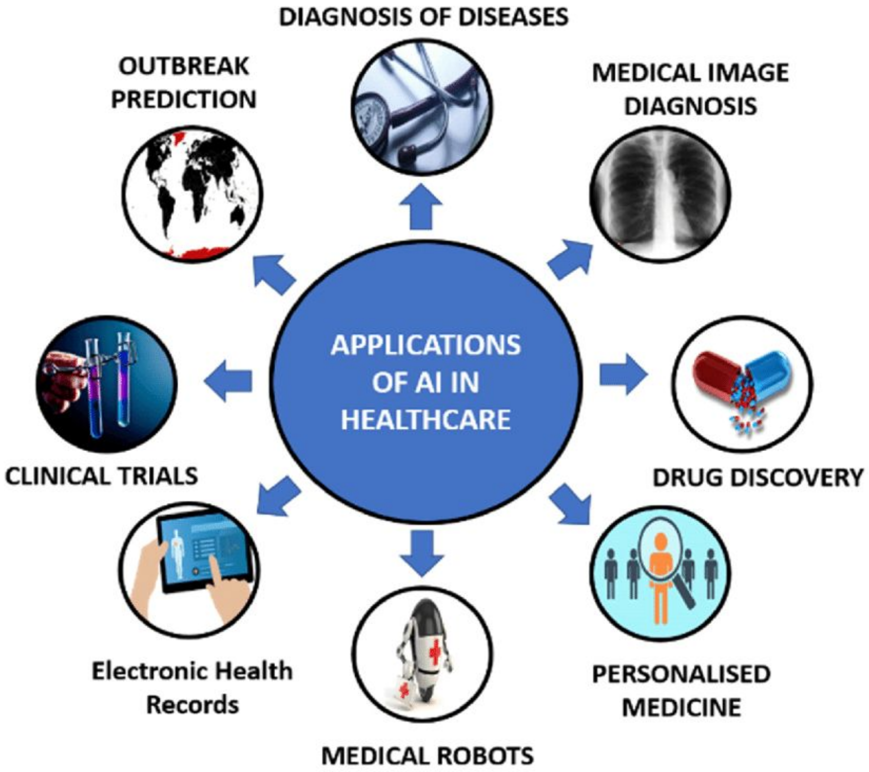
Google Explore CSR

LATAM UNDERGRADUATE
RESEARCH PROGRAM

AI in healthcare: Closing gaps in LATAM

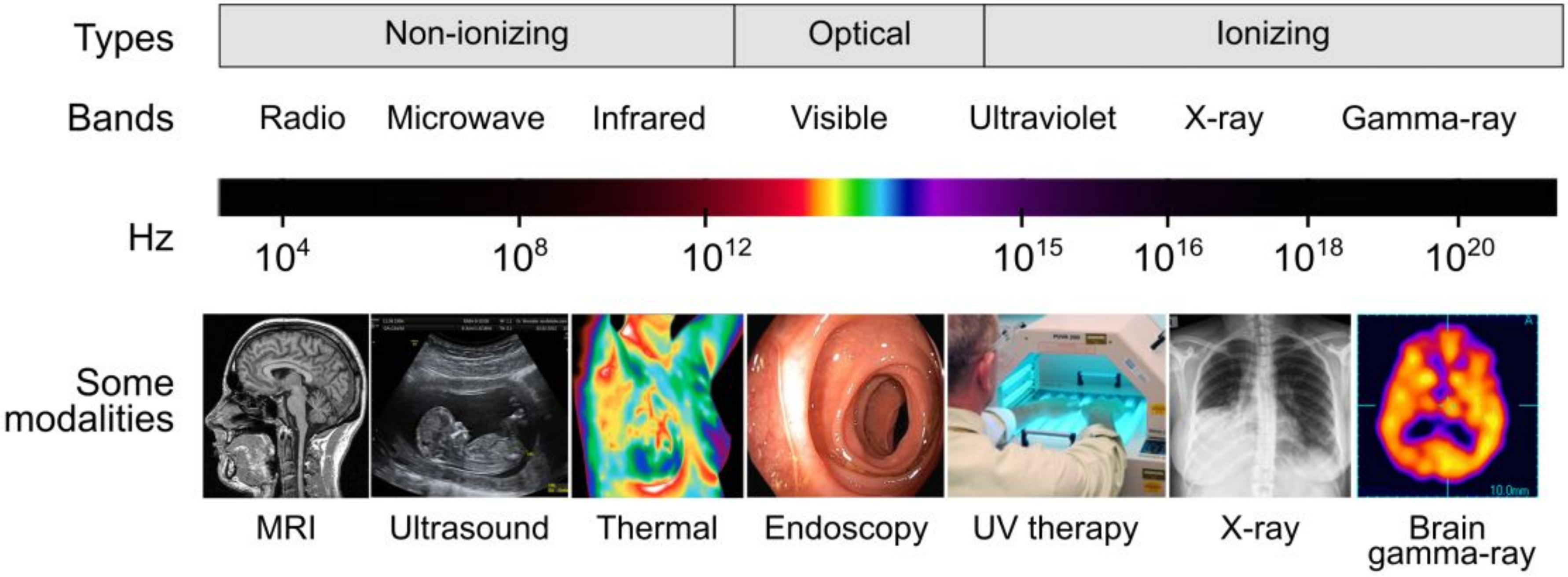
Ph.D. Karen Y. Sánchez Q.

AI in Healthcare



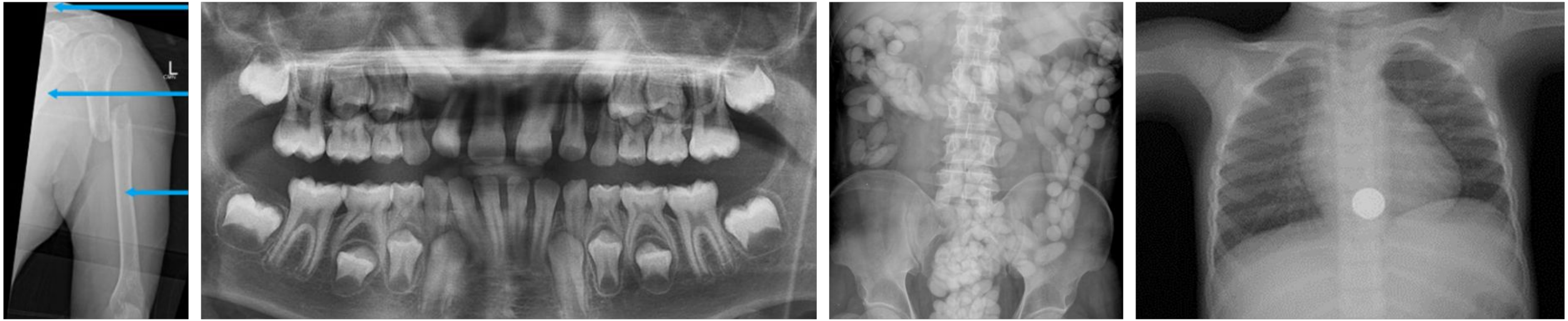
Medical Imaging Modalities

Medical imaging is the set of techniques to visualize the human body, or parts of it, for clinical purposes.



Artificial intelligence in medical imaging

- While some medical images could be easy for expert physicians to analyze, several tasks significantly benefit from computer vision assistance.



Bone fracture | Pediatric dental X-ray | Drug capsules | Location of a coin in the trachea

Fig. 6: Traditional uses of X-ray images.

With AI: More analyzed images in less time; remote care; prediction, diagnosis and assistance in the treatment.

Deep learning (DL) applications in medical imaging

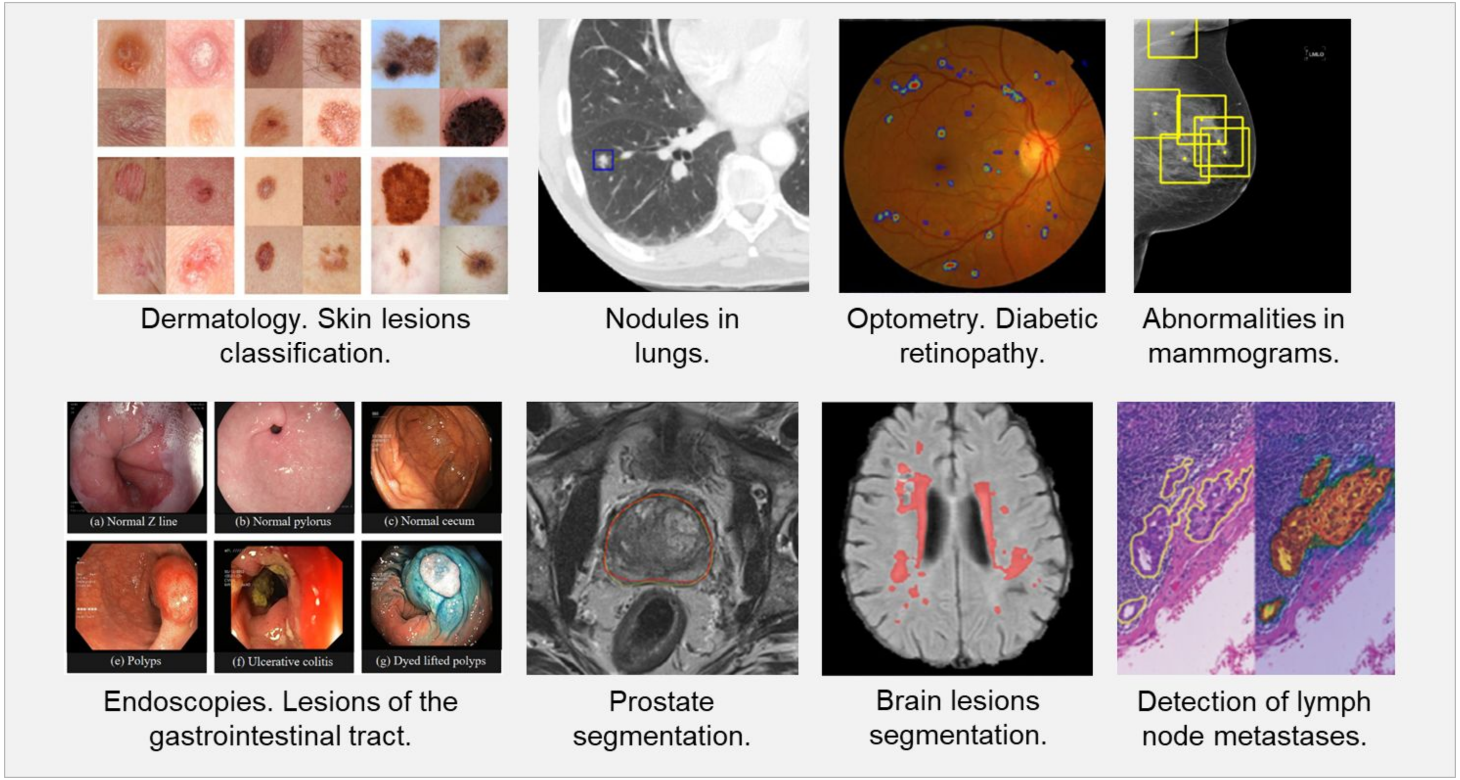
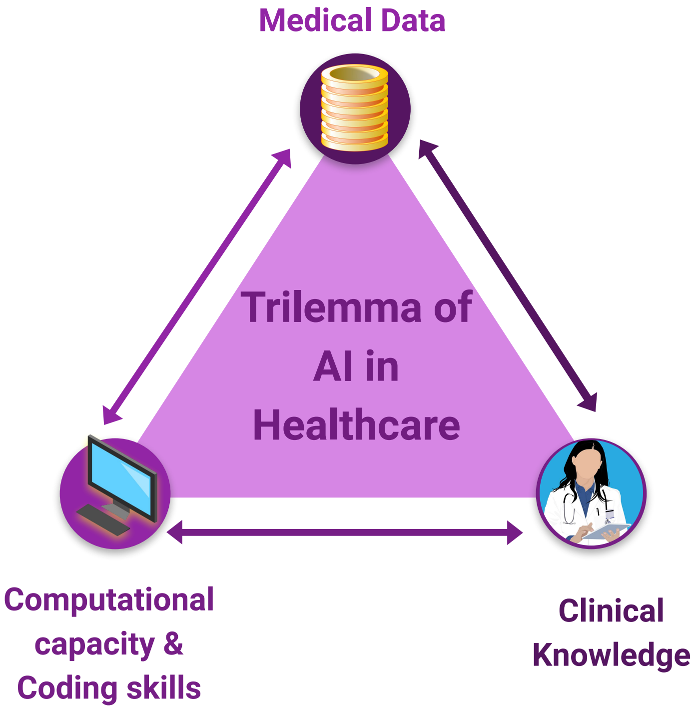
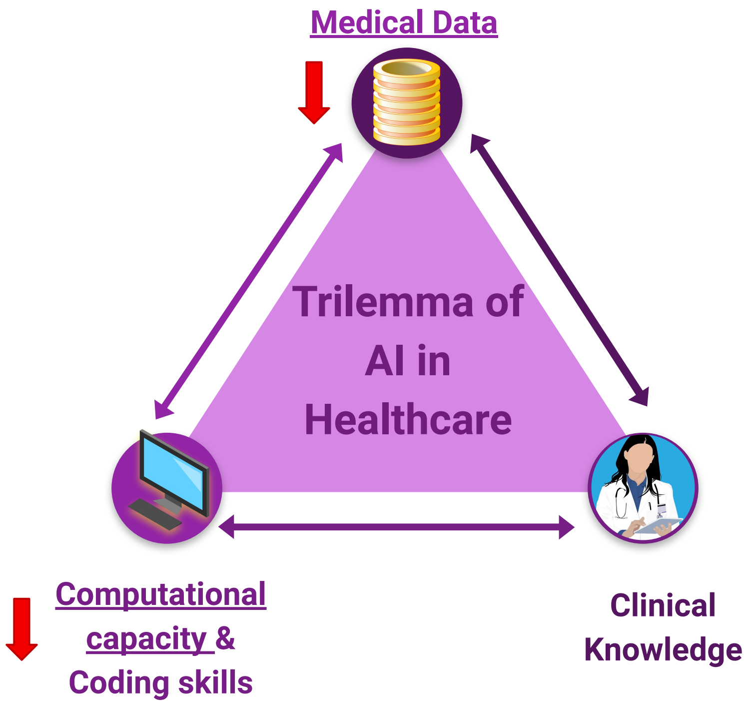


Fig. 7: Some relevant applications in the health area based on deep learning methods.


Medical Data
Trilemma of
AI in
Healthcare
Computational
capacity &
Coding skills
Clinical
Knowledge

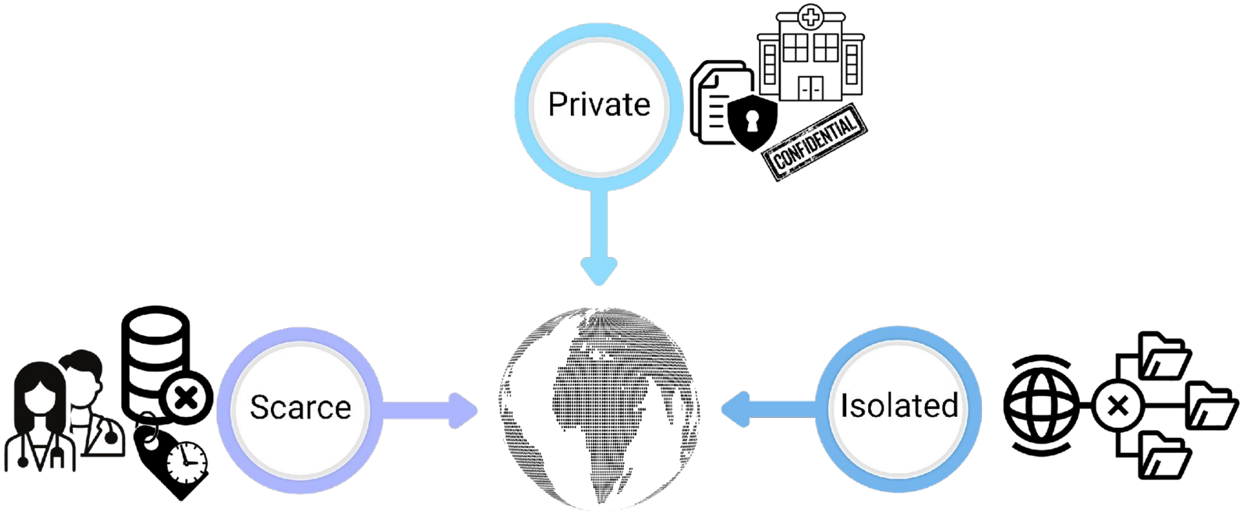
Challenges in Latin America



Challenges of AI in Healthcare

Challenge 1

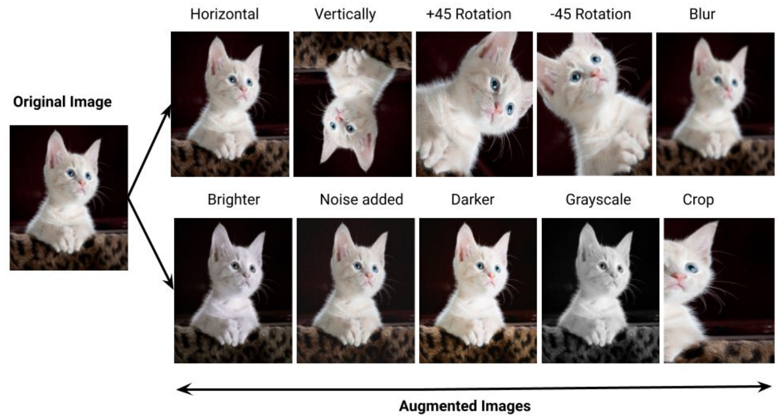
Labeled medical data is limited. *"Accuracy of deep learning models depends heavily on large amounts of labeled data."* Medical data is often scarce, isolated, and private. Labeling data is expensive, time-consuming by experienced clinicians.

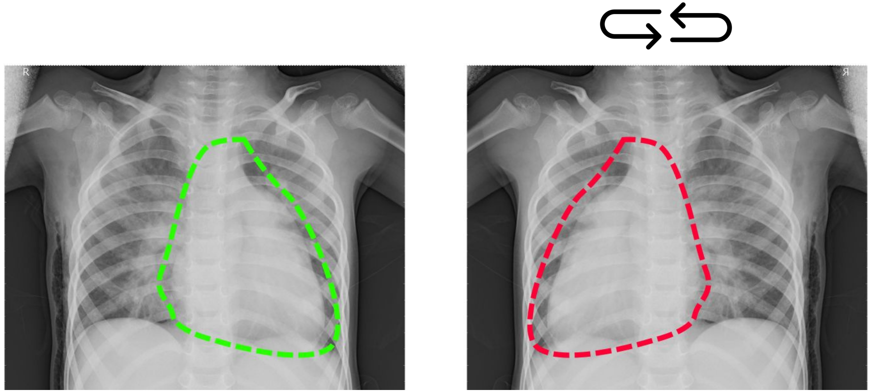


Medical data is often scarce, isolated, and private.

Alternative/Solutions

Traditional data augmentation used in natural images can lead to anatomical errors in medical applications.





Original image
Pneumonia

New image
Dextrocardia and pneumonia

Therefore, the state of the art encourages the creation of “**generative models**” with GANs, variational autoencoders and/or diffusion techniques capable of producing synthetic medical images with a correct and useful anatomical distribution.

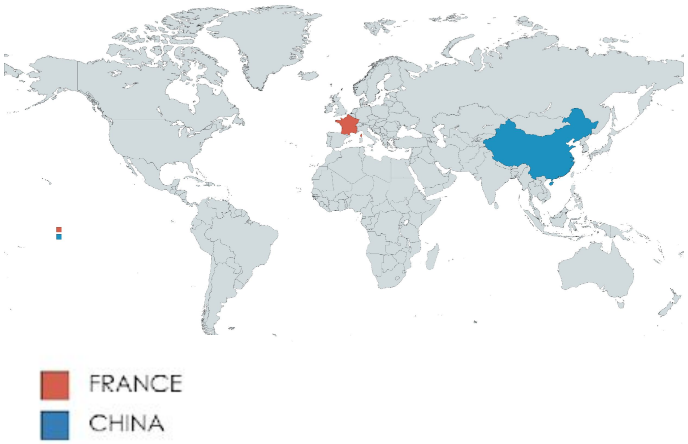
SANCHEZ, Karen, et al. **Mask-Guided Data Augmentation for Multiparametric MRI Generation with a Rare Hepatocellular Carcinoma**. En 2023 IEEE 20th International Symposium on Biomedical Imaging (ISBI). IEEE, 2023. p. 1-5.

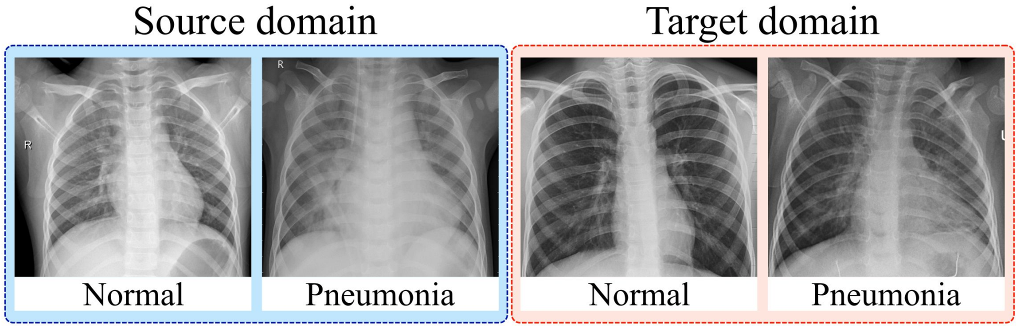
Challenges of AI in Healthcare

Challenge 2

Distribution discrepancies on medical data from different domain sources.

"Due to the scarcity of medical image data, deep learning classifiers often over-fit to a particular data domain." Medical images from different clinical centers often vary in appearance due to different technological, professional, and demographic conditions.





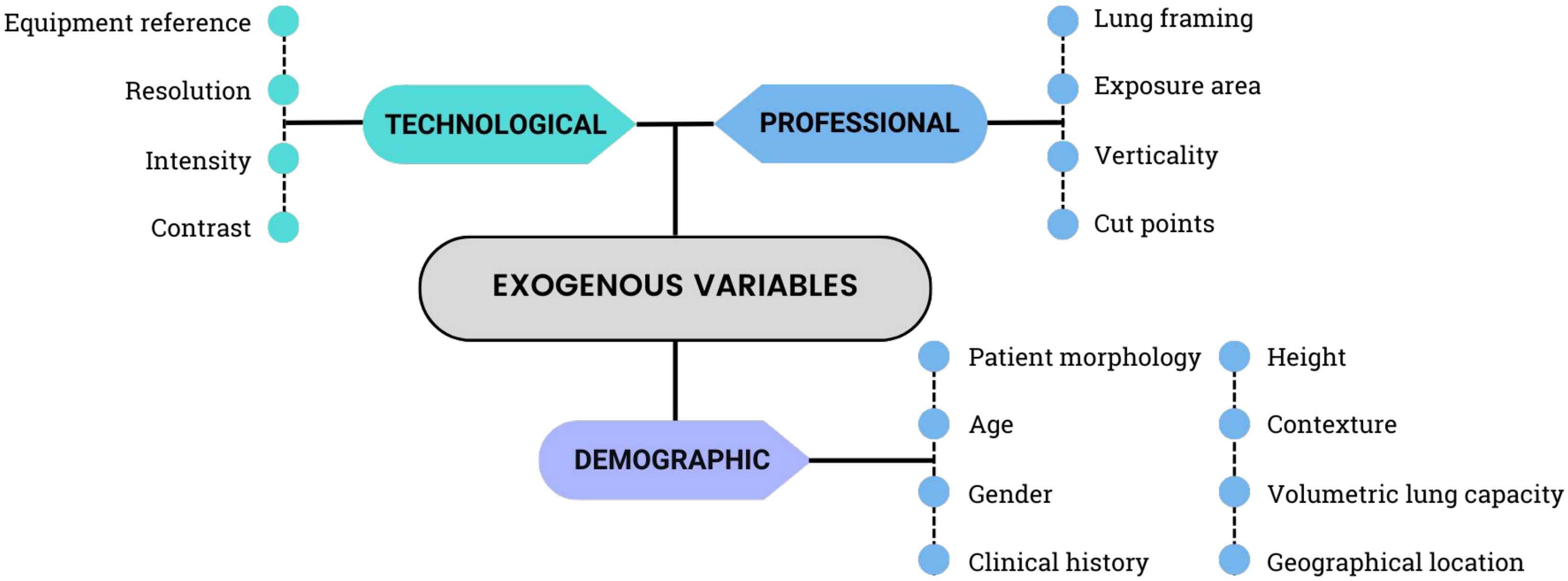
Guangzhou Women and Children's Medical Center, China [6]
Public domain

Hôpitaux de Toulouse, France.
Private domain

Challenges of AI in Healthcare

Challenge 2

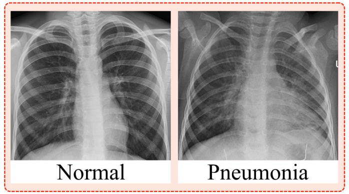
"Medical data varies in appearance across different medical centers."

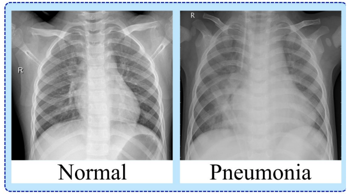


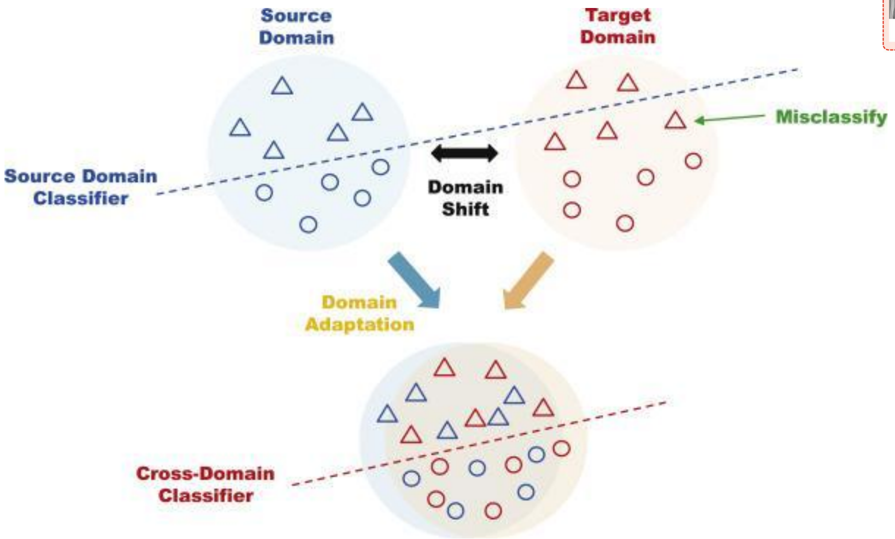
Example of some exogenous variables that can intervene in the distribution discrepancies on chest X-rays acquired in different clinical center worldwide.

Alternative/Solution

Domain Adaptation in machine learning.







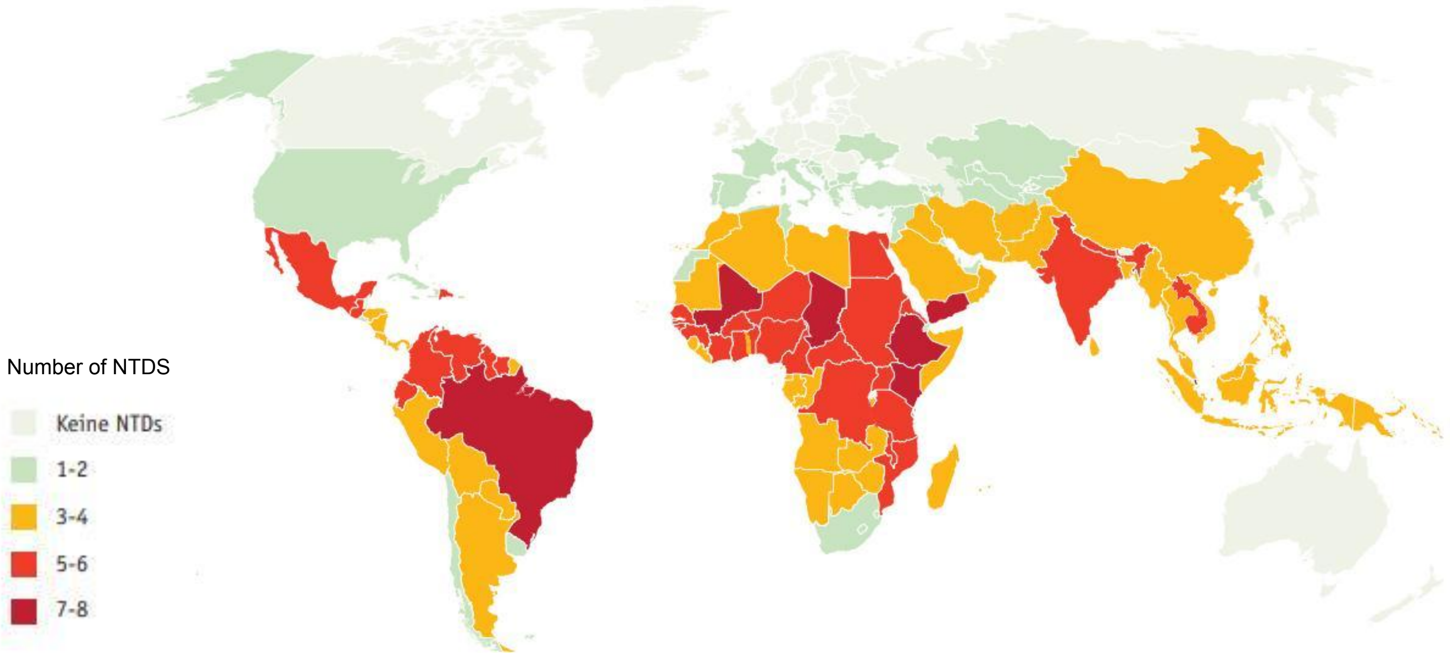
Take advantage of public data acquired in different centers worldwide to improve the performance of deep learning strategies on small data sets from Latin America through the development of **Domain Adaptation techniques**.

SANCHEZ, Karen, et al. **CX-DaGAN: Domain adaptation for pneumonia diagnosis on a small chest X-ray dataset**. *IEEE Transactions on Medical Imaging*, 2022, vol. 41, no 11, p. 3278-3288.

Challenges of AI in Healthcare

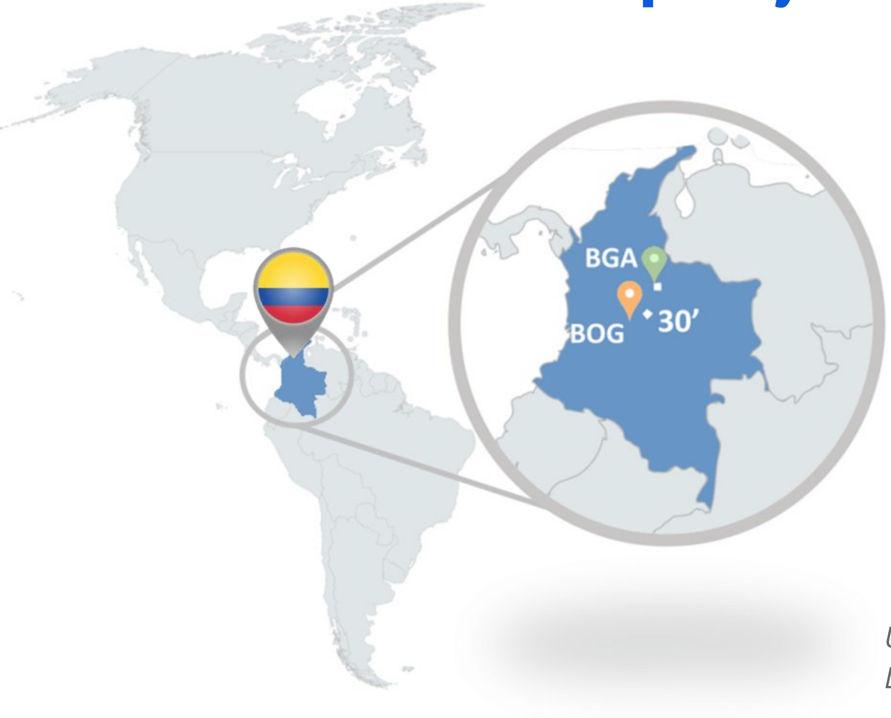
⚠️ Challenge 3

Neglected Tropical Diseases (NTDs) need our attention.



Distribution of NTDs in the world. 2024 Bernhard-Nocht-Institut für Tropenmedizin.

SIMATEC: Chronic Wounds Medical Assessment and Tracking Framework on Leprosy Patients Based on Deep Learning

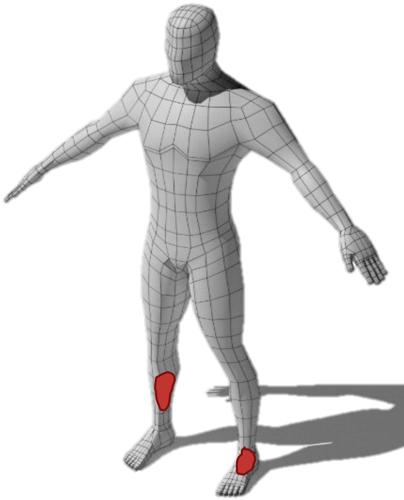


Universidad Industrial de Santander

High Dimensional Signal Processing Research Group

Sanatorio de Contratación E.S.E.

SIMATEC



Universidad Industrial de Santander, Bucaramanga, Colombia.
Leprosy Control Program, Sanatorio de Contratación E.S.E., Colombia.

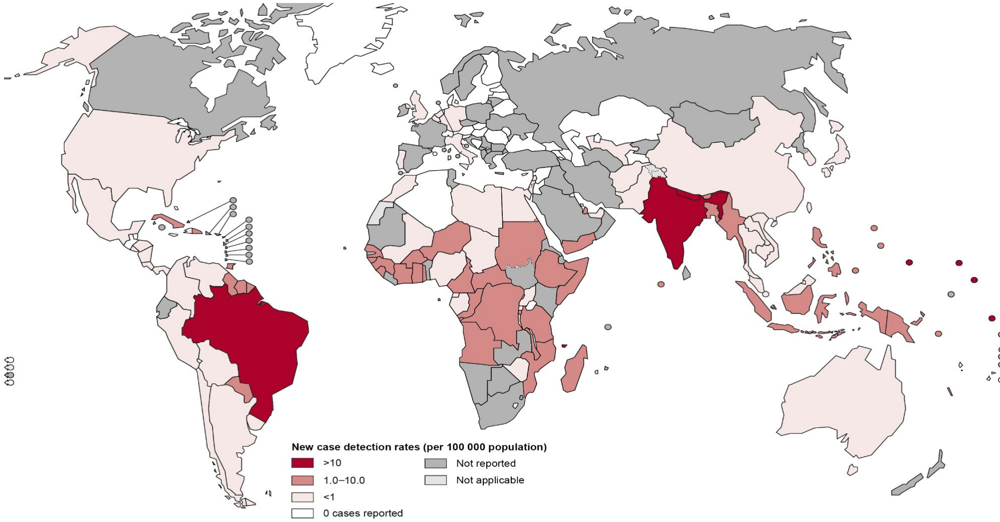
MONROY, Brayan, SANCHEZ, Karen, et al. **Automated chronic wounds medical assessment and tracking framework based on deep learning**. *Computers in Biology and Medicine*, 2023, vol. 165, p. 107335.

Context: Chronic Wounds

- **Chronic wounds** affect **40,000,000** people worldwide.

Chronic wounds are caused by different conditions:

- Type-2 diabetes.
- Cardiovascular affections.
- Neglected tropical diseases such as **leprosy.**



New cases of leprosy by country in 2021. Source: World Health Organization.

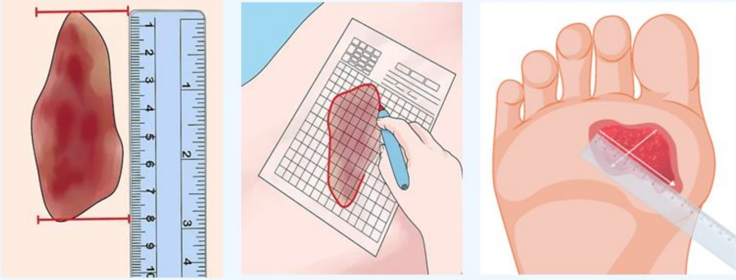
Motivation

2023

Residents in the town: **3,800**
Number of leprosy cases: **250**

In Santander, Colombia, there is a small town called **"Contratación"** created specially to **house leprosy patients from all over the country**.

The ***Contratación*** medical staff carries out periodic visual inspection of the chronic wounds to determine their **evolution** and appropriate treatment.



However, traditional methods for **measuring wounds** are challenging.

Sanatorio de Contratación E.S.E.

Motivation

2023

Residents in the town: **3,800**
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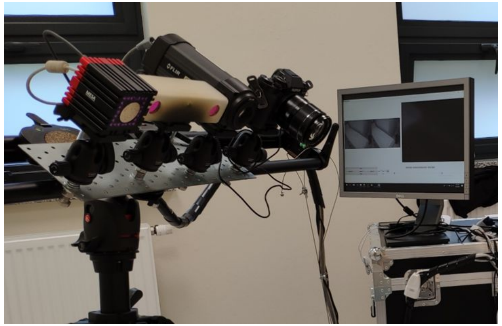
In Santander, Colombia, there is a small town called **"Contratación"** created specially to **house leprosy patients from all over the country**.

The ***Contratación*** medical staff carries out periodic visual inspection of the chronic wounds to determine their **evolution** and appropriate treatment.

Access to medical centres from **rural areas** in Colombia is troublesome which leads to **infrequent patient visits.**

Sanatorio de Contratación E.S.E.

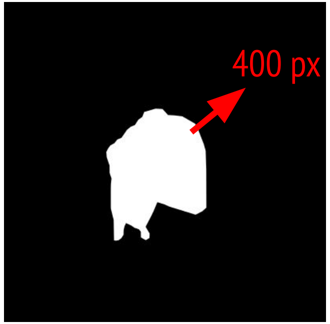
Current AI methods for wound analysis



Expensive equipments

Scarce chronic wound data available to train models

There are no datasets of chronic leprosy wounds



Not measurements in traditional metrics

However...

Public *CW-DB* dataset.
Images of patients with type 2 **diabetes** from **Poland**

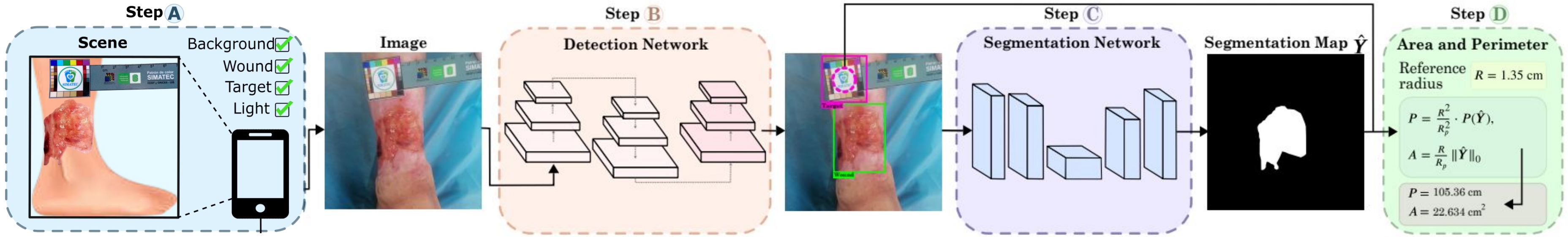
Dataset acquired during this project.
Images of patients with **leprosy** from **Contratación**

(a) (b)

Comparison of chronic wound images from (a) European diabetes patients (public dataset [14]), and (b) Colombian patients with wounds caused by leprosy.

Proposed Framework

SIMATEC
Teamwork of HDSP, GRISES,
and Sanatorio de Contratación.
Sponsored by the UIS. Code 2707.
My role: Leader of the project.

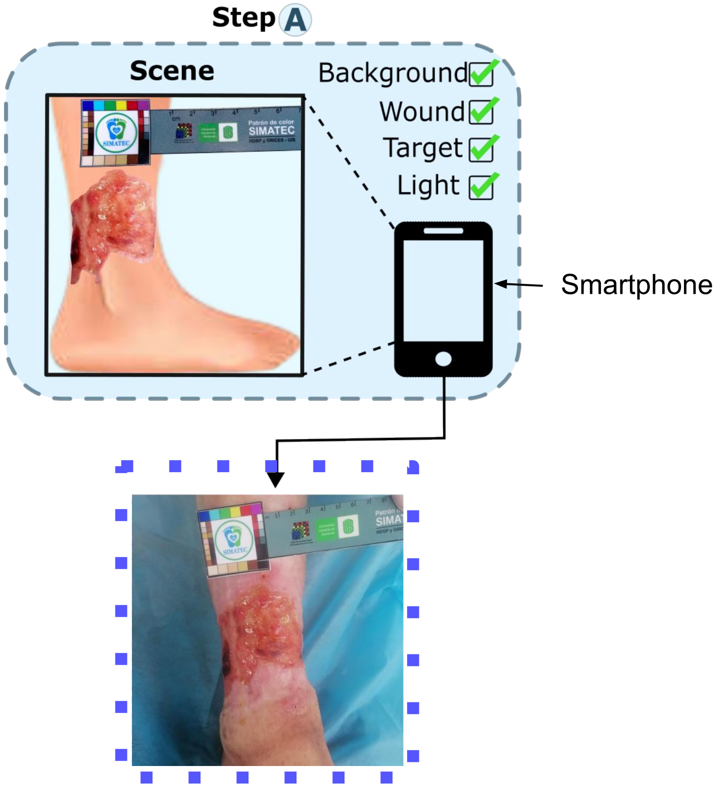


General scheme of the proposed CO2Dnet deep learning-based framework for automatic segmentation and measurement of chronic wounds in RGB images acquired with traditional smartphones.

The estimated metrics from multiple captures at different dates enable a **temporal analysis** of the evolution of the chronic wound and, allow the medical staff to monitor the patient's condition.

MONROY, Brayan, SANCHEZ, Karen, et al. **Automated chronic wounds medical assessment and tracking framework based on deep learning**. *Computers in Biology and Medicine*, 2023, vol. 165, p. 107335.

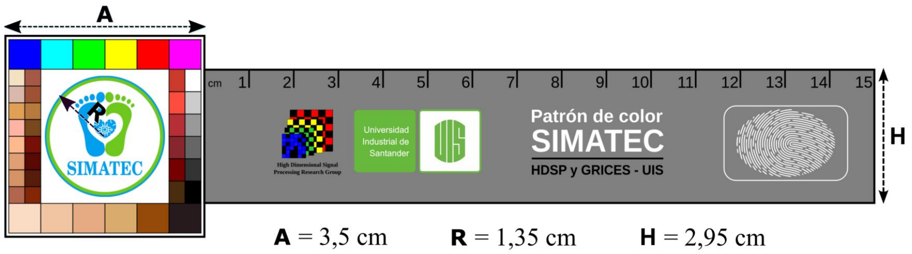
Proposed method: Step A



Data Acquisition Protocol.

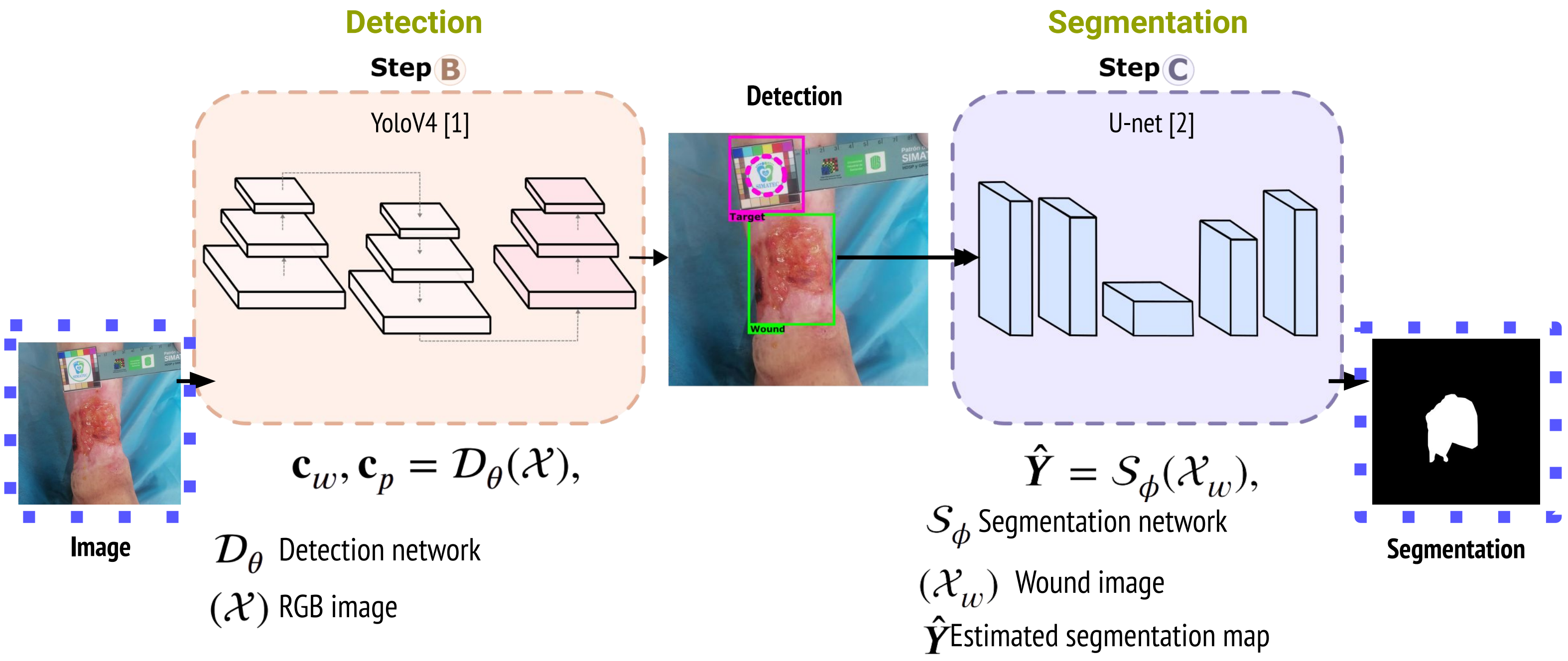
Target: A customized calibration pattern designed for this project. Colors of the target includes:

- RGB and CMYK colors
- Fitzpatrick Skin Color Scale



Calibration pattern to be used in Step A during the image acquisition and then in the calculation of measurements in Stage D.

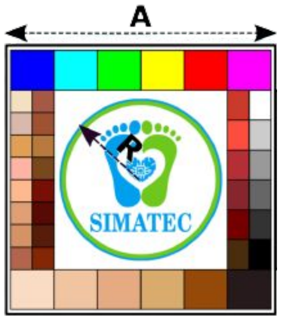
Proposed method: Steps B and C



[1] Alexey Bochkovskiy, Chien-Yao Wang, and HongYuan Mark Liao. Yolov4: Optimal speed and accuracy of object detection. *arXiv preprint arXiv:2004.10934, 2020.*
[2] Olaf Ronneberger, Philipp Fischer, and Thomas Brox, “U-net: Convolutional networks for biomedical image segmentation,” in *International Conference on Medical image computing and computer-assisted intervention. Springer, 2015, pp. 234–241.*

Proposed method: Step D

Area and Perimeter

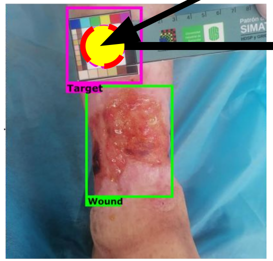


R = 1.35 cm

Extract measurements in pixels and **convert them to cm** using as reference the radius **R** of the circle in the detected target.

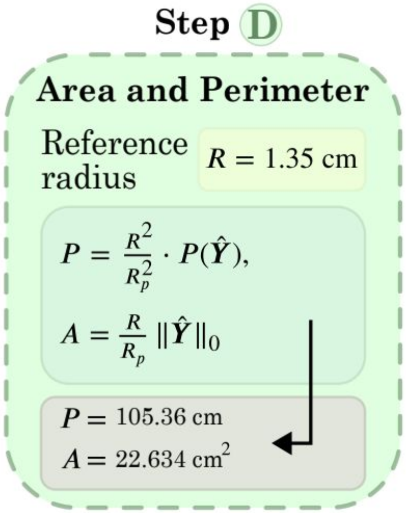
Detection

R = 1.35 cm



Segmentation

Area and perimeter of the wound in Pixels is extracted with Python



Results

A new dataset: CO2Wounds

We publicly present the CO2Wounds dataset:

- This dataset contains 164 RGB images of chronic wound from leprosy patients of the Sanatorio de Contratación E.S.E., Colombia, and their ground truth.
- Acquired with smartphones during 9 months on 69 patients.

Four samples from the new dataset with their respective binary wound segmentation masks.

Ablation study. **Importance of each step** in the performance of the proposed method.

Quantitative segmentation results of the Ablation study 1. Importance of each step in the performance of the proposed framework (10-fold cross-validation)

TL=Transfer-Learning, D=Detection, DA=Data-Augmentation.

Ablation Settings			(↑) **Metrics** (mean±std)		
TL	**D**	**DA**	**F1-score**	**Precision**	**Recall**
✓	-	-	71.2±6.36	79.8±11.3	66.6±8.69
✓	✓	-	79.2±3.96	77.7±5.79	81.0±4.68
-	✓	-	77.4±5.59	75.3±6.58	80.4±4.24
-	✓	✓	76.7±4.44	80.7±6.55	79.7±5.39
✓	✓	✓	**83.2±3.81**	**84.5±4.51**	**81.9±4.71**

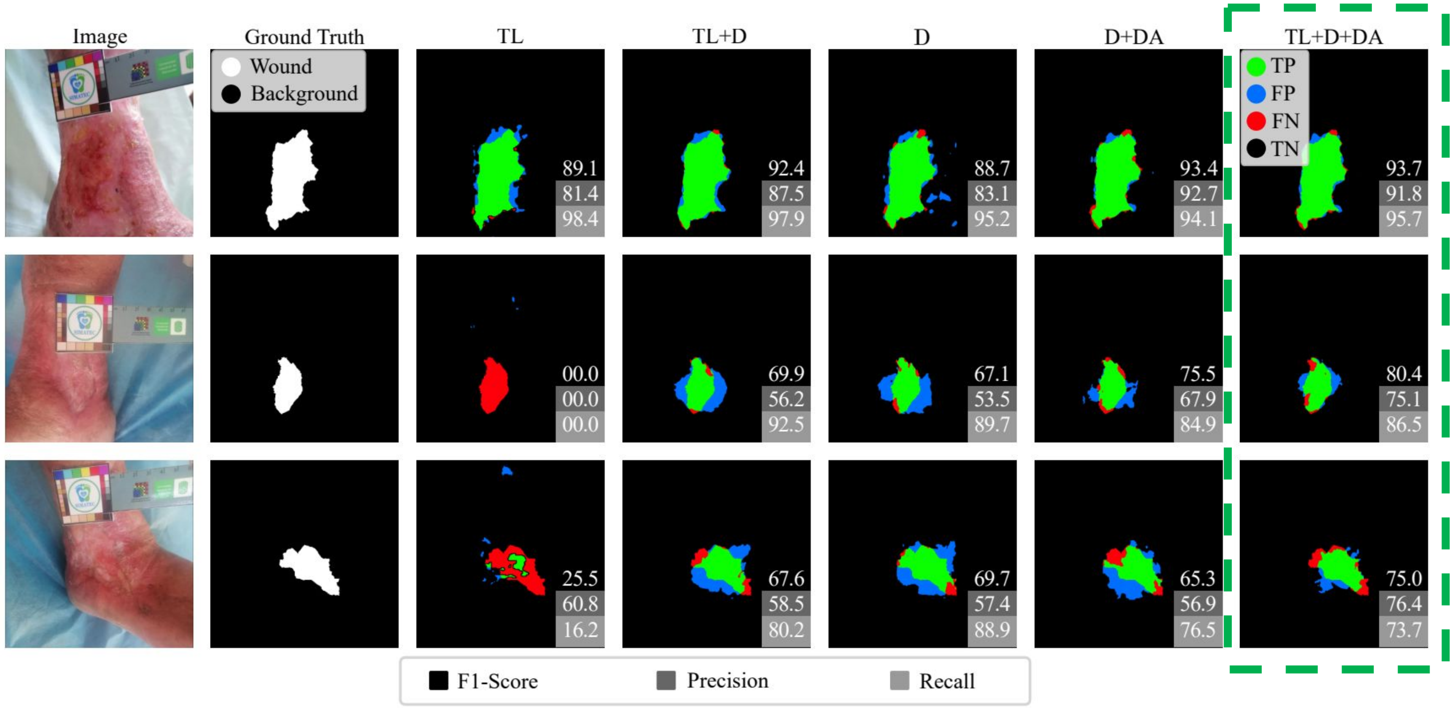
Results

Accuracy **segmentation results** of the entire proposed method (CO2Dnet) on the dataset acquired in this project, **compared with other segmentation** algorithms of the SOTA.

Segmentation comparison with state-of-the-art and deep-learning-based segmentation methods on the CO2Wounds data set.

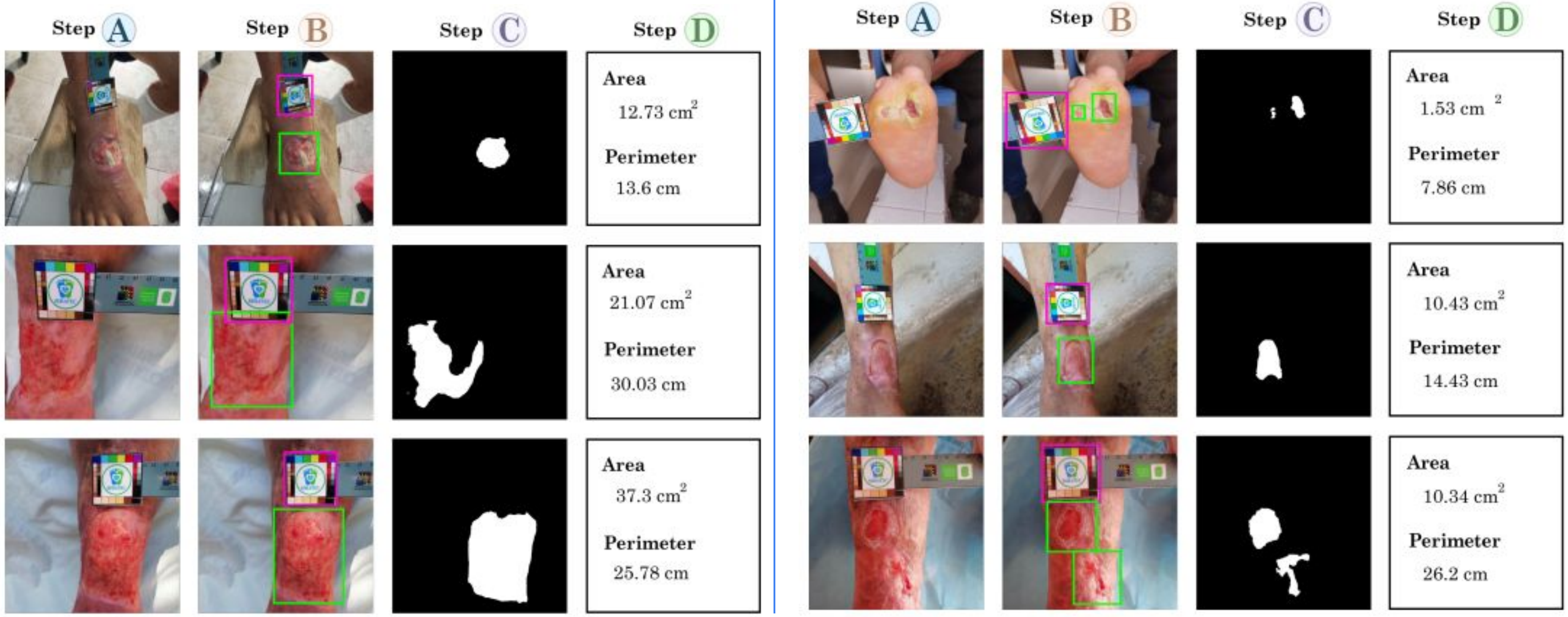
Methods	($\uparrow$) **Metrics** (mean$\pm$std)			
	IoU	**F1-Score**	**Precision**	**Recall**
VGG16 (Goyal et al., 2017)	53.6$\pm$7.25	60.6$\pm$7.33	68.7$\pm$12.7	53.9$\pm$8.71
SegNet (Wang et al., 2015)	48.4$\pm$5.45	58.80$\pm$5.23	68.4$\pm$11.4	51.5$\pm$7.17
MobileNetV2 (Wang et al., 2020a)	60.1$\pm$7.72	68.2$\pm$8.12	65.9$\pm$12.5	70.7$\pm$12.6
Unet (Ronneberger et al., 2015)	64.3$\pm$5.92	73.9$\pm$7.19	82.7$\pm$7.02	66.7$\pm$8.45
CO2Dnet framework (Ours)	**80.3$\pm$2.83**	**83.2$\pm$3.81**	**84.5$\pm$4.51**	**81.9$\pm$4.71**

Results



Visual results of the CO2Dnet proposed method. Images of the test set from the CO2Wound database. Ground truth. Ablation study results using different steps, and the complete proposed method.

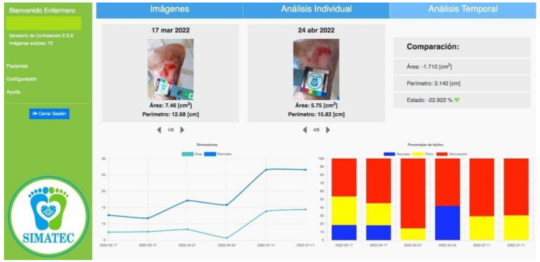
Results



Step-by-step visual results of the proposed framework for six images from the CO2Wounds data set (rows). Each column corresponds to one step of the framework.

Results: Clinical tracking evaluation

Teamwork of SIMATEC and medical staff of the *Leprosy Control Program* in Contratación, **users of the proposed algorithm**, through the platform:
http://simatec.digital



To date, more than 1,500 images of leprosy chronic wounds have been evaluated with SIMATEC.

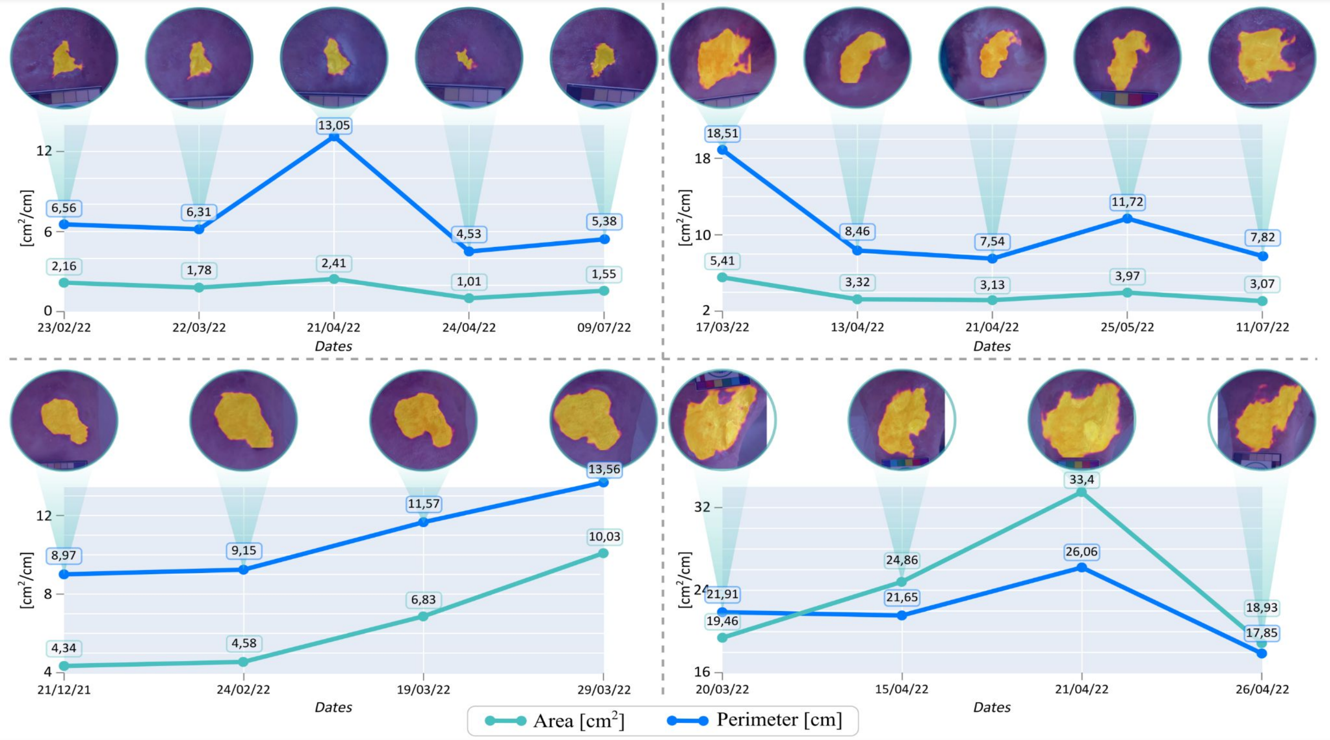
Leprosy control program. Users of the proposed method. Co-authors of the CO2Wound dataset.

Results: Clinical tracking evaluation

Use of the SIMATEC tool by the ***Leprosy control program of Sanatorio de Contratación***, in the Colombian town of Contratación, Santander.

Medical staff can make informed decisions related to the treatment.

From November 2021, this algorithm is part of the **daily tools** of the medical staff from **Contratación.**



Tracking results of four leprosy chronic wounds using the proposed framework.

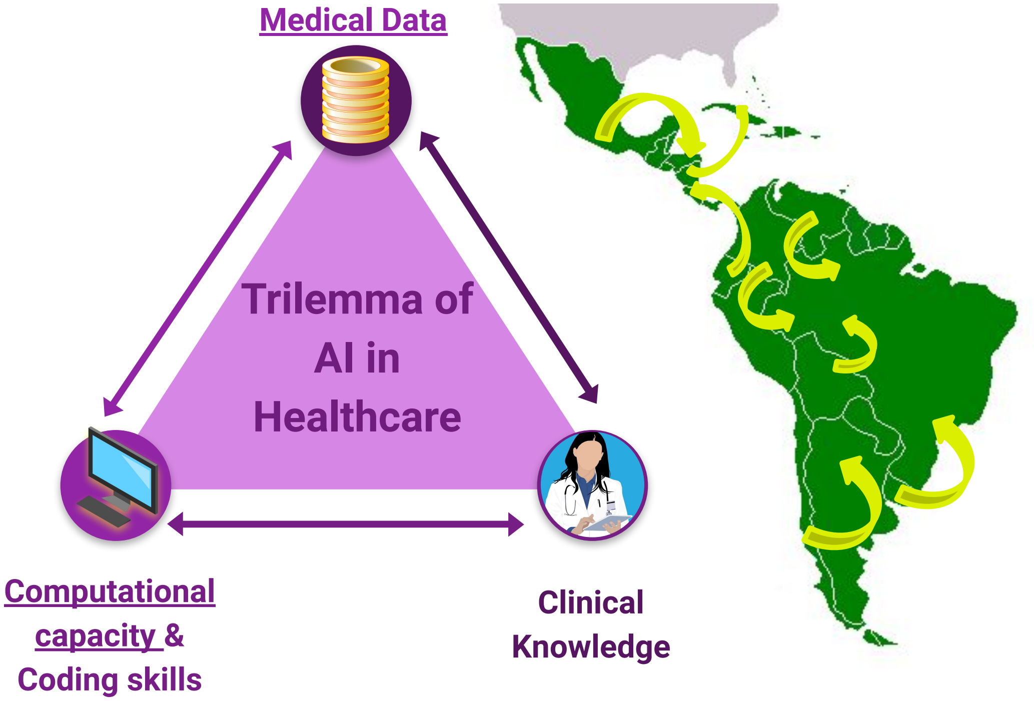
Reminder:
The most important part of the AI for Healthcare...

...is the patients.

Results: Social impact

AI for Healthcare. Take away...

- Creation of **synthetic data** with the characteristics of LATAM population.
- **Domain adaptation** techniques to take advantage of international models and data.
- Projects focused on addressing our **local problems.**
- Passion, commitment, and ethics.



Thank you!

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