Imagine 2029: Our data, our health, our care – 20th anniversary of EHTEL

EHTEL 2019 Symposium

Kindly hosted by TIC Salut Social – Technology, innovation and digital transformation.

14:30 – 16:00 [S4]

Aula 1
First Floor

Artificial Intelligence as a Trustful Enabler for Better Health and Better Care

Working with AI: Improve health and care through enhanced services and new diagnostic and therapeutic options. Better manage chronic diseases. Explore benefits vs. risks/challenges.

Session Chair: Stephan Schug, EHTEL

AI in practice: Enabling a Smart Phone for Predicting, Detecting and Staging Disorders
Jan Stener Jørgensen, CIMT, Odense University Hospital, Denmark

AI Applied to Screening for Diabetic Retinopathy
Aïda Valls, Rovira i Virgili University, Tarragona, Catalonia, Spain

AI for Diagnosis and Treatment of Infectious Diseases
Carolina Garcia, Hospital Clinic of Barcelona, Spain

AI for Diagnosis and Treatment in Dermatology
Marc Combalia, , Hospital Clinic of Barcelona, Spain

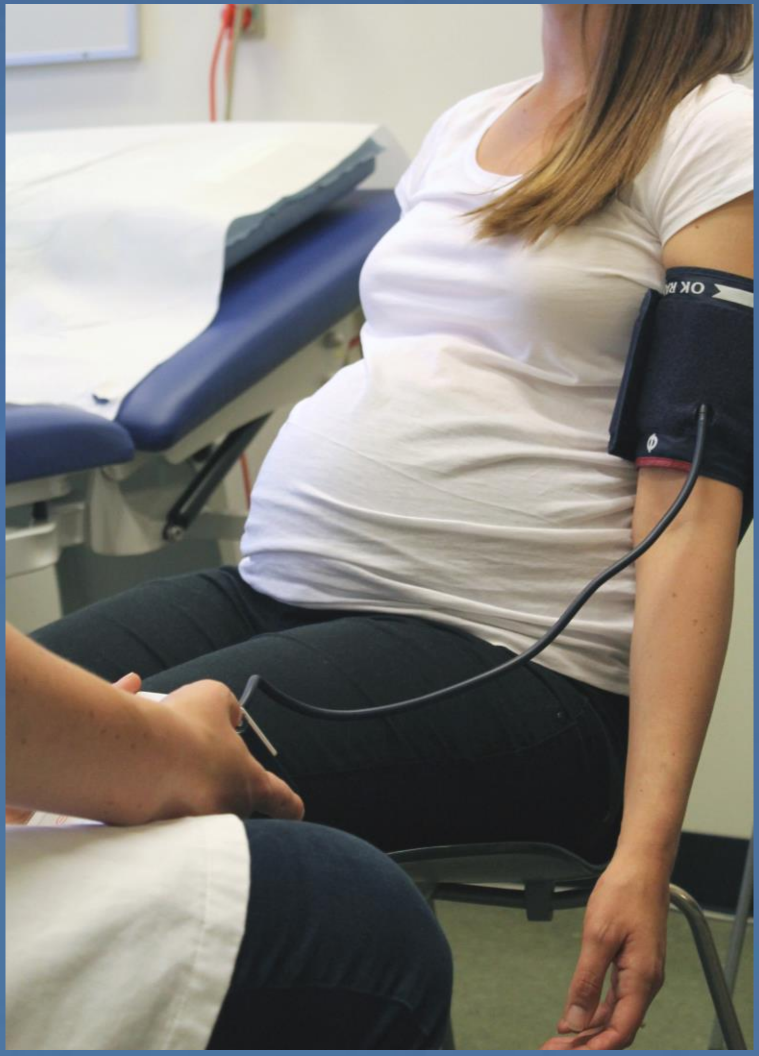
Deep Lung: Deep Learning in Imaging for Better Detection and Assessment of Lung Cancer
Vicent Ribas Ripol, Eurecat Technology Center, Barcelona, Spain

Q&A and Conclusions by the Session Chair

#EHTEL_Symposium #EHTEL_BCN @ehtel_eHealth

Monitoring and detection of very early signs of preeclampsia (PE) by automatic image processing of pregnant women's faces captured by daylight cameras

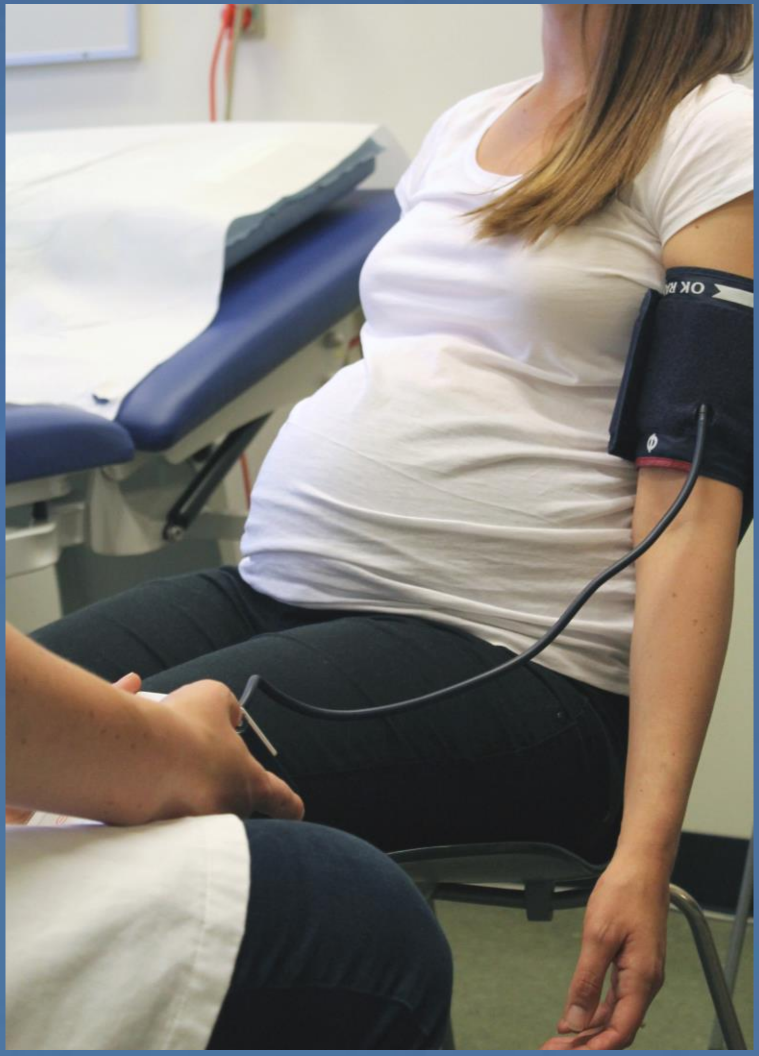
Jan Stener Jørgensen
Prof. MD PhD
CIMT- Odense University Hospital
Denmark



UNIVERSITY OF SOUTHERN DENMARK

In the EHTEL prpgram announced as:

AI in practice: Enabling a Smart Phone for Predicting, Detecting and Staging Disorders



Preeclampsia definition

- **Pregnancy-related**
- **Syndrome**

    (5 [3-15] % of all pregnancies)

- **after 20 weeks** gestation

Preeclampsia definition

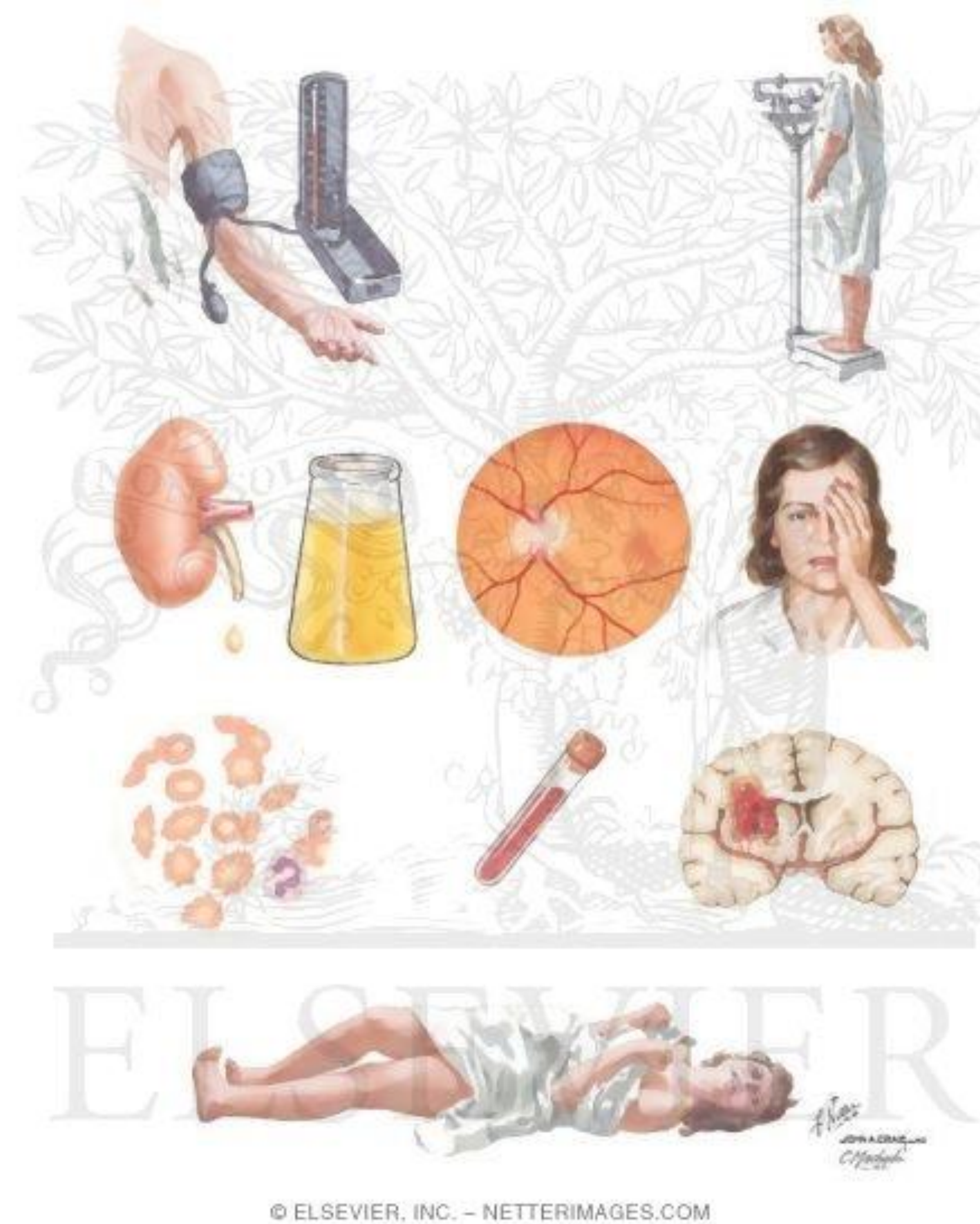
Manifestations

- varying degrees of **hypertension**
- **proteinuria**

- **and/or** to a variable extent:

- **other organ involvement**

  - liver,
  - kidney,
  - brain
  - cardiovascular



Preeclampsia:

increased future maternal cardiovascular risk

- **Irgens HU et al, BMJ 2001**
  Preterm PE: risk of death from: CVD 8↑
  stroke 5↑
- **Smith GC et al, Lancet 2001**
  PE: risk for CVD 2↑
  PE and <2.5 kg baby : risk for CVD 7↑
- **Bellamy L et al (Williams D), BMJ 2007**
  PE > 10 years*:* 4↑ risk for hypertension
  2↑ risk for ischemic heart disease/stroke

  Lykke JA et al, Hypertension 2009
  PE: ↑ risk for hypertension (PE severity-dependent)

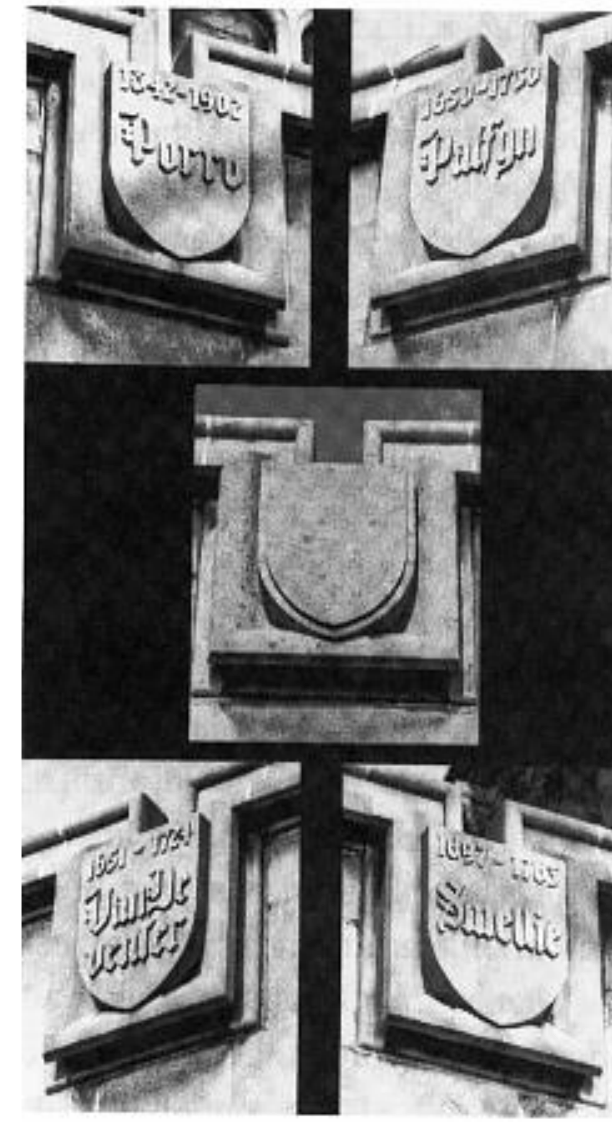
Pathogenesis of preeclampsia

Unknown

- ***"Disease of theories"***

- **anti-angiogenesis**
- **microvascular damage**

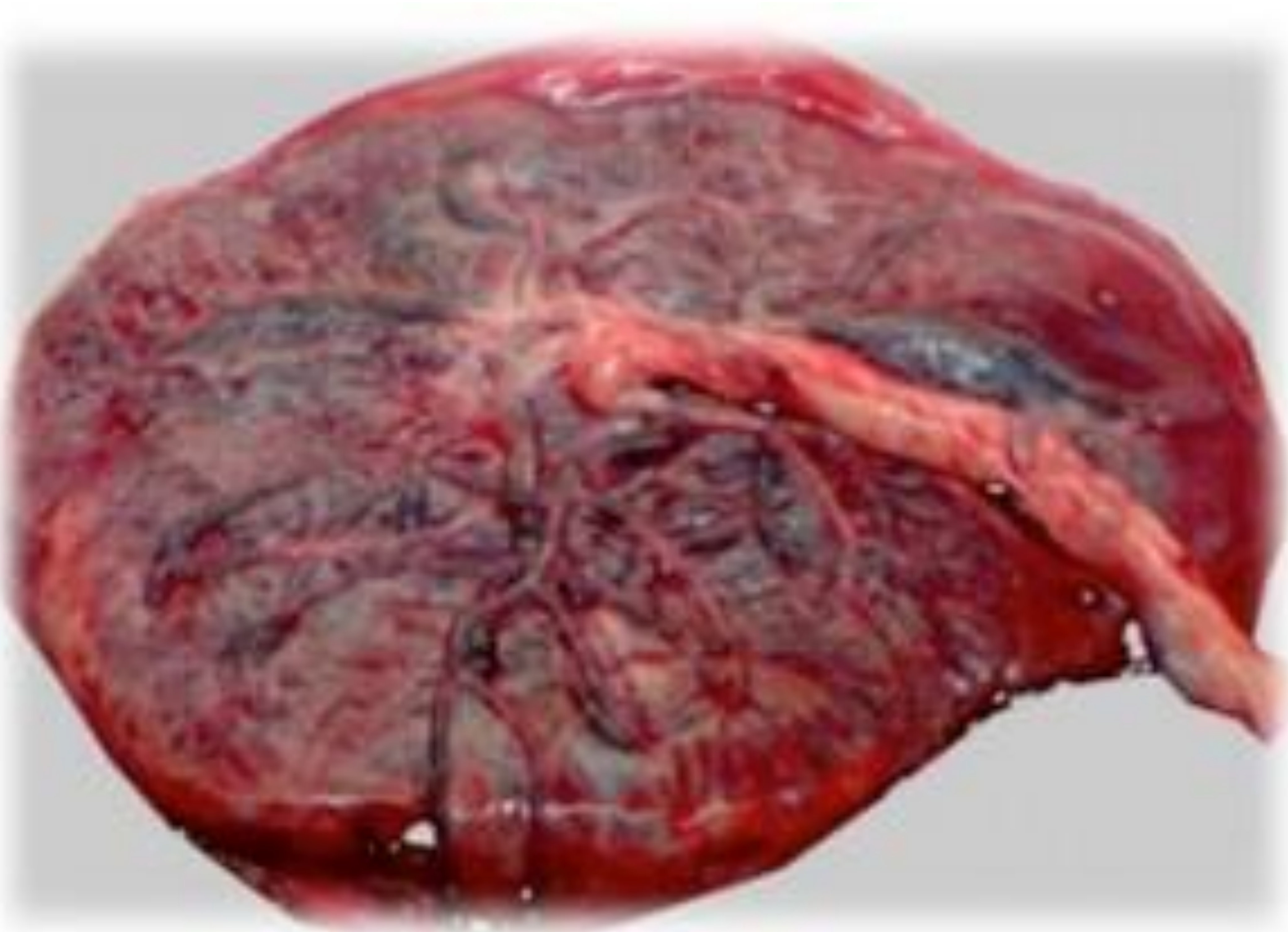
Engraved plaques at the Chicago Lying-in Hospital



” … reserved for the scientist who discovers the cause and cure of preeclampsia. ……”

It is still blank today ……

.. it is somehow linked to the placenta



Redefining Preeclampsia

+ sFlt-1/PlGF

Hypertension

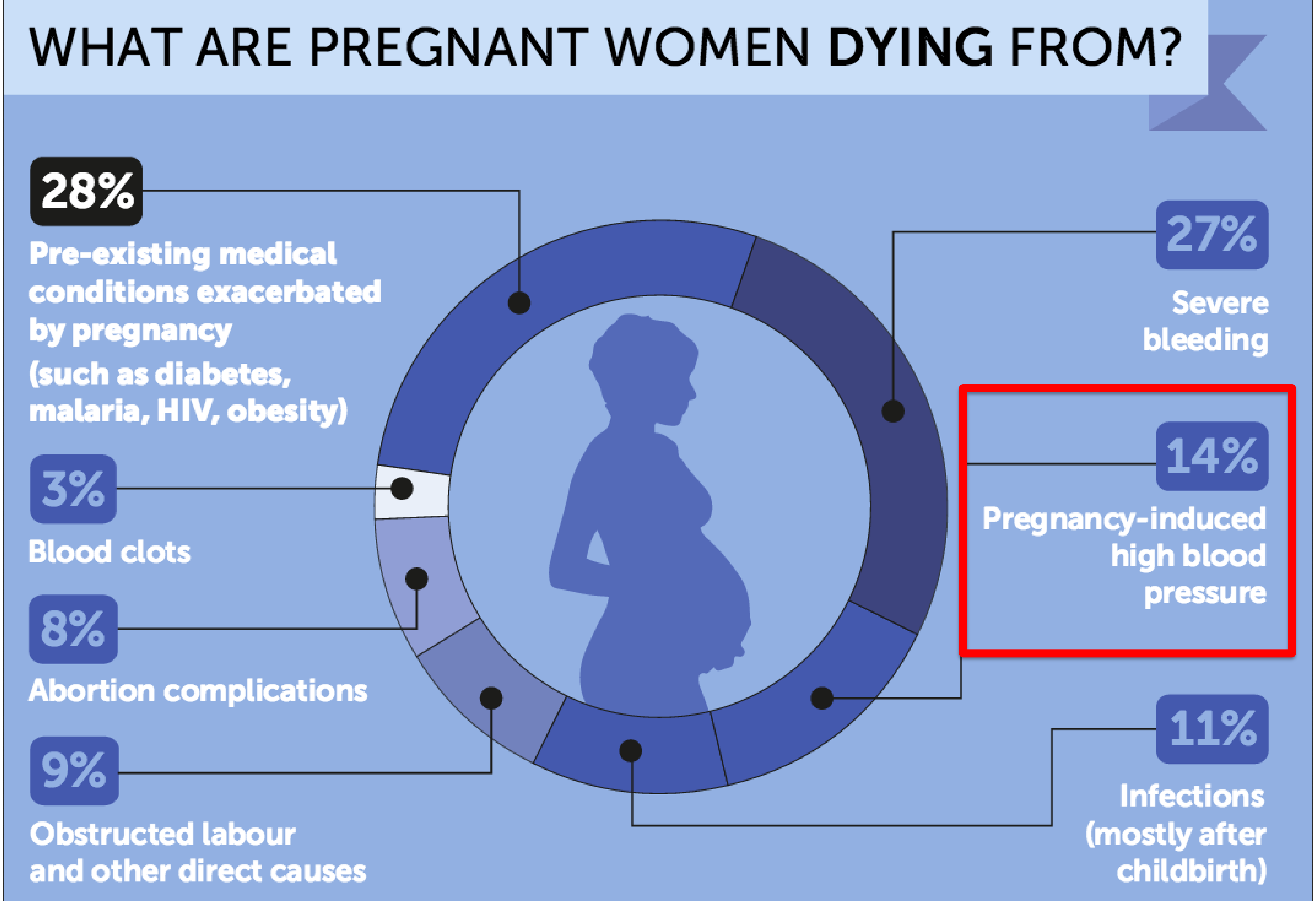
Journal of the American Heart Association

American Heart Association

Redefining Preeclampsia Using Placenta-Derived Biomarkers

Anne Cathrine Staff, Samantha J. Benton, Peter von Dadelszen, James M. Roberts, Robert N. Taylor, Robert W. Powers, D. Stephen Charnock-Jones and Christopher W.G. Redman

+ sFlt-1/PlGF


WHAT ARE PREGNANT WOMEN DYING FROM?
28%
Pre-existing medical conditions exacerbated by pregnancy
(such as diabetes, malaria, HIV, obesity)
3%
Blood clots
8%
Abortion complications
9%
Obstructed labour and other direct causes
27%
Severe bleeding
14%
Pregnancy-induced high blood pressure
11%
Infections (mostly after childbirth)

Global burden of Preeclampsia

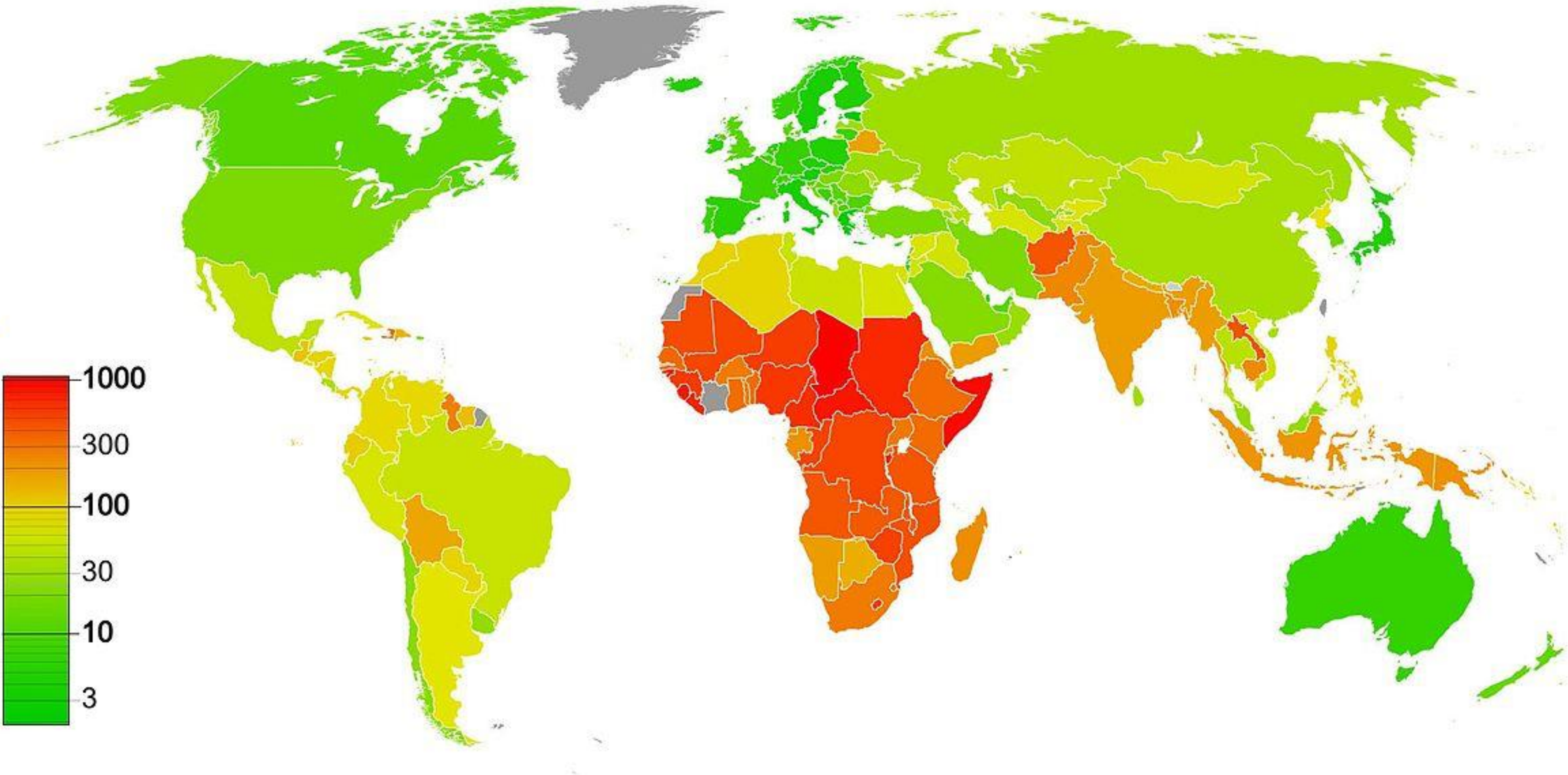
2010 data

- **WHO** estimates that worldwide, and ***on a daily basis, up to 800 women die*** due to pregnancy and birth-related complications that potentially could have been prevented

- **Preeclampsia is the third leading cause** of maternal death - and is one of **the major causes of preterm birth - ** and **fetal morbidity and mortality**

….. ≈ 100 women die of PE

……….every day



Maternal Mortality Rates – WHO 2010


EARLY
DETECTION
Saves Lives

Concept I

- An utopic, yet possible scenario:

  - by using our smart phones we record a short video of some regions of interest (ROI) in our body (e.g. our face or our tongue)

- By using artificial intelligence (AI) transforming this ordinary smart phone into an ingenious equipment for detecting, predicting or even staging disorders –

  such as preeclampsia

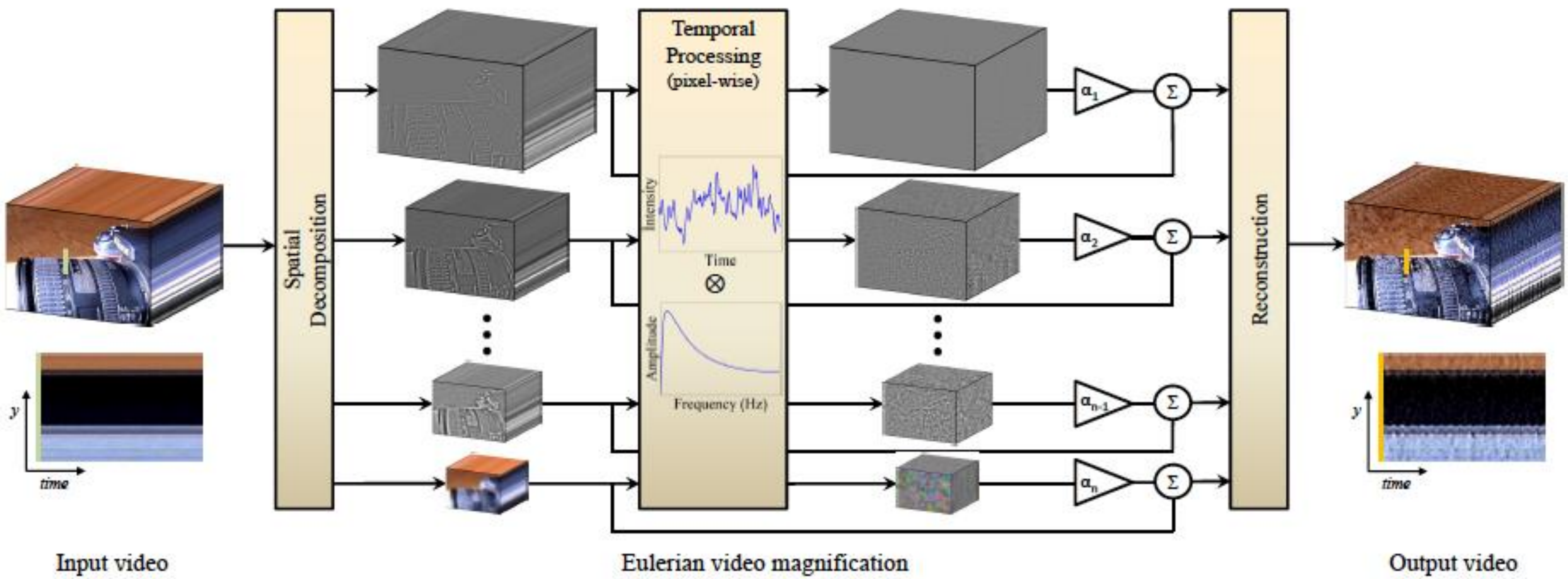
Concept II

- By examining subtle changes such as motions, colors and deformations invisible to the naked eye

- we could unveil hidden, but crucial, health information

….will this pregnant woman later develop manifest PE..?

The AI technology



The main steps

video processing technology ref. E Nadimi

- **Firstly decomposing the input video sequence into a sequence of frames, where each frame is an image.**
- **In the first layer, each image goes though decomposition into different spatial frequency bands.**
- **The spatial decomposition is a filter that blurs the image at different degrees.**

The main steps

video processing technology ref. E Nadimi :

:

- In the second layer, the method applies a temporal filter to all bands. This temporal filter and its lower frequency and higher frequency limit, will depend on the specific application.

- The filtered spatial bands are then amplified by a given factor, and added back to the original signal

- The fourth layer is a spatial composition, in which the image is reconstructed by the composition of the enhanced images, to generate the final output video.

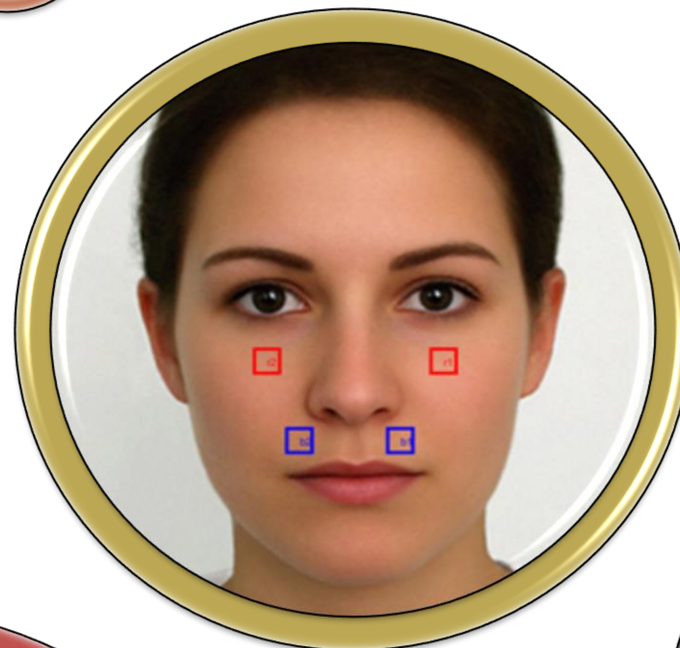
Proof of concept study

The final goal:

- **prevent** consequences of PE
- provide a **feasible** and cost effective **mobile health tool**
- allowing **automatic and continuous risk assessment** of PE -related pregnancy complications.

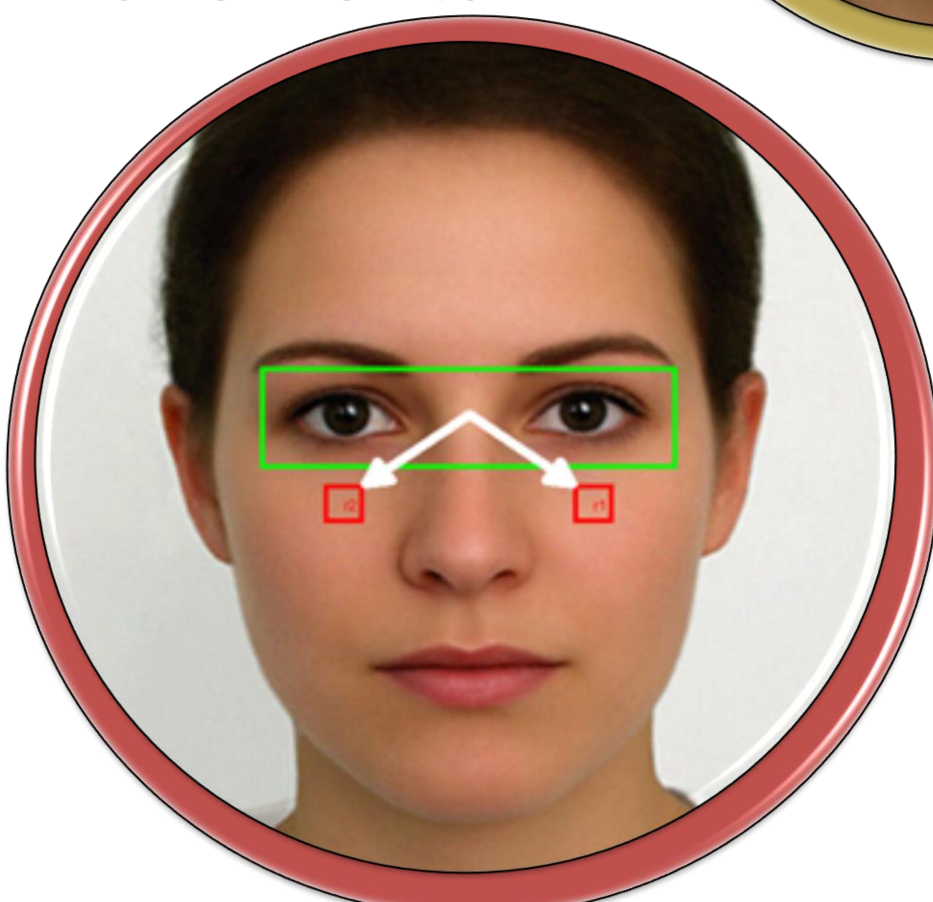
Videocamera/ smartphone project - Preeclampsia

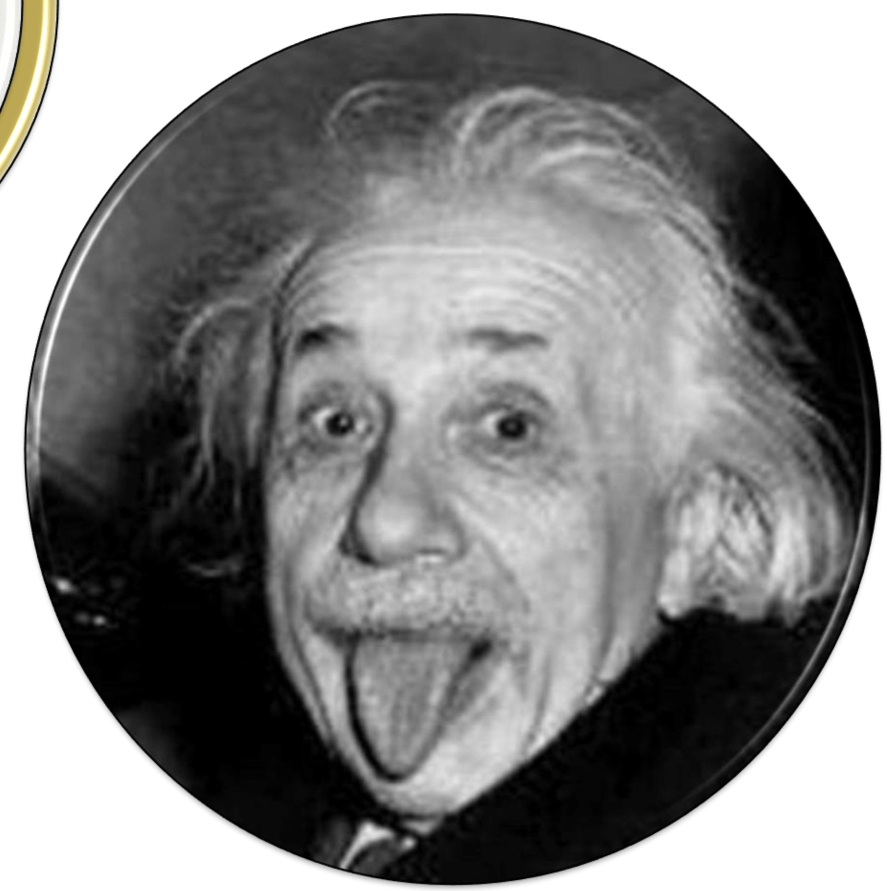
- **Case/control study based on believed pathofysiology of pre-eclampasia**
- **Recordings of pregnant womens faces 3 times during pregnancy**
- **Changes in colors of micropixel measured over time**
- **Inflammation in micro vessels → increased ”redness” in the skin**
- **Will this increased redness be present before on-set of clinical symptoms?**



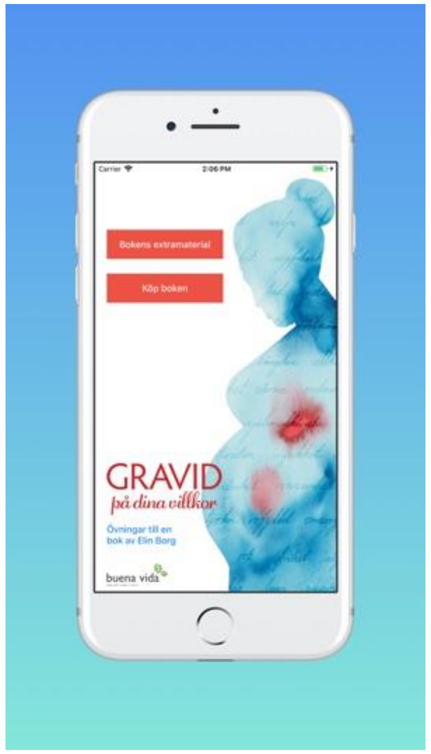
Colour changes in skin

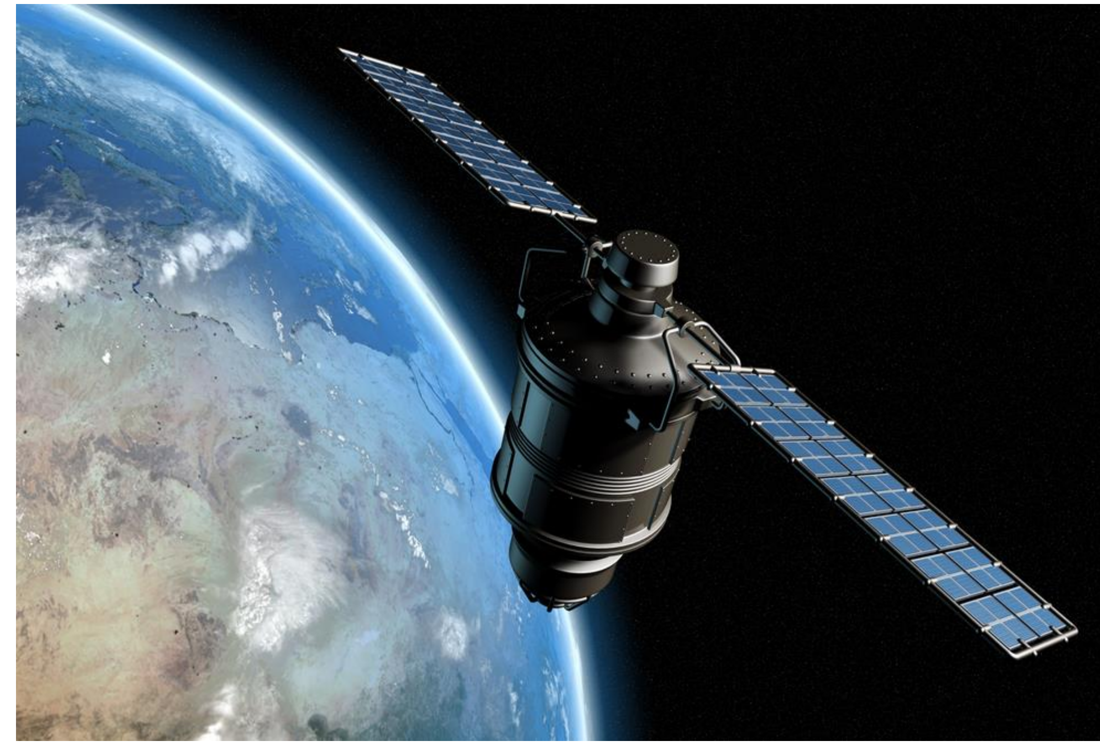
Eye movements



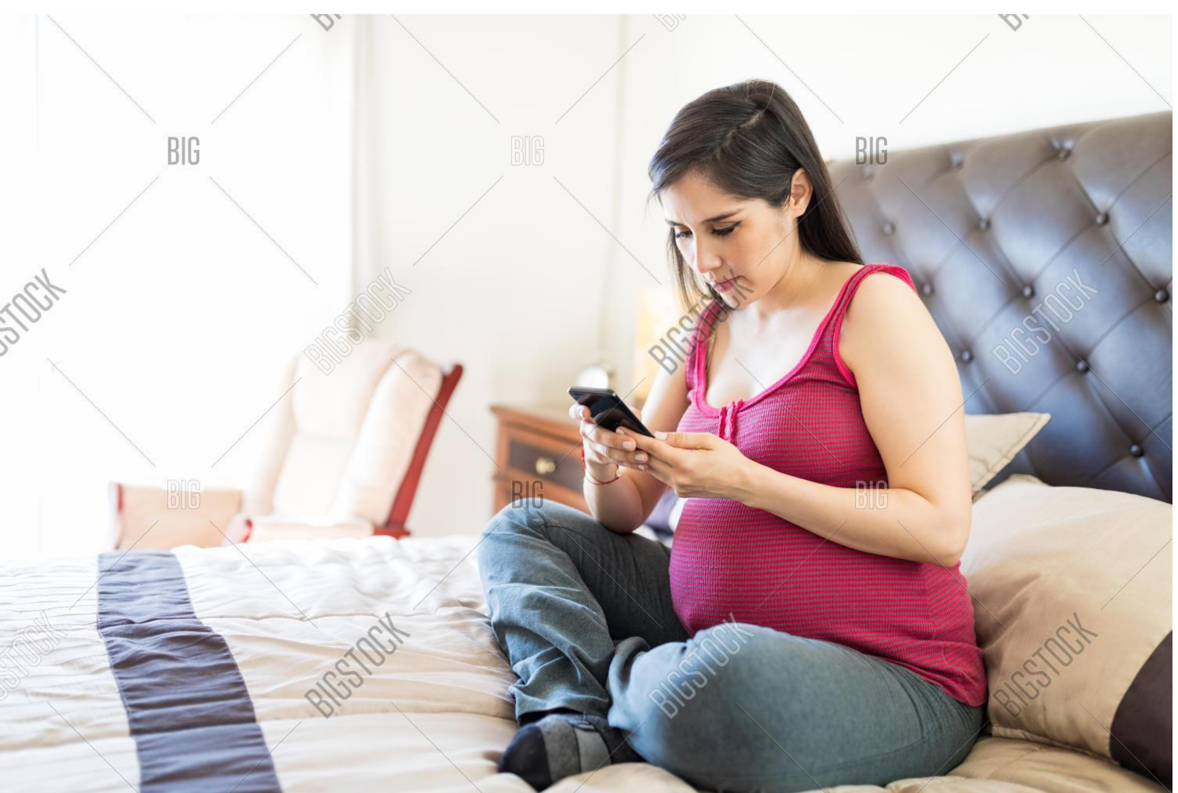


Colour changes on tongue





Antenatal Clinic



Don’t give up !

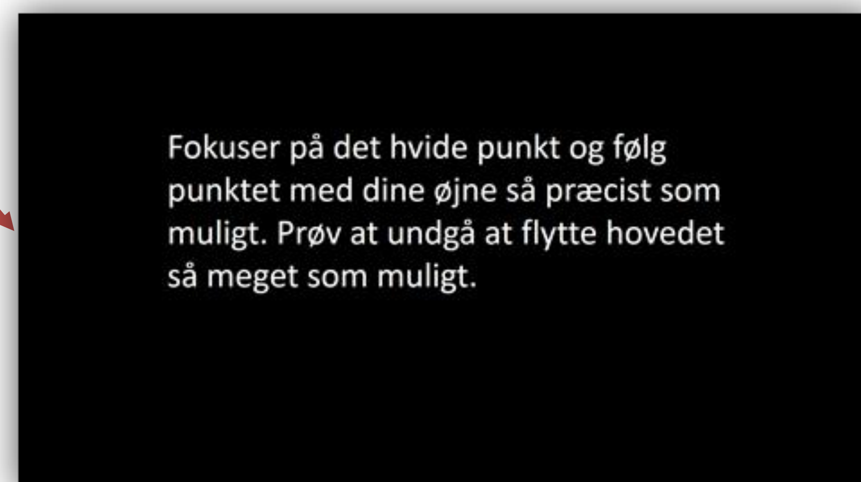
Extra Slides

Progress and Results (beforehand from diabetes patients)

1. Designing the experimental setup

Facial redness and its variation

Head movements



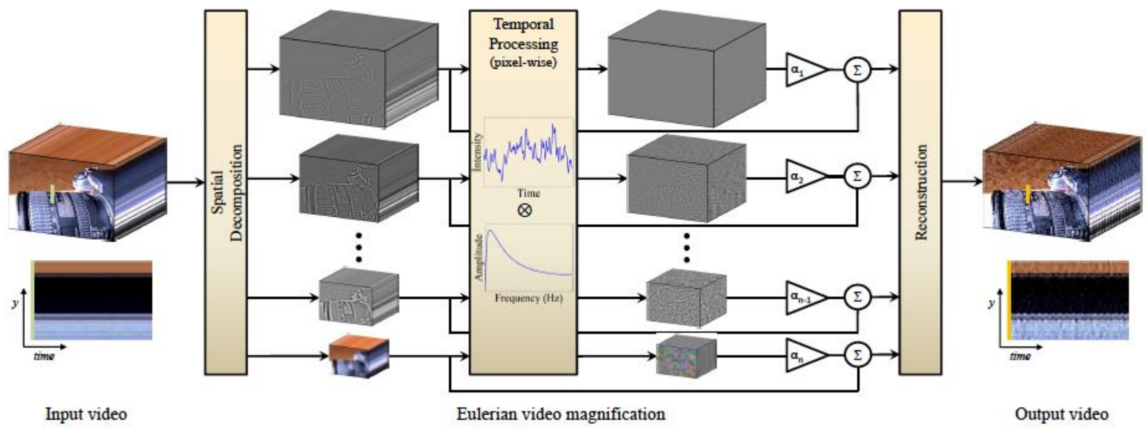
Saccades

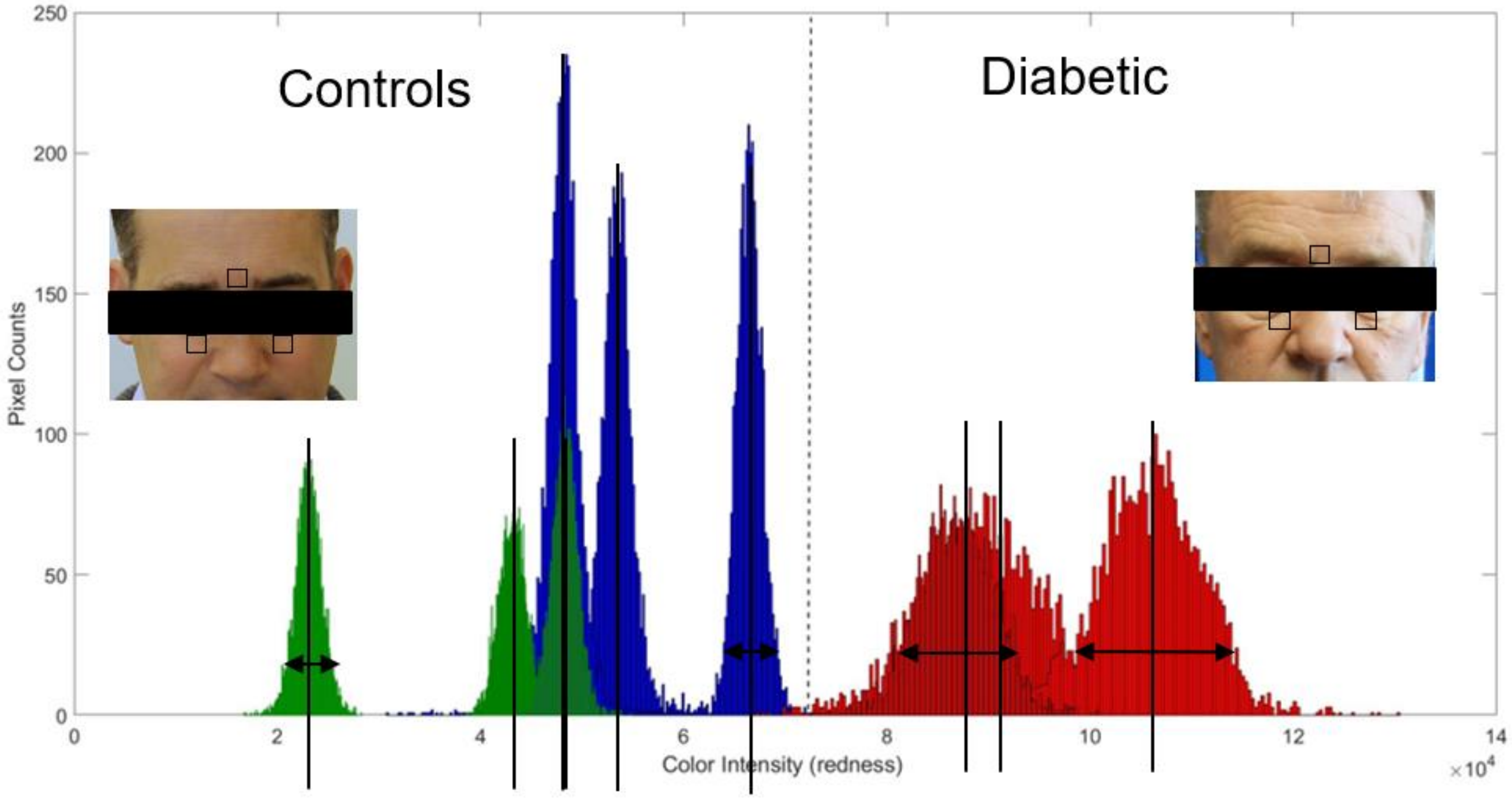
Smooth pursuit movements

Progress (beforehand from diabetes patients)

3. Quantitative feature extraction and analysis

3.1. Revealing invisible facial color changes



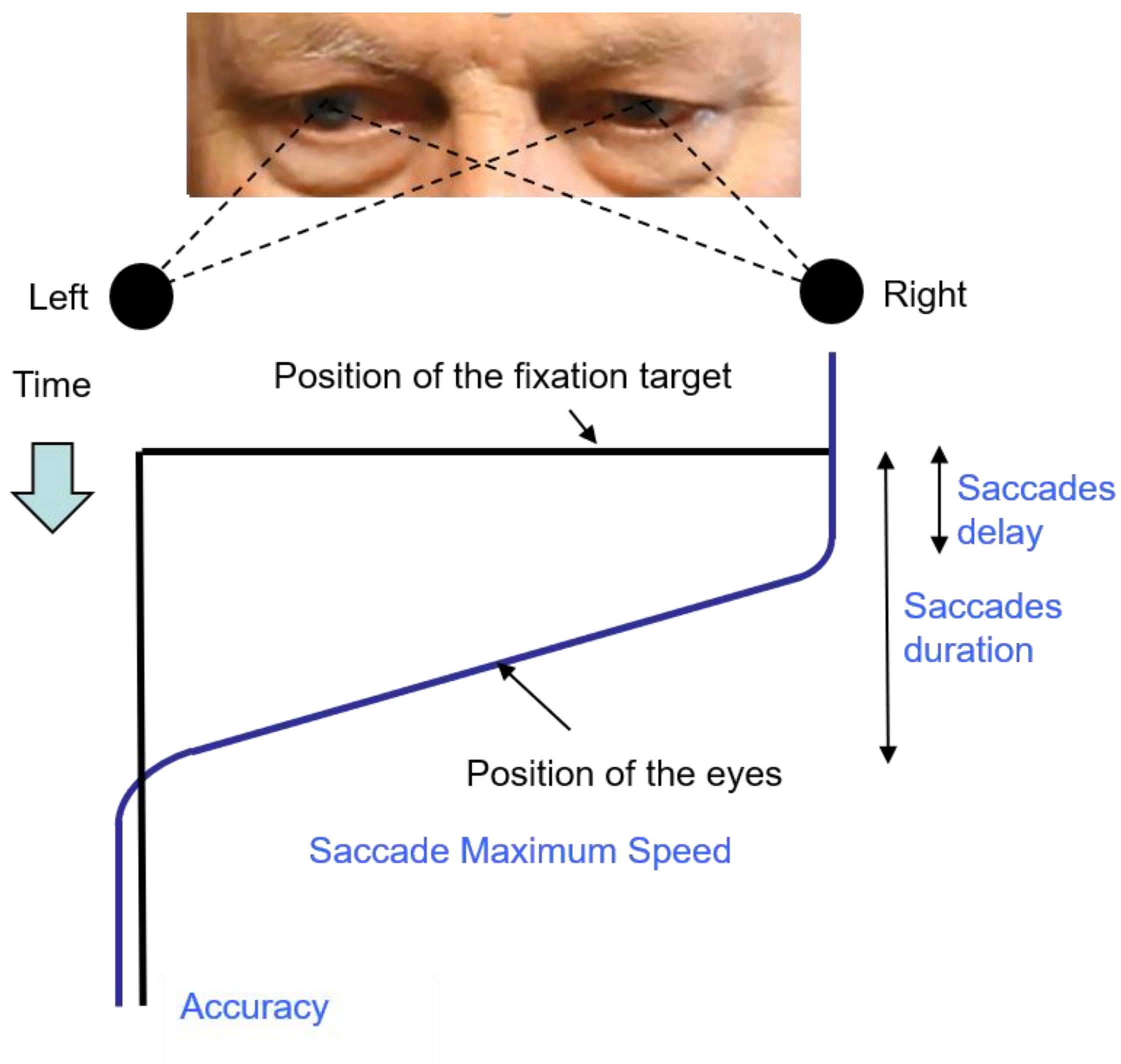


- The facial redness appears to be higher in diabetic patients (even in those diabetic patients in which Rubeosis Faciei is not evident)
- The variation in facial redness appears to be higher in diabetic patients.
- The facial redness appears to be normally distributed in diabetic patients.

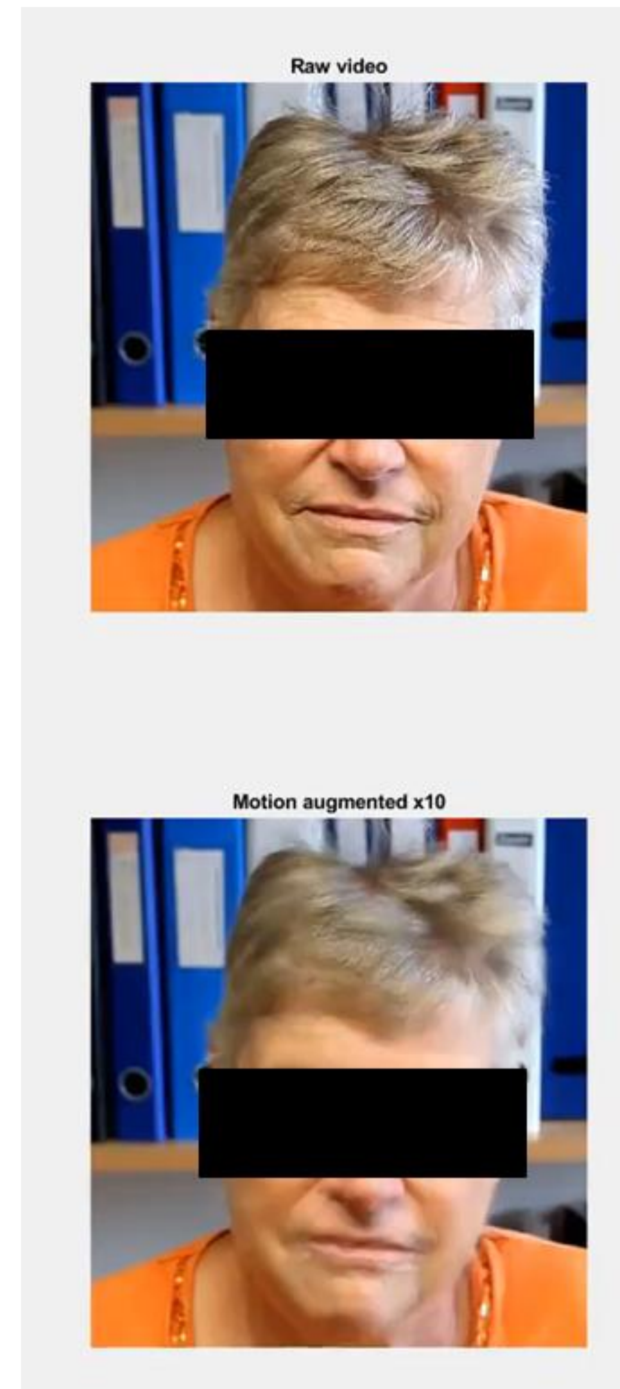
Progress (beforehand from diabetes patients)

3. Quantitative feature extraction and analysis

3.2. Metrics of the saccadic eye movements



3.3. Pulse detection from magnification of head movements



AI applied to screening for Diabetic Retinopathy

RETIPROGRAM

Dr. Aida Valls-Mateu
Doctor in Artificial Intelligence
Engineer in Computer Science
Associate professor at Universitat Rovira i Virgili (Tarragona, Catalonia)
Head of ITAKA research group aida.valls@urv.cat

Work done in collaboration with Hospital Universitari Sant Joan de Reus
Head Ophthalmology: Dr. Pere Romero-Aroca promero@grupsagessa.com

AI applied to screening of Diabetic Retinopathy

Diabetic retinopathy (DR) is a health problem that affects many people and whose incidence is increasing:

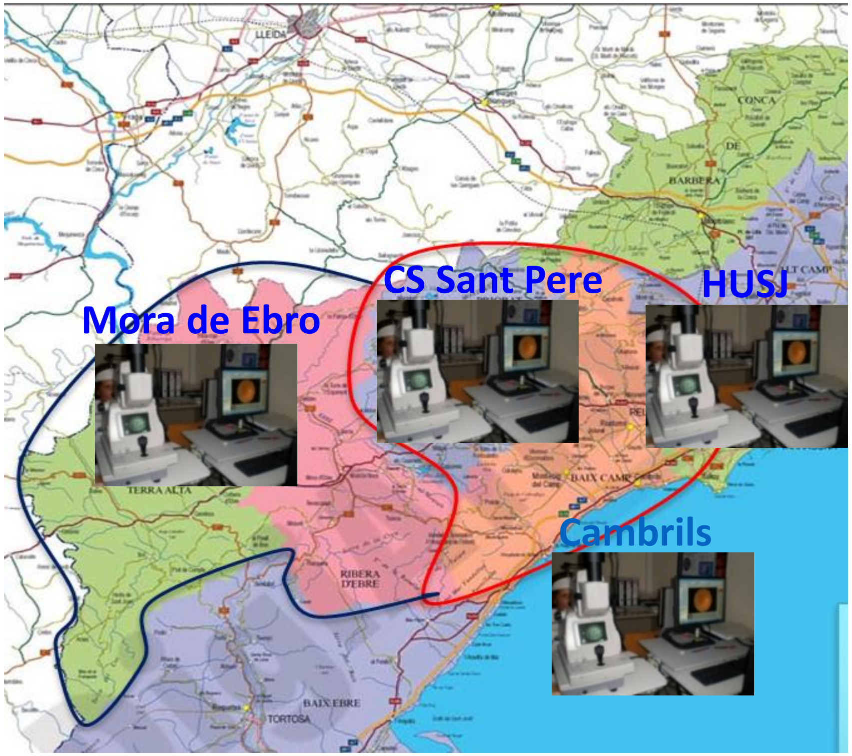
- 415 millions of adults with diabetes in the world
- Increase of 50% until 2025
- 35% - 50% of diabetic people may have DR
- 10% in in risk of becoming blind due to DR = This is about 20 millions of people

http://www.idf.org

South of Catalonia study:

Hospital Universitario Sant Joan (HUSJ):

- Reference population: 247.174
- Patients with diabetes mellitus: 17.792
- Health care centers: 15
- Non midryatic cameras for DR detection: 4 (since 2007)



Hospital Universitari Sant Joan REUS

ITAKA

IRCV INTELLIGENT ROBOTICS AND COMPUTER VISION

IISPV INSTITUT D'INVESTIGACIÓ SANITÀRIA PERE VIRGILI

UNIVERSITAT ROVIRA i VIRGILI

AI applied to screening of Diabetic Retinopathy

RETIPROGRAM

Automatic Image Classification

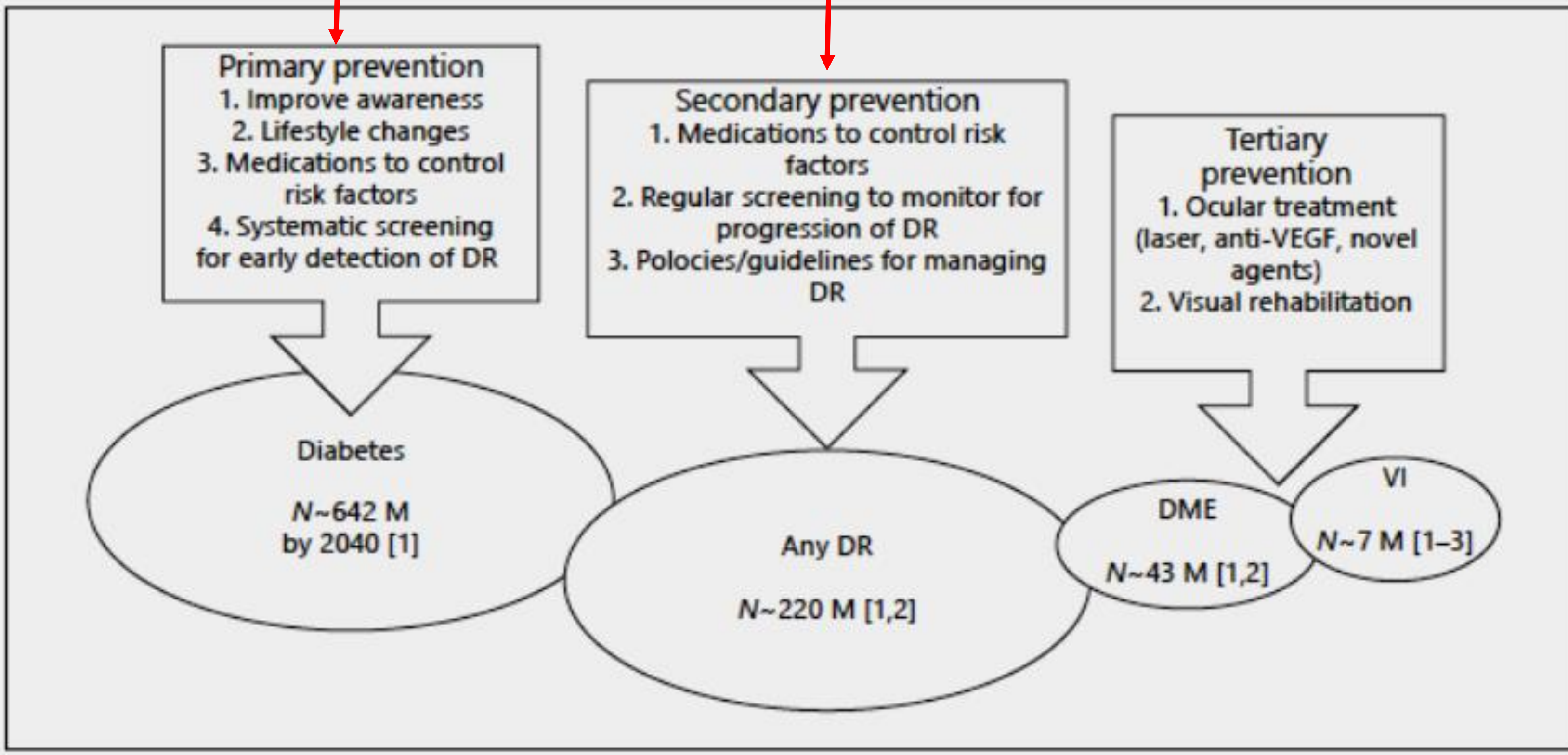


Fig. 1. Prevention strategies for tackling the epidemic of diabetic retinopathy. DR, diabetic retinopathy; DME, diabetic macular edema; VI, visual impairments; M, 1 million people.

Wong TY, Sabanayagam C. Strategies to Tackle the Global Burden of Diabetic Retinopathy: From Epidemiology to Artificial Intelligence. Ophthalmologica, 2019 DOI: 10.1159/000502387

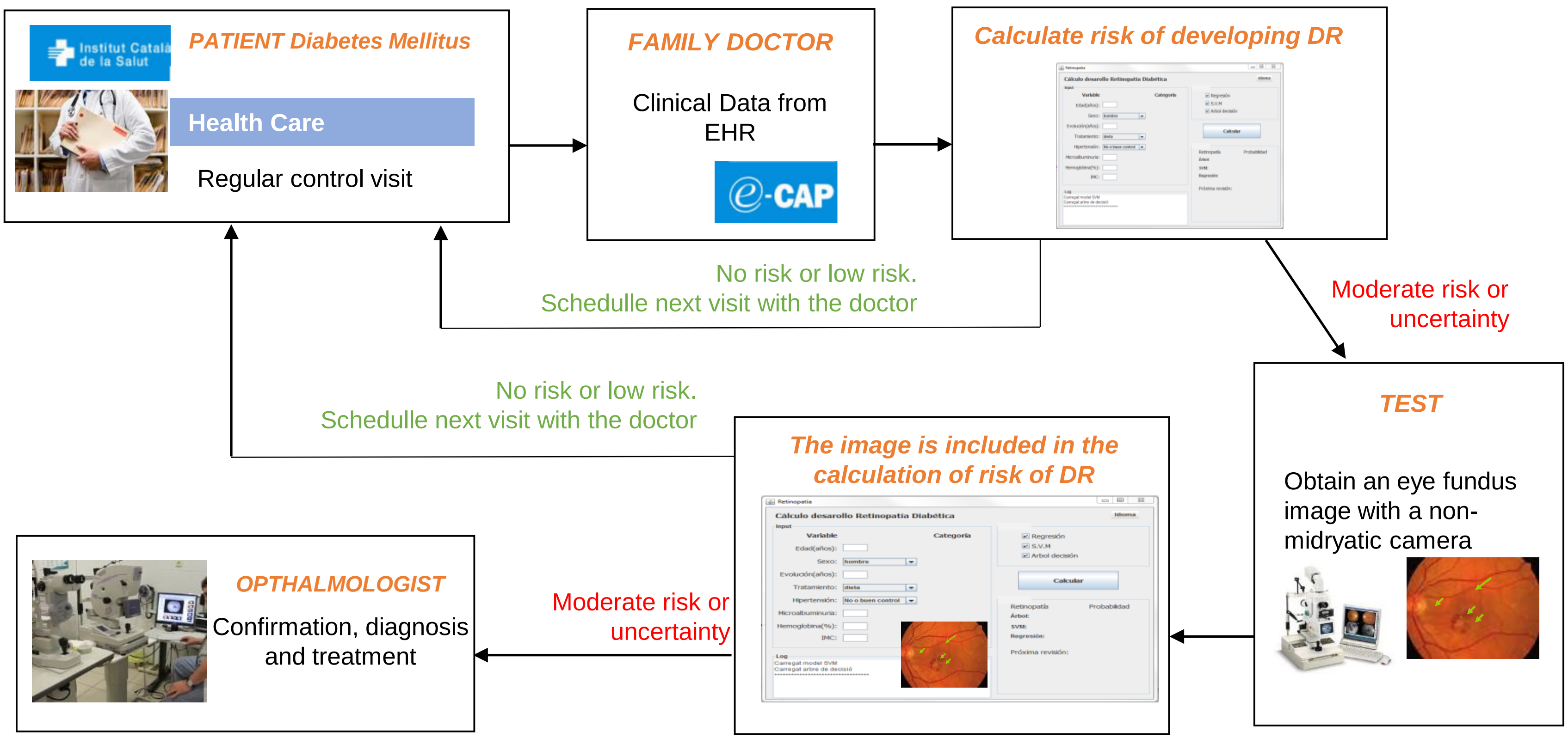
Both systems have been constructed using **Machine Learning** techniques from AI:

- **Retiprogram** uses Fuzzy Random Forests to build a set of rules with linguistic variables.
- **Image classification** model is constructed with Deep Learning techniques based on neural networks.
- In both cases the learning algorithm needs a large set of labelled training data to build the model. This model is validated with a different dataset of testing data, also labelled.

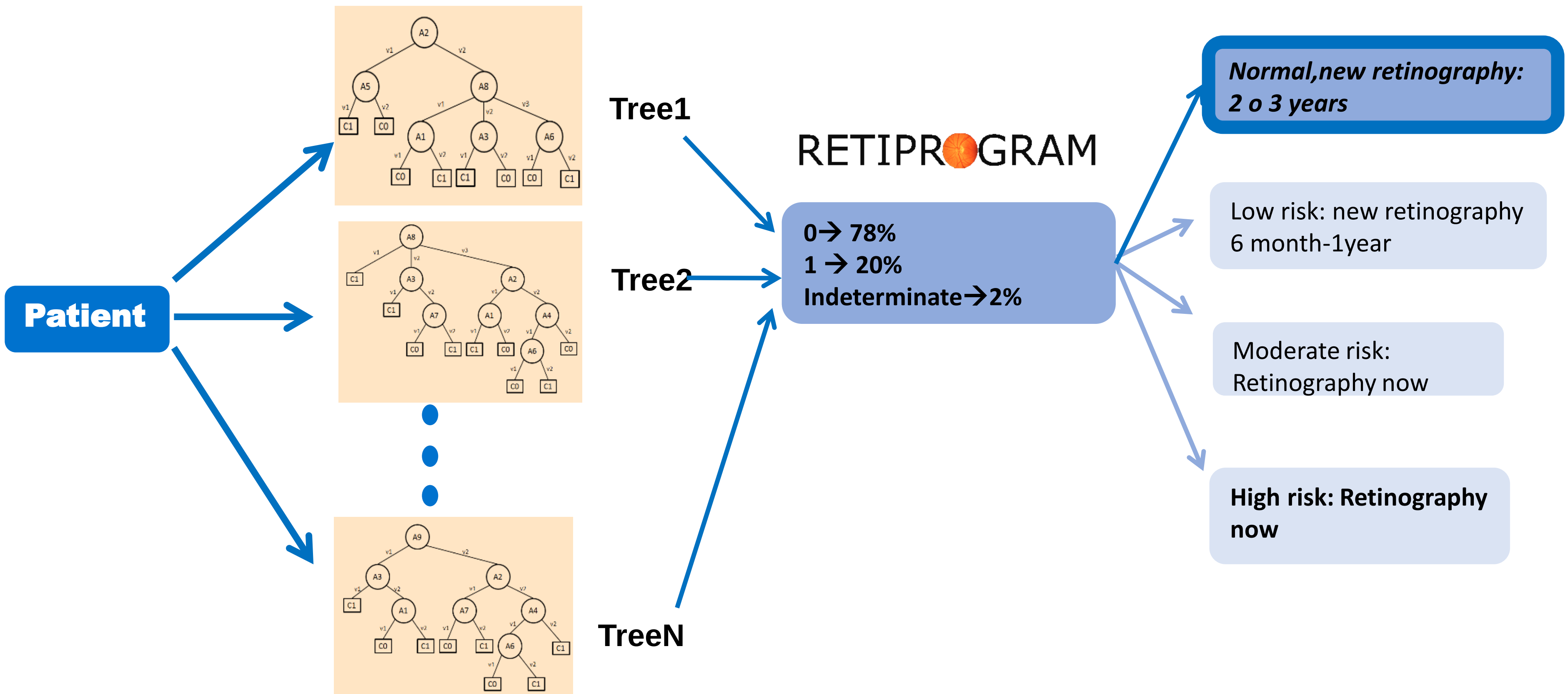
This work has benn possible thanks to 3 Funded Projects by Instituto de Investigación Sanitaria Carlos III and FEDER funds.

GOBIERNO DE ESPAÑA
MINISTERIO DE ECONOMÍA Y COMPETITIVIDAD
Instituto de Salud Carlos III
Unión Europea
Fondo Europeo de Desarrollo Regional
"Una manera de hacer Europa"

AI applied to screening of Diabetic Retinopathy



AI applied to screening of Diabetic Retinopathy



- **The model uses 9 risk factors from EHR**: age, treatment type, body mass index, creatinine, etc.
- **Random forest model** has **200** trees, with an average of **80** rules on each tree.
- **Each rules** uses around **3 to 7** of the risk factors.

AI applied to screening of Diabetic Retinopathy

Examples of fuzzy rules:

- IF Evol is short and
  HTAR with good control and
  BMI is normal_low THEN
  riskDR=NO
- IF Evol is short and
  HTAR with bad control and
  CKDEPI is low and
  Age is Old THEN
  riskDR=Yes
- IF Evol is very_long and
  BMI is obese_high THEN
  riskDR=Yes

AI applied to screening of Diabetic Retinopathy

- We obtain Specificity around 85% and Sensitivity around 80%.
- False Positives are much higher than False Negatives.

15000 patients from HUSJ	
Training	11000
Testing	4000

RETIPROGRAM

Validation with 28000 patients from other Catalan population

Validation with 108000 patients from Catalonia population (2018)

ONGOING
Use in a pilot test at HJSU (Reus)

AI applied to screening of Diabetic Retinopathy

RETIPROGRAM

Automatic Image Classification

Model 1:
Image Classification in 5 levels of DR

Model 2:
Detection if an imatge is good/bad

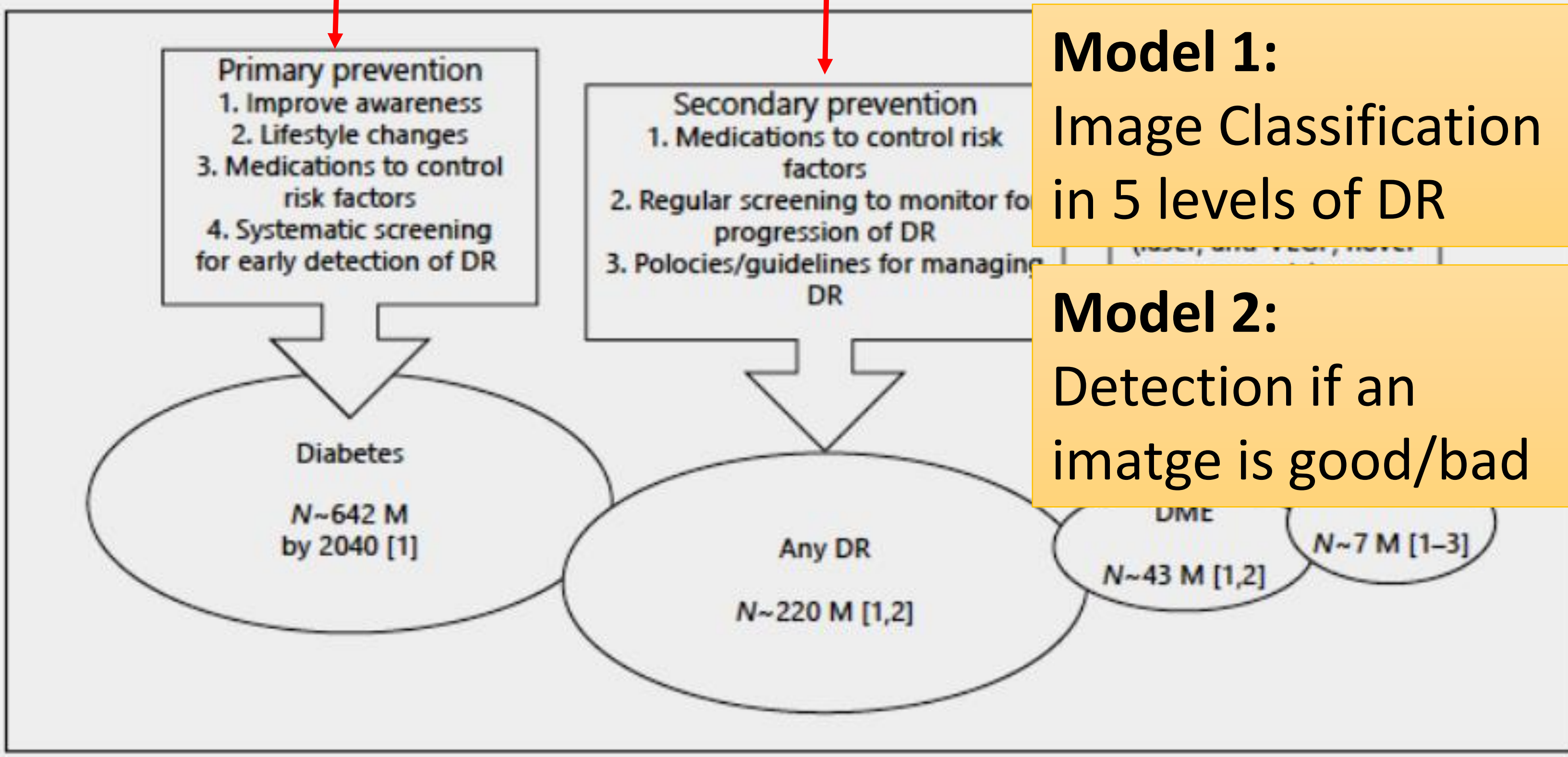


Fig. 1. Prevention strategies for tackling the epidemic of diabetic retinopathy. DR, diabetic retinopathy; DME, diabetic macular edema; VI, visual impairments; M, 1 million people.

Wong TY, Sabanayagam C. Strategies to Tackle the Global Burden of Diabetic Retinopathy: From Epidemiology to Artificial Intelligence. Ophthalmologica, 2019 DOI: 10.1159/000502387

Journal of Diabetes Science and Technology
Volume 3, Issue 3, May 2009

ORIGINAL ARTICLES

EyePACS: An Adaptable Telemedicine System for Diabetic Retinopathy Screening

Jorge Cuadros, O.D., Ph.D.[1] and George Bresnick, M.D., M.P.A.[2]

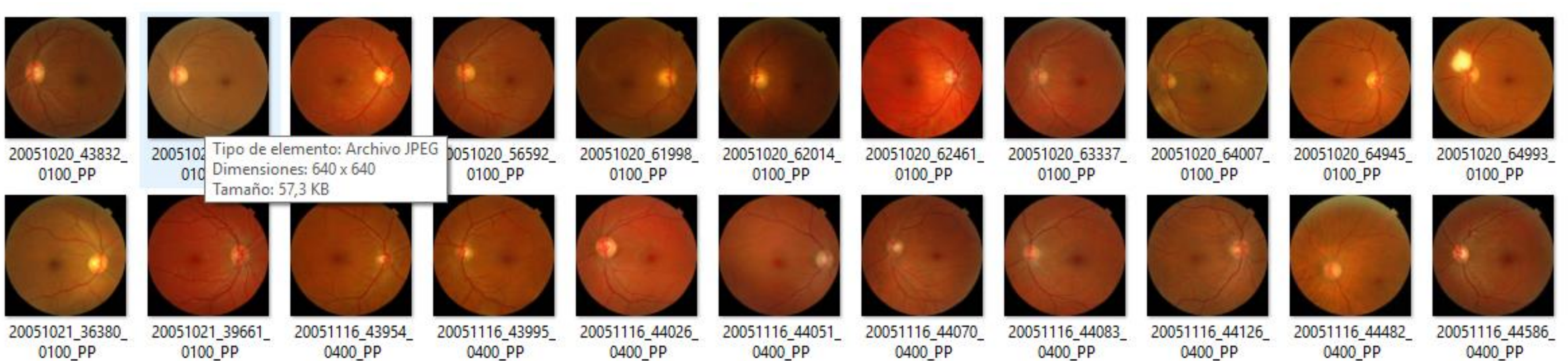
Model constructed with EyePACS dataset

Validation and re-training with Messidor-2 dataset

MESSIDOR

Methods for Evaluating Segmentation and Indexing techniques Dedicated to Retinal Ophthalmology

MESSIDOR is a project funded by the French Ministry of Research and Defense within a 2004 TECHNO-VISION program.



Deep Learning for Image Classification

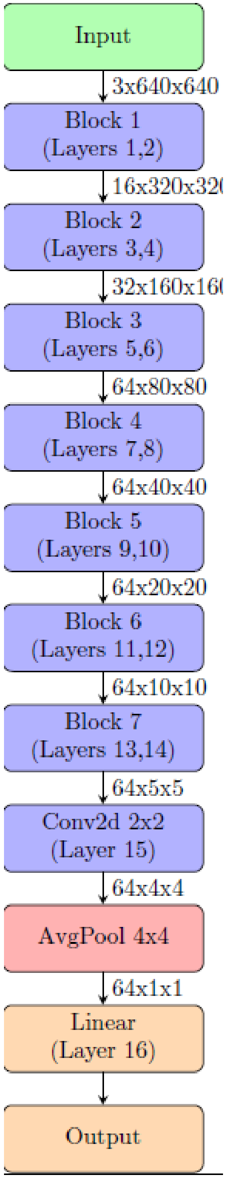
- Important difference with other Deep Learning models (i.e.Google): we are able to **classify into 4 different classes.** Others only binary classification (YES/NO)
- Results of the validation with images HUSJ data: 5.122 images

Model Classification

Ophthalmologists Classification

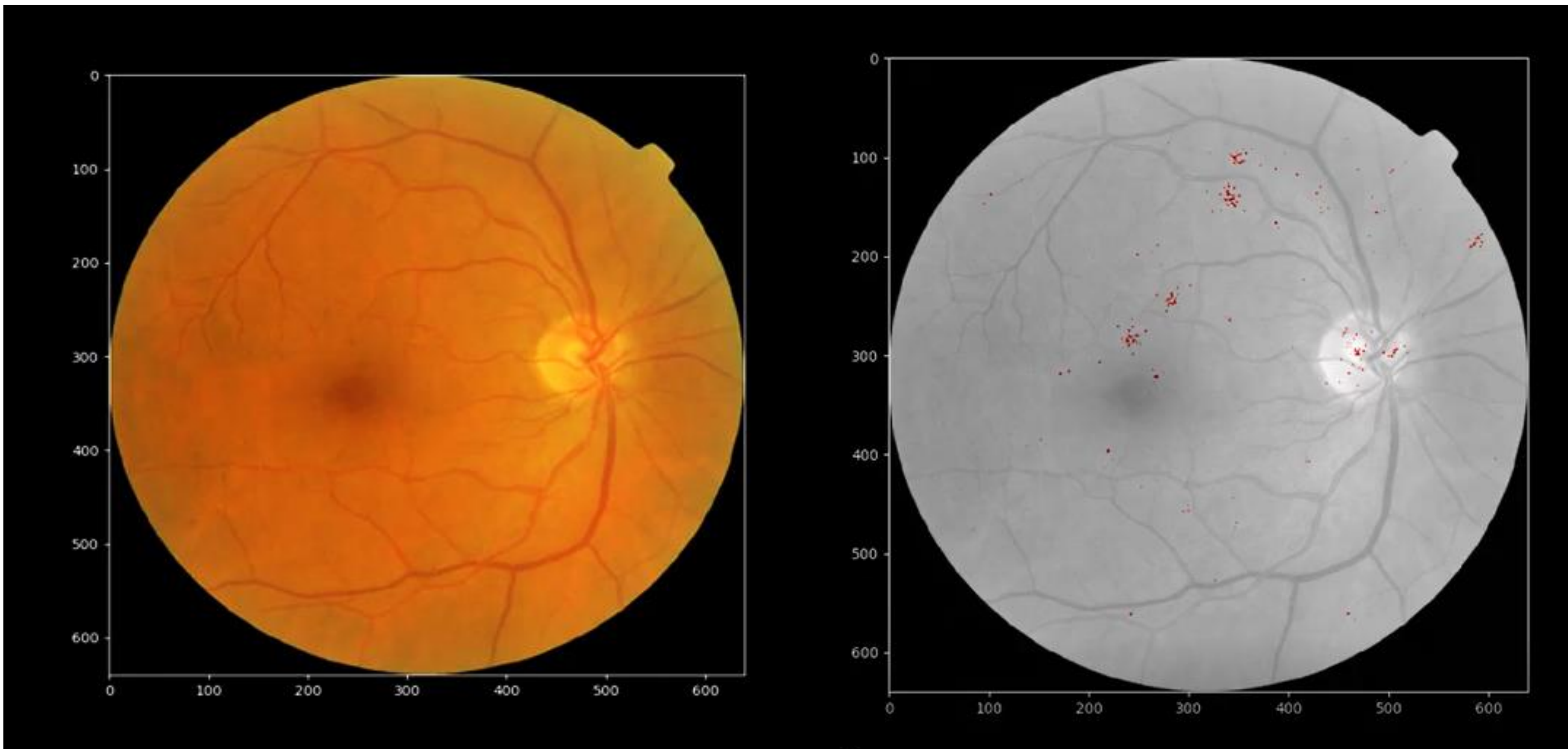
	0	**1**	**2**	**3**
0	4322	54	8	4
1	71	110	47	9
2	6	36	122	27
3	1	0	23	160

	NO retinop	**YES retinop**
NO retinop	**4322**	**66**
YES retinop	**78**	**534**



- The system developed is able to display the pixels that have been used by the model to make the classification.
- We are studying the relation between these pixels and the eye lesions.

Example with class 1 : mild Retinopathy



Deep Learning for Image Classification

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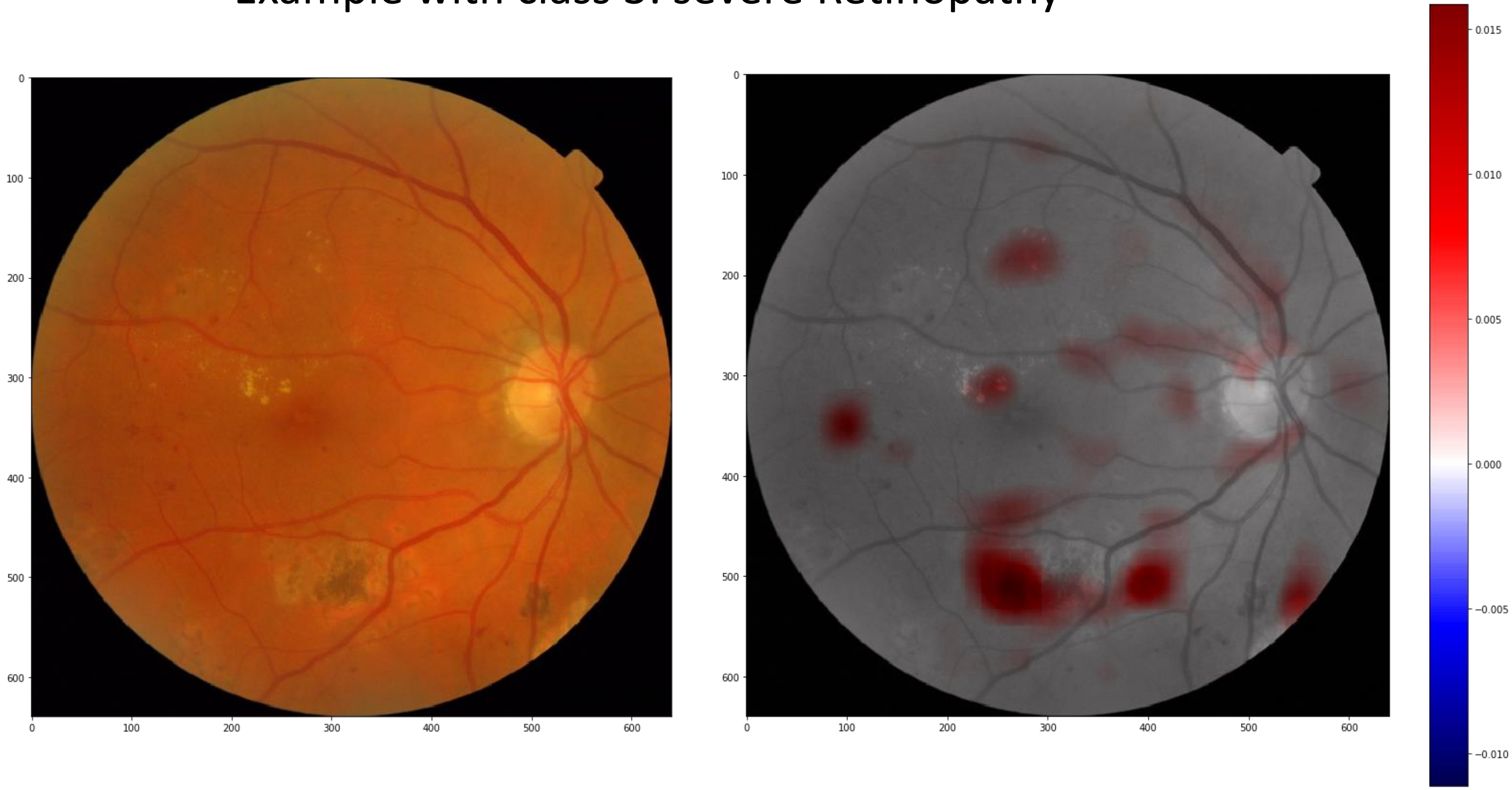
- We are studying the relation between these pixels and the eye lesions.

Example with class 3: severe Retinopathy



AI applied to screening of Diabetic Retinopathy

RETIPROGRAM

Automatic Image Classification

Model 1:
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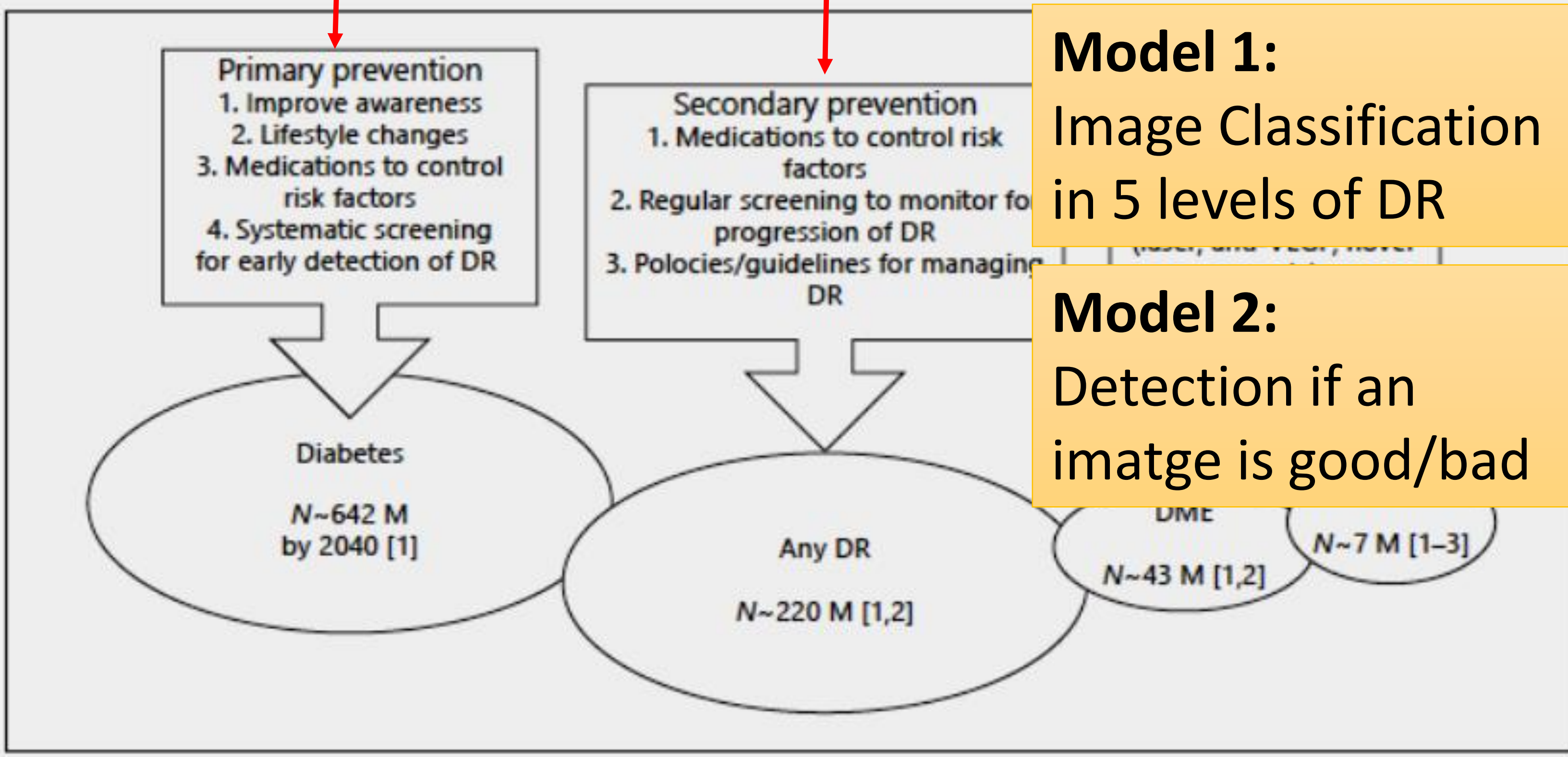

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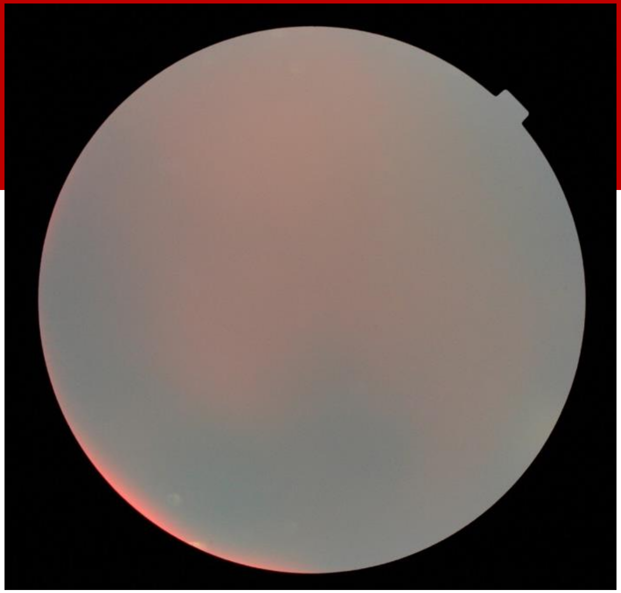
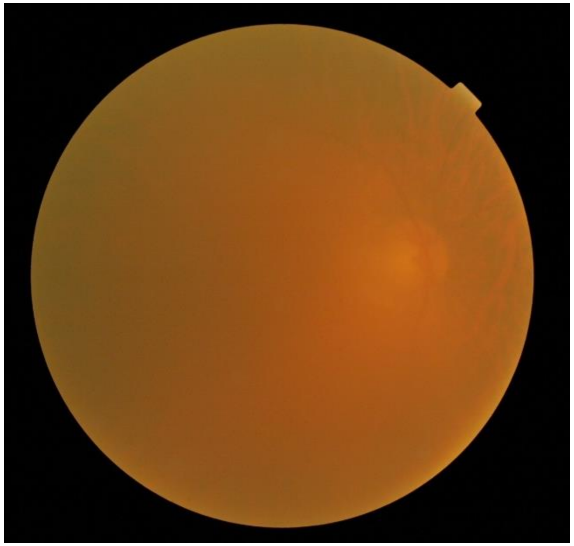
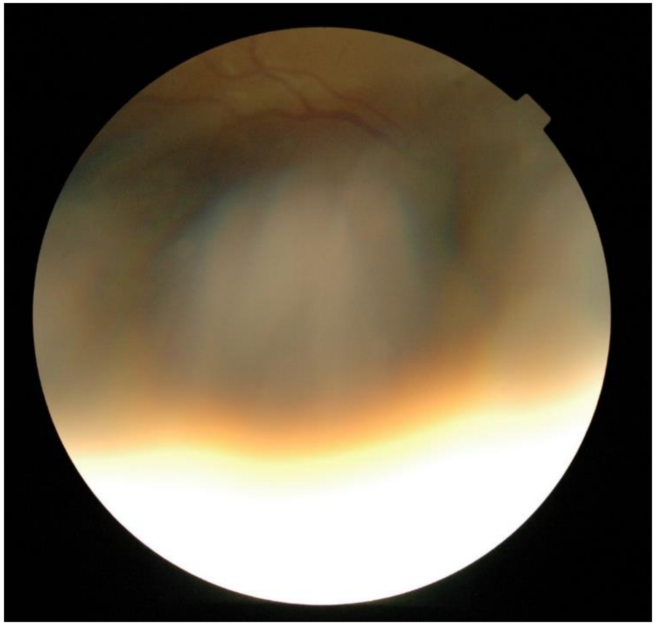
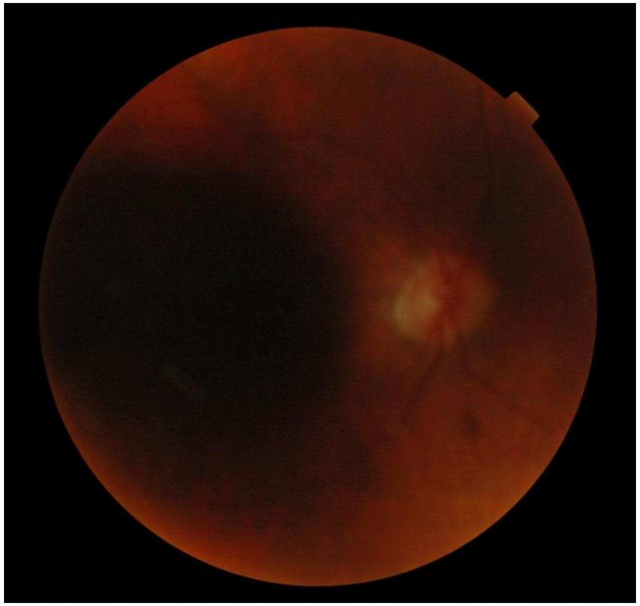
Learning for Image Classification

Is the image good enough to detect DR?





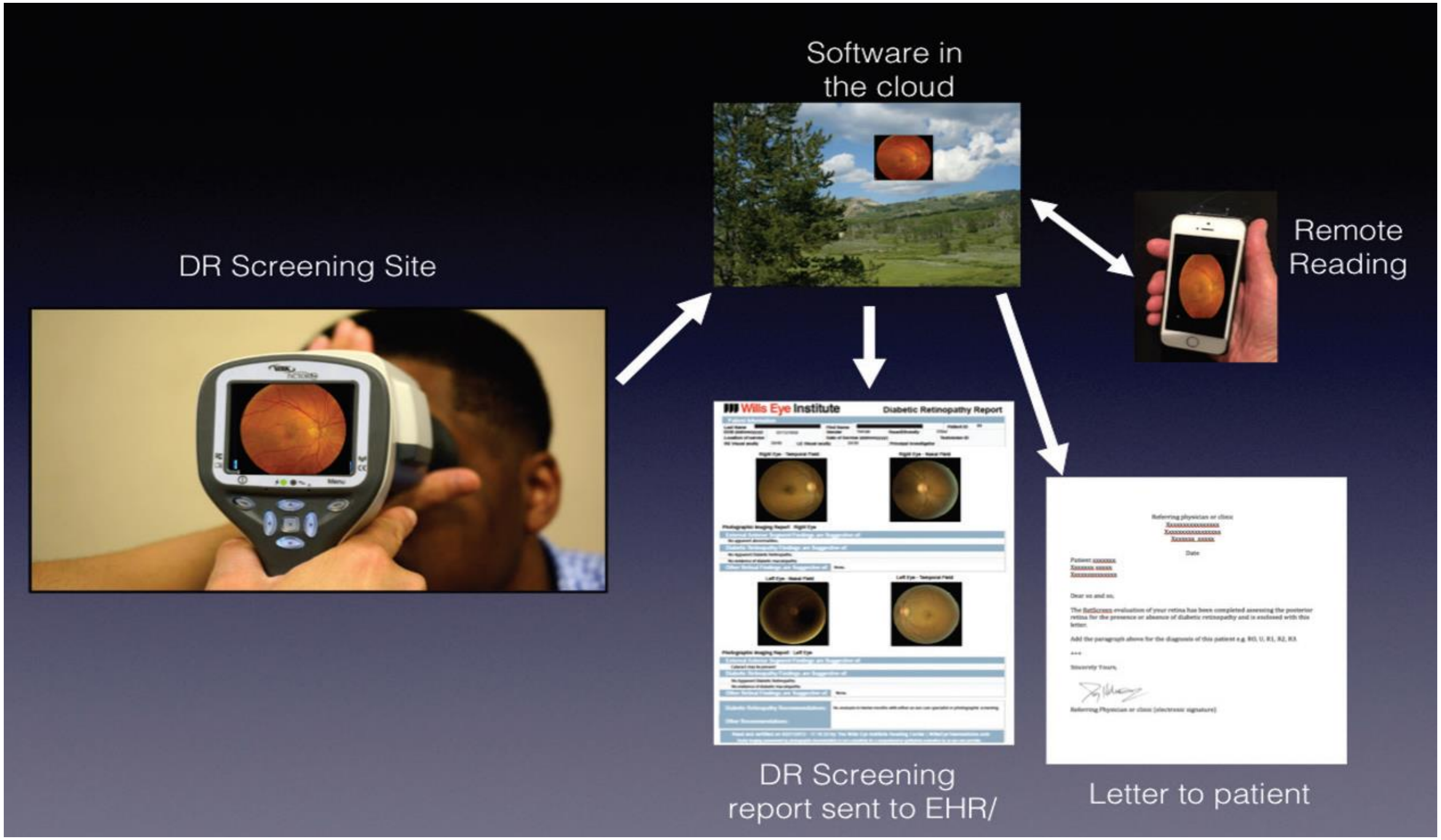




AI applied to screening of Diabetic Retinopathy

Current work:

1. Extract indicators from the images to be included in Retiprogram.
2. We are exploring the possibility of developing an online self-assessment system for image reading and classification.



AI applied to screening of Diabetic Retinopathy

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Dr. Pere Romero-Aroca
IISPV, Hospital Universitari Sant Joan de Reus promero@grupsagessa.com

Publicacions:

1. Romero-Aroca Pedro, Valls-Mateu Aida, Moreno-Ribas Antonio, Sagarra-Alamo Ramon, Basora-Gallisa Josep, Saleh Emran, Baget-Bernaldiz Marc, Puig Domenec. A Clinical Decision Support System (CDSS) for diabetic retinopathy screening. Creating a clinical support application. Telemed J E Health. 2019. v.25:1,pp. 31-40. doi: 10.1089/tmj.2017.0282.

2. Saleh E, Błaszczyński J, Moreno A, Valls A, Romero-Aroca P, de la Riva-Fernández S, Słowiński R. Learning ensemble classifiers for diabetic retinopathy assessment. Artif Intell Med. 2018. v.85 pp.50-63. doi: 10.1016/j.artmed.2017.09.006

3. De la Torre, J., Valls, A., Puig, D., A deep learning interpretable classifier for diabetic retinopathy disease grading. Neurocomputing. 2019. In press. doi: 10.1016/j.neucom.2018.07.102.

4. Romero-Aroca P, Navarro-Gil R, Valls-Mateu A, Sagarra-Alamo R, Moreno-Ribas A, Soler N. Differences in incidence of diabetic retinopathy between type 1 and 2 diabetes mellitus: a nine-year follow-up study. Br J Ophthalmol. 2017 Oct; 10 (10): 1346-1351. doi: 10.1136/bjophthalmol-2016-310063.

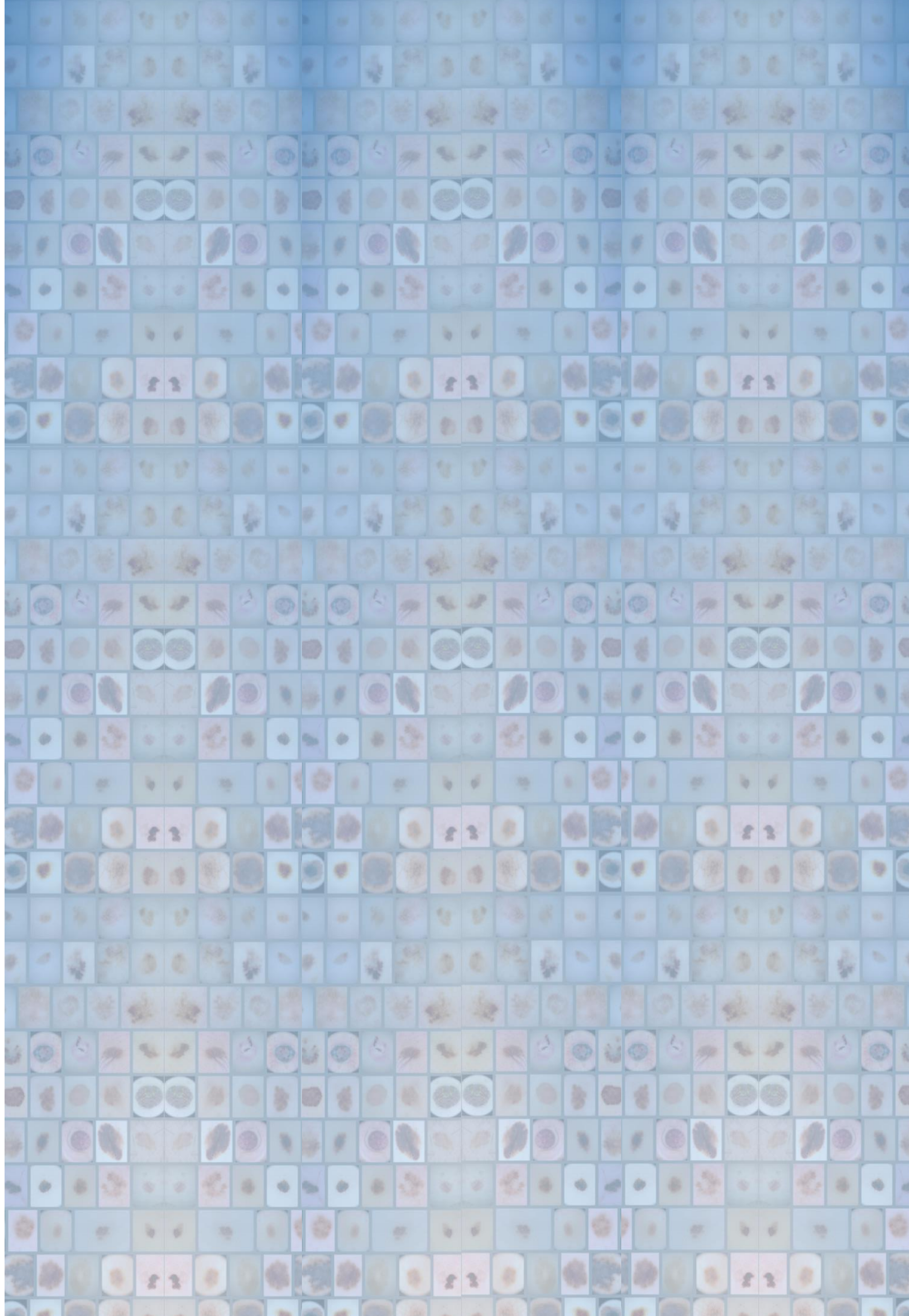
5. Romero-Aroca P, de la Riva-Fernandez S, Valls-Mateu A, Sagarra-Alamo R, Moreno-Ribas A, Soler N, Puig D. Cost of diabetic retinopathy and macular oedema in a population, an eight year follow up. BMC Ophthalmol. 2016 Aug 4;16(1):136. doi: 10.1186/s12886-016-0318-x.

6. Pedro Romero-Aroca, Sofia De La Riva-Fernandez , Aida Valls-Mateu Ramon Sagarra-Alamo , Antonio Moreno-Ribas , Nuria Soler. Changes observed in diabetic retinopathy. Eight year follow up of a Spanish population. Br J Ophthalmol 2016;100: 1366–1371. doi:10.1136/bjophthalmol-2015-307689

7. Romero-Aroca P, Sagarra-Alamo R, Pareja-Rios A, López M. Importance of telemedicine in diabetes care: Relationships between family physicians and ophthalmologists. World J Diabetes 2015; 6(8): 1005-1008 DOI: http://dx.doi.org/10.4239/wjd.v6.i8.1005

Artificial Intelligence for Diagnosis and Treatment in Dermatology

Marc Combalia Escudero
Hospital Clínic de Barcelona



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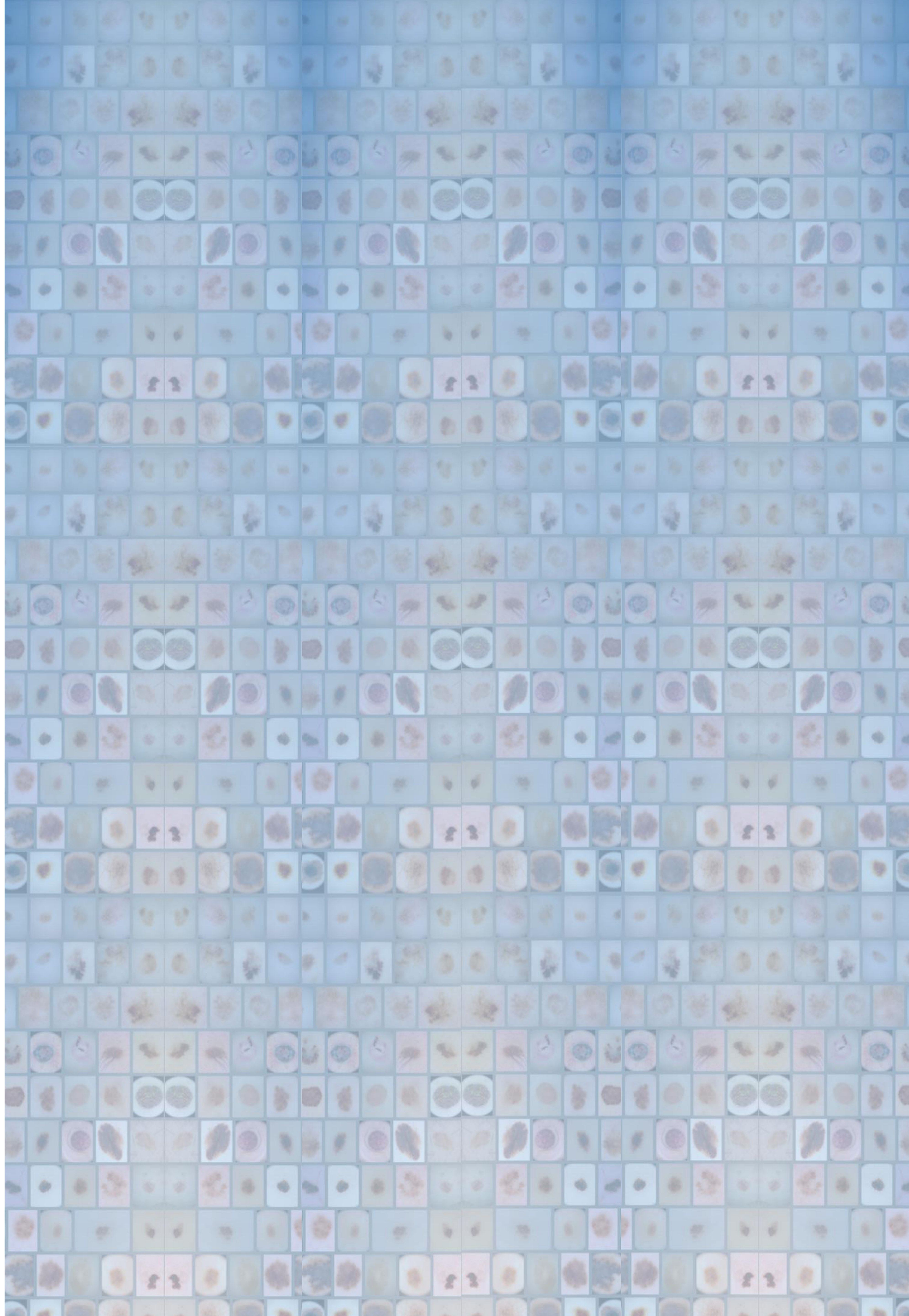

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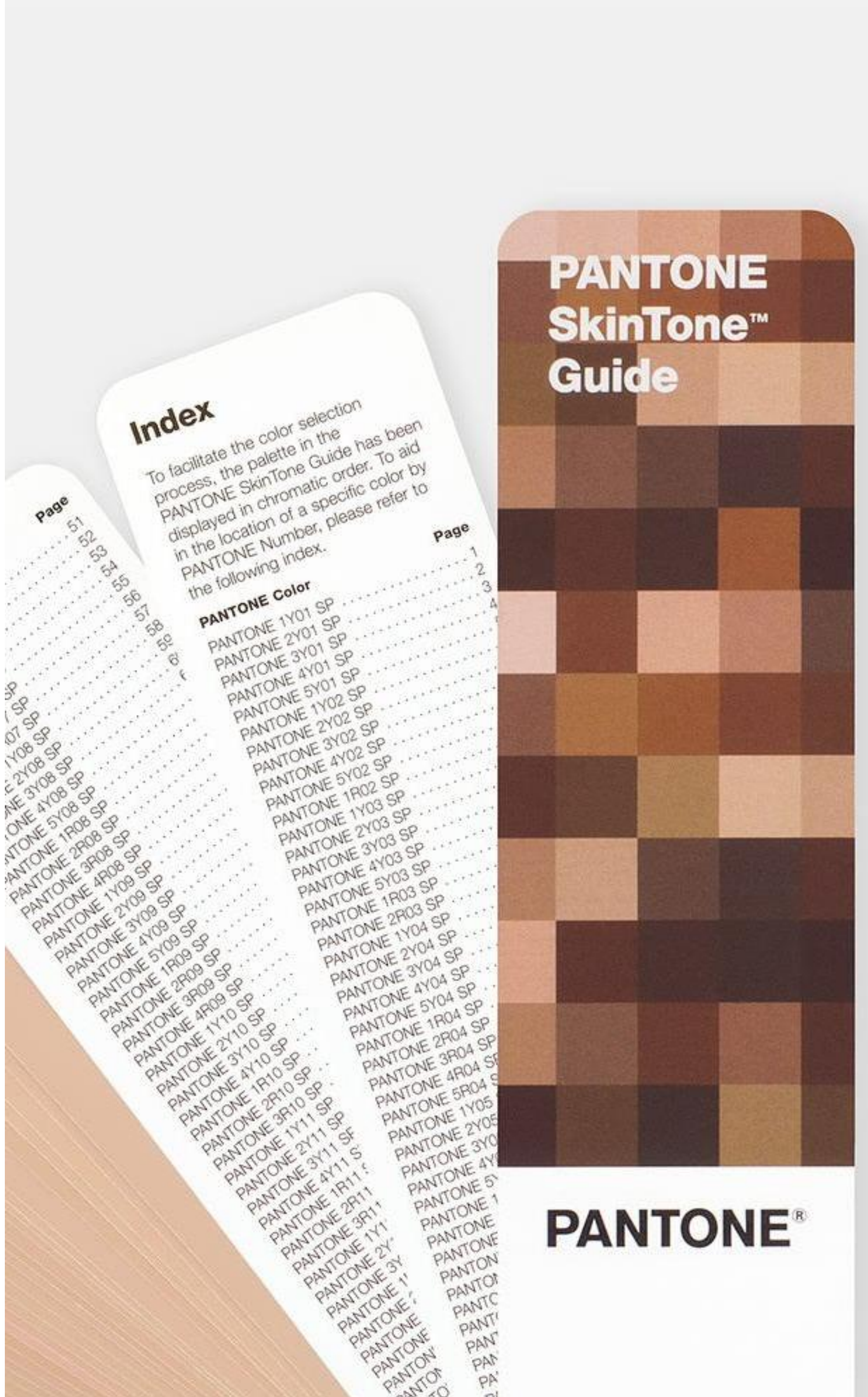
1. Why skin cancer?

1.1. Why skin cancer?

- Skin
  - Largest organ of the human body
  - Main entry barrier
  - Temperature regulation
  - Cutaneous sensibility
  - …



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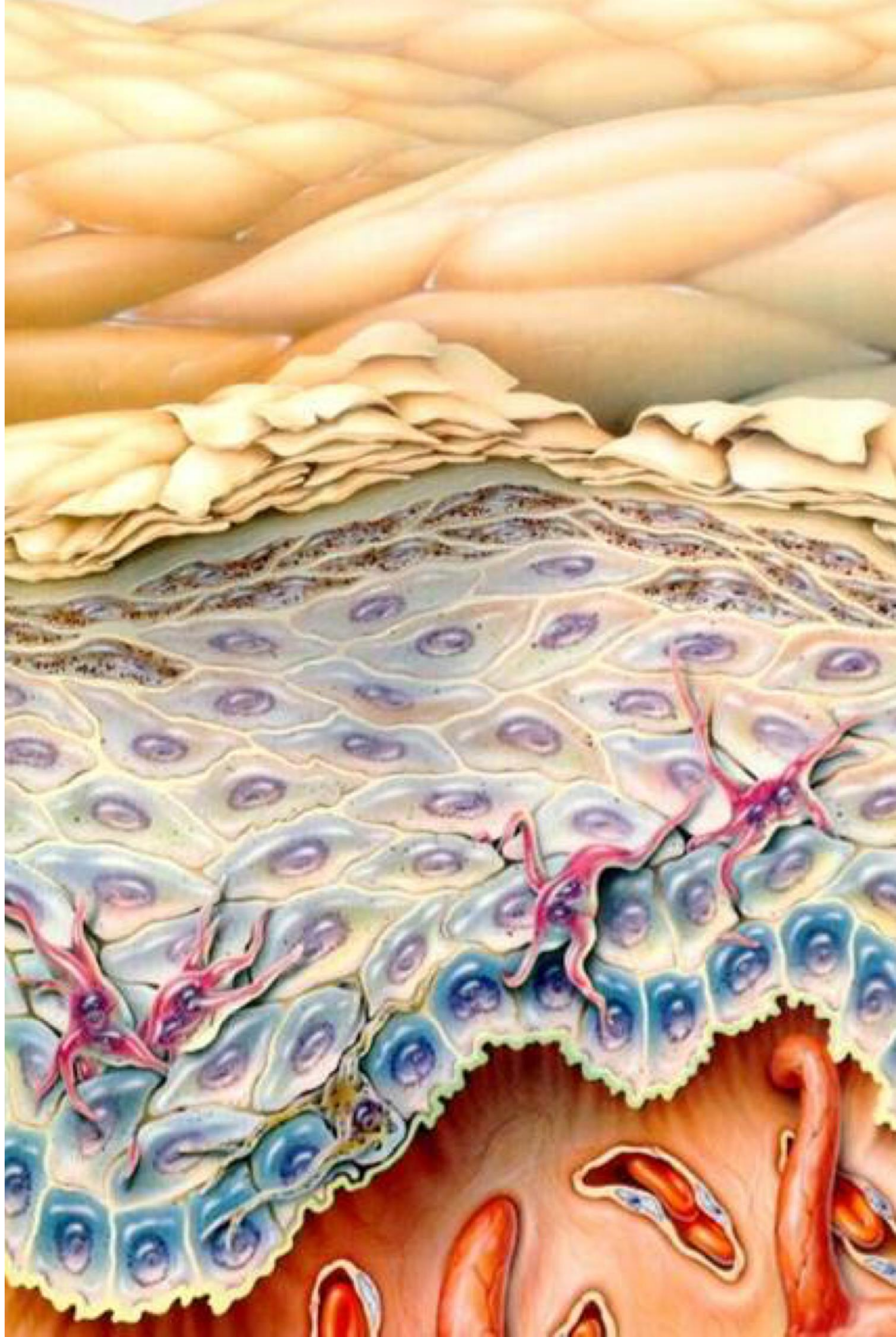
1.2. Why skin cancer?

- Skin cancer
  - Uncontrolled growth of abnormal skin cells
  - Most diagnosed cancer in the US
  - Increasing incidence rates in all the age ranges



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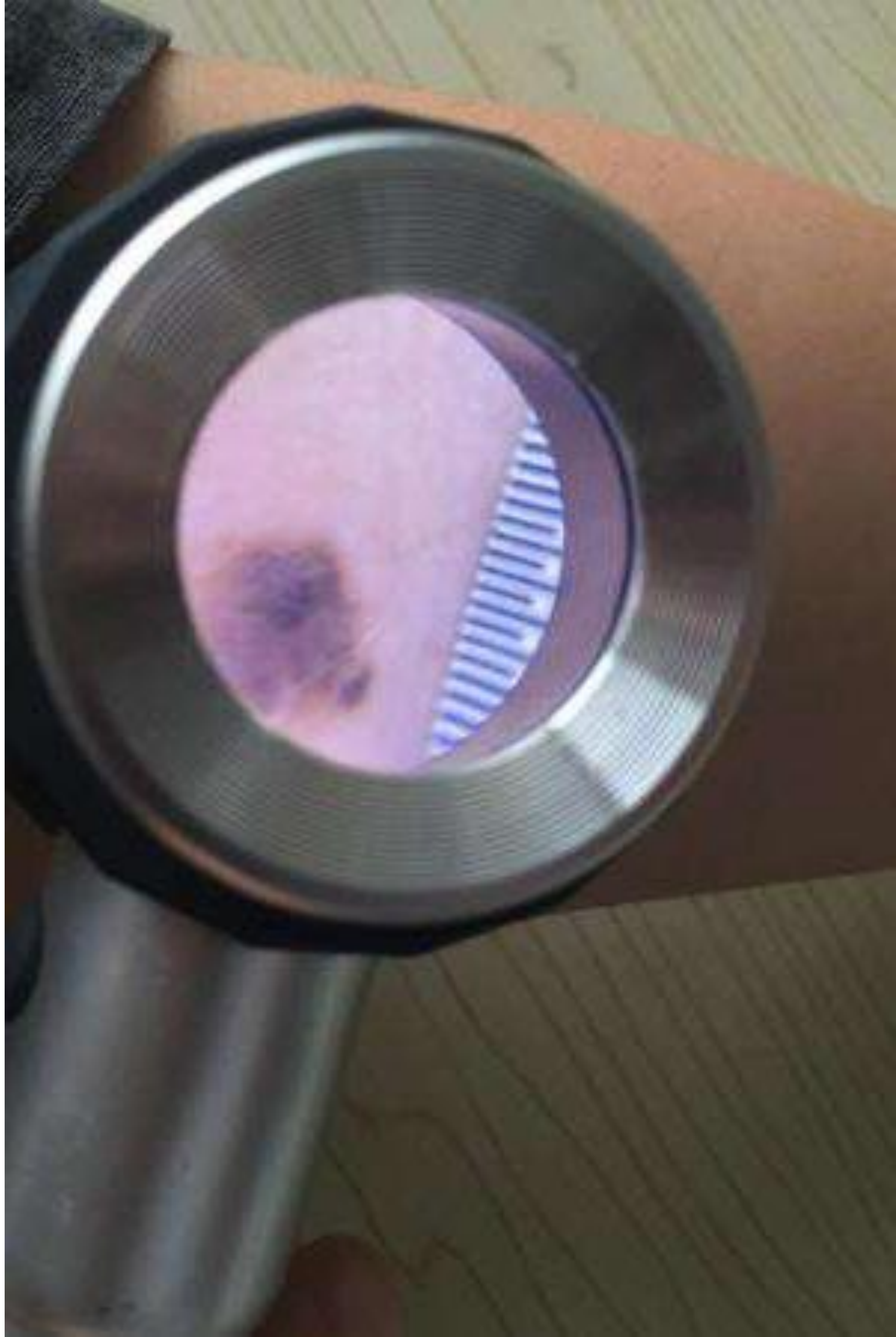
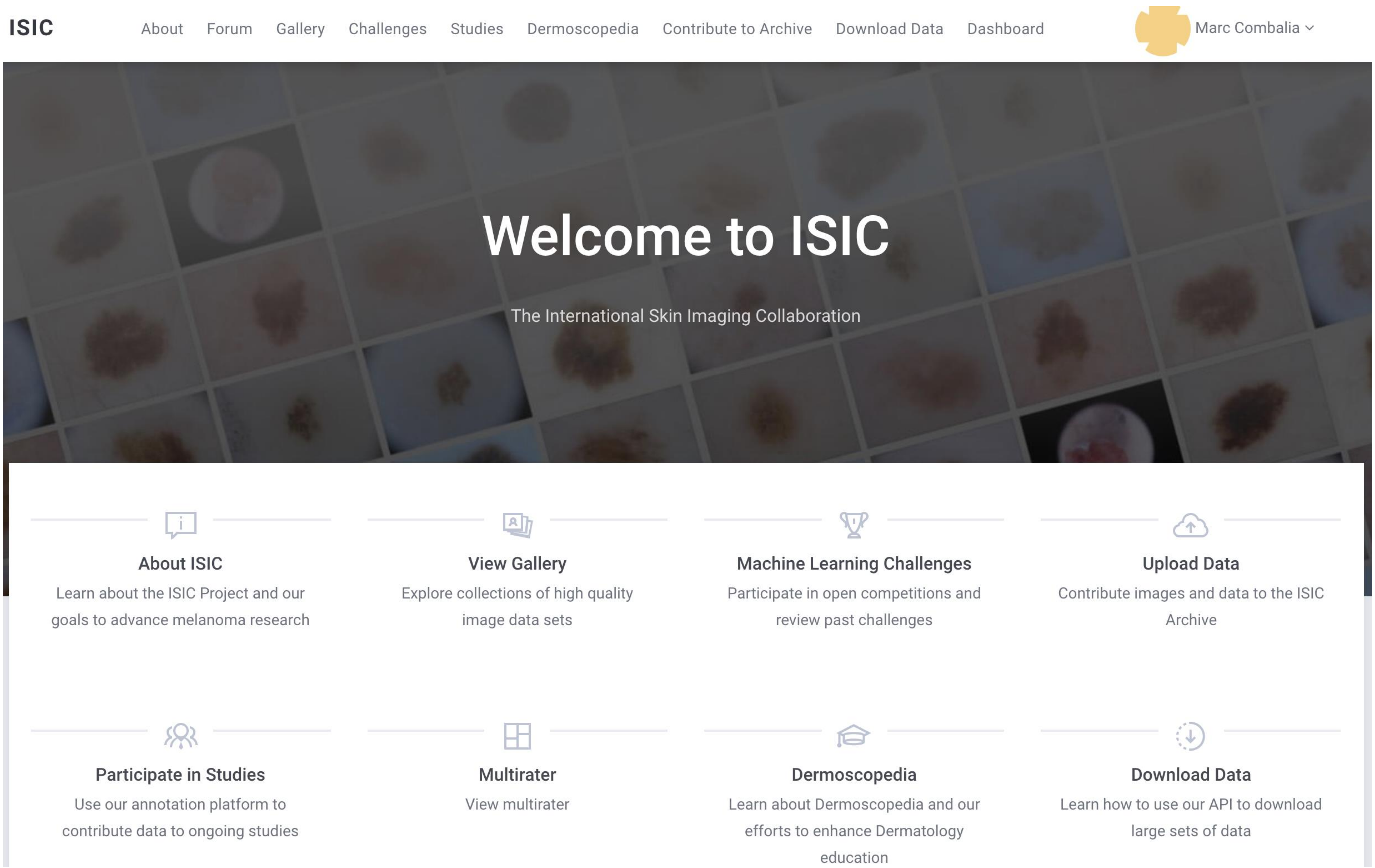
1.3. Why skin cancer?

- Skin cancer can be diagnosed via visual inspection
- Skin cancer is easy to treat (most times excision of the lesion suffices) if detected early
- Great opportunity for artificial intelligence



2. Artificial Intelligence for Skin Cancer Diagnosis

2.1. Our collaboration with ISIC (International Skin Imaging Collaboration)



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2.2. ISIC 2019 Challenge

Is artificial intelligence prepared for the clinical reality?

ISIC 2019

Skin Lesion Analysis Towards Melanoma Detection

Notify me about updates to the challenge! Enter your email address **Submit**

Background

Skin cancer is the most common cancer globally, with melanoma being the most deadly form. Dermoscopy is a skin imaging modality that has demonstrated improvement for diagnosis of skin cancer compared to unaided visual inspection. However, clinicians should receive adequate training for those improvements to be realized. In order to make expertise more widely available, the International Skin Imaging Collaboration (ISIC) has developed the ISIC Archive, an international repository of dermoscopic images, for both the purposes of clinical training, and for supporting technical research toward automated algorithmic analysis by hosting the ISIC Challenges.

Task

The goal for ISIC 2019 is classify dermoscopic images among nine different diagnostic categories:

1. Melanoma
2. Melanocytic nevus
3. Basal cell carcinoma
4. Actinic keratosis
5. Benign keratosis (solar lentigo / seborrheic keratosis / lichen planus-like keratosis)
6. Dermatofibroma
7. Vascular lesion
8. Squamous cell carcinoma

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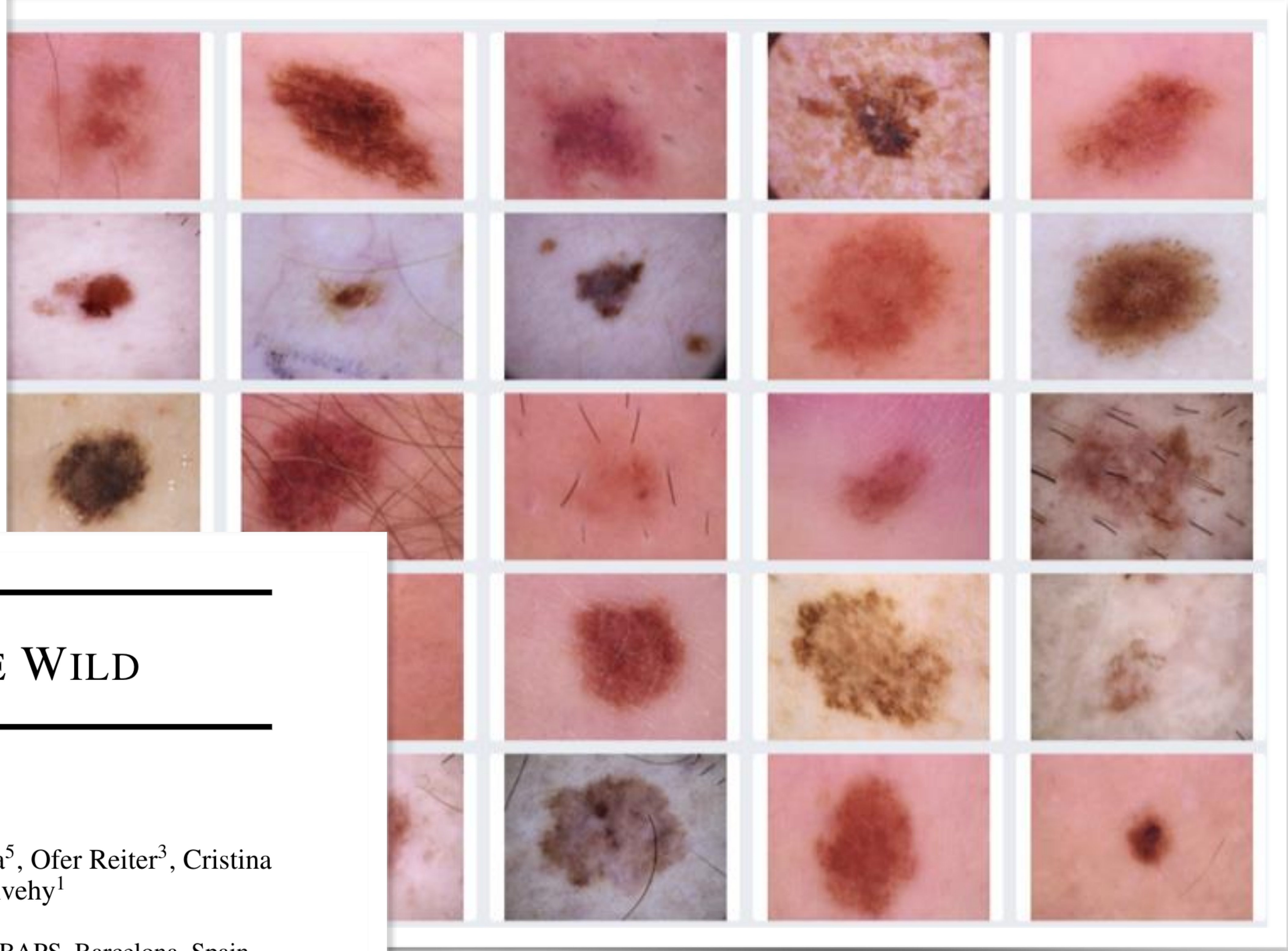
SCIENTIFIC DATA

OPEN

Data Descriptor: The HAM10000 dataset, a large collection of multi-source dermatoscopic images of

Received: 25 April 2018
Accepted: 26 June 2018

Philipp



BCN20000: Dermoscopic Lesions in the Wild

A Preprint

Marc Combalia[1], Noel C. F. Codella[2], Veronica Rotemberg[3], Brian Helba[4], Veronica Vilaplana[5], Ofer Reiter[3], Cristina Carrera[1], Alicia Barreiro[1], Allan C. Halpern[3], Susana Puig[1], and Josep Malvehy[1]

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[4]Kitware, Clifton Park, NY, USA
[5]Signal Theory and Communications, Universitat Politècnica de Catalunya, Barcelona, Spain

Abstract

This article summarizes the BCN20000 dataset, composed of 19424 dermoscopic images of skin lesions captured from 2010 to 2016 in the facilities of the Hospital Clínic in Barcelona. With this dataset, we aim to study the problem of unconstrained classification of dermoscopic images of skin cancer, including lesions found in hard-to-diagnose locations (nails and mucosa), large lesions which do not fit in the aperture of the dermoscopy device, and hypo-pigmented lesions. The BCN20000 will be provided to the participants of the ISIC Challenge 2019 [8], where they will be asked to train algorithms to classify dermoscopic images of skin cancer automatically.

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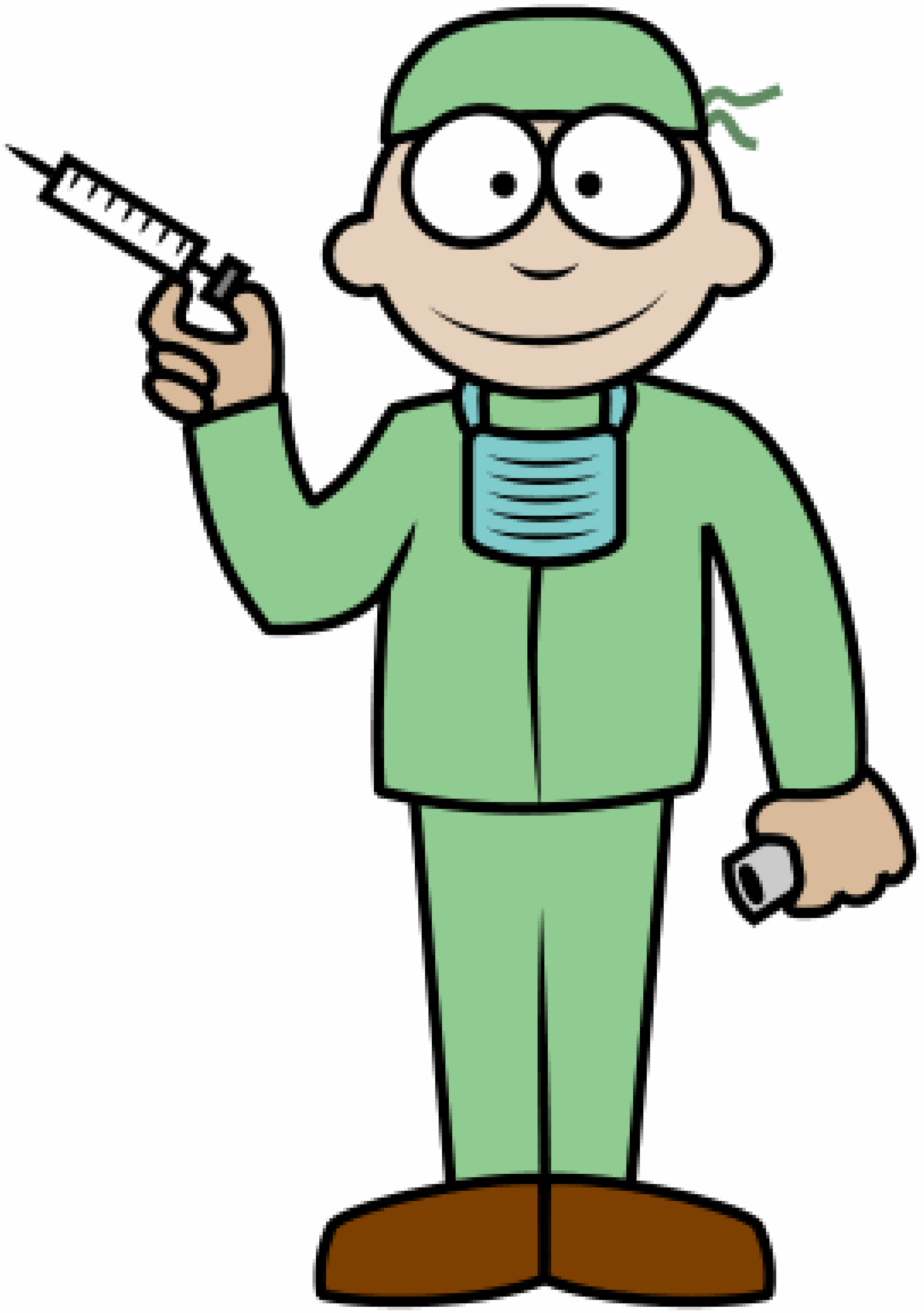
ISIC Challenge 2019
Task Overview

- **Skin lesion classification**
- **Unfiltered lesions**
  - Non-Pigmented lesions
  - Uncommon anatomic locations
  - Large lesions
  - Ulcerated lesions
  - Out of distribution lesions
- **Metadata around patients**



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2.3. ISIC Challenge 2019 Reader Study

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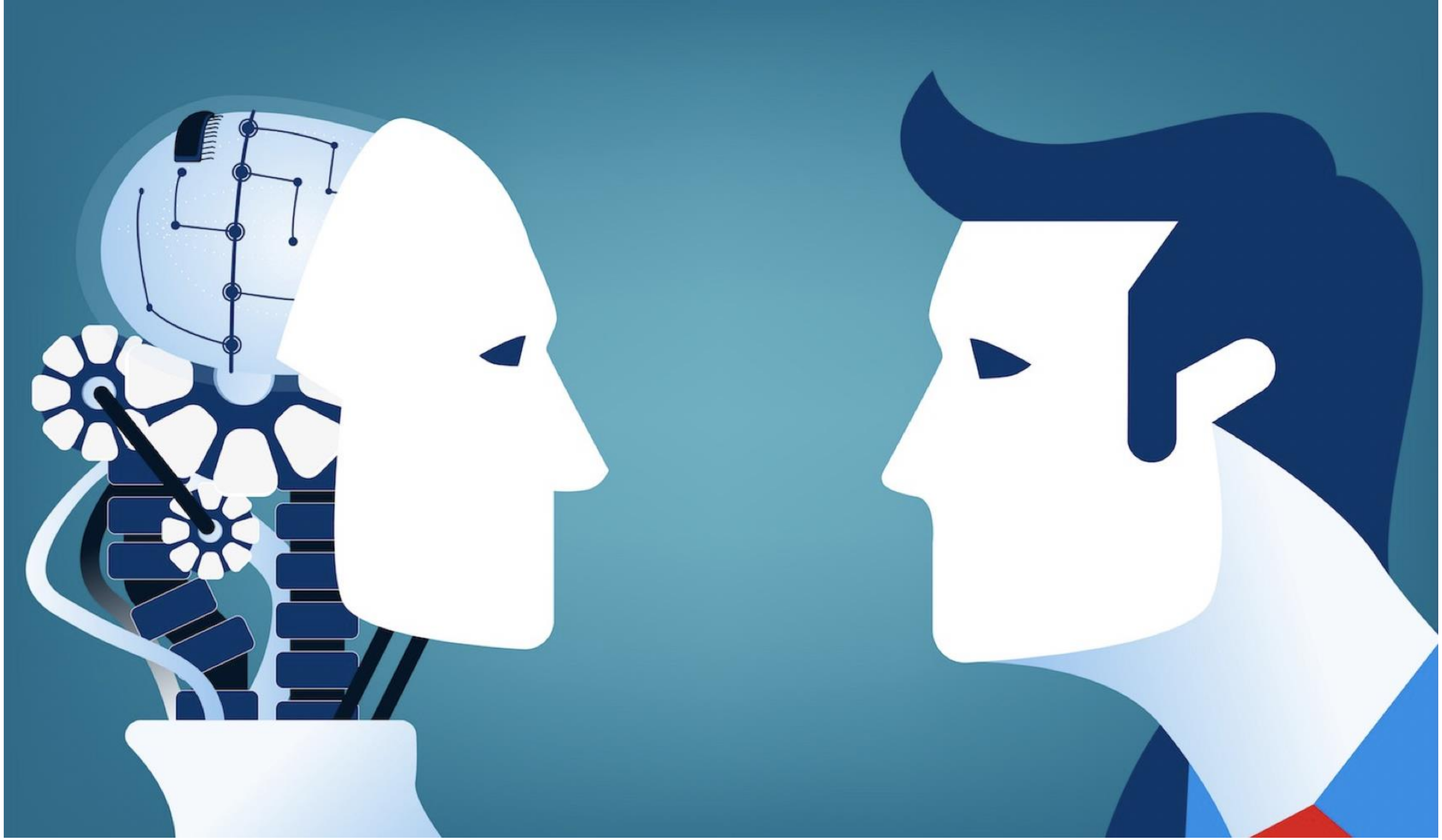

ISIC Reader Study 2019

ISIC Organizers

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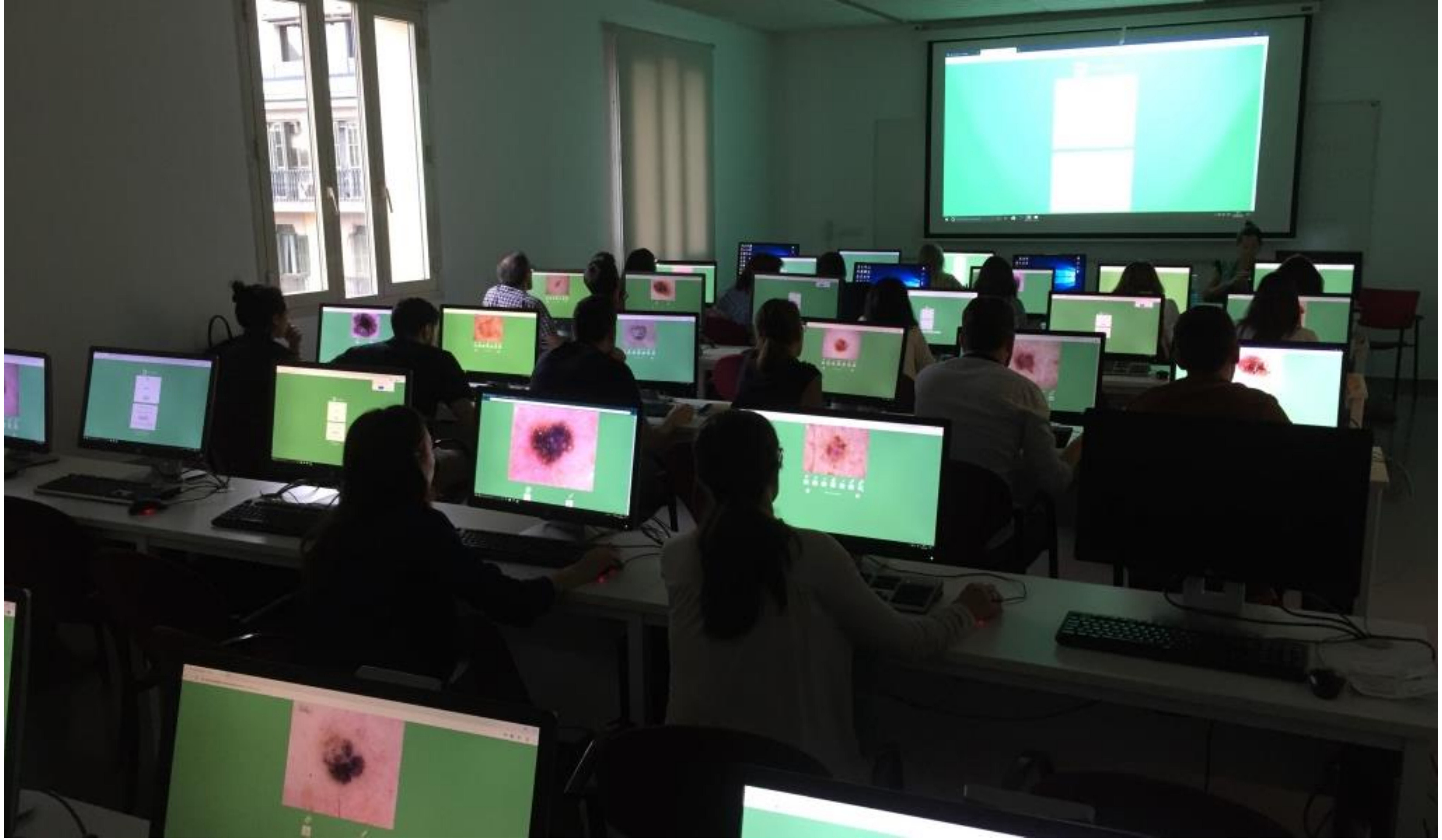

ISIC Reader Study 2019

ISIC Organizers

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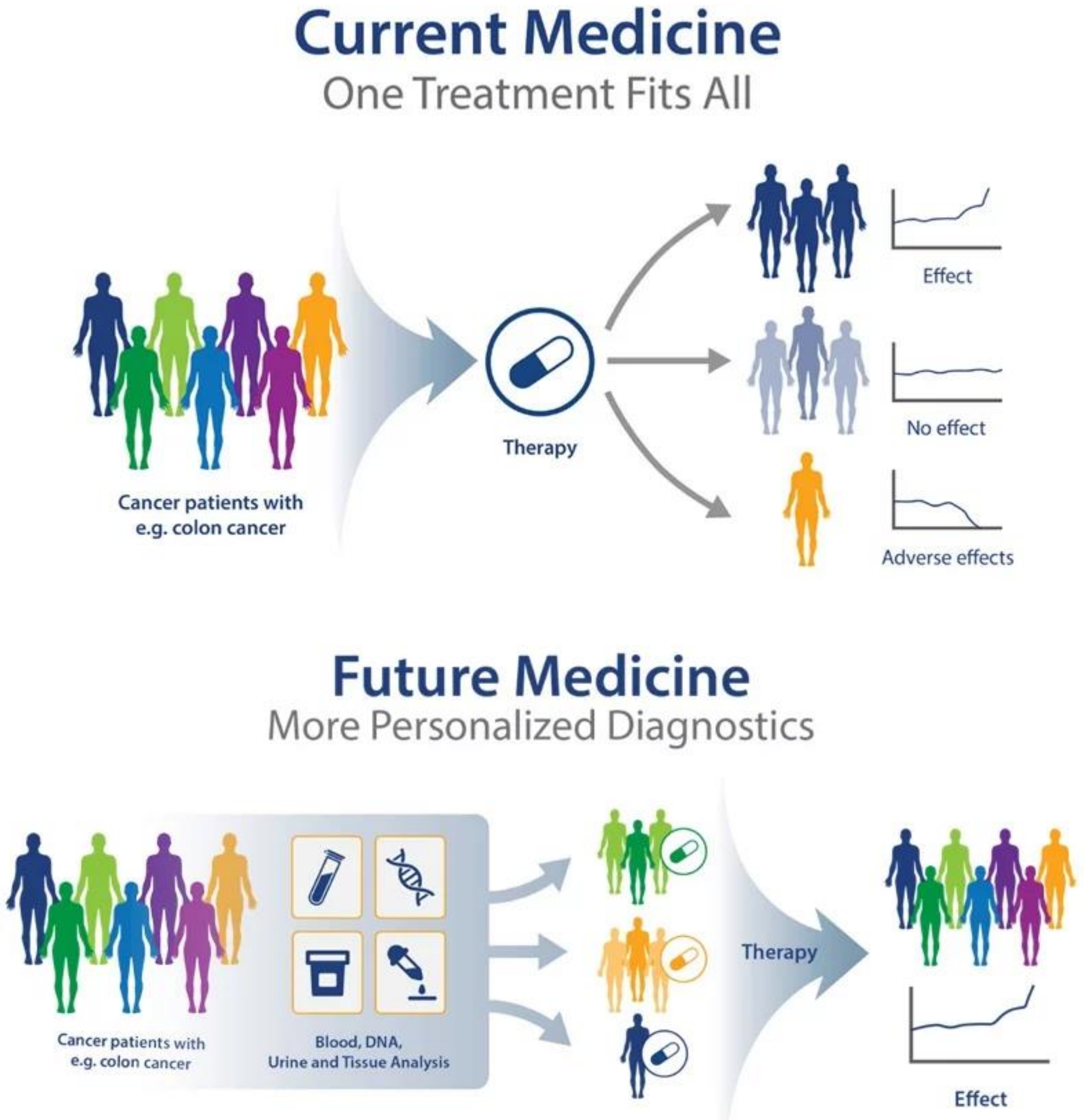
3. Artificial Intelligence for Skin Cancer Risk Assessment

Lifelines

- **Mortality and Relapse data**
  - Very hard to obtain
- **Patient features**
  - Genetic features
  - Tumor features
  - Imaging features
  - Blood analyses
- **Treatment features**
  - Treatment over time



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Artificial Intelligence is going to be a Key Player in the Medicine of the Near Future eurecat

Centre Tecnològic de Catalunya

Deep Lung – Lung Cancer Detection with Deep Learning
EHTEL Symposium 2019

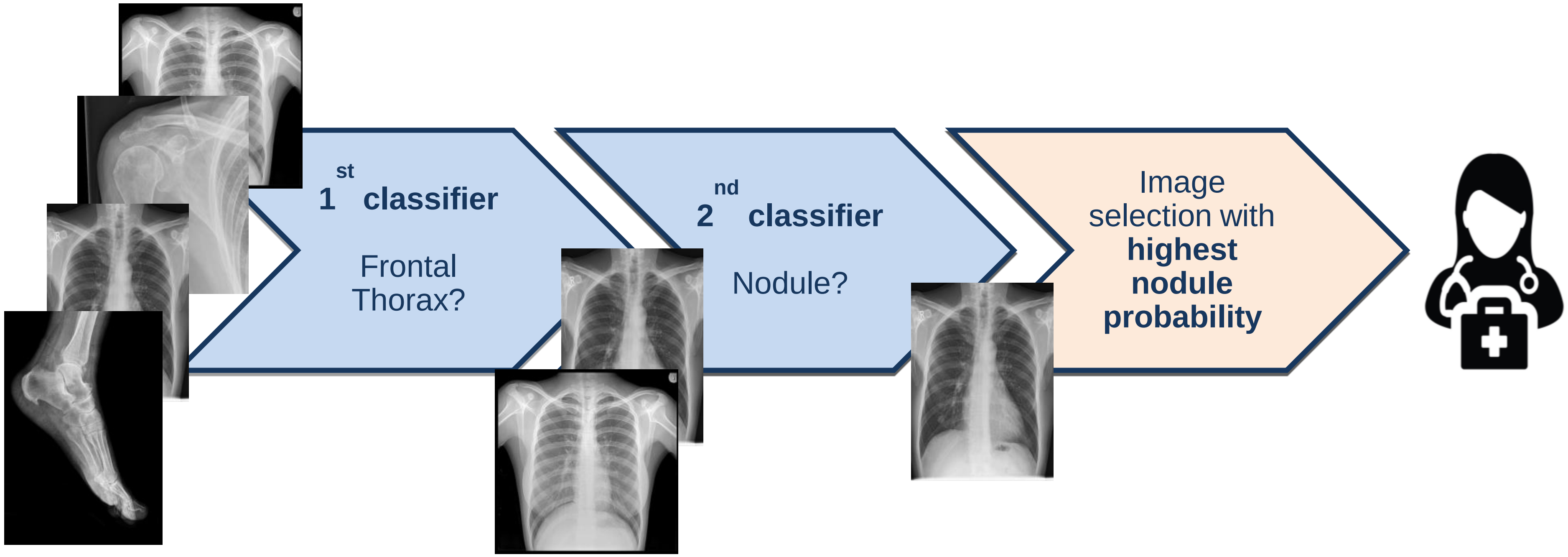
Xavier Rafael, Giuseppe Pezzano, Ilaria Bonavita, Paula Subías, Anton Aubanell MD, Esther Pallissa MD, Oscar Persiva MD, Miguel Ángel González PhD, Laura Ruiz PhD, Carles Rubies, Eduard Monsó MD PhD, Xavier Gallardo MD PhD, Vicent Ribas PhD.

Objectives

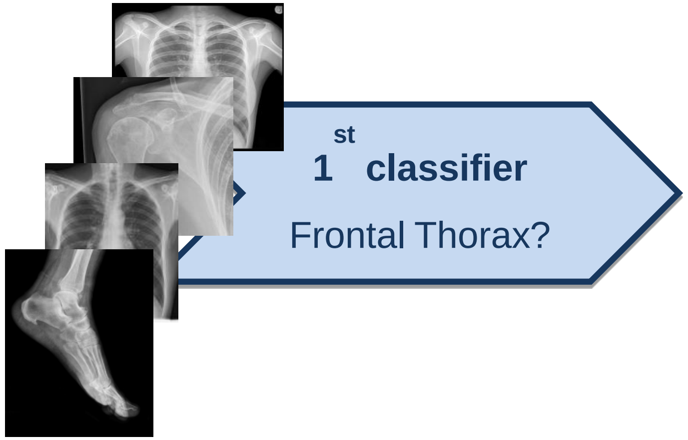
- According to the American Cancer Society, Lung Cancer (LC) is the second most common cancer and the most lethal. LC kills more people than colon, prostate and breast cancers all together.
- **Deep Lung** aims at providing automatic analyses of medical images through Deep Learning techniques to improve the detection of LC.
- The project develops three tools:
  - Study of thorax RX for the incidental detection of lung masses.
  - Study of CT scans for nodule detection
  - Segmentation of lung nodules and study their malignancy.
- The project is validated through two clinical studies at Hospital Vall d'Hebron (CT) and Hospital Parc Taulí (RX).

Mass detection from RX

GOAL: improve nodule detection on X-ray thorax images, in order to reduce radiologists amount of work and helping to an early treatment of the disease



Mass detection from RX



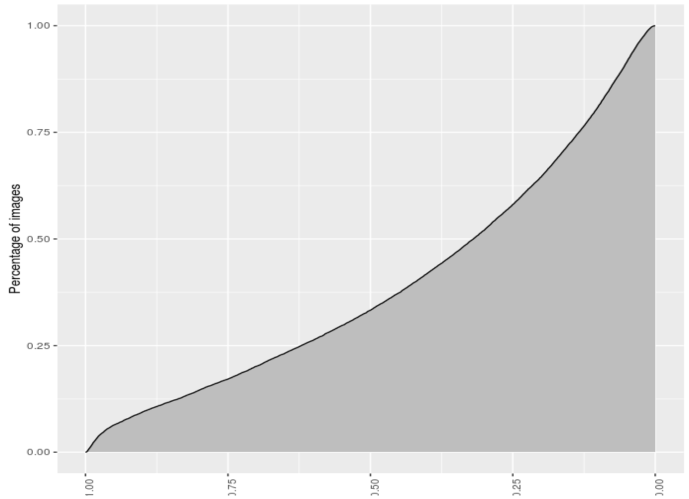
- Classifier using convolutional networks (ResNet-50)
- Results:
  - Accuracy: **99%**

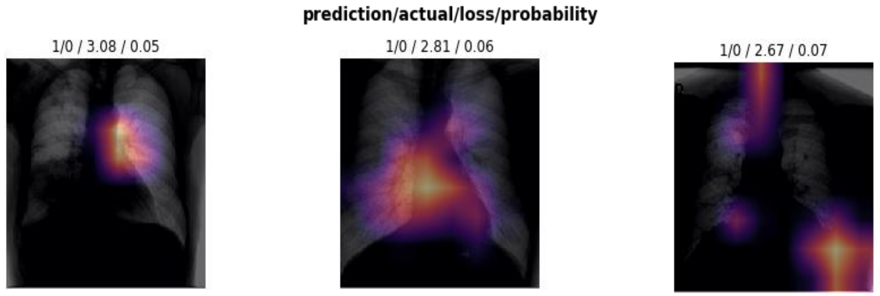
- Data: 2200 images
- (600 positive + 1600 controls)
- Classifier with convolutional networks 2D (ResNet-34*)
- Results:
  - Accuracy: **78%**
  - Sensitivity: **76%**
  - Specificity: **79%**

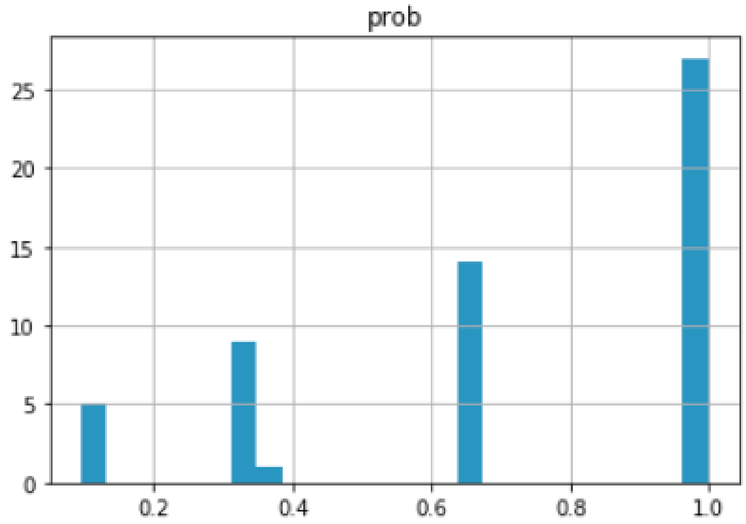
Mass detection from RX

Test on 24685 unlabeled images

- Mean time per image:
  - Classifier I: **0.63 s**
  - Classifier II: **0.45 s**

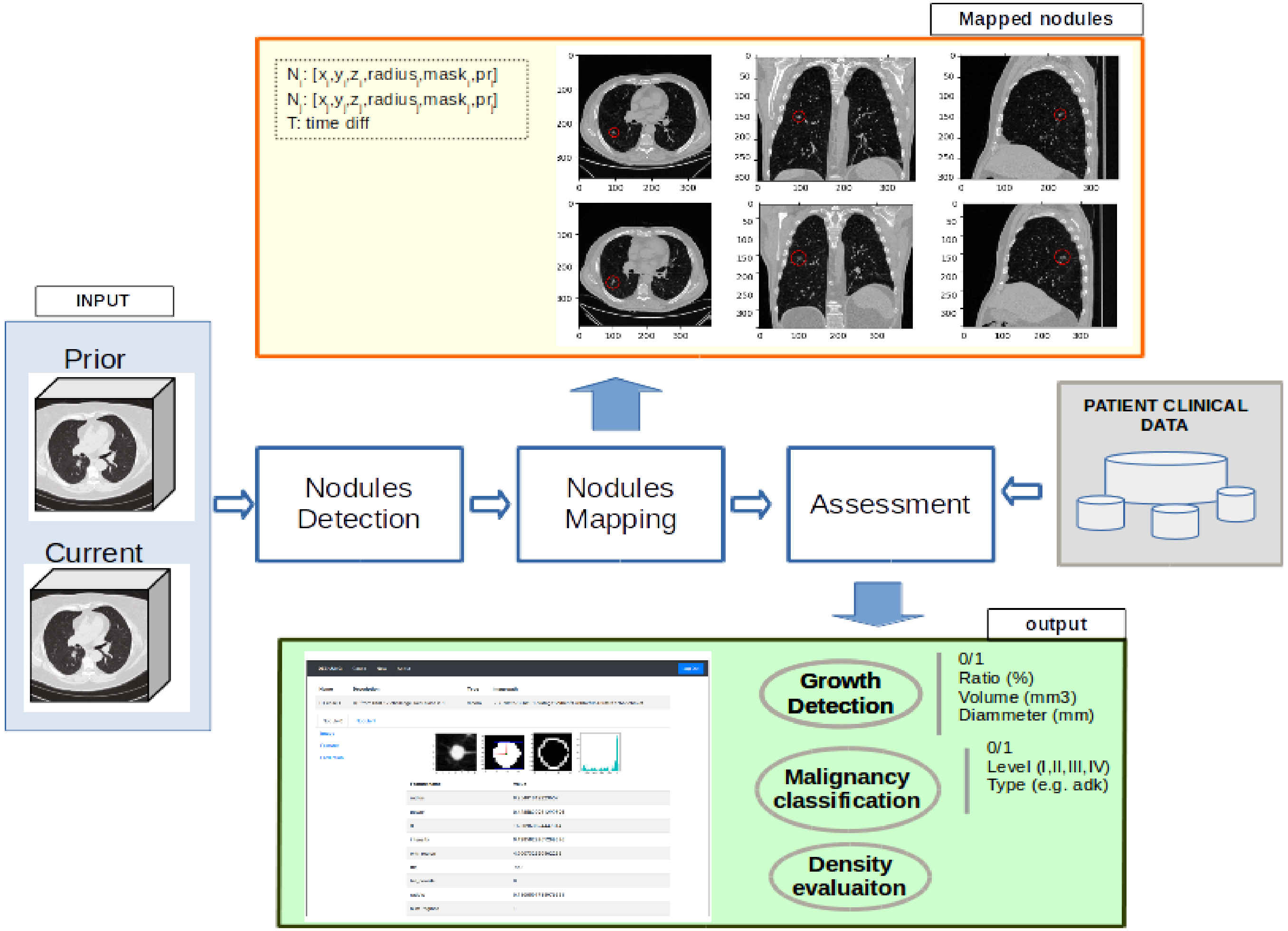






Nodule detection from CT Scans

Need: Improve the predictive capability and reduce the radiologist's workload in the detection of lung nodules (>=6 mm, <3 cm) and assess their growth over time

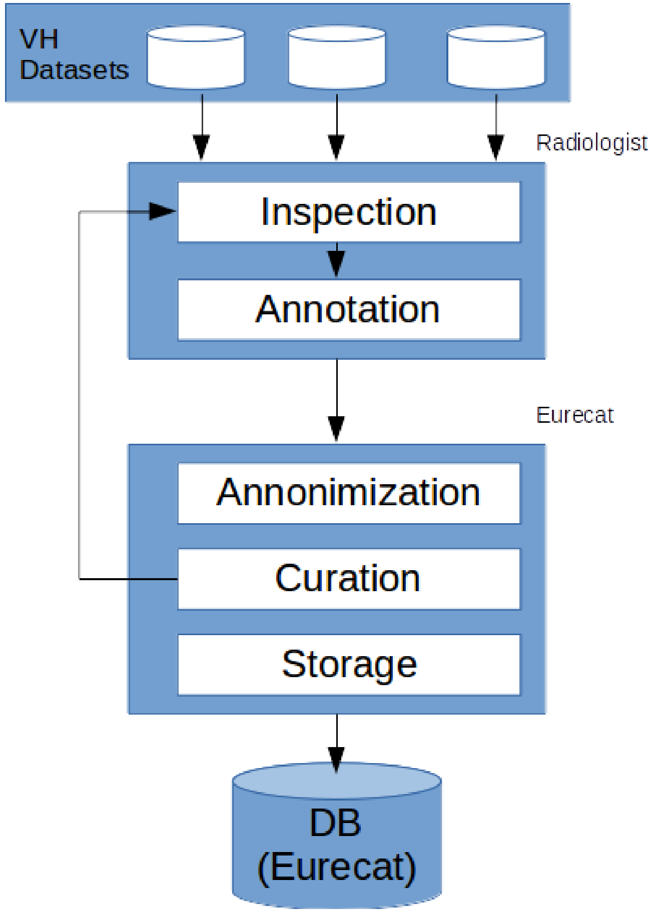


Nodule detection from CT Scans

Total annonimized cases:
- 170 CT-pairs (>500K slices)
- 113 Cancer/57 Bening

Clinical data:
- Age
- Gender
- Smoker or former smoker
- Drinker or former drinker
- Previous Neoplasms
- Exitus

Annotations:
- Diameter
- Type cancer
- Type nodule
- Malignancy (0/1 cancer)

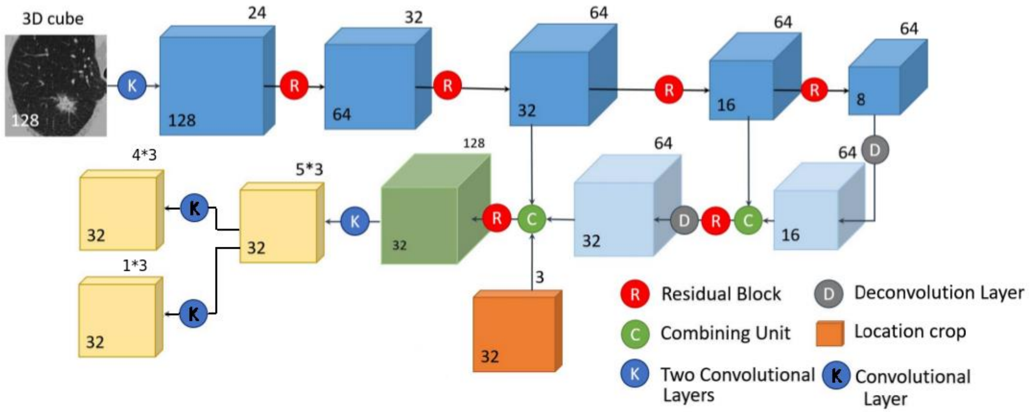


VH & Eurecat workflow for dataset collection

Nodule detection from CT Scans

Experiment

- 3D Faster-RCNN [2]
- ResNet-18 + U-net [4]
- Does not require segmentation of lung tissue
- Input 128 | Output 32 ,3,5
- 3 anchor sizes (5,10,20)



Data:

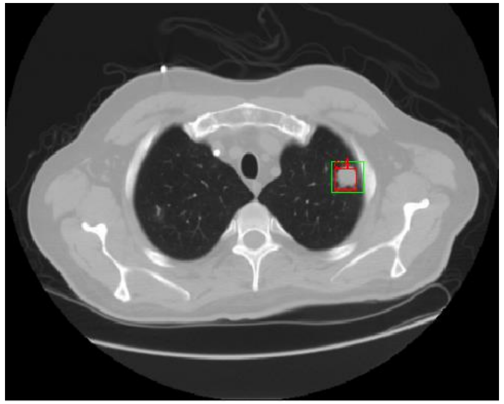
LIDC/IDRI dataset

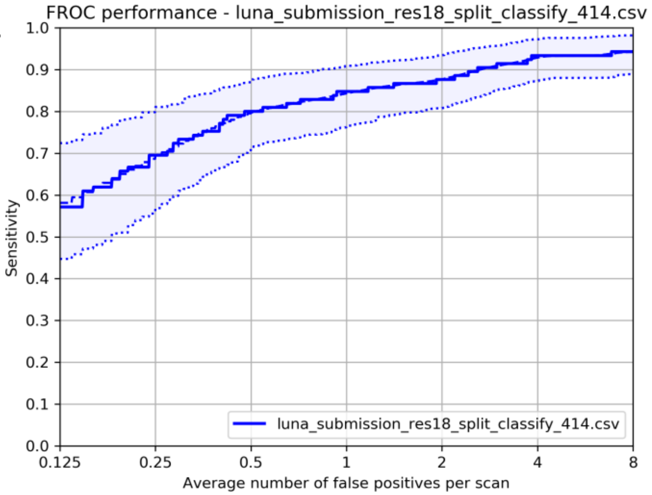
~ 900 CTs
~ 1200 labelled nodules
Annotation (4 radiologists)
Nodules >=3 mm
N providers (e.g. Siemens)
M resolutions (<5mm)

Resultats

Avg FROC: 0.8084

:



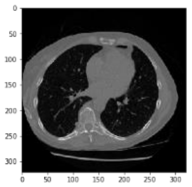


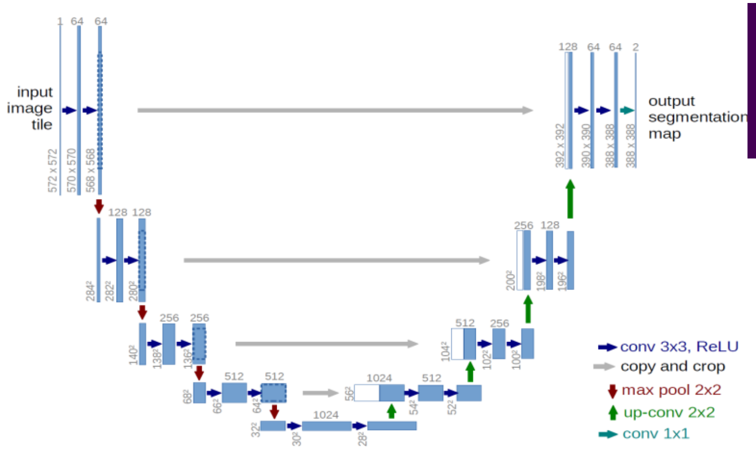
[2] Ren, Shaoqing, et al. "Faster r-cnn: Towards real-time object detection with region proposal networks." Advances in neural information processing systems. 2015.
[3] Ronneberger, Olaf, et al. "U-net: Convolutional networks for biomedical image segmentation." International Conference on Medical image computing and computer-assisted intervention. Springer, Cham, 2015.

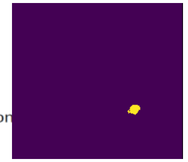
Nodule segmentation

Experiment

- **Axial segmentation of nodules (2D)**
- Methods:
  - U-net adapted
  - Data augmentation
  - Transfer learning,…
- Input: 512x512x 3
  - 3 consecutive axial cuts + mask
- Output: Mask (nodule/no nodule)







Data:

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Nodules>=3 mm
N providers (e.g. Siemens)
M resolutions (<5mm)

Results

- Test on **104** cases

Precision	0.9892
Recall	0.9019
Accuracy	0.8932
Avg Dice	0.6548

Nodule segmentation

Experiment

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- Methods:
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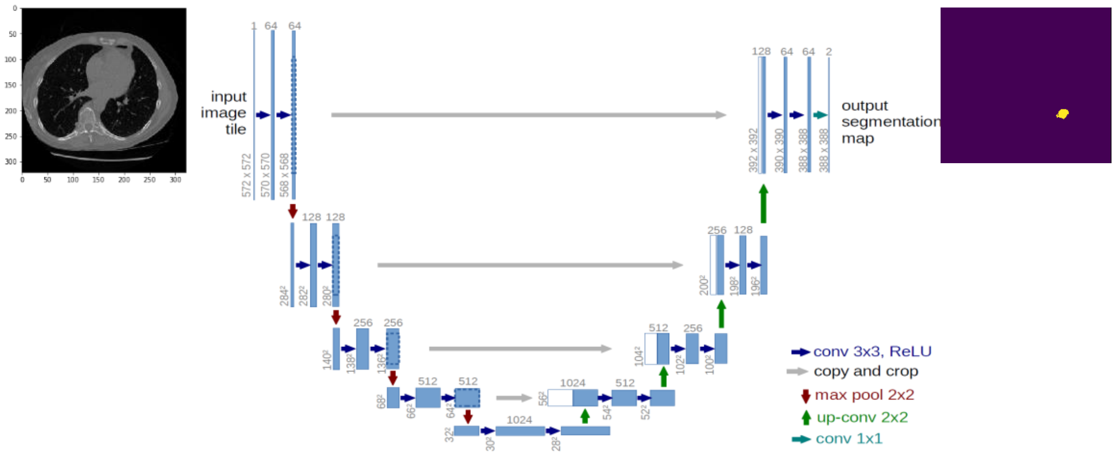

Data:

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- Test on **104** cases

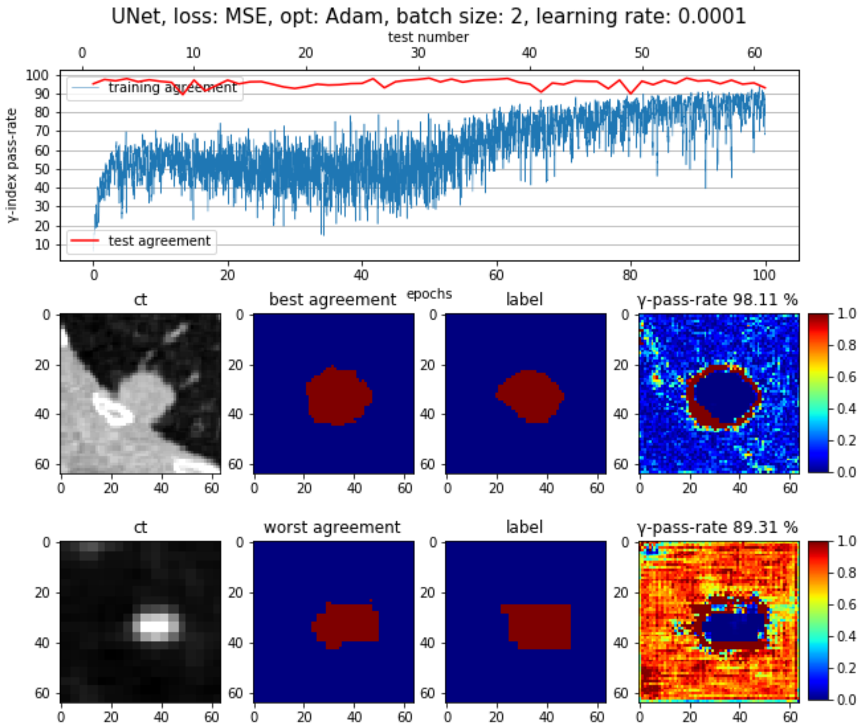
Precision	0.9892
Recall	0.9019
Accuracy	0.8932
Avg Dice	0.6548

Nodule segmentation

Experiment

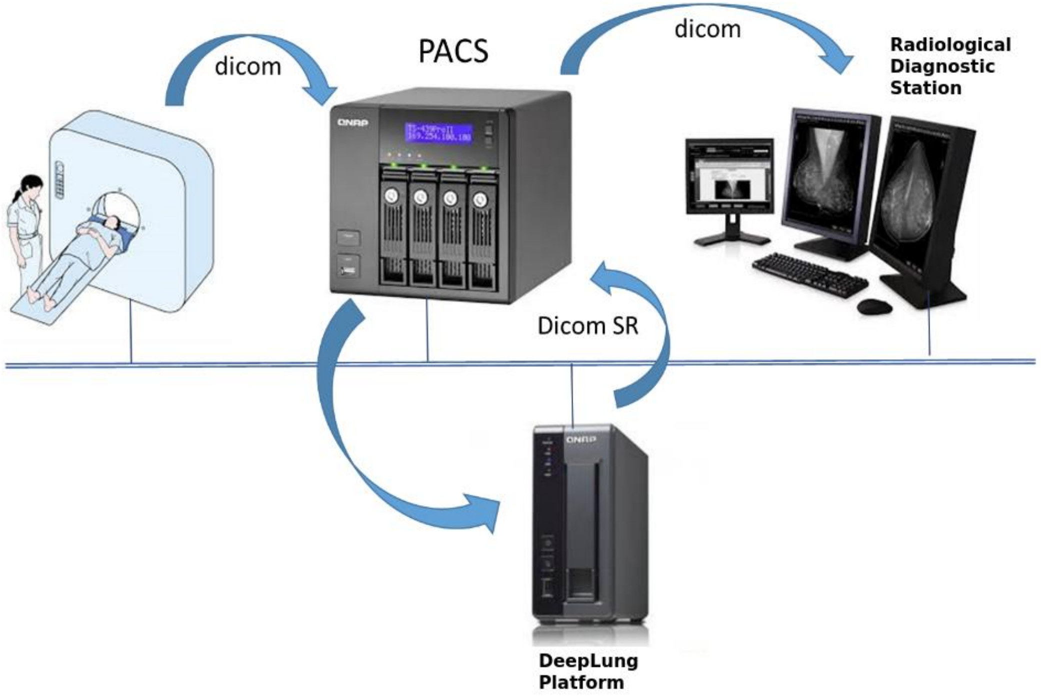
- **3D segmentation in cubes**
- Methods:
  - 3D U-net
  - Data Augmentation
- Input: 64x64x64 + 3D nodule masks
- Output: 3D Pixel-wise mask predictions

Results



Conclusions

- The project is being validated in **two clinical studies** and a pilot (Hospital Vall d’Hebron and Parc Taulí).
- The potential of the project lies in the fact that it takes into consideration the **temporal evolution of nodules**.
- The project is aligned with the **radiology workflow** and, therefore, may represent an **improvement on the efficiency** of this process and **productivity.**



eurecat
Centre Tecnològic de Catalunya

Deep Lung

Moltes gràcies!
¡Muchas gracias!
Thank you!
Grazie!
Merci!
Tack!

vicent.ribas@eurecat.org