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Procesamiento de Imágenes

Universidad Tecnológica de Bolívar
CARTAGENA DE INDIAS

Medical Digital Image Processing in Ophthalmology: Successes and Current Challenges

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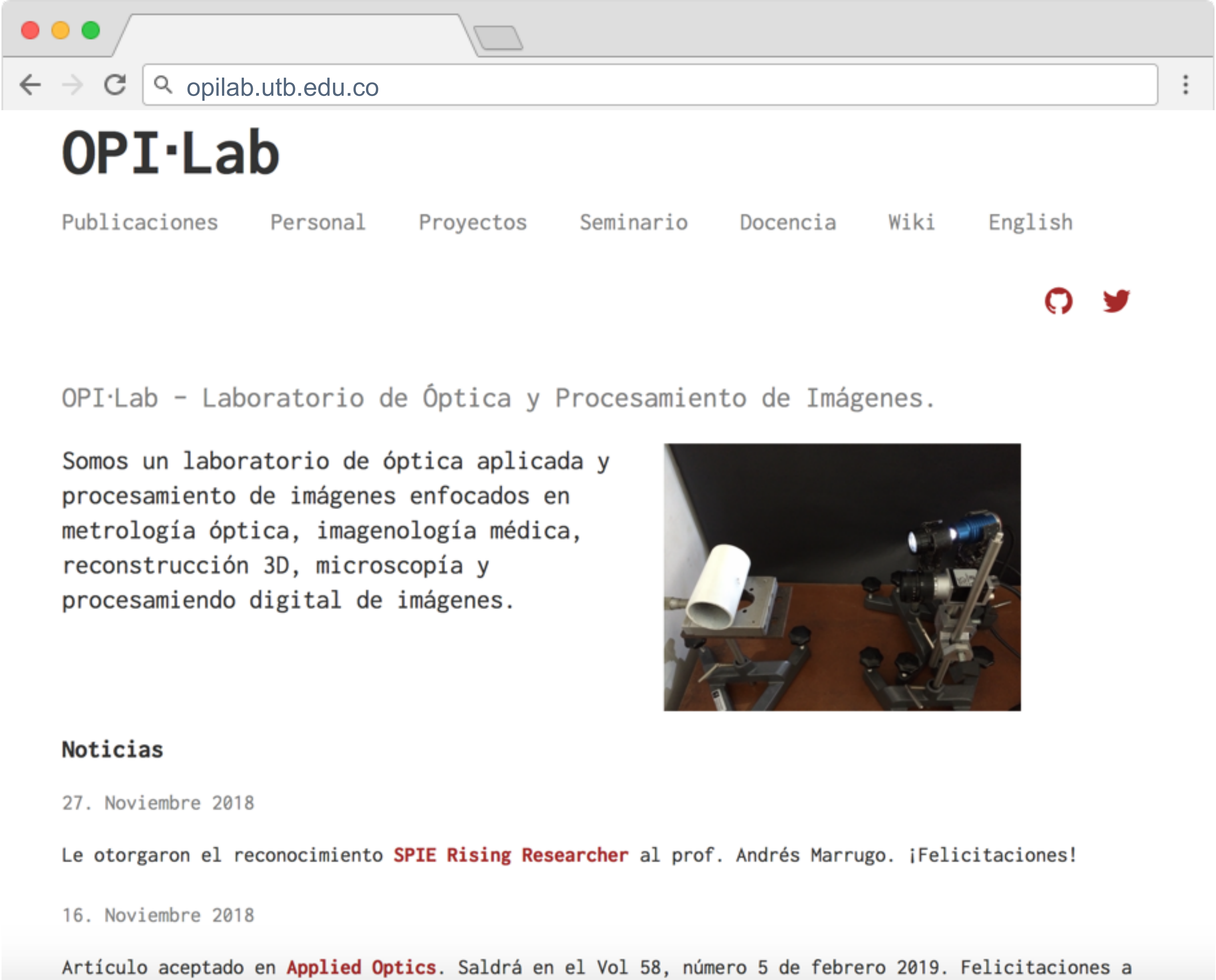
Terrassa, January 31st, 2019

Universidad Tecnológica de Bolívar
CARTAGENA DE INDIAS

- Founded in 1533
- UNESCO World Heritage Site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Somos un laboratorio de óptica aplicada y procesamiento de imágenes enfocados en metrología óptica, imagenología médica, reconstrucción 3D, microscopía y procesamiendo digital de imágenes.
Noticias
27. Noviembre 2018
Le otorgaron el reconocimiento SPIE Rising Researcher al prof. Andrés Marrugo. ¡Felicitaciones!
16. Noviembre 2018
Artículo aceptado en Applied Optics. Saldrá en el Vol 58, número 5 de febrero 2019. Felicitaciones a

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Medical Imaging
Optical Metrology

Lenny Romero

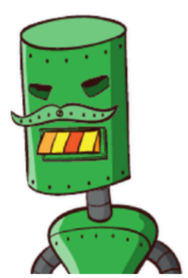
Profesora asociada

Image Processing
Optical Metrology
Diffractive Optics

Hernando Altamar

Profesor asistente / Estudiante de doctorado

Microscopy
Image Processing



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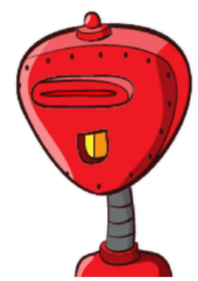
Estudiante de maestría



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Enrique Sierra

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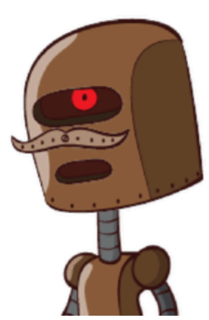

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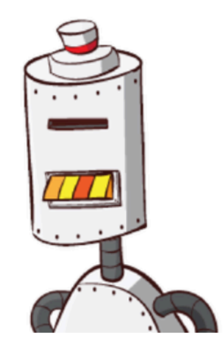


Juan Sierra

Estudiante de pregrado

I'm going to talk about three things:

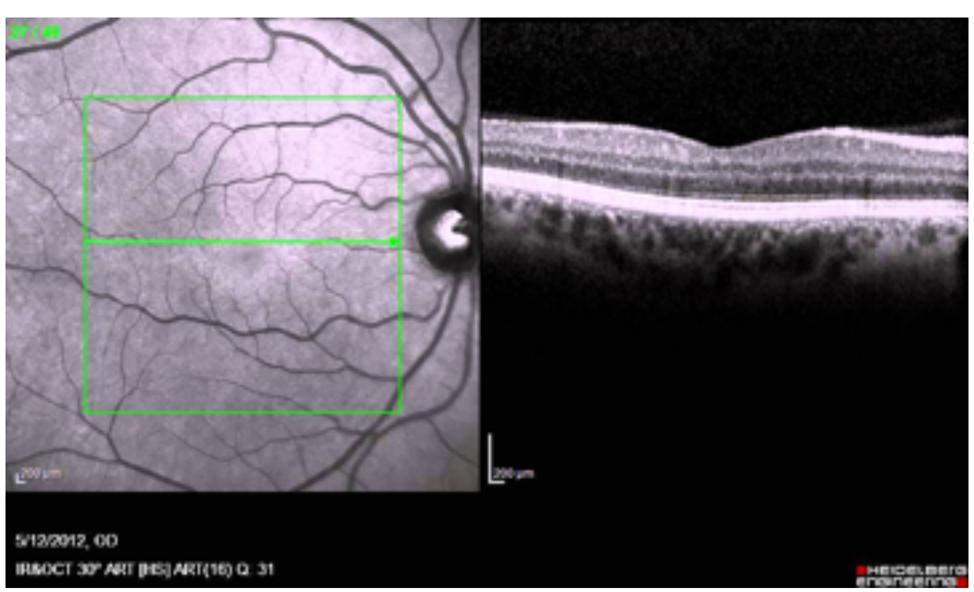
1. How **medical imaging** has dramatically changed in recent years.
2. **New technologies in digital image processing** are enabling **computer-aided diagnogstics,** treatment, etc.
3. **Still many challenges** in the underlying technology.

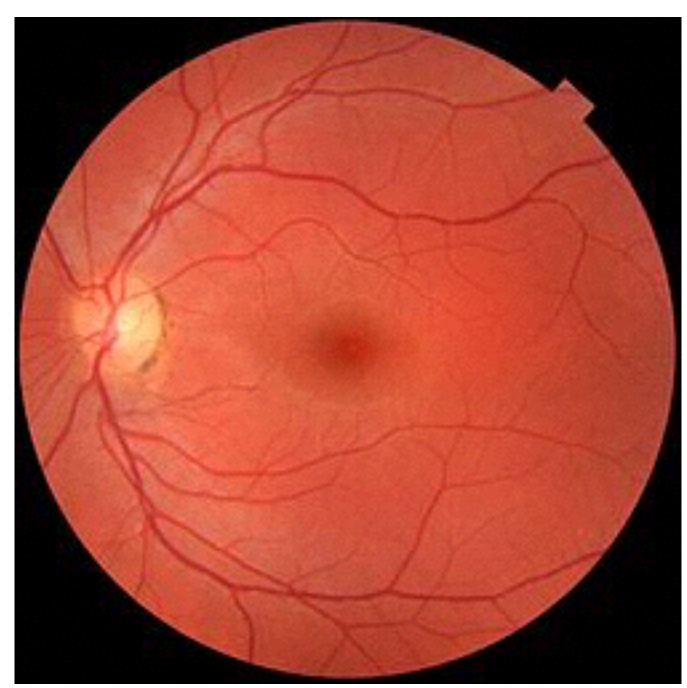
Caveats

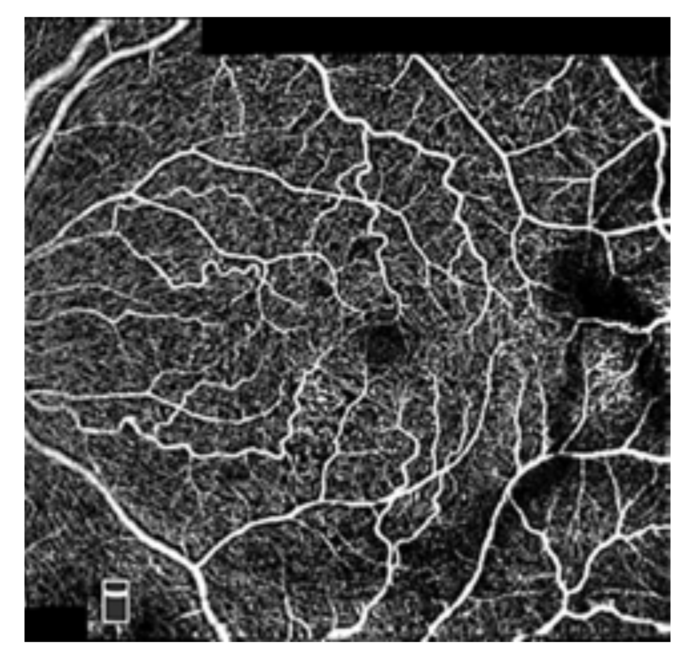
- This talk does not intend to be a comprehensive review of ophthalmic imaging.
- The topics presented here have come to our attention due to our research interests.

1. Medical **Imaging**

Ophthalmology is a field heavily dependent on images.







1. Medical **Imaging**

Ophthalmology is a field heavily dependent on images

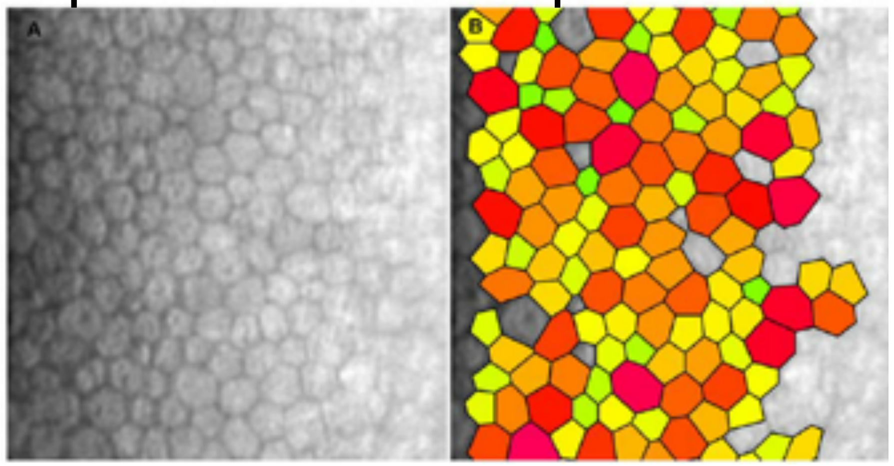
Diagnostic / screening purposes.

Disease progression assessment.

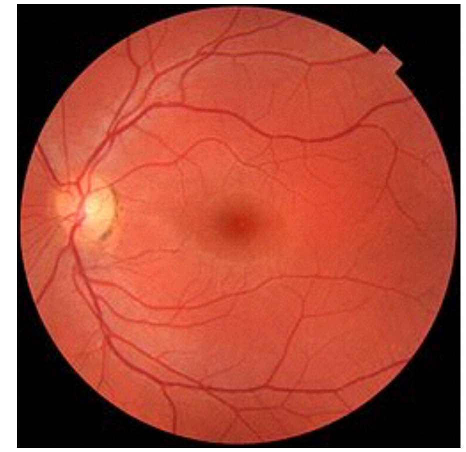
Surgical planning, intraoperative guidance

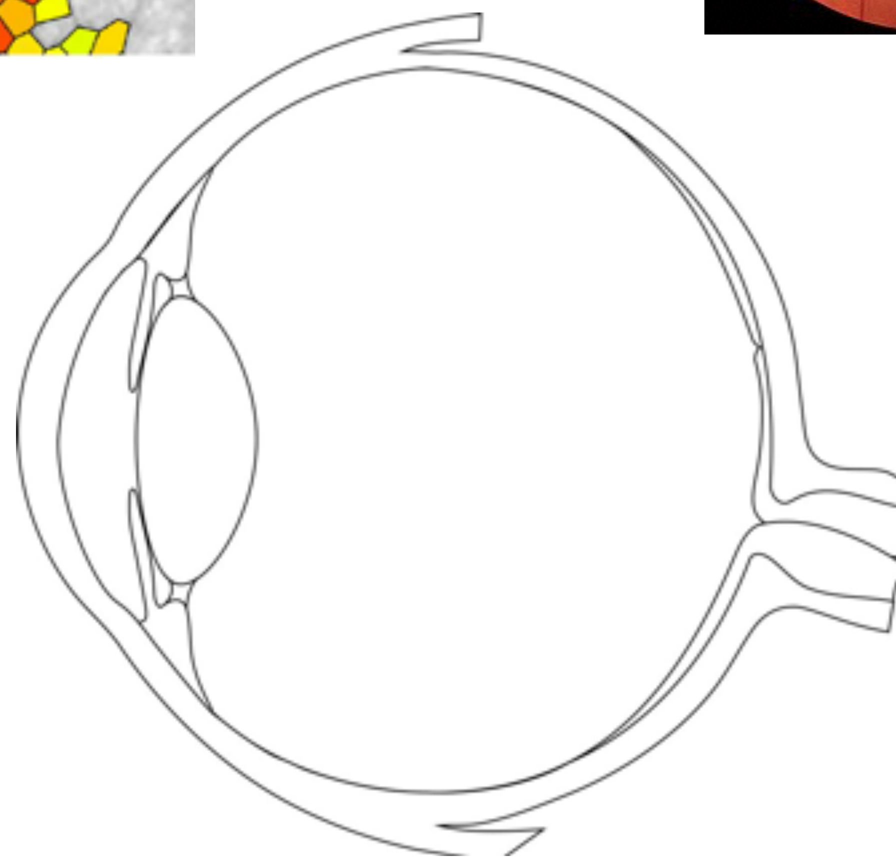
And many other.

Specular microscope

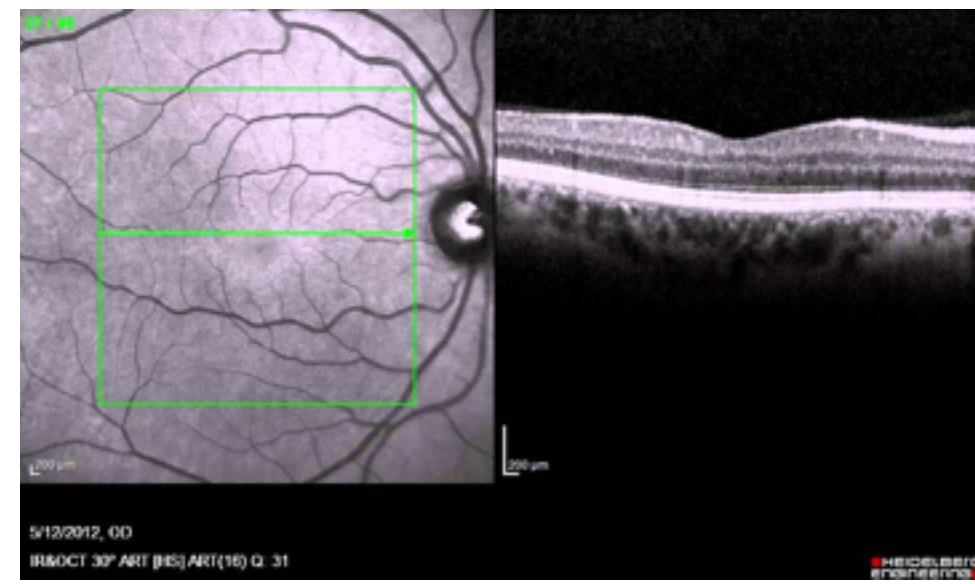


Fundus images

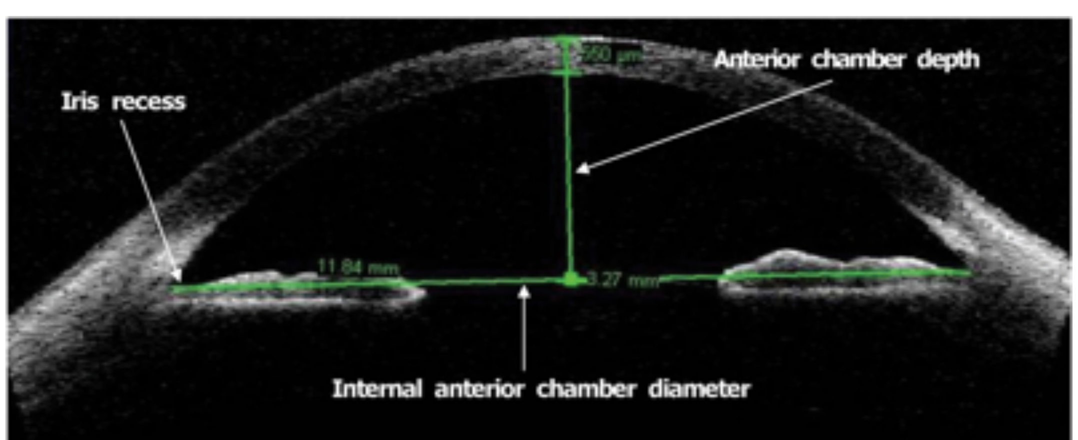




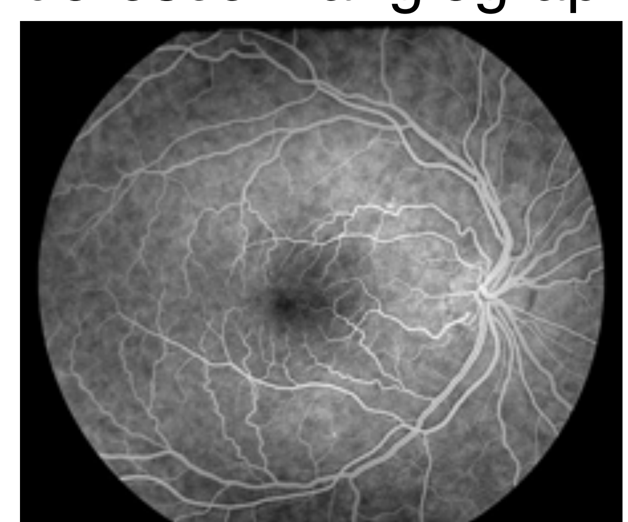
OCT



Anterior OCT



Fluorescein angiography



Until recently:

Technology enabled us to “see” the different parts of the eye **BUT**

- Image interpretation and understanding **relied on expert**
- **Quantitative image analysis** was often not done.

Today:

1. Quantitative analysis is a **must**.
2. Image understanding is **needed.**

Specialist scarcity & Cost-effective screening.

Identifying overlook features.

Improving sensitivity/specificity.

Today:

1. Quantitative analysis is a **must**.
2. Image understanding is **needed.**

Bottom-line: The field **needs help** from **computers**.

Ophthalmic Imaging Timeline

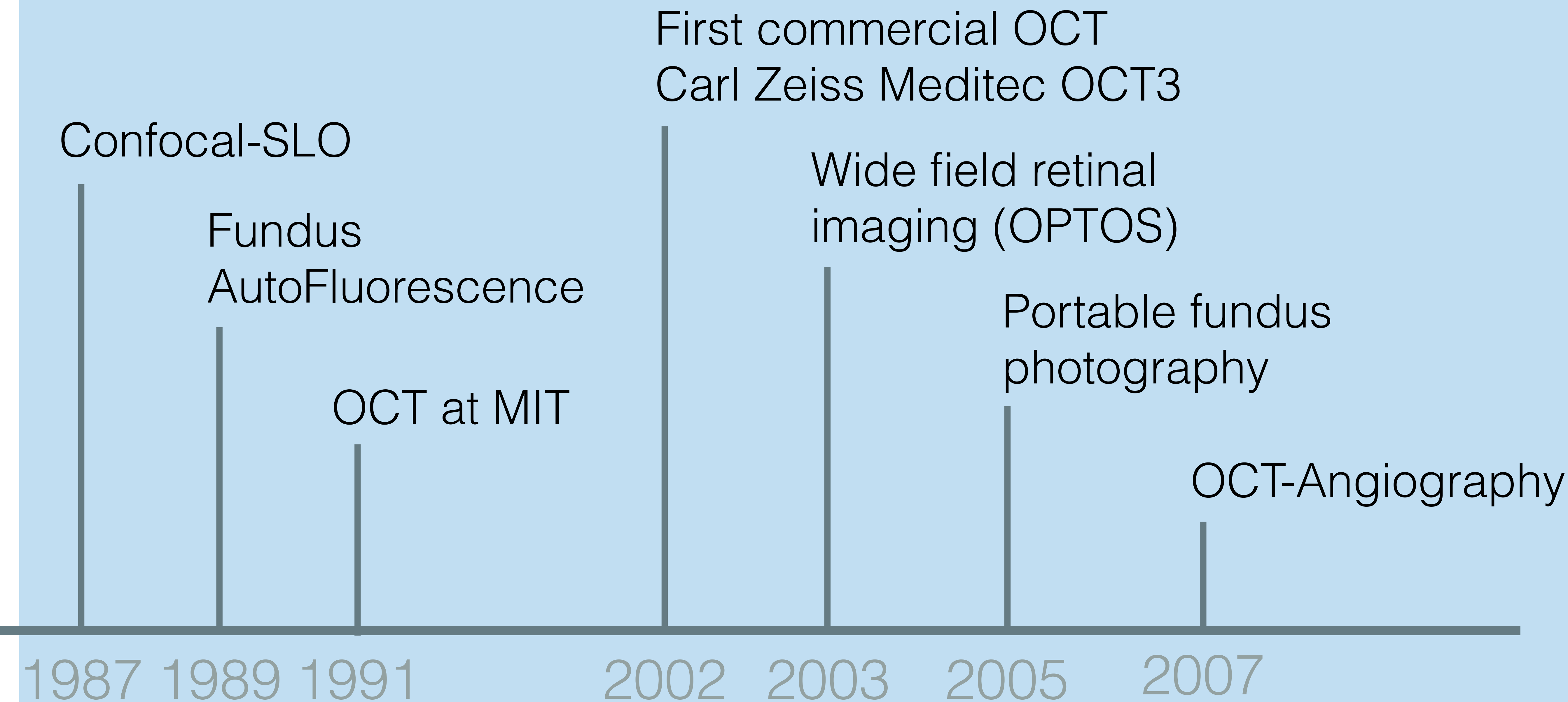
Direct Ophthalmoscope
(Helmholtz)

First in vivo photograph
of retina (Jackman and
Webster)

Fluorescein Angiography
(Indiana University)

1851 1886 1961

Digital Era


First commercial OCT
Carl Zeiss Meditec OCT3
Confocal-SLO
Wide field retinal
imaging (OPTOS)
Fundus
AutoFluorescence
Portable fundus
photography
OCT at MIT
OCT-Angiography
1987
1989
1991
2002
2003
2005
2007

Despite the unprecedented advances of recent years, **considerable deficiencies exist in our retinal imaging capability**. While angiographic techniques provide exquisite detail of vascular structures, our **ability to quantify chorioretinal blood flow and subsequent oxygen saturations – in a noninvasive manner – remains inadequate**. While **OCT** provides cross-sectional images of the neurosensory retina (and more recently the choroid) with high axial resolution, its **transverse resolution is limited**, and our ability to assess many retinal cell types remains poor (e.g., Müller cells, microglia, astrocytes, and individual neuronal elements). Furthermore, many advances in microscopic techniques that permit **“molecular” imaging** in basic science research have yet to make the transition to human clinical studies.

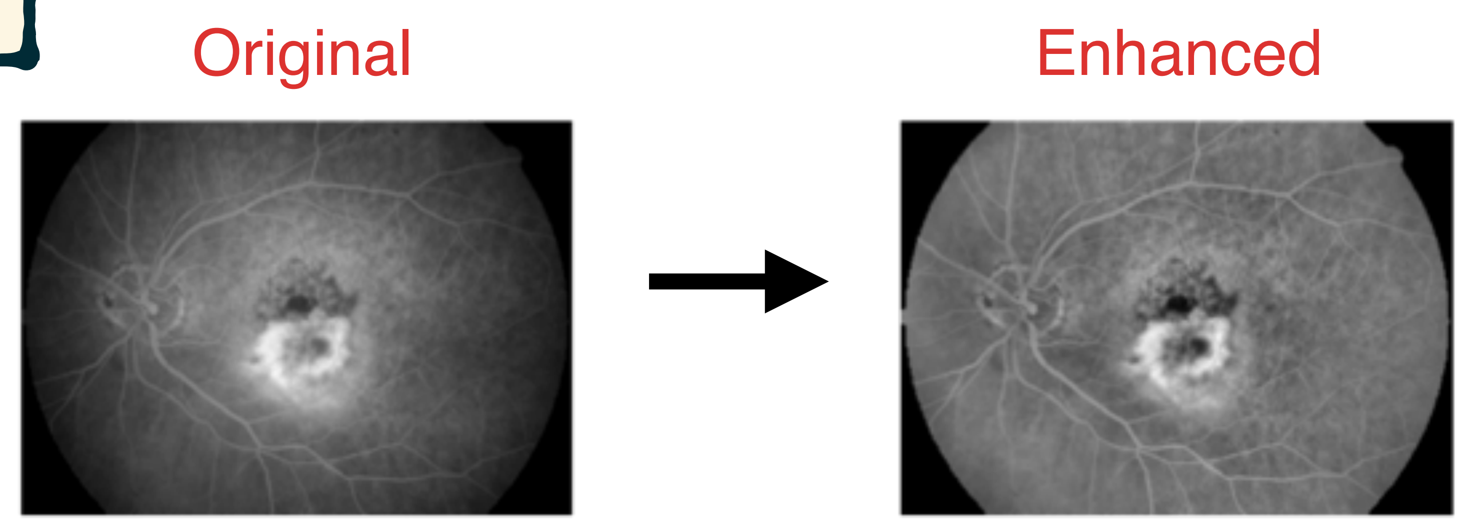
Michael D. Abràmoff, MD, PhD Retina specialist and the Robert C. Watzke, MD, Professor of Ophthalmology and Visual Sciences, Electrical and Computer Engineering, and Biomedical Engineering in the Department of Ophthalmology and Visual Sciences at the University of Iowa and the VA Medical Center,

M. Abramoff, 2017

Image Processing (Computer Vision)

How it typically is.

- Preprocessing
- Detection
- Segmentation
- Registration
- Interpretation



Remove variability without losing essential information.

A. G. Marrugo and M. S. Millán., 2011

Image Processing (Computer Vision)

How it typically is.

- Preprocessing
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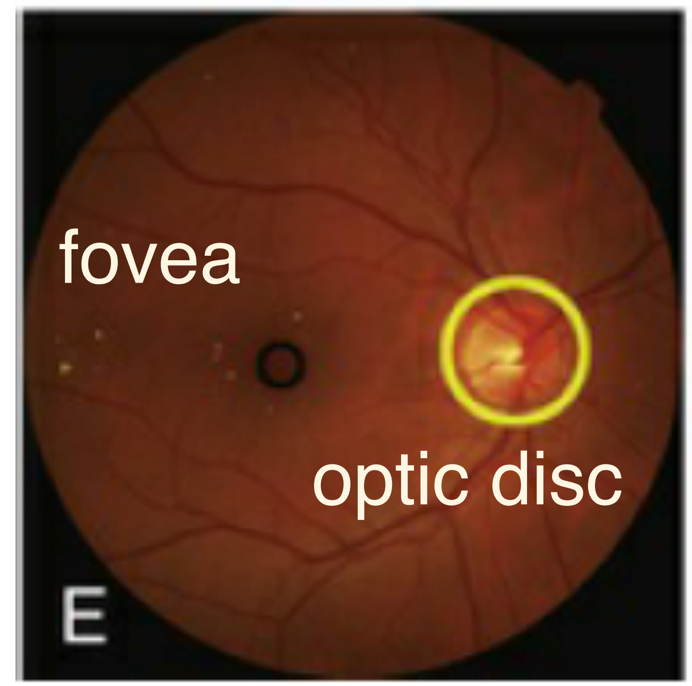
- Interpretation



Locate specific structures of interest, or features.

Hoover and Golbaum., 2005

Image Processing (Computer Vision)

How it typically is.

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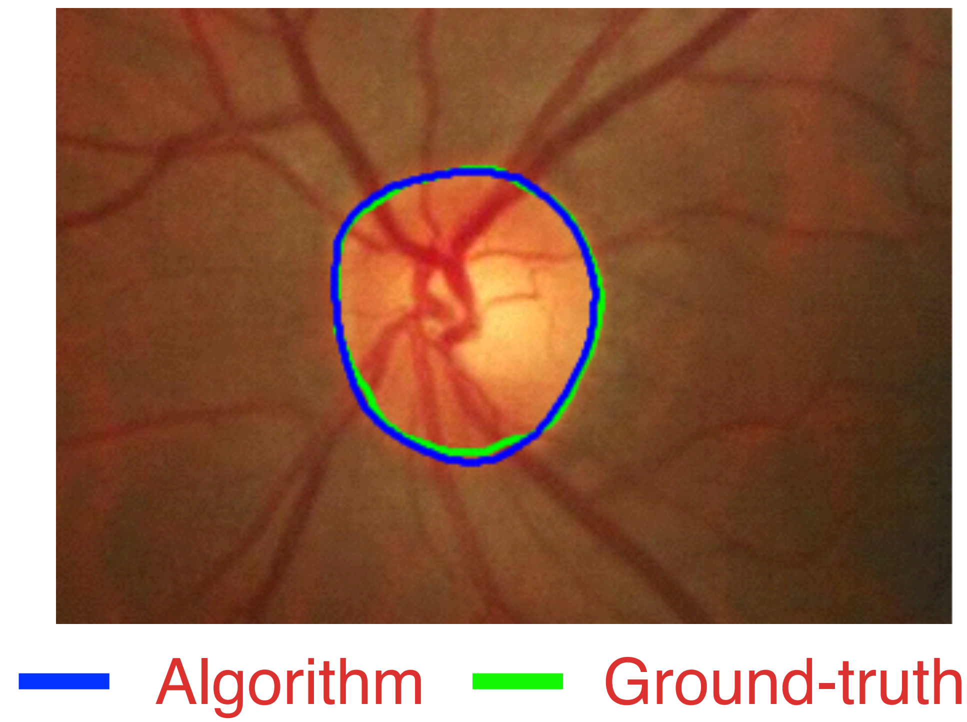
- Registration
- Interpretation



To determine precise boundaries of objects.

A. G. Marrugo and M. S. Millán., 2010

Image Processing (Computer Vision)

How it typically is.

- Preprocessing
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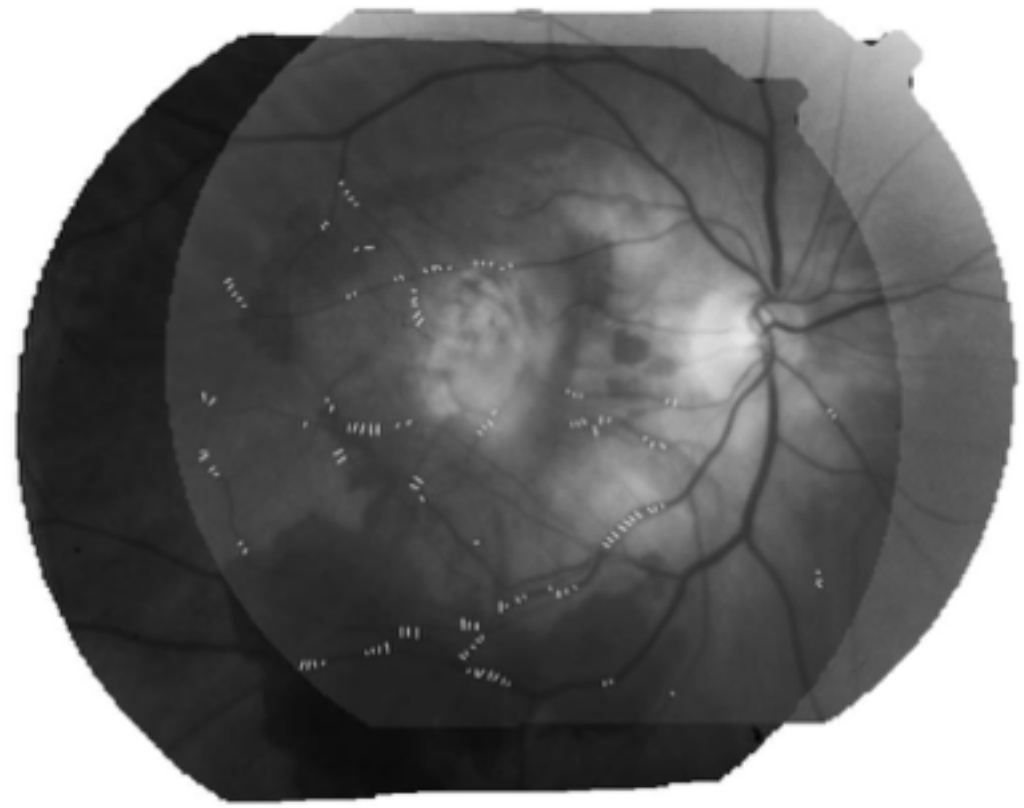
- Segmentation
- Registration
- Interpretation



To find similar regions in two or more images

C. Stewart et al., 2003

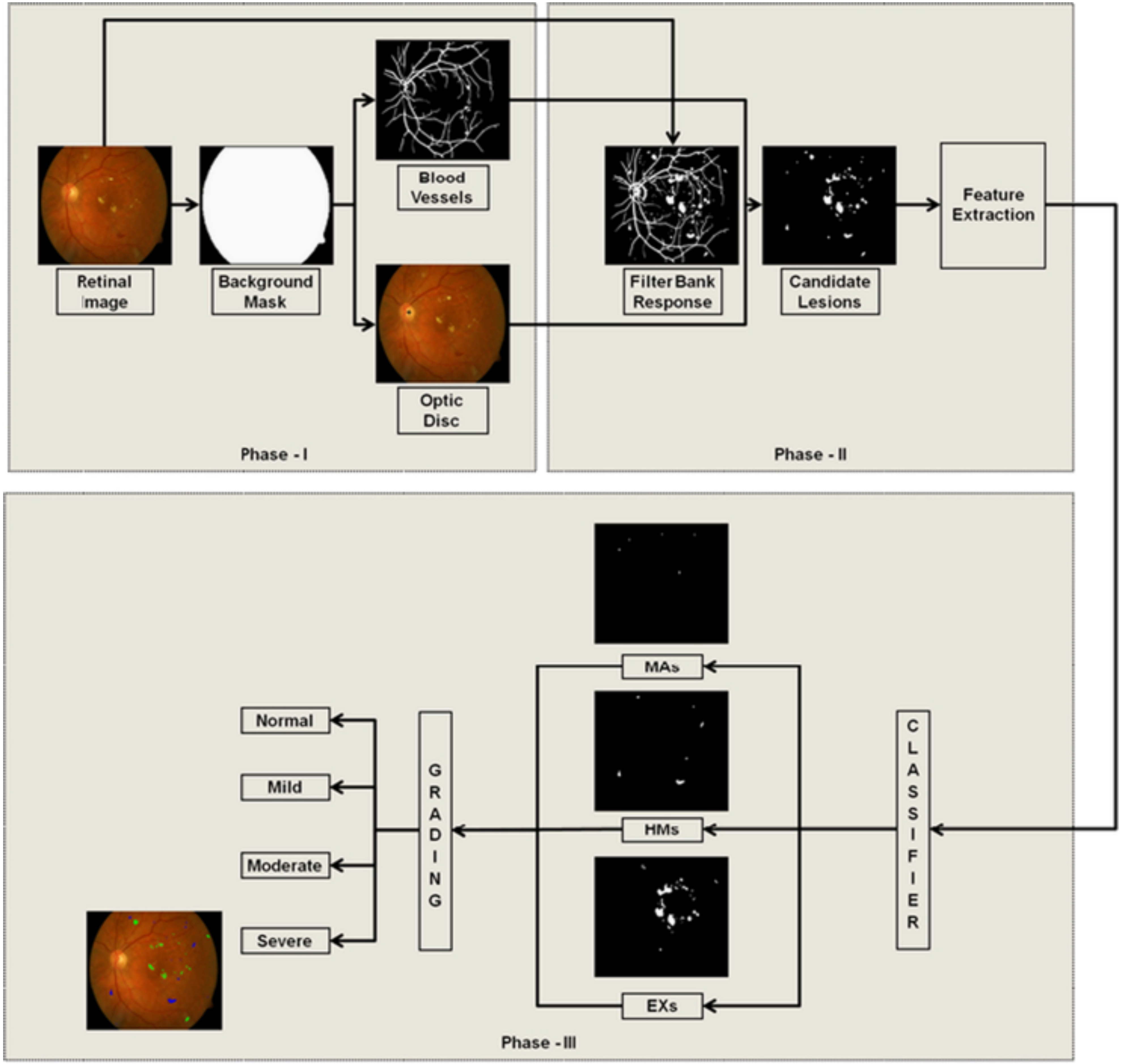
Image Processing (Computer Vision)

How it typically is.

- Preprocessing
- Detection
- Segmentation
- Registration
- Interpretation

Integration of previous steps, and output clinically relevant information.

Typical Pipeline



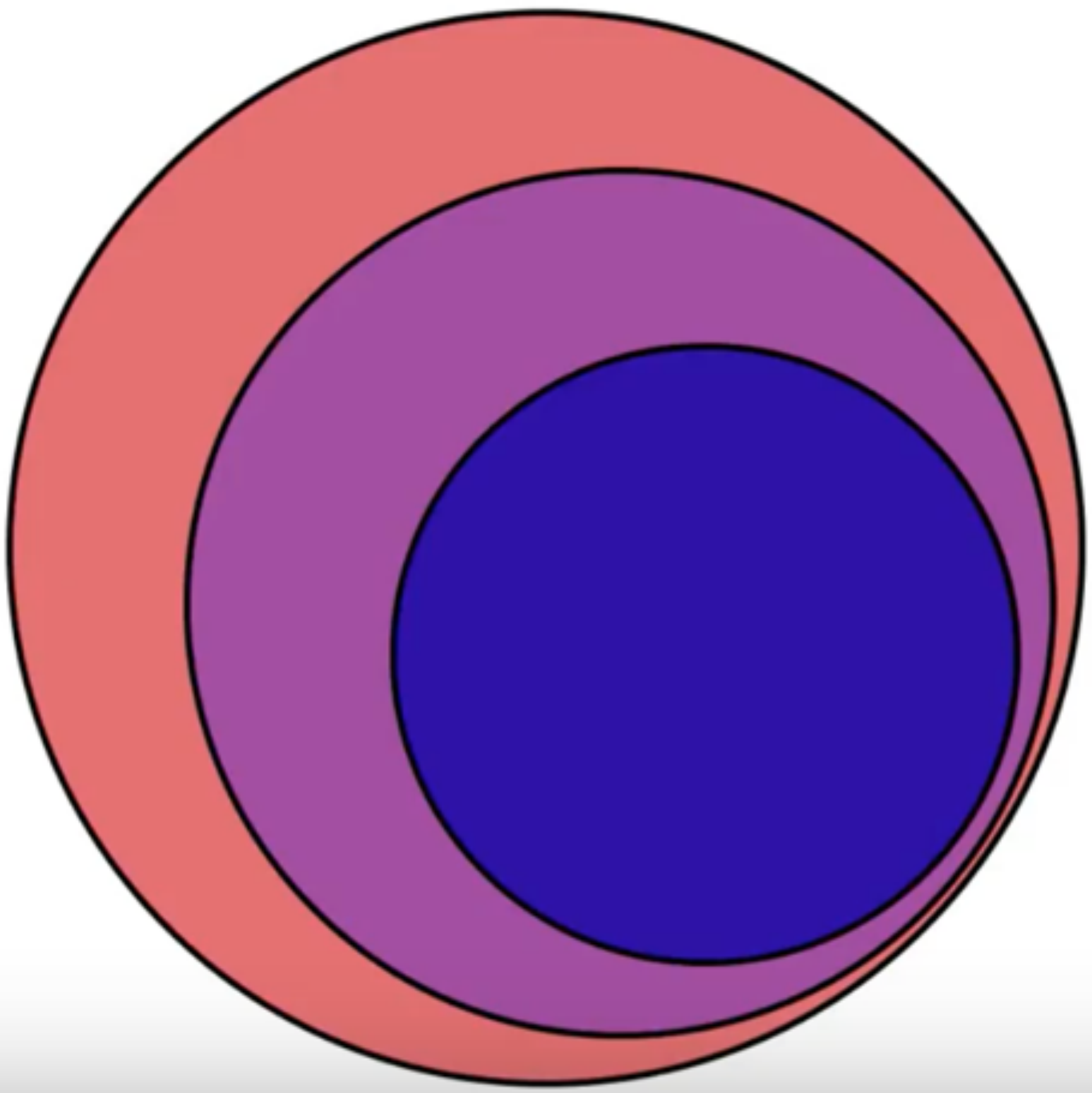
M. U. Akram et al., 2014

Image Processing (Computer Vision)

How it is becoming.

- Previous processing steps are typically explicitly created by the image analysis developers.
- The so called deep-learning approaches do not have these explicit steps, instead having learned these implicitly.

Image Processing (Computer Vision)



artificial intelligence

grand project to build non-human intelligence

machine learning

machines that learn to be smarter

deep learning

particular kind of machine learning

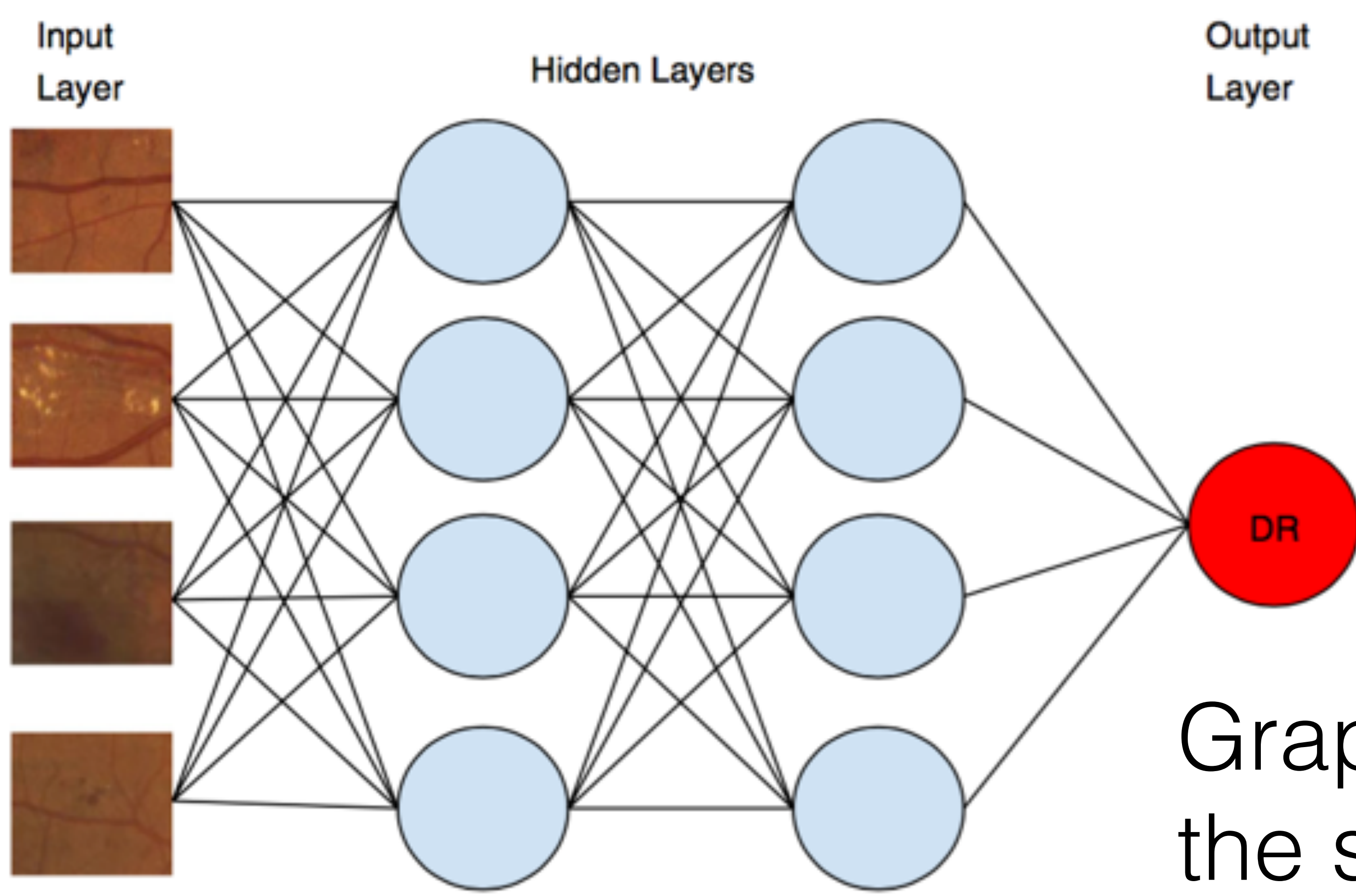
Image Processing (Computer Vision)

How it is becoming.

Research in Artificial Intelligence (AI) shifts from a knowledge-driven approach to a data-driven approach.

Image Processing (Computer Vision)

How it is becoming.



Graphical representation of the structure of an artificial neural network (ANN).

Image Processing (Computer Vision)

A comparison between a conventional approach and a black-box approach.

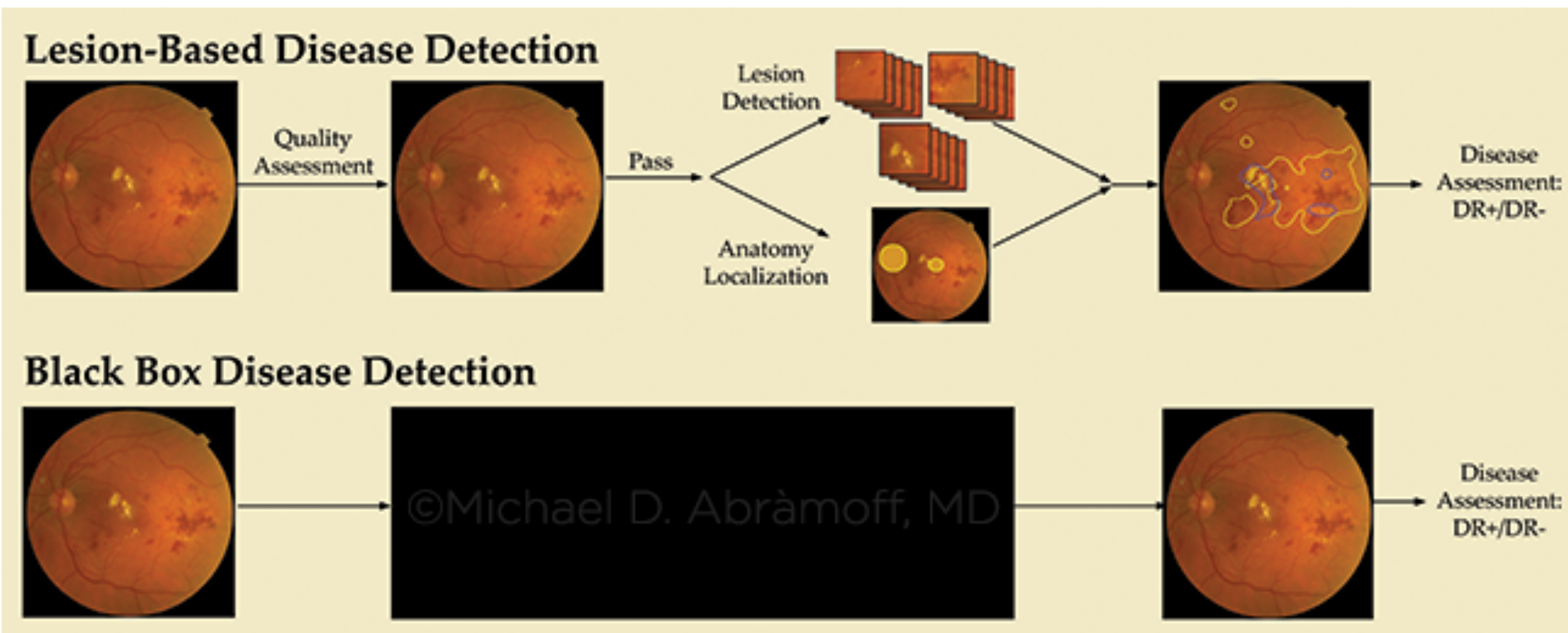


Image Processing (Computer Vision)

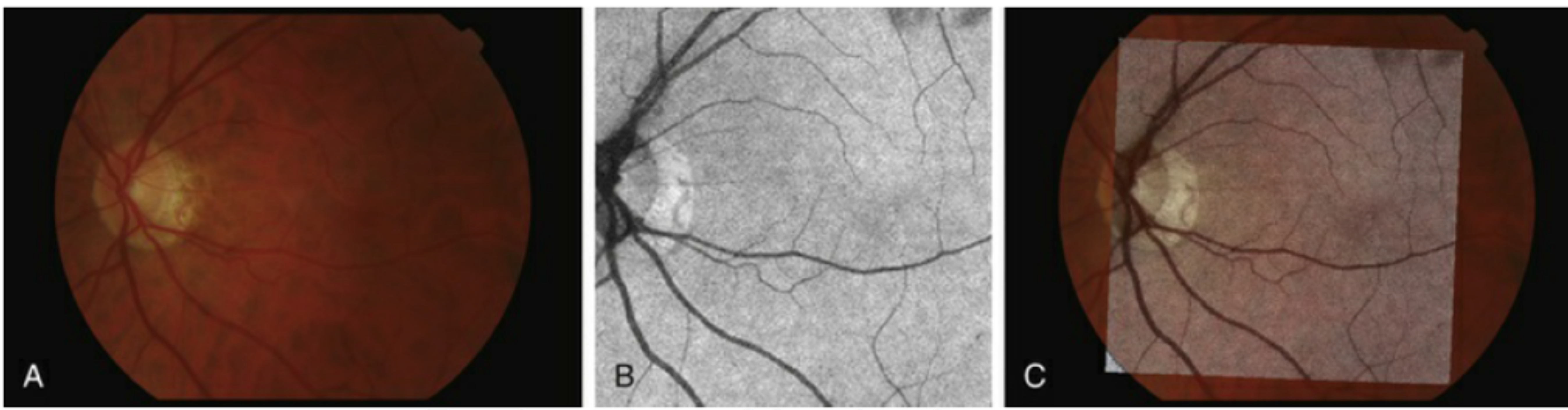
Image analysis has mostly operated reactively.

We expect more integration in device development and image analysis.

2. Enabling new technologies …

Successes to date

Multimodal registration

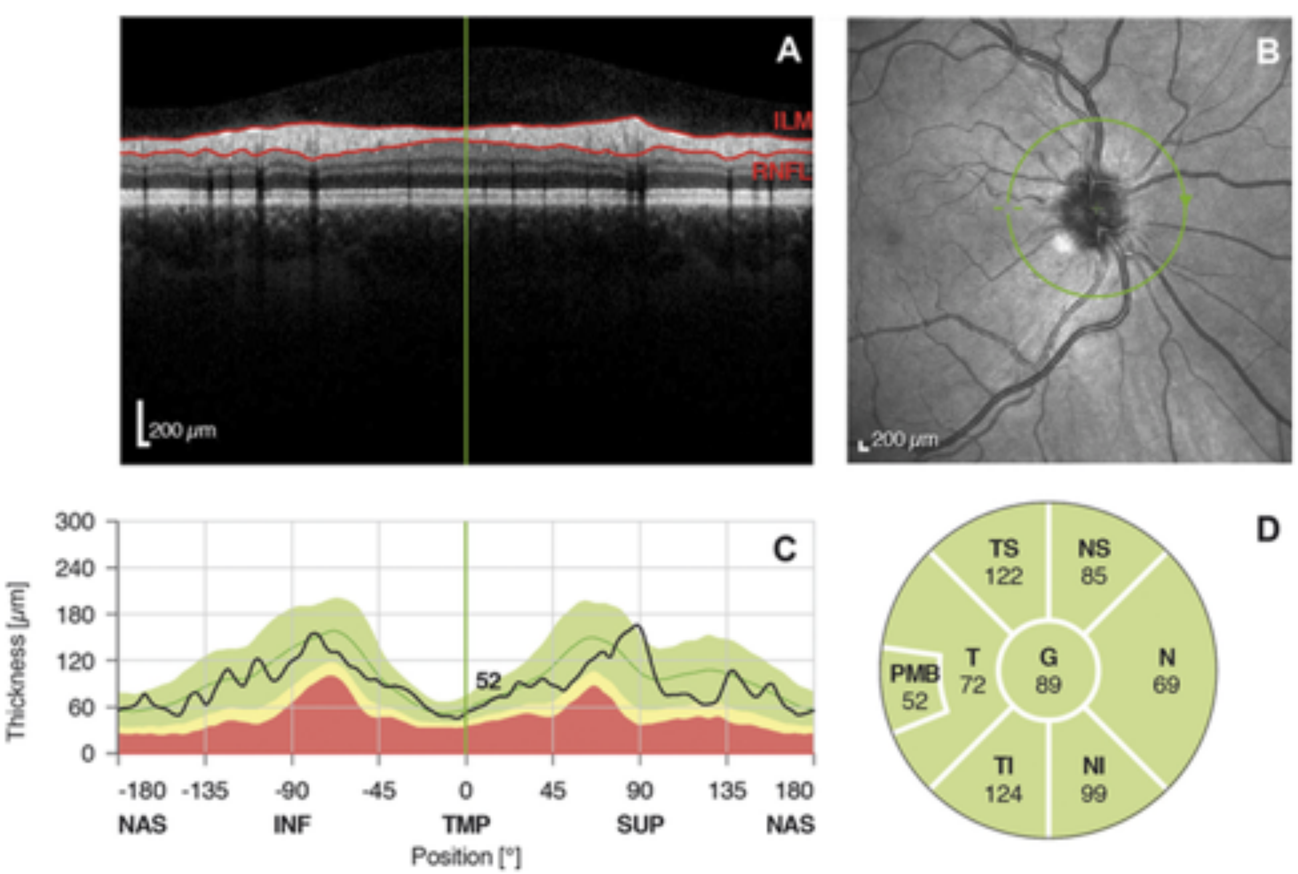


Fundus image 3D OCT Registration

M. Abramoff et al., 2010

Successes to date

Eye-tracking technology and reproducibility in OCT

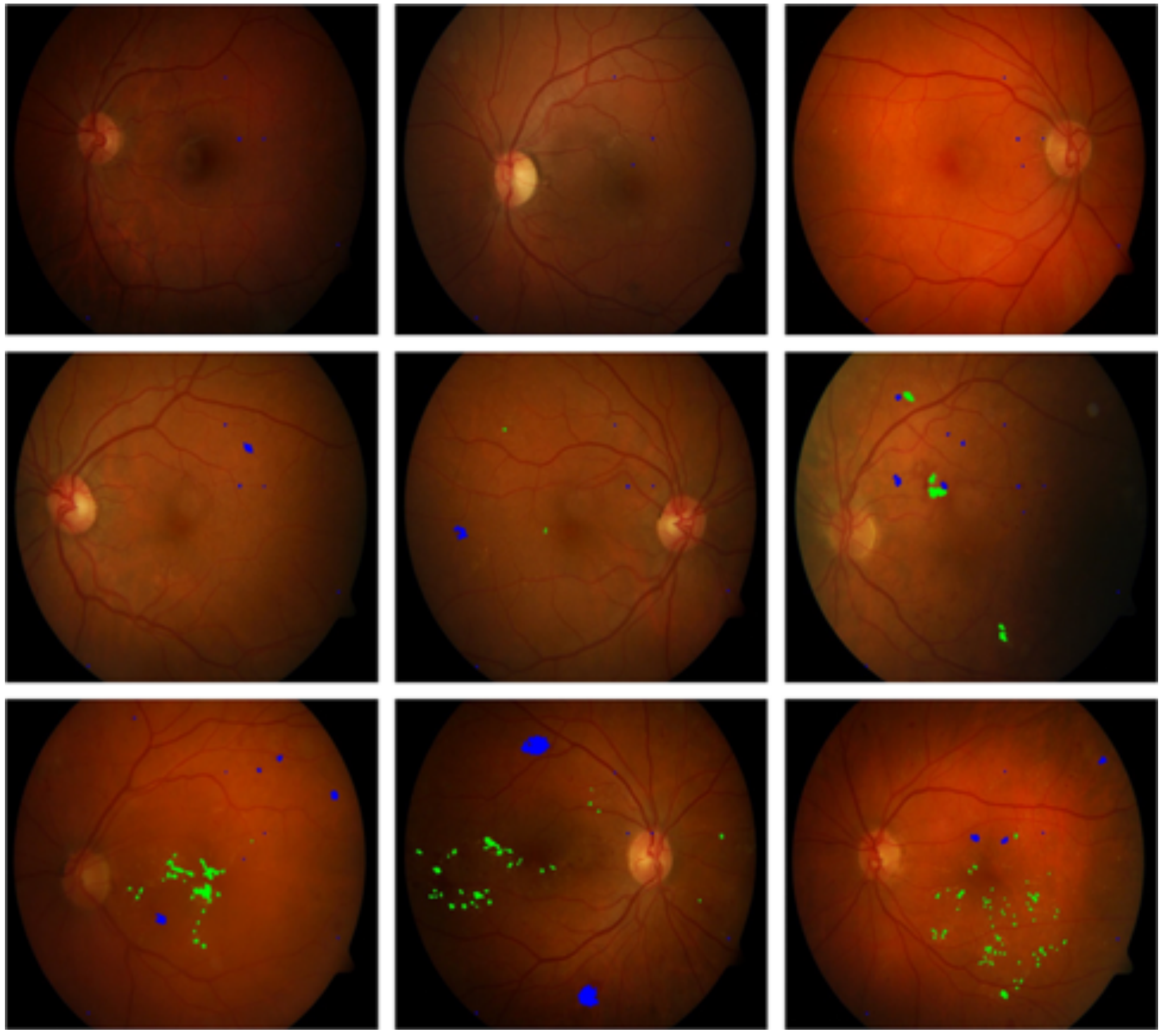


The reproducibility of RNFL measurements with Spectralis SD-OCT is excellent in both normal and glaucomatous eyes and can be significantly improved by using the eye tracker and retest software.

Langenegger et al., 2011

Successes to date

Retinal Lesion Detection



Conventional step-by-step algorithms have achieved high lesion detection rates.

M. U. Akram et al., 2014

Successes to date

Data-driven approach

nature biomedical engineering

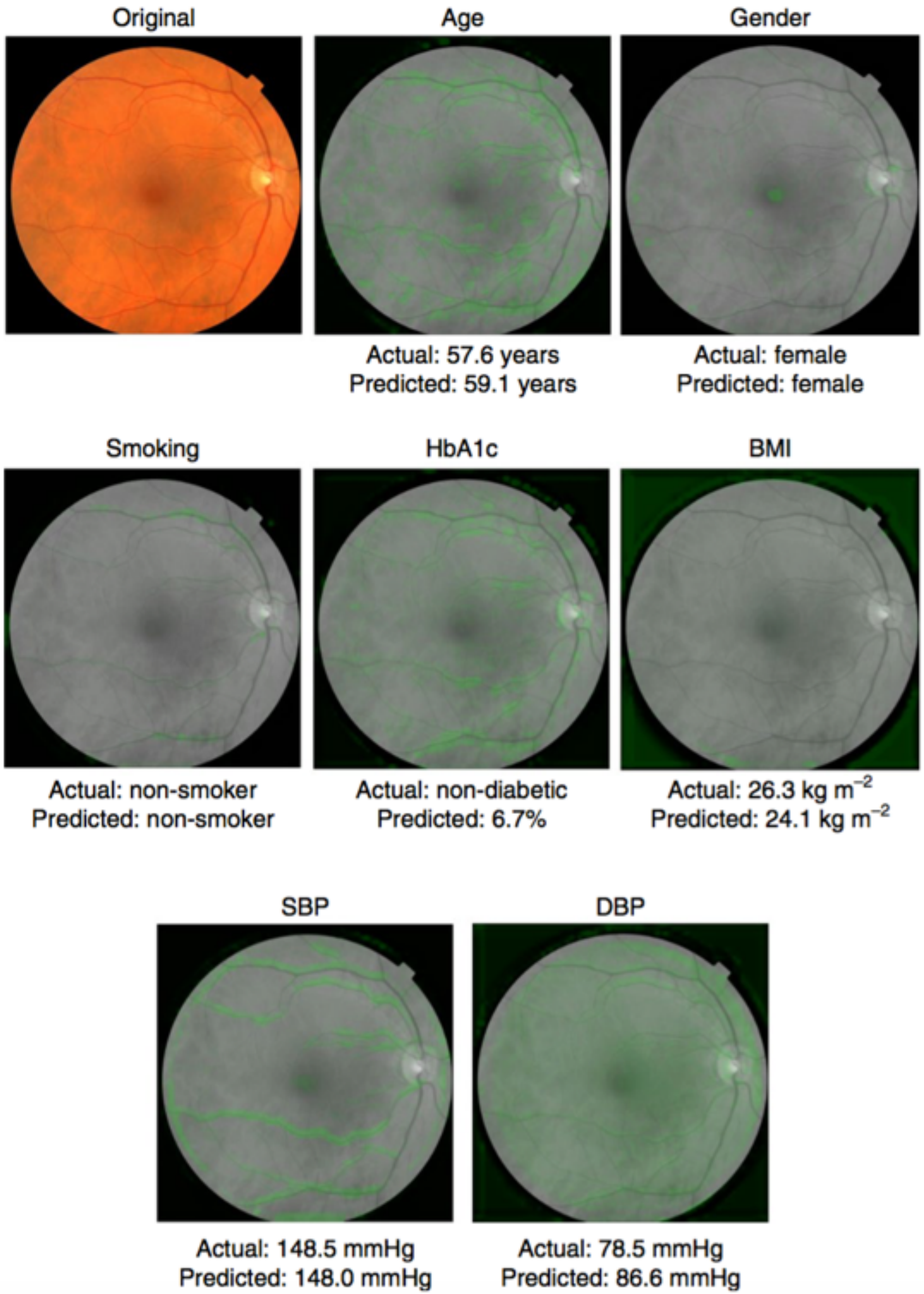
ARTICLES

https://doi.org/10.1038/s41551-018-0195-0

Prediction of cardiovascular risk factors from retinal fundus photographs via deep learning

Ryan Poplin[1,4], Avinash V. Varadarajan[1,4], Katy Blumer[1], Yun Liu[1], Michael V. McConnell[2,3], Greg S. Corrado[1], Lily Peng[1,4]* and Dale R. Webster[1,4]

R. Poplin et al., 2018



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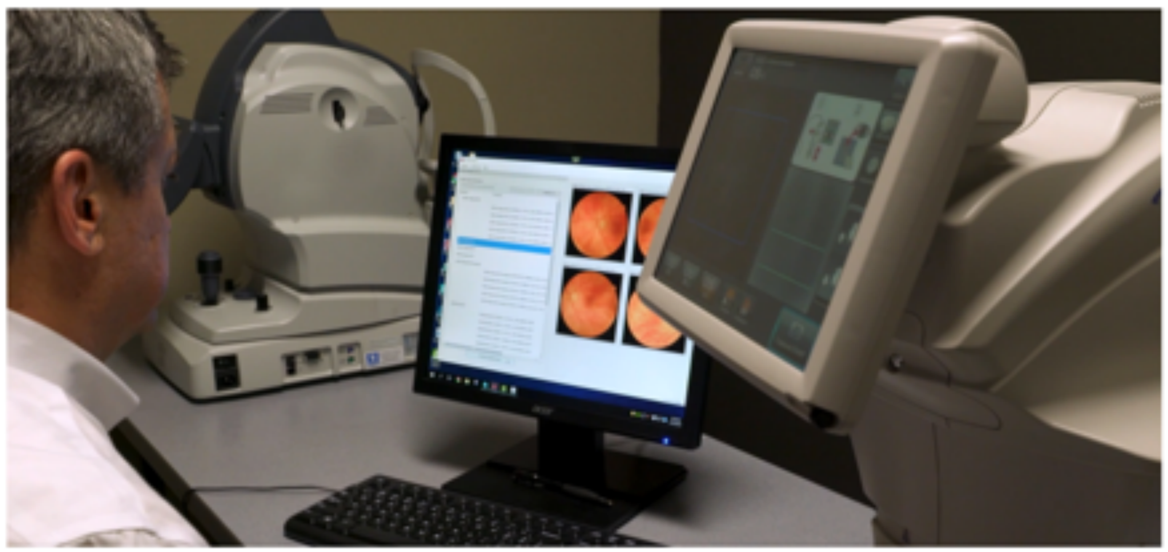
They predicted cardiovascular risk factors not previously thought to be present or quantifiable in retinal images.

R. Poplin et al., 2018

Successes to date

IDX-DR first AI system approved by FDA



IDx-DR

The first ever autonomous AI system cleared by the FDA to provide a diagnostic decision

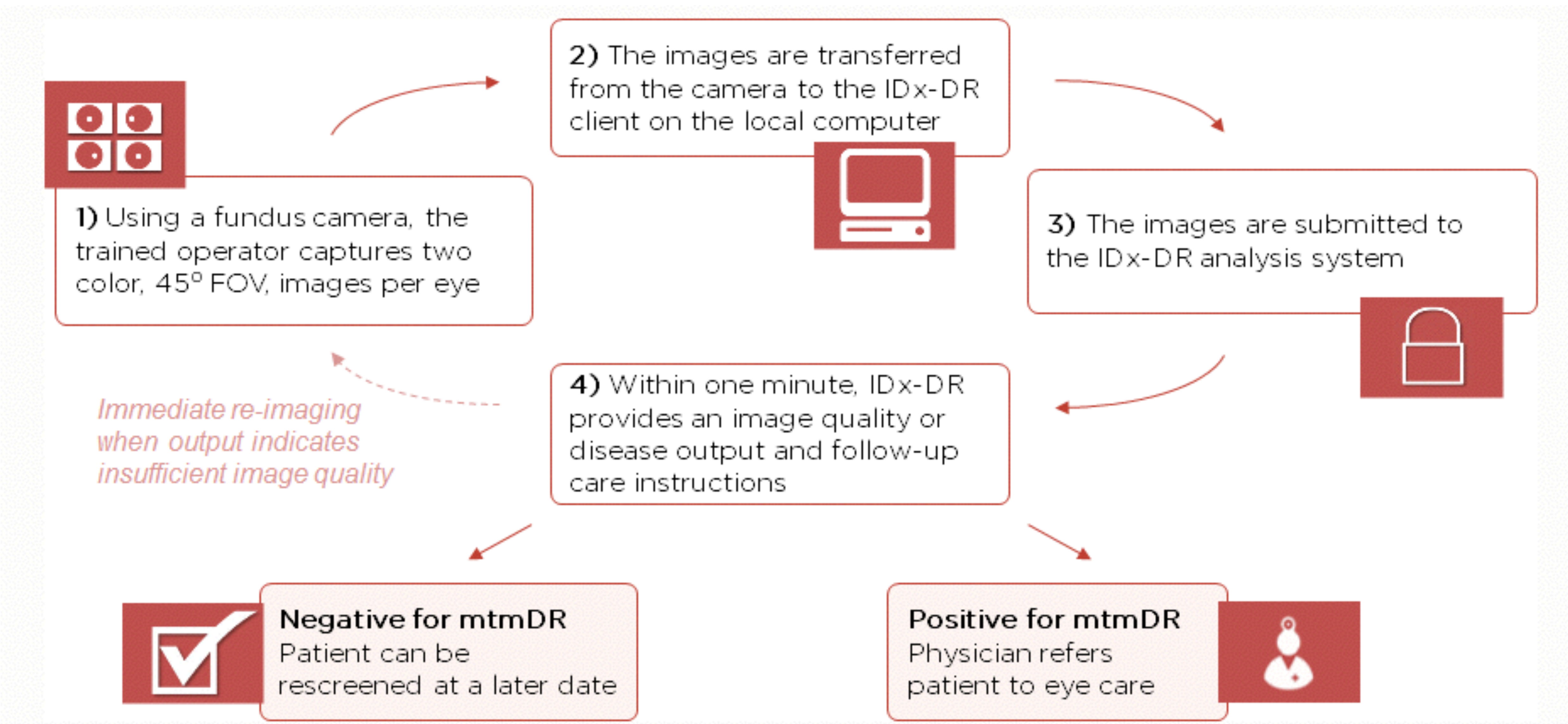
87% Sensitivity
90% Specificity
96% Imageability

Endpoints Exceeded By A Wide Margin

https://www.eyediagnosis.co/

Successes to date

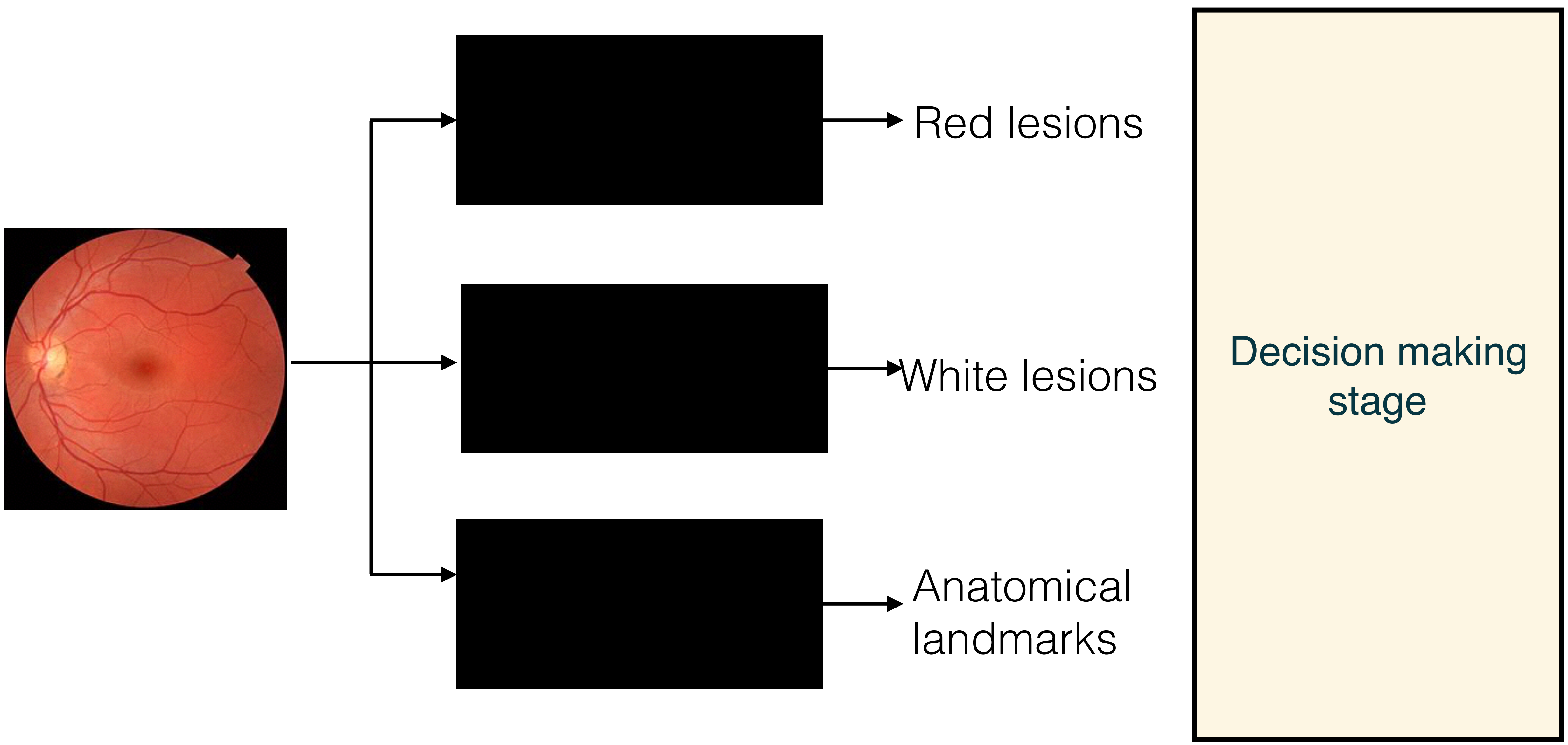
IDX-DR first AI system approved by FDA



https://www.eyediagnosis.co/

Successes to date

Hybrid approach in DR automated detection



3. Challenges ahead…

Challenges

1. Due to imaging technology **(hardware)**.
2. Due to image processing **(software).**

Challenges

Black-box systems detecting DR

OPEN ACCESS

ARVO Annual Meeting Abstract | June 2017

Catastrophic Failure in Image-Based Convolutional Neural Network Algorithms for Detecting Diabetic Retinopathy

Stephanie Klein Lynch; Abhay Shah; James C Folk; Xiaodong Wu; Michael David Abramoff

S K Lynch et al., 2017

Challenges

OPEN ACCESS
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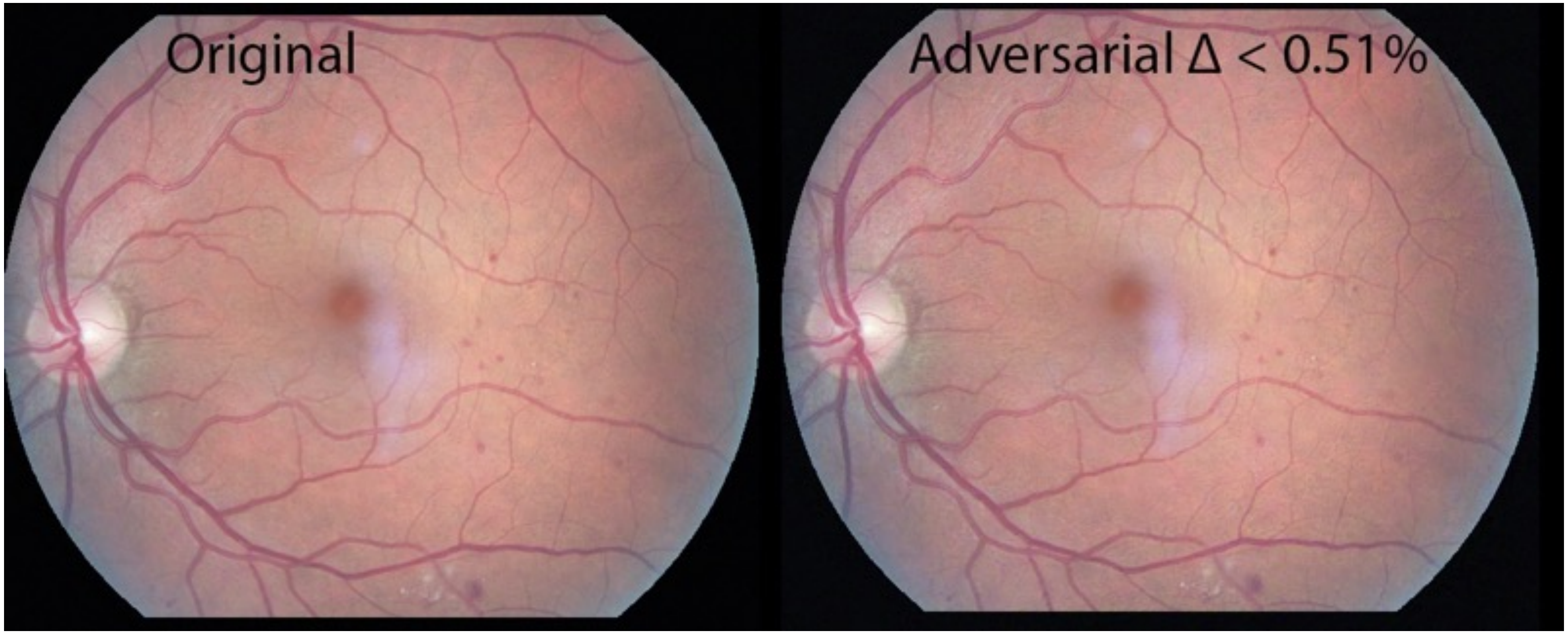
Black-box systems detecting DR



Specialist ✓ Hybrid algorithm ✓ Image-based algorithm ✗

S K Lynch et al., 2017

Challenges

Different generation devices & different results

	Topcon 3DOCT1000	Topcon 3D OCT2000
Ganglion layer	32.5 ± 5.8 μm	36.2 ± 5.3 μm
Outer Nuclear layer	87.2 ± 8.8 μm	90.5 ± 8.2 μm
RPE	19.5 ± 1.6 μm	16.9 ± 0.9 μm

Results using the same robust algorithm.

Winkelman et al., 2007

Challenges

Different generation devices & different results

Probably due to difference in image quality between OCT devices.

> Comparing pixel intensity distributions indeed showed qualitative differences, with the second generation OCT system having less variance in dark region intensities and fatter high intensity tails. ”

Winkelman et al., 2007

Challenges

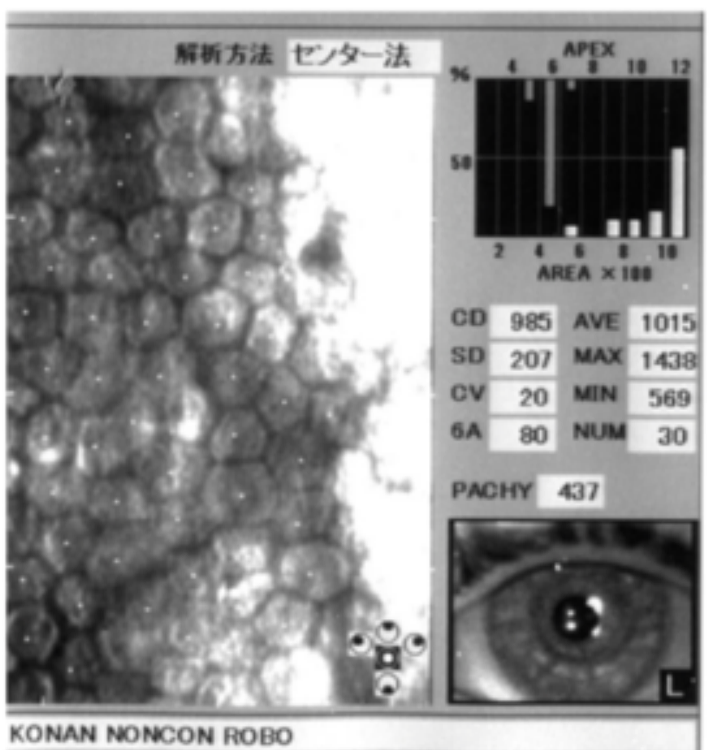
Different generation devices & different results

Bottom-line: Automated parameters should be **interpreted with caution** when comparing data from different devices.

Challenges

Cell counting in optical specular microscope

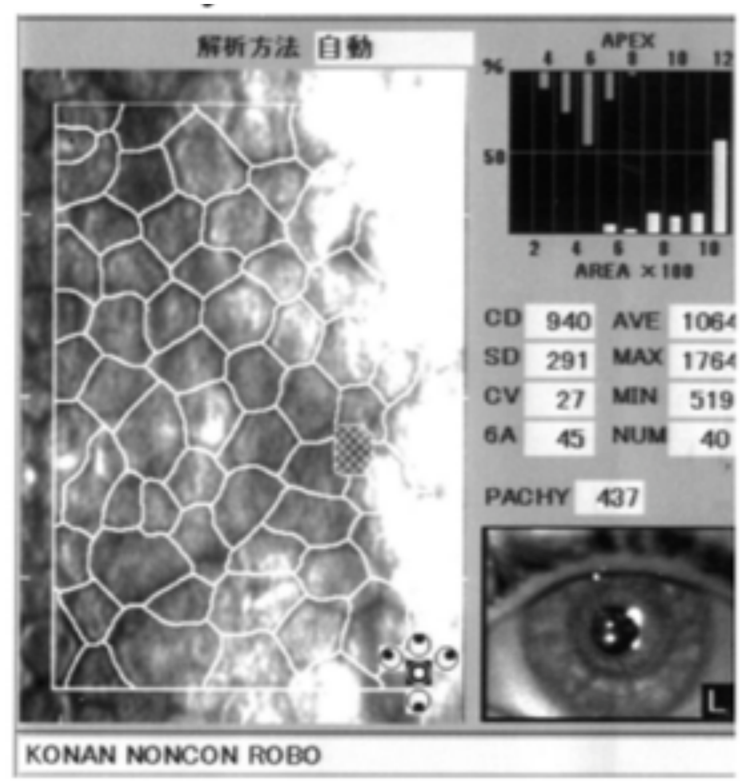
Semi-automated



Labor intensive

Time consuming

Fully automated



No intervention

S. Maruoka et al., 2017

Challenges

Cell counting in optical specular microscope

Low precision in fully automated method vs semi-automated.

Larger error in patients with low ECD.

S. Maruoka et al., 2017

Challenges

Screening with portable/low cost devices

There is clearly excellent potential in smartphone-based DR screening.

Questionable ability to provide fundus images through undilated pupils poses a problem for screening programs.

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Thank you.

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