ACIM
HUP La Fe

The Influence of AI in Oncology Multidisciplinary Teams Decisions

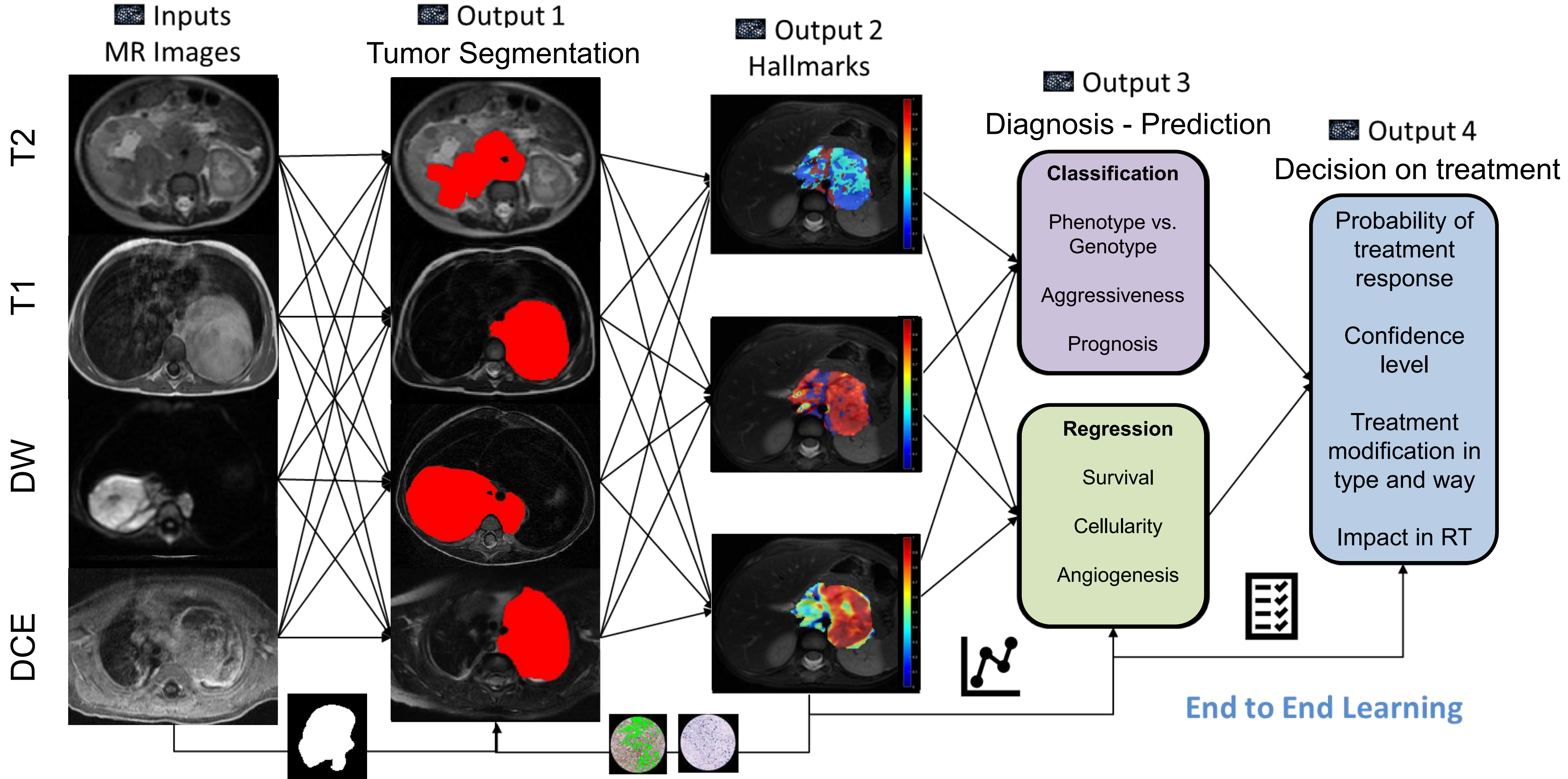
Leonor Cerdá Alberich, PhD

Co-PI and Head of Computing & AI @ Biomedical Imaging Research Group
La Fe Health Research Institute (Valencia)

11.06.2025

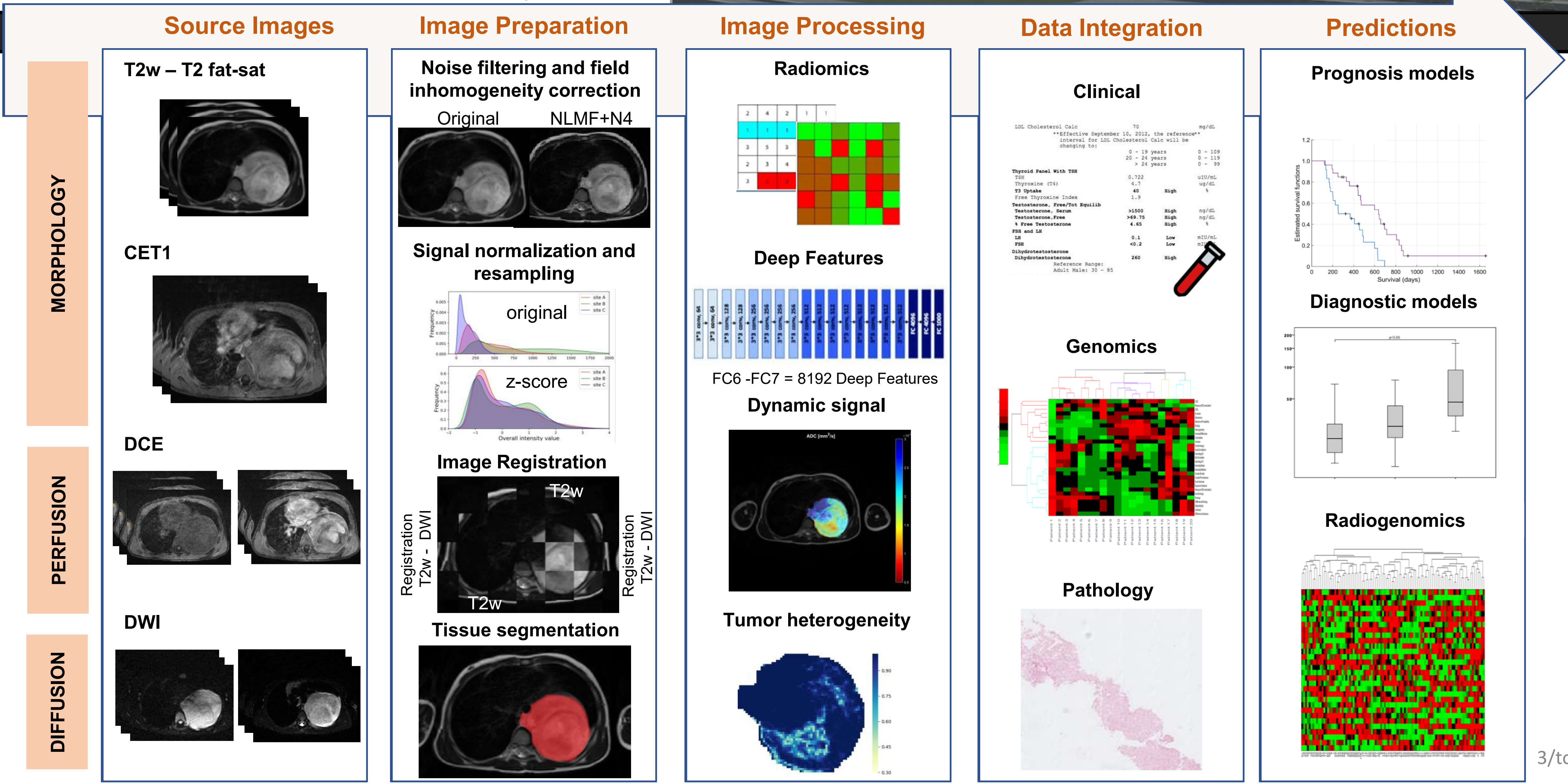
ACIM
HUP La Fe

Virtual Biopsy in Oncology

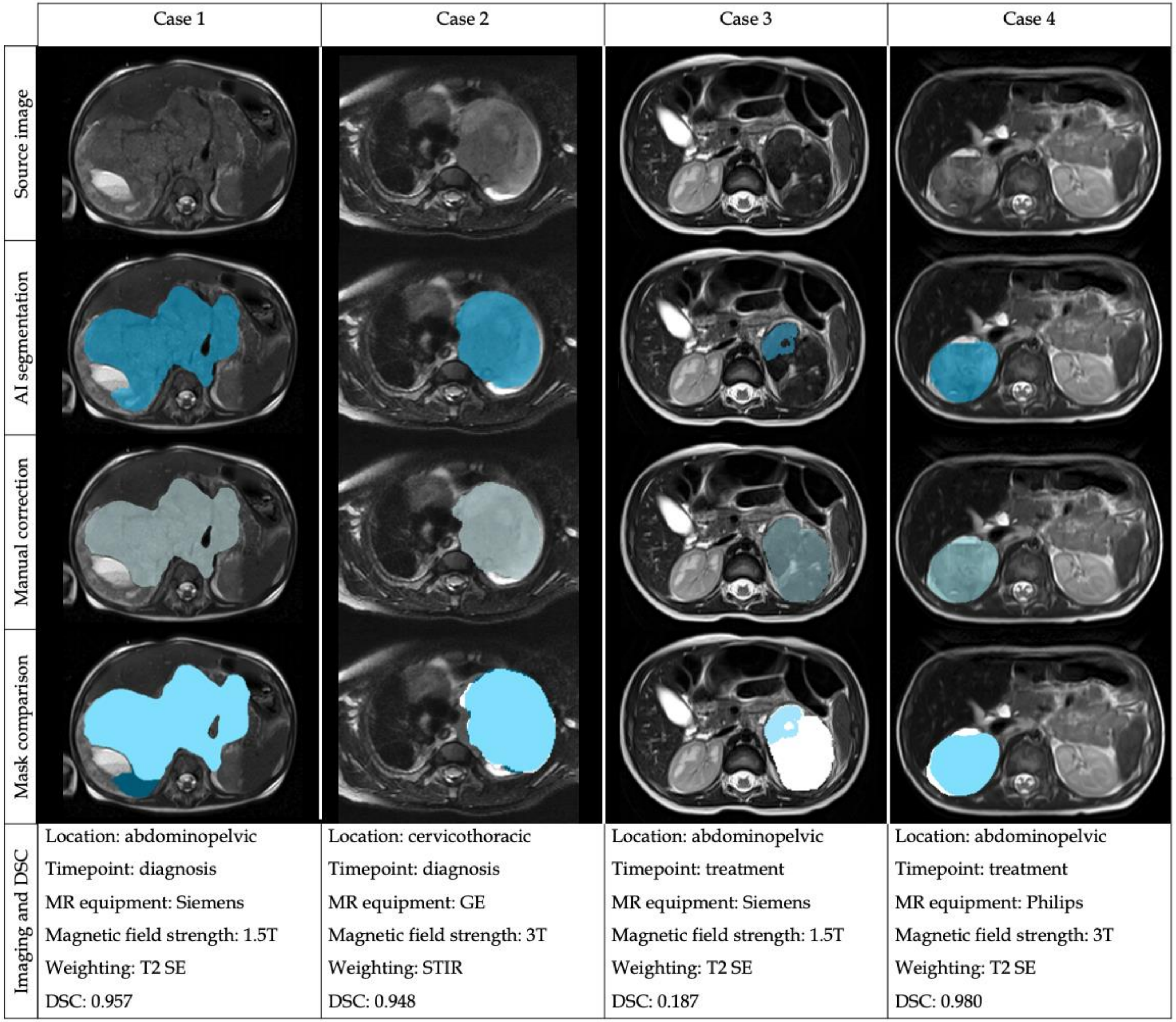


ACIM
HUP La Fe

Image processing pipeline



AI detection and segmentation



To locate and segment neuroblastic tumors on T2/T2-weighted MRI images, regardless of the location and characteristics of the MR scanner.

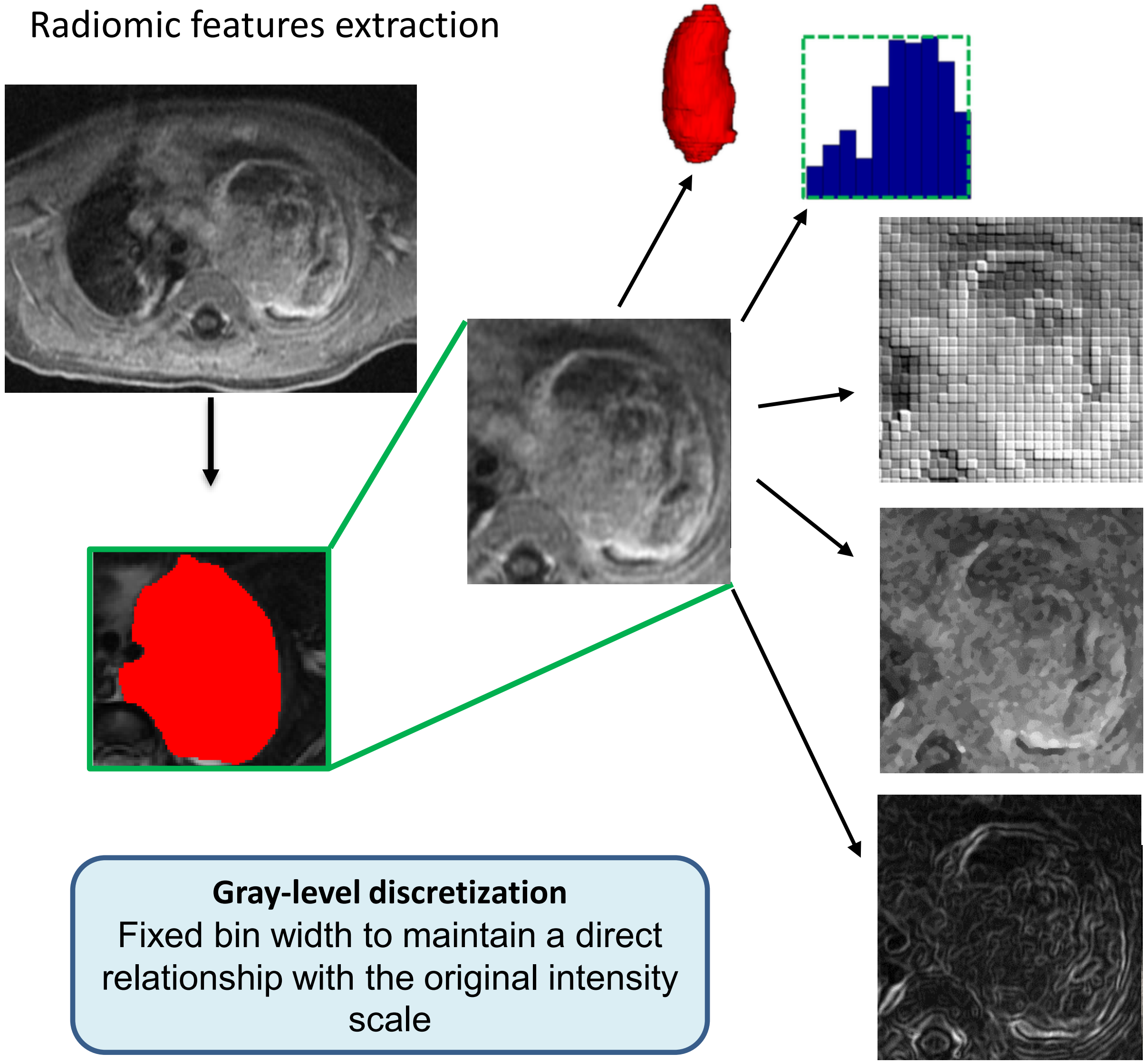
DSC at diagnosis is 0.999, and after treatment is 0.902.

Veiga-Canuto, D.; Cerdà-Alberich, L.; et al. Independent Validation of a Deep Learning nnU-Net Tool for Neuroblastoma Detection and Segmentation in MR Images. *Cancers* **2023**, *15*, 1622.

ACIM
HUP La Fe

Radiomics

Radiomic features extraction



Gray-level discretization
Fixed bin width to maintain a direct relationship with the original intensity scale

Shape
- Volume
- Elongation
- Sphericity
- Surface area
- Surface-Volume Ratio
- Flatness

Intensity
- Minimum
- Maximum
- Mean
- Variance
- Kurtosis
- Median
- SD
- RMS
- Skewness
- Energy
- Entropy
- Uniformity

Gray Level Cooccurence Matrix (GLCM)
- Joint energy
- Contrast
- Joint entropy
- Homogeneity
- Correlation
- Autocorrelation
- Sum average
- Sum variance
- Maximum probability
- Inverse variance
- Difference entropy
- Cluster Prominence

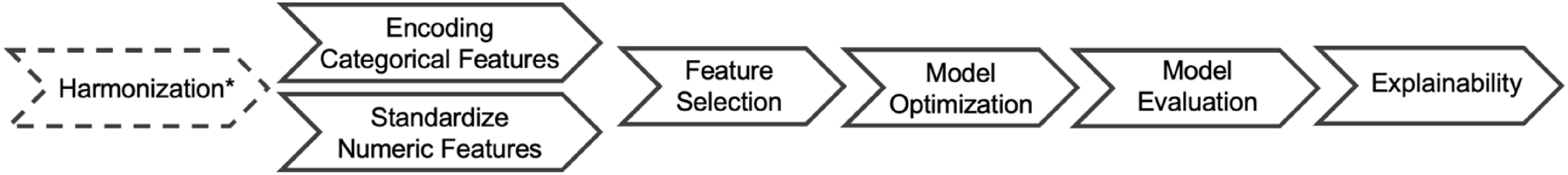
Gray Level Run Length Matrix (GLRLM)
- Small area emphasis
- Large area emphasis
- Gray level non-uniformity
- Size zone non-uniformity
- Zone percentage
- Gray level variance
- Zone variance
- Zone entropy
- Low / High gray level zone emphasis

Gray Level Size Zone Matrix (GLSZM)
- Short run emphasis
- Long run emphasis
- Gray level non-uniformity
- Run length non-uniformity
- Run percentage
- Run entropy
- Run variance
- Low gray level run emphasis
- High gray level run emphasis

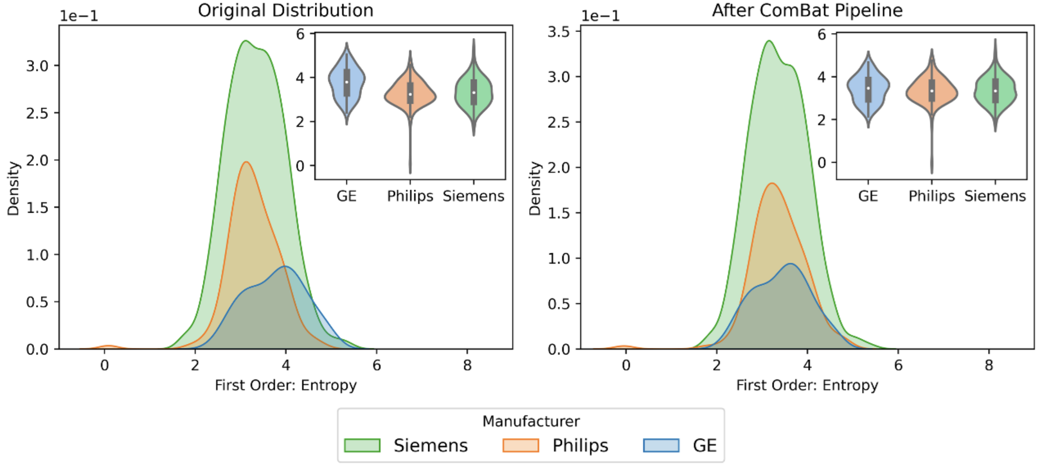
GIBI2[30]
GRUPO DE INVESTIGACIÓN BIOMÉDICA EN IMAGEN

ACIM
HUP La Fe

Modeling pipeline



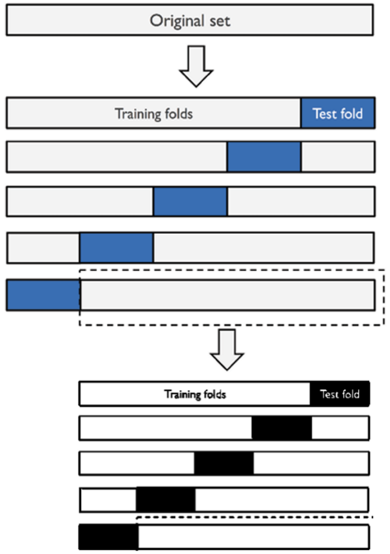
Feature Harmonization



Nested-ComBat methodology to harmonize radiomic features

Corrections by *Manufacturer* and *Magnetic Field Strength*

Nested Cross-Validation



Test Performance

Outer Folds

Evaluate performance on unseen data

Validation Performance

Inner Folds

Obtain best preprocessing, feature selection method and optimal hyperparameters

Multimodal AI models

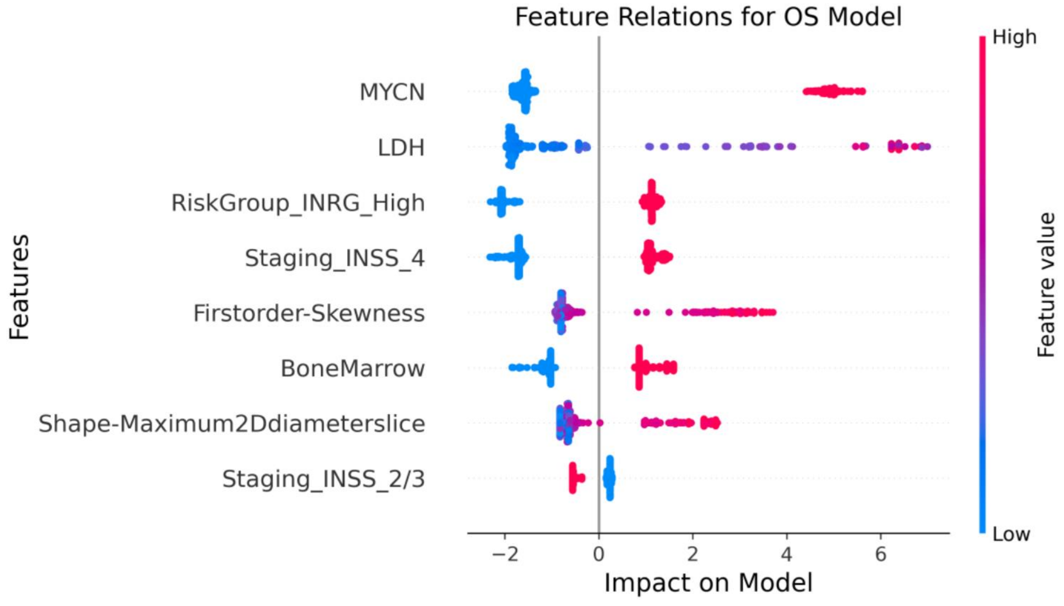
Survival analysis is a collection of statistical procedures for data analysis where the outcome variable of interest is time until an event (death) occurs.

Cross-validation results of the survival models

Features	Patients	C Index	Time-Dependent AUC
		Test	Test
Risk Group INRG	375	0.71 ± 0.03	0.71 ± 0.05
Radiomics T2W	513	0.66 ± 0.01	0.66 ± 0.06
Clinical Variables	513	0.76 ± 0.04	0.77 ± 0.02
Radiomics T2W + Clinical Variables	513	**0.79 ± 0.05**	**0.78 ± 0.06**
Radiomics T2W + Clinical Variables + Tumor Growth	513	**0.90 ± 0.04**	**0.89 ± 0.03**

Model used: Random Survival Forest

Explainability of the multimodal survival model



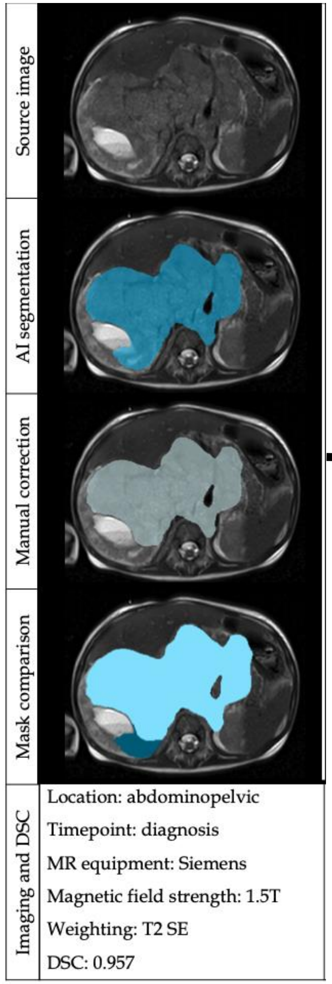
GRUPO DE INVESTIGACIÓN BIOMÉDICA EN IMAGEN

ACIM
HUP La Fe

Clinical decision support system

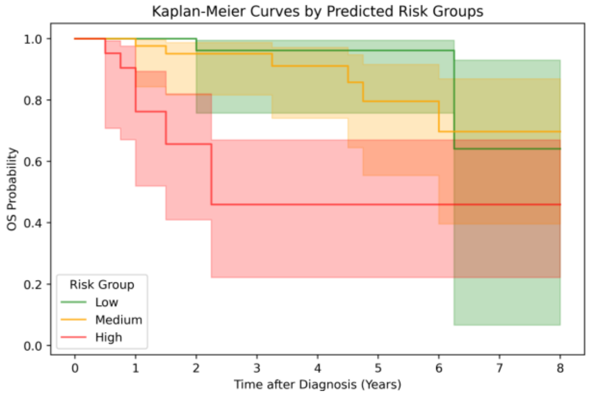
Oncologists use the PRIMAGE platform as a clinical decision support system.

AI tumor detection and segmentation

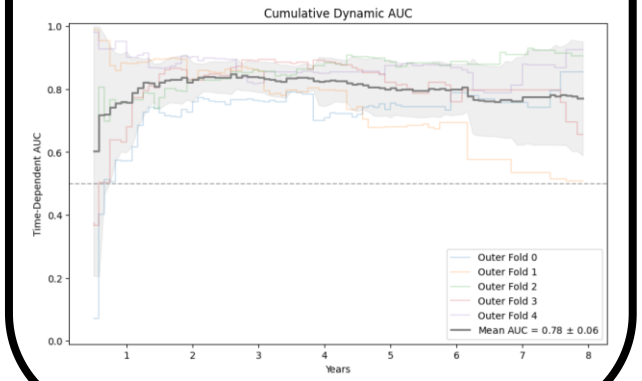


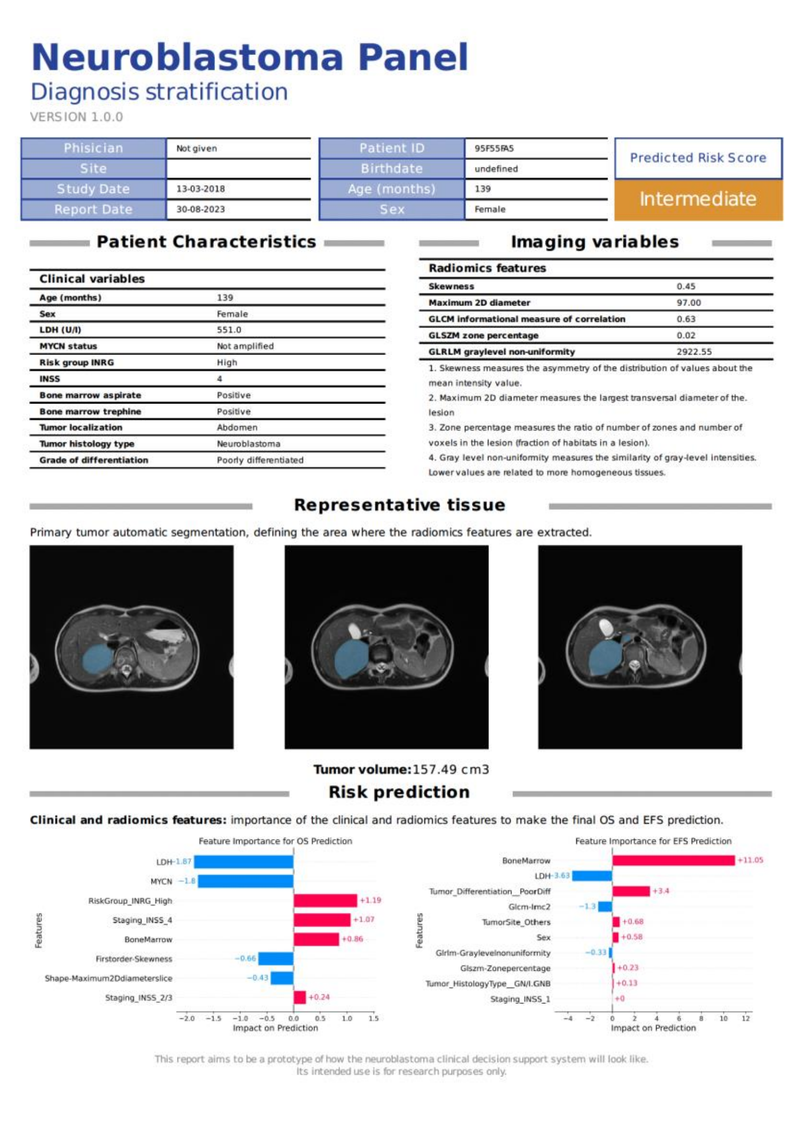
AI model prediction

Overall Survival Analysis



Area under the ROC curve





Neuroblastoma Panel

Diagnosis stratification

VERSION 1.0.0

Phisician	Not given	Patient ID	95F55FA5	Predicted Risk Score
Site		Birthdate	undefined	Intermediate
Study Date	13-03-2018	Age (months)	139	
Report Date	30-08-2023	Sex	Female	

Patient Characteristics

Clinical variables	
Age (months)	139
Sex	Female
LDH (U/l)	551.0
MYCN status	Not amplified
Risk group INRG	High
INSS	4
Bone marrow aspirate	Positive
Bone marrow trephine	Positive
Tumor localization	Abdomen
Tumor histology type	Neuroblastoma
Grade of differentiation	Poorly differentiated

Imaging variables

Radiomics features	
Skewness	0.45
Maximum 2D diameter	97.00
GLCM informational measure of correlation	0.63
GLSZM zone percentage	0.02
GLRLM graylevel non-uniformity	2922.55

1. Skewness measures the asymmetry of the distribution of values about the mean intensity value.
2. Maximum 2D diameter measures the largest transversal diameter of the. lesion
3. Zone percentage measures the ratio of number of zones and number of voxels in the lesion (fraction of habitats in a lesion).
4. Gray level non-uniformity measures the similarity of gray-level intensities. Lower values are related to more homogeneous tissues.

Representative tissue

Primary tumor automatic segmentation, defining the area where the radiomics features are extracted.

Tumor volume:157.49 cm3

Risk prediction

Clinical and radiomics features: importance of the clinical and radiomics features to make the final OS and EFS prediction.

This report aims to be a prototype of how the neuroblastoma clinical decision support system will look like.
Its intended use is for research purposes only.

Model explainability

Input variables:

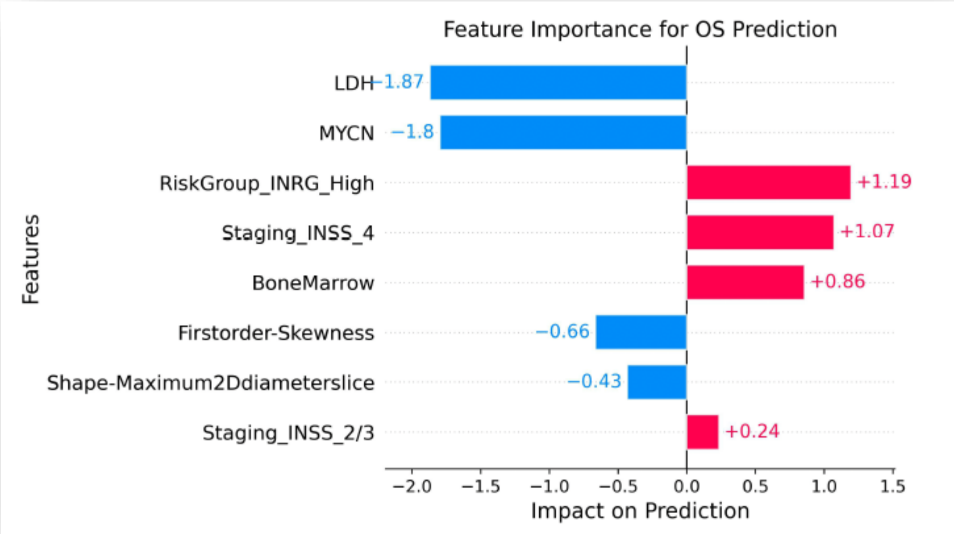
- Sex: Female
- Age: 139 months
- LDH (IU/L): 551
- Histology: Neuroblastoma
- Degree of differentiation: Poorly differentiated
- MYCN: Not amplified
- Primary tumor location: Abdomen
- **INRG: High**
- INSS: 4

Predicted Risk Score

Intermediate

Clinical outcomes:

- Overall survival: 1484 days
- Status: Alive



Input variables:

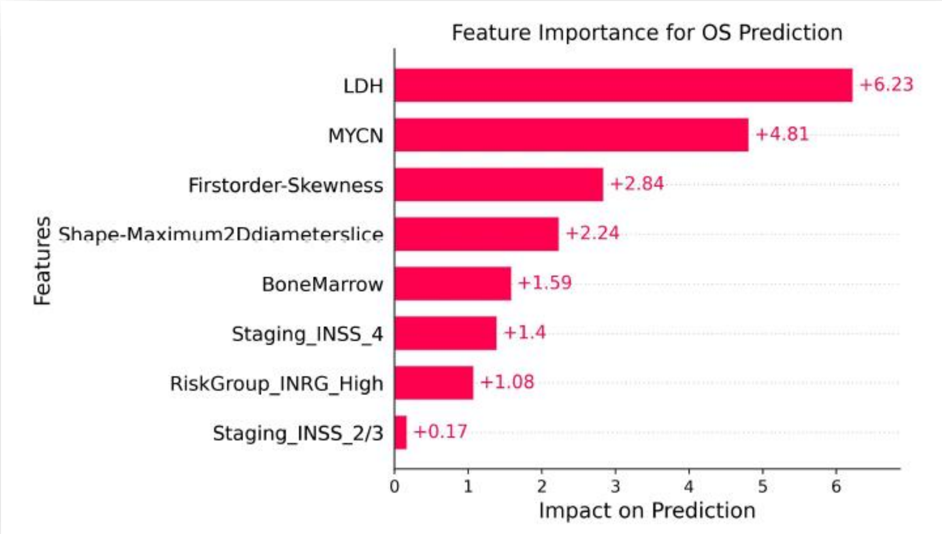
- Sex: Female
- Age: 19 months
- LDH (IU/L): 16400
- Histology: Neuroblastoma
- Degree of differentiation: Not differentiated
- MYCN: Amplified
- Primary tumor location: Abdomen
- **INRG: High**
- INSS: 4

Predicted Risk Score

High

Clinical outcomes:

- Overall survival: 201 days
- Status: Dead

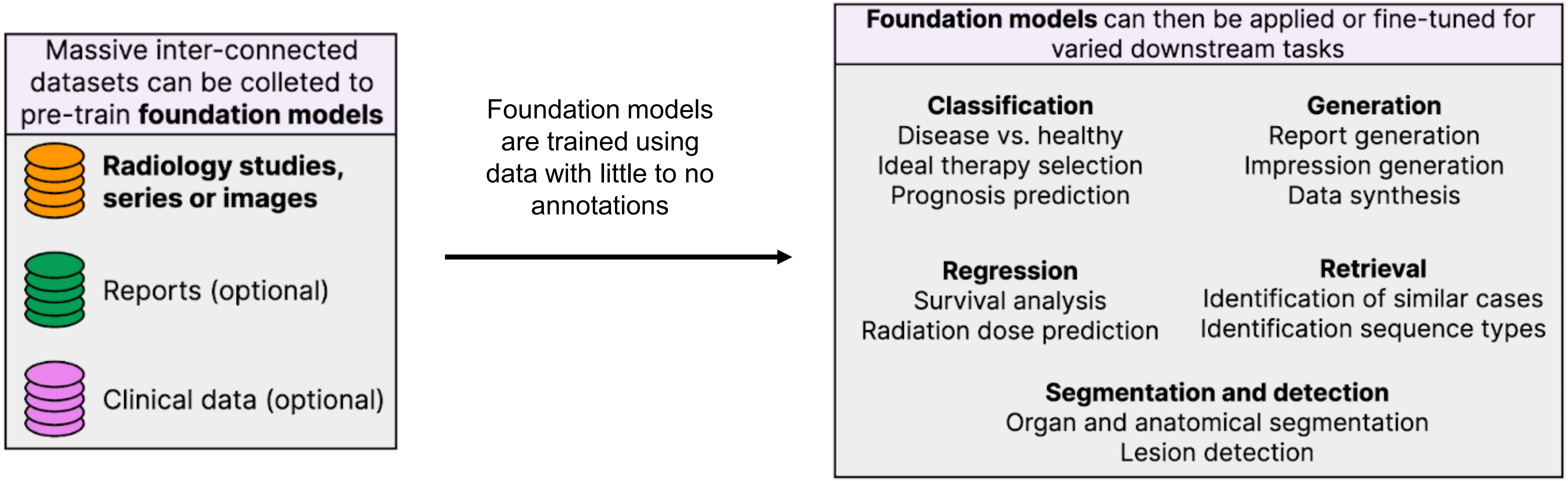


ACIM
HUP La Fe

Foundation models and GenAI

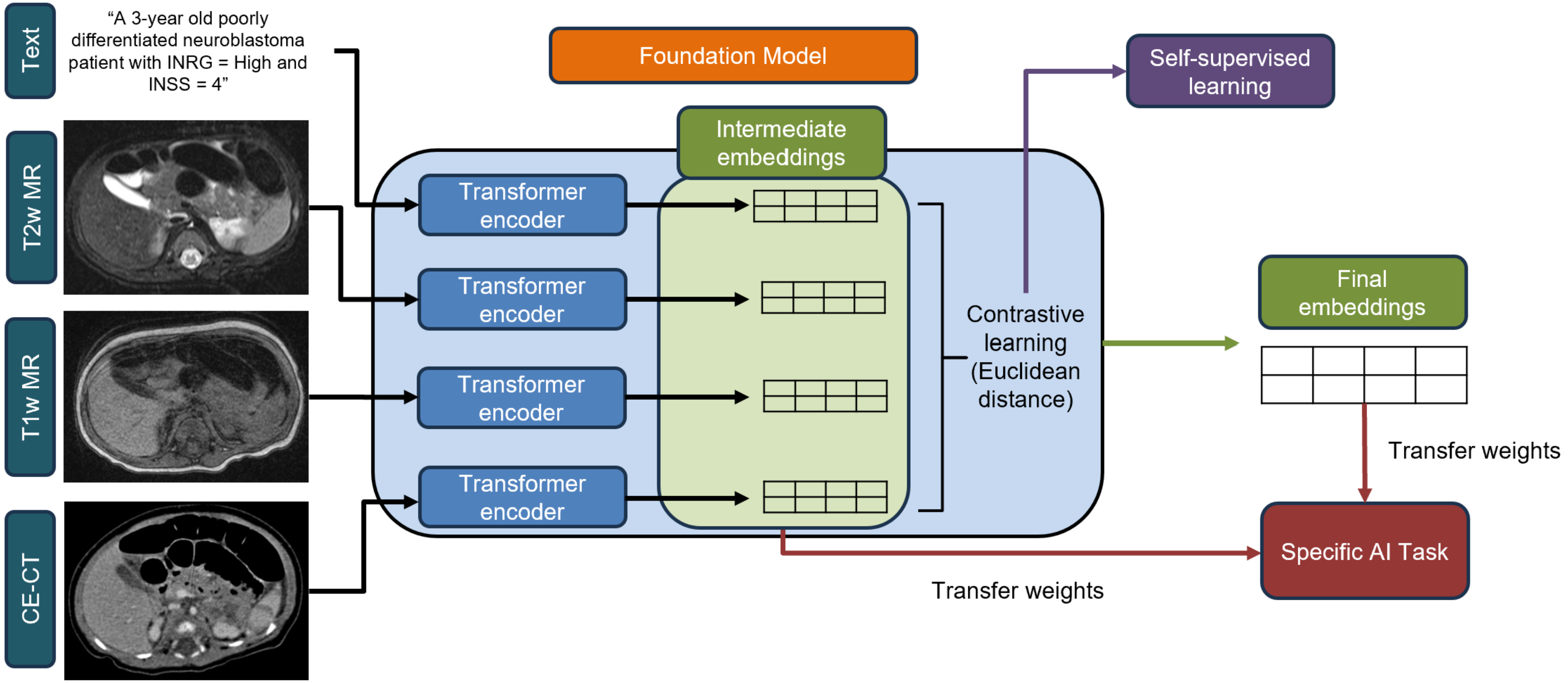
- **Foundation Models**: Large-scale AI models trained on diverse, unannotated data that can be fine-tuned for specific applications.

- **Generative AI**: A subset of foundation models that synthesizes new data (text, images, or multi-modal content).



Why foundation models for oncology?

- Traditional AI models require large amounts of labeled data, which is **expensive** and **time-consuming**.
- Foundation models leverage **self-supervised learning** to extract knowledge from vast, unstructured datasets.
- Enables transfer learning across clinical tasks with minimal fine-tuning.

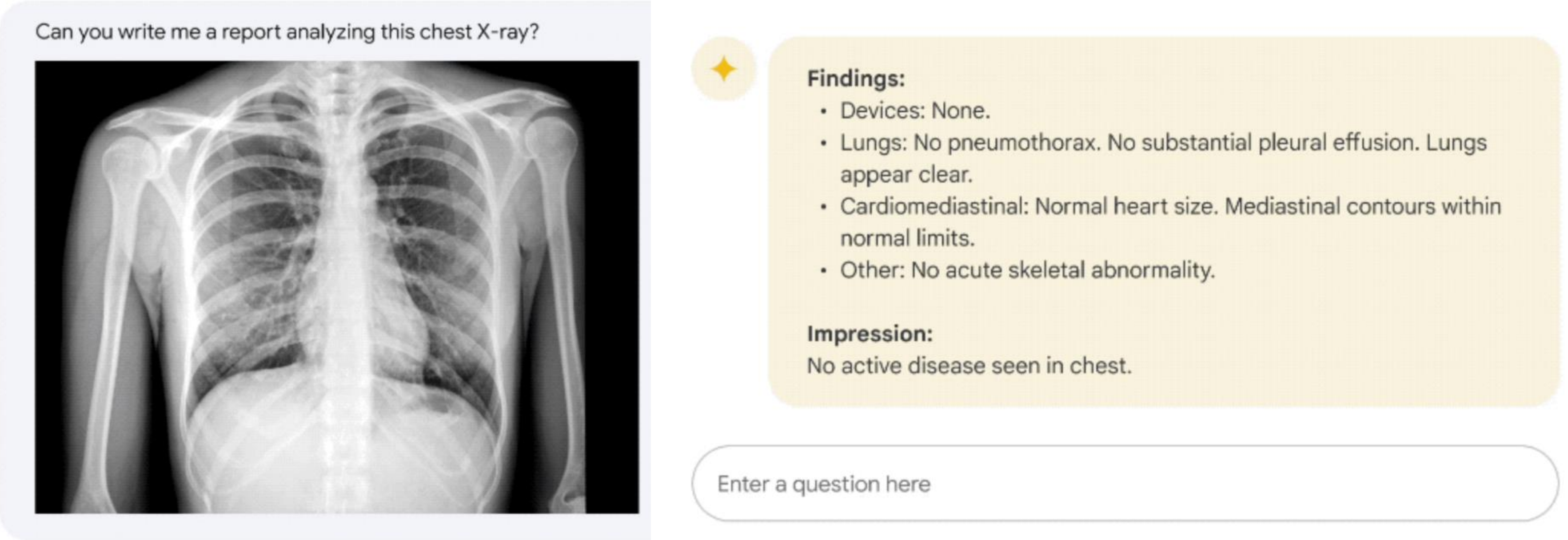


ACIM
HUP La Fe

Applications in Radiology

Automated Image Interpretation	Multimodal Learning	Synthetic Data Generation	Workflow Optimization
Enhancing detection of abnormalities (e.g., nodules in chest X-rays, tumors in MRI scans).	Integrating imaging with genomics and clinical data for holistic disease modeling.	Addressing data scarcity by creating high-fidelity synthetic medical images.	AI-driven report generation, automated segmentation, and decision support.

Med-PaLM can **synthesize and communicate information** from images like chest X-rays, mammograms, and more to help doctors provide better patient care.



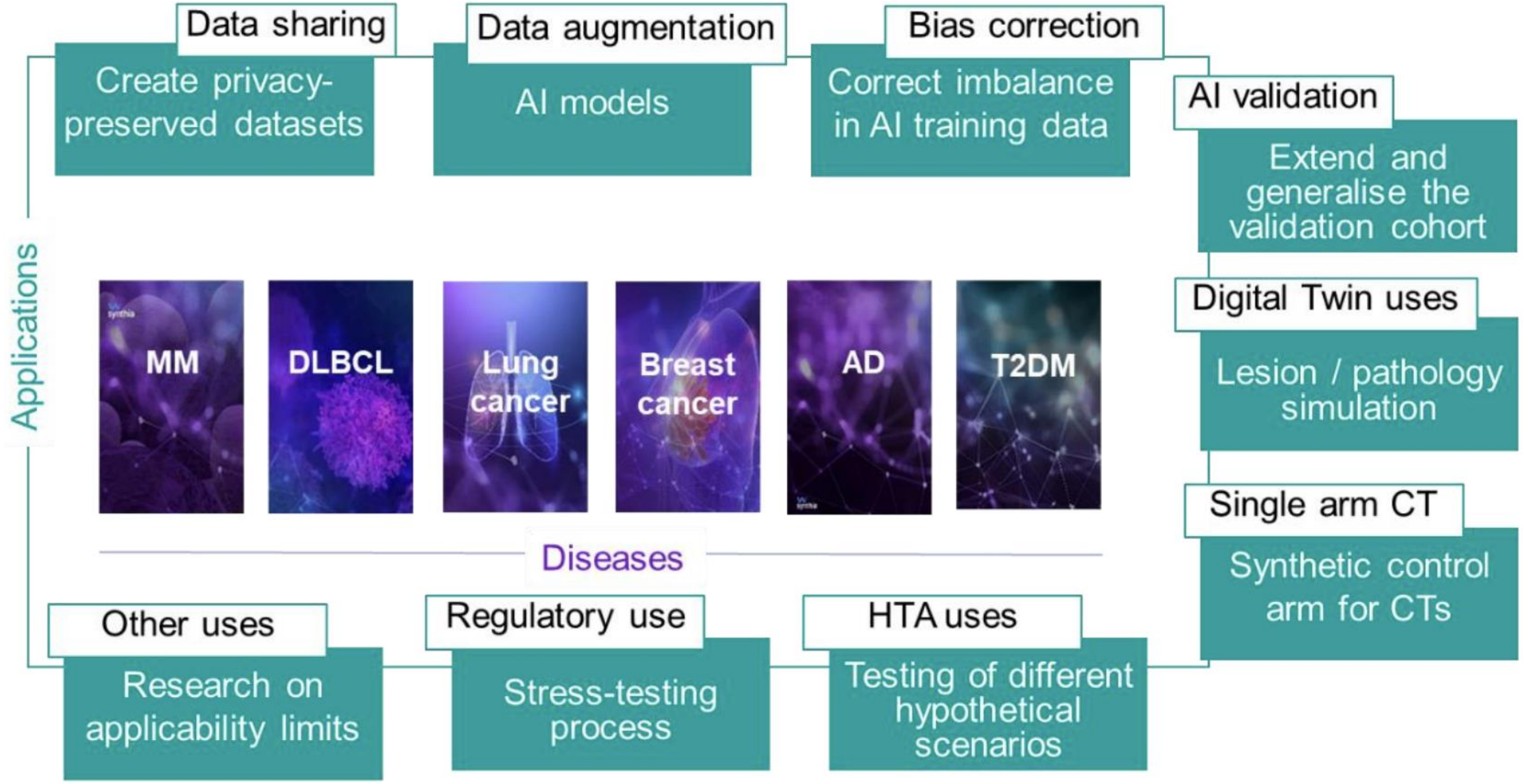
Synthetic Data for Oncology

ACIM
HUP La Fe

AI can generate high-quality synthetic images to train models without requiring extensive real patient data.

Applications include:

- Balancing datasets to mitigate biases.
- Enhancing rare disease detection.
- Preserving patient privacy while enabling AI model development.

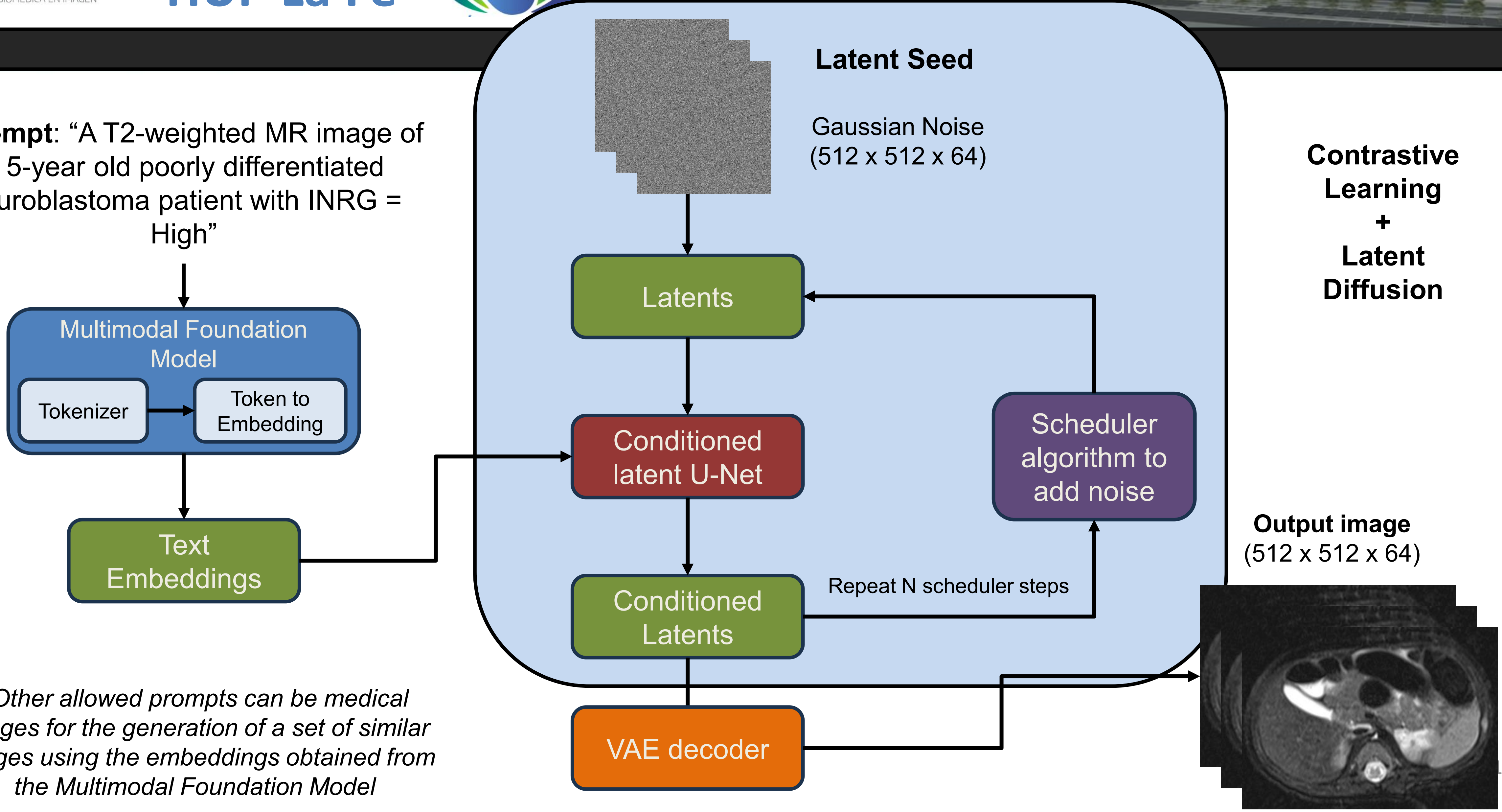


Synthetic Data Generation

ACIM
HUP La Fe

GIBI2[30] GRUPO DE INVESTIGACIÓN BIOMÉDICA EN IMAGEN

*__Prompt__: “A T2-weighted MR image of a 5-year old poorly differentiated neuroblastoma patient with INRG = High”

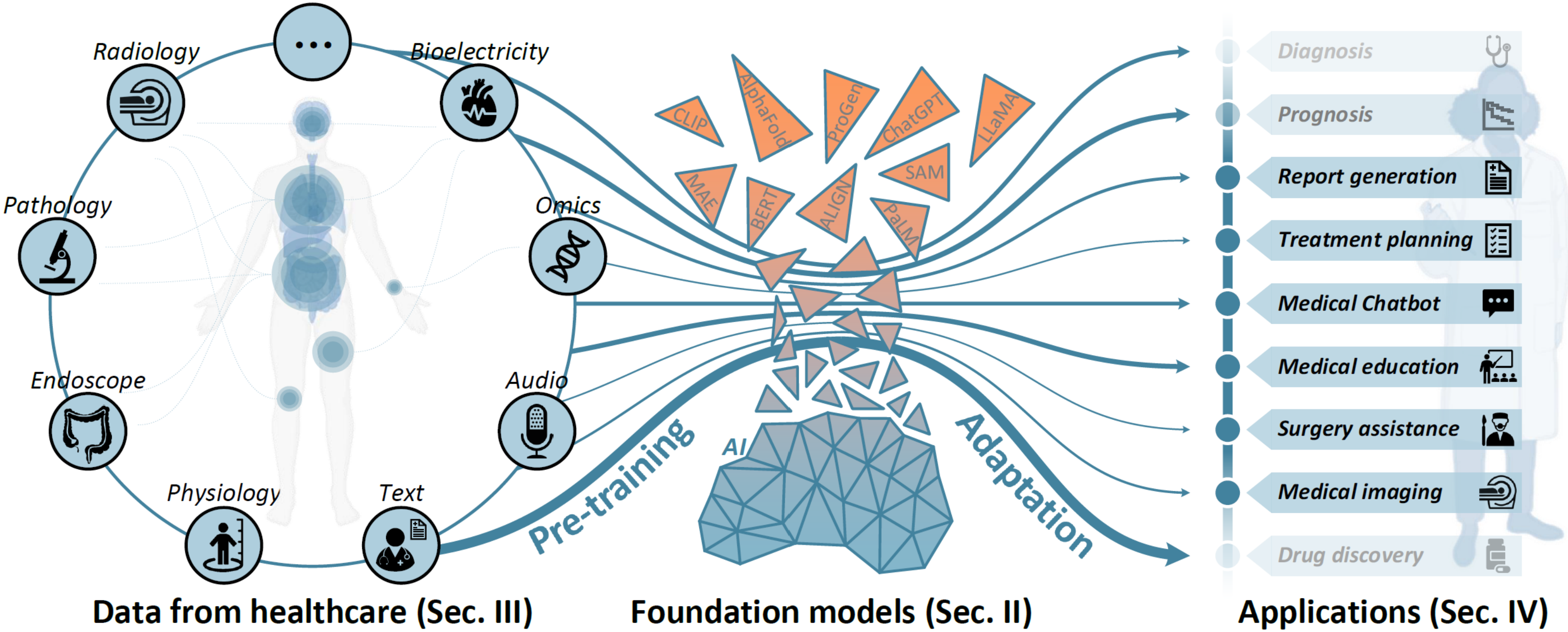


Contrastive Learning + Latent Diffusion

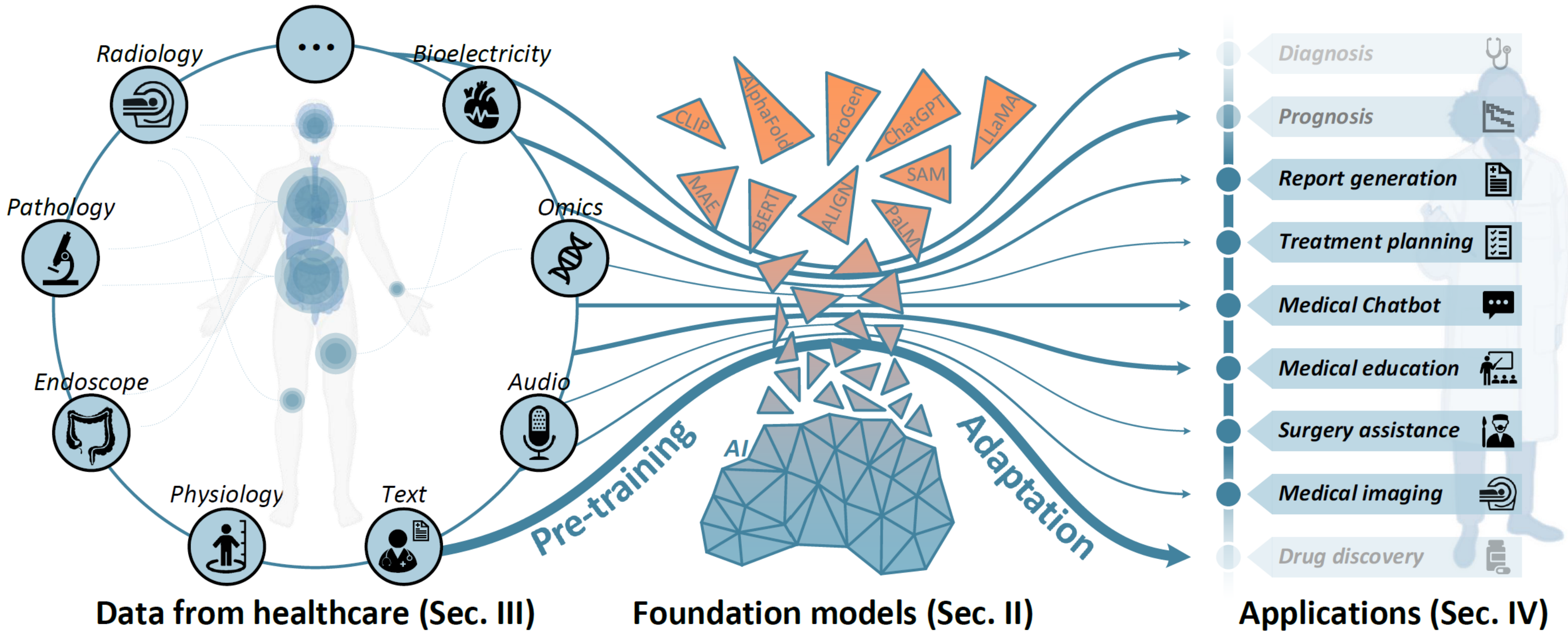
**Other allowed prompts can be medical images for the generation of a set of similar images using the embeddings obtained from the Multimodal Foundation Model*

Multimodal AI for Precision Medicine

- Foundation models integrate multiple data types to improve diagnostic accuracy.
- Enables deeper understanding of disease mechanisms beyond single-modality analysis.

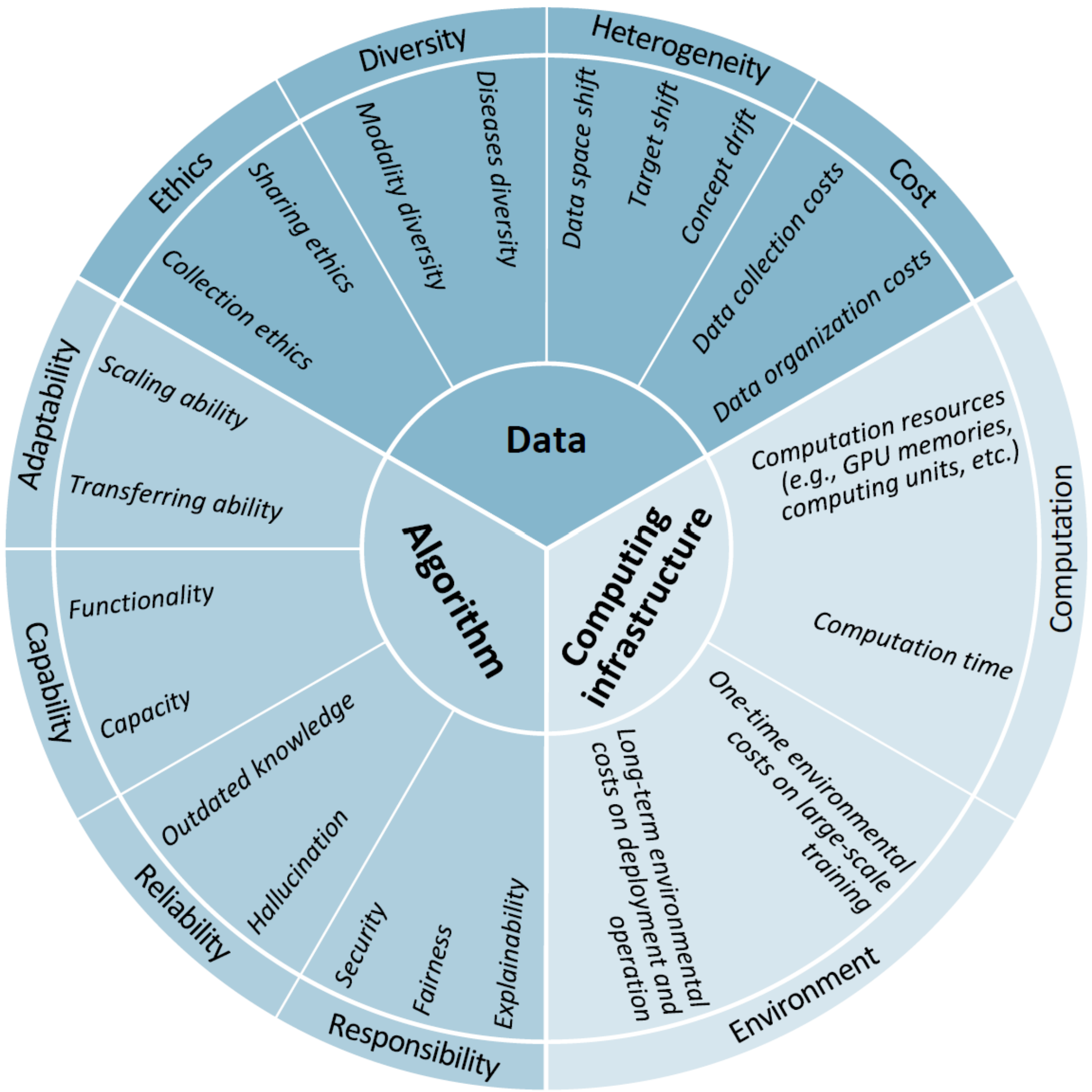


Foundation models are becoming increasingly common in oncology research. However, the biases affecting other models also affect foundation models: It is important to pursue their development while ensuring good training and continuous validation.



Challenges and Pitfalls

- **Bias and Fairness**: Models trained on biased datasets can lead to disparities in patient outcomes.
- **Explainability & Transparency**: Black-box models limit clinical trust and adoption.
- **Generalization Issues**: Performance drops when applied to external datasets or new clinical settings.
- **Ethical & Regulatory Hurdles**: Compliance with AI governance frameworks like the EU AI Act.
- **Data Privacy & Security**: Protecting patient data in AI-driven workflows.



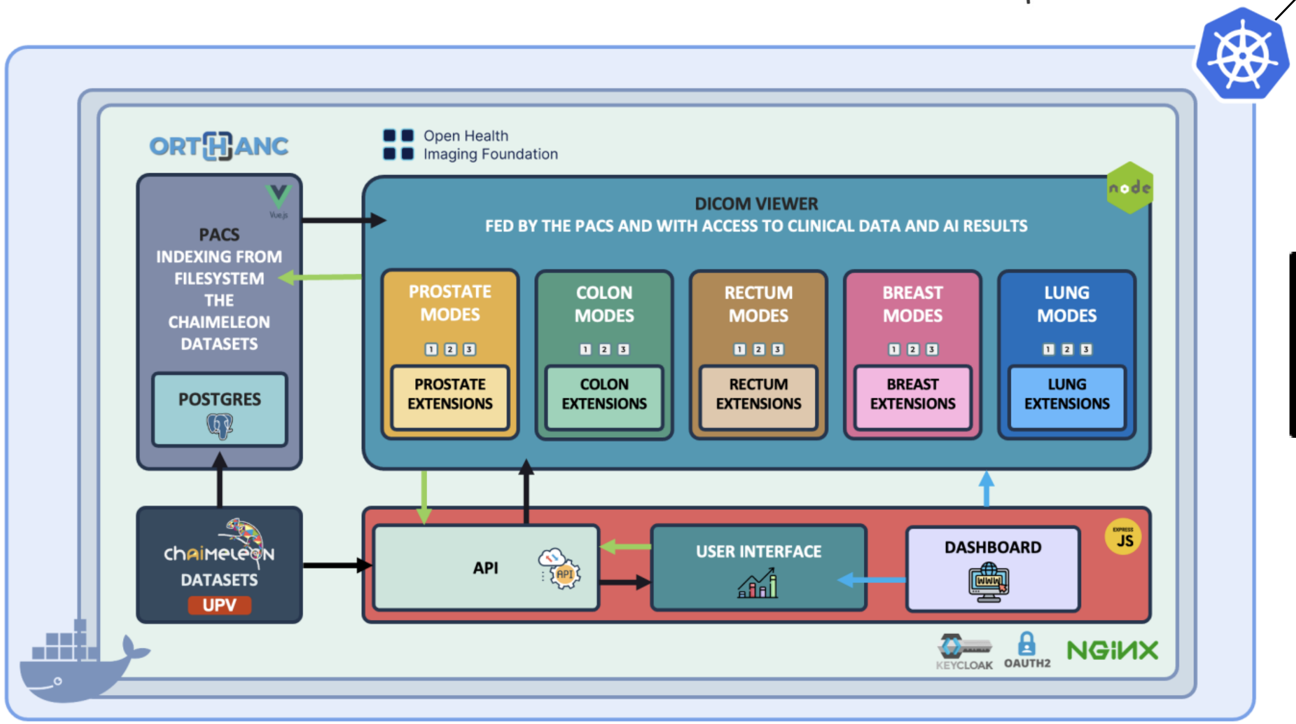
GIBI2[30]
GRUPO DE INVESTIGACIÓN BIOMÉDICA EN IMAGEN

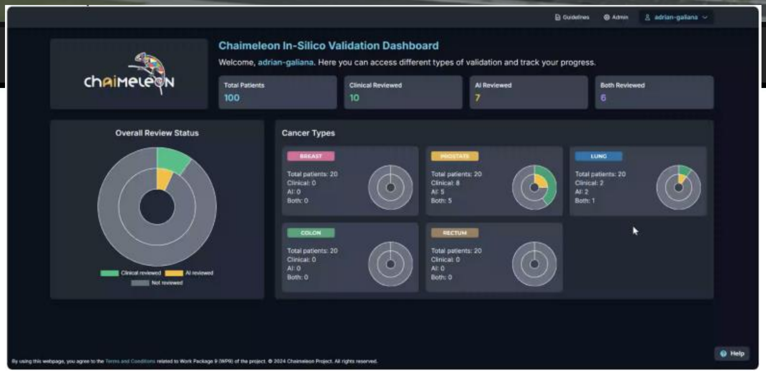
ACIM
HUP La Fe

In Silico Clinical Validation

CHAIMELEON Project

chaimeleon





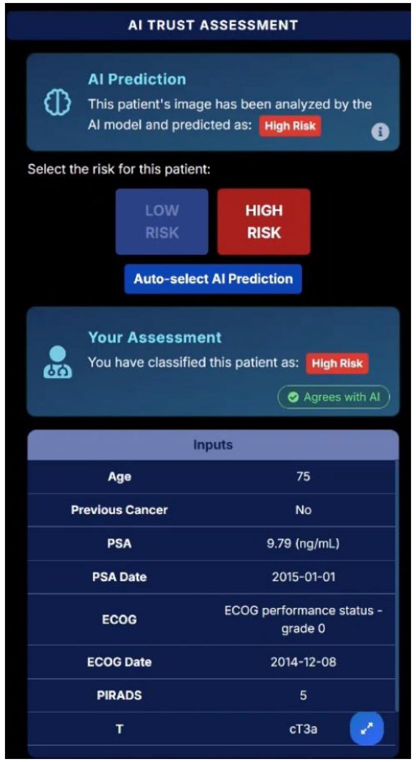
A user-friendly platform developed to improve user experience during clinical validation (timing per case evaluated with/without AI, potential result biases, feedback and comments through a survey.

GIBI2[30]
GRUPO DE INVESTIGACIÓN BIOMÉDICA EN IMAGEN

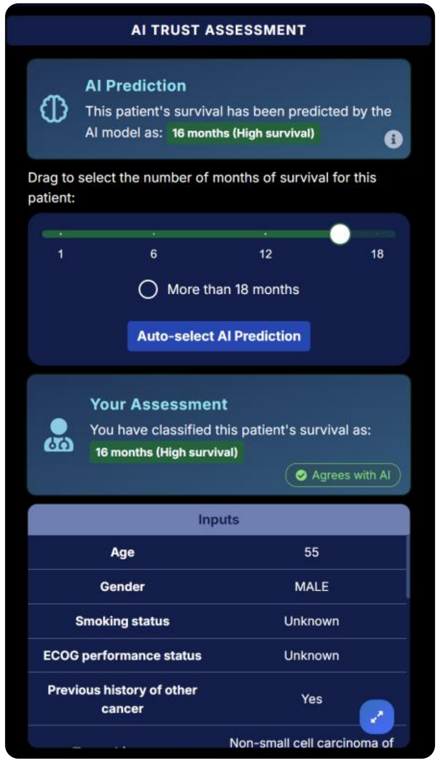
ACIM
HUP La Fe

In Silico Clinical Validation

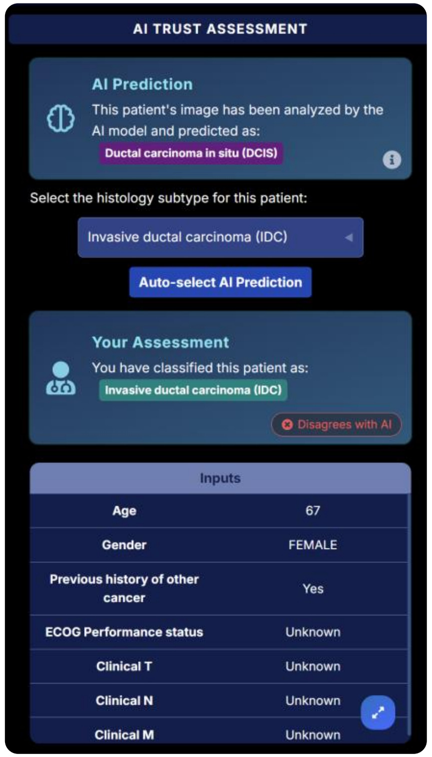
PROSTATE



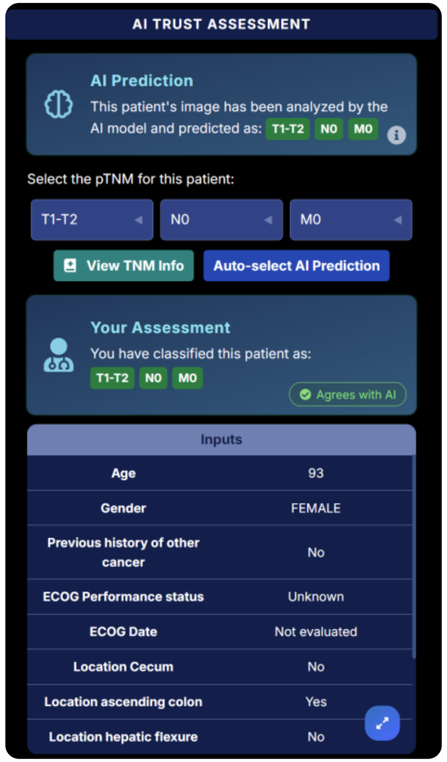
LUNG



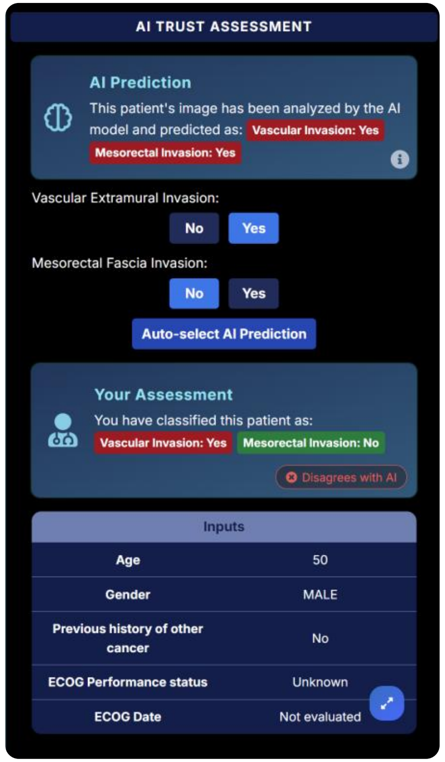
BREAST



COLON

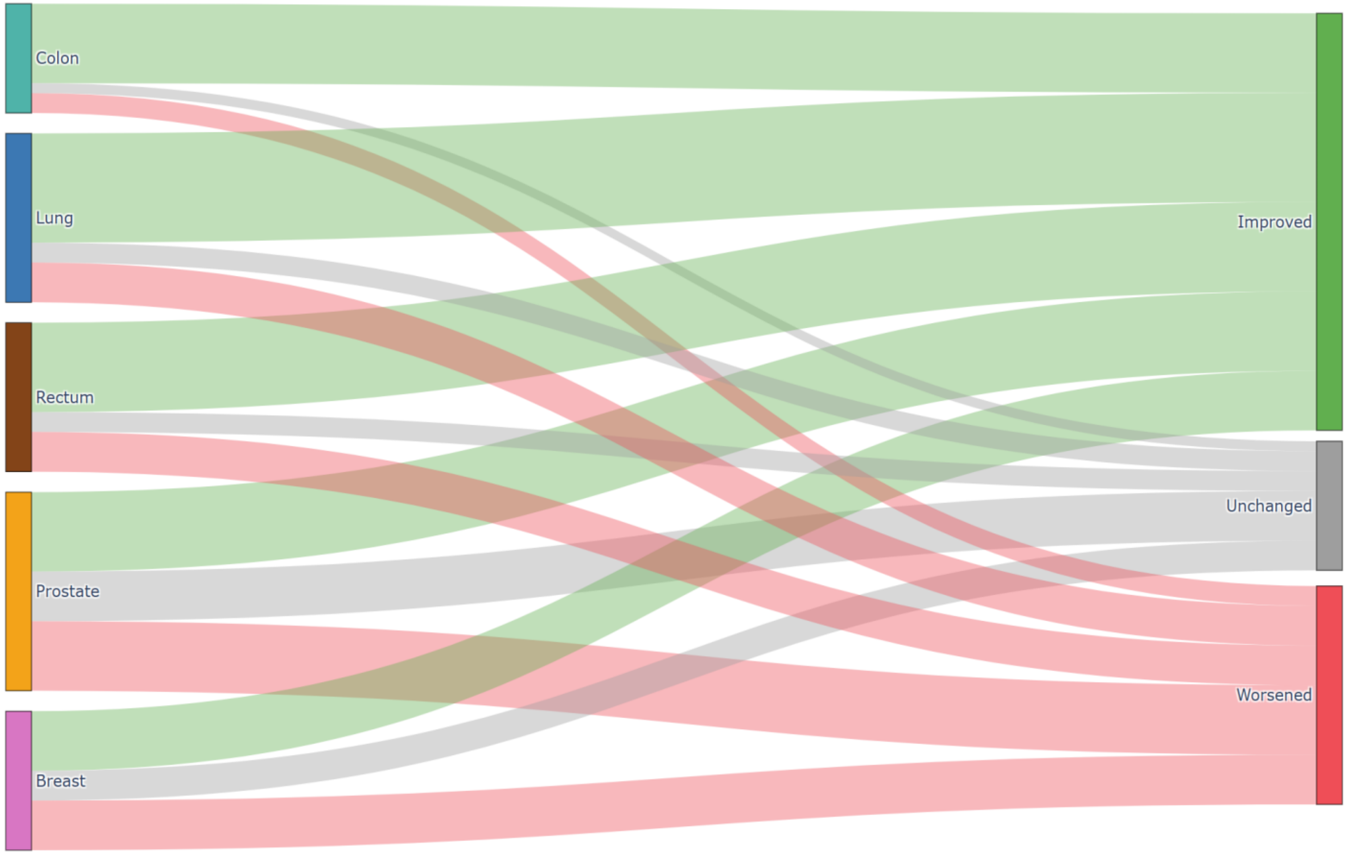


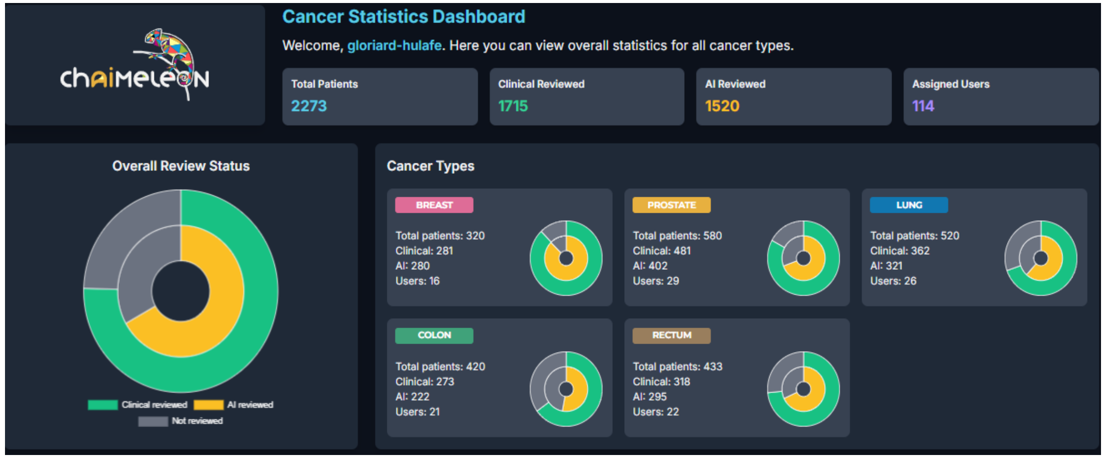
RECTUM



ACIM
HUP La Fe

In Silico Clinical Validation





- Cases: 1,553 (5 tumors).
- Observers: 77 (34 radiologist and 43 physicians).
- Different Experience Level (14: <5 year, 7: 5-10 years, 56: >10 years).
- 54% improved, 17% unchanged, 29% worsened.

The Future of AI in Oncology

	Role	*Implementation*	*Application*	*Emphasis*
Conventional paradigms	AI versus humans to ***automatically*** perform ***repetitive*** healthcare tasks	Static AI model is fixed to ***specific*** healthcare tasks	In ideal settings for ***specific issues*** and ***certain situations***	Explore AI methods for ***capability***
Future directions	AI cooperates with humans to ***jointly*** energize ***challenging*** healthcare tasks	Dynamic AI model adapts to ***general*** healthcare tasks	In real world for ***complex issues*** and ***uncertain situations***	Trust AI behaviors for ***responsibility***

GIBI230
GRUPO DE INVESTIGACIÓN BIOMÉDICA EN IMAGEN

ACIM
HUP La Fe

Key Takeaways

- ✓ AI will increasingly act as a **virtual assistant** for oncologists.
- ✓ **Foundation models** and **GenAI** will evolve to provide **real-time, personalized diagnostics**.
- ✓ Integration with **radiology, robotic surgery, digital pathology, and genomics** will reshape precision medicine.
- ✓ **AI's success depends on human trust**: Transparency, accountability, and validation will be the determining factors for adoption.
- ✓ The biggest challenge is not just building better AI but **rethinking how we integrate AI into the clinical workflow** in ways that are meaningful, ethical, and sustainable.
- ✓ **Future AI ecosystems** will rely on collaboration (among **AI developers, clinicians, and regulators**) and continuous validation.

GIBI2³⁰
GRUPO DE INVESTIGACIÓN BIOMÉDICA EN IMAGEN

ACIM
HUP La Fe

THANK YOU

Leonor Cerdá Alberich, PhD | leonor_cerda@iislafe.es

Biomedical Imaging Research Group (Valencia)