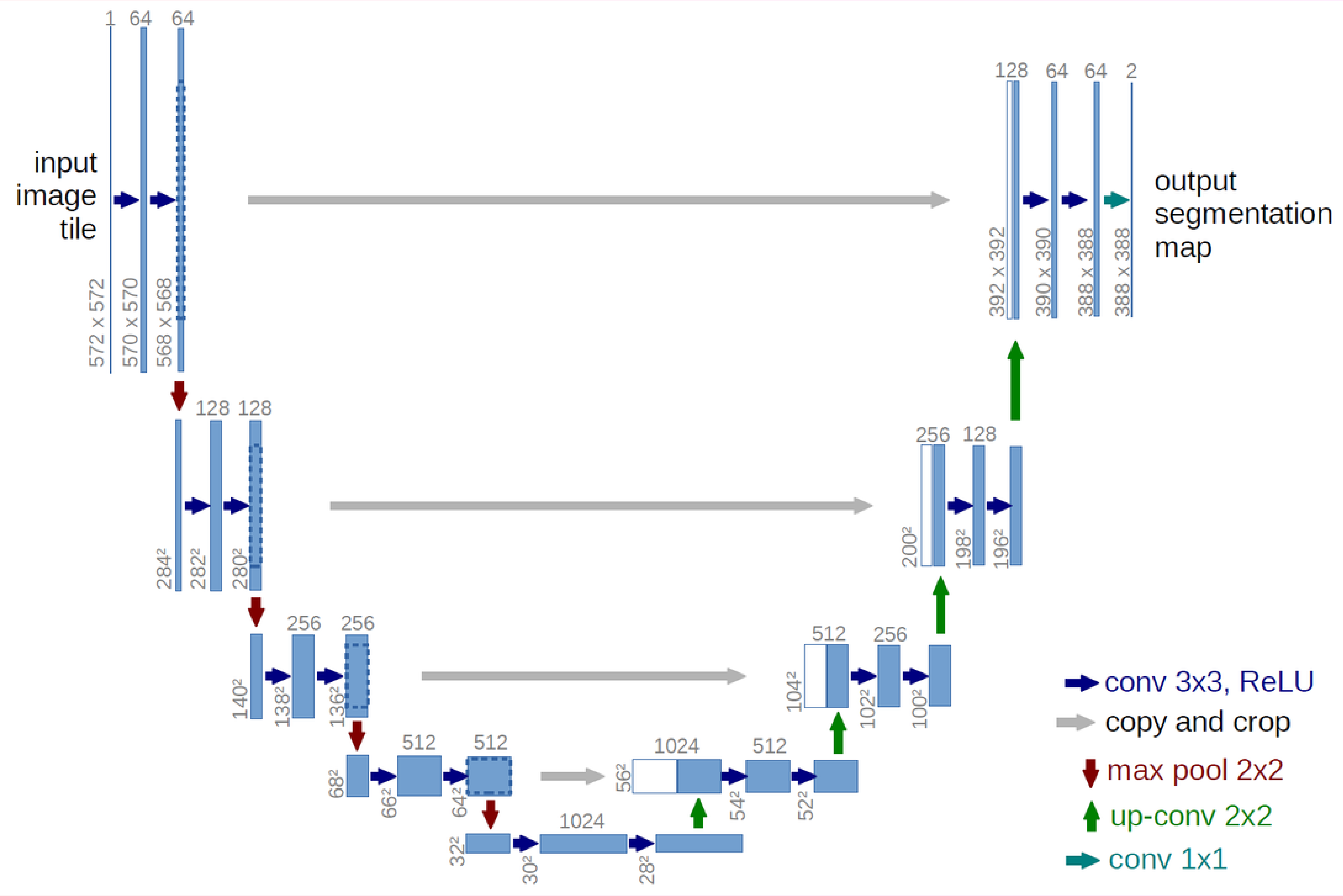
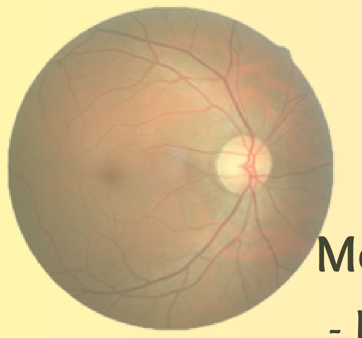


Figure 1: Architecture of the U-Net Image Segmentation Model.

Experiment set up



Method and Architecture:

- Utilize U-Net [3] architecture.
- Train models with Adam optimizer [4] (learning rate: 1e-4, β1: 0.9, β2: 0.999).
- No learning rate scheduling algorithms used.

Training Details:

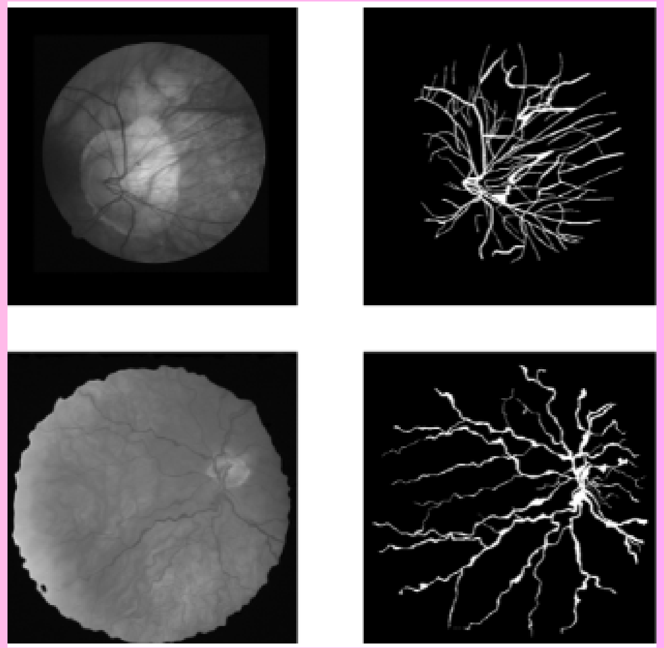
- Mini-batches of size 3 for DRIVE dataset experiments.
- Dropout probability of 0.1 on the fourth and fifth convolutional layers.
- Training involves binary cross-entropy loss, with experimentation using dice loss and a combination of both [5].
- Best results achieved with binary cross-entropy loss.

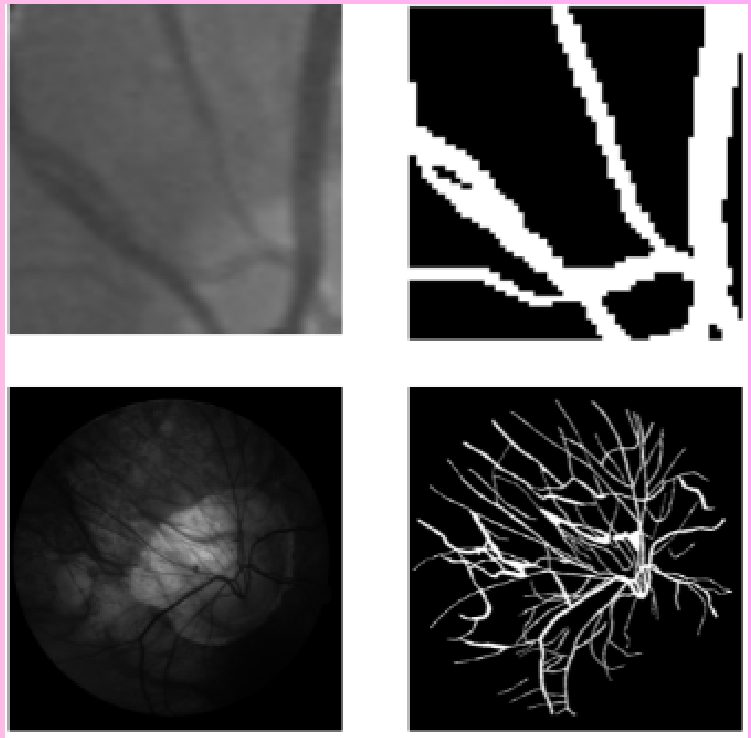
Data Augmentation:

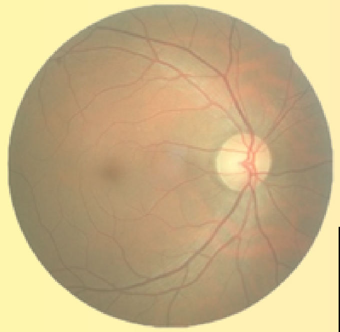
- Generated 70 images from 20 using augmentation.
- Augmentation techniques include:
  - Rotation (30*k) and flipping
  - Zoom out
  - White noise, elastic deformations, and shift
  - Gamma correction, random crop, grid, and optical distortion
  - Blurring, dropout, equalization histogram

Library Usage:

- Utilized albumentations and imagecorruptions libraries for extensive augmentations.







Results

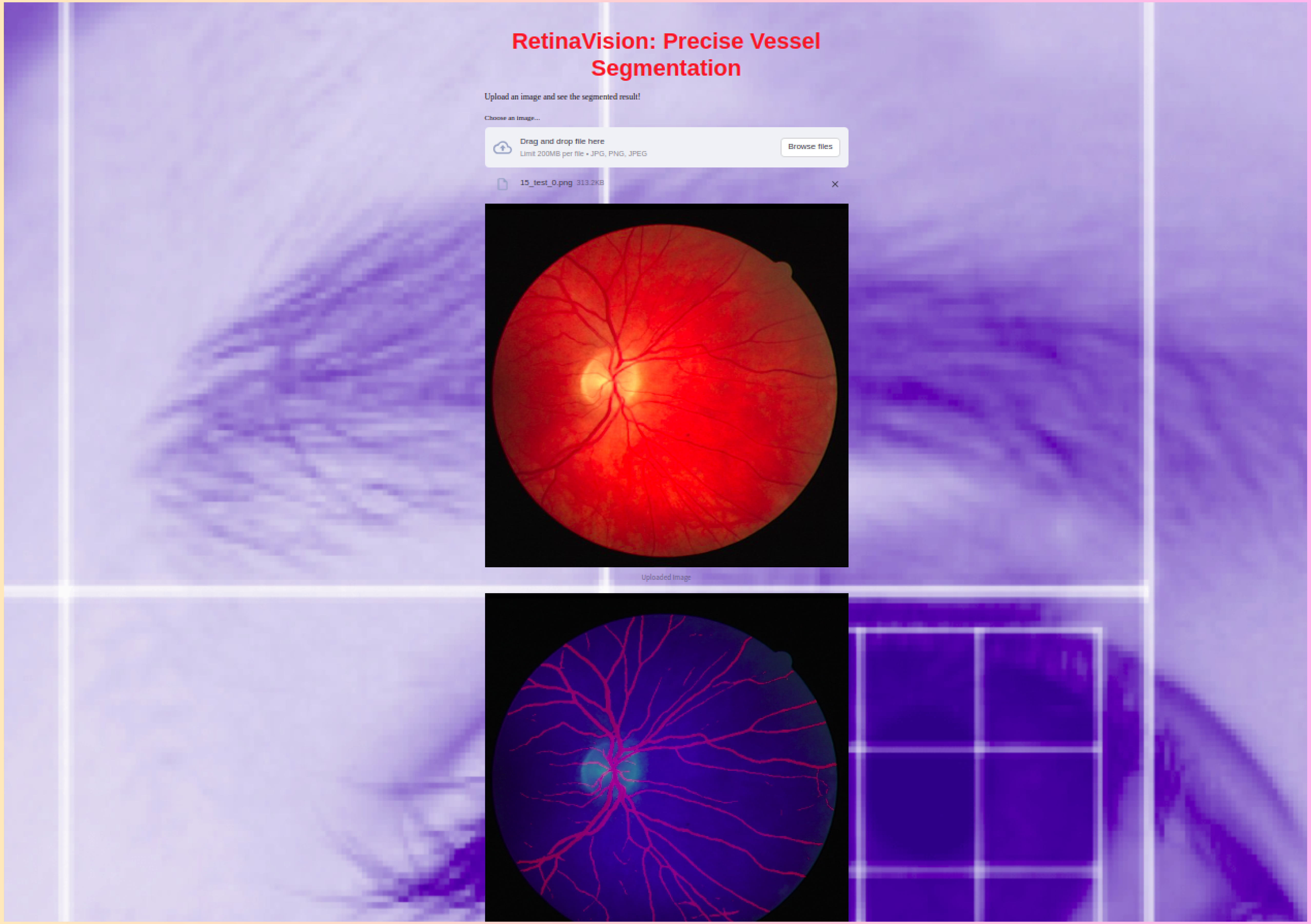
DRIVE	Accuracy	AUC	Mean Dice Coef
Rotation (30*k) And Flipping	0,970	0,971	0,809
+ Zoom Out	0,971	0,983	0,820
+ White Noise/Elastic Deformations/Shift	0,970	0,985	0,822
+ Gamma Correction/Random Crop/Grid and Optical Distortion	0,971	0,983	0,824
+ Blurring/Dropout/Eq. Histogram	0,971	0,985	0,826

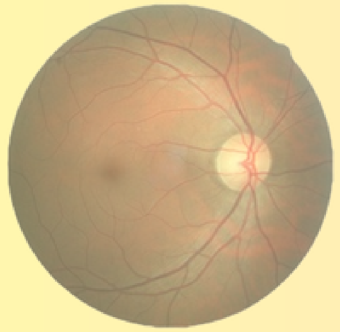
Result calculated for different kind of augmentation

Method	AUC	Accuracy
UNet (2018*)	0,9752	0,9555
Residual UNet (2018)	0,9779	0,9553
IterNet (2019)	0,9816	0,9571
SUD-GAN (2020)	0,9786	0,9560
RV-GAN (2020)	0,9887	0,9790
U-Net with Augmentation	0,9848	0,9712

Performance comparison for different Methods

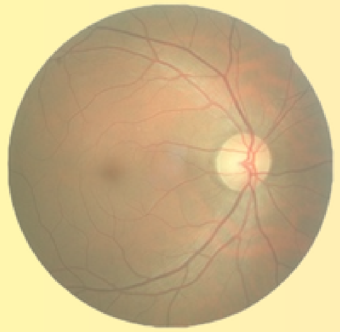
Retina-Vision





Code Repository

- https://github.com/abuzarmd-ML/Image-Segmentation-DRIVE-dataset



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[2] https://arxiv.org/pdf/2007.15883v2.pdf

[3] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. U-Net: Convolutional Networks for Biomedical Image Segmentation. 2015. arXiv: 1505.04597 [cs.CV].

[4] Diederik P. Kingma and Jimmy Ba. Adam: A Method for Stochastic Optimization. 2017. arXiv: 1412.6980 [cs.LG].

[5] Carole H. Sudre et al. "Generalised Dice Overlap as a Deep Learning Loss Function for Highly Unbalanced Segmentations". In: Lecture Notes in Computer Science (2017), pp. 240–248. ISSN : 1611-3349. DOI : 10.1007/ 978-3-319-67558-9_28. URL : http://dx.doi.org/10.1007/978-3-319-67558-9_28.

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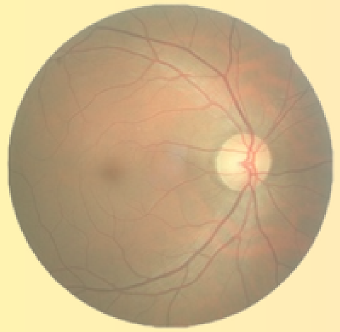

THANK YOU