

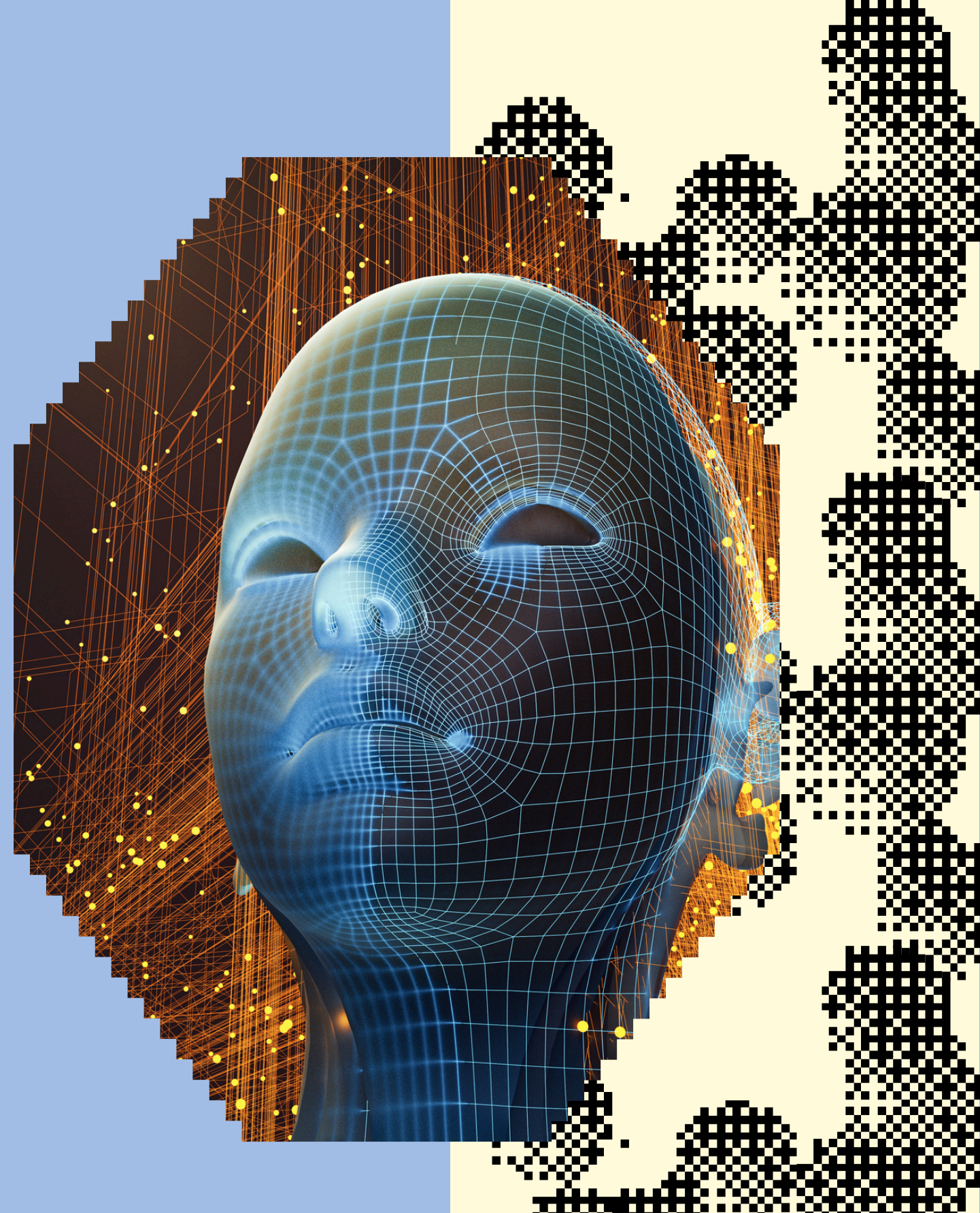
University of Donja Gorica

May 27, 2025 @ 2:00 P.M.

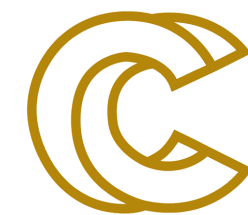
AI MEETS BIOMARKERS OF AGING

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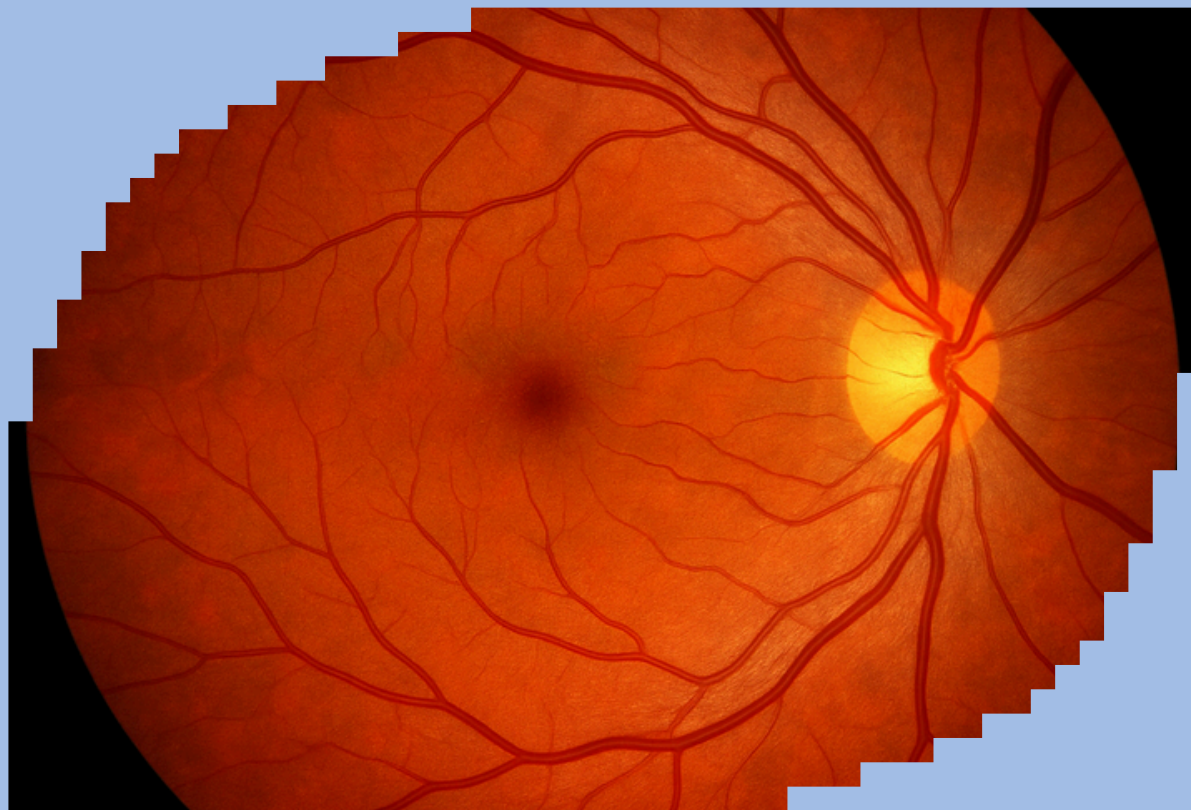


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MSc student, CV

Check our research at:

<https://www.researchgate.net/lab/University-of-Donja-Gorica-AI-Lab-Tomo-Popovic>

OVERVIEW OF KEY TOPICS TODAY



Exploring the intersection of AI and biomarkers in medicine

- Introduction to AIAGE project
- Explanation of key terms (retina, biomarkers)
- Practical applications in healthcare and research
- Benefits of integration in diagnostics
- Future directions and research

AI-AGE

Artificial Intelligence Supported Identification of
Novel Non-invasive Biomarkers of Aging



Government
of Montenegro



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AI-AGE WEBSITE



ABOUT PROJECT

Colaborative initiative	Faculty for Information Systems and Technologies (UDG) & Faculty of Medicine (UOM)
Nationally funded project	Ministry of Education, Science and Innovation
Overall project aim	The project aims to enhance research excellence by integrating artificial intelligence (AI) and high-performance computing (HPC) in the study of health and aging, improving the foundation for related research and innovation in medicine on national level. Project supports young researchers and doctoral students at collaboration institutions.
Primary objectives	Identify new non-invasive biomarkers of aging by applying machine learning algorithms to biomedical images and related medical data. A significant focus is on analyzing retinal fundus images, as the eye provides a non-invasive window into vascular and neural health.
Utilization of large-scale datasets	The project utilizes a large dataset of retinal fundus images from the UK Biobank to develop predictive models.

MILESTONES



AI-AGE has enhanced the HPC infrastructure at UDG, adding a new computing node.



The project completed initial recruitment of patients in primary healthcare clinics in Podgorica, Montenegro.

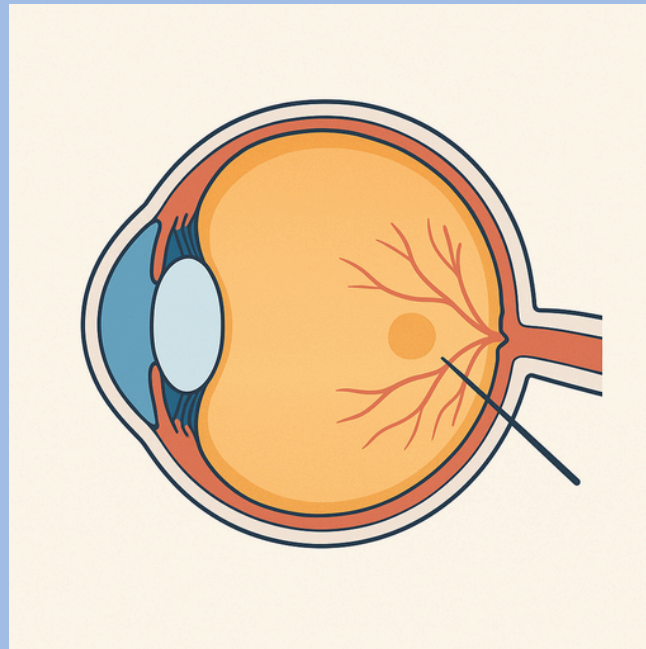


Successfully gained access to the extensive datasets available through the UK Biobank.

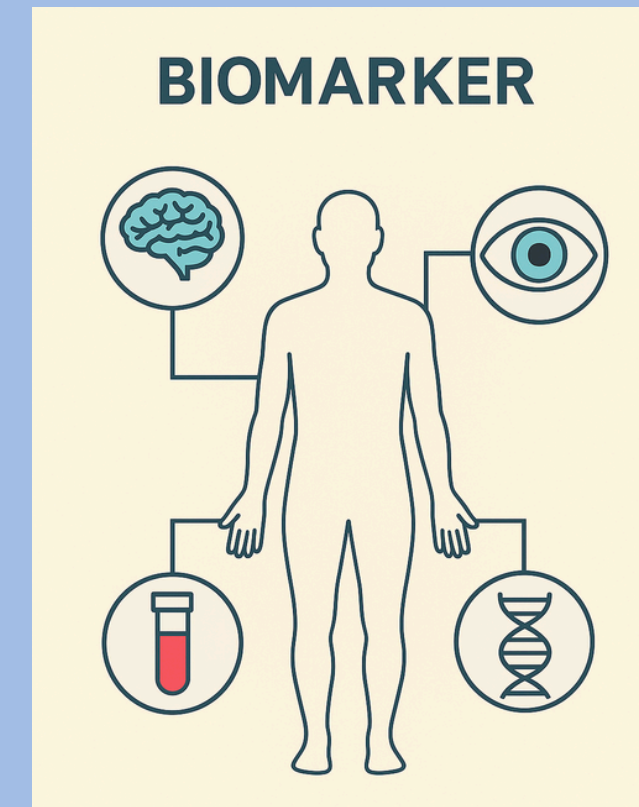


The research team is finalizing two articles for peer review, one on their custom retina segmentation solution and the other on fundus image quality assessment.

KEY TERMS

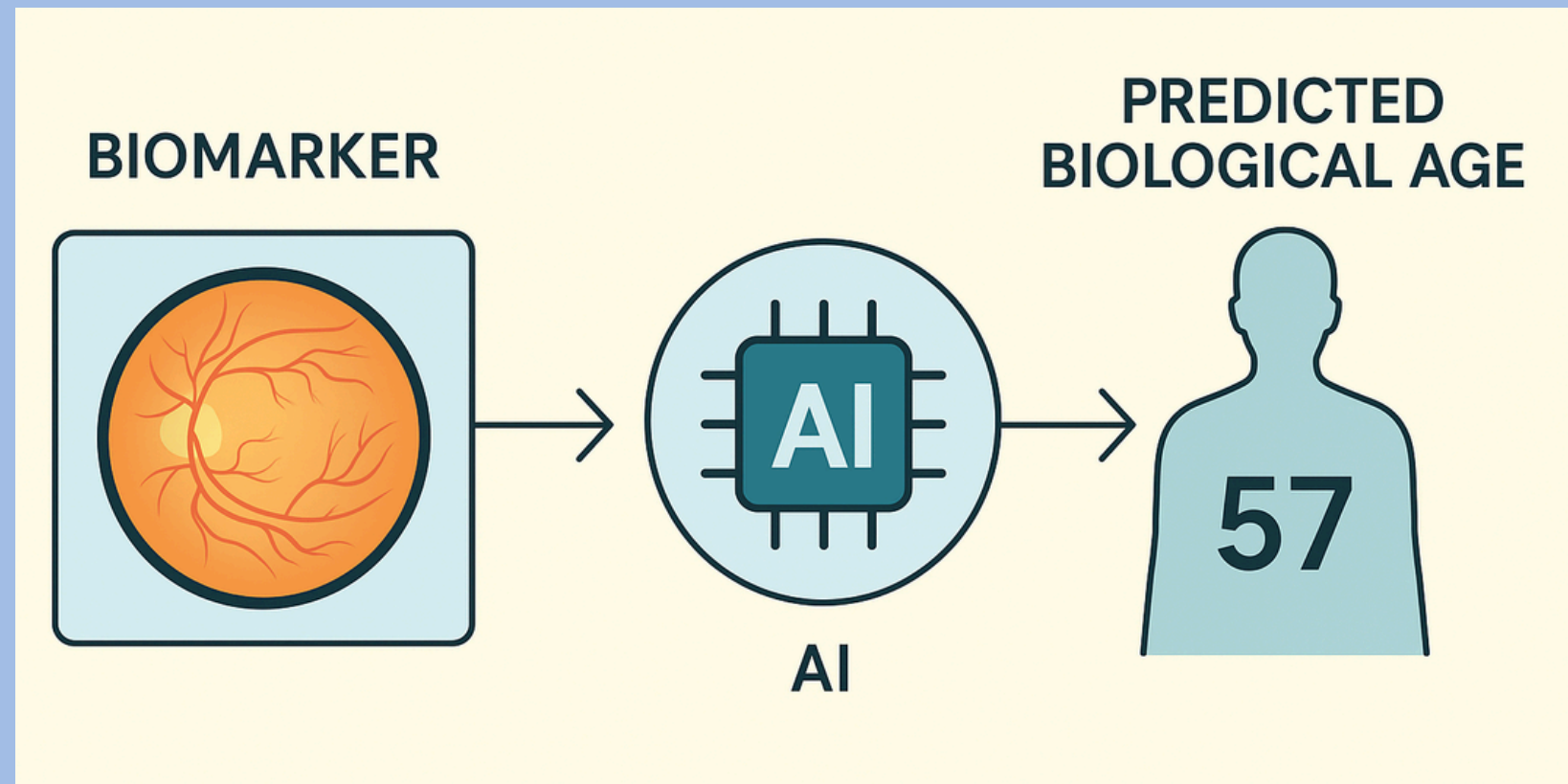


The retina is the innermost layer of the eye, responsible for converting light into electrical signals that are sent to the brain. The retina contains a network of blood vessels that supply oxygen and nutrients essential for visual function. The retina can be non-invasively examined using imaging techniques.



A biomarker is a measurable indicator of a biological condition or process. It can be a molecule, gene, protein, or physical sign that helps detect or monitor diseases, track treatment response, or predict health outcomes.

RETINA AS DIGITAL BIOMARKER



Natasa Popovic, MD PhD
Associate Professor,
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Isidora Rubezic Lukic, MD
PhD candidate, MEDF

STRAIGHTFORWARD?

- Image quality limitations
- Vascular analysis is essential
- Biomarkers of aging in the retina such as vessel tortuosity or microvascular density are subtle, requiring precise annotation or detection.
- Chronological age is easy to obtain, but ground truth for biological age is much harder to define



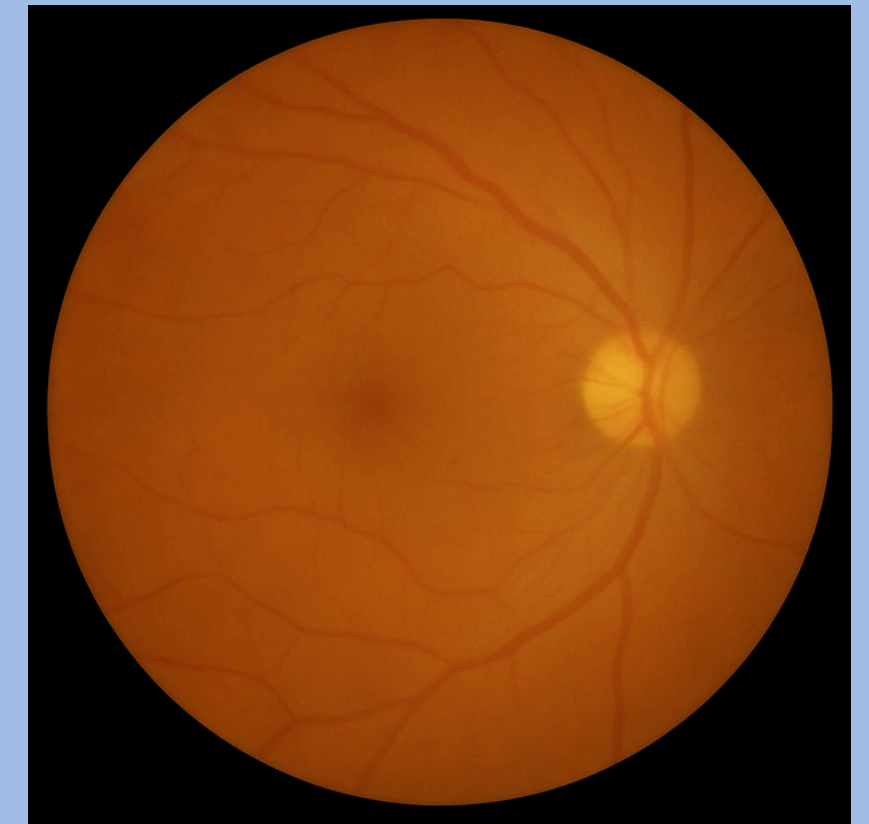
AI-based retinal image quality assessment



Developed AI-based vessel segmentation model

RETINAL IMAGE QUALITY ASSESSMENT

- UK Biobank contains over 130,000 retinal images
- Approximately, over 25% of images lack medical quality
- Manual image curation at this scale is not feasible
- How can we effectively automate this process?
- 2,074 images from the original dataset were manually annotated
- Annotation focused on clear visibility of the optic disc, macula, fovea, and capillary plexuses



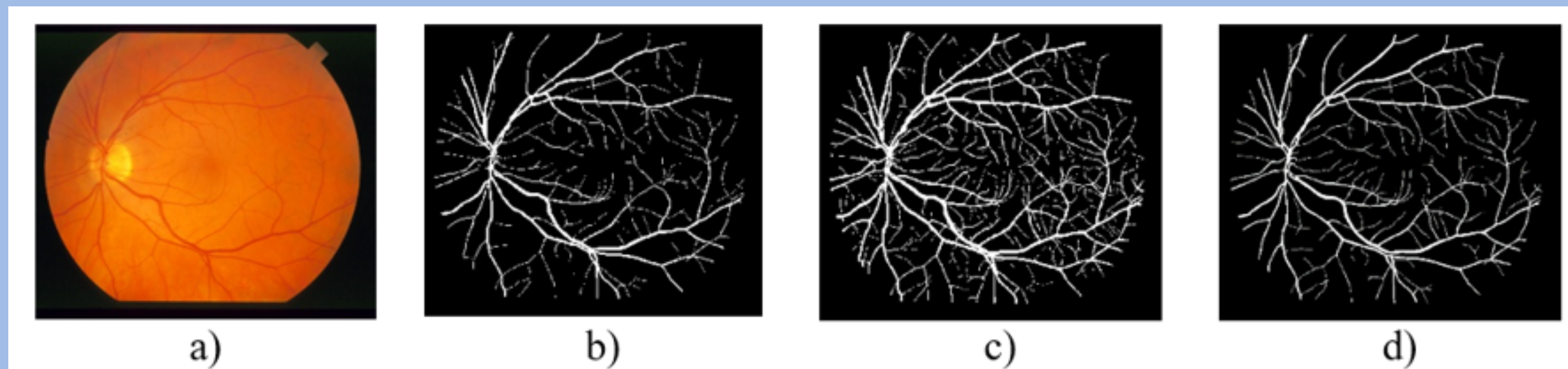
RETINAL IMAGE QUALITY ASSESSMENT

- Transfer learning was used
- Utilized SWIN Transformer and ResNet enhanced with attention mechanisms for feature extraction
- No explicit preprocessing was applied to the input images
- No preprocessing applied
- Horizontal flipping was the only augmentation technique employed (4,148 images)

	Accuracy	F1-score
SWIN transformer	95%	94.6%
ResNet + attention	94.22%	93.6%

RETINAL VESSEL SEGMENTATION

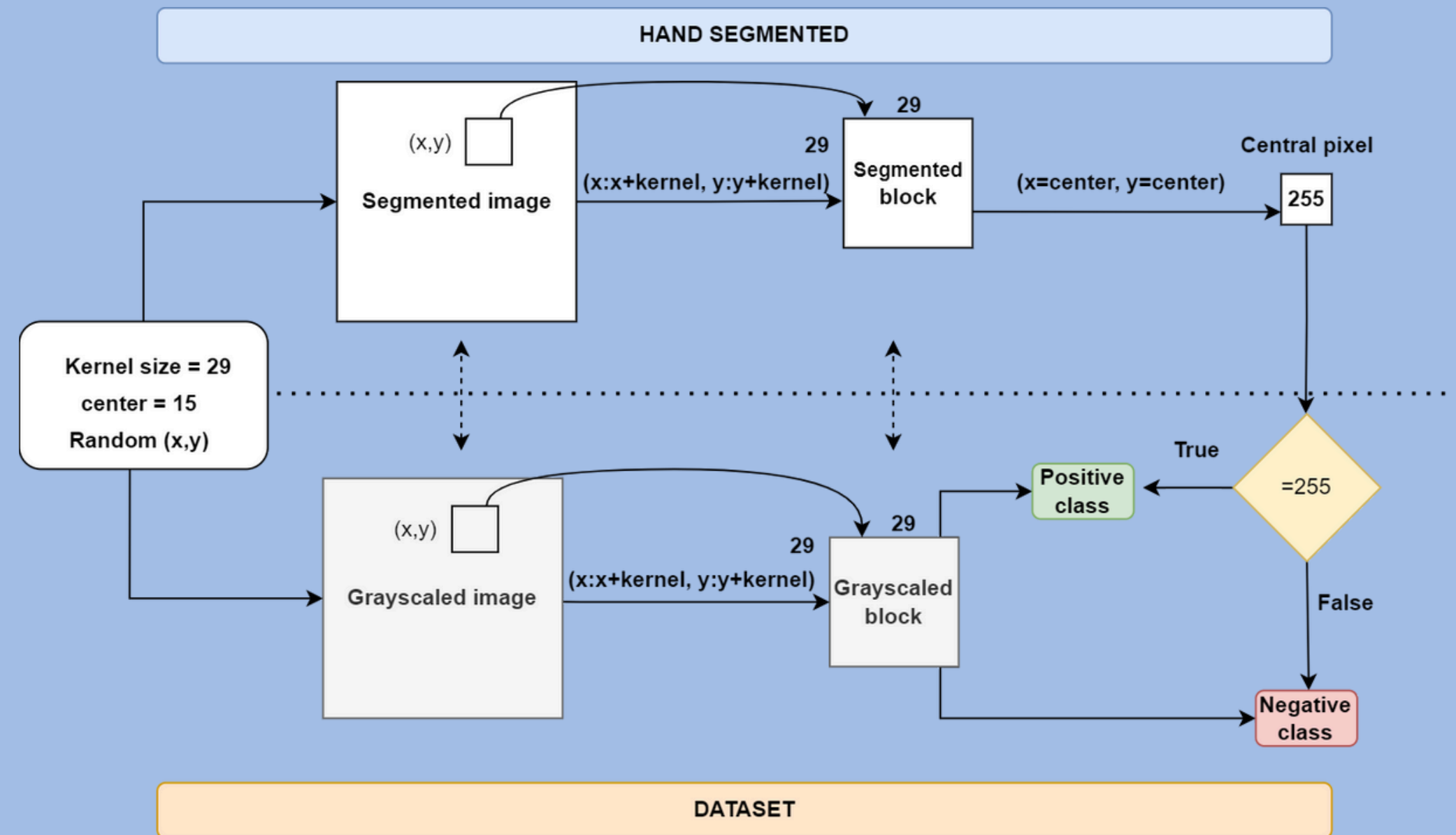
- The condition of blood vessels in retina can indicate the presence of various diseases, but can also be insightful on overall individual health
- AI-supported segmentation as an intermediate step in analyzing retina
- Original retina images dataset: STARE database (400 images, 605x700)
- Annotated images: (Popovic et al. (37 images); Hoover & Kuznetsova, et al. (20 images each))
- 77 used images from both original and annotated datasets
- Training datasets had 148 and 80 images (depending on which annotated dataset was used)



STARE database and segmentation: a) im0162 (STARE database) [CC BY 4.0]; b) and c) AH & VK segmentations (im0162) [CC BY 4.0]; d) NP segmentation (N162) [CC BY 4.0].

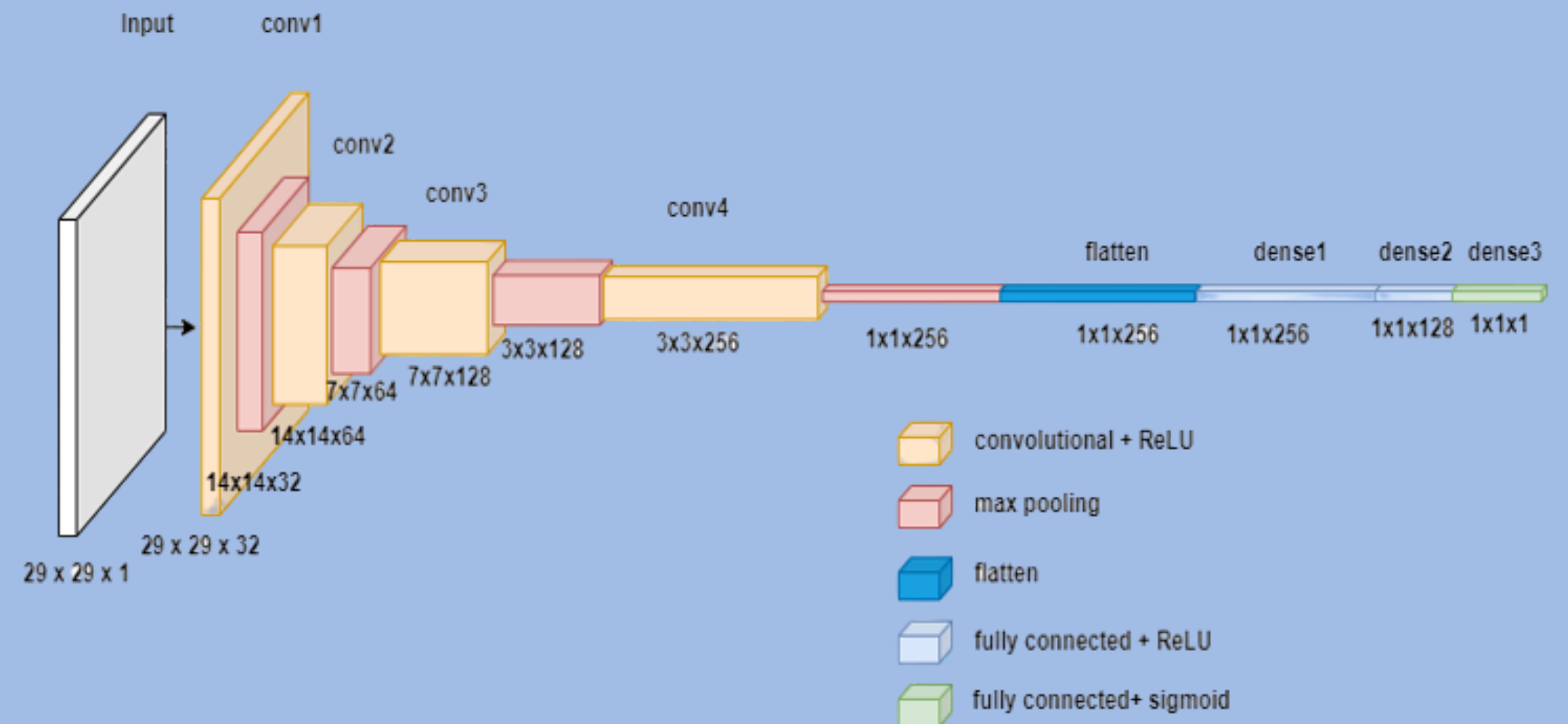
RETINAL VESSEL SEGMENTATION

- Customized approach to dataset creation
- Creating corresponding 29x29 blocks from both original and annotated images
- Positive class is the block with blood vessel in middle pixel
- Negative class is the block with no blood vessel in middle pixel of the block
- 1.31 million and 736 thousand blocks for one training dataset



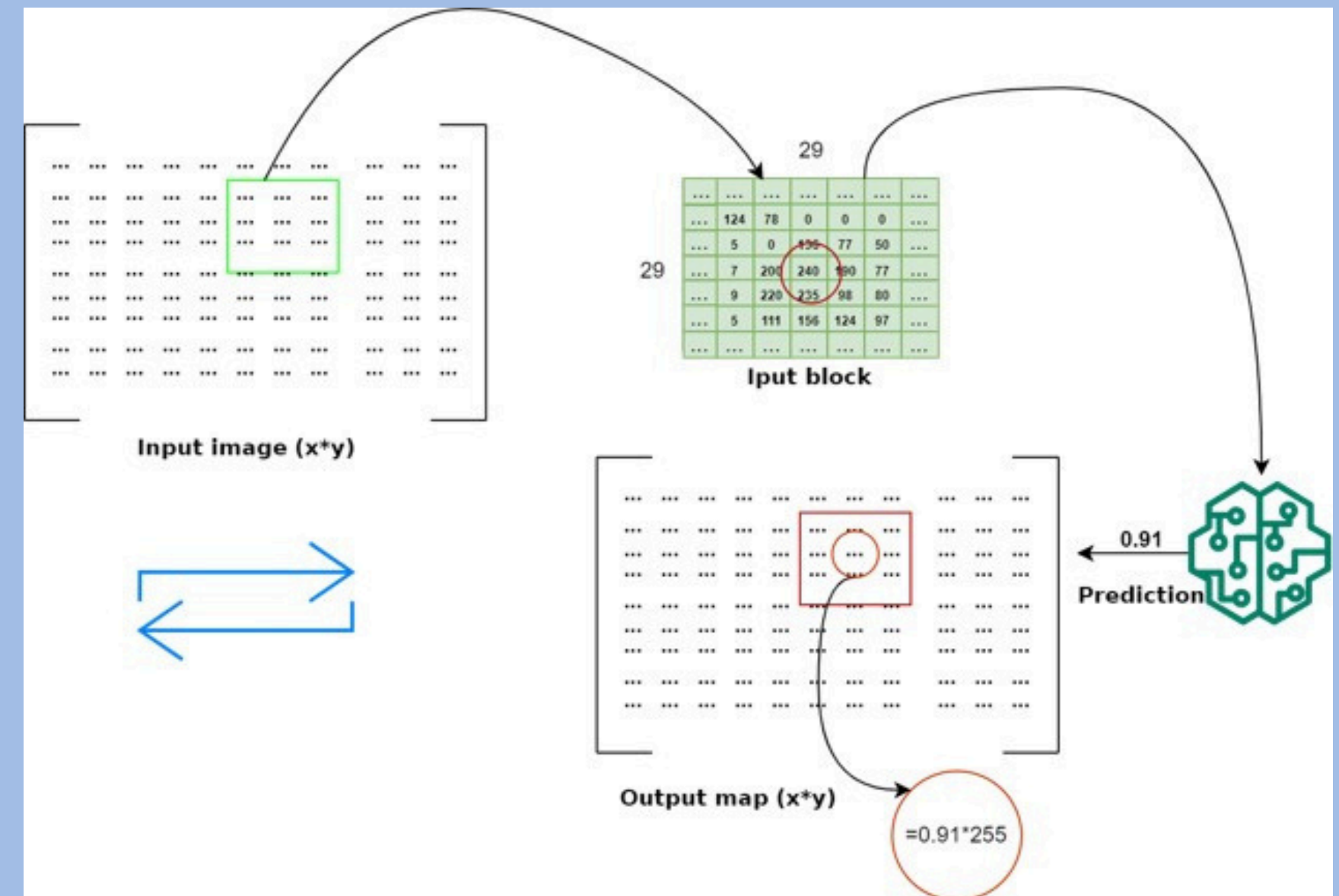
RETINAL VESSEL SEGMENTATION

- Input 29x29 block
- 486,657 parameters
- Trained in 100 epochs
- 25-50 hours per model



RETINAL VESSEL SEGMENTATION

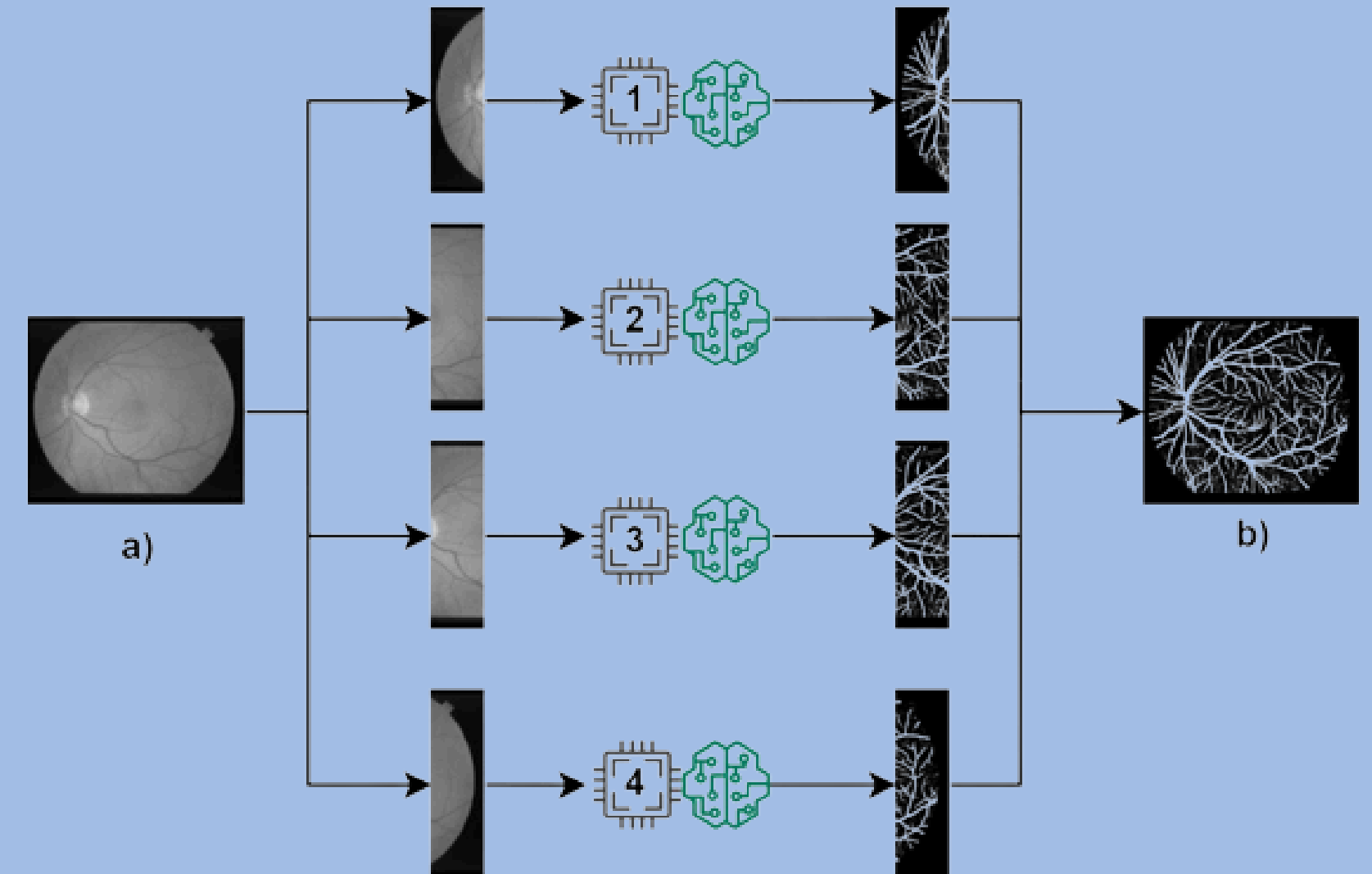
- "Sliding" 29x29 block across original gray-scaled image by 1 pixel every iteration
- Block is given as input to the model, and model output is multiplied by intensity of white pixel, representing the blood vessel in an empty image
- Suitable for parallelization



RETINAL VESSEL SEGMENTATION

- CPU parallelization (2 and 4 cpus)
- Couldn't utilize GPU
- From 35 to 10 minutes

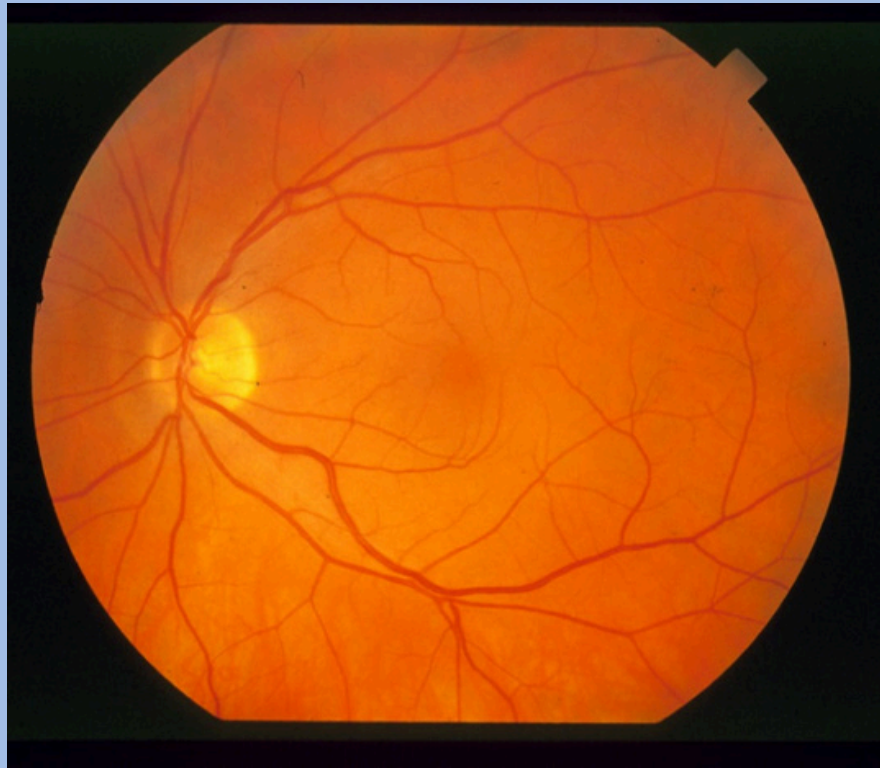
	Time	Reduction	Efficacy
1 cpu	35 minutes	/	/
2 cpu	18 minutes	195.46%	97.73%
4 cpu	10 minutes	351.83%	87.96%



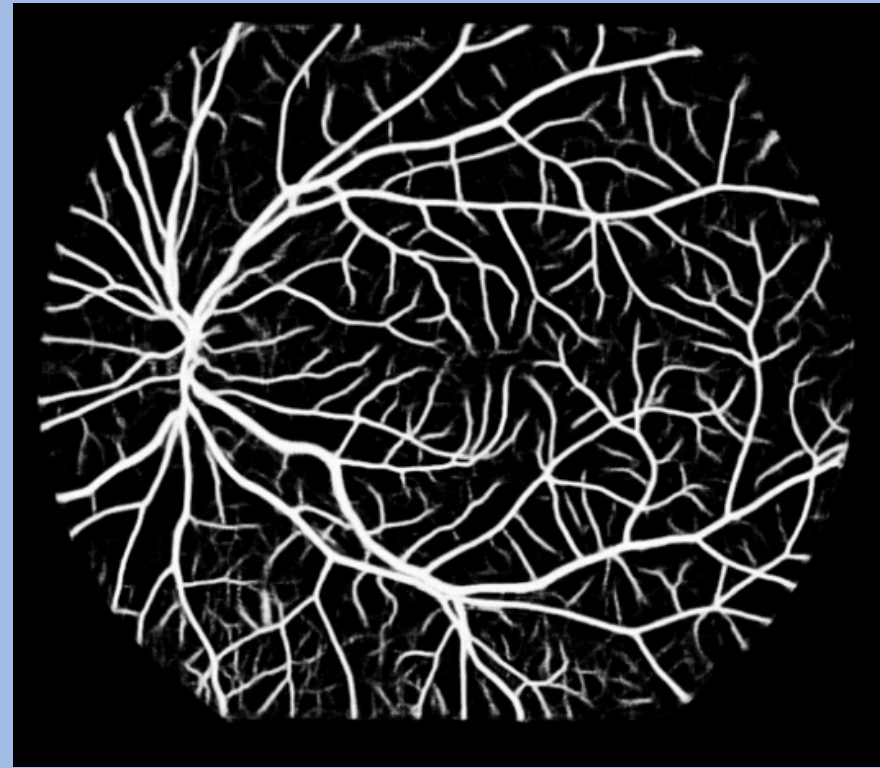
RETINAL VESSEL SEGMENTATION

MODELS	Accuracy	Precision	Recall	Specificity	F1 scor
AH	95.28%	95.48%	95.02%	95.33%	95.25%
NP	92.80%	93.15%	92.38%	93.21%	92.77%
VK	91.33%	92.22%	90.28%	92.38%	91.24%
COMBINED	92.19%	91.81%	92.65%	91.73%	92.22%

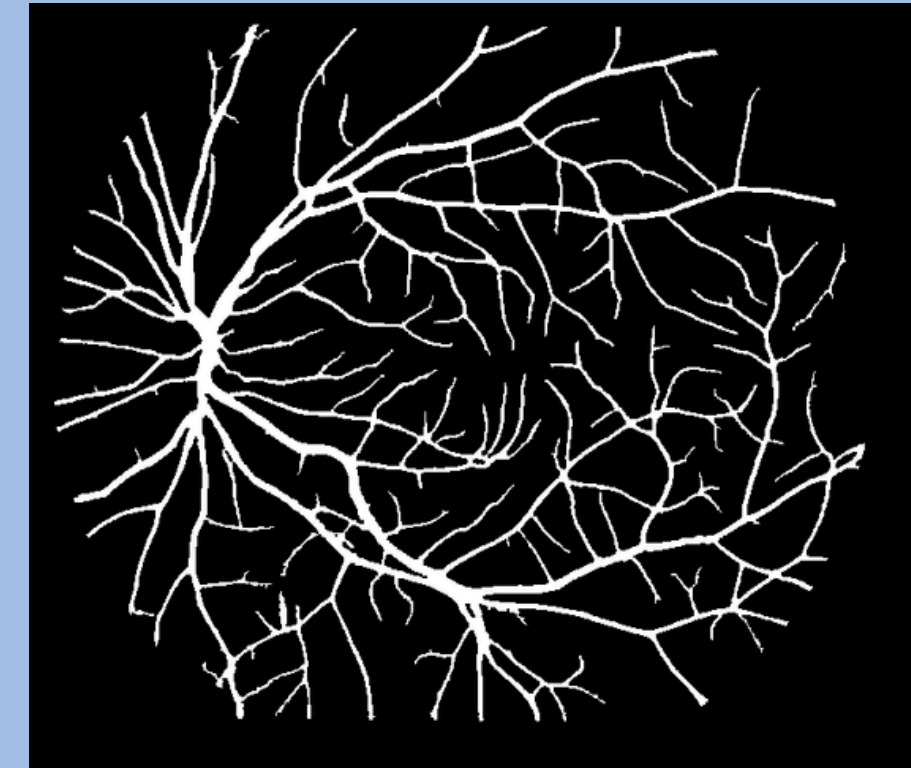
RETINA BLOOD VESSELS SEGMENTATION EXAMPLE



a)



b)



c)

Example of AH model segmentation. a) im0162 (STARE database) [CC BY 4.0]; b) Blood vessel segmentation of image "a"; c) Image "b" after noise removal.