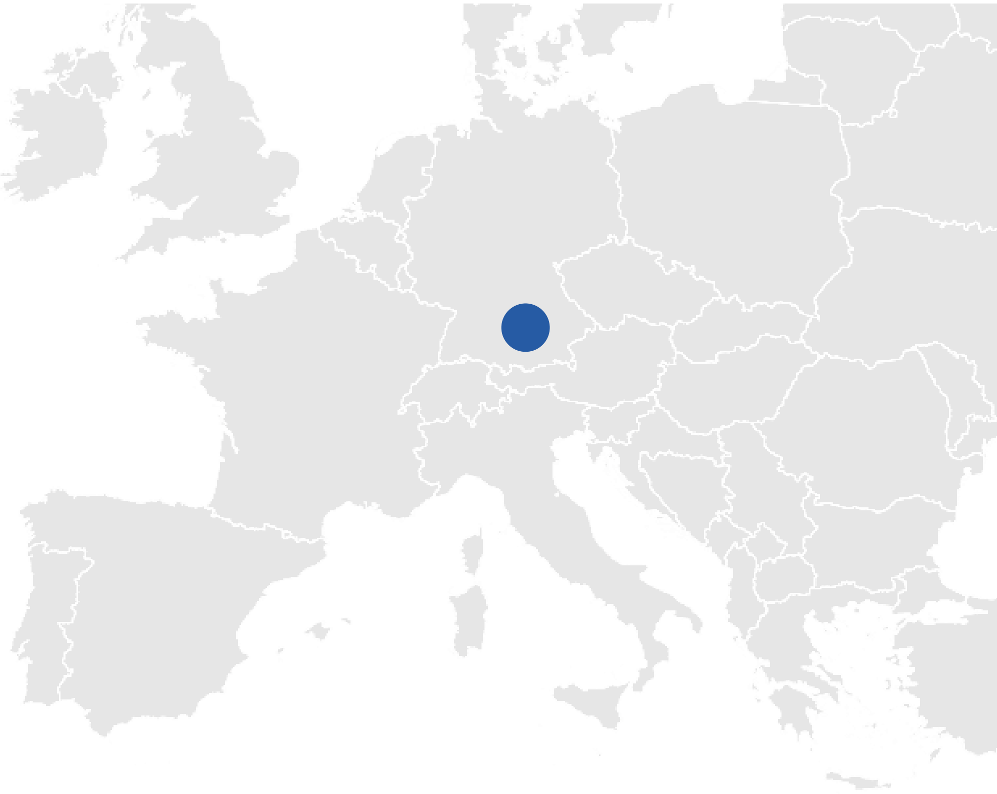
Diffusion Models: From Synthetic Data to Detecting the Unknown

A journey through how diffusion models are transforming medical imaging research.

CB by Cosmin I. Bercea

Hello from Munich




Julia Schnabel


Bene Wiestler


Daniel Rueckert

https://compai-lab.github.io

https://ai-idt.github.io

https://aim-lab.io

Hello from Munich

Cosmin I. Bercea

Sibiu

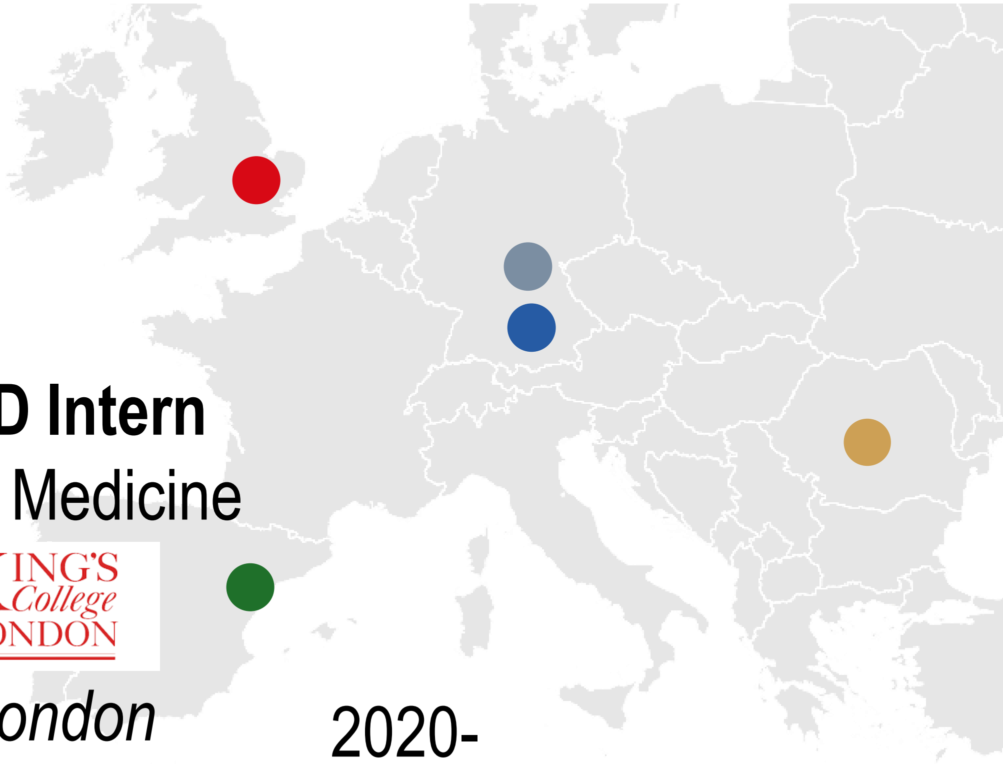
Fraunhofer IIS

SIEMENS Healthineers

B.Sc. / M. Sc.
Informatics
FAU
Erlangen
2011-2018

2016
BOSCH
Barcelona
UAB CVC
Centre de Visió per Computador
M.Sc. Intern
AI in Computer Vision

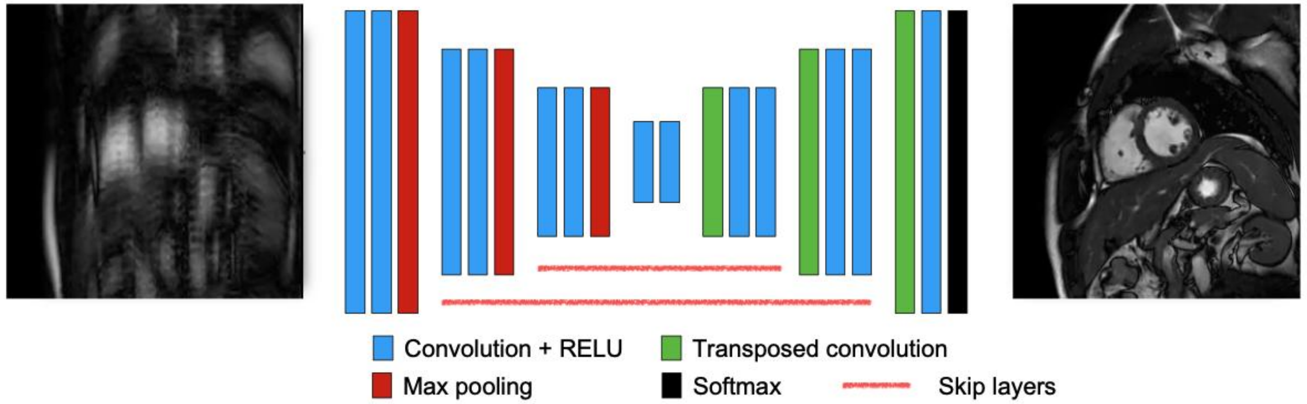
PhD Intern
AI in Medicine
King's College London
London
2022



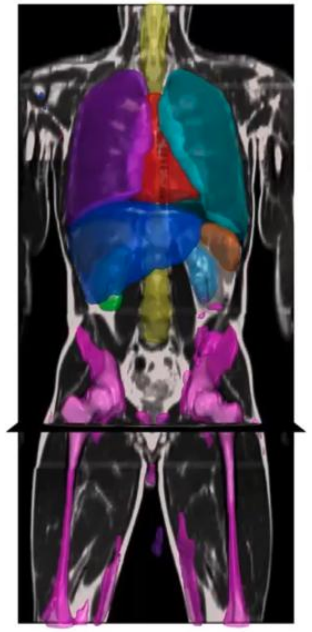
2020-2024
Munich
TUM
Dr. rer. nat
AI in Medicine

Postdoctoral researcher

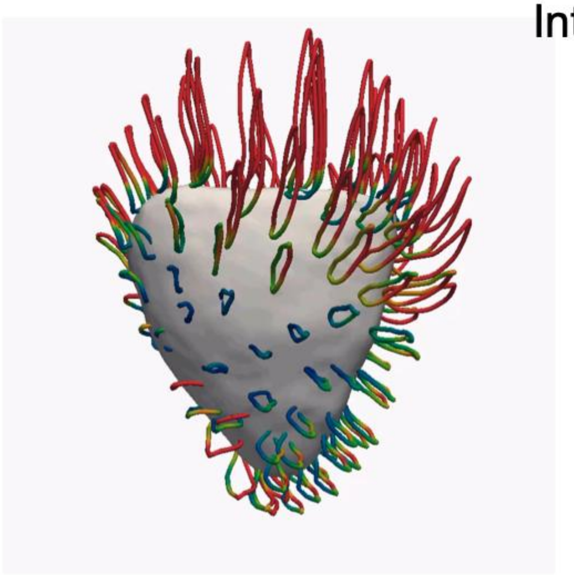
Our Research Topics



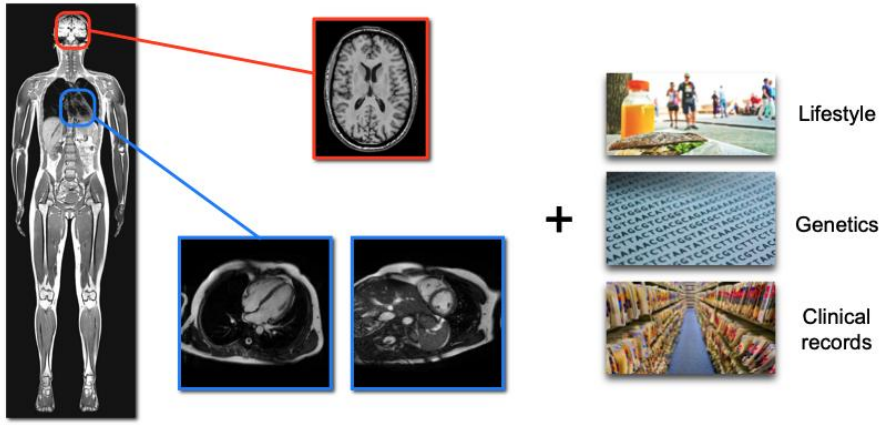
Intelligent Imaging



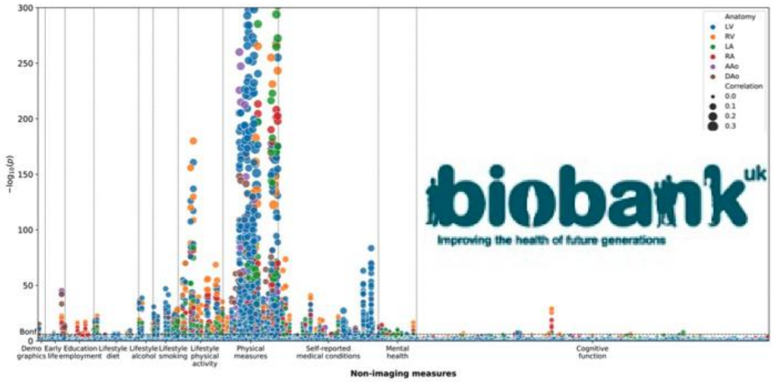
Medical Image Computing



Biomedical Computing and Modelling

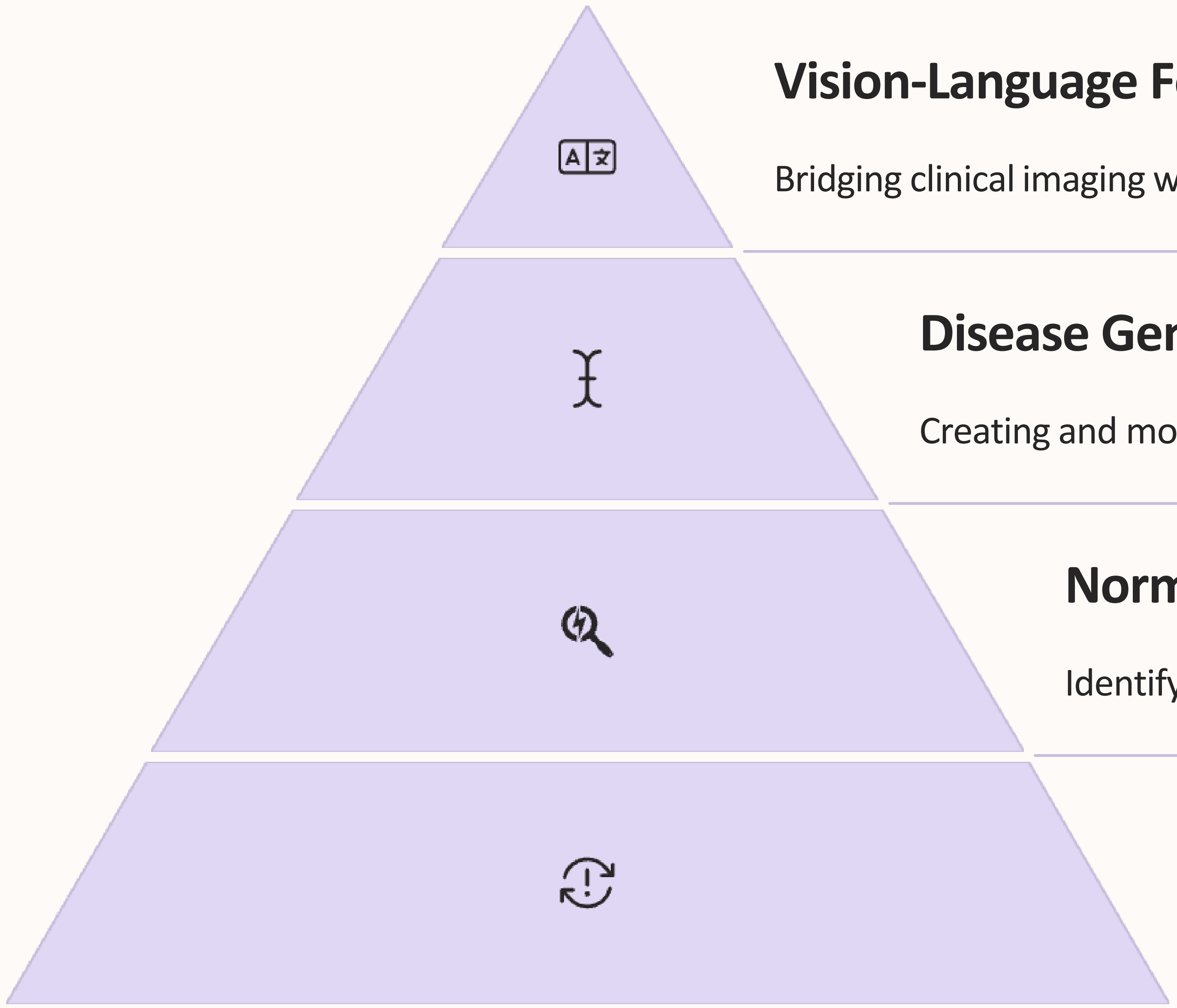


Multi-modal learning



Population studies

Our Research Topics



Vision-Language Foundations

Bridging clinical imaging with natural language understanding

Disease Generation & Editing

Creating and modifying pathological features

Normative Modeling & Anomaly Detection

Identifying unknown abnormalities

Image Restoration & MRI Reconstruction

Enhancing undersampled images

AI in Medicine – Hype vs. Hope

AI in Medicine – Hype vs. Hope

MIT Technology Review

Artificial intelligence / Machine learning

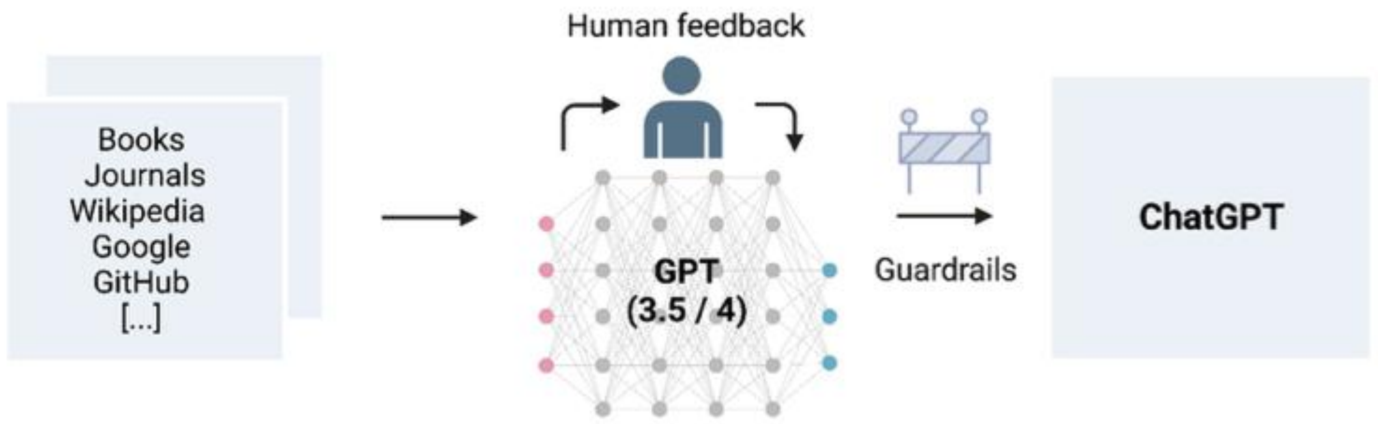
Hundreds of AI tools have been built to catch covid. None of them helped.

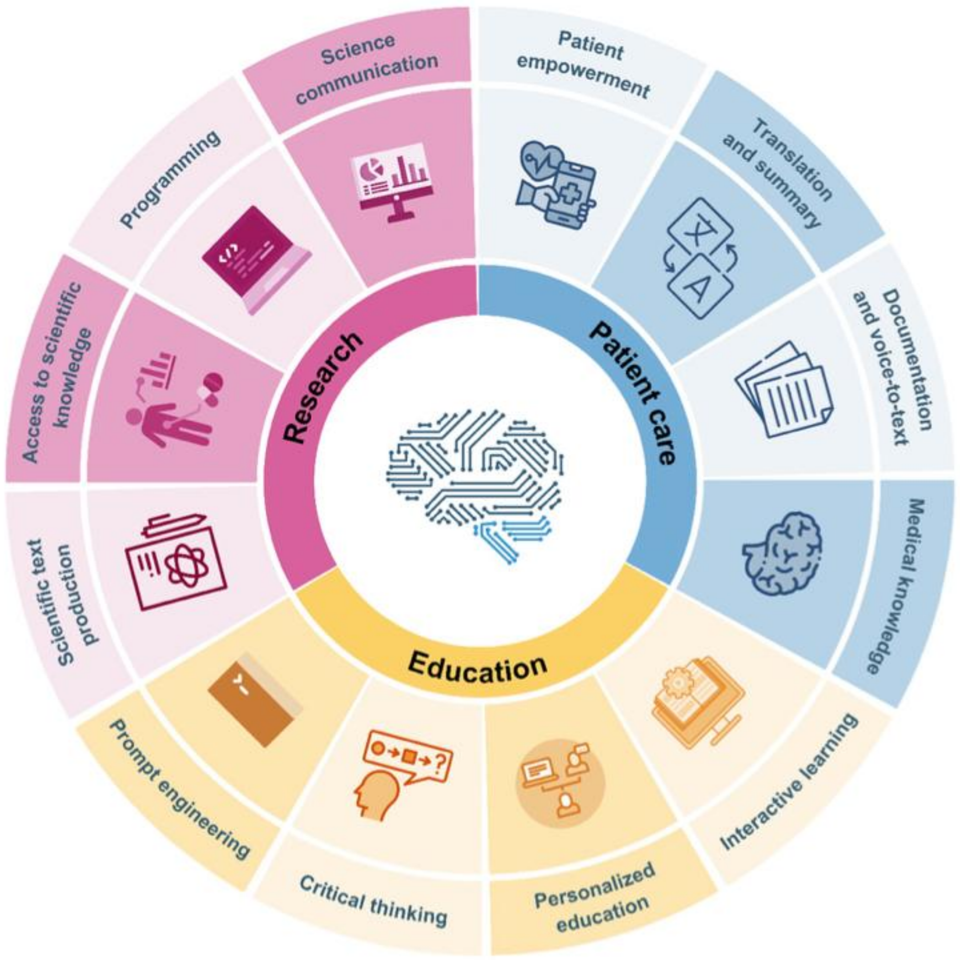
Some have been used in hospitals, despite not being properly tested. But the pandemic could help make medical AI better.

by **Will Douglas Heaven**

July 30, 2021

AI Trends Shaping Imaging
LLMs



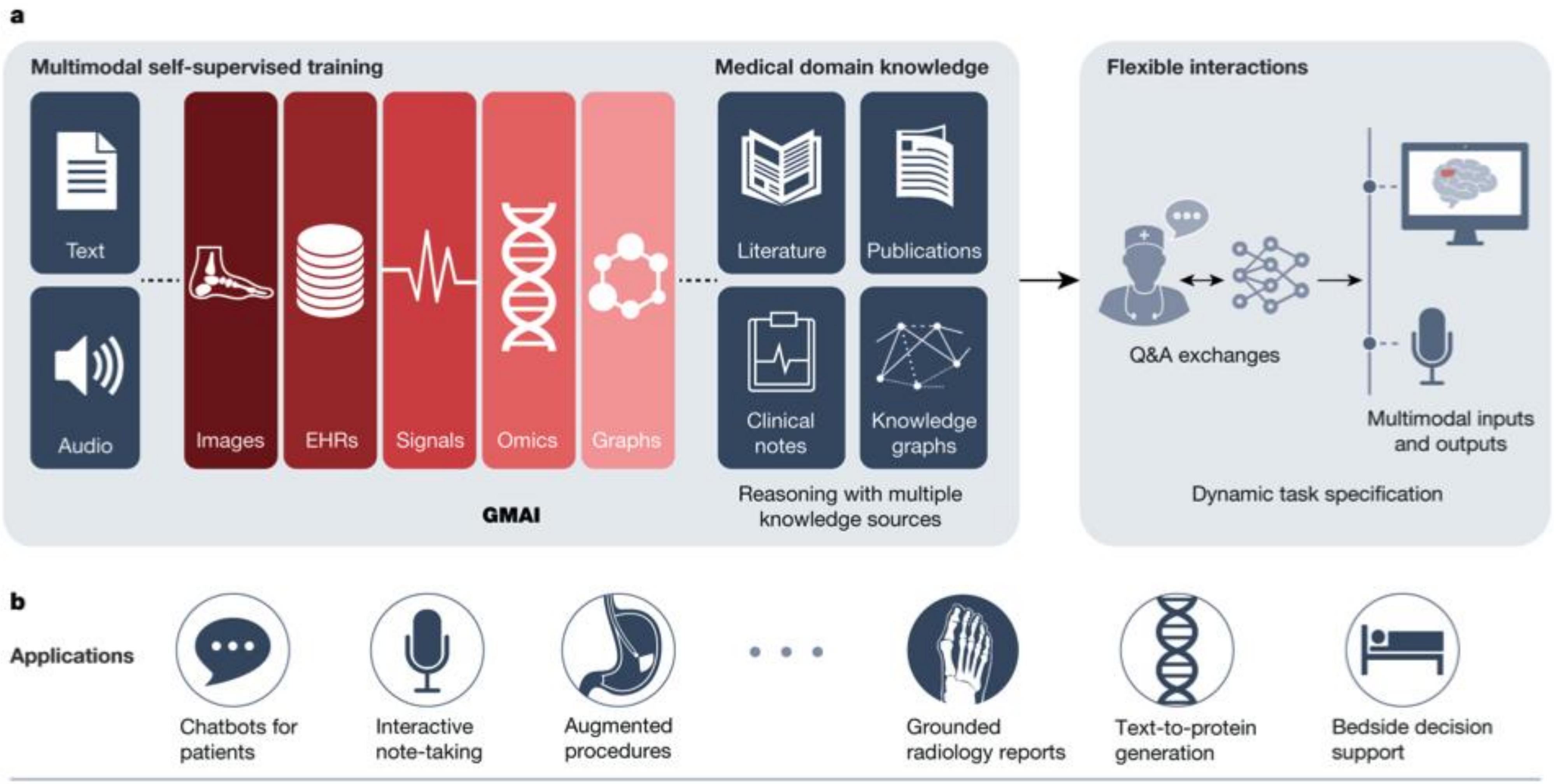


Overview of potential LLM applications

Clusmann, J., Kolbinger, F.R., Muti, H.S. et al. The future landscape of large language models in medicine. Commun Med 3, 141 (2023). https://doi.org/10.1038/s43856-023-00370-1

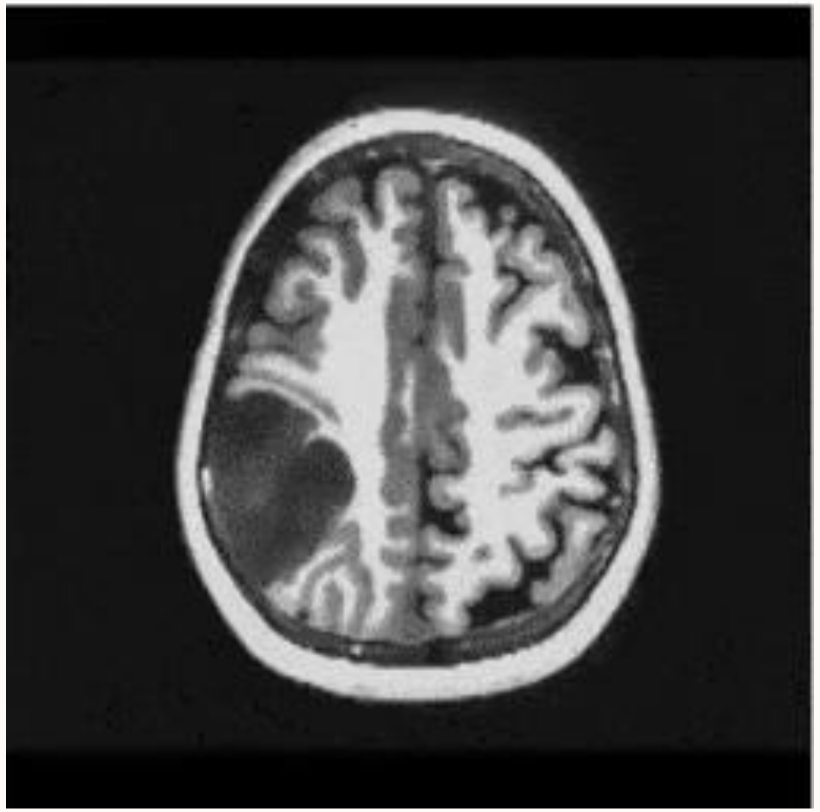
AI Trends Shaping Imaging

Foundation models



Moor, M., Banerjee, O., Abad, Z.S.H. et al. Foundation models for generalist medical artificial intelligence. Nature 616, 259–265 (2023). https://doi.org/10.1038/s41586-023-05881-4

AI Trends Shaping Imaging Diffusion models



Revolutionizing Diagnostics

Enhance detail in low-quality scans, revealing subtle anomalies.

Accelerating Research

Generated datasets accelerate rare disease studies, enabling research without privacy constraints.

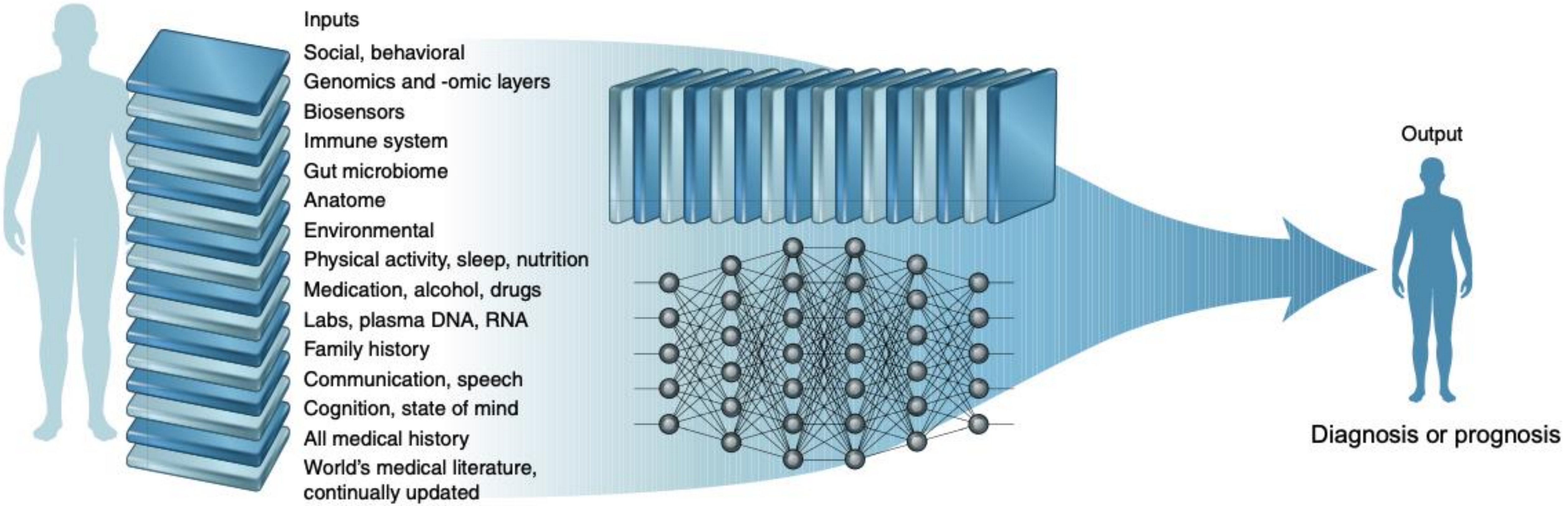
Personalized Medicine

Simulations predict patient-specific treatment responses, visualizing outcomes.

Ethical AI

Synthetic data reduces bias in medical datasets, promoting equitable models.

The Data We Work With



E. Topol, 2017

The Data We Work With

X-Ray & CT

Uses ionizing radiation to create images. Fast but involves radiation exposure.

- CT provides 3D visualization of internal structures
- Widely used for bone and lung imaging

MRI

Uses magnetic fields to generate detailed tissue images. Non-ionizing and safe.

- Superior soft tissue contrast
- Functional MRI captures brain activity

Ultrasound & Nuclear

Ultrasound uses sound waves. Nuclear imaging requires radioactive tracers.

- Ultrasound is real-time and non-invasive
- PET/SPECT show metabolic function

Challenges

High volume of scans

Challenges

- # Radiology scans
- # Trained radiologists

High volume of scans

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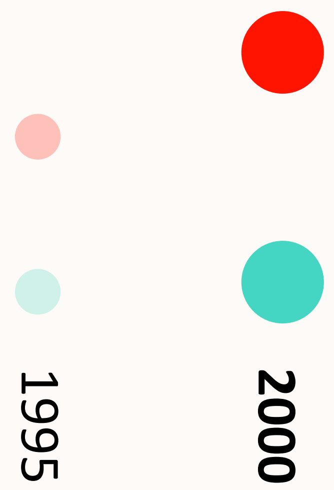
High volume of scans

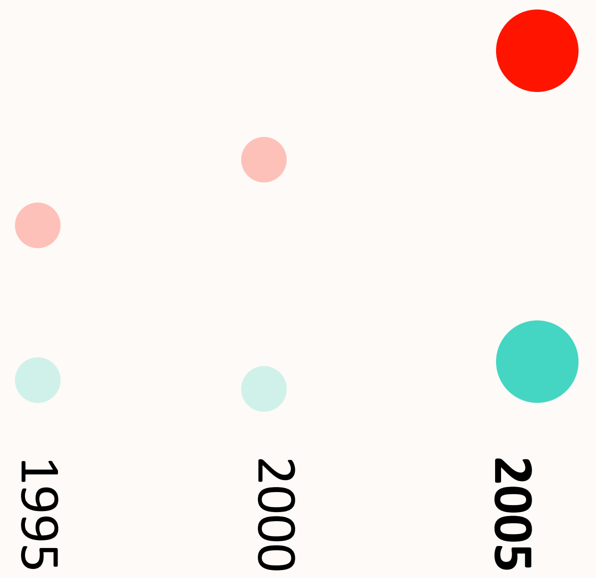


Challenges

Radiology scans

Trained radiologists

High volume of scans



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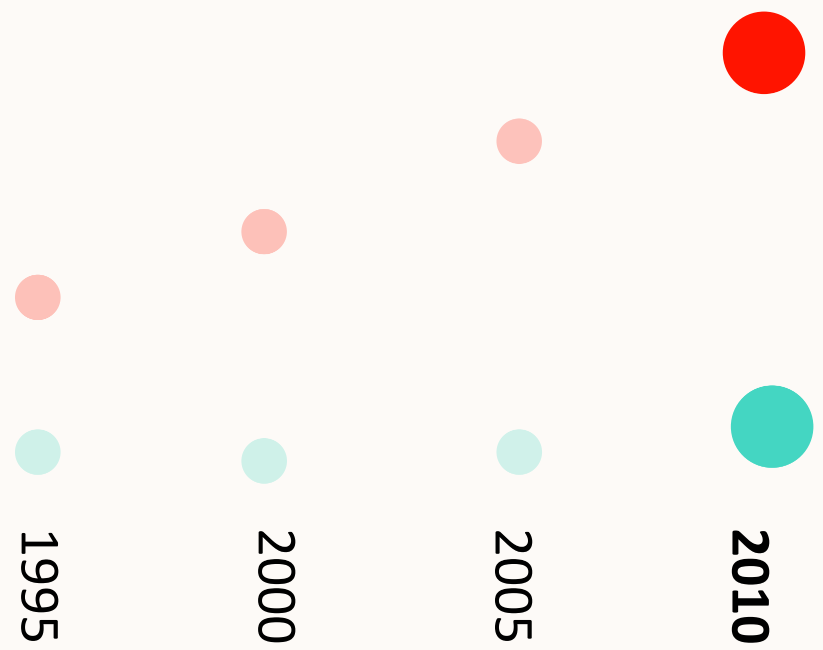

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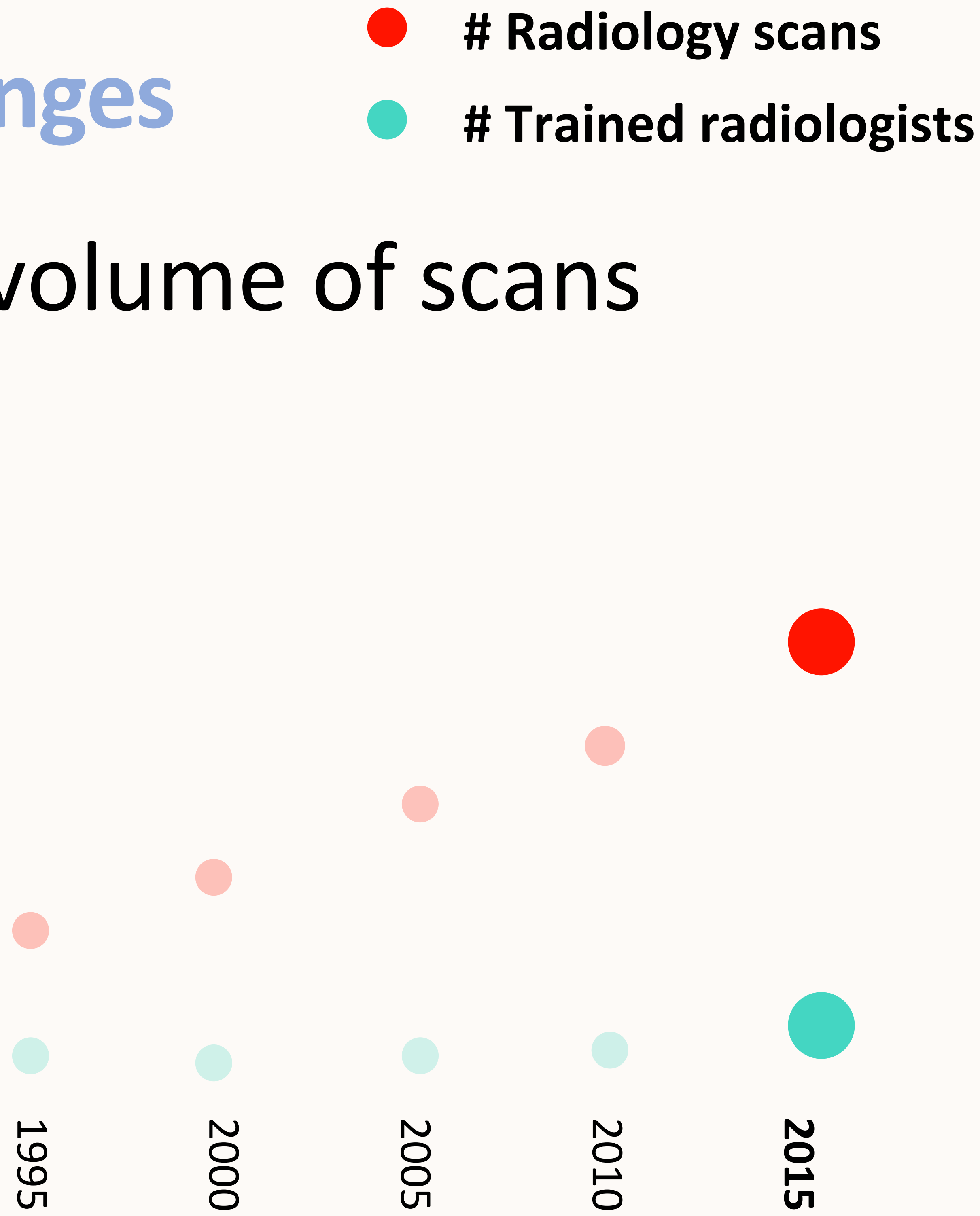

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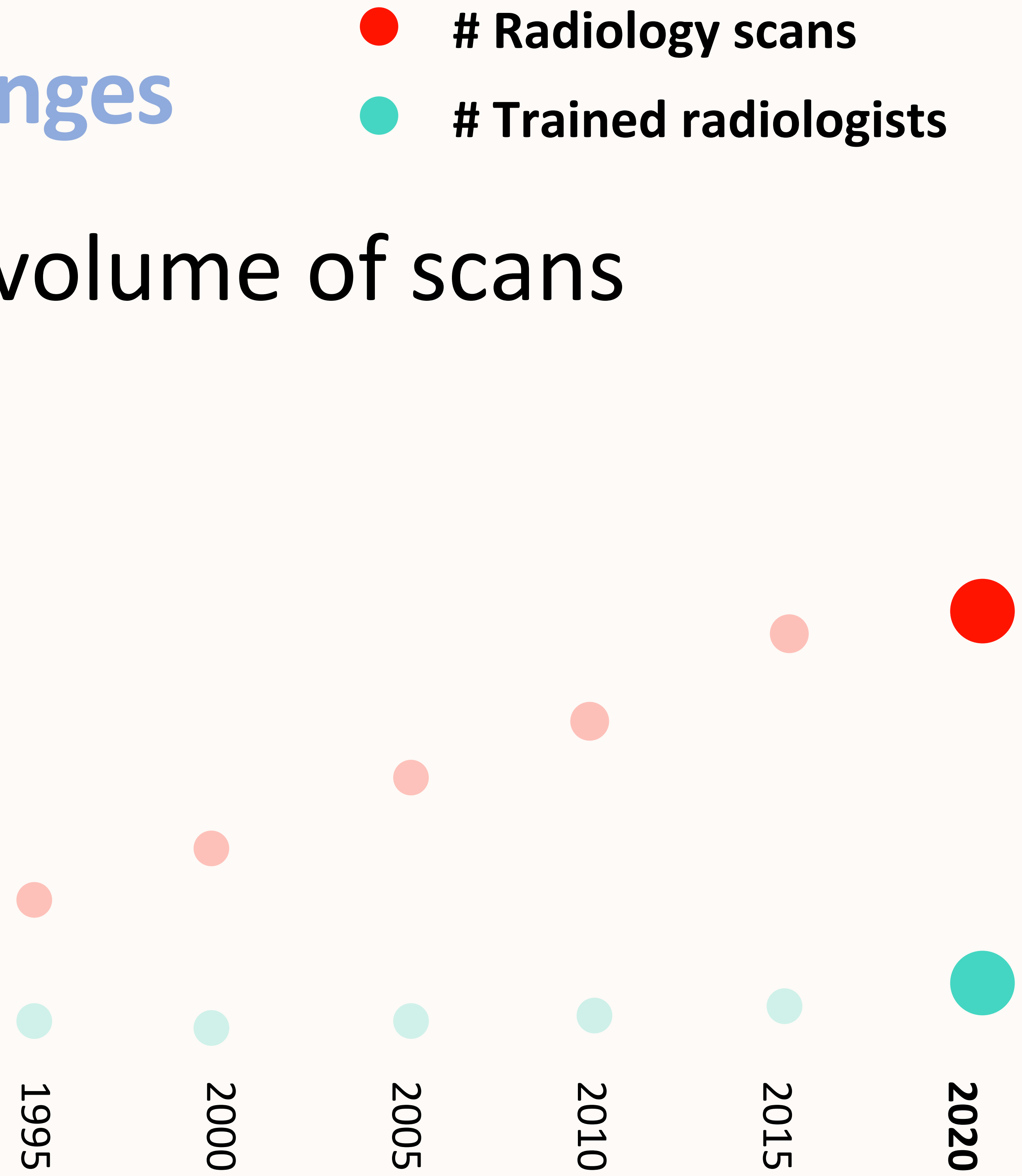

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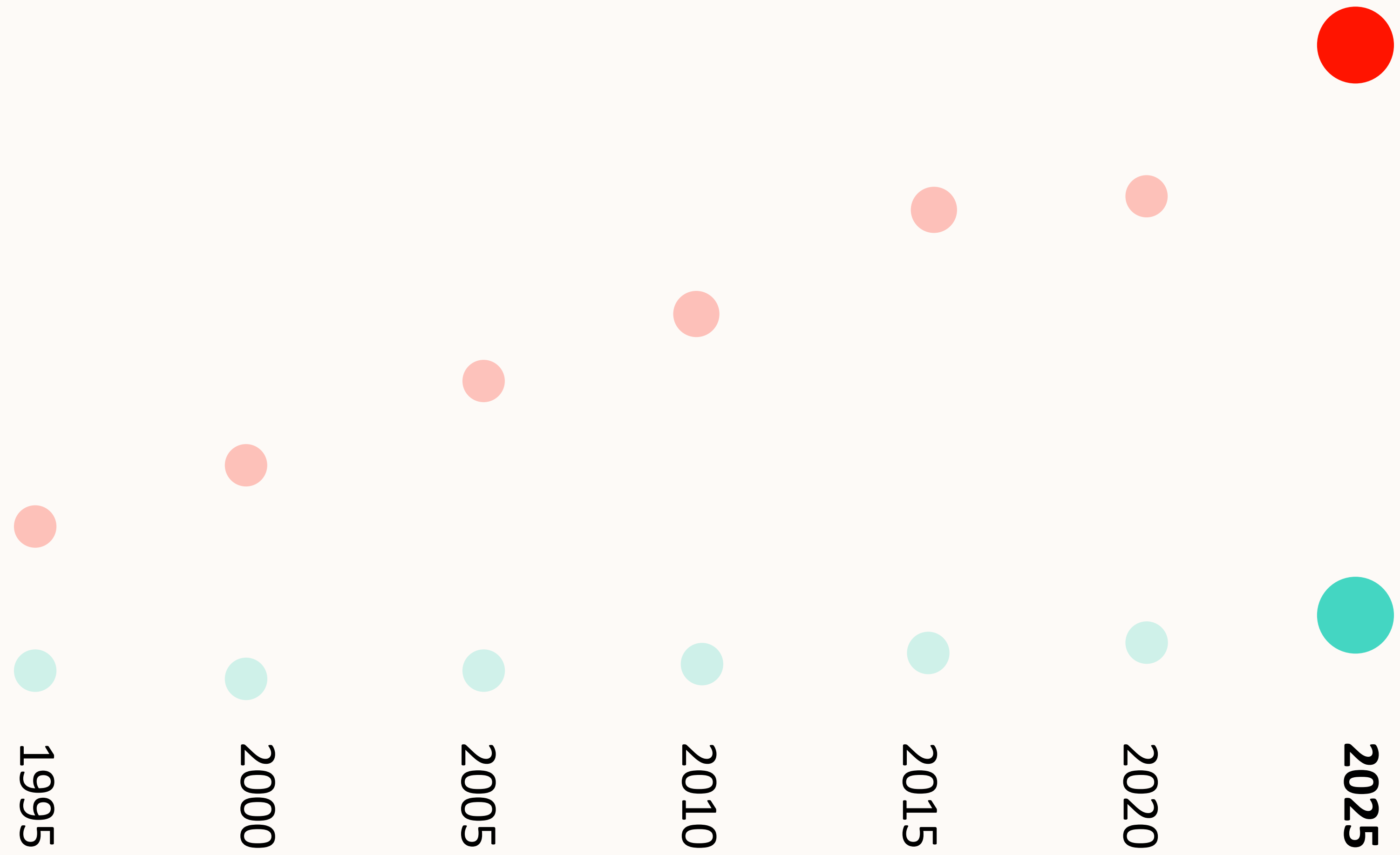

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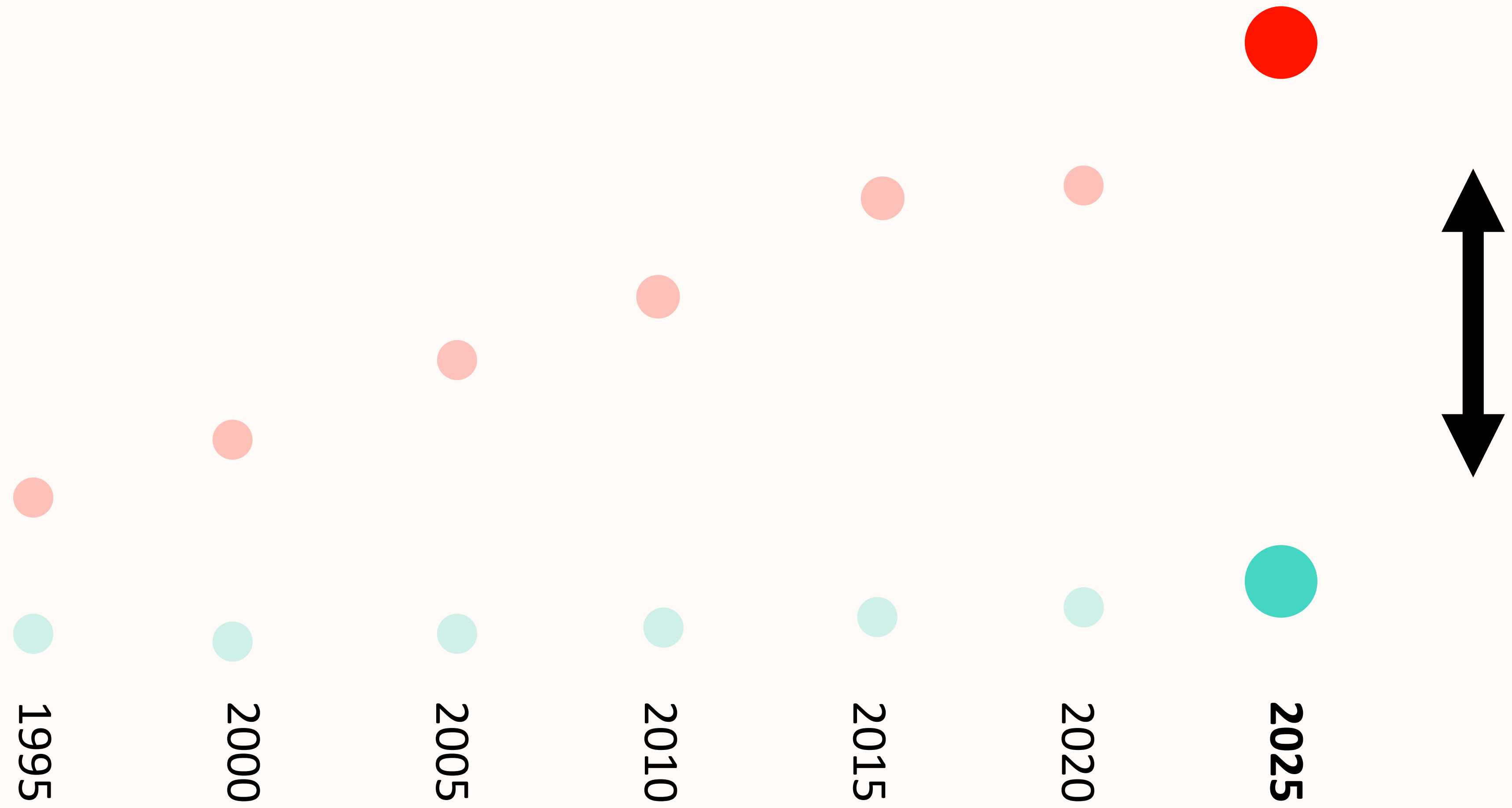

Radiologist shortage

Challenges

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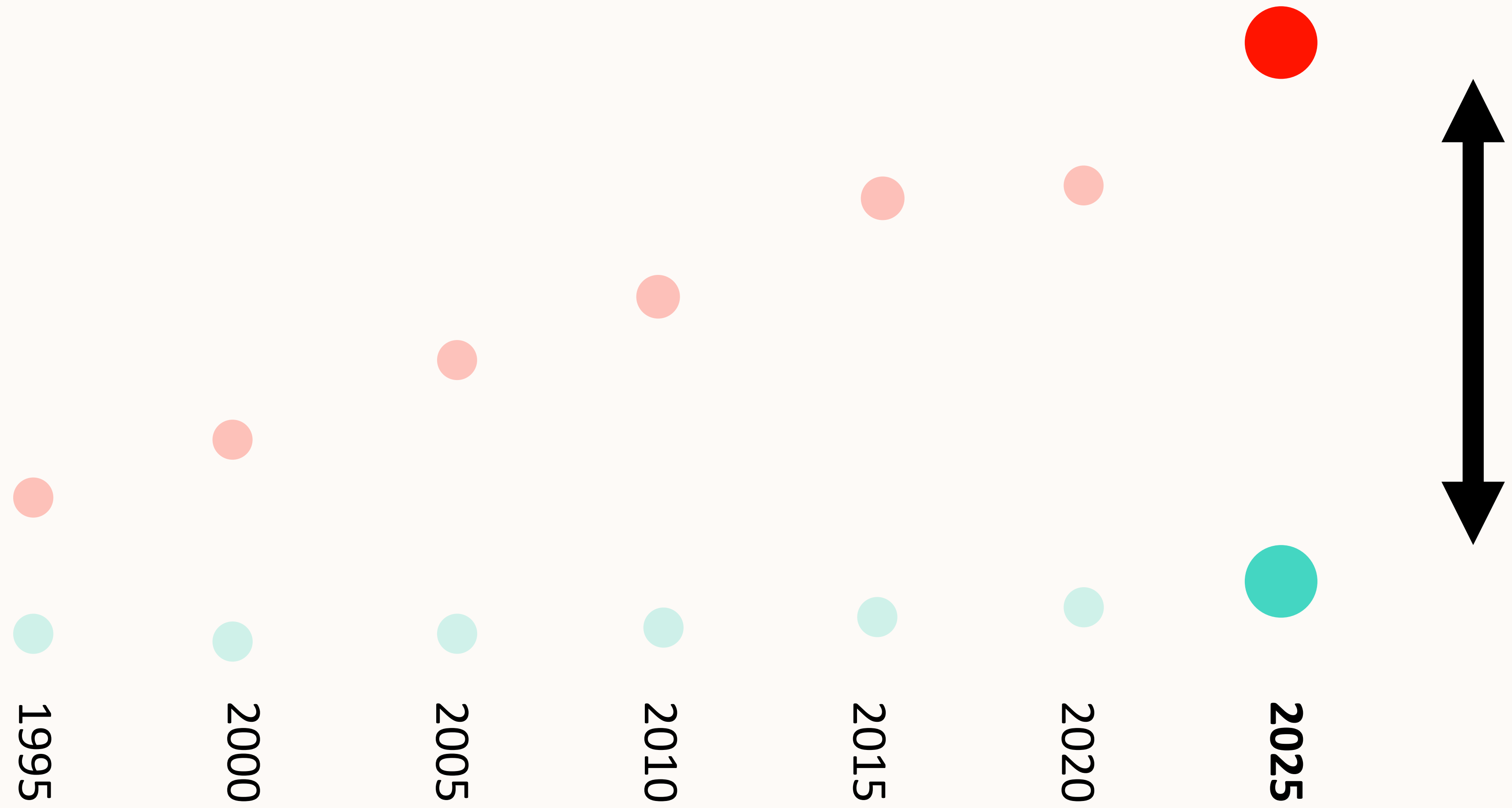

0 %

Radiologist shortage

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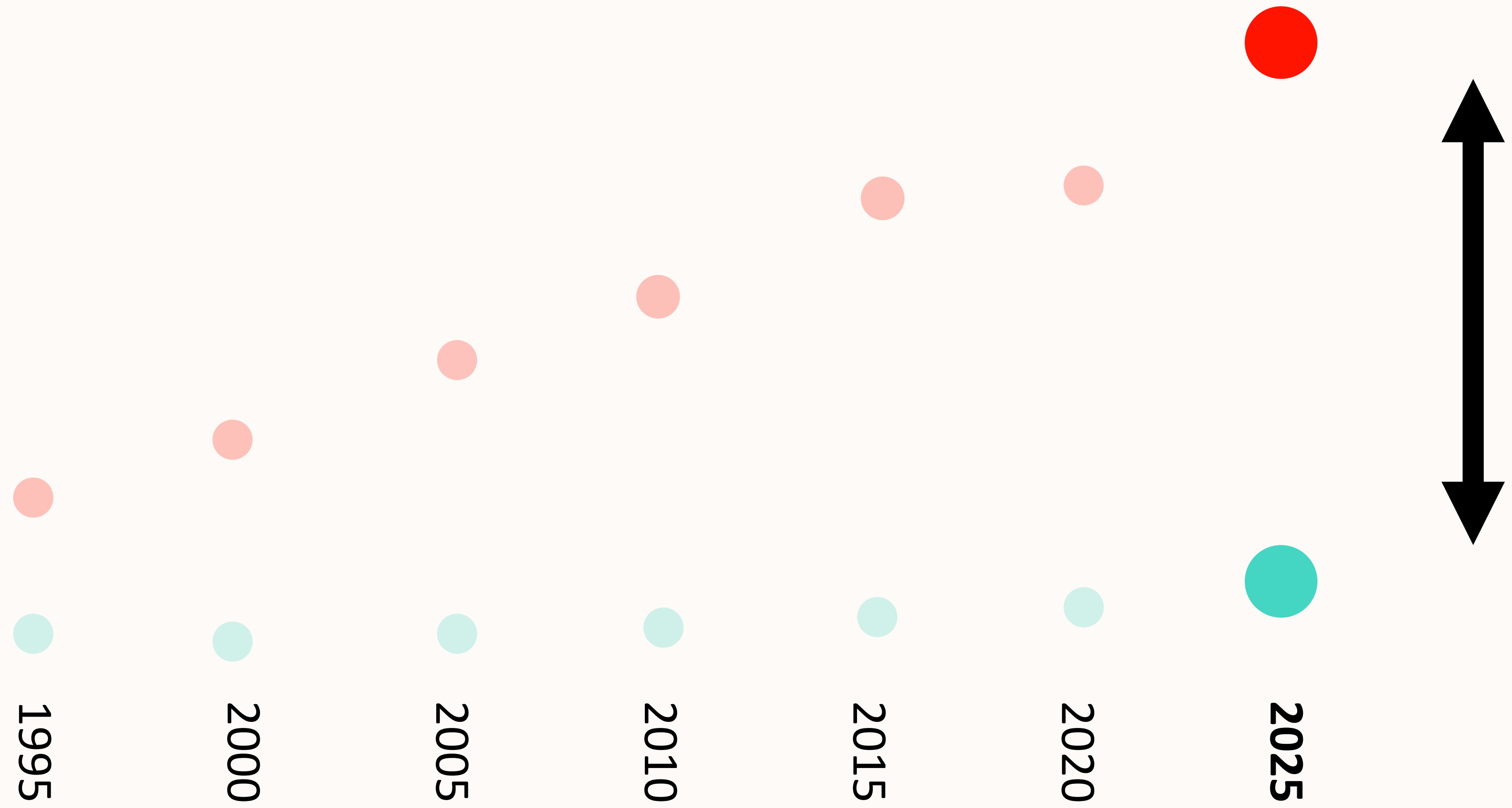

50 %

Radiologist shortage

Challenges

Radiology scans

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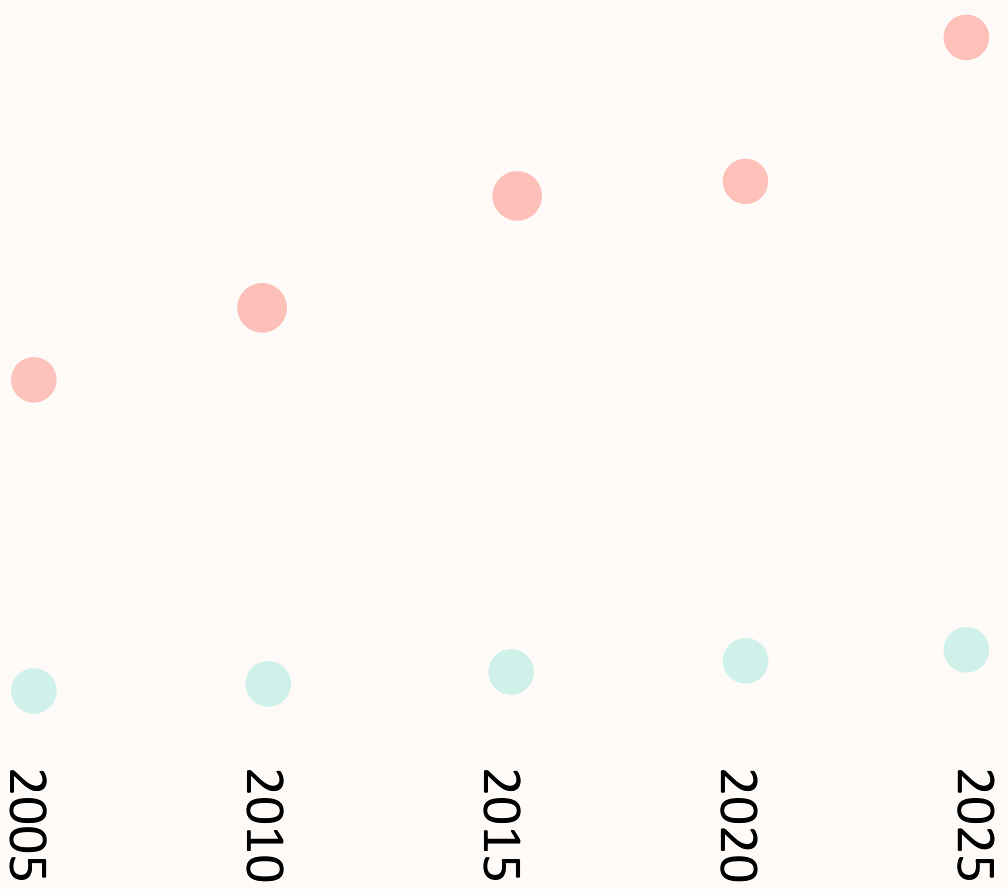

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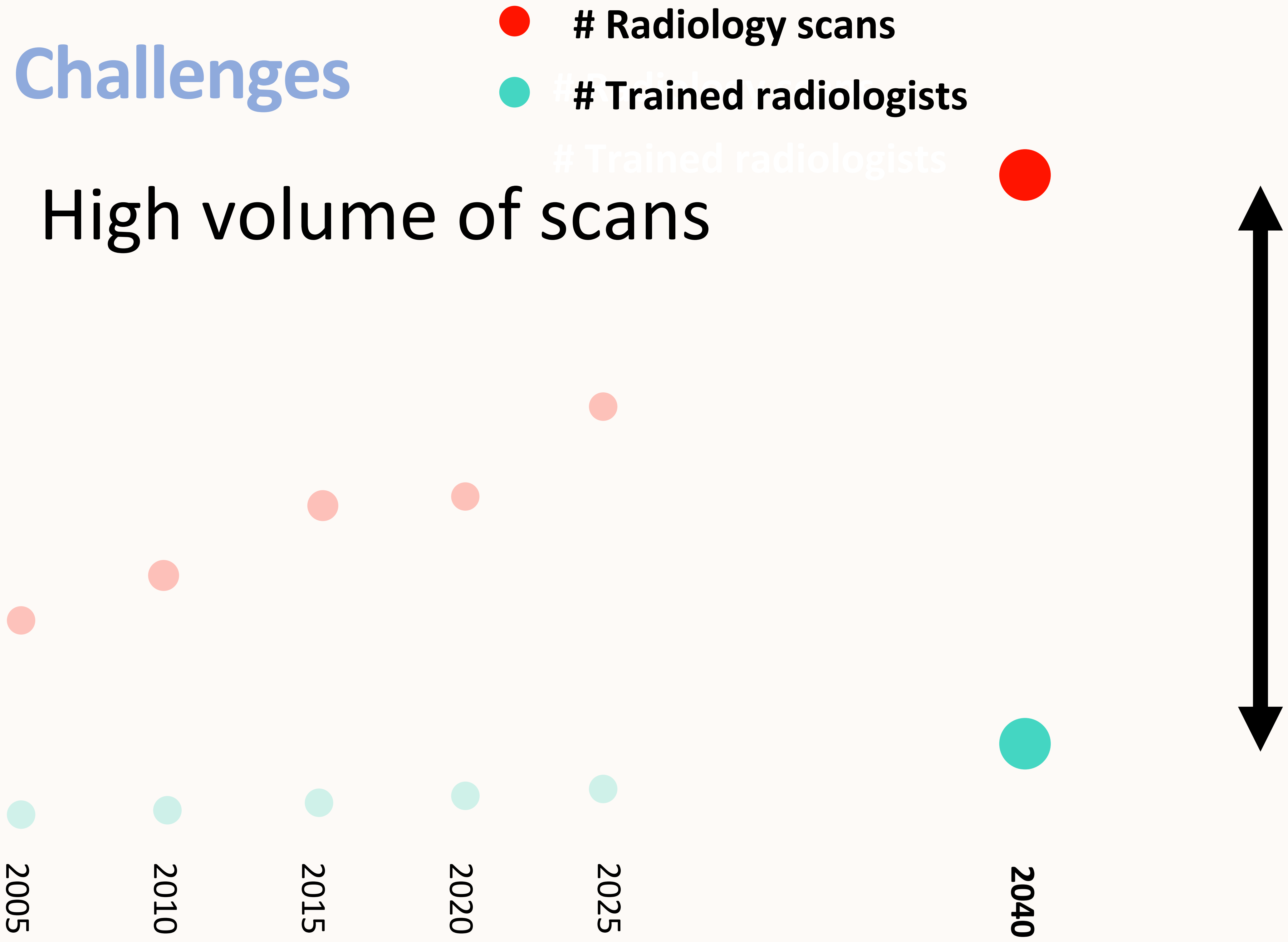
Challenges

High volume of scans



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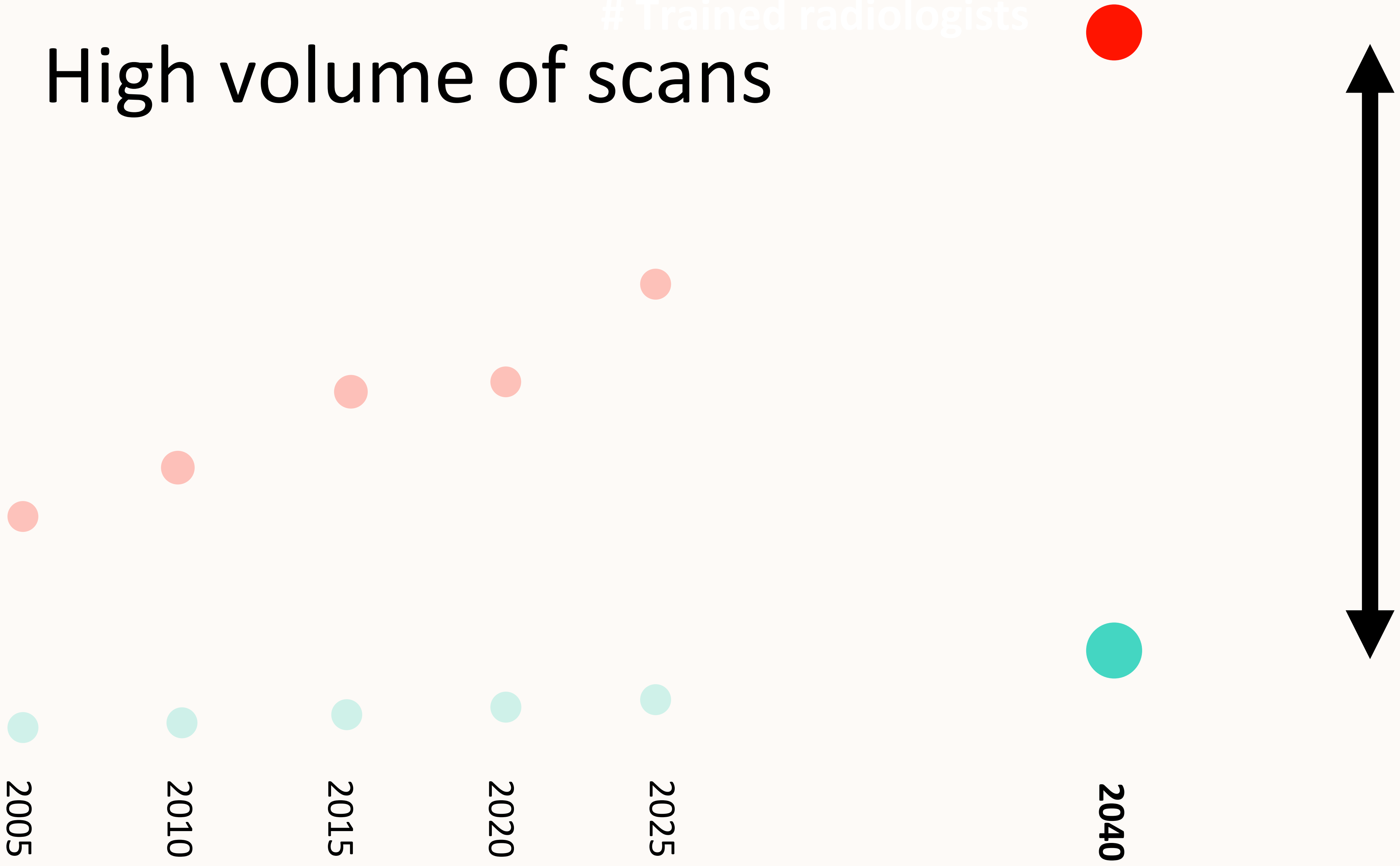

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Radiologist shortage

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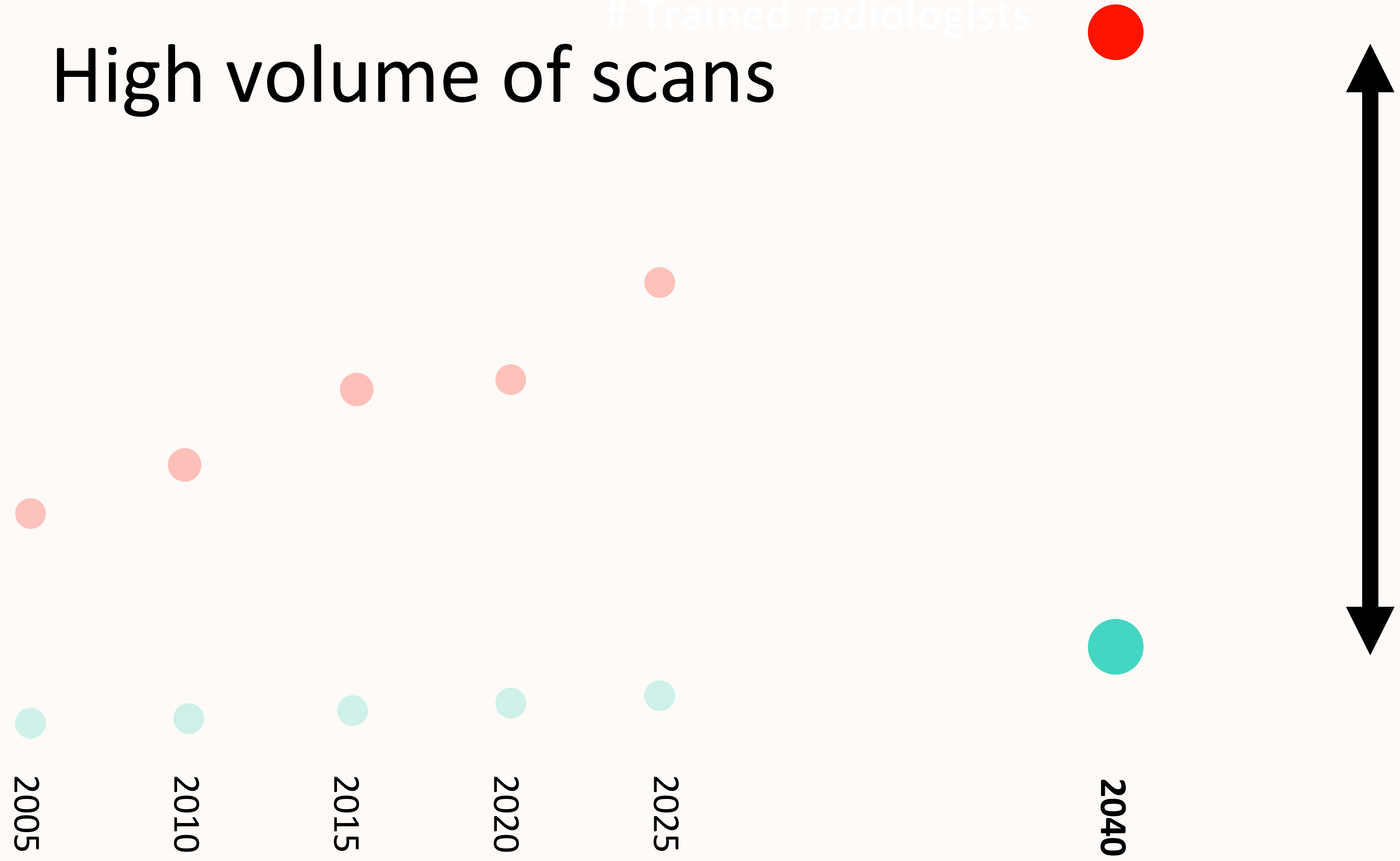

75 %

Radiologist shortage

Challenges

Trained radiologists

75 %

Radiologist
shortage

Challenges

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75 %

Radiologist shortage

Challenges

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Radiologist shortage

Challenges

Trained radiologists

Increased workloads

Strain on radiologists with increased workloads

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Radiologist shortage

Challenges

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Reporting delays

> 220K scans reported after 28 days in the UK in 2024

75 %

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Missed pathologies

> 40 Million errors worldwide

Challenges

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75 %

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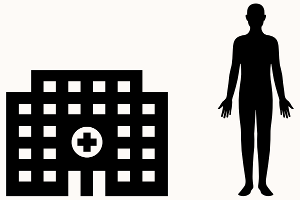

Where do most errors occur?

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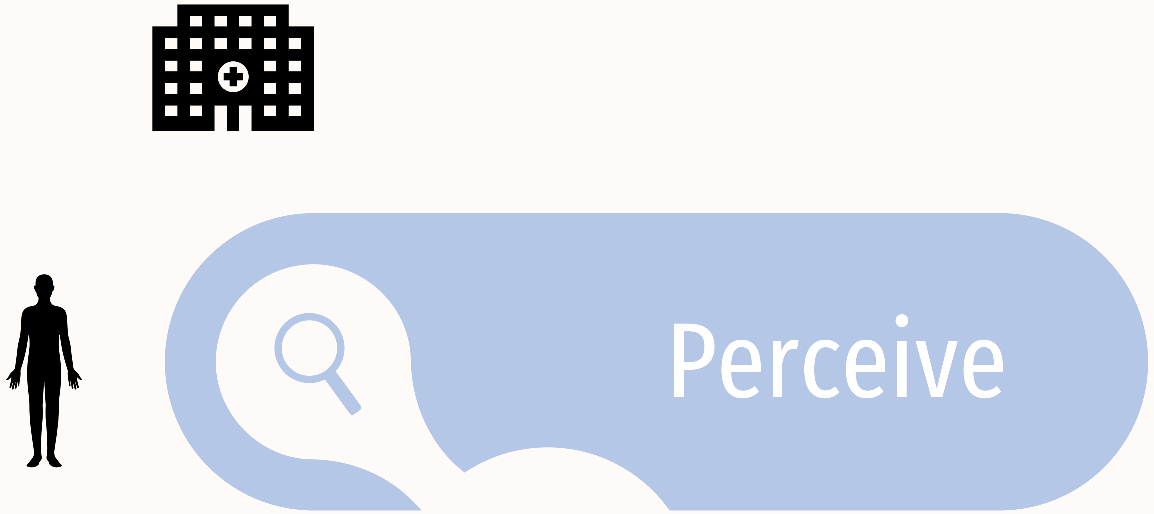
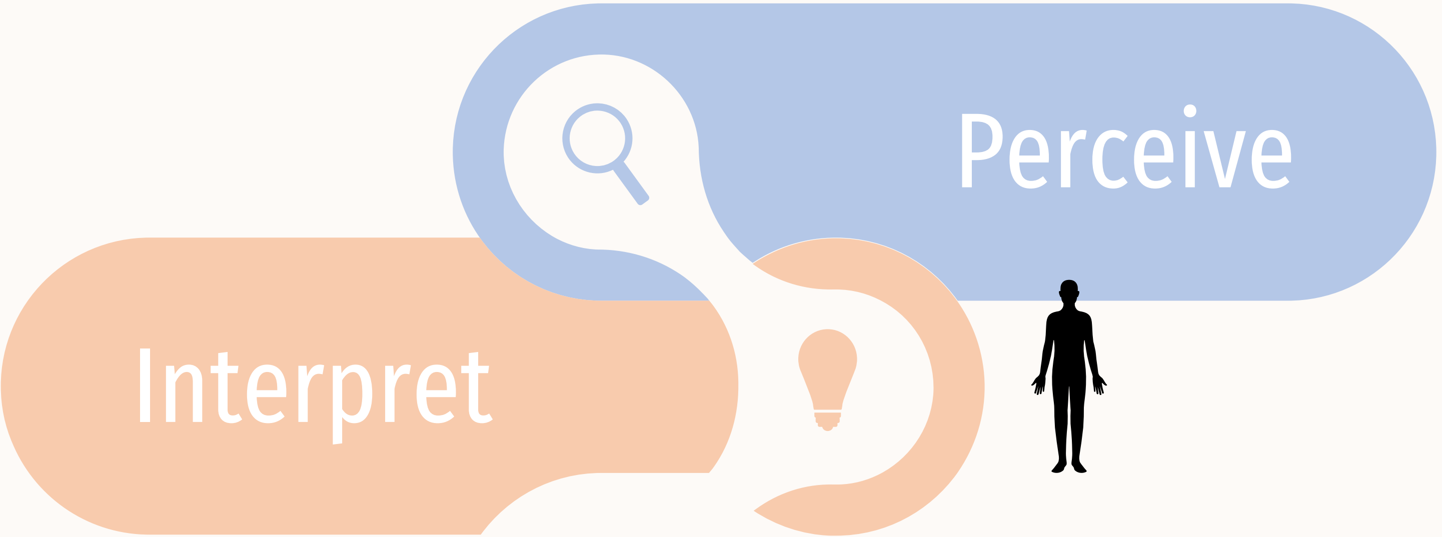


Detect and localize radiological findings

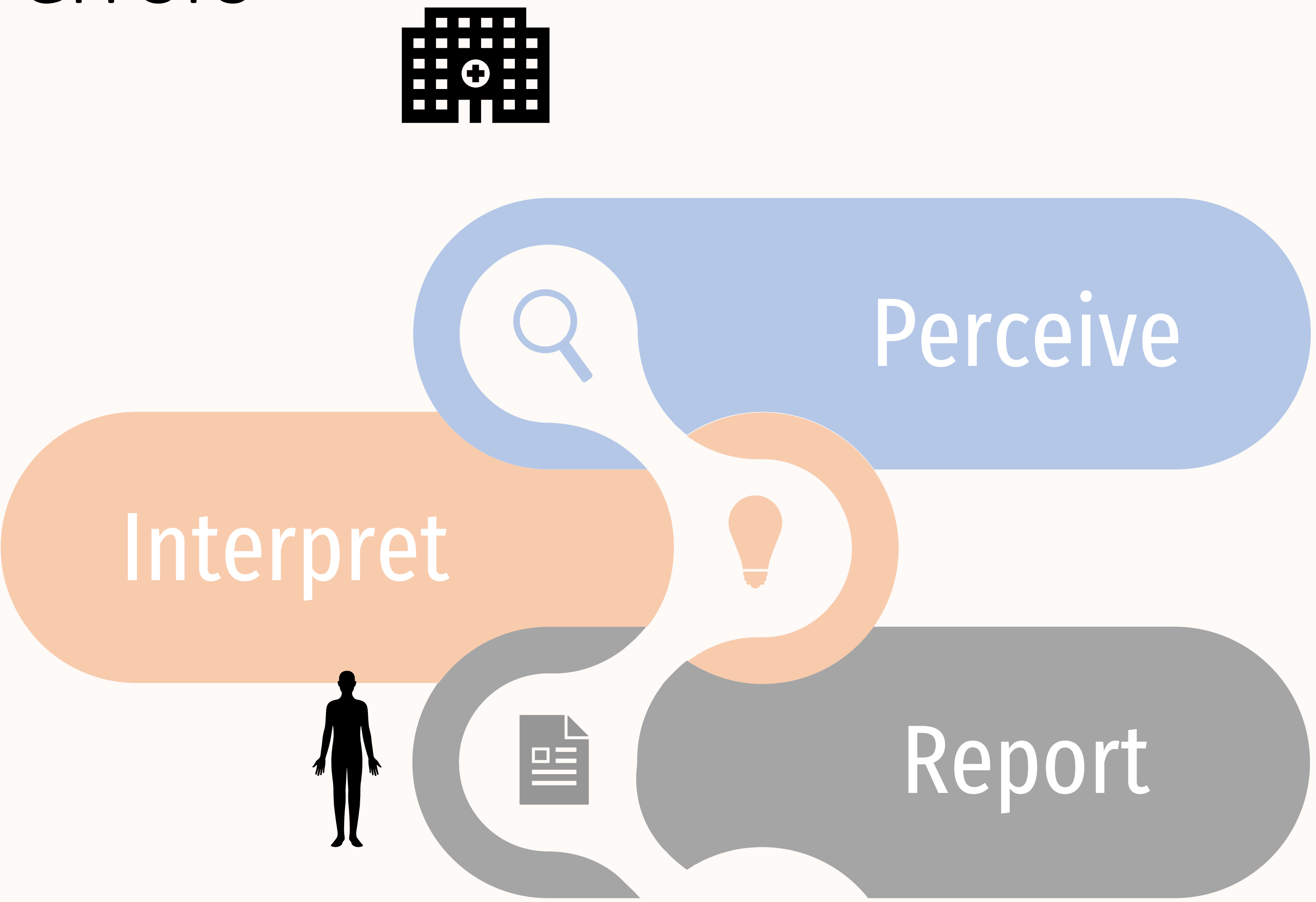
Where do most errors occur?



Detect and localize radiological findings

Diagnostic inference
Decision Making

Where do most errors occur?

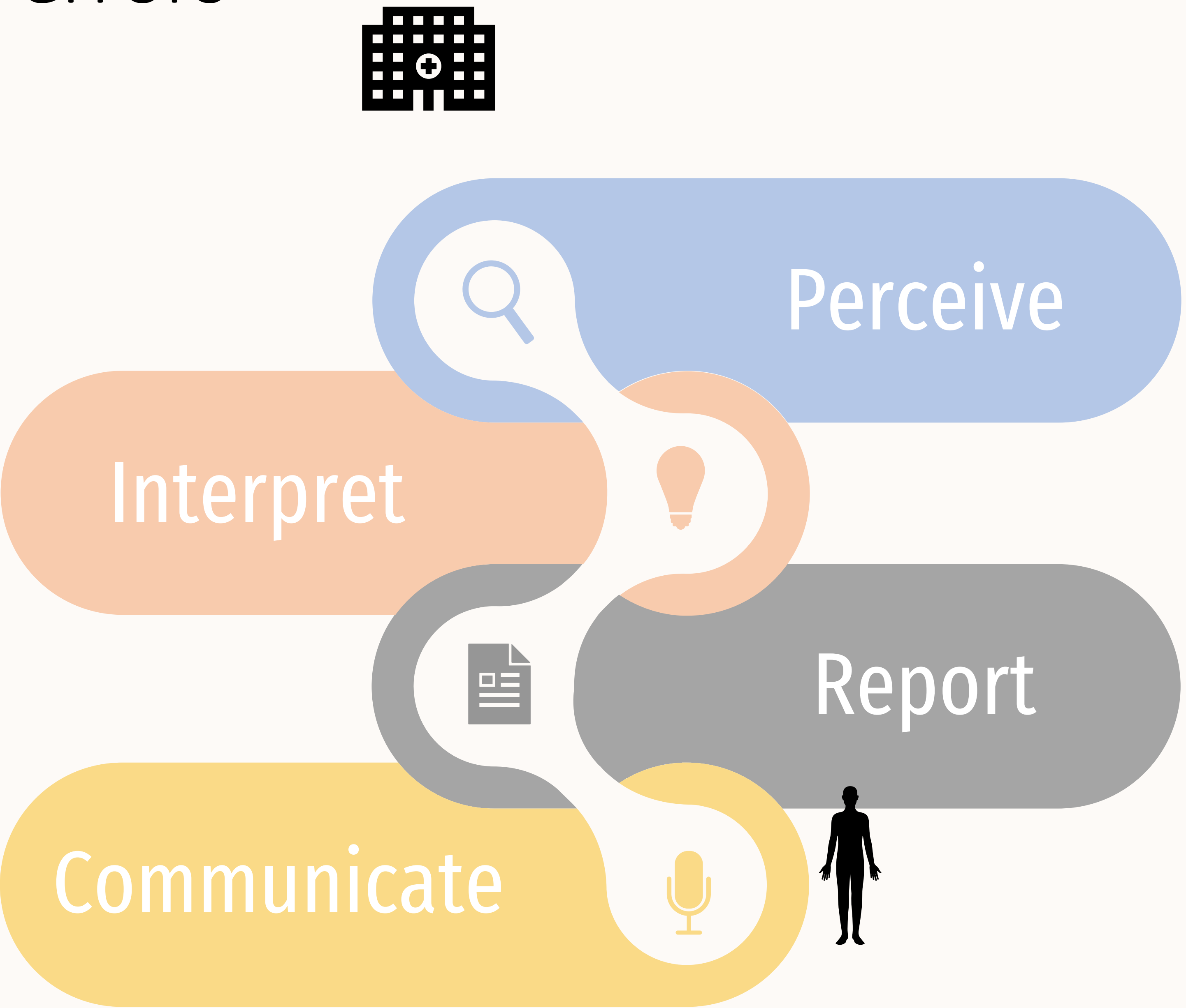


Detect and localize radiological findings

Diagnostic inference
Decision Making

Documentation of the radiological findings

Where do most errors occur?



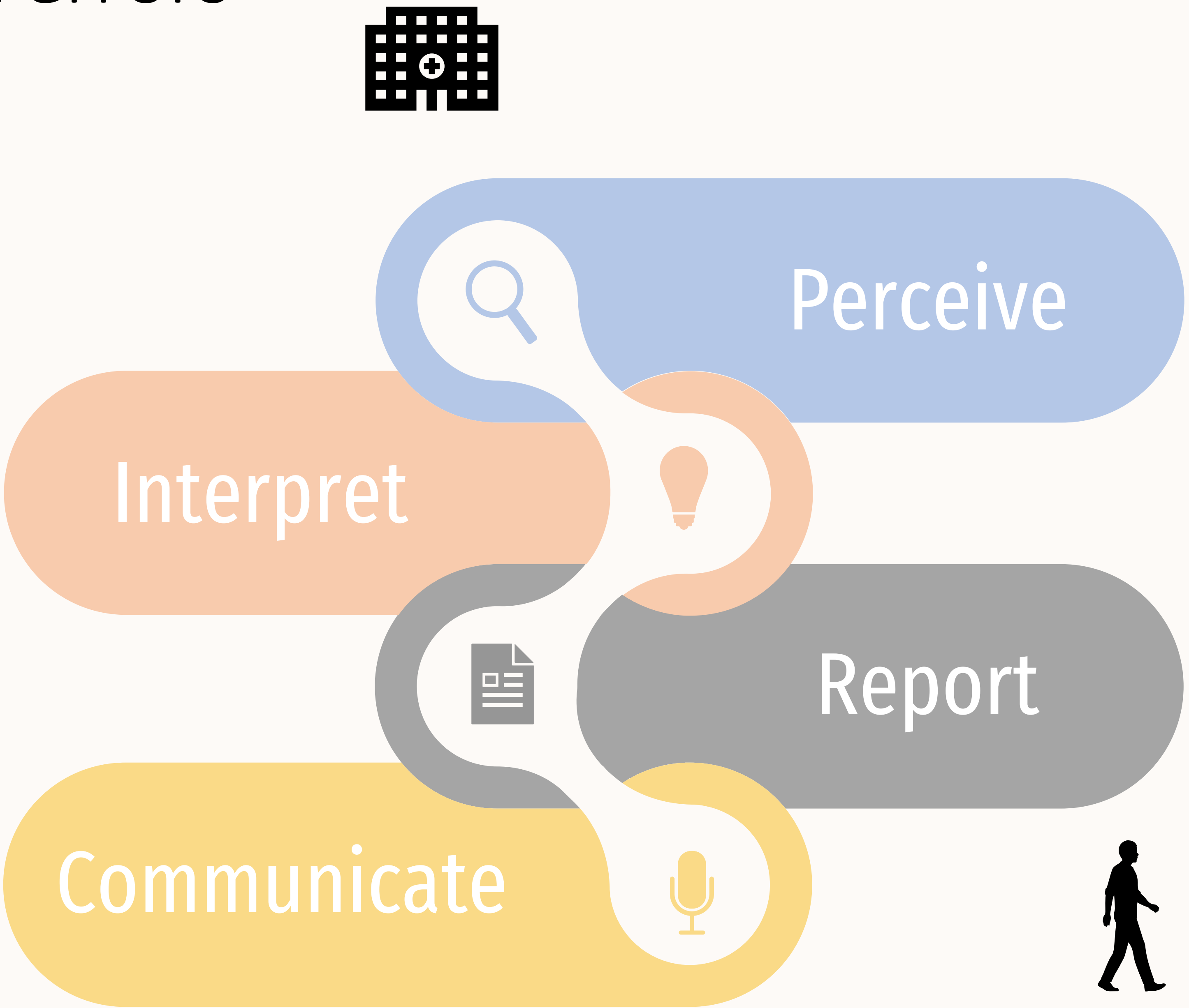
Detect and localize radiological findings

Diagnostic inference
Decision Making

Documentation of the radiological findings

Results communication
Actioning
Treatment planning

Where do most errors occur?



Detect and localize radiological findings

Diagnostic inference
Decision Making

Documentation of the radiological findings

Results communication
Actioning
Treatment planning

Where do most errors occur?

Most human errors made

Detect and localize radiological findings

Diagnostic inference
Decision Making

Documentation of the radiological findings

Results communication
Actioning
Treatment planning

Diagnostic inference
Decision Making

Results communication
Actioning
Treatment planning

Detect and localize
radiological findings

Documentation of the
radiological findings

AI can assist radiologists!

Medical Imaging Pipeline

Acquisition

Raw data collection from MRI, CT, or other imaging devices.

Undersampling & Reconstruction

Accelerates imaging by filling in missing data points.

Synthesis & Editing

Creates realistic synthetic pathologies for training.

Normative Modeling & UAD

Identifies abnormalities without explicit labels.

Language-Driven Diagnosis

Future: LLMs will interpret findings and guide examination.

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What Are Diffusion Models?

Forward Process

Gradually add Gaussian noise to data until it becomes pure noise.

Reverse Process

Learn to denoise step-by-step, reconstructing the original data.

Score Function

Estimate gradient of data distribution log probability.

Diffusion Models

Forward Process

$q(x_t|x_{t-1}) = N(x_t; \sqrt{(1-\beta_t)}x_{t-1}, \beta_t I)$

Gradually add noise to medical images until they become pure Gaussian noise.

Neural Network

$\varepsilon_\theta(x_t, t) \approx$ noise

Model learns to predict the noise added at each timestep.

Reverse Process

$p_\theta(x_{t-1}|x_t) = N(x_{t-1}; \mu_\theta(x_t,t), \Sigma_\theta(x_t,t))$

Generate synthetic medical data by reversing noise addition step-by-step.

Synthetic data generation solves the challenge of rare disease underrepresentation and privacy constraints in medical datasets.

Synthetic Data — Why It Matters

Privacy-Preserving

Generated data shares no identifiable information from real patients.

Enables broader sharing and collaboration across institutions.

Rare Disease Representation

Create unlimited examples of conditions with limited real samples.

Balance datasets that would otherwise be heavily skewed.

Data Augmentation

Improve model robustness through diverse synthetic examples.

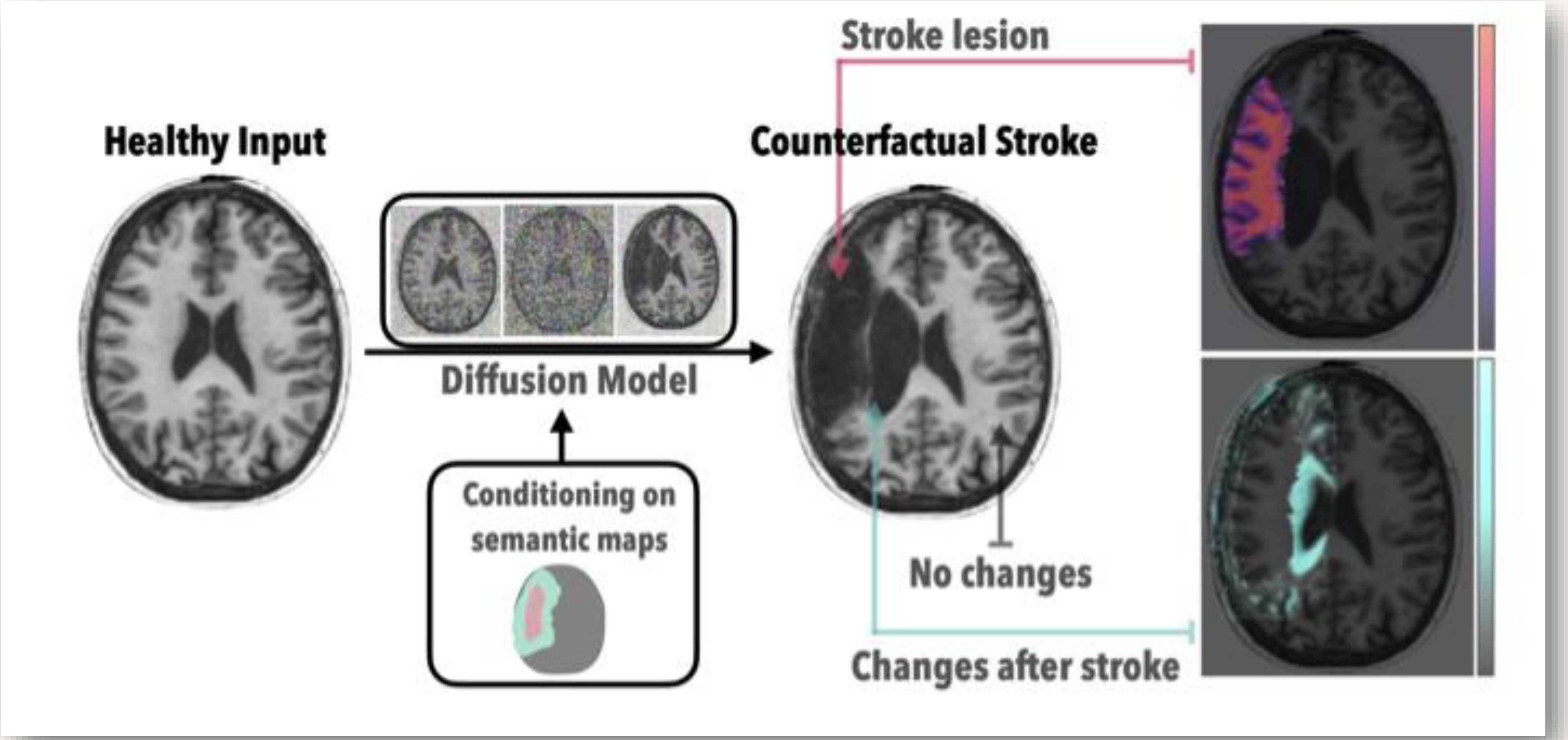
Test against variations not present in original data.

Conditional Generation

“An image of the pope”

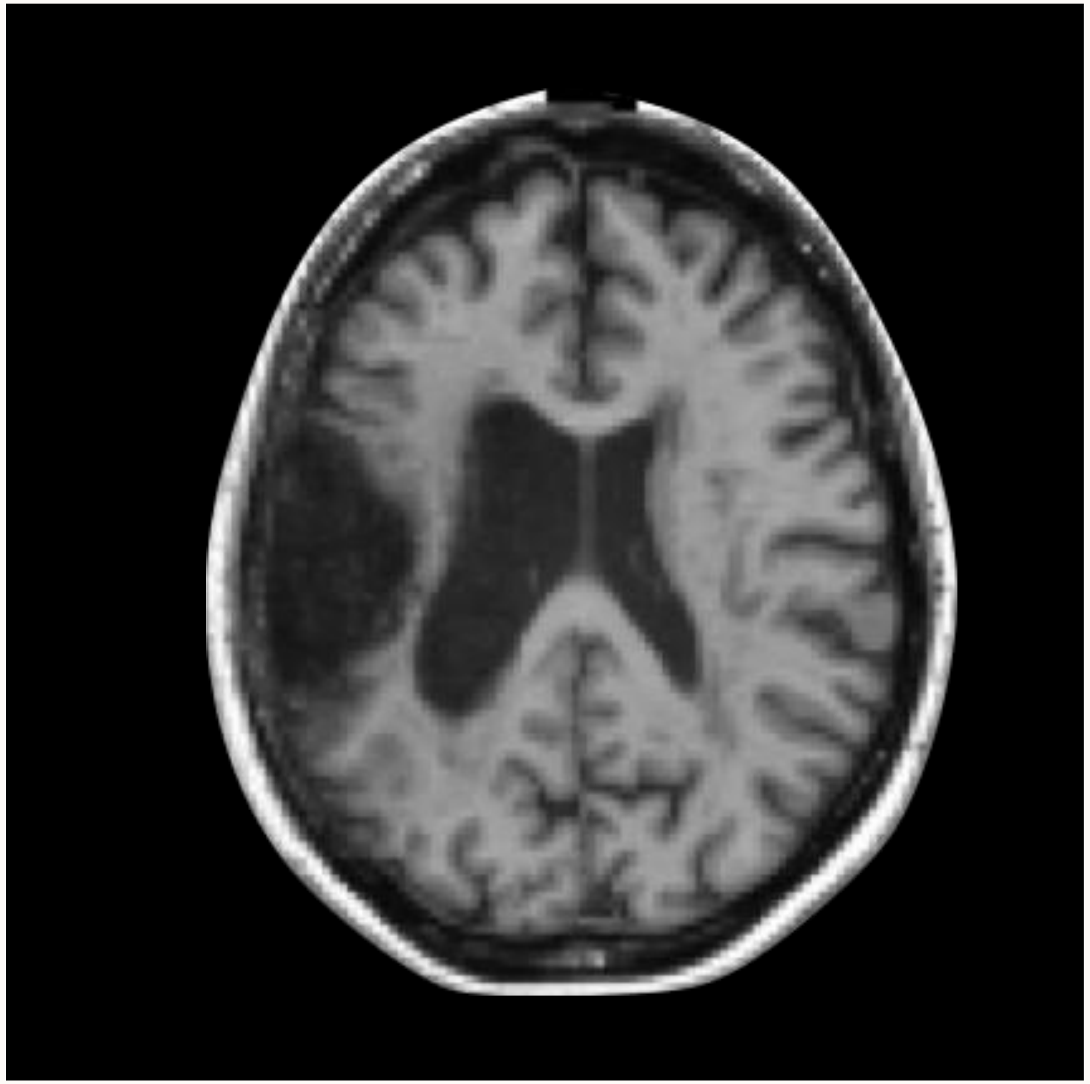
MedEDIT

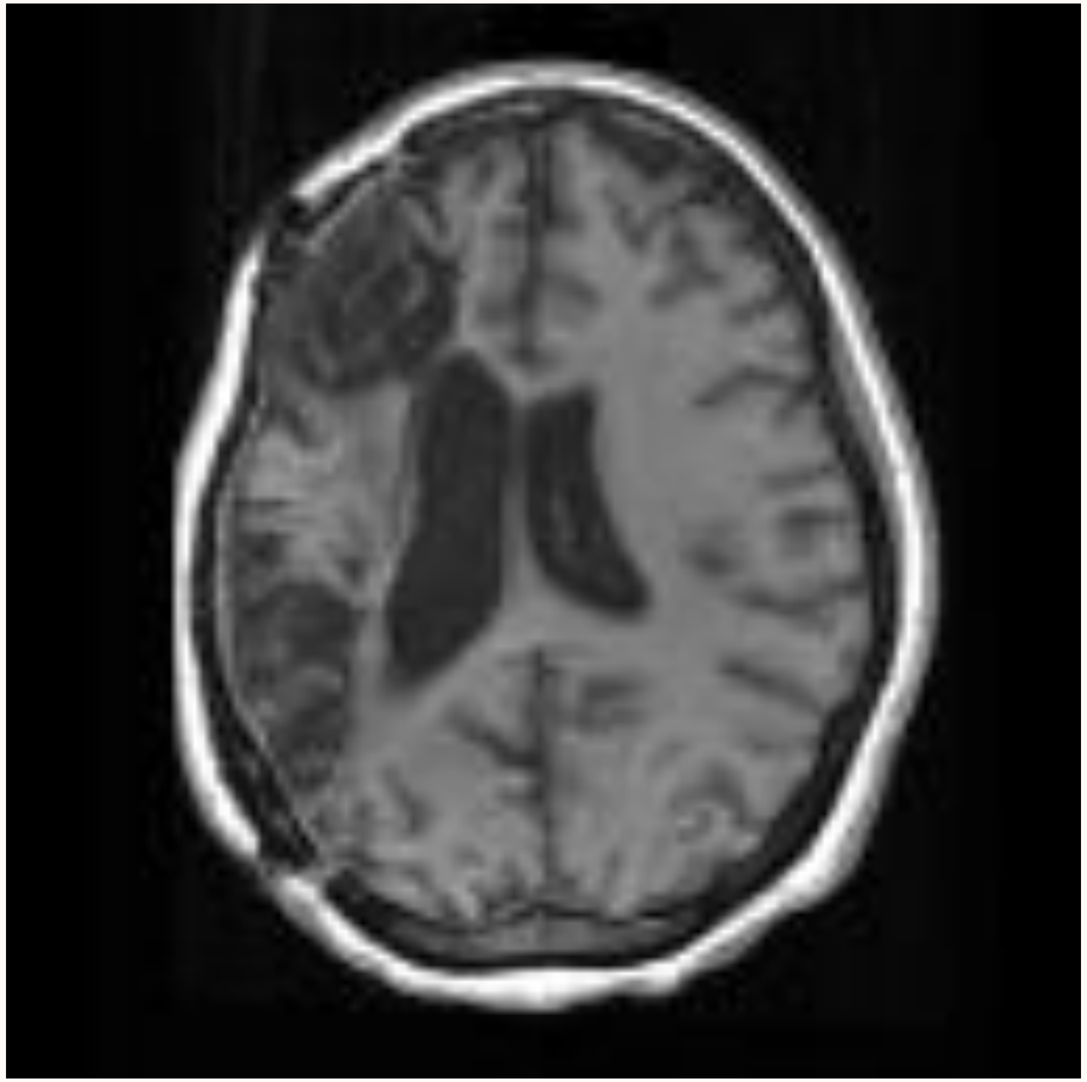
Malek Ben Alaya



Alaya, M. B., Lang, D. M., Wiestler, B., Schnabel, J. A., & **Bercea, C. I.** (2024, October). MedEdit: Counterfactual Diffusion-Based Image Editing on Brain MRI. In *International Workshop on Simulation and Synthesis in Medical Imaging*(pp. 167-176). Cham: Springer Nature Switzerland.

Real or AI?





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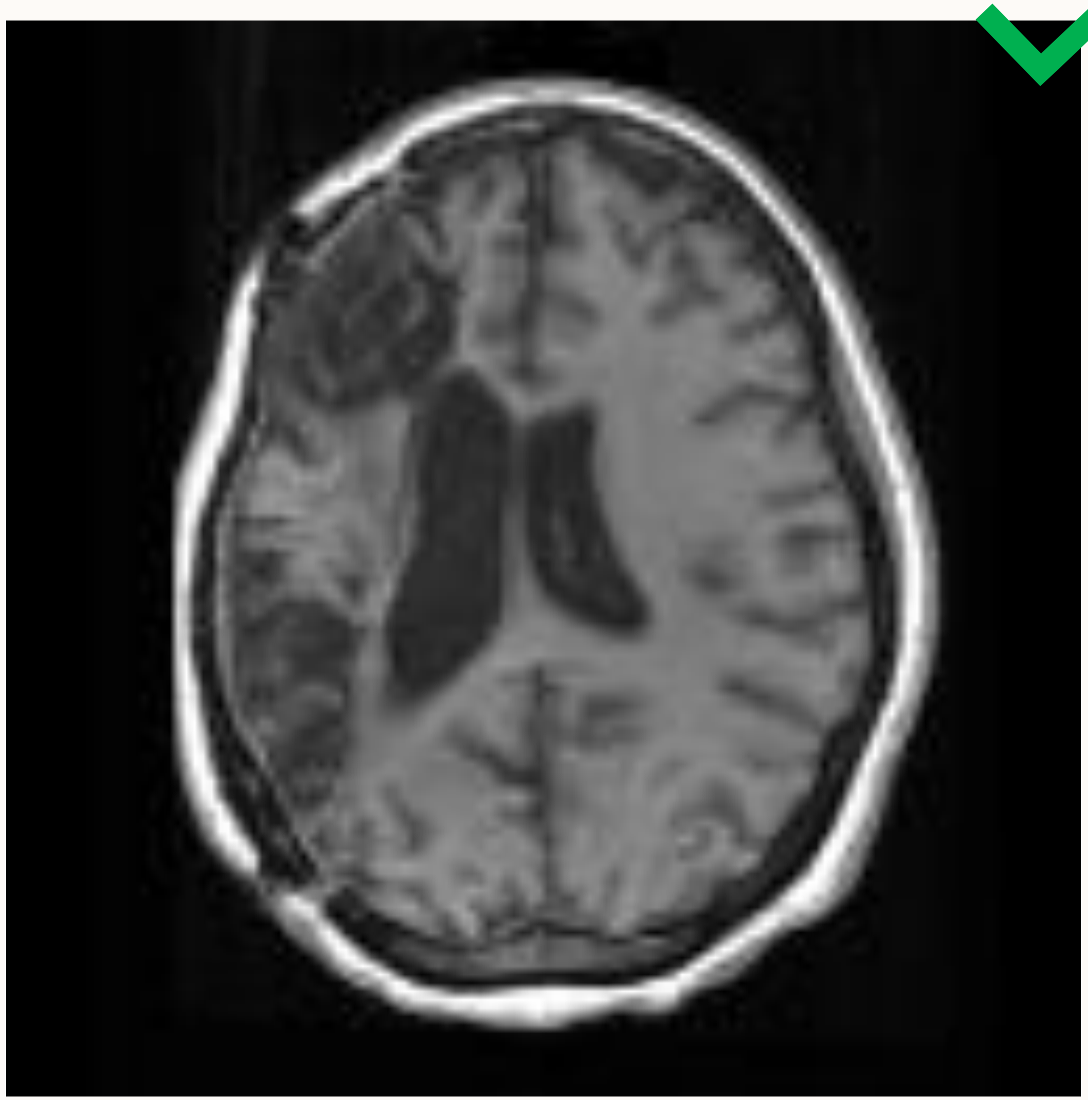

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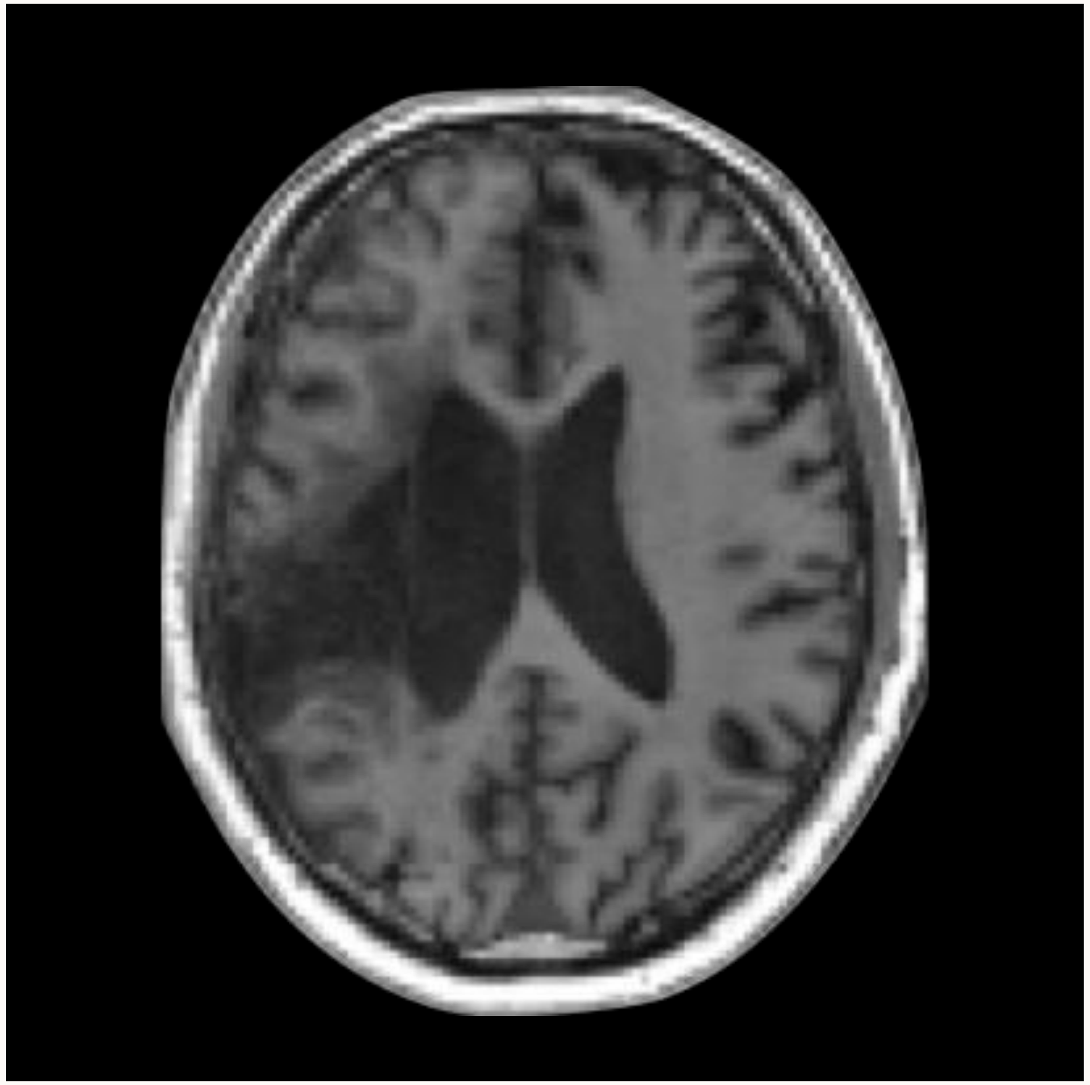

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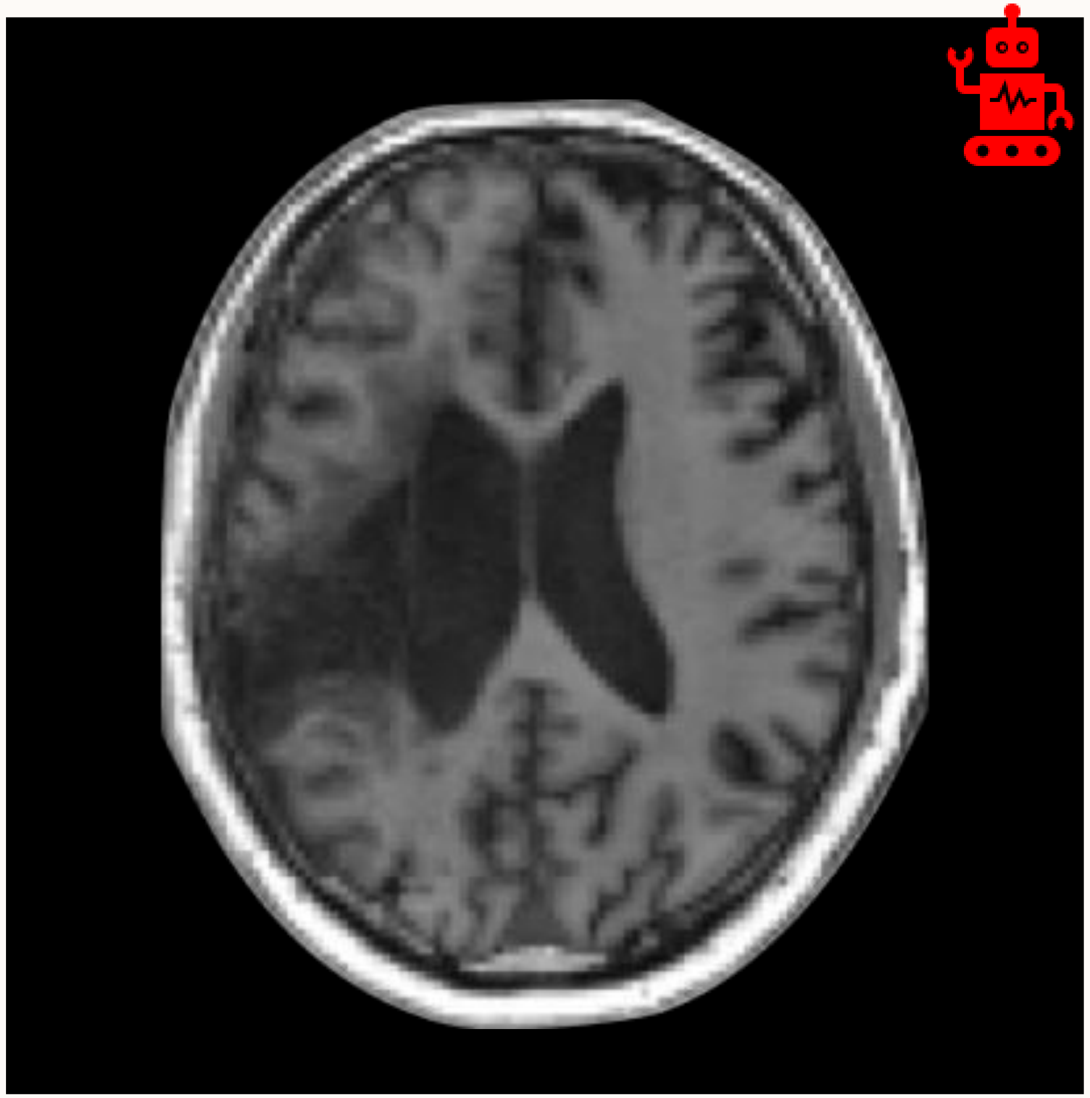


Language-based Image Editing

Kawar, Bahjat, et al. "Imagic: Text-based real image editing with diffusion models." *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*. 2023.

Language-based Image Editing

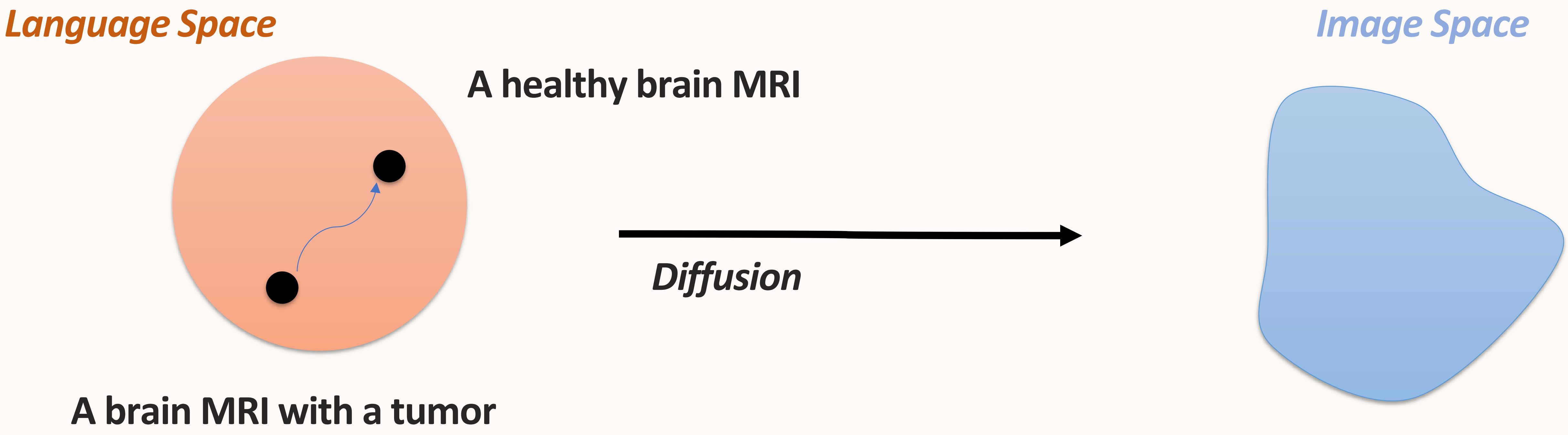
"An image of the pope"

Language-based Image Editing

"An image of the pope… in traditional portuguese clothes"

Language-based Image Editing

Karim ElGhandour



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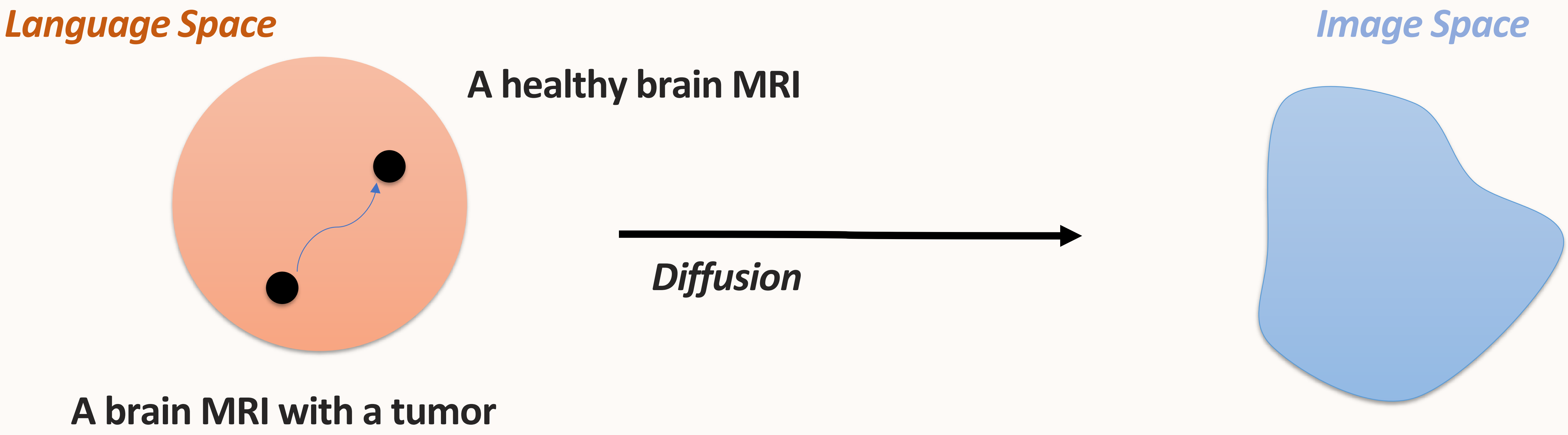

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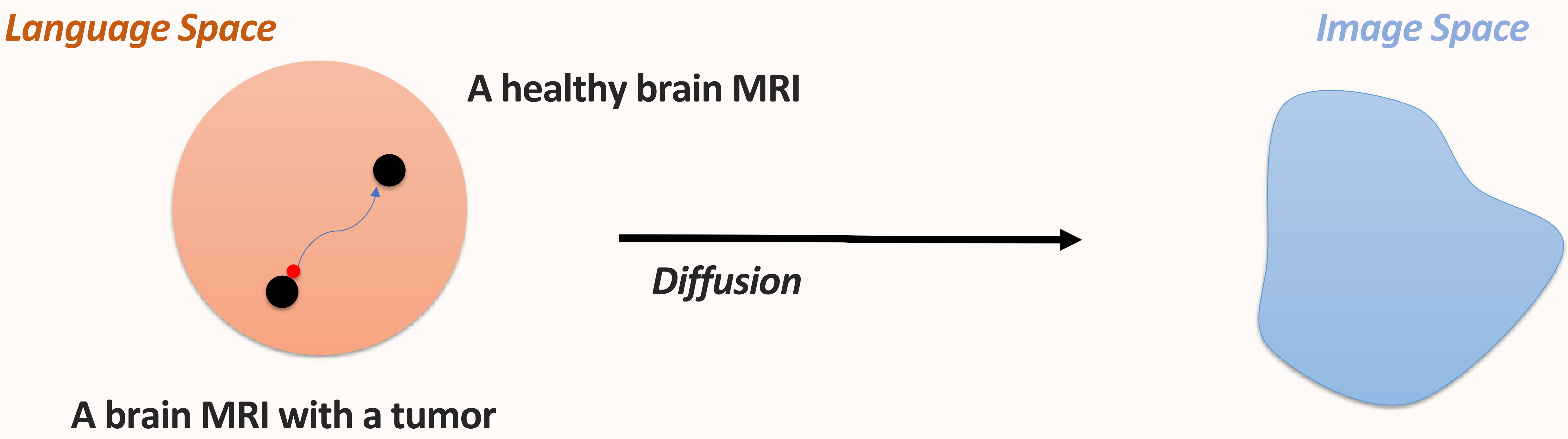

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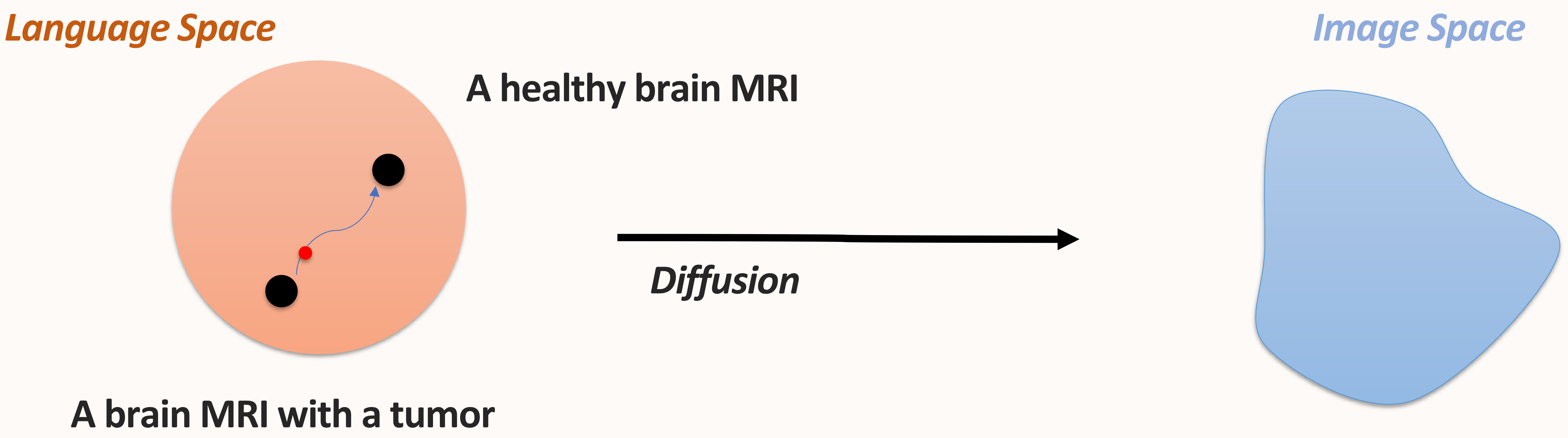

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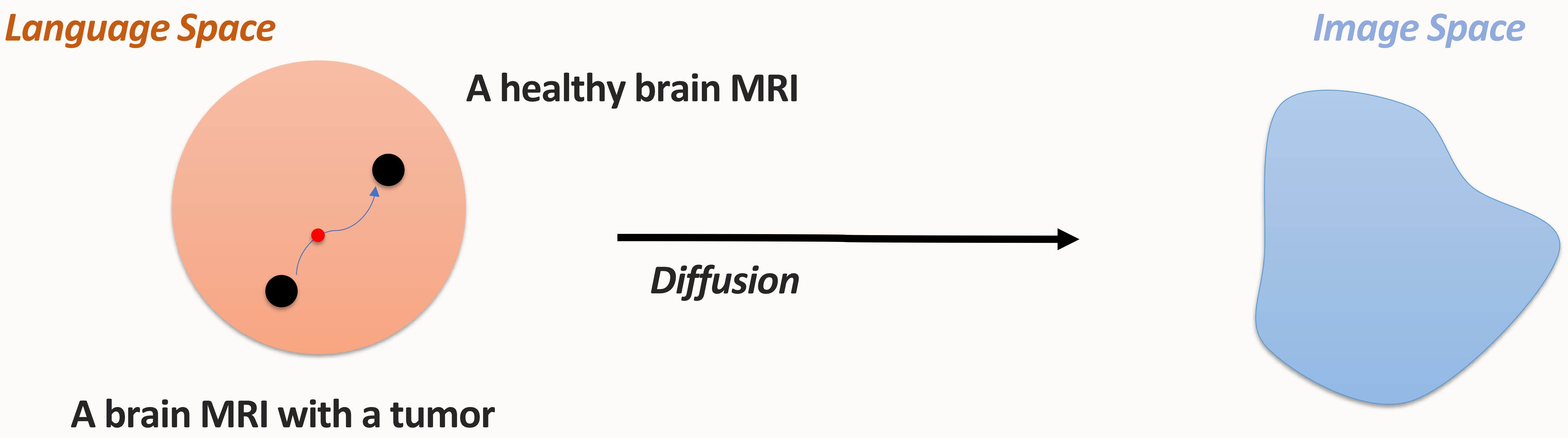

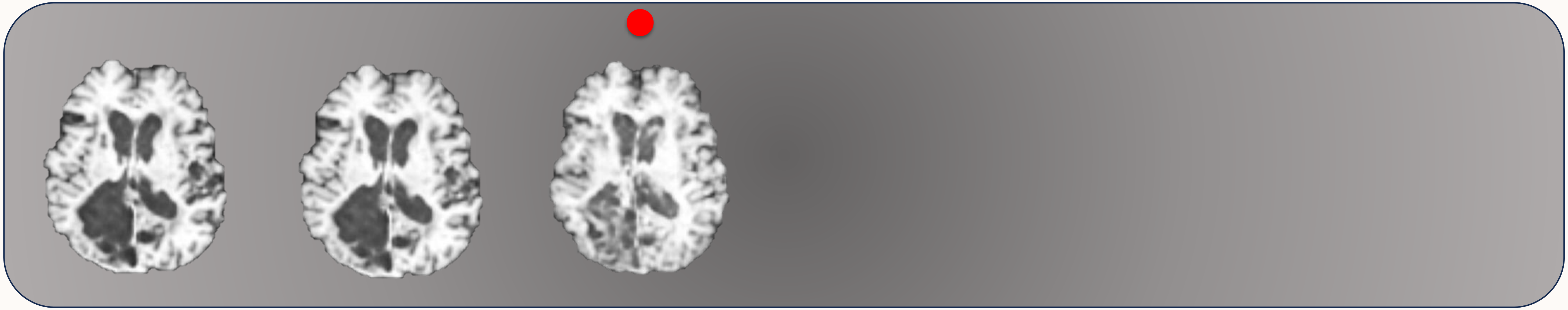

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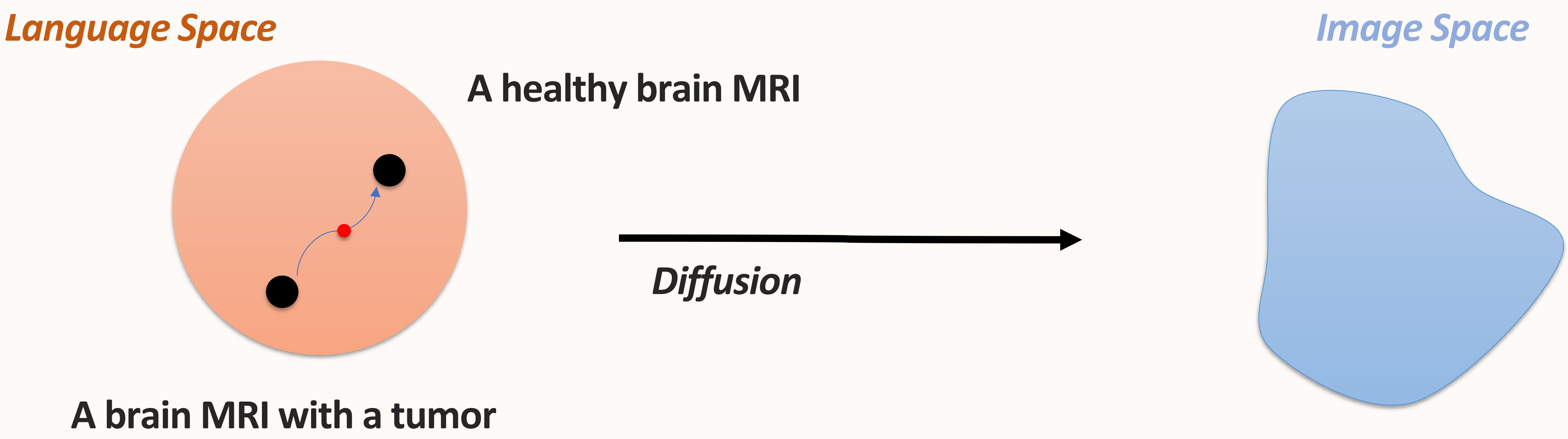

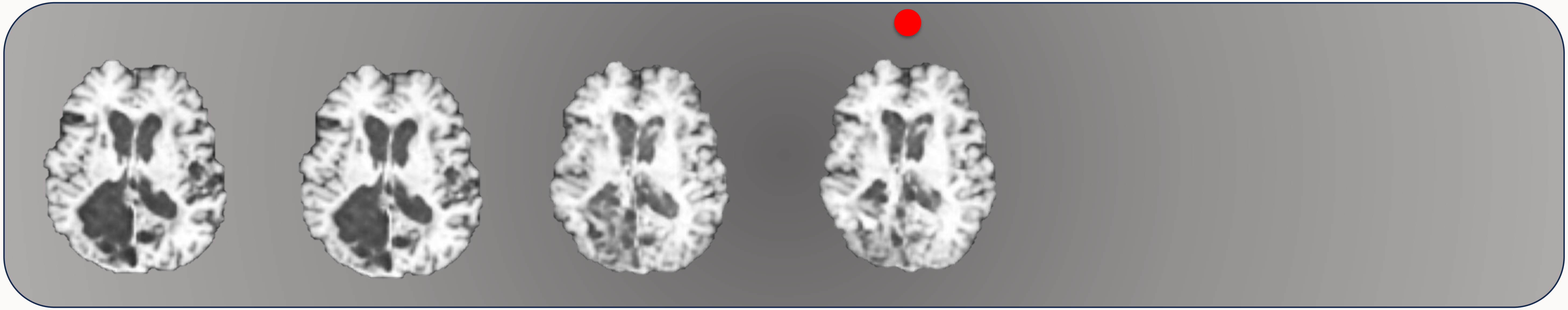

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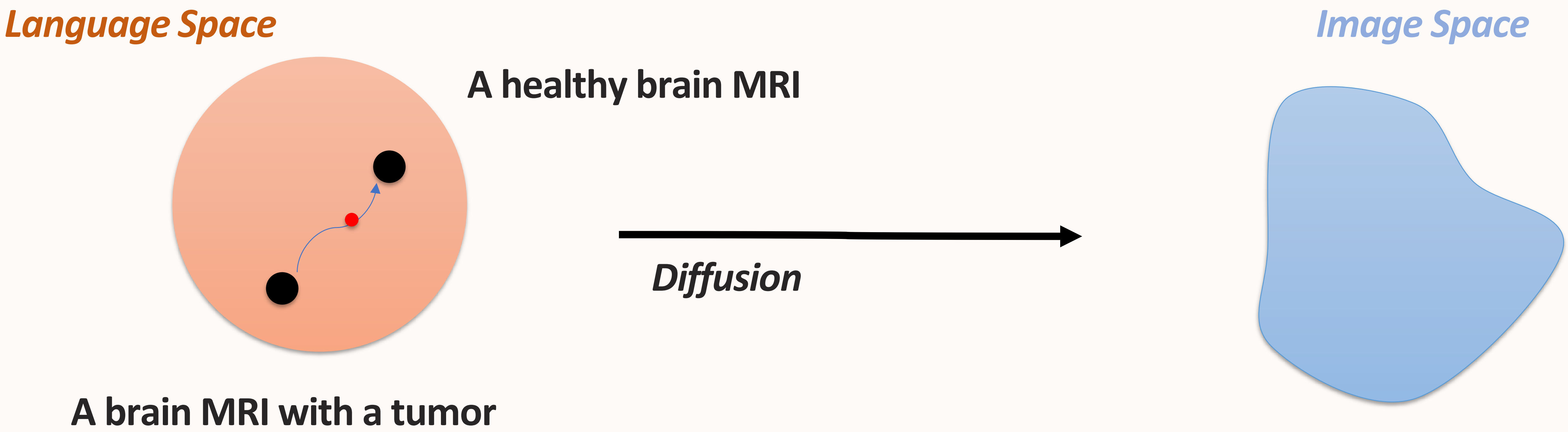

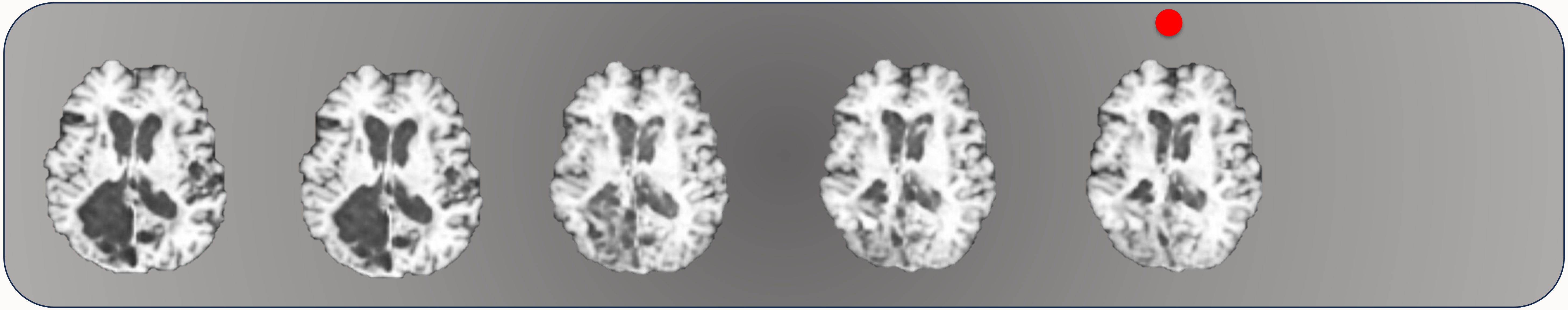

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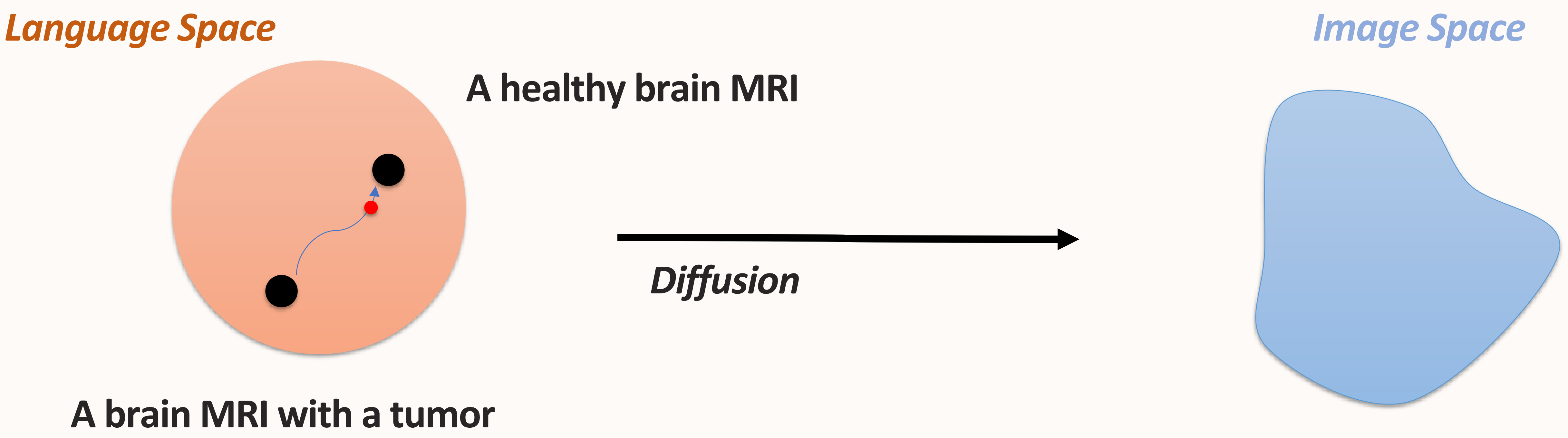
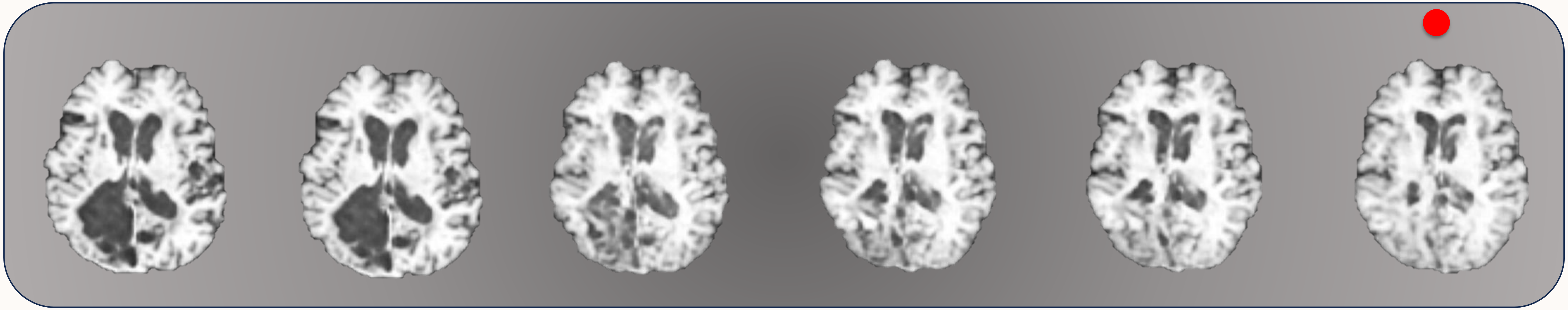
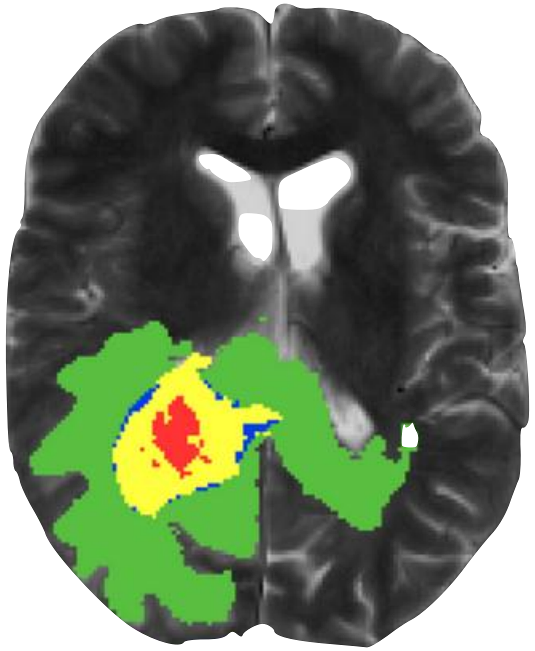




What for? Anomaly Detection (Supervised)

Input Brain MRI



Automatic Segmentation

Edema

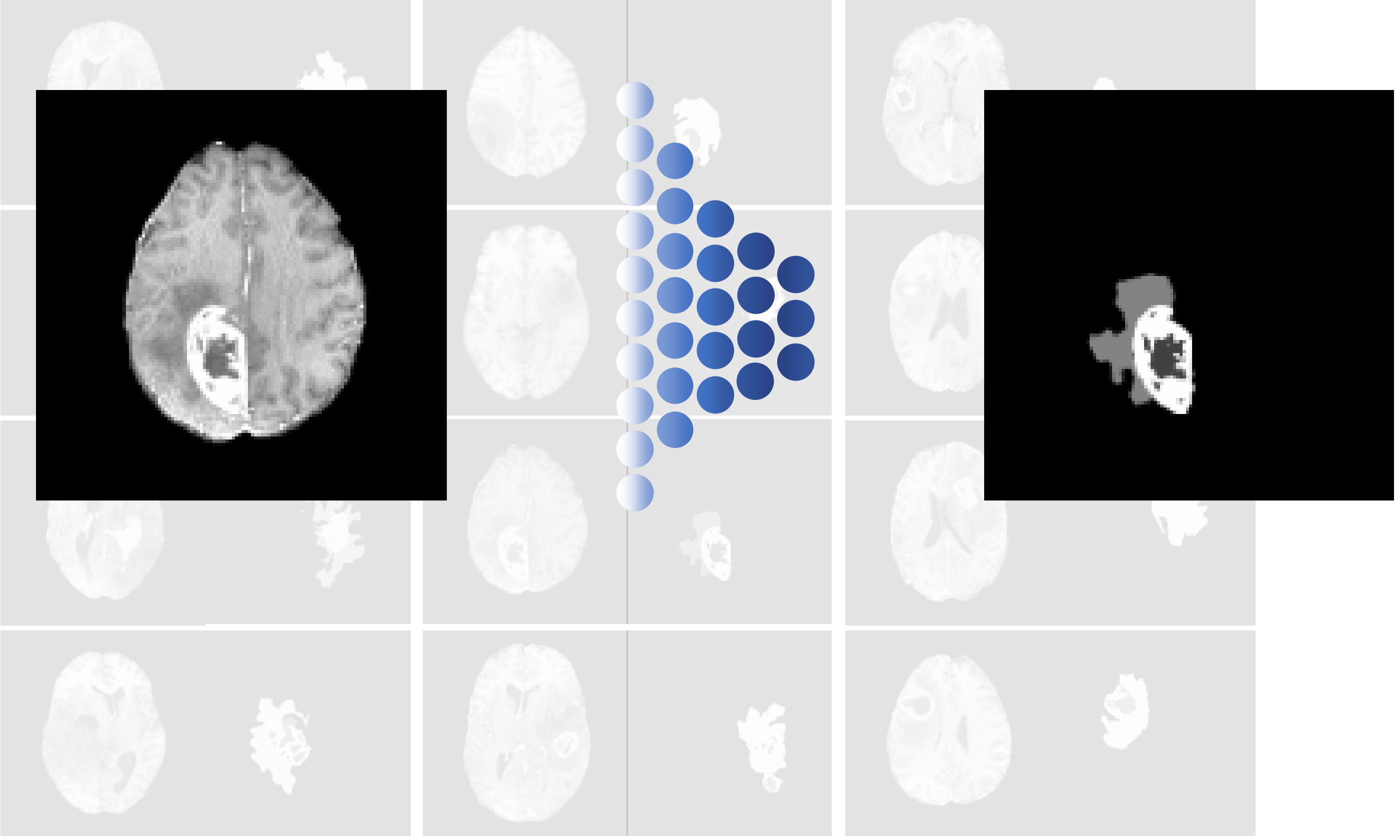
Advancing tumor

Non-advancing tumor

Necrotic tumor core

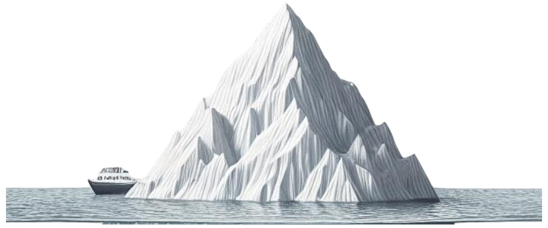
Train

Neural networks are trained to imitate radiologists and learn image -> anomaly masks mappings



Annotated dataset of images + masks

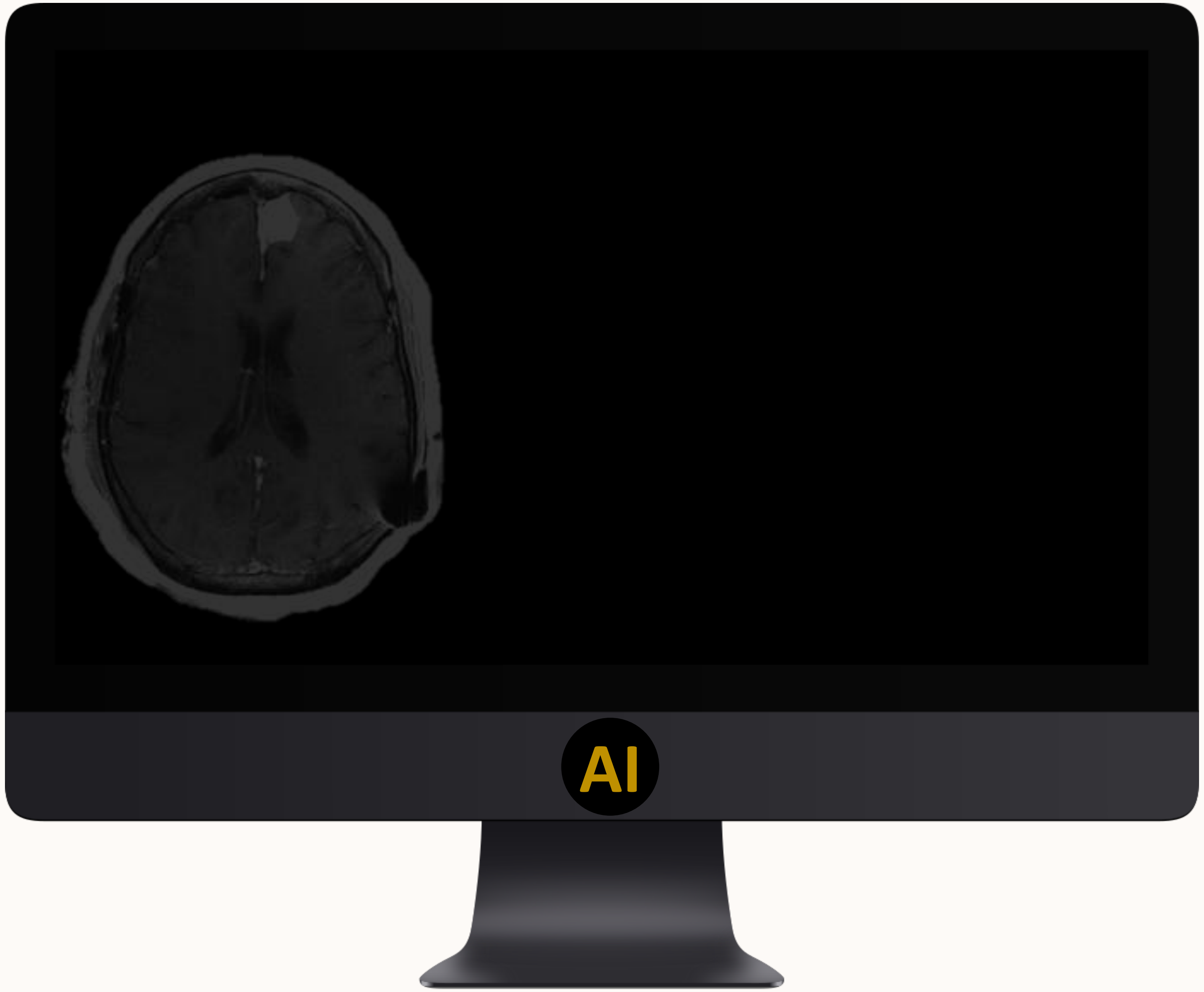
Known Diseases



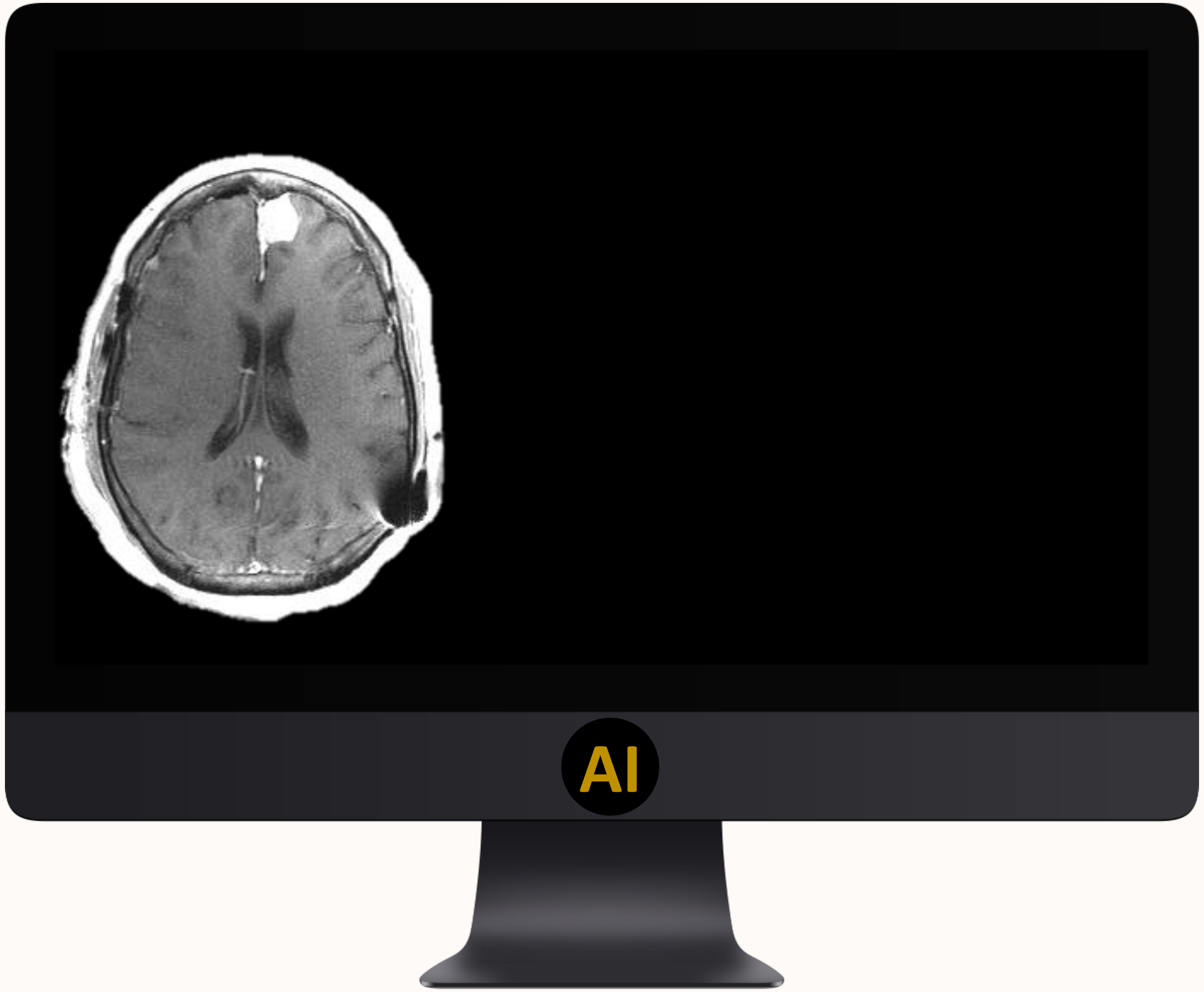
Expert Clinician

AI can detect common diseases

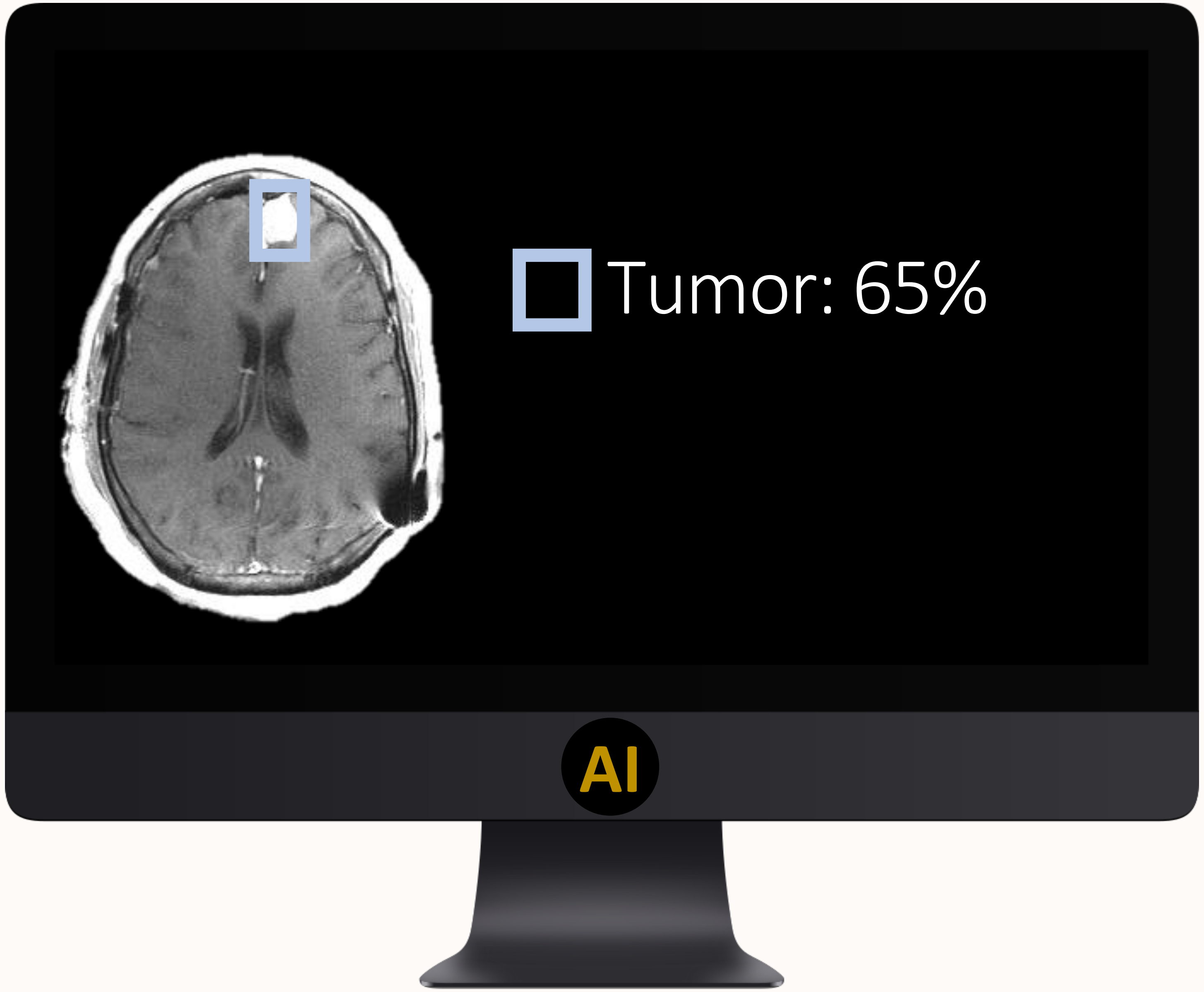
AI can detect common diseases



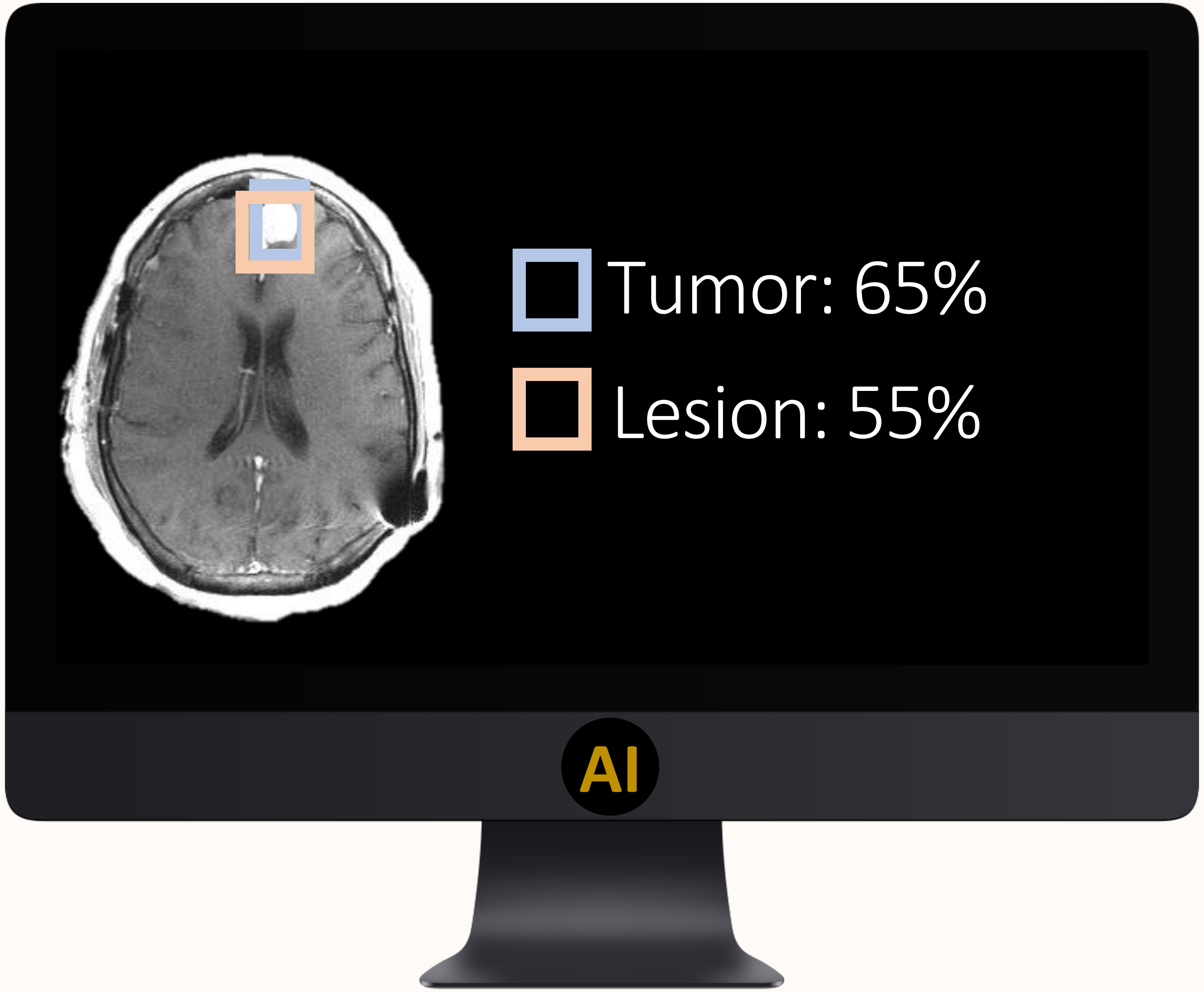
AI can detect common diseases



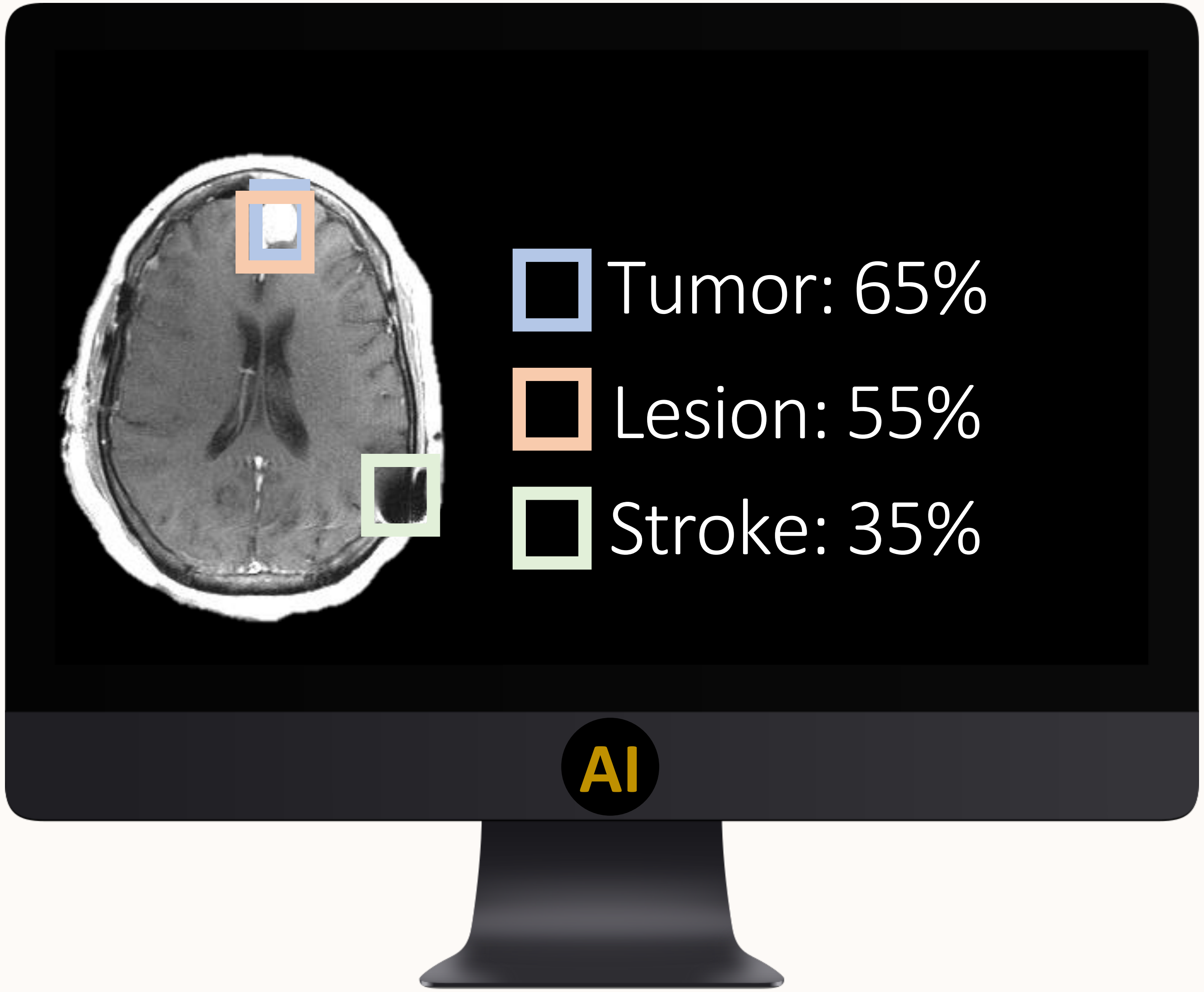
AI can detect common diseases



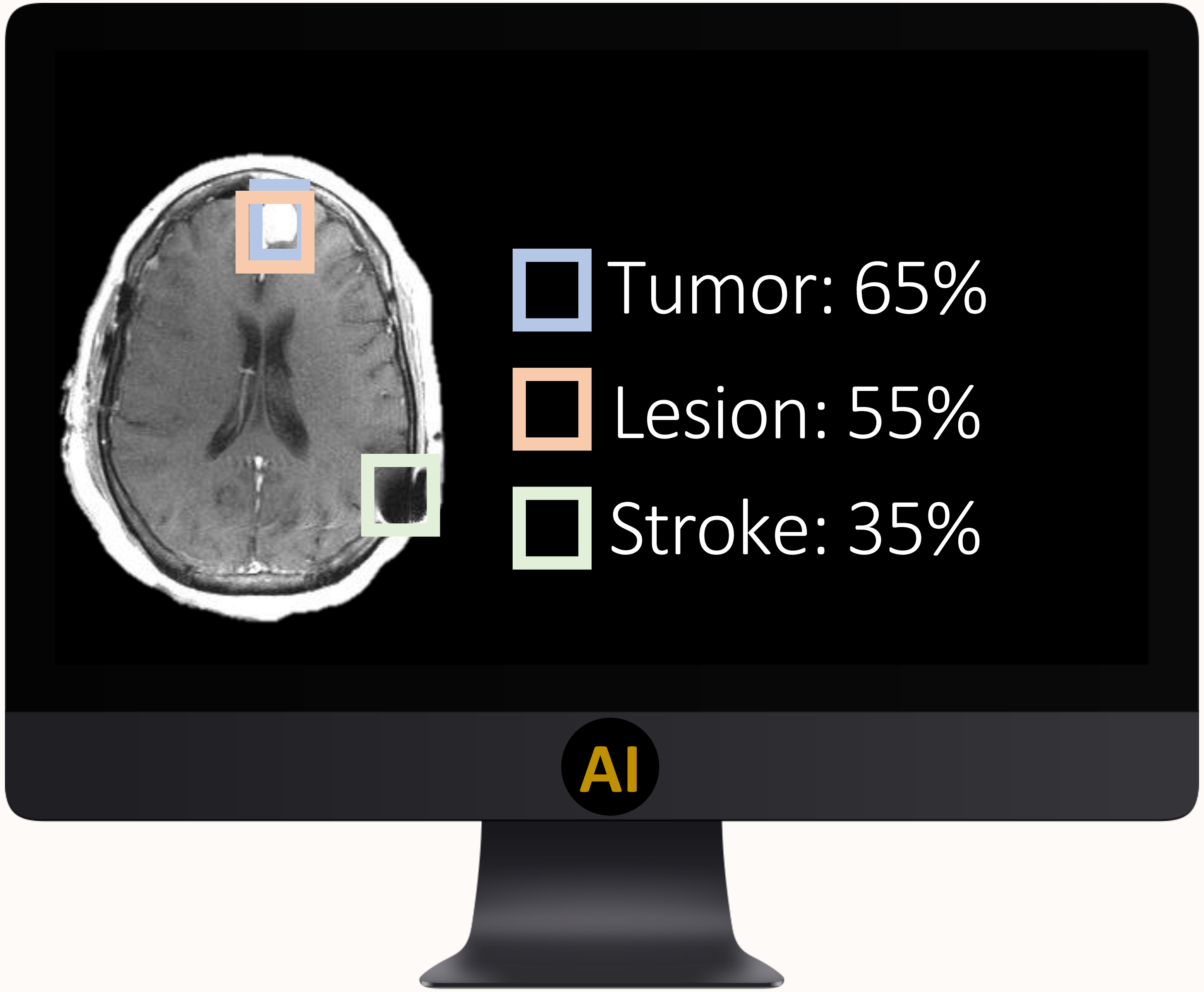
AI can detect common diseases



AI can detect common diseases

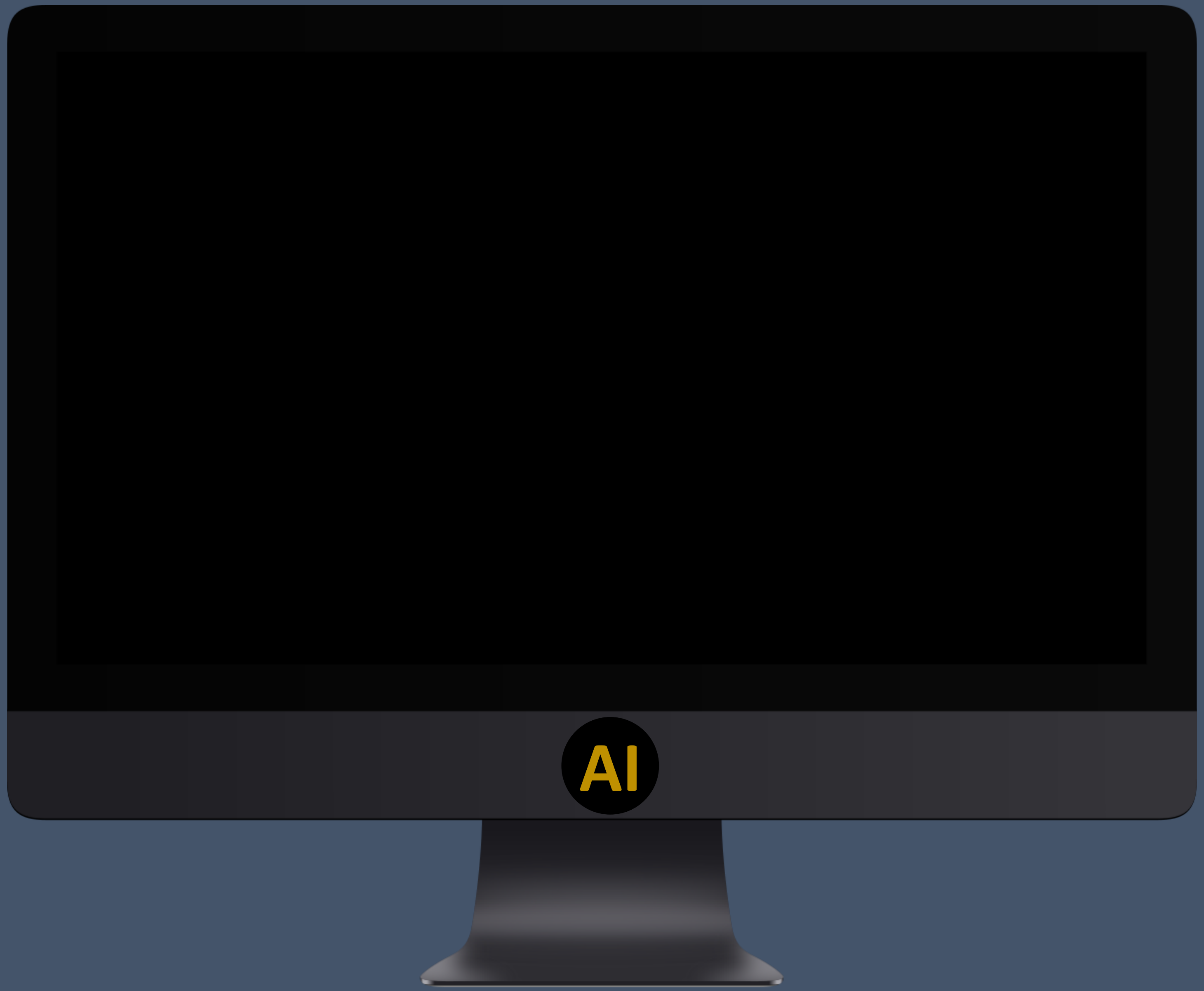


Can **AI** detect common diseases ?

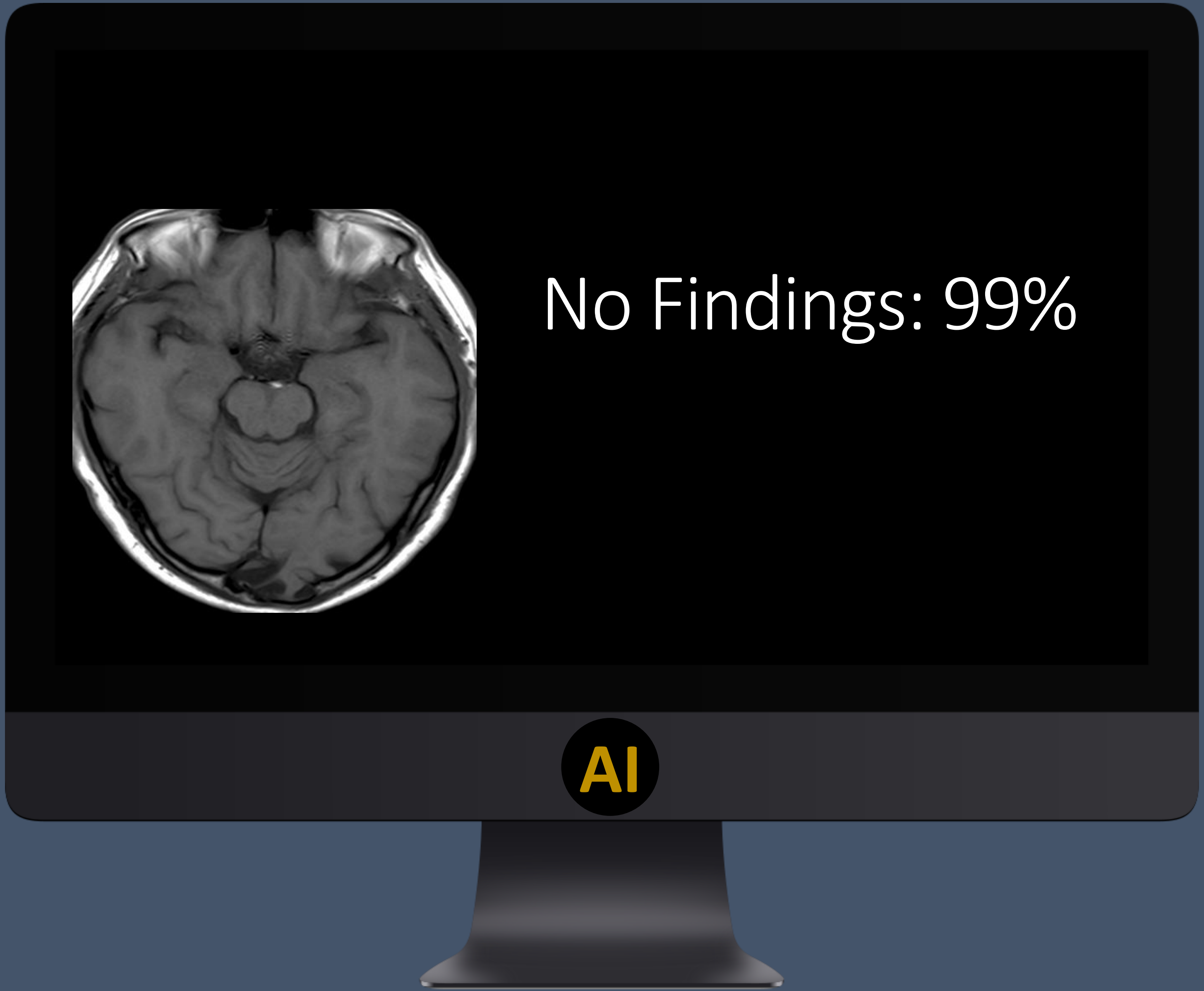


- No explanations
- Unintuitive “confidence”
- Prone to miss-diagnosis

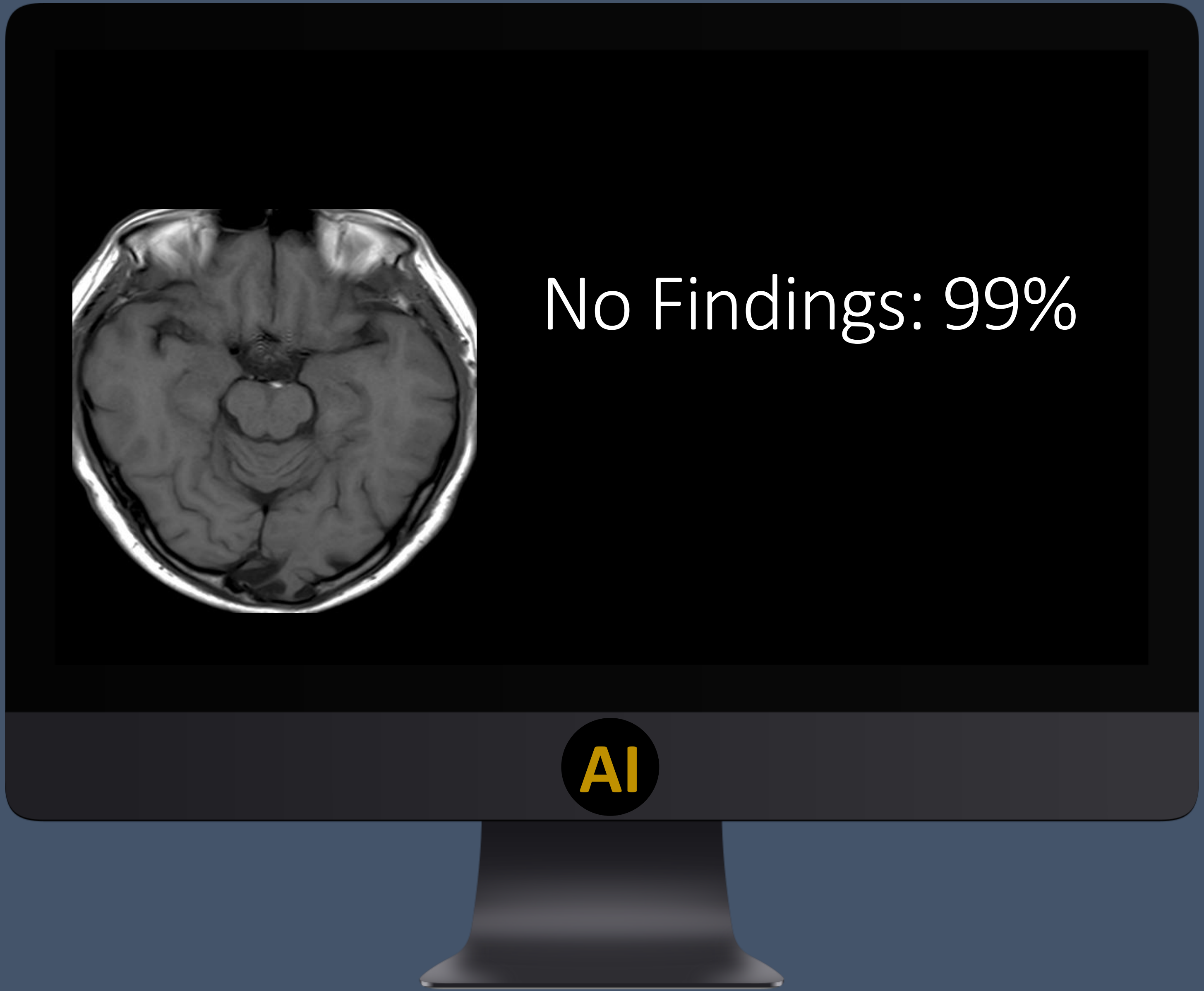
Can **AI** detect **rare** diseases ?



Can **AI** detect **rare** diseases ?

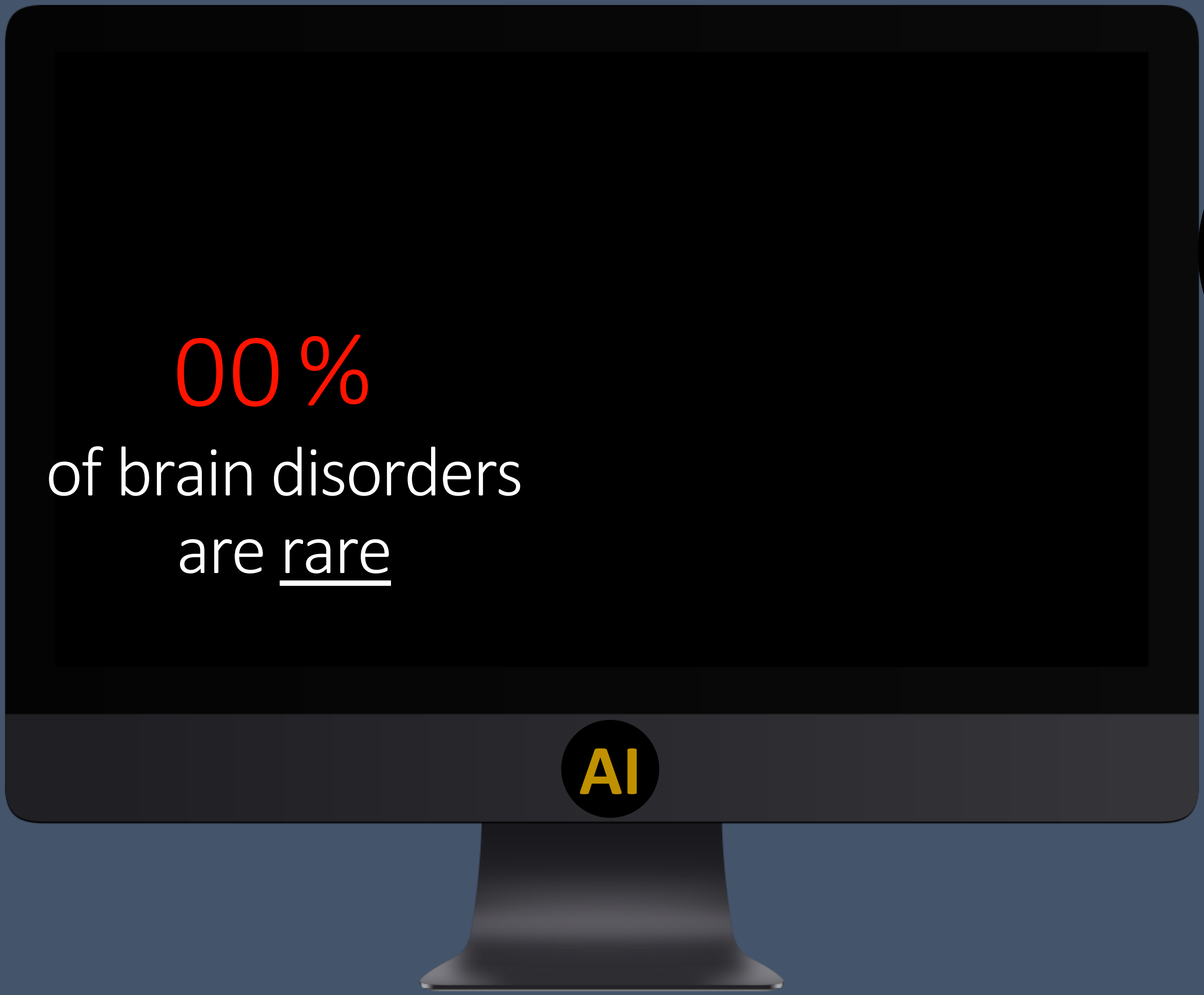


Can AI detect **rare** diseases ?



Can **AI** detect **rare** diseases ?

Can AI detect **rare** diseases ?



Rare **is not** rare

Can **AI** detect **rare** diseases ?

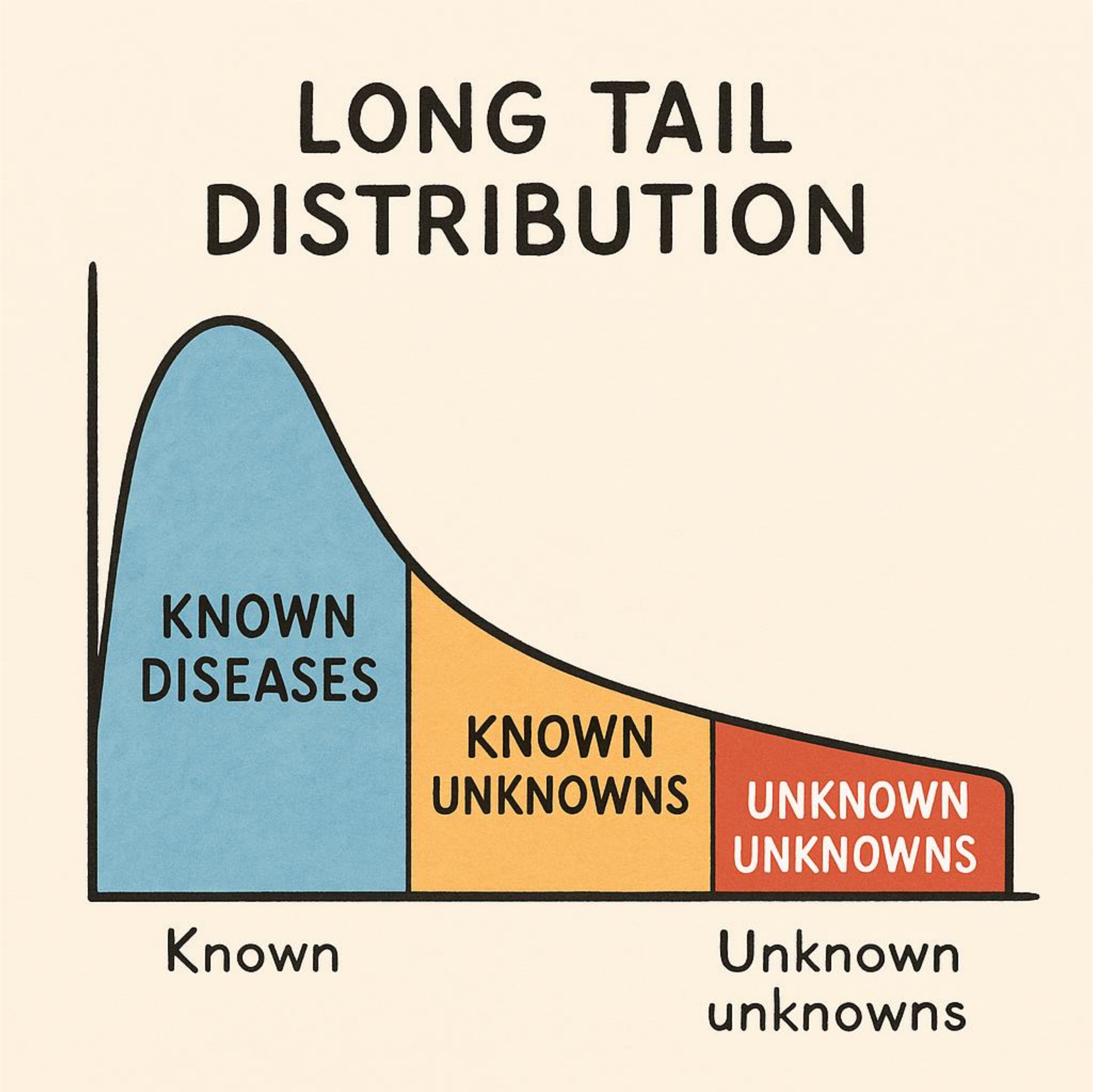
33 %
of brain disorders are rare

>10K
different rare diseases

AI

Rare **is not** rare

The Long Tail Distribution of Medical Anomalies

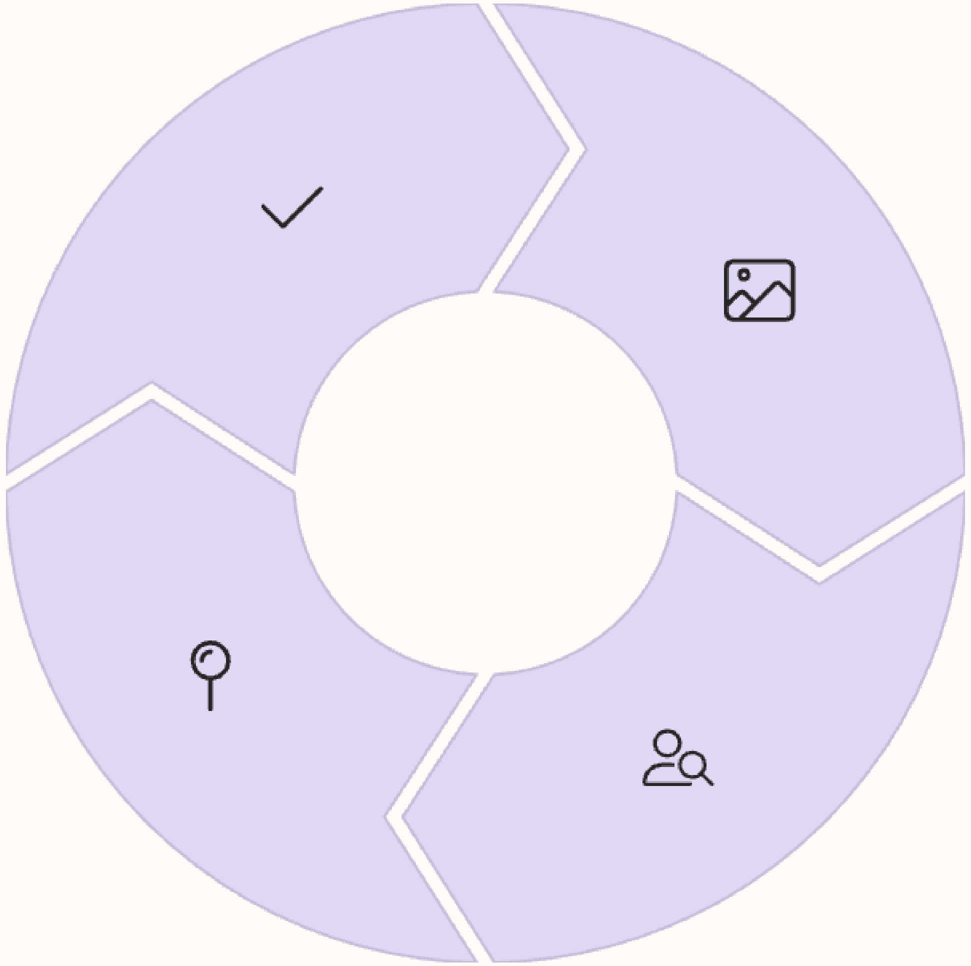


https://bernhard-kainz.com

How Do Doctors Detect the Unknown?

Doctors recognize subtle **deviations from normal**—not every possible disease.

Learning the Normal to Detect the Unknown



Train on Healthy Only

Model learns to reconstruct normal anatomical patterns

Test on Any Image

Apply to images that may contain pathologies

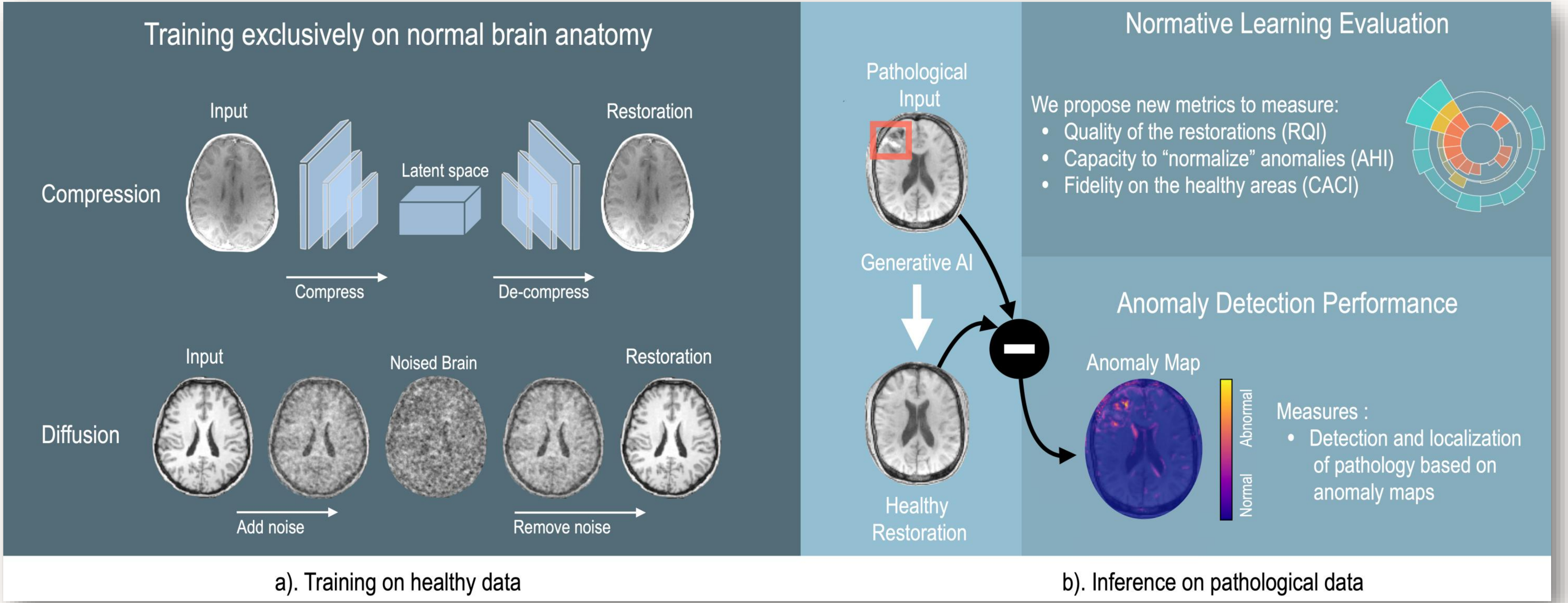
Compute Differences

Discrepancies reveal anomalous regions

Generate Anomaly Maps

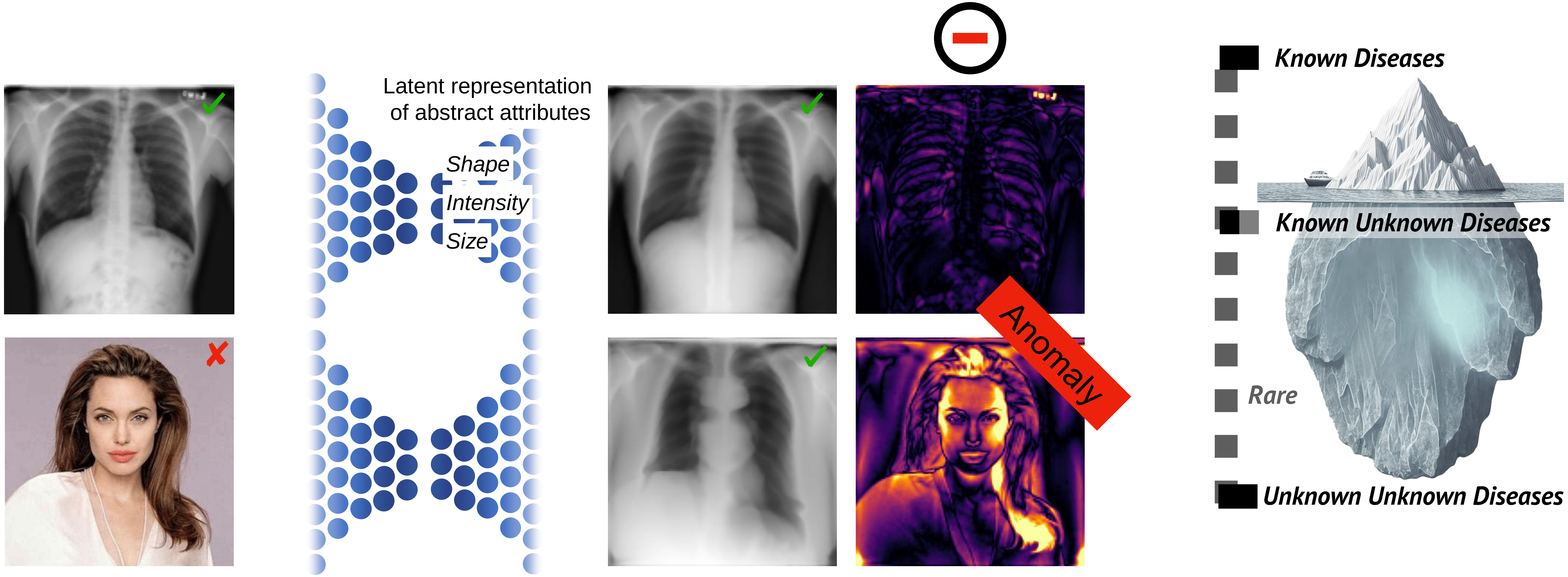
Highlight deviations for clinical interpretation

Learning the Normal to Detect the Unknown



Bercea, C. I., Wiestler, B., Rueckert, D., & Schnabel, J. A. (2025). Evaluating normative representation learning in generative AI for robust anomaly detection in brain imaging. *Nature Communications*, *16*(1), 1624.

Learning the Normal to Detect the Unknown



✓ *In-distribution, e.g., healthy chest X-rays*

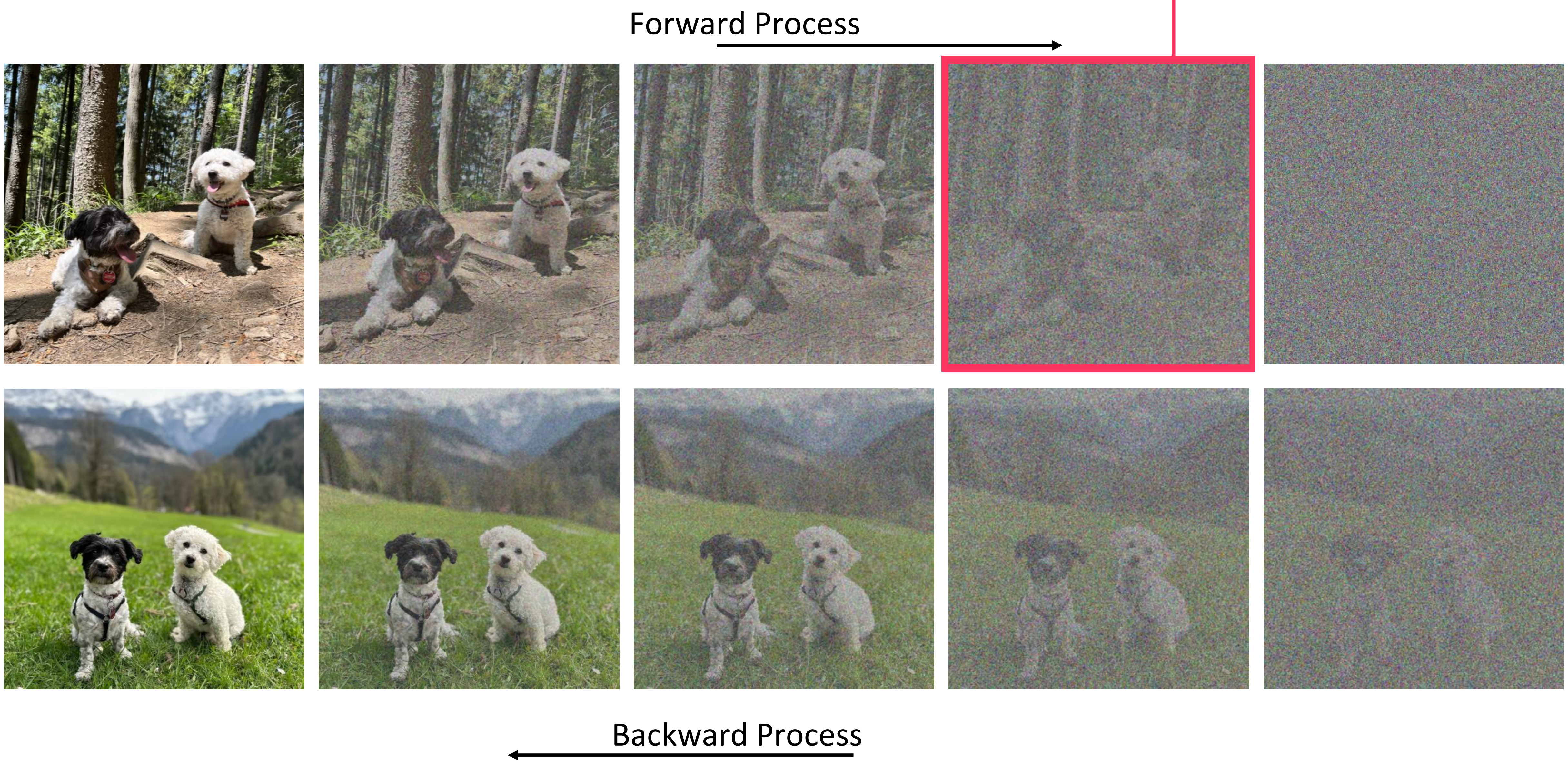
✗ *Out-of-distribution, e.g., pathology*

Bercea, C. I., Rueckert, D., & Schnabel, J. A. (2023, October). What do aes learn? challenging common assumptions in unsupervised anomaly detection. In *International Conference on Medical Image Computing and Computer-Assisted Intervention* (pp. 304-314). Cham: Springer Nature Switzerland

Diffusion Models for Anomaly Detection

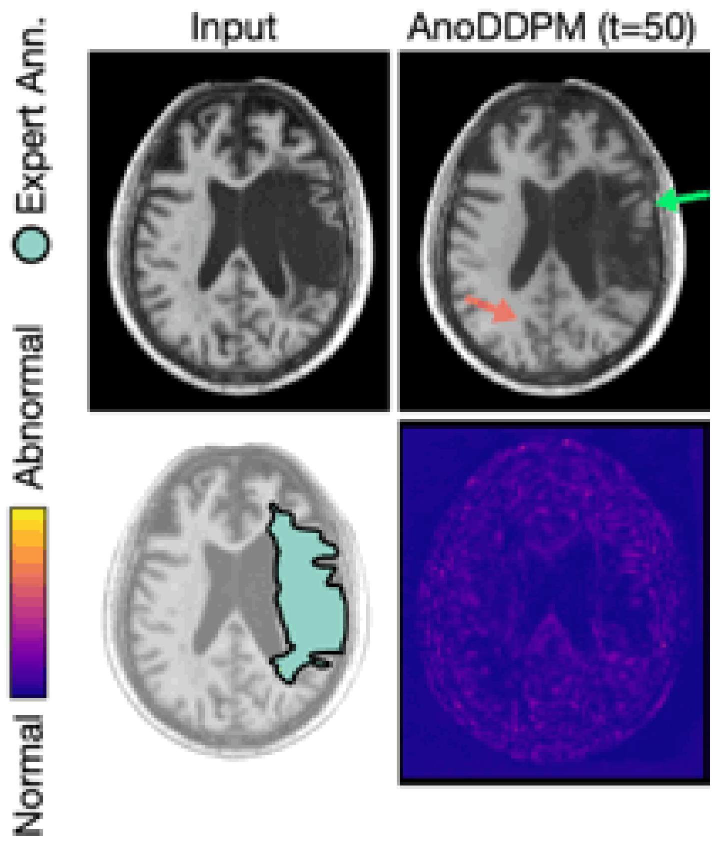
Goal: Learn the data distribution by gradually *adding* and *removing* noise!

In anomaly detection, the **backward** starts from a **selected time *t*.**



The noise paradox

*Increasing noise levels **t** →*



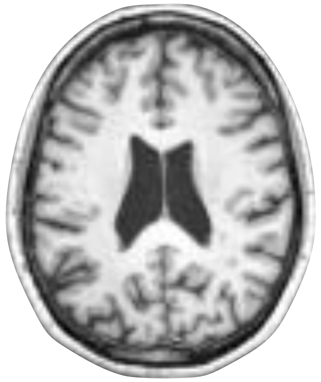
Noise Paradox: Removing anomalies vs. Preserving healthy tissues

Reversing the Abnormal

Bercea, C. I., Wiestler, B., Rueckert, D., & Schnabel, J. A. (2023, October). Reversing the abnormal: Pseudo-healthy generative networks for anomaly detection. In *International Conference on Medical Image Computing and Computer-Assisted Intervention* (pp. 293-303). Cham: Springer Nature Switzerland.

GANs

Goal: The Generator improves over time until the Discriminator can no longer tell the difference between real and generated data.



Real brain MRI

It's fake!

Artist (Generator)

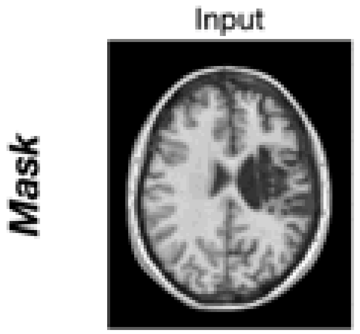
Creates fake data (e.g., MRI) trying to fool the critic.

Feedback

Critic (Discriminator)

Evaluates data authenticity and provides feedback.

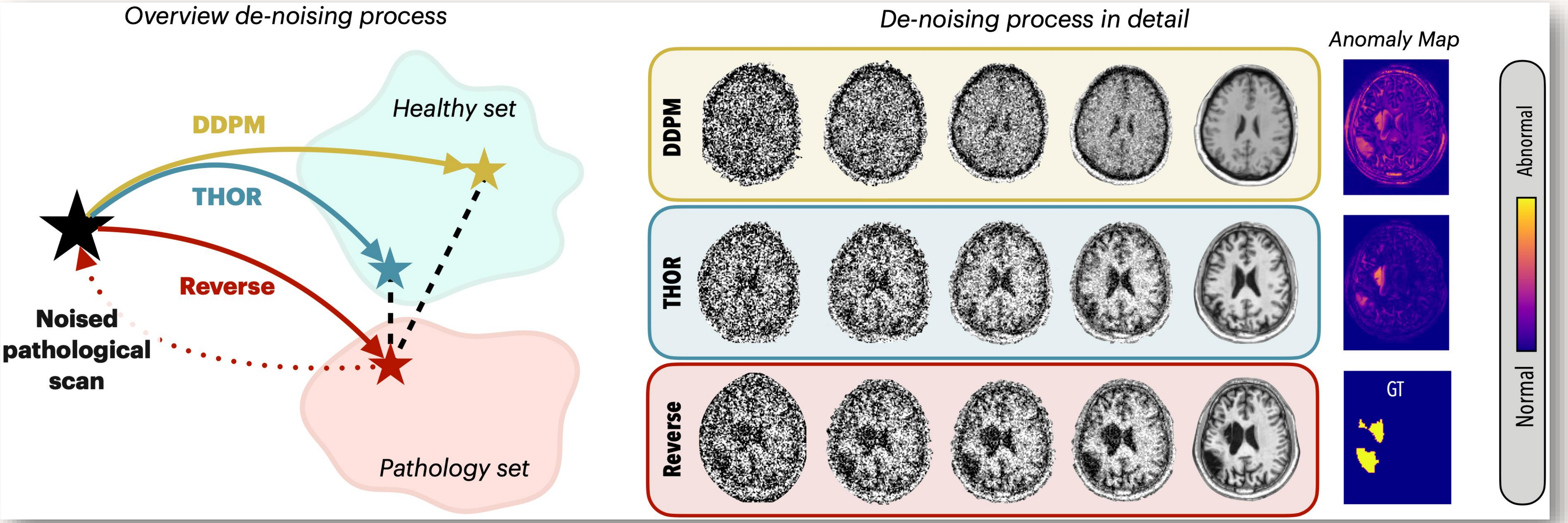
Mask, Stich, and Re-Sample



Michael Neumayr

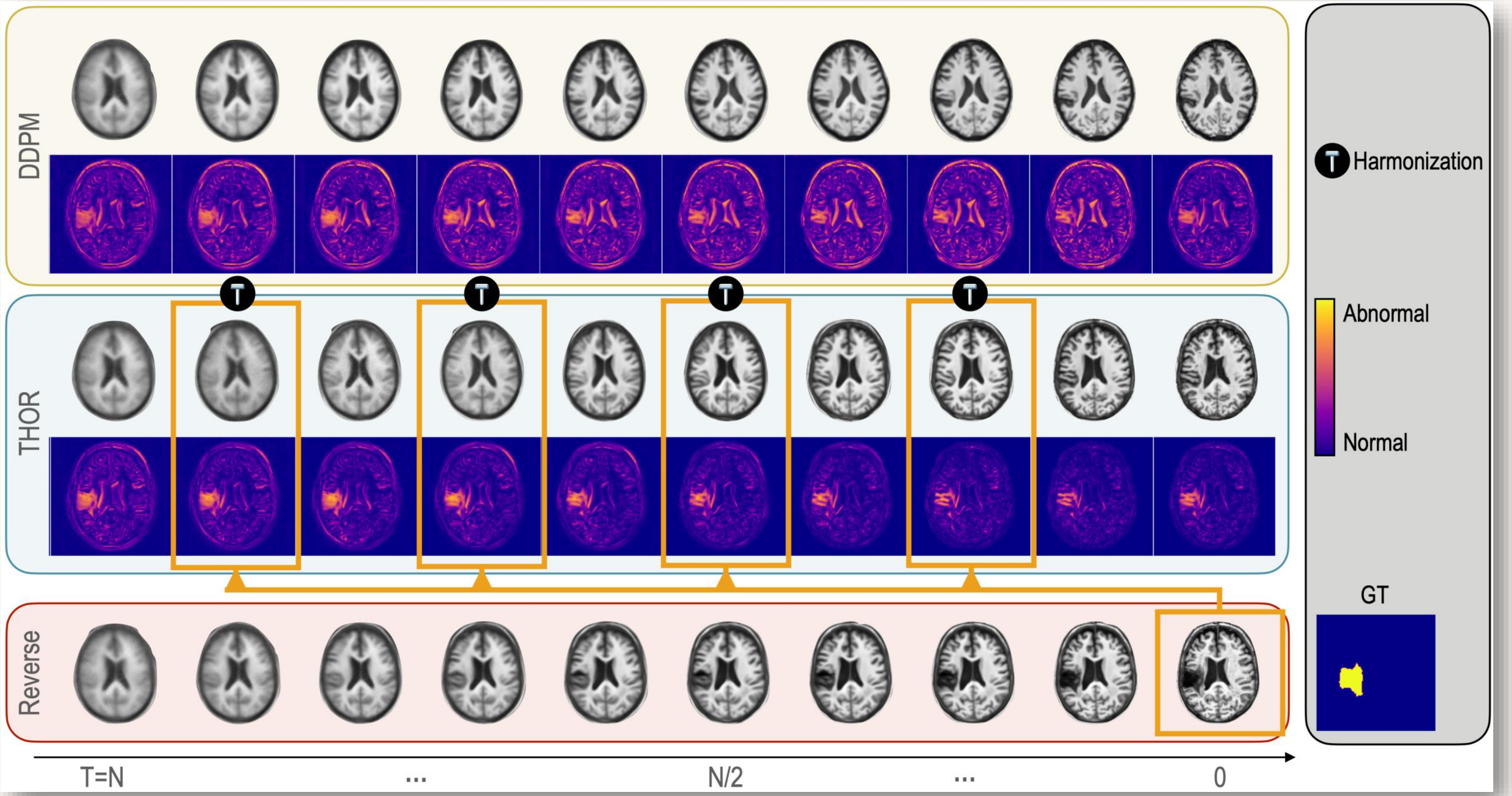
Bercea, C. I., Neumayr, M., Rueckert, D., & Schnabel, J. A. Mask, Stitch, and Re-Sample: Enhancing Robustness and Generalizability in Anomaly Detection through Automatic Diffusion Models. In *ICML 3rd Workshop on Interpretable Machine Learning in Healthcare (IMLH)*.

THOR



Bercea, C. I., Wiestler, B., Rueckert, D., & Schnabel, J. A. (2024, October). Diffusion models with implicit guidance for medical anomaly detection. In *International Conference on Medical Image Computing and Computer-Assisted Intervention* (pp. 211-220). Cham: Springer Nature Switzerland.

THOR



Vision-Language Diffusion Models

Text Conditioning

Natural language prompts guide image generation and editing.

Semantic Transformation

Convert descriptions like "healthy" to "showing tumor" visually.

Rare Disease Discovery

Language models help identify unusual patterns in images.

MORPHAEUS — MICCAI 23

MIDL 23

PHANES — MICCAI 23

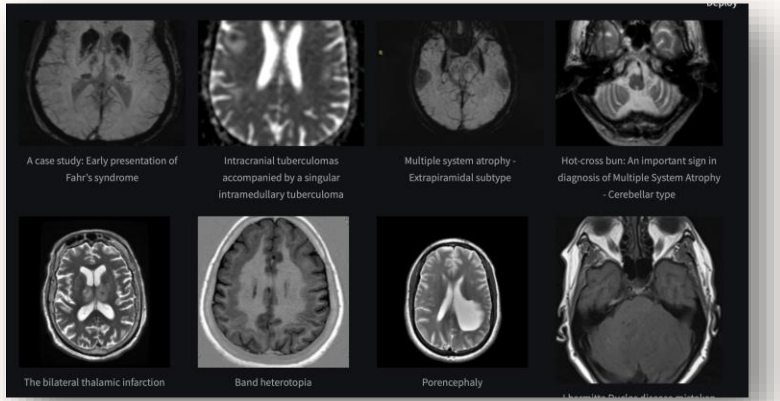
autoDDPM — ICML W 23

THOR — MICCAI 24

FedDIS — Nature Machine Intelligence 22

Open source - Code is available on GitHub:

GenAI — Nature Communications 24

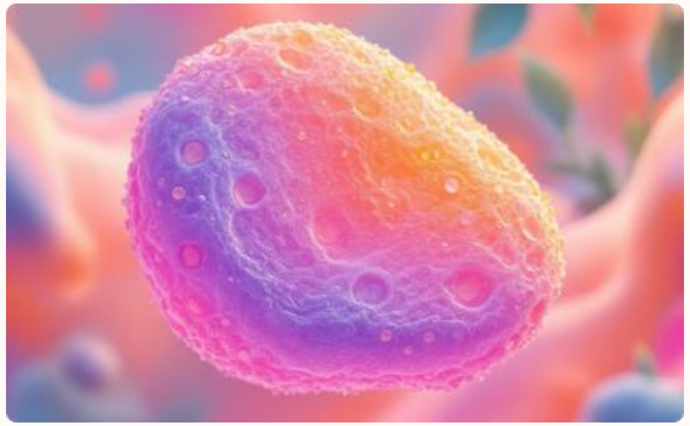


Medical Out-of-Distribution Analysis Challenge – MICCAI 25

Moo(D) – CoW Track □ Real rare clinical anomalies

https://zenodo.org/records/15083914

From Noise to Knowledge



Controlled Generation

Diffusion models allow complex medical images to be synthesized from noise with greater precision.

Language Guided Editing

Edit medical images based on natural language instructions, enabling precise alterations.

Interactive Question/Answers Explainable AI through Language Diffusion

Answer clinical questions and provide explanations with integrated AI.

Multimodal Integration

Combine different imaging modalities for a comprehensive patient view

Clinician In-The-Loop

Integrate clinician expertise with AI tools for collaborative diagnosis and treatment planning.

Detecting Unknown Unknowns

Identify rare anomalies by learning normal patterns and highlighting deviations.