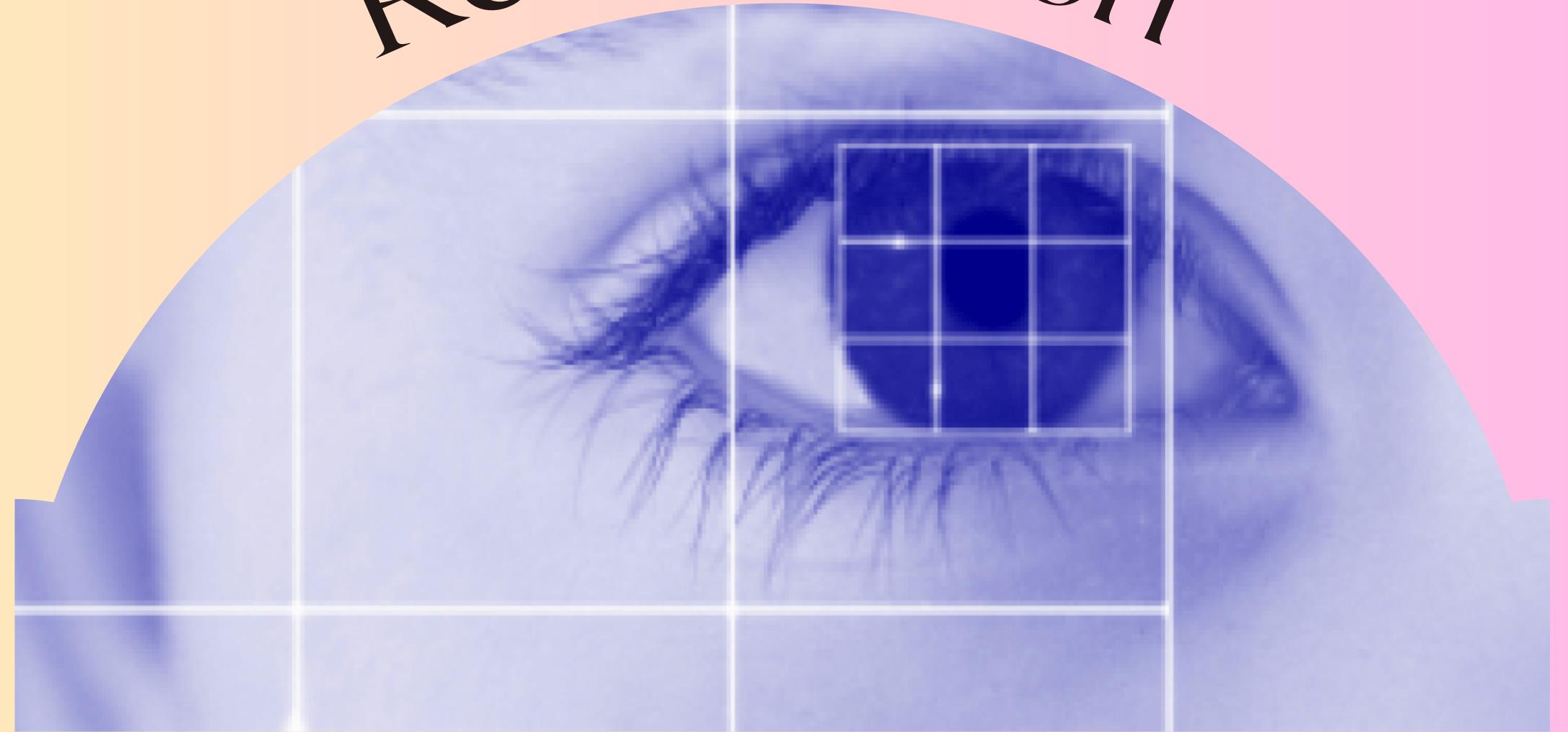


# RetinaVision

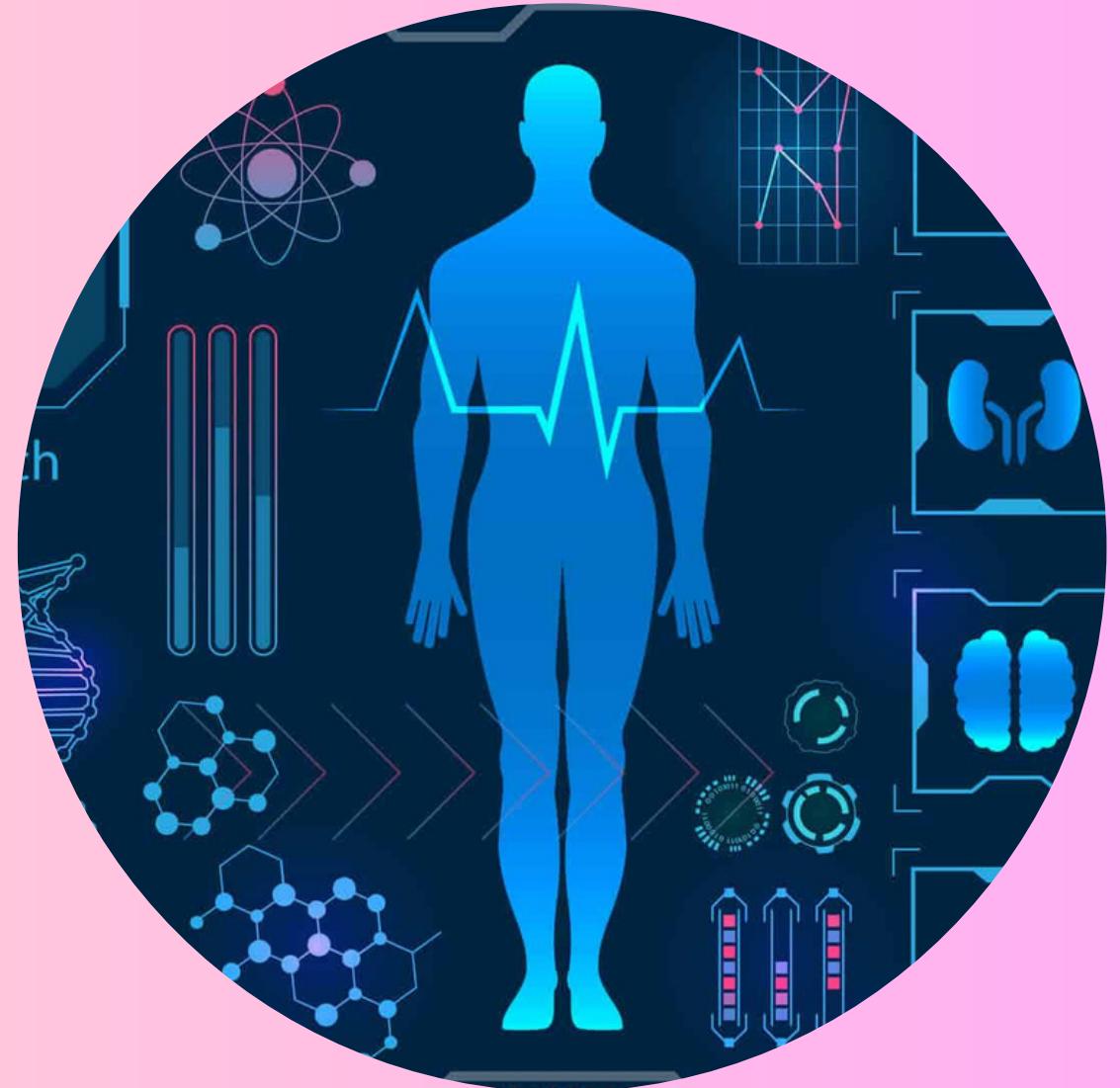


## Tracing Retinal Vessels for Deeper Insights

HARBOUR SPACE  
UNIVERSITY

# Artificial Intelligence in Healthcare

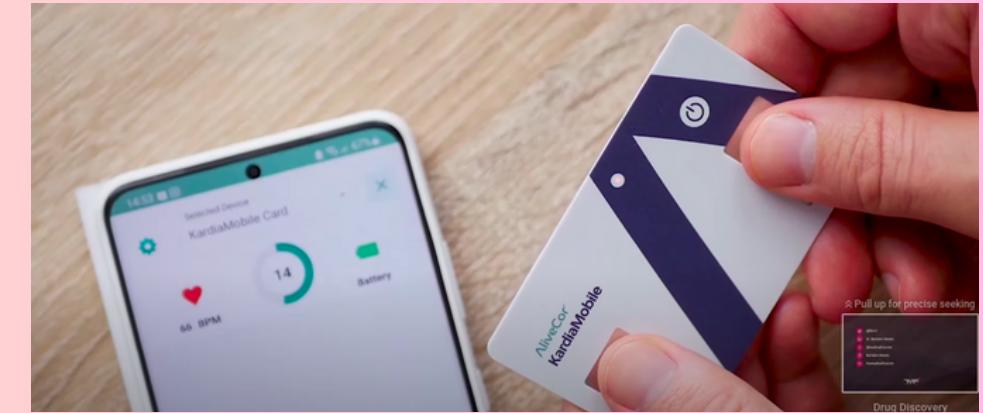
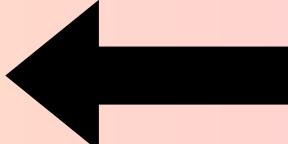
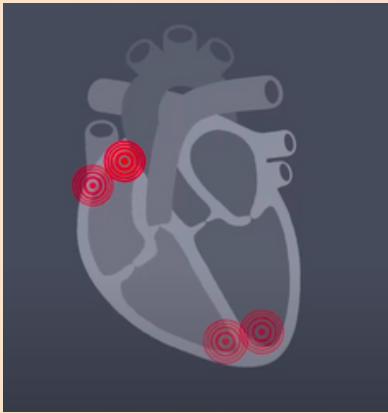
Can you name some diagnostic tool that is AI-enabled?



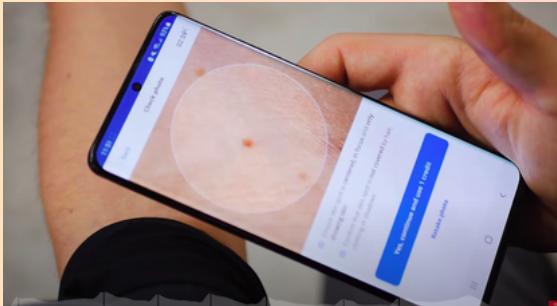
# Artificial Intelligence in Healthcare

Lets see How AI is transforming the HealthCare

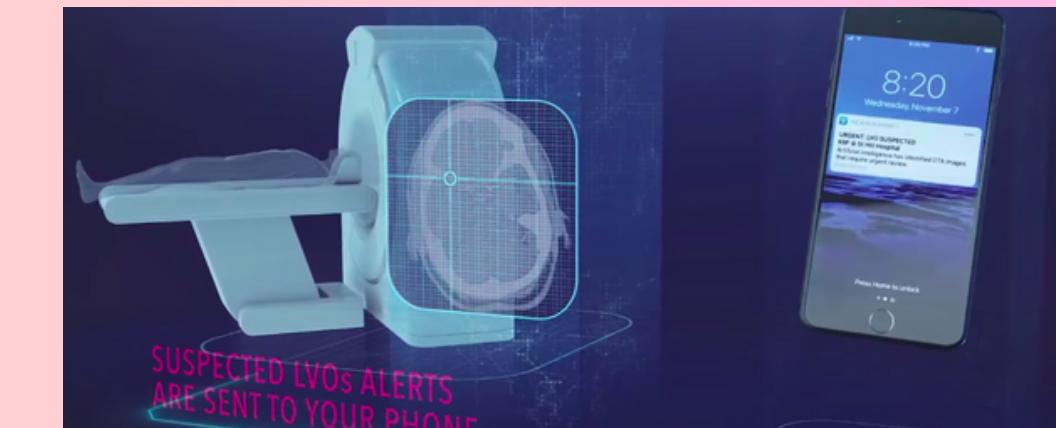
1. Detecting Arrhythmias:



2. Skin checking Apps



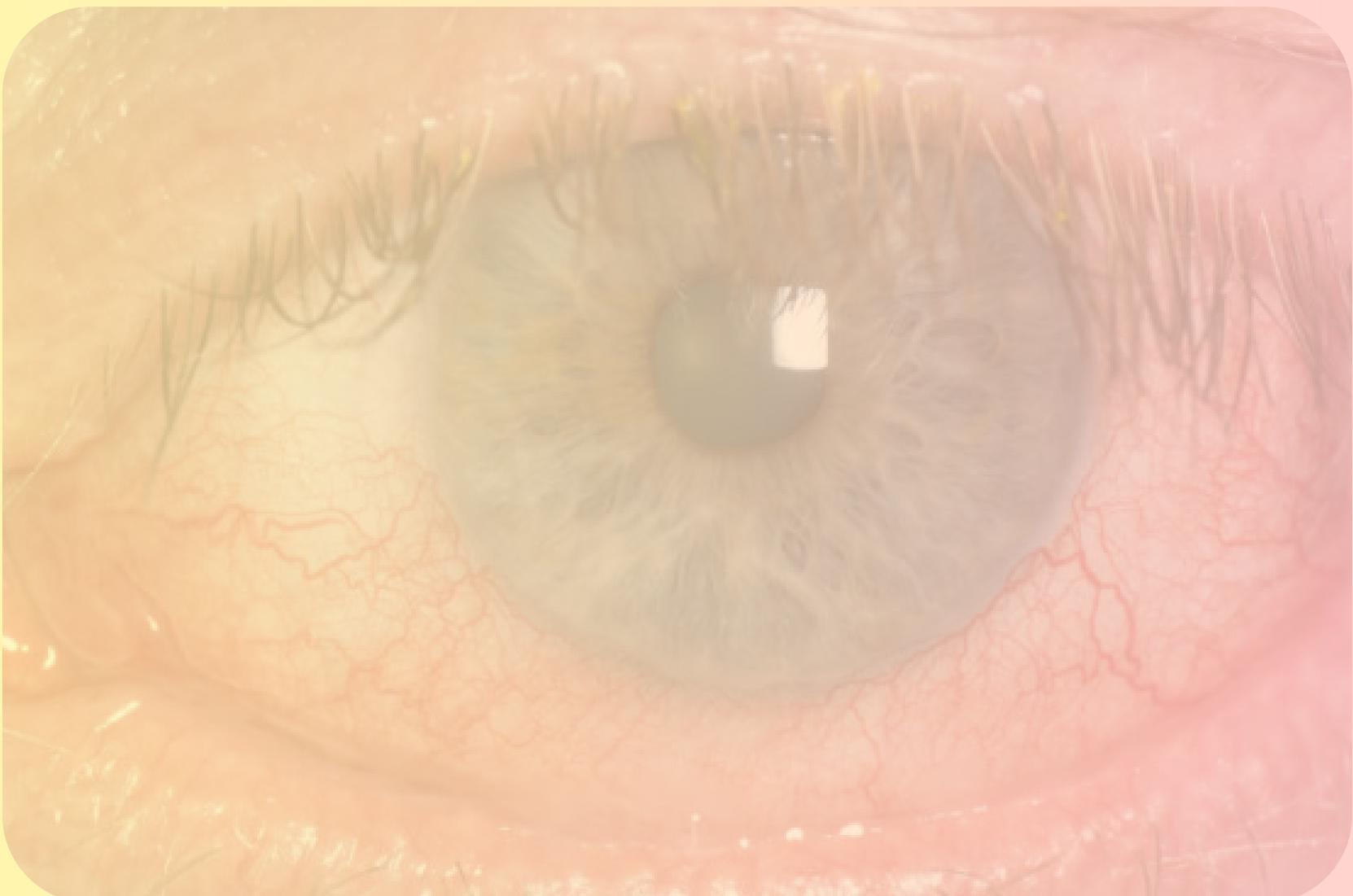
3. Stroke Detection



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

# Artificial Intelligence in Healthcare

## How AI can improve Eye Care ?



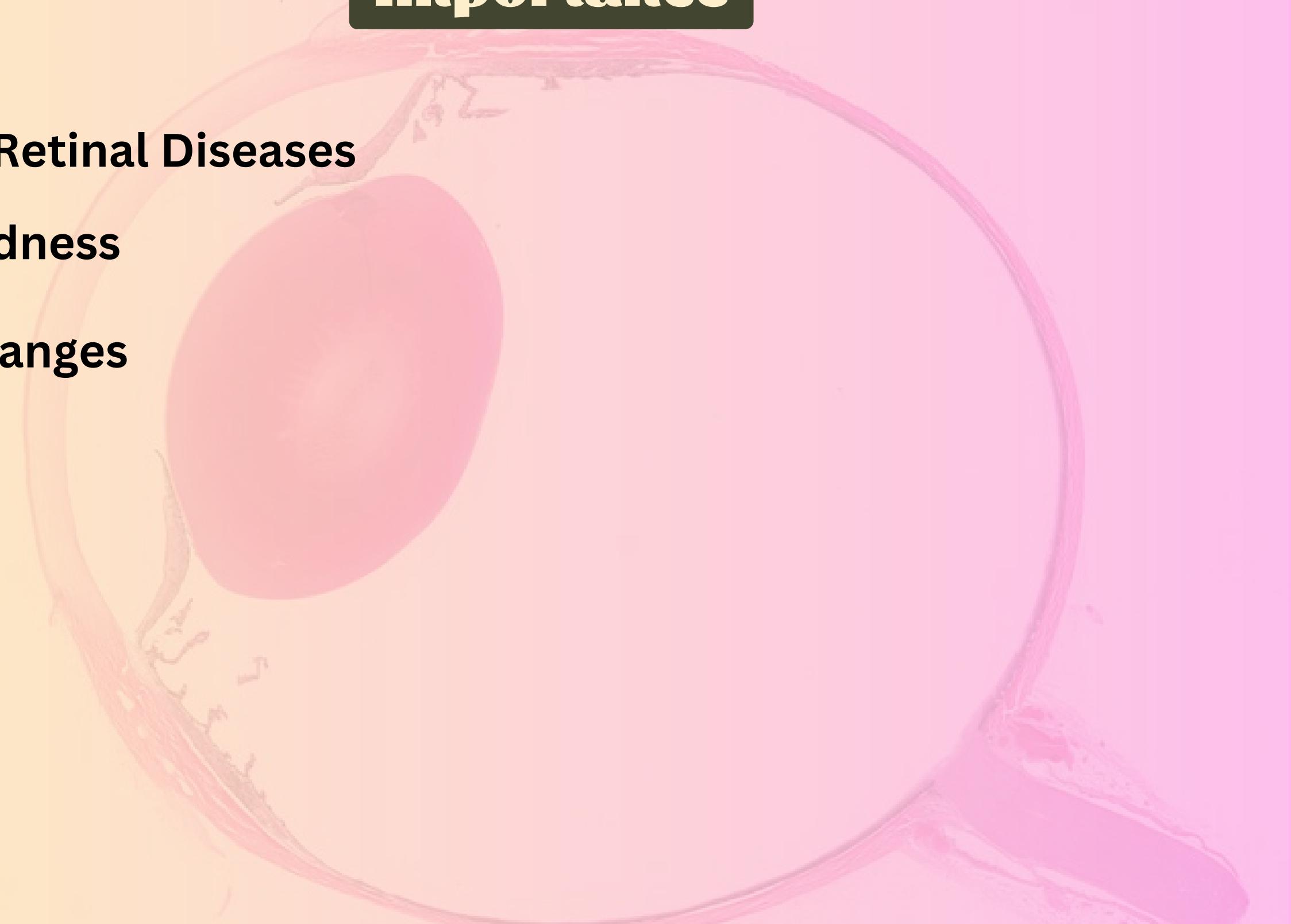
## Retina-Vision Importance

**Global Prevalence of Retinal Diseases**

**Leading Cause of Blindness**

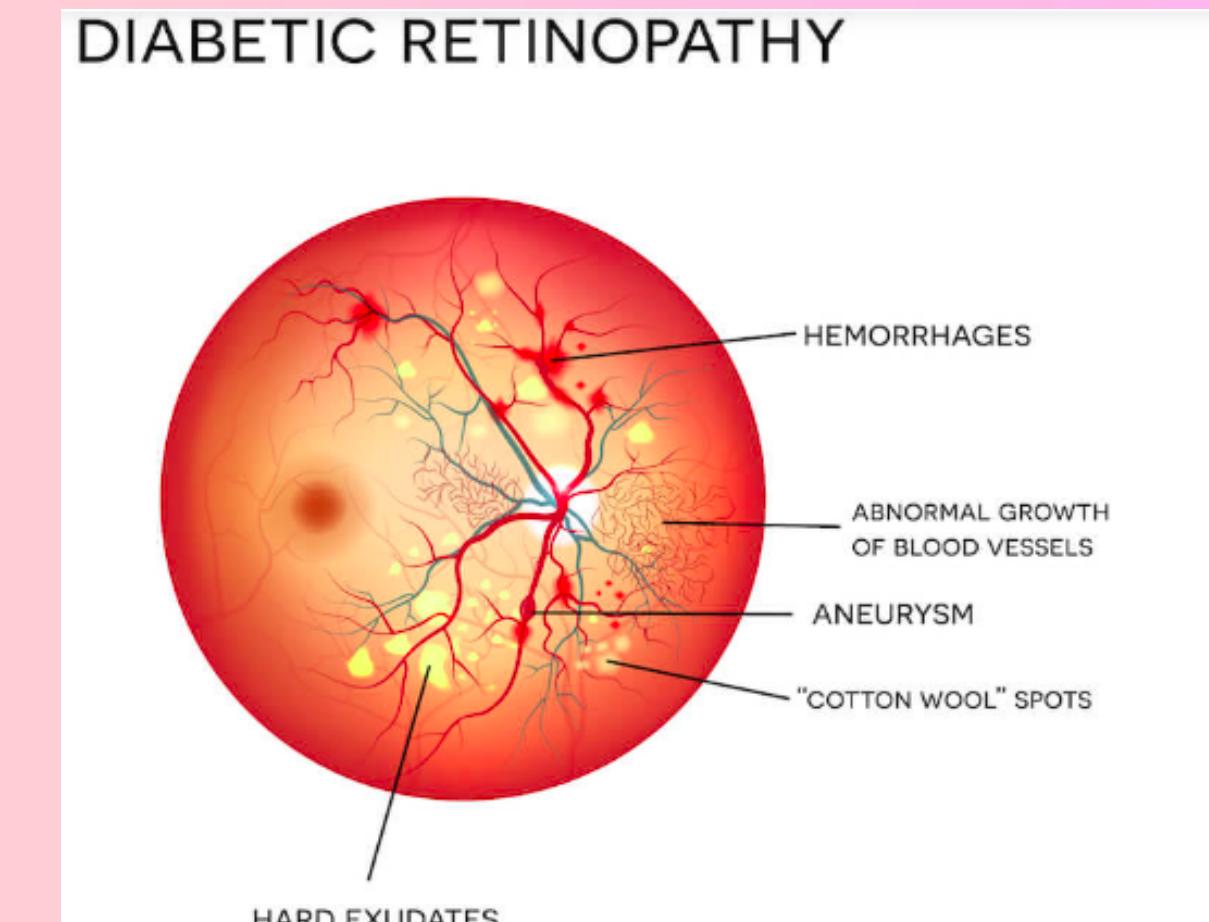
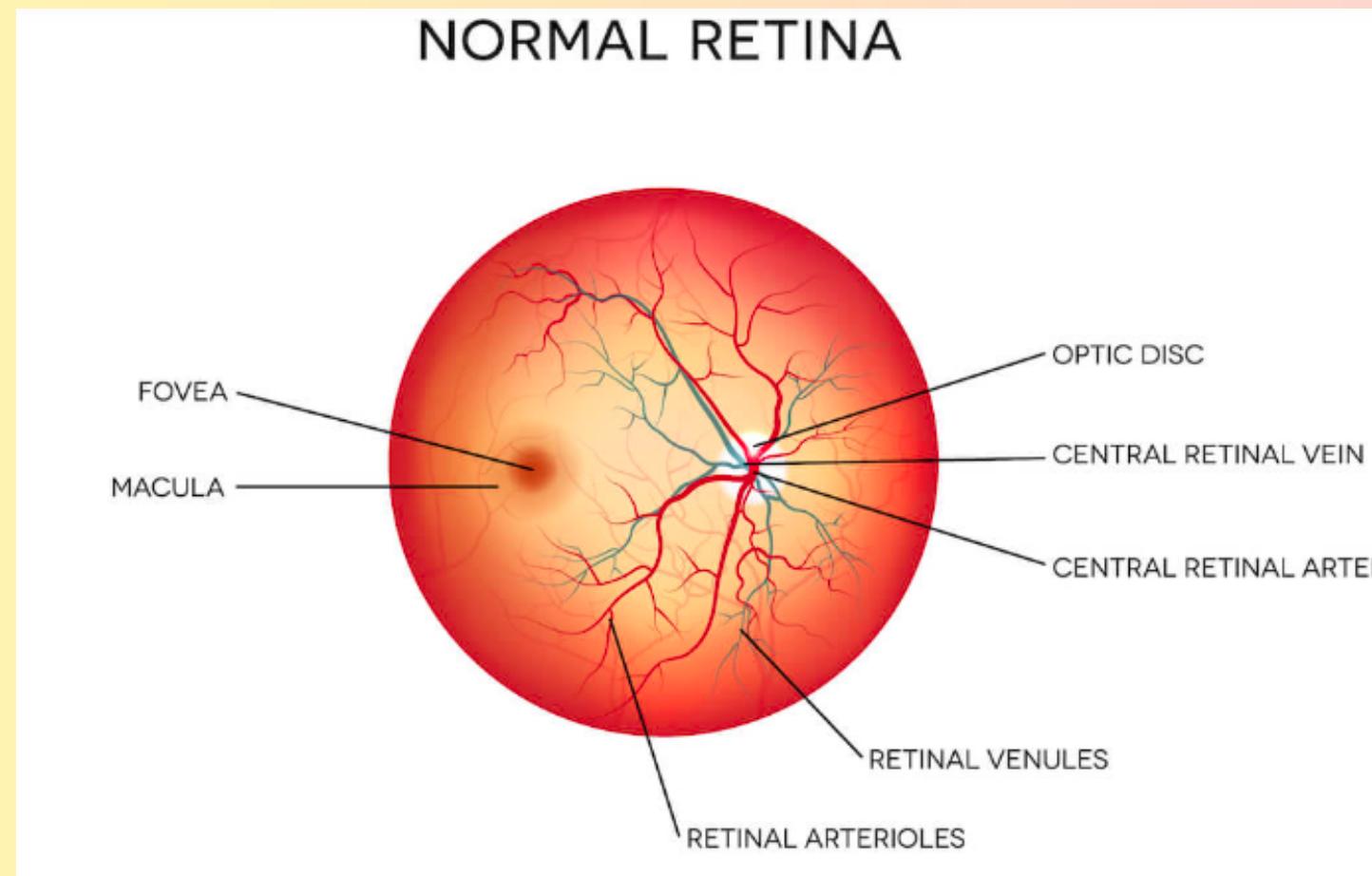
**Age-Related Vision Changes**

**Gender Disparities**

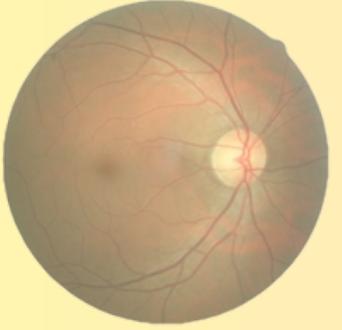


# Retina-Vision

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 !!



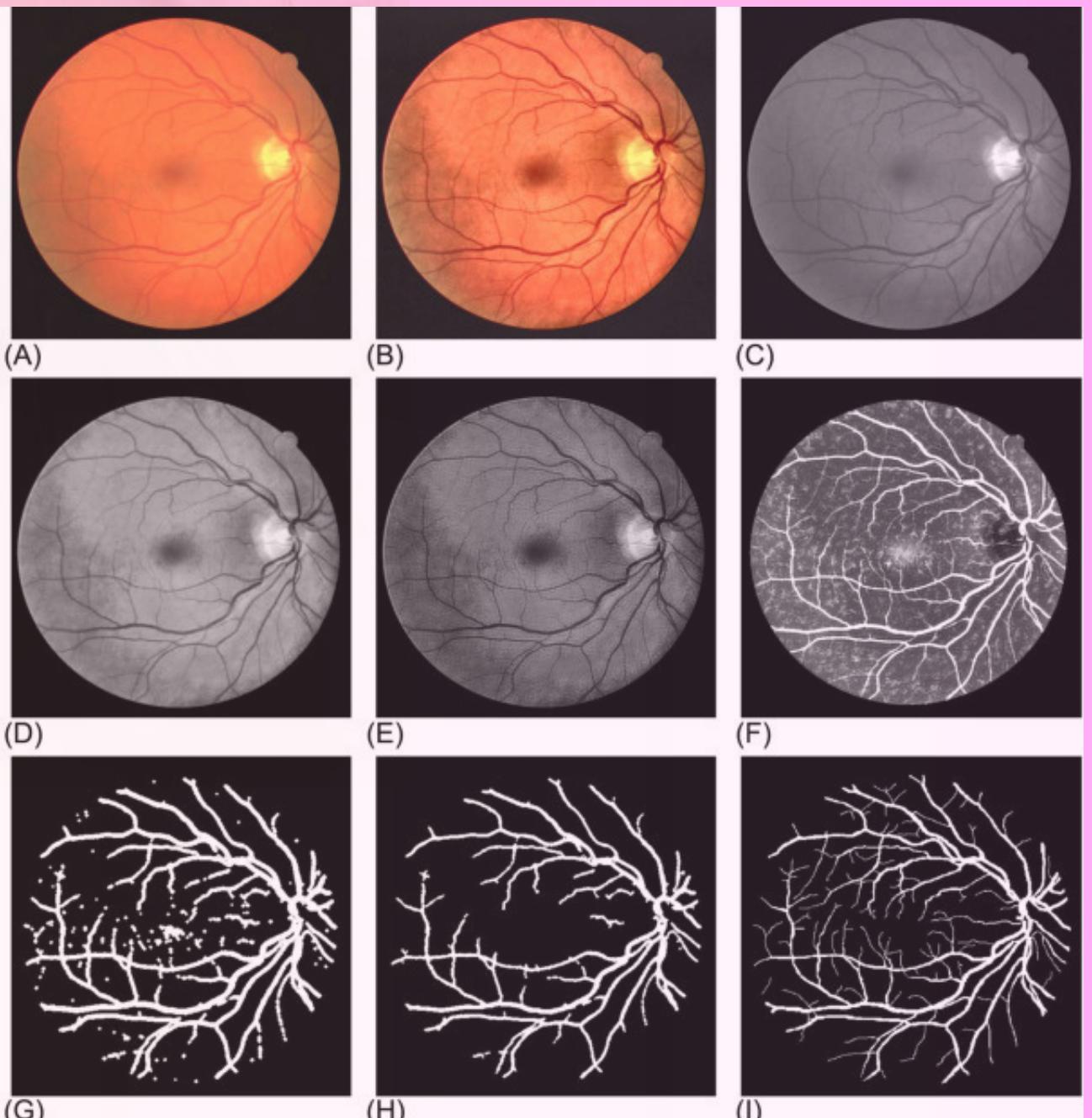
## Retina-Vision End User

- Medical professionals
- ophthalmologists and retinal specialists.
- Accurate vessel segmentation is important for diagnosing diseases such as diabetic retinopathy, macular edema, and arteriosclerosis.



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

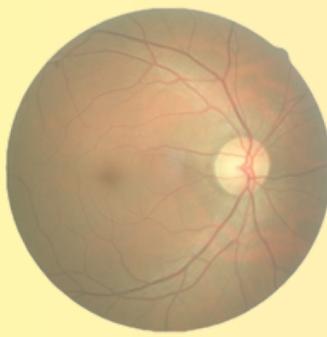
## Retinal Blood Vessel Segmentation



# Introduction

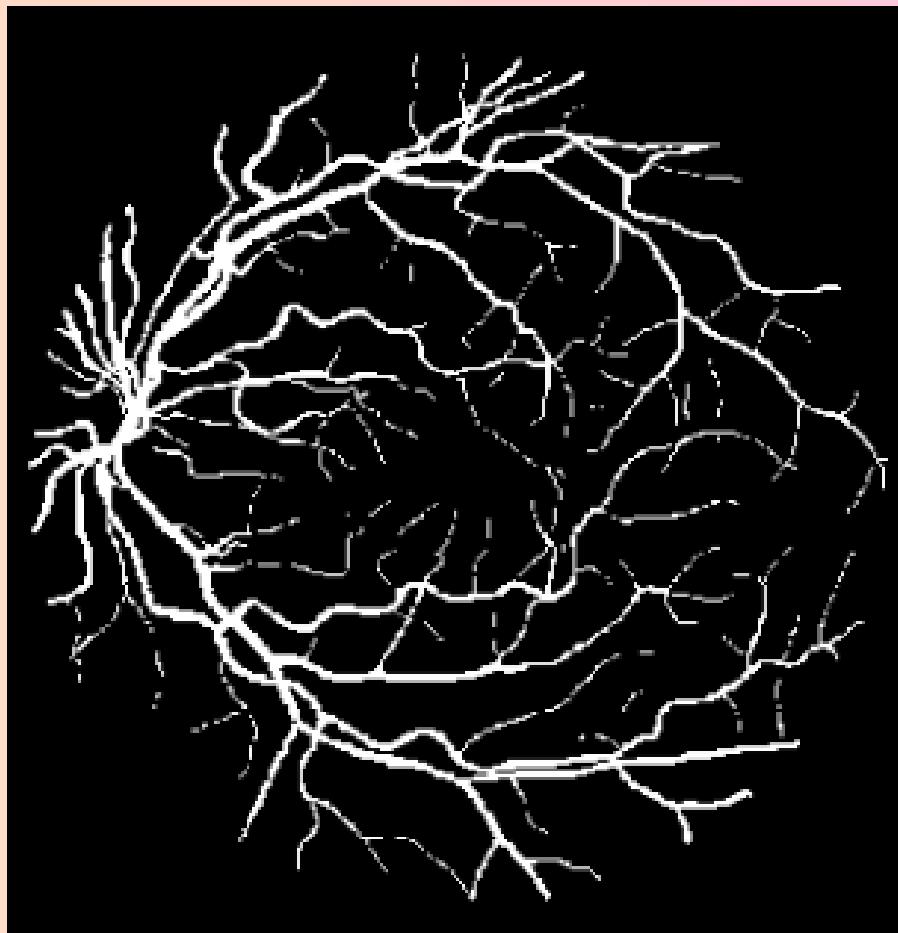
- Analysis of retinal vessel networks yields valuable insights into eye conditions.
- Segmenting blood vessels from fundoscopic images is a challenging task due to thin vessel edges, poor image quality, noise, and potential detail loss.
- Errors in vessel segmentation can lead to incorrect diagnoses, either falsely identifying a disease or missing one.
- The study uses the DRIVE dataset, which presents challenges such as limited annotated data.
- 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.



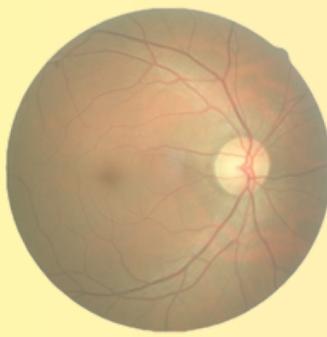


## DataSet

- Utilizing the DRIVE dataset from Kaggle.
- 20 train and 20 test images.
- Each image represents a different disease.
- Challenging due to limited annotated data.

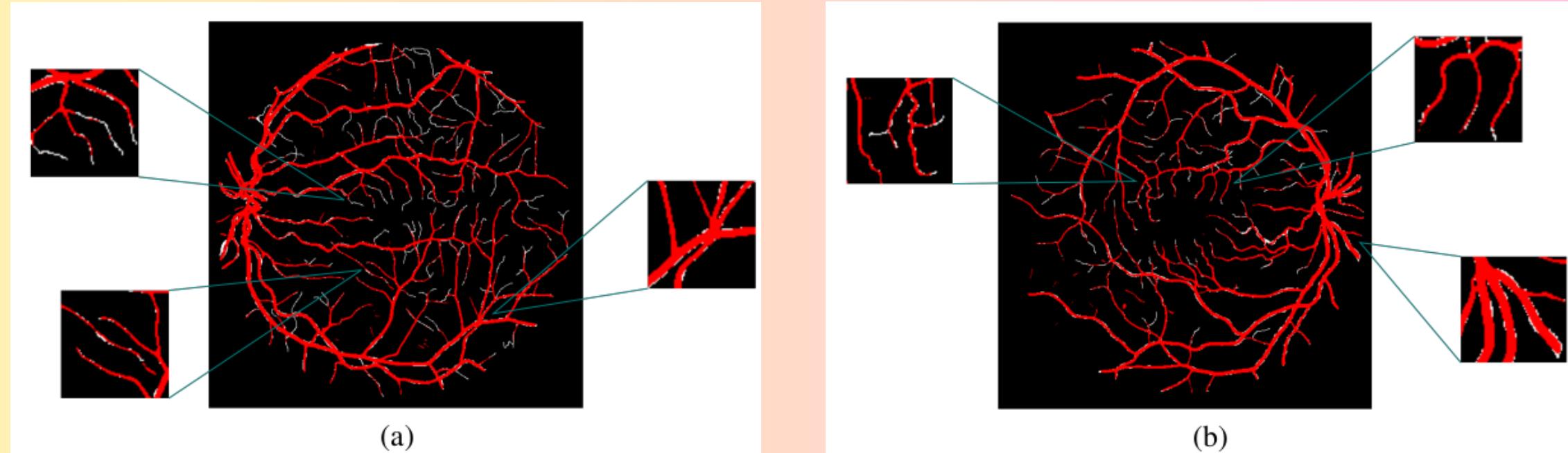


Training sample from DRIVE dataset

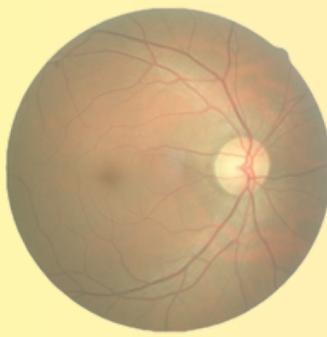


## Problem with DataSet

1. The actual problem with the dataset is the segmentation of the minor vessels.
2. The scarcity of the data.

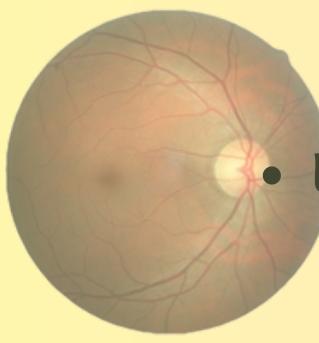


It can be seen that the majority of the incorrect segmentations occur at the minor vessels.



## Literature Review

- Convolutional networks have been limited by small training sets and network sizes.
- Commonly used for image classification, but many tasks, especially in biomedical imaging, require pixel-level labeling.
- Biomedical tasks often lack thousands of annotated images.
- Paper[1] proposes a network and training strategy that heavily uses data augmentation for efficient use of available annotated samples.
- Paper[2] outlines various augmentation techniques:
  - Gamma Correction, Random Crop, Grid and Optical Distortion
  - White Noise, Elastic Deformations, Shift, Blurring, Dropout, Histogram Equalization
  - Rotation and Flipping



# Architecture

- **U-Net Overview:**
  - A specialized computer model for image processing.
  - 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.

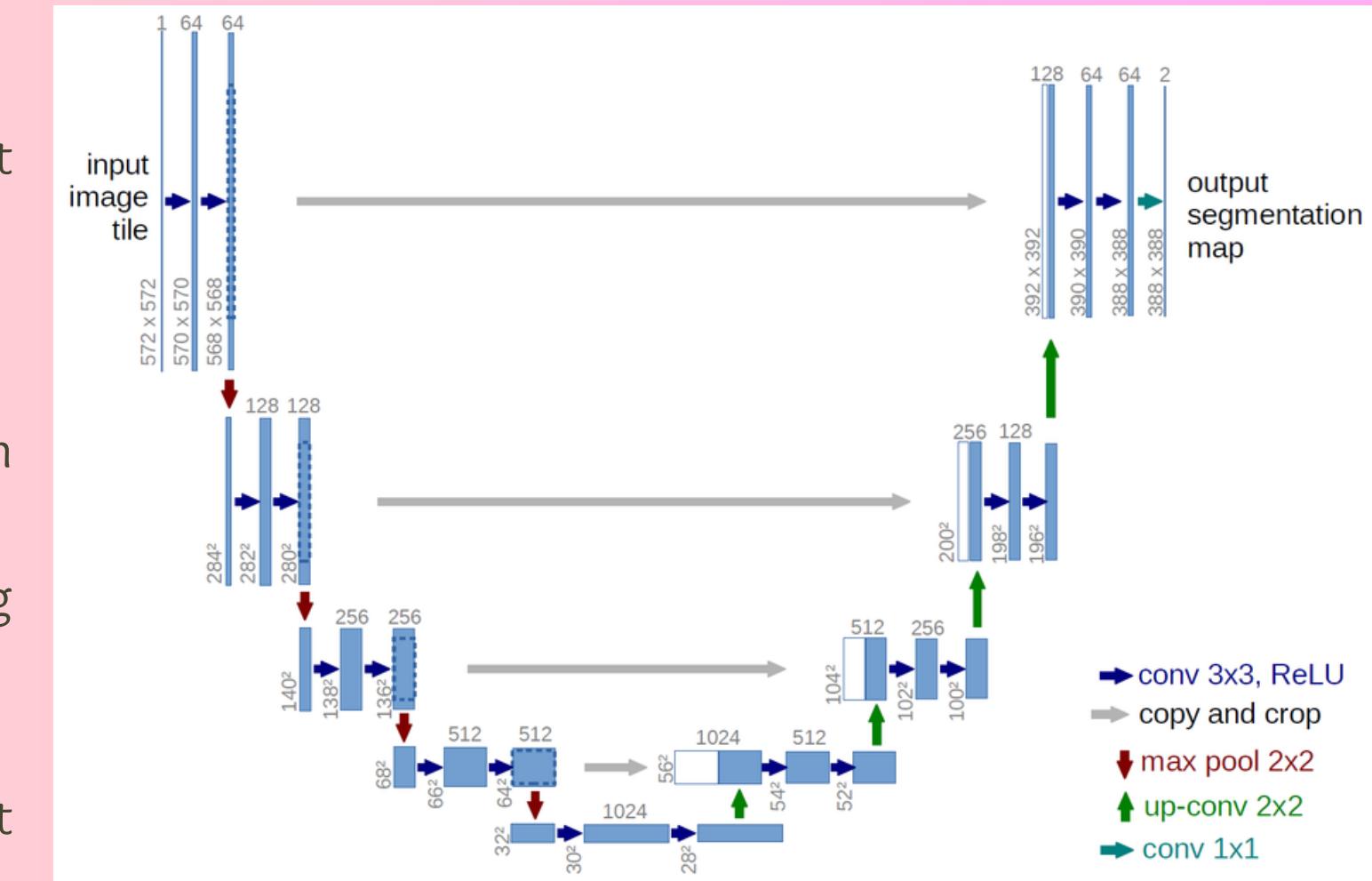
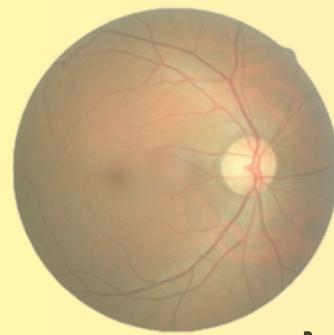


Figure 1: Architecture of the U-Net Image Segmentation Model.

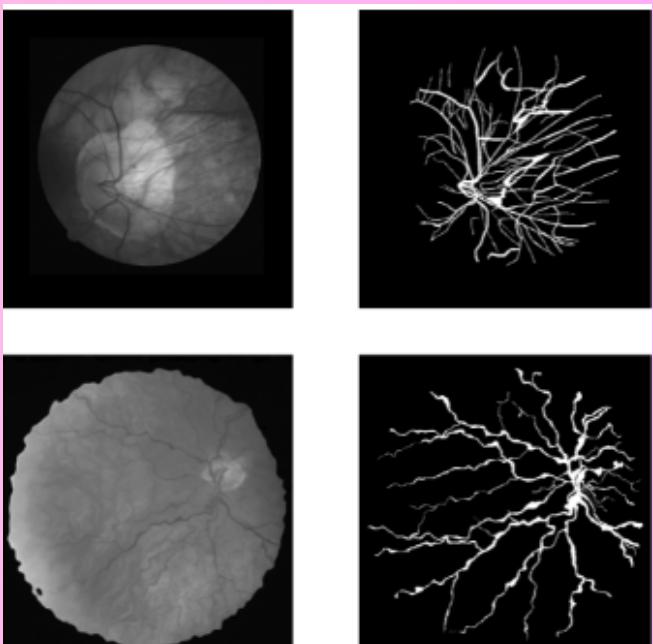
- **In Simple Terms:**
  - U-Net is like a skilled artist that outlines important things in pictures, aiding doctors in understanding what's happening inside the body.

# Experiment set up



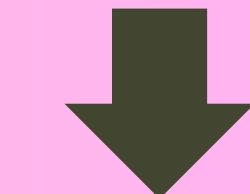
## Method and Architecture:

- Utilize U-Net [3] architecture.
- Train models with Adam optimizer [4] (learning rate: 1e-4,  $\beta_1$ : 0.9,  $\beta_2$ : 0.999).



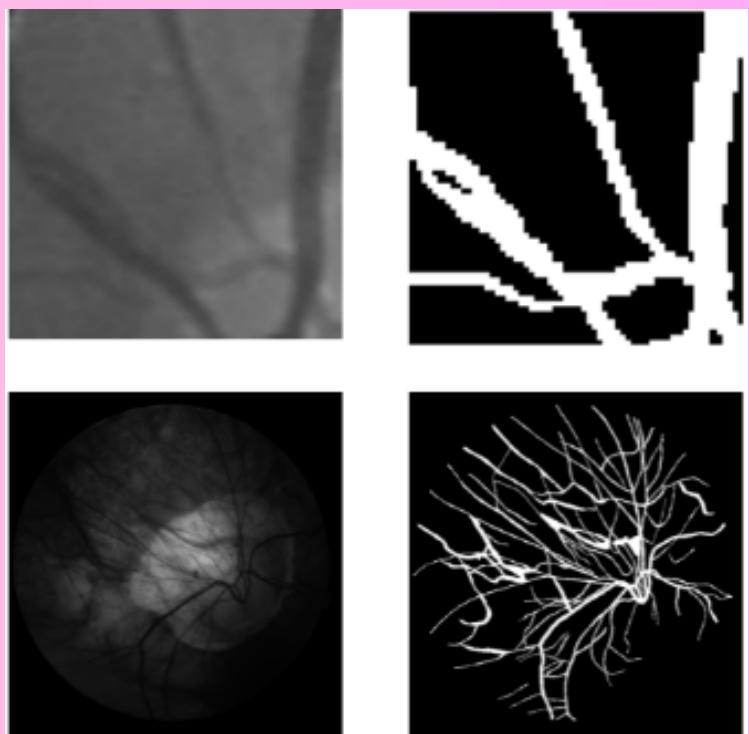
## Training Details:

- Mini-batches of size 3 for DRIVE dataset experiments.
- Best results achieved with binary cross-entropy loss.



## Data Augmentation:

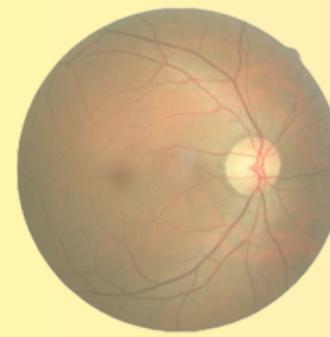
- Generated 70 images from 20 using augmentation.
- Augmentation techniques include:
  - Rotation ( $30^*k$ ) and flipping, Zoom out, White noise, elastic deformations, and shift.



## Library Usage:

- Utilized `albumentations` and `imagecorruptions` libraries for extensive augmentations.

# Results



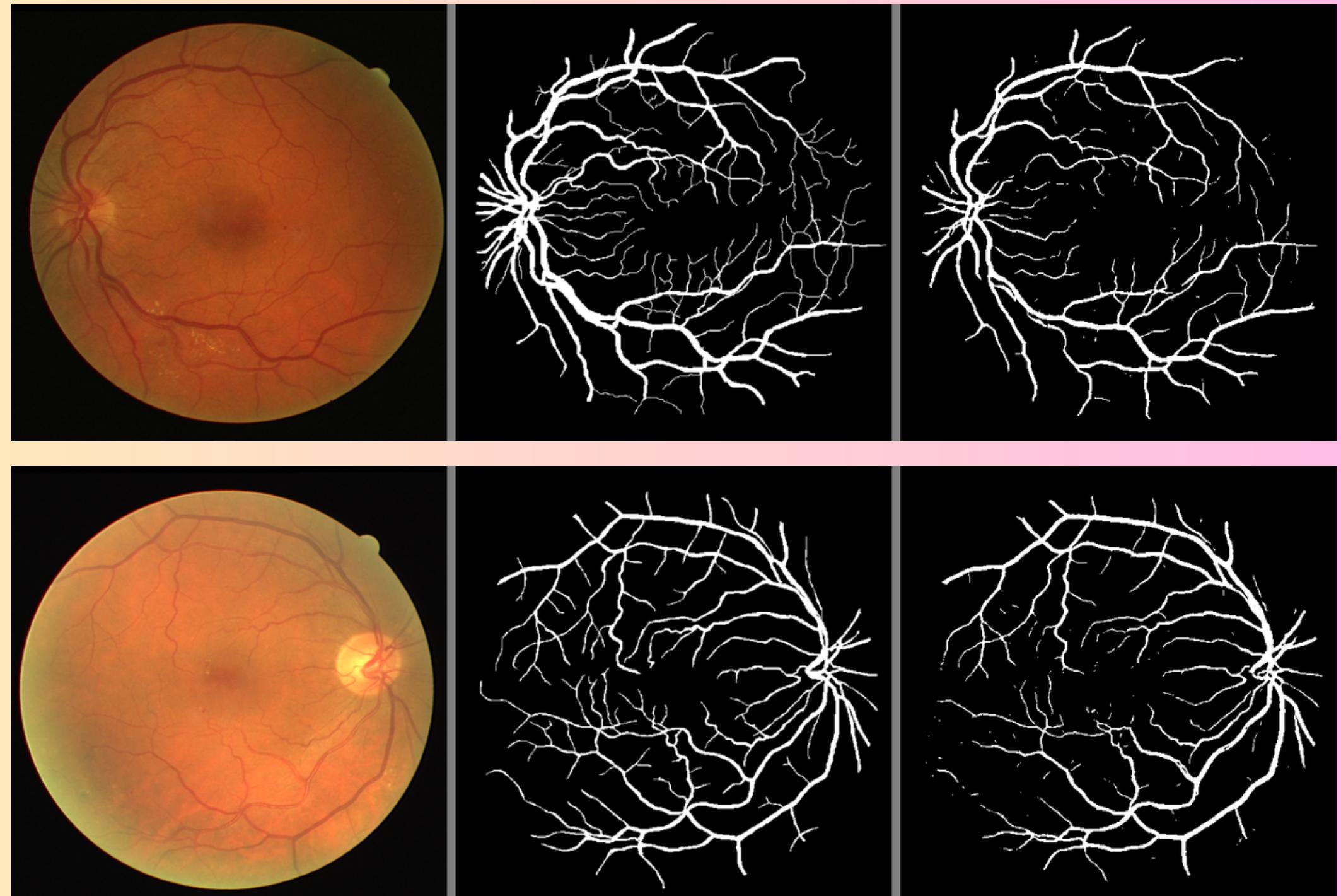
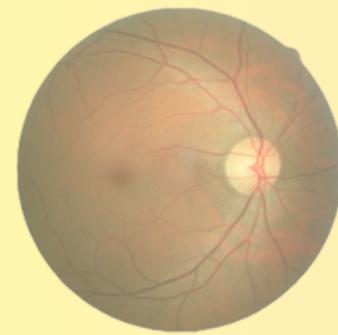
DRIVE	Accuracy	AUC	Mean Dice Coef
Rotation (30*k) And Flipping	0,970	0,971	0,809
+ Zoom Out	0,971	0,983	0,820
+ White Noise/Elastic Deformations/Shift	0,970	0,985	0,822
+ Gamma Correction/Random Crop/Grid and Optical Distortion	0,971	0,983	0,824
+ Blurring/Dropout/ Eq. Histogram	0,971	0,985	0,826

Result calculated for different kind of augmentation

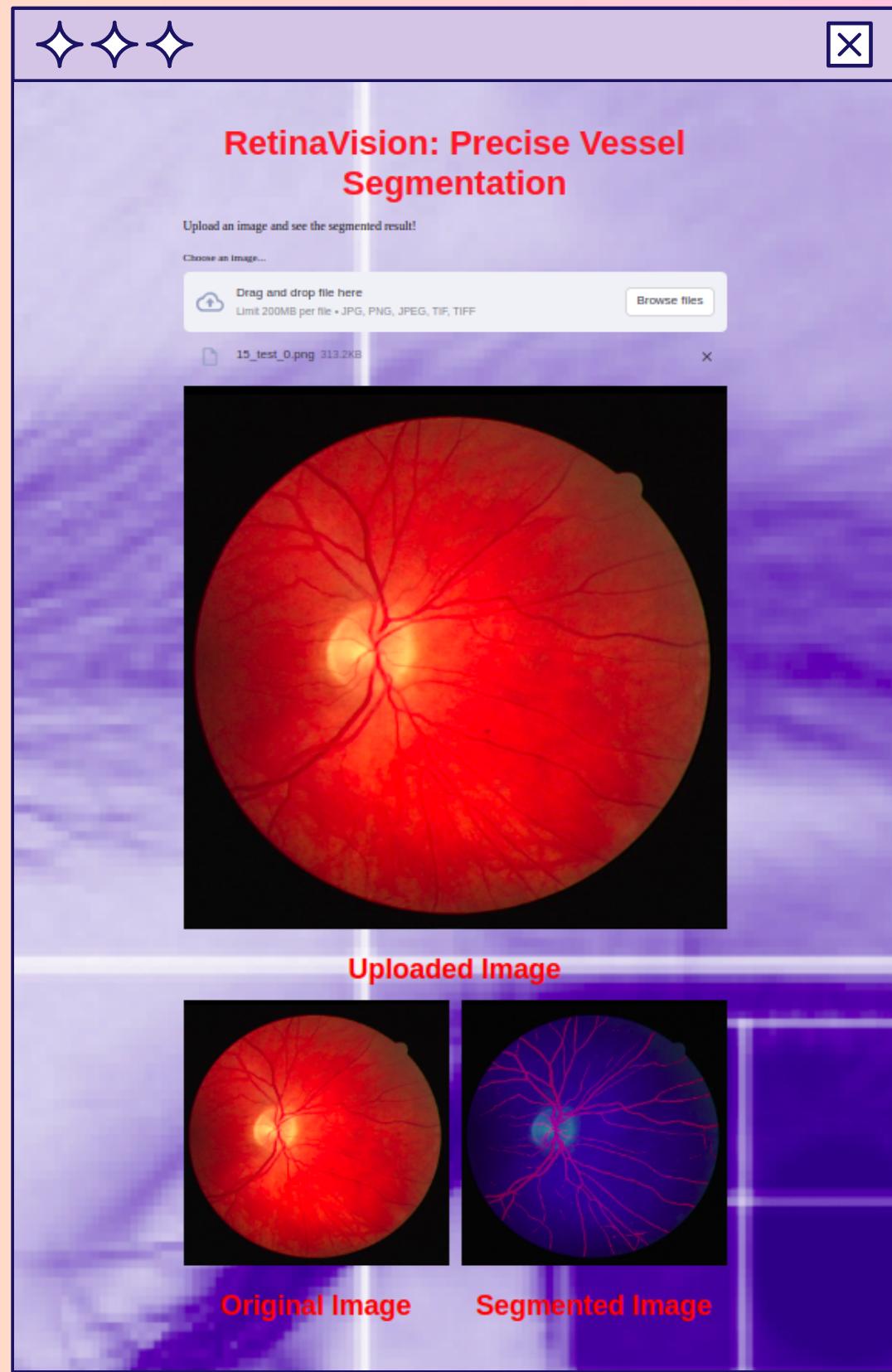
Method	AUC	Accuracy
UNet (2018*)	0,9752	0,9555
Residual UNet (2018)	0,9779	0,9553
IterNet (2019)	0,9816	0,9571
SUD-GAN (2020)	0,9786	0,9560
RV-GAN (2020)	0,9887	0,9790
<b>U-Net with Augmentation</b>	<b>0,9848</b>	<b>0,9712</b>

Performance comparison for different Methods

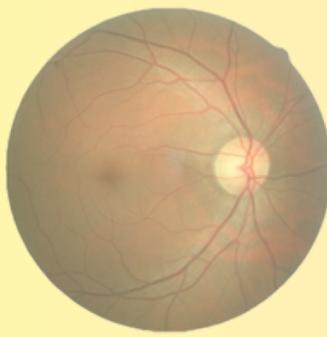
# Results



# Retina-Vision

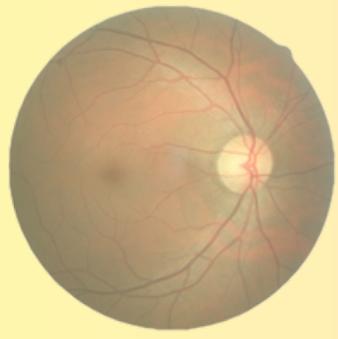


***Demo !!!***



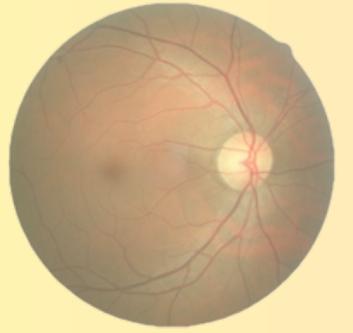
## References

- [1] <https://arxiv.org/pdf/2105.09365v2.pdf>
- [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](http://dx.doi.org/10.1007/978-3-319-67558-9_28).
- [6] Di Li et al. "Residual U-Net for Retinal Vessel Segmentation". In: 2019 IEEE International Conference on Image Processing (ICIP). 2019, pp. 1425–1429. DOI : 10.1109/ICIP.2019.8803101.



## Code Repository

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



# THANK YOU