

10th September 2024

How can I detect that something is wrong in my pizza?

Or: Anomaly detection in neuroimaging and computer-aided diagnosis for brain disorders

Inria Junior Seminar

Maëlys Solal



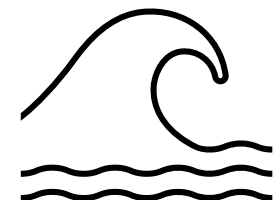
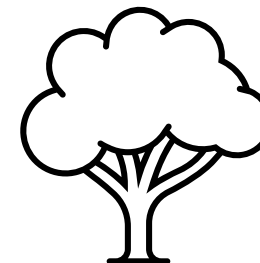
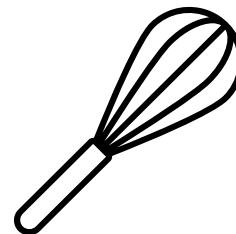
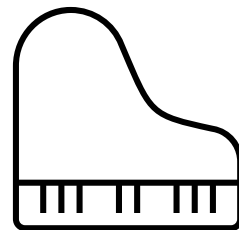
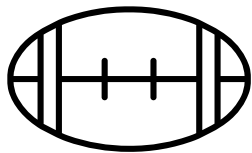
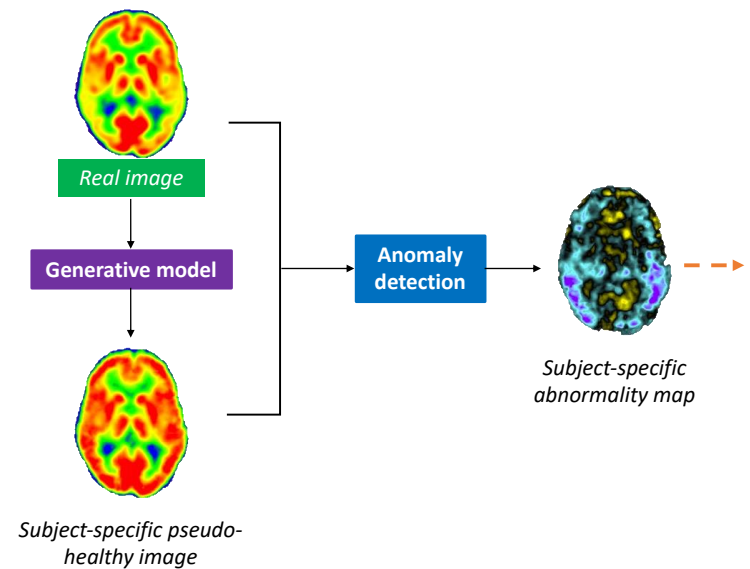
Who am I?



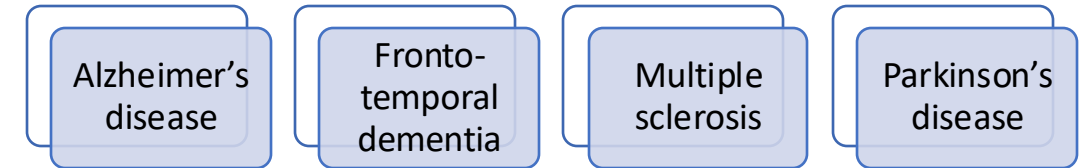
Who am I?

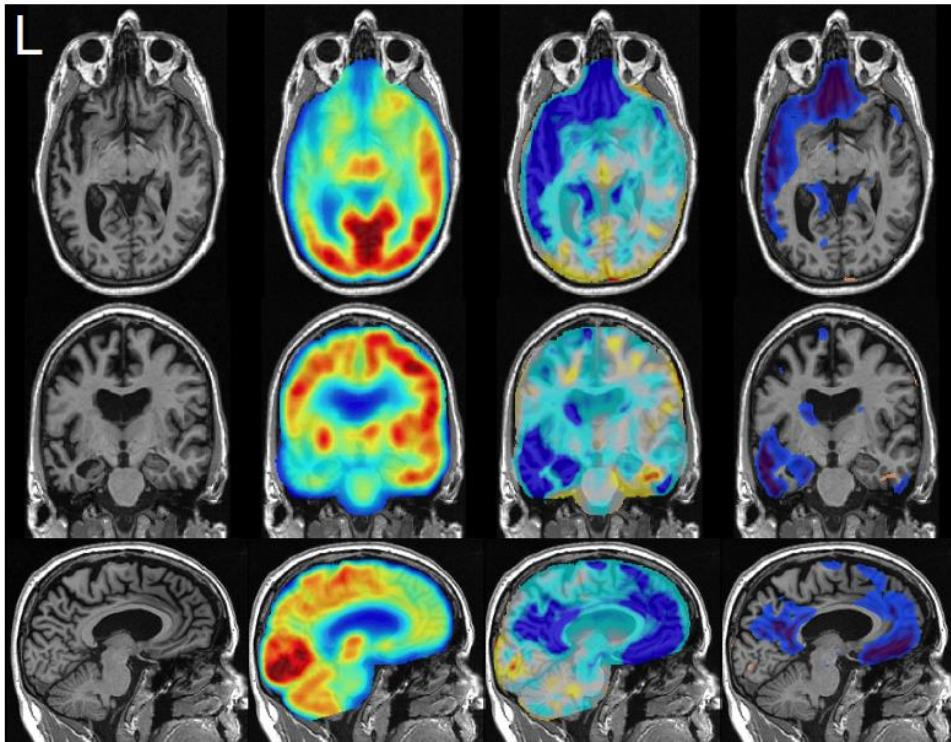
PhD student, starting my 2nd year
ARAMIS Lab

PhD topic: Robust anomaly detection for
multimodal neuroimaging
Supervisor: Ninon Burgos, CR from CNRS

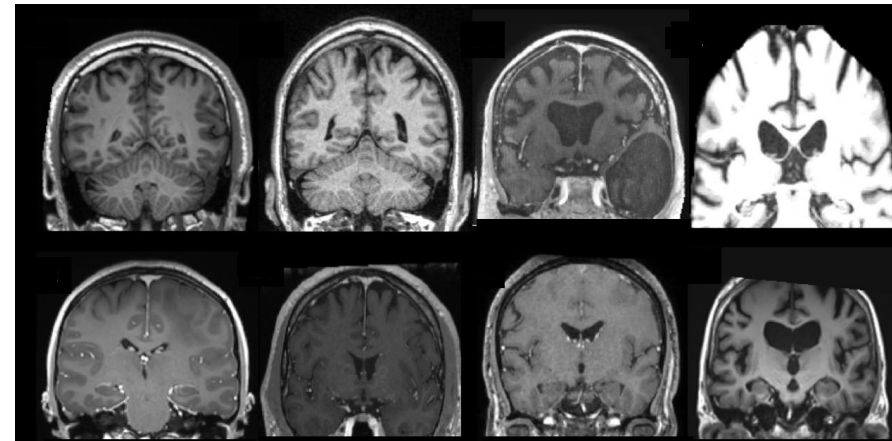


Inria & Paris Brain Institute: Methodology & Applications





Anomaly detection



Decision support systems for
clinical routine data

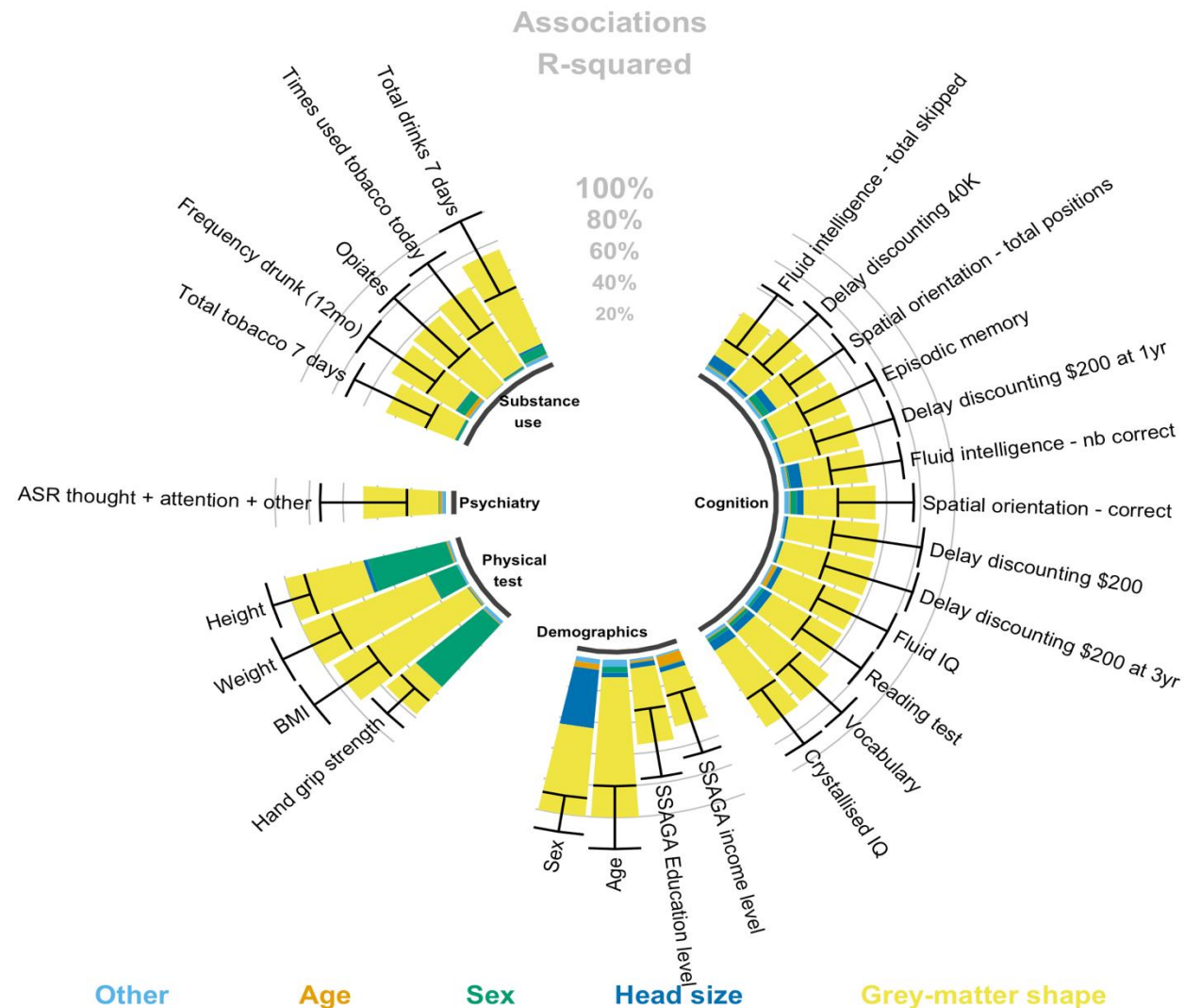


Olivier Colliot



Ninon Burgos

High-dimensional multimodal data (genetic, environment, imaging)



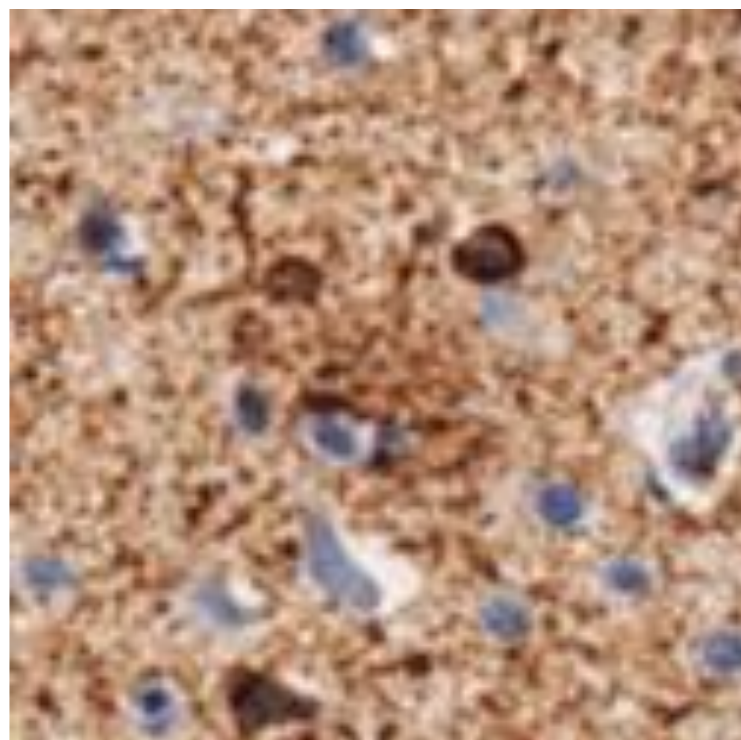
Olivier Colliot



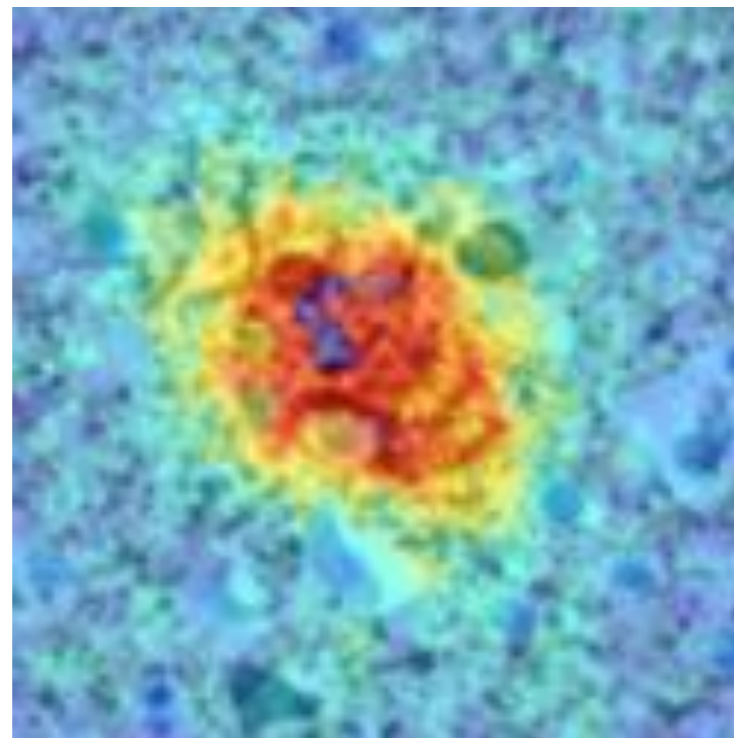
Baptiste Couvy-Duchesne

New statistical models for high-dimensional association

Computational pathology and high-content microscopy



Plaque object in WSI patch



Attention map



Stanley Durrleman



Daniel Racoceanu

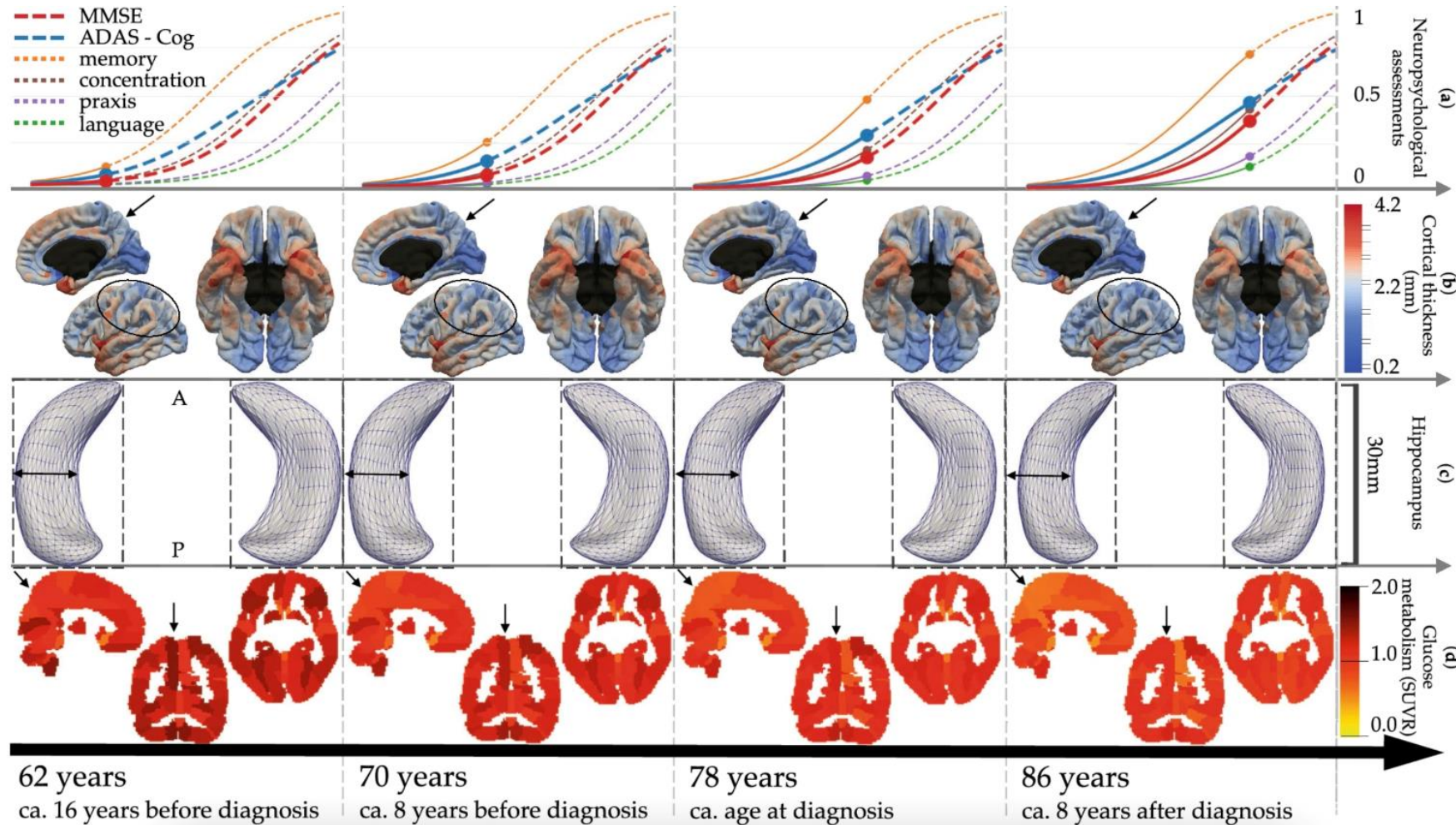
Disease progression modelling for trial design



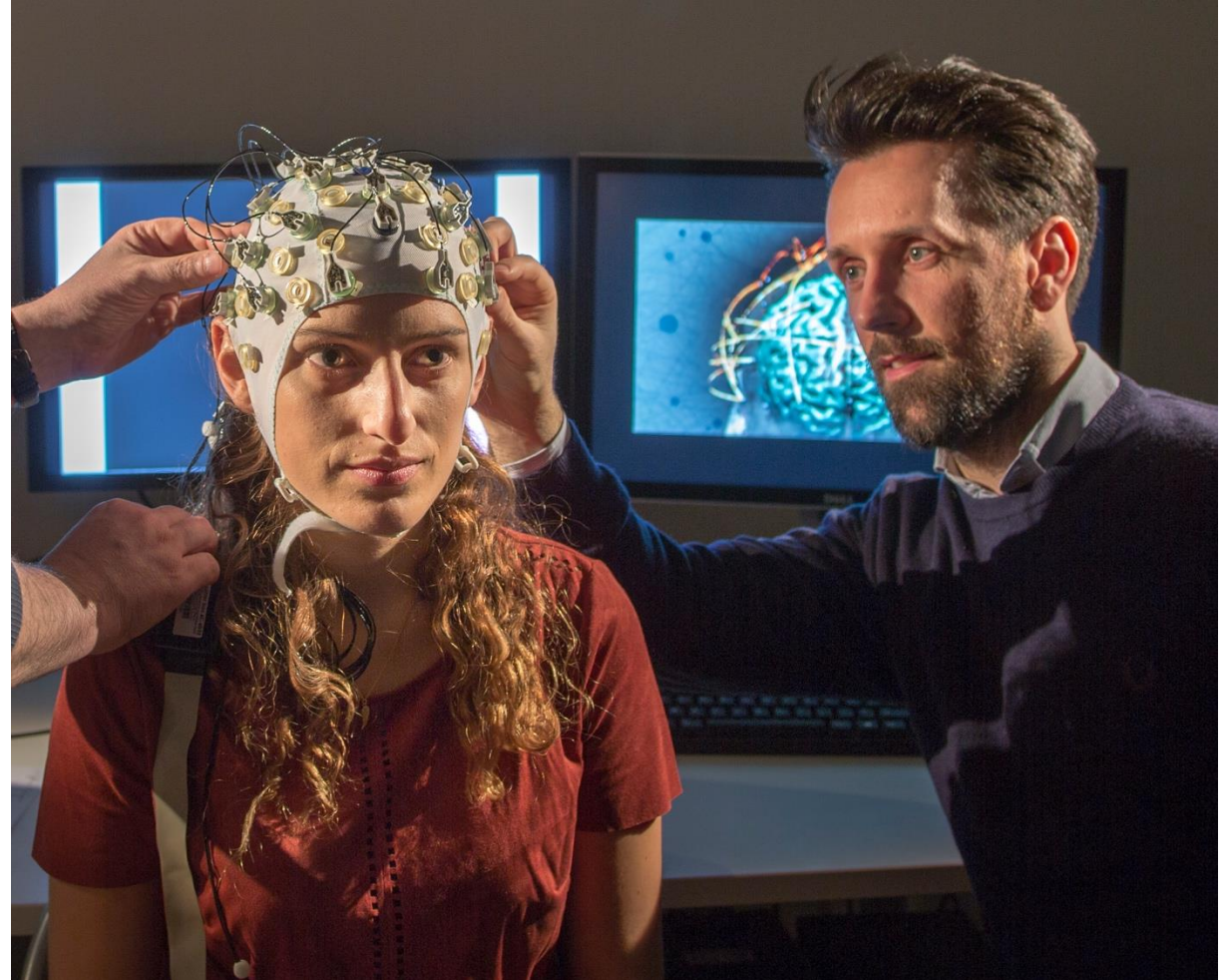
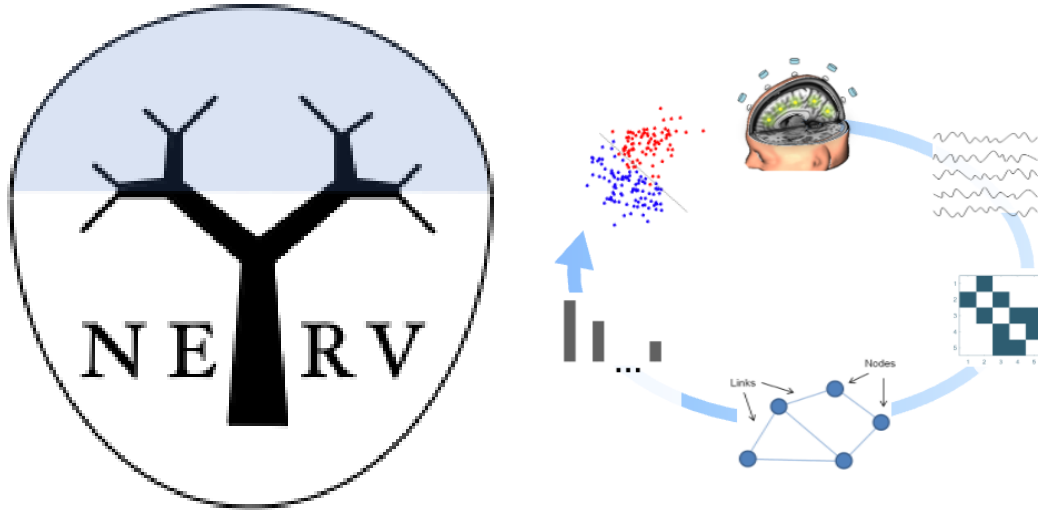
Stanley Durrleman



Sophie Tezenas
du Montcel



NERV Lab. Systems neuroengineering, complex networks and brain computer-interfaces



Motivations for Anomaly Detection in Medical Imaging

Anomaly detection for the diagnosis of brain disorders



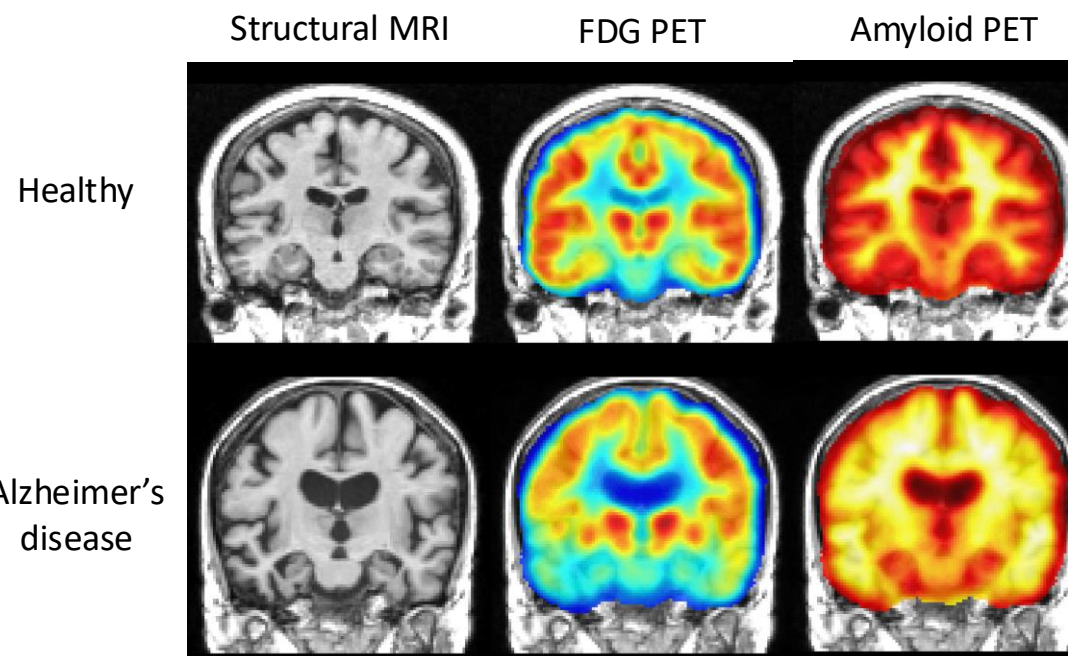
Alzheimer's disease

Neurodegenerative disorder
10% of people ≥ 65 years old



Currently

Diagnosis from clinical
symptoms & cognitive tests



Research Gap. Onset of clinical symptoms is
preceded by neurophysiological changes
(years or decades prior)

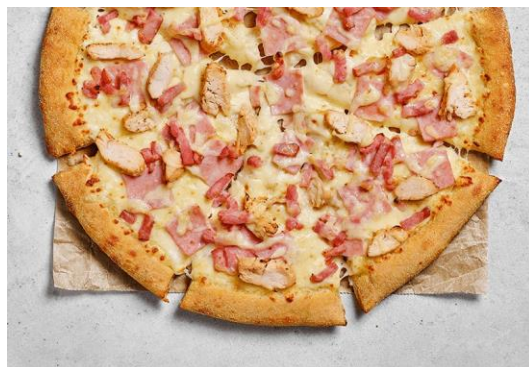


In the future

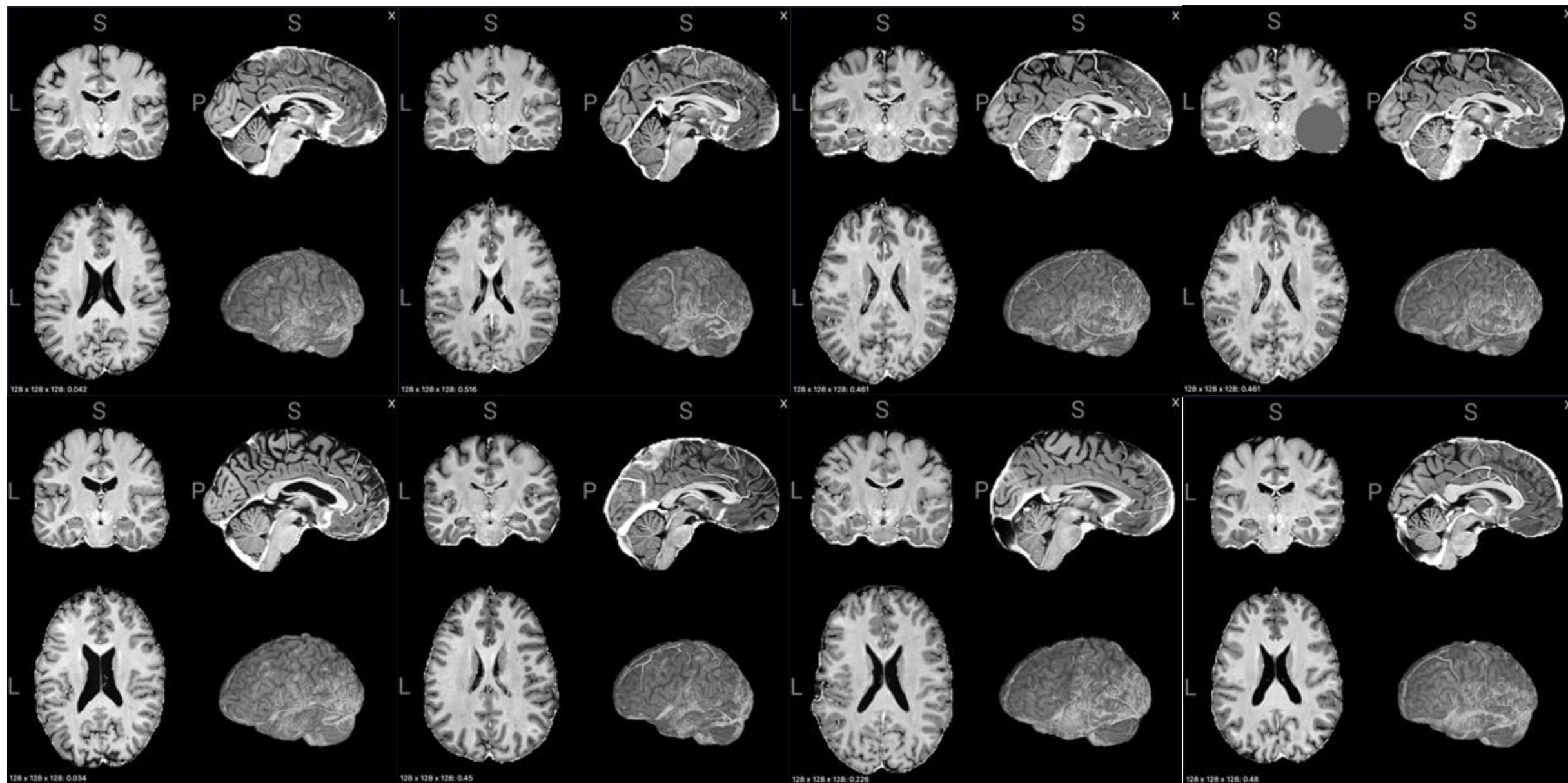
Improved diagnosis and
treatment, with
neuroimaging?

→ How can we improve the analysis of neuroimaging data to aid the diagnosis of brain disorders?

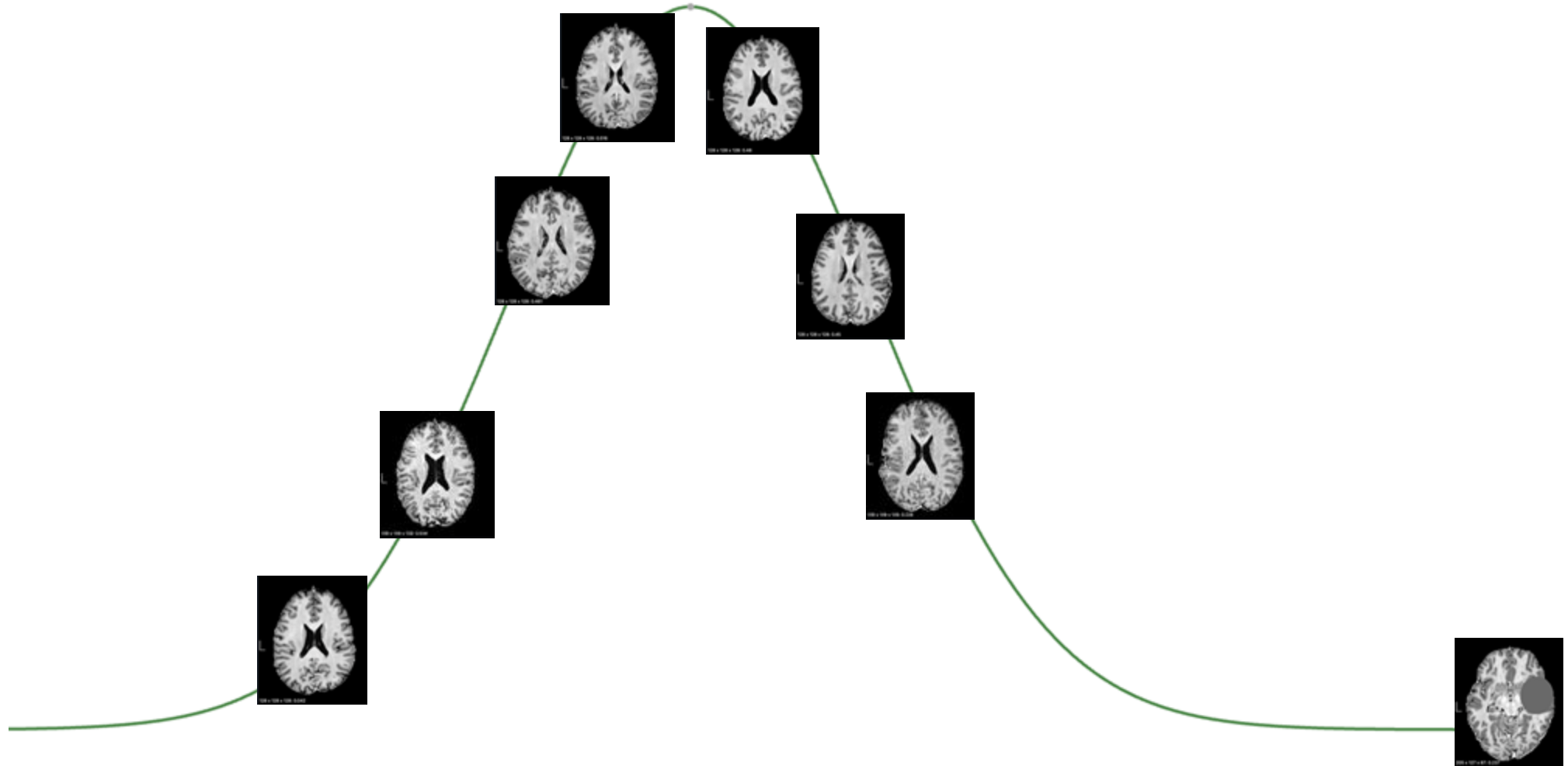
Which pizza is out-of-distribution / anomalous?



Which brain is out-of-distribution / anomalous?

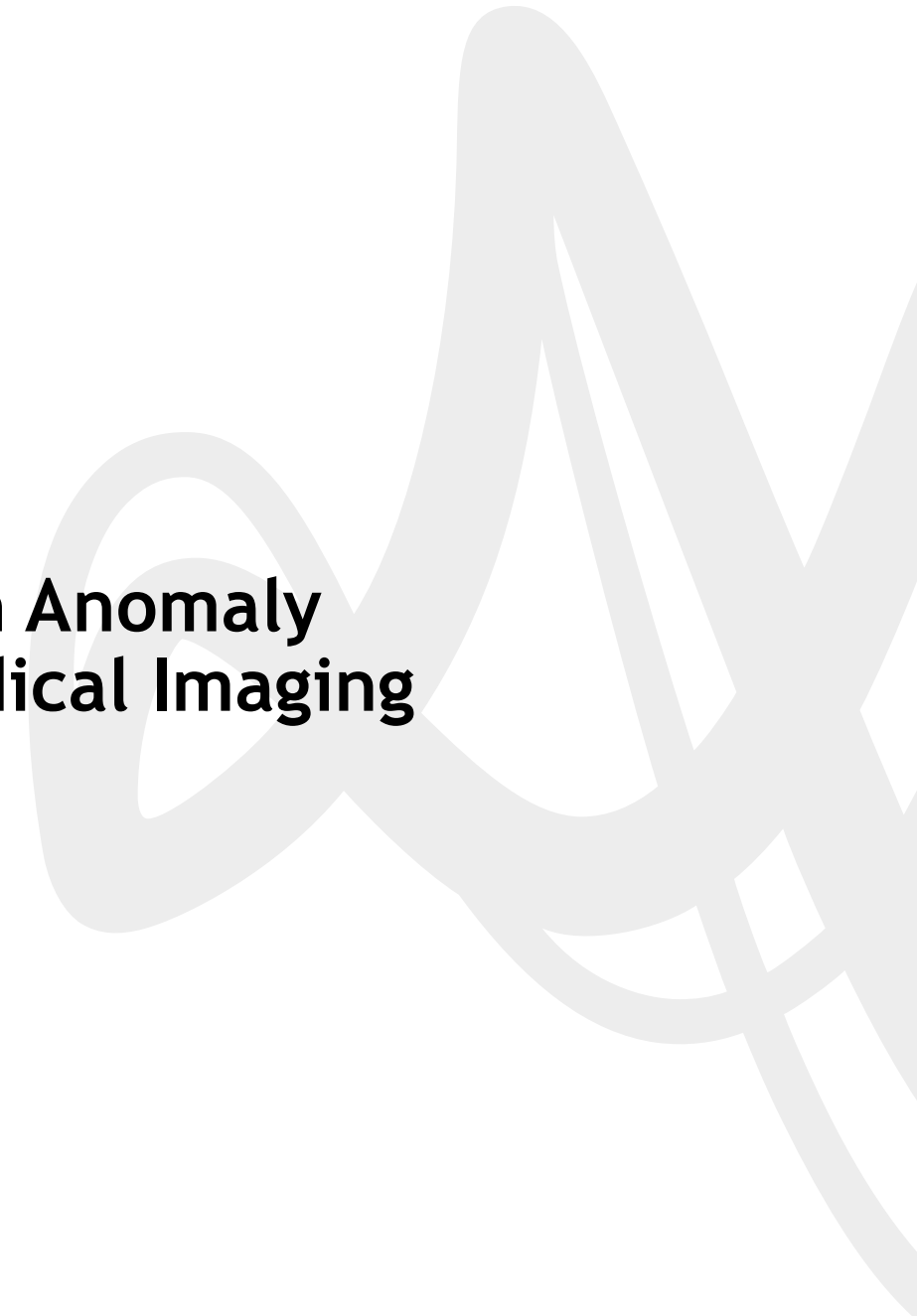


Out of Distribution Detection

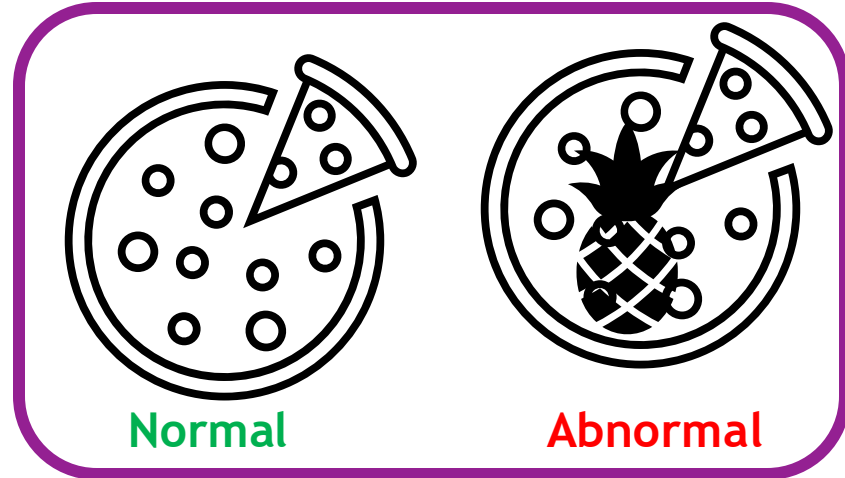




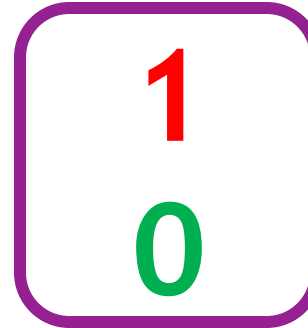
State of the Art in Anomaly Detection for Medical Imaging



Supervised Learning



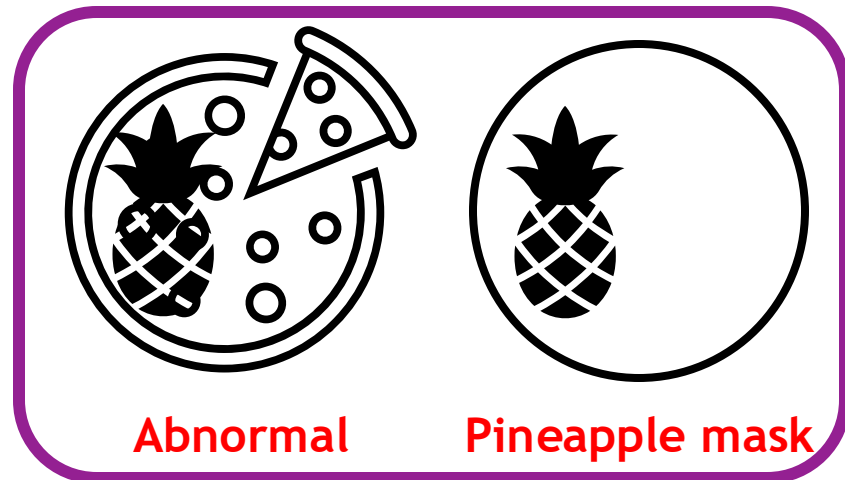
Classification
Model



Highly accurate



Requires annotated
training data



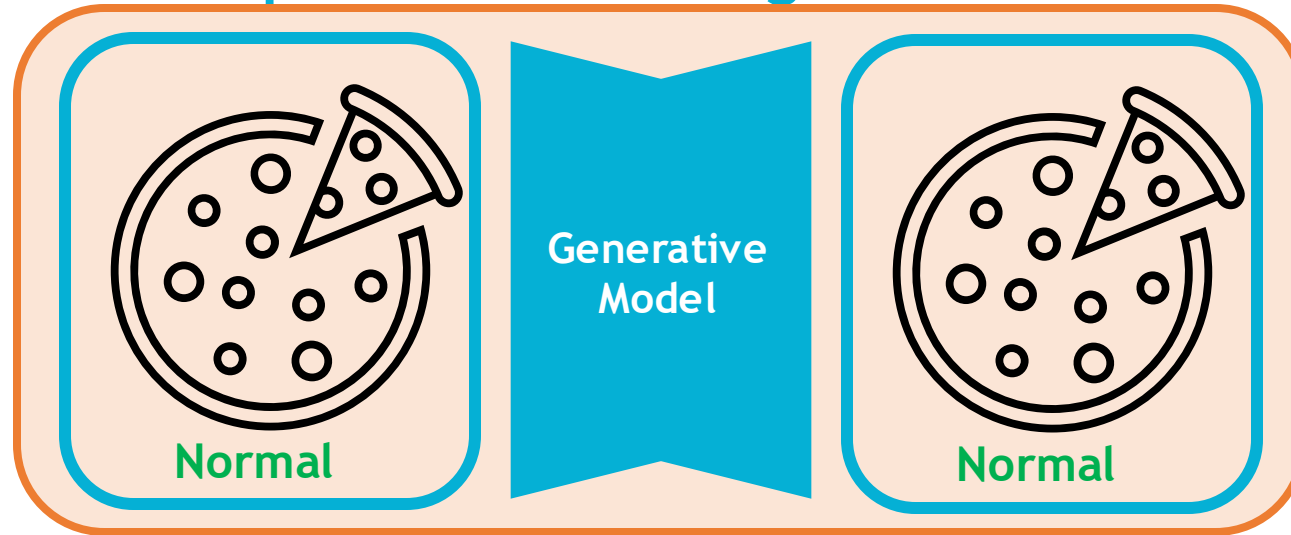
Segmentation
Model



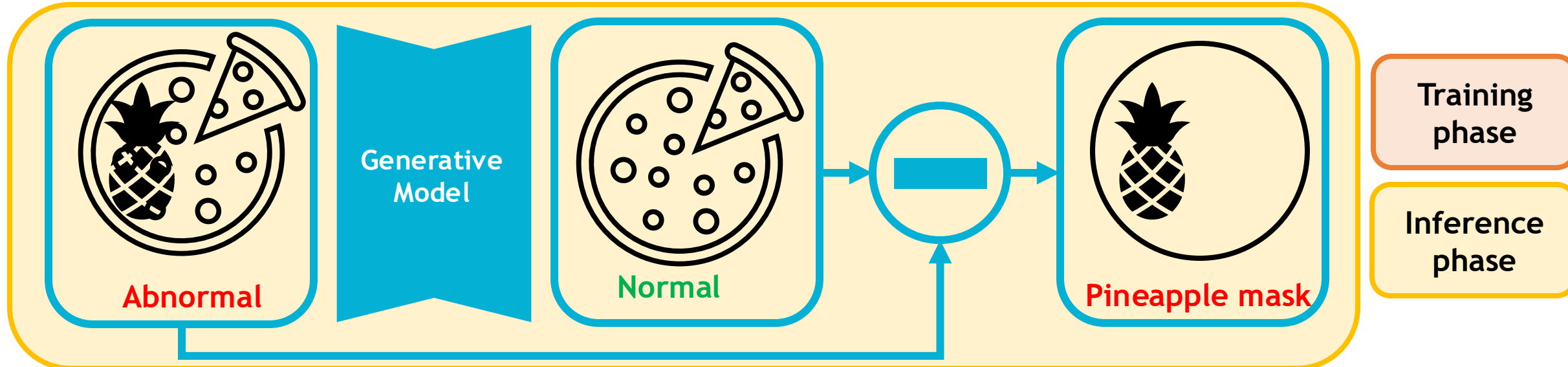
Difficult to
generalise to
different types of
anomalies

State of the Art in Medical Anomaly Detection

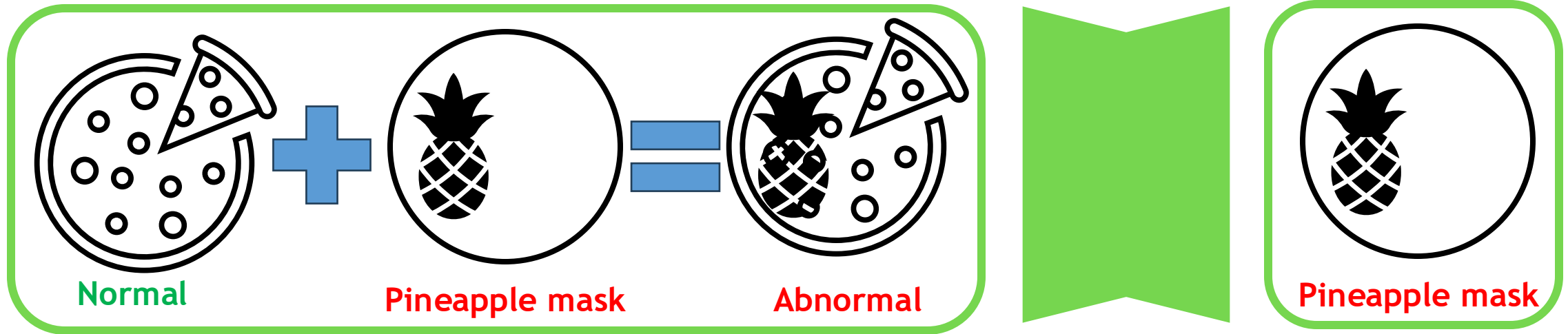
Unsupervised Learning




- + Trained on healthy data
- + No need for annotated training data
- + Good generalization abilities
- Harder to train



Self-supervised Learning

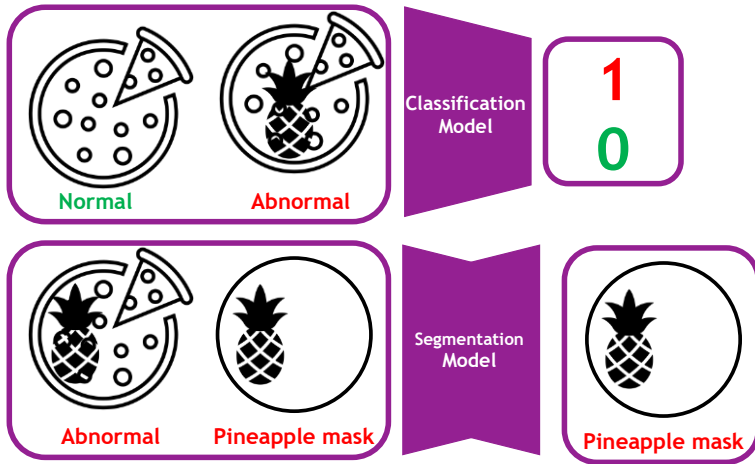


 Trained on synthetic abnormal scans

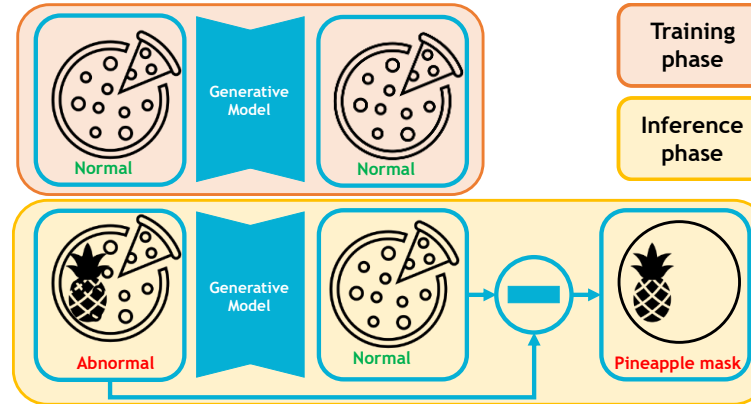
 Difficult to generalise to different types of anomalies

State of the Art in Medical Anomaly Detection

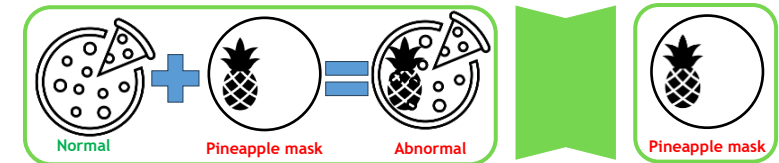
Supervised Learning




Unsupervised Learning



Self-supervised Learning



 Highly accurate

 Requires annotated training data
Difficult to generalise

Trained on healthy data
No need for annotated training data
Good generalization abilities

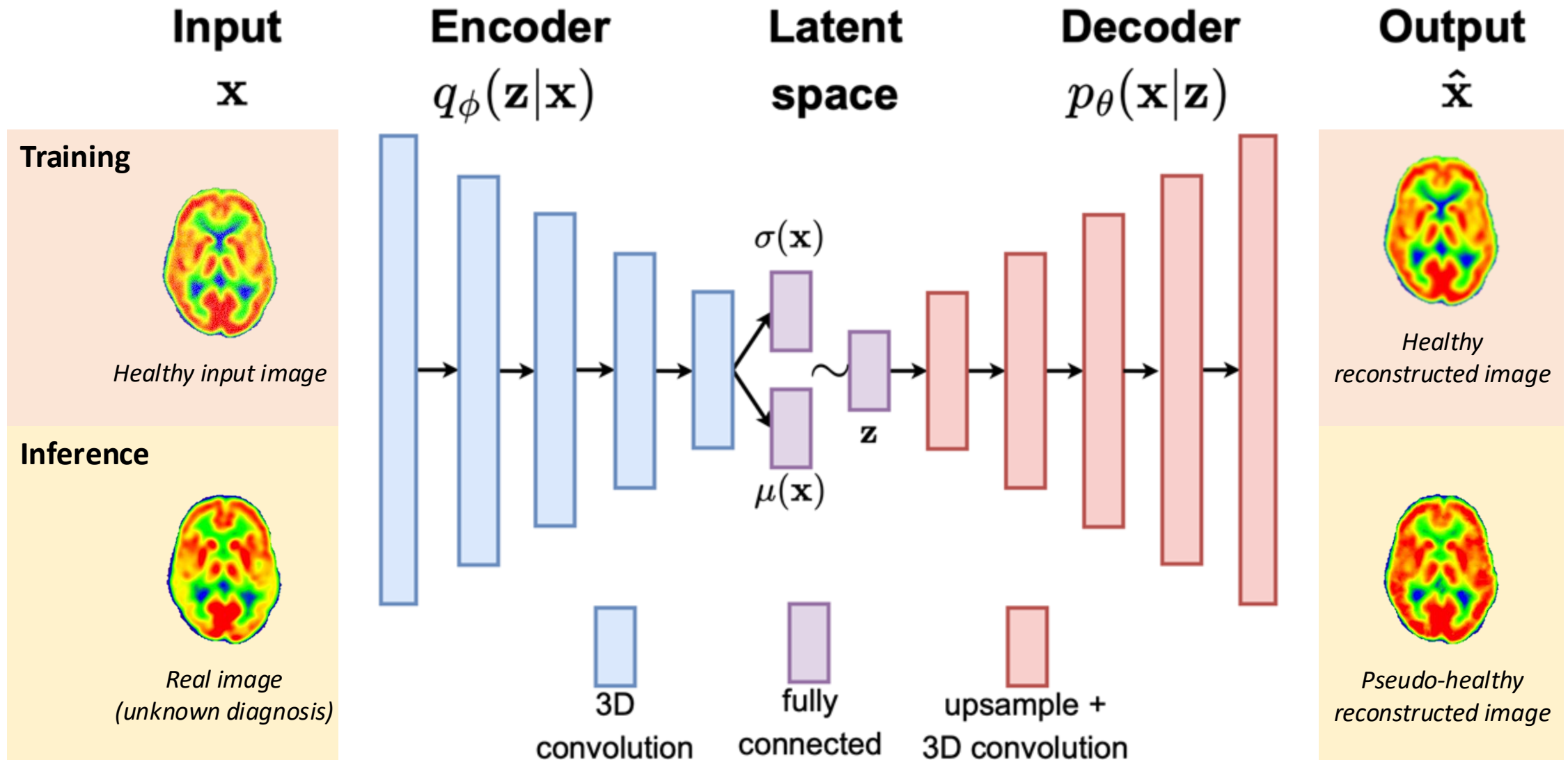
Harder to train

Trained on synthetic abnormal scans

Difficult to generalise to different types of anomalies

Unsupervised Anomaly Detection via Pseudo-Healthy Reconstruction, an Example

Variational Autoencoder (VAE)



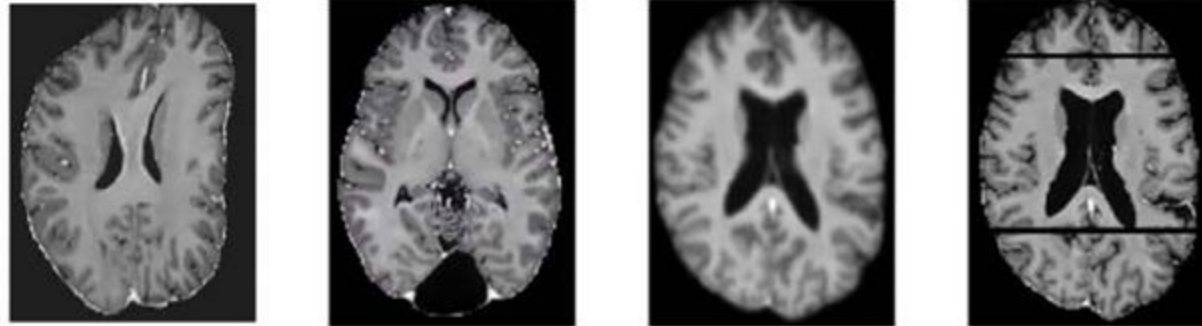
$$\mathcal{L}_{\theta, \phi}(\mathbf{x}) = \mathbb{E}_{q_{\phi}(\mathbf{z}|\mathbf{x})}[\log p_{\theta}(\mathbf{x}|\mathbf{z})] - \mathcal{D}_{KL}(q_{\phi}(\mathbf{z}|\mathbf{x}) || p_{\theta}(\mathbf{z}))$$

Medical Out-of-Distribution Challenge (MOOD)



MOOD Types of Anomalies

Global



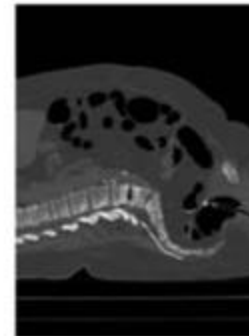
Corruptions



Medical
conditions

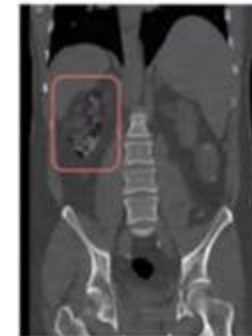
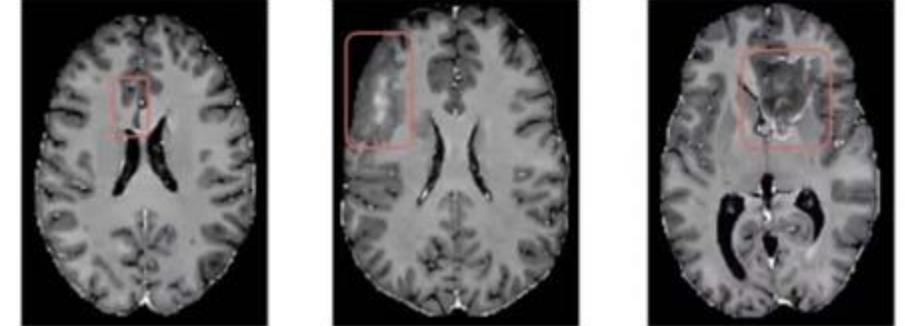


Alterations

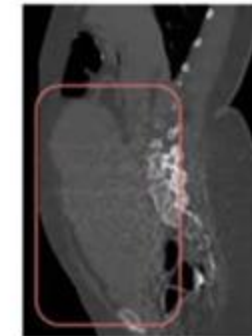


Destructions

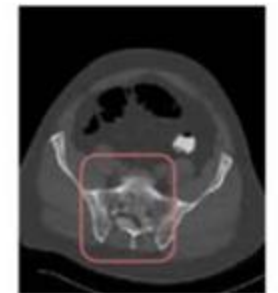
Local



Corruptions

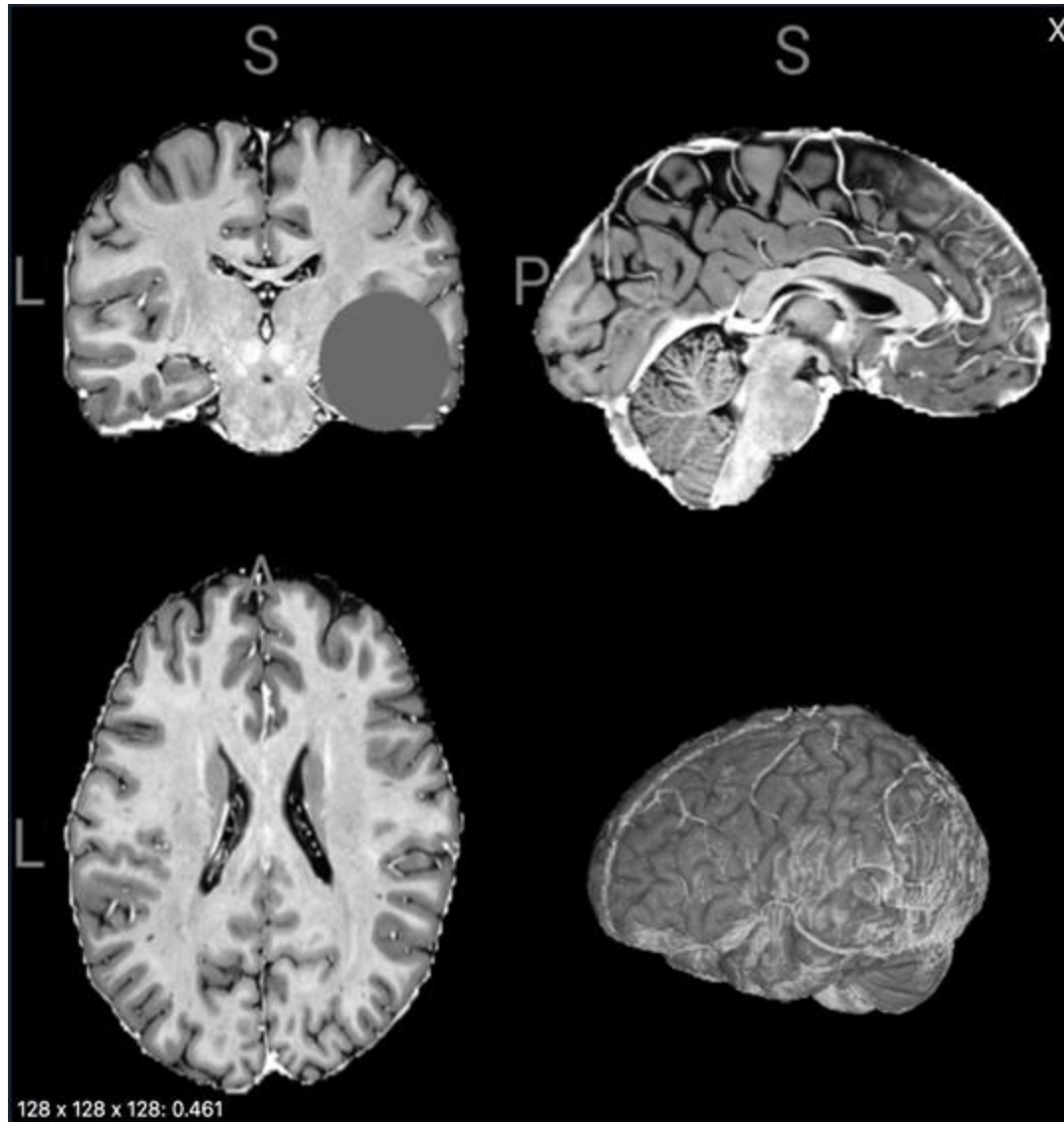


Pathologies



Images

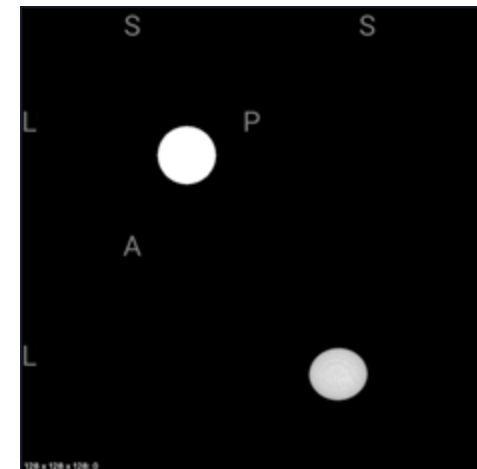
MOOD Tasks



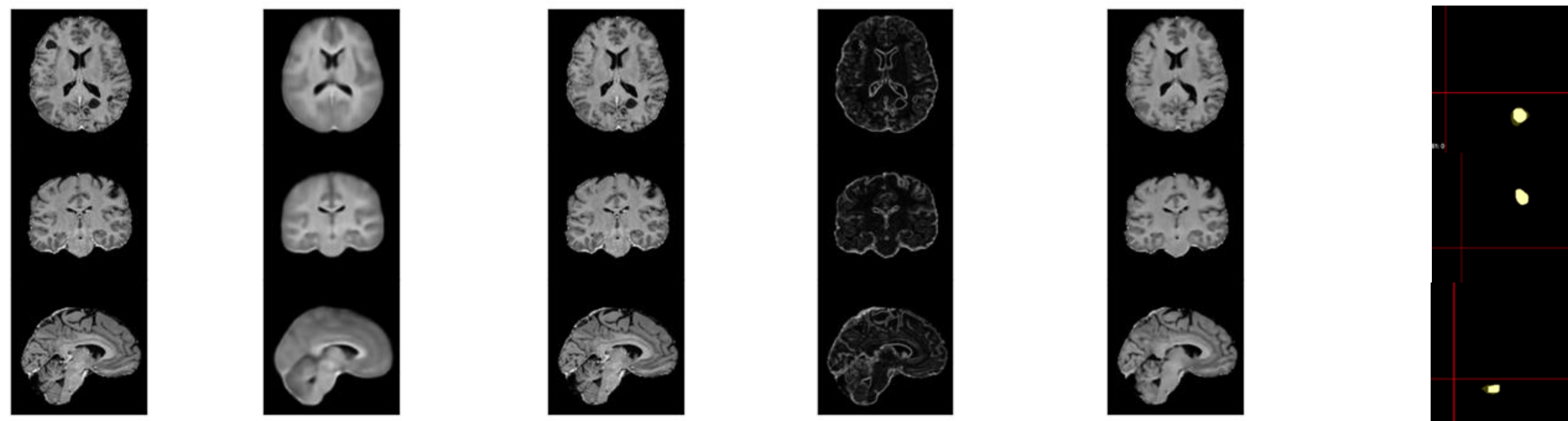
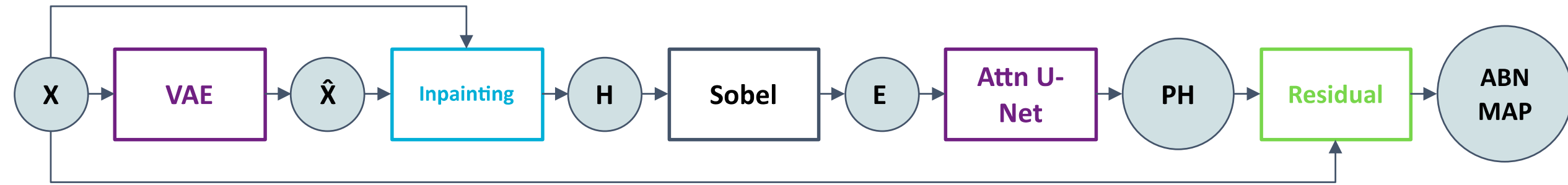
1. Sample-level: label 1 or 0 if image is out-of-distribution

1

2. Object-level: mask of anomalies



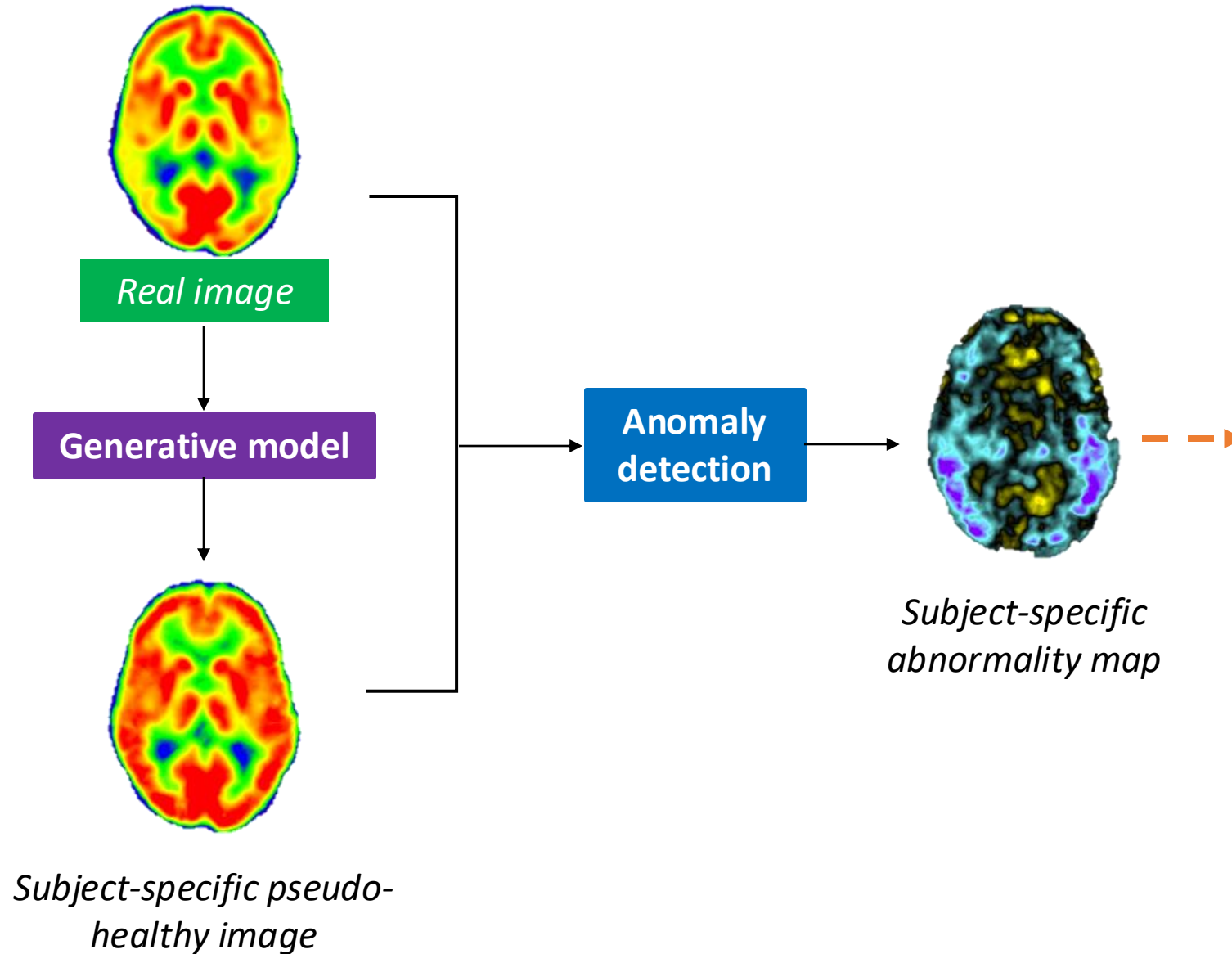
Proposed Approach





Perspectives





Research objectives:

1. Improve the quality of pseudo-healthy images
2. Generate robust abnormality maps by modelling uncertainty
3. Extend the detection of anomalies to multimodal neuroimaging data
4. Validate the approach with the support of clinicians



10th September 2024

Thank you for listening

Inria Junior Seminar

Maëlys Solal

