Challenges and Opportunities of AI in Medical Imaging

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Who am I?

Machine Learning & Artificial Intelligence + **Multimodal and high-dimensional clinical data**

life.augmented

PhD

UNIVERSITY OF SURREY

visual atoms

Imperial College London

The Hamlyn Centre for Robotic Surgery

UCL

weiss

cmic

UH

2008 | 2011 | 2014 | 2017 | 2021

My Background

Deep learning

Endomicroscopy imaging

Computer vision

Disease progression modelling

Wearable devices

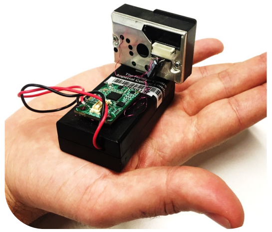
Tissue segmentation

Remote monitoring

Super-resolution

Hyperspectral imaging

using



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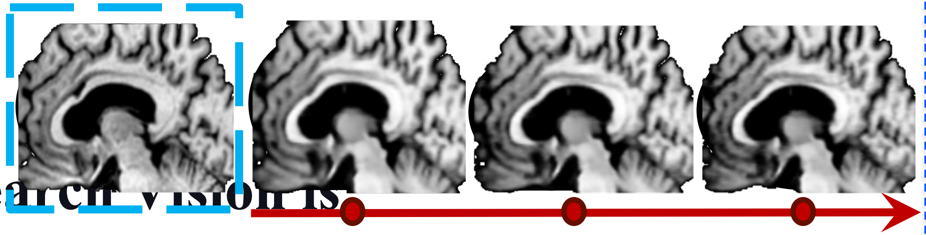
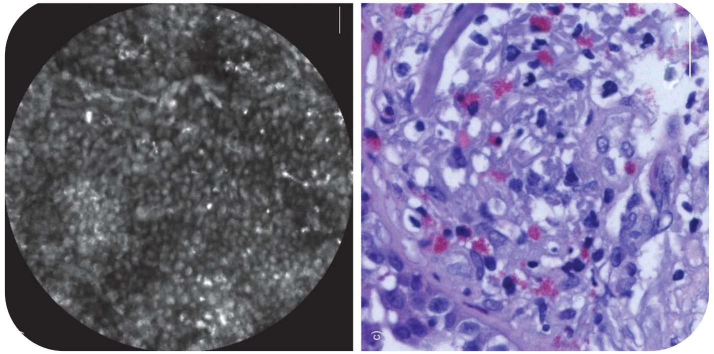
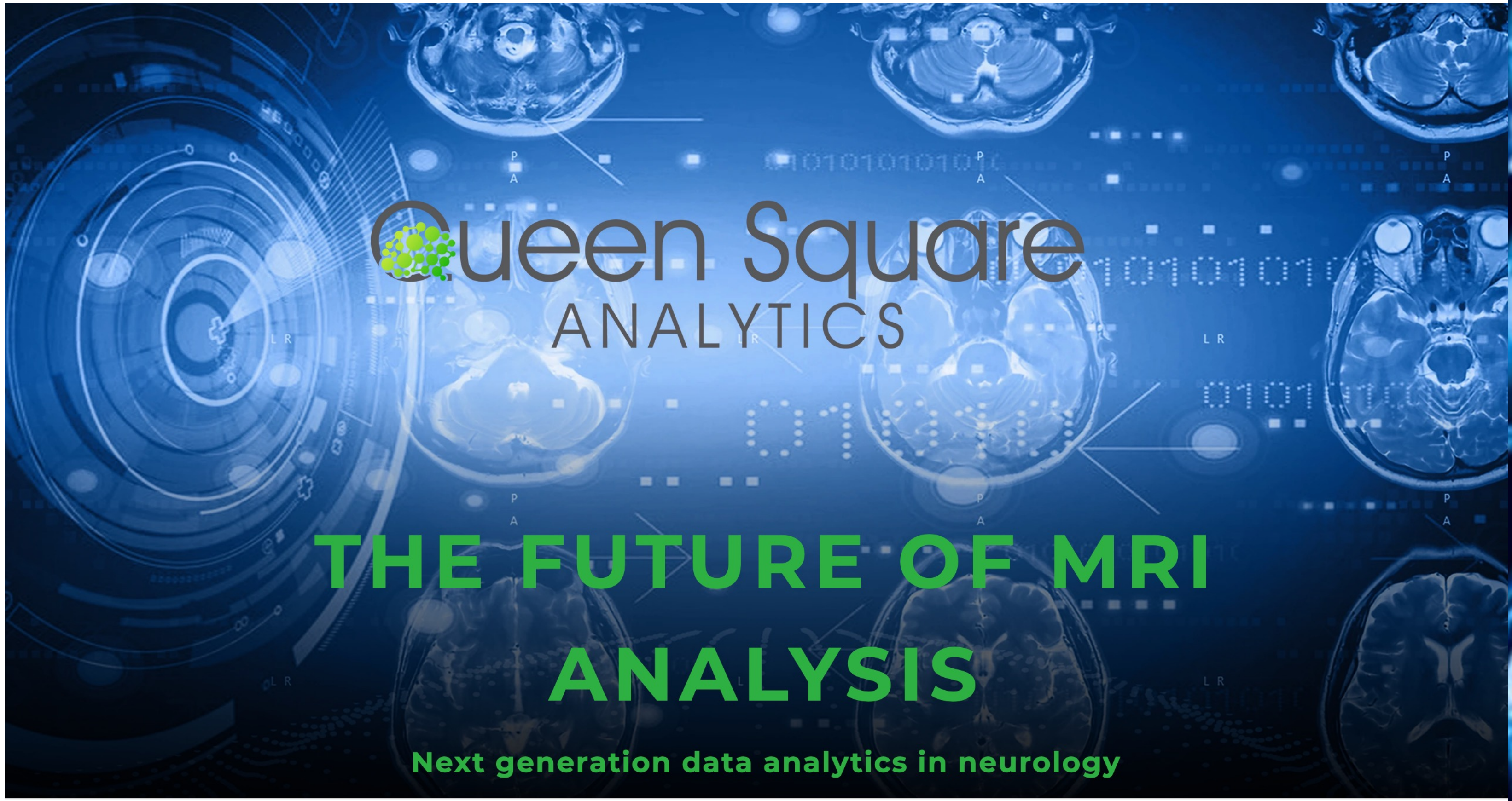


Applying AI to solve challenging problems that can revolutionize the way we identify diseases, improve patient treatments and patient monitoring

using



Queen Square Analytics – UCL Startup



WHY QSA

World leading expertise with commercial flexibility

QSA offers the latest technology in neurological image analysis supported by a team of top experts in the field leading path-breaking research projects at UCL.

Agenda

- Motivations
- Medical Imaging
  - Introduction to the Different Modalities
- Applications
  - Image Retrieval
  - Artifacts Detections
  - Tissue Segmentation
  - Super-Resolution
  - Disease Progression Modelling
  - Smart Sensing
- Conclusion

Question: How AI Is Transforming The Future Of Healthcare?

Why AI in Medical Imaging?

- National health systems in various countries facing crisis after COVID-19 pandemic
- We see everywhere overwhelmed healthcare infrastructure and lack of resources
- Crisis has exposed **pre-existing issues** in healthcare systems such as **underfunding** and staffing shortages.
- The crisis is particularly important in **low-income countries** where the healthcare system is already fragile.

This article is more than **6 months old**

Doctors forced to work overnight shifts at last minute in NHS staffing crisis

Junior medics in England being sent home from day shifts and told to come back to plug gaps at night

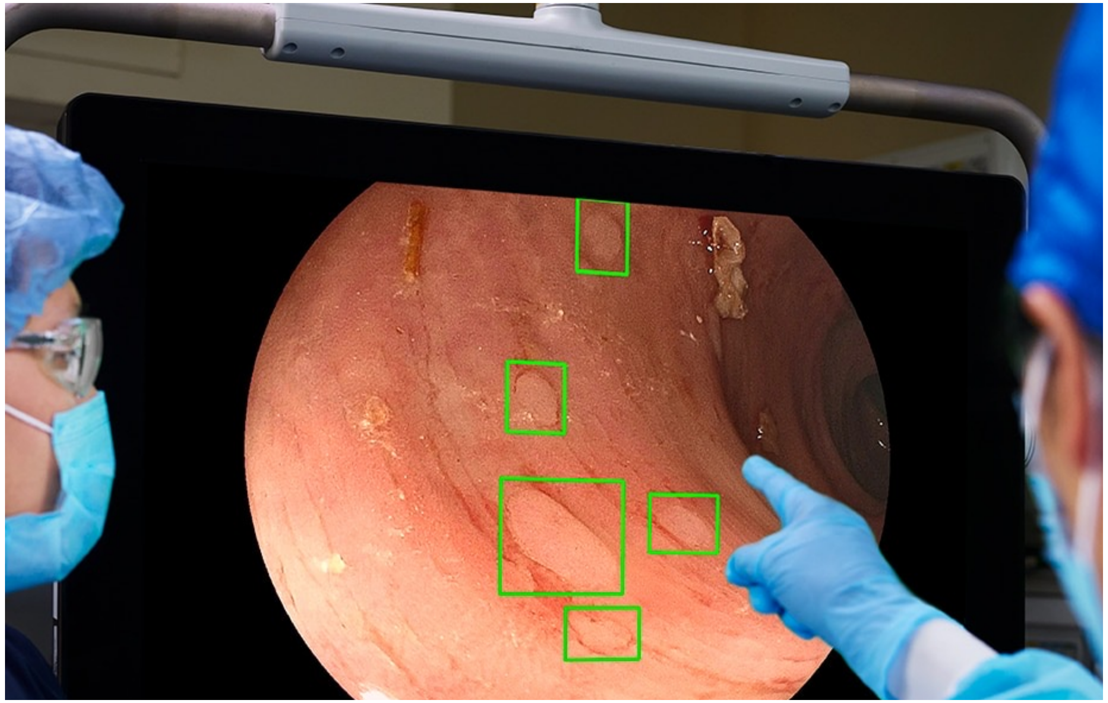
Letters

Recruitment drives alone won't fix the NHS staffing crisis

Anas Nader says the focus should be on retention, while **Amanda Grantham** looks to volunteer helpers. Plus **Jeremy Seymour** on early retirement and **Dr Sharon Holland** on apprenticeships

GI Genius™ intelligent endoscopy

- The first-to-market, computer-aided polyp detection system **powered by AI**
  - Approved by FDA
- Detect colorectal polyps through enhanced visualization during **colonoscopy**



DELIVER
BETTER
OUTCOMES

Medtronic

GI Genius™ has been shown to increase adenoma detection rates by **up to 14.4%.**

Medical Imaging promises to improve the healthcare system

Medical Imaging Applications:

1. Improved Diagnostic Accuracy
2. Enhanced Patient Care
3. Shortening Hospitalization
4. Increased Healthcare Professional Efficiency
5. Clinical Decision Making Support
6. Image-Guided Surgery
7. Clinical Trial Assistance
8. Telemedicine Capabilities

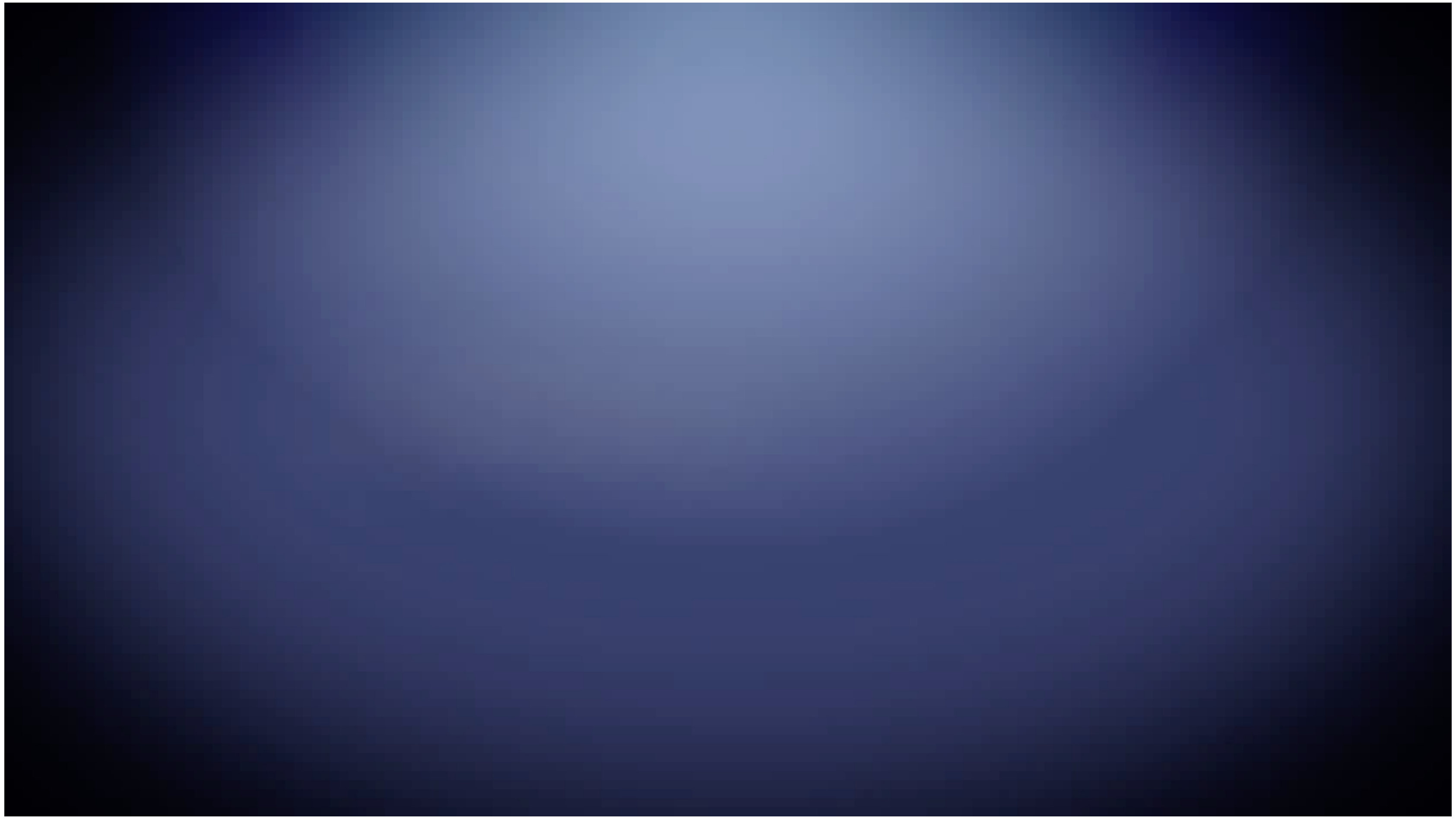
AI can improve medical services:

1. Decrease the costs
2. Make them more efficient
3. Less prone to mistakes
4. Save lifes

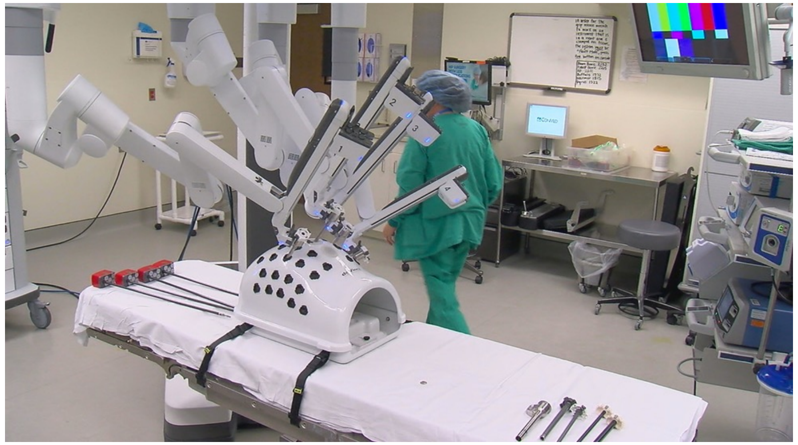
Image-guided robotic surgery: Da Vinci Robot

- Surgical robots can achieve **superhuman** performance during minimally invasive surgery

- AI can boost the capability of surgical robotic systems in perceiving complex environments, conducting decision-making, and performing the desired tasks

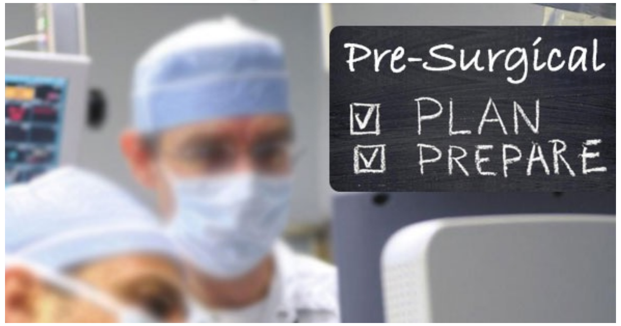


Applications in Image-guided robotic surgery



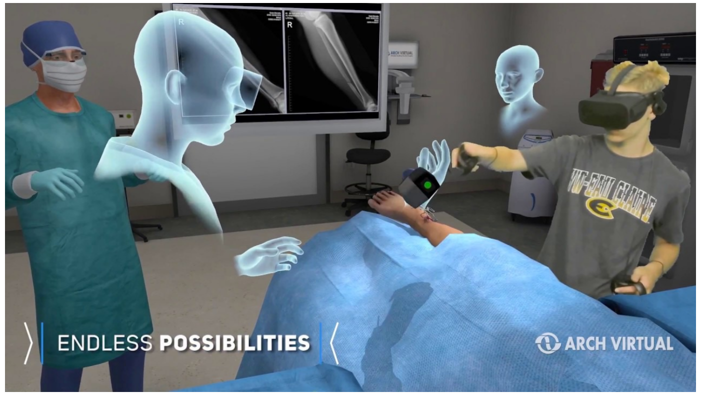
Minimally Invasive Robotic Surgery

1



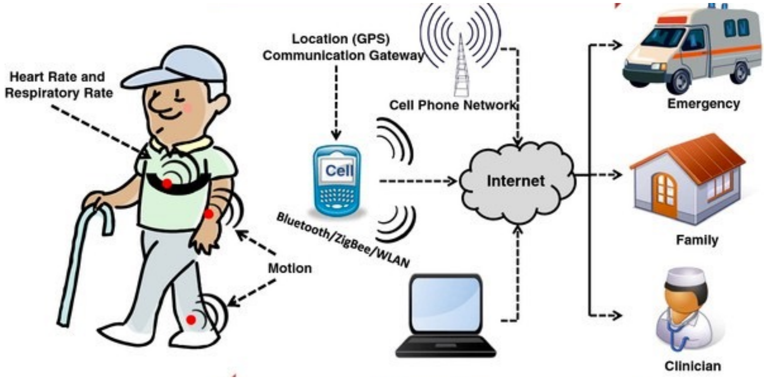
Pre-operative simulation & planning

2



Intra-operative guidance & AR

3



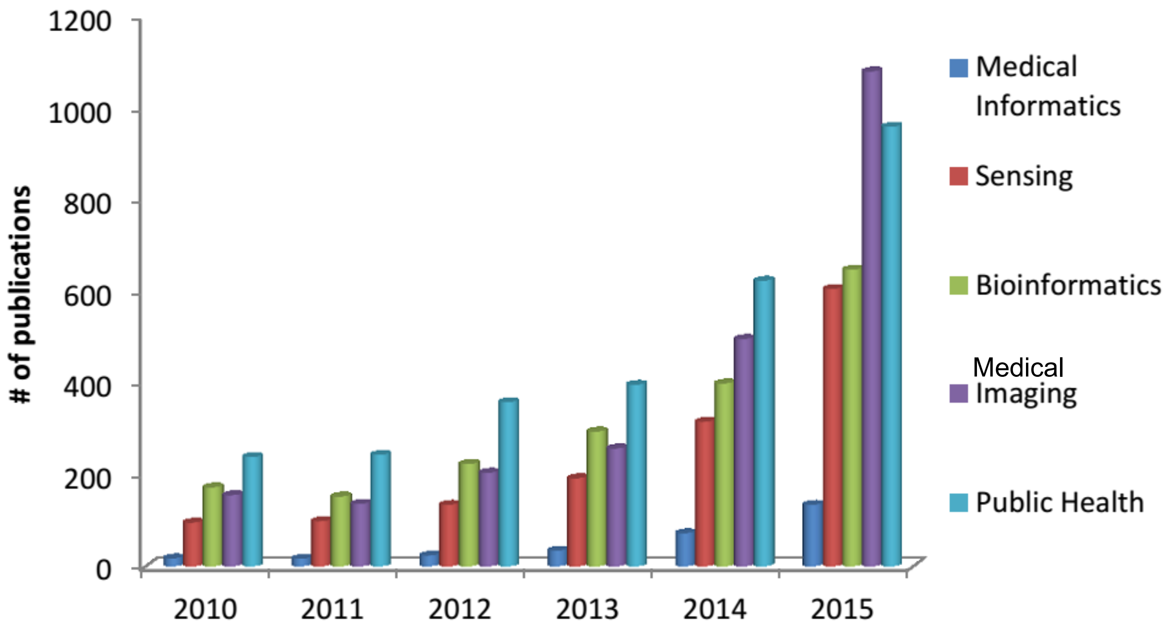
Post-operative care
Telemedicine & Smart Sensing

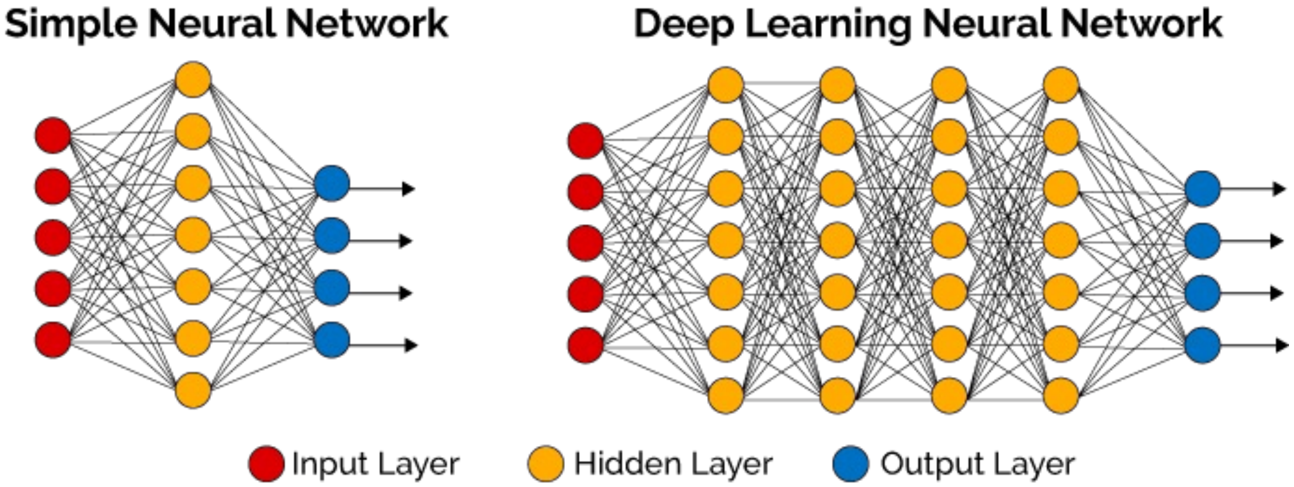
AI & Deep Learning

Rapid uptake in healthcare due to:

1. Many medical centers that collect and organize large sets of patient data

2. Computational hardware improvements
   - High performance computing
   - Cloud computing
   - GPUs
   - Fast data storage

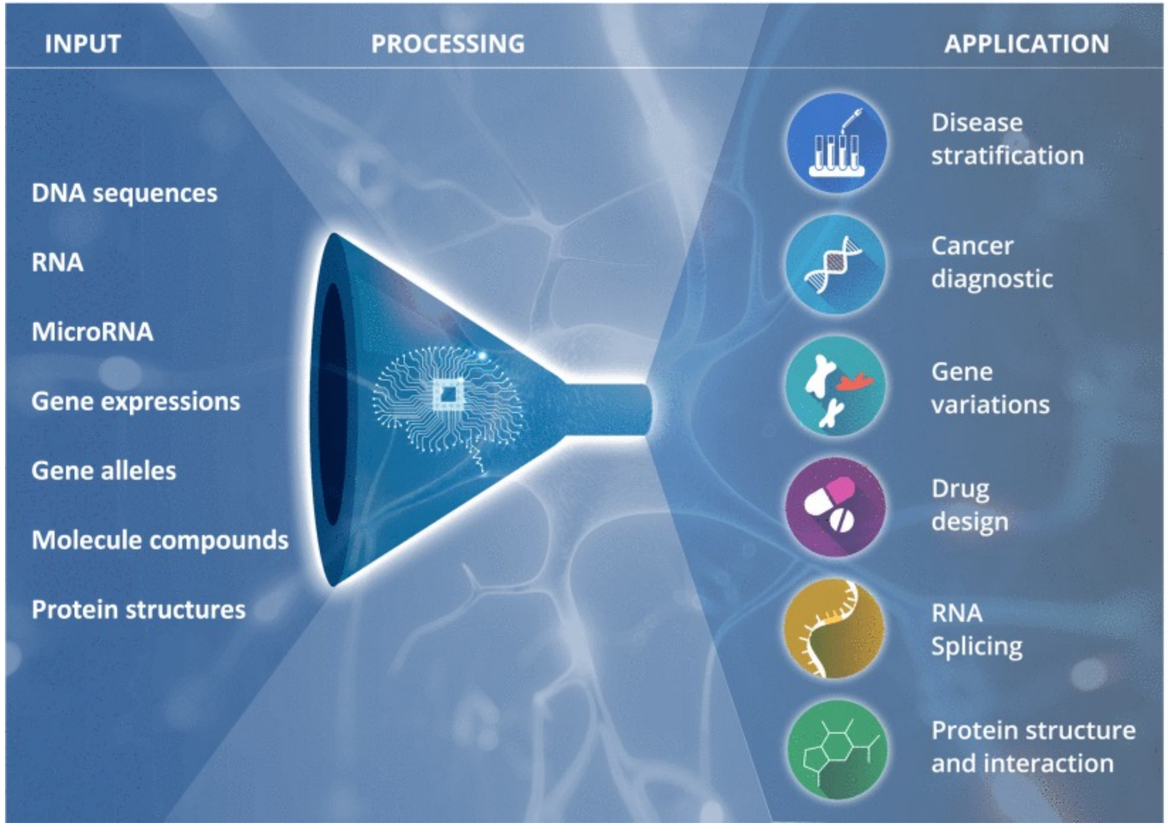




Ravì, Daniele, et al. "Deep learning for health informatics." *IEEE journal of biomedical and health informatics* 21.1 (2016): 4-21

Applications of AI in Health Informatics

	Applications	Input Data
Bioinformatics	Cancer diagnosis Gene selection/classification Gene variants	Gene expression MicroRNA Microarray data
	Drug design	Molecule compounds
	Compound-Protein interaction RNA binding protein DNA methylation	Protein structures Molecule compounds Genes/RNA/DNA sequences
Medical Imaging	3D brain reconstruction Neural cells classification Brain tissues classification Alzheimer/MCI diagnosis	MRI/fMRI Fundus images PET scans
	Tissue classification Organ segmentation Cell clustering Hemorrhage detection Tumour detection	MRI/CT Images Endoscopy images Microscopy Fundus Images X-ray images Hyperspectral images



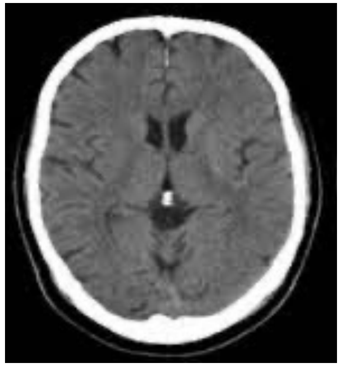
Applications of AI in Health Informatics

	Applications	Input Data
Pervasive Sensing	Anomaly detection Biological parameters monitoring	EEG ECG Implantable device
	Human activity recognition	Video Wearable device
	Hand gesture recognition Obstacle detection Sign language recognition	Depth camera RGB-D camera Real-Sense camera
	Food intake Energy expenditure	Wearable device RGB Image Mobile device
Medical Informatics	Prediction of disease Human behaviour monitoring Data mining	Electronic health records Big medical dataset Blood/Lab tests
Public Health	Predicting demographic info Lifestyle diseases Infectious disease epidemics Air pollutant prediction	Social media data Mobile phone metadata Geo-tagged images Text messages

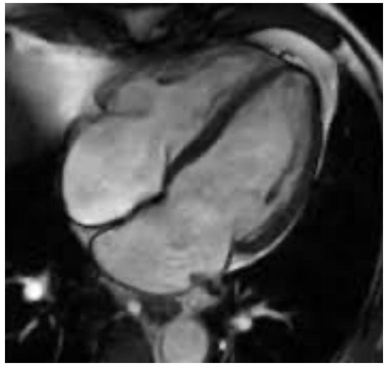
What is Medical imaging?

Encompasses a range of techniques used to obtain tissue information, with the goal of **aiding diagnosis, monitoring, and treatment of various health conditions.**

Chest X-rays

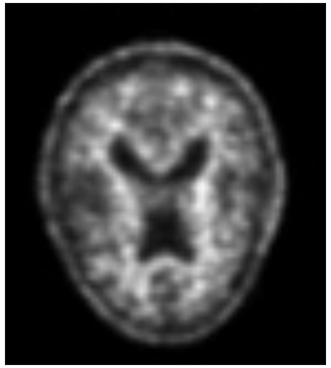


Brain Computed Tomography

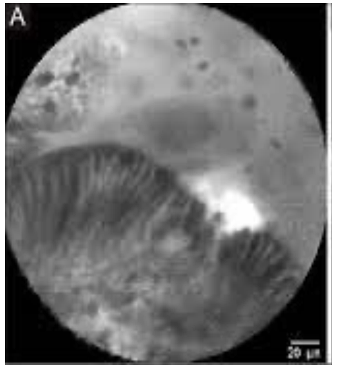


Cardiac MRI

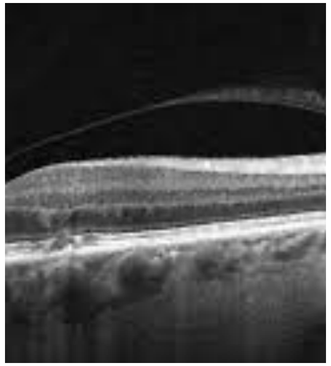
Abdominal Ultrasound



Brain Positron emission tomography



Tissue Endomicroscopy



Retina Optical Coherence Tomography

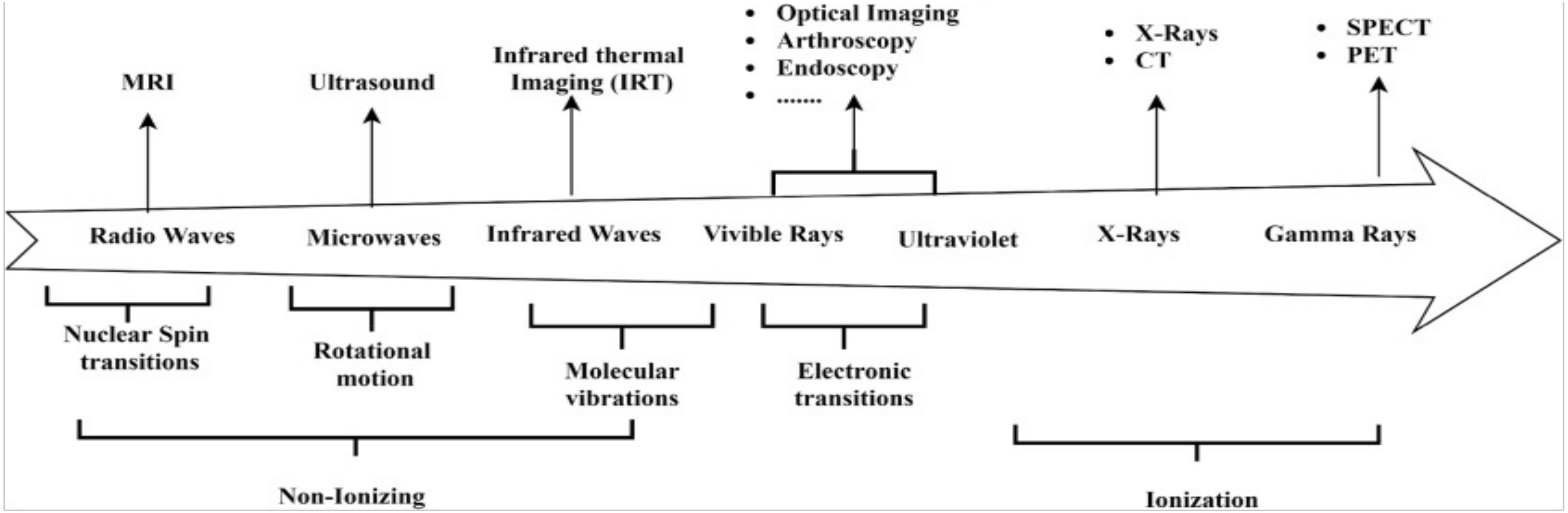
And many more…..

1. Functional MRI- fMRI
2. Hyperspectral imaging
3. Diffusion MRI
4. Endoscopy
5. Fluoroscopy
6. Angiography
7. Mammography

Image Modalities: Taxonomy

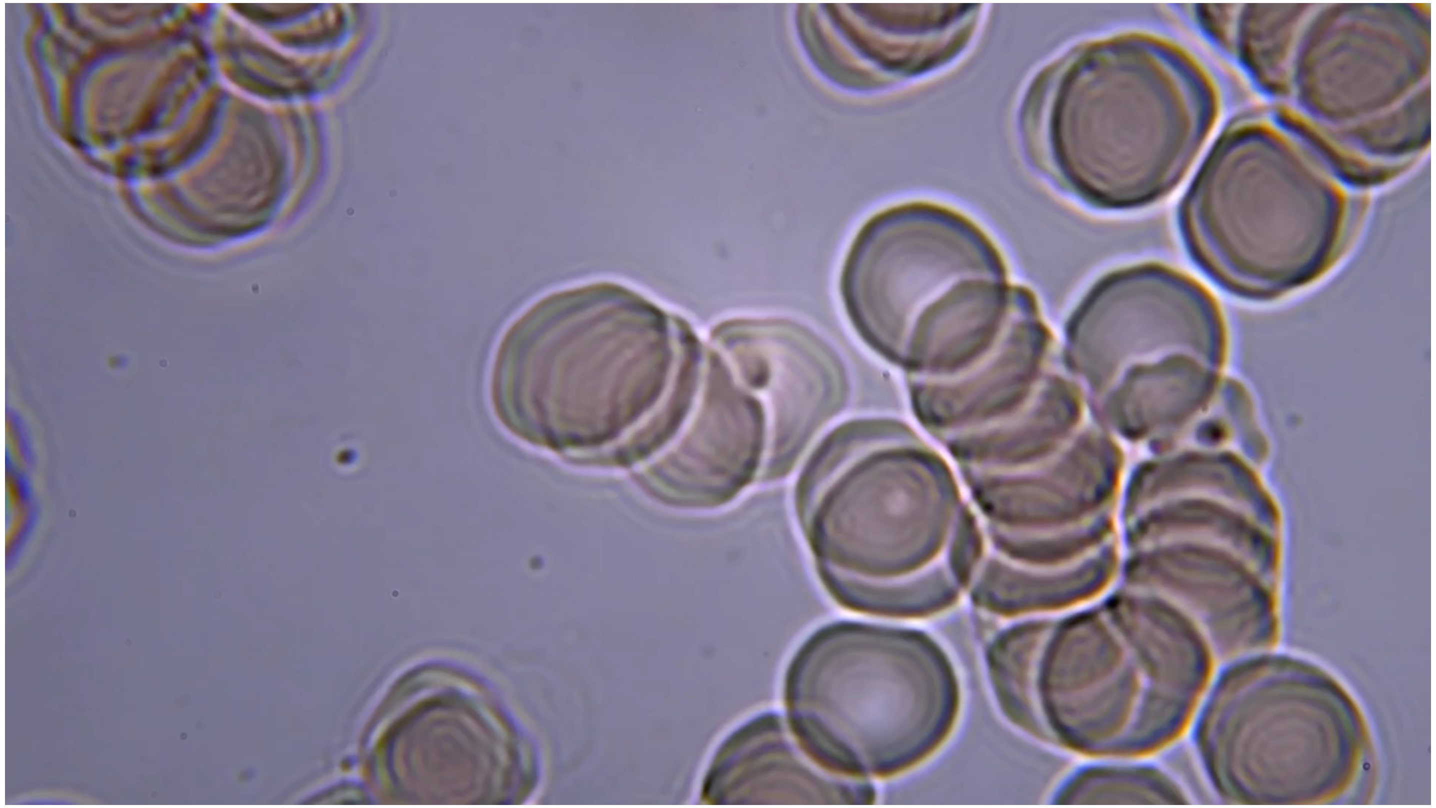
Different imaging modalities vary in:
- Acquisition scanner
- Image resolution
- Tissue properties captured
- Invasiveness of the associated procedure
- Ionizing properties of the associated scanner

These differences result in:
- Varying costs
- Different image quality
- Different diagnostic capabilities
- Different surgical procedures
- Potential risks

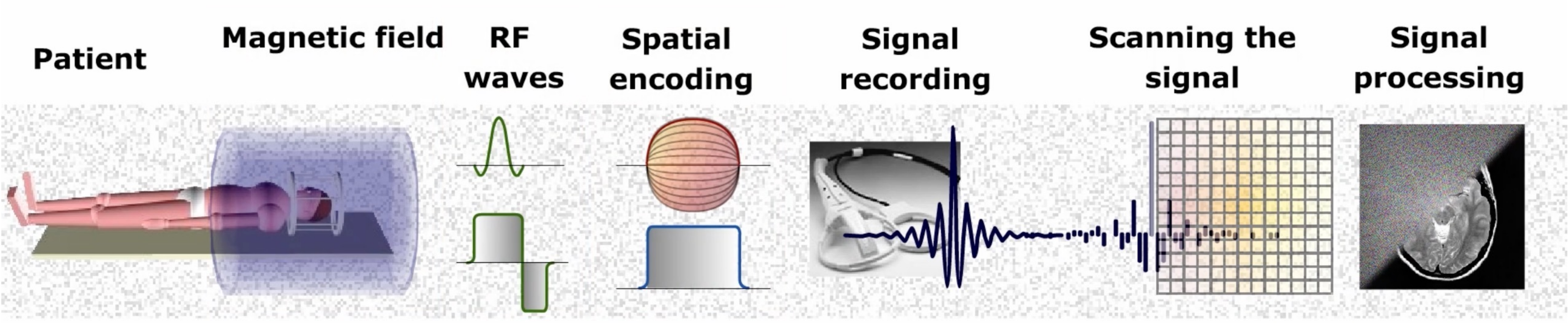


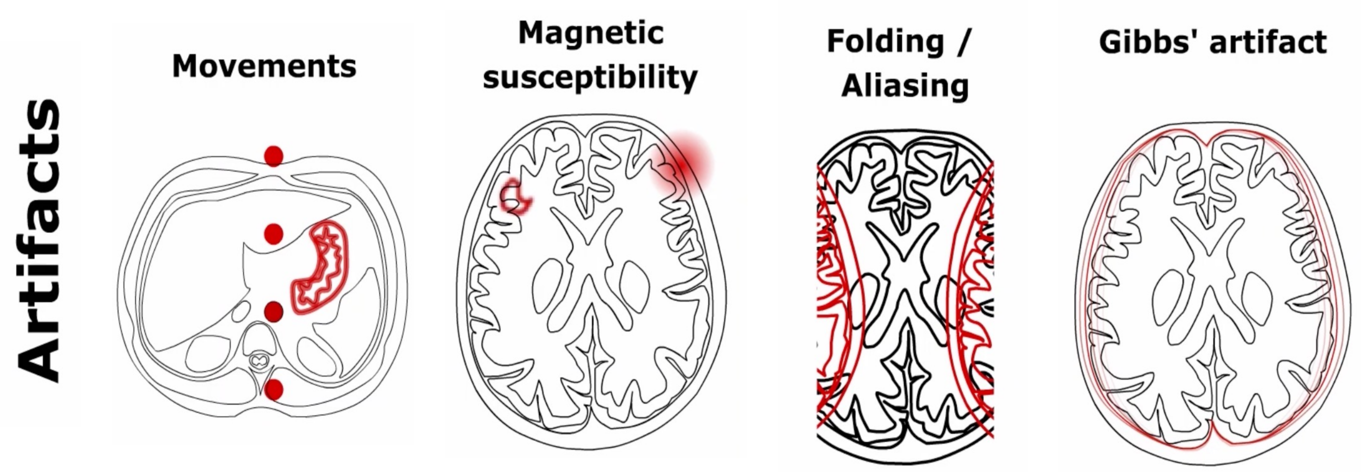
Milestones in Medical Imaging

16th Century - Microscope | 1895 - X-ray | 1956 - Ultrasound | 1972 - CT | 1977- MRI



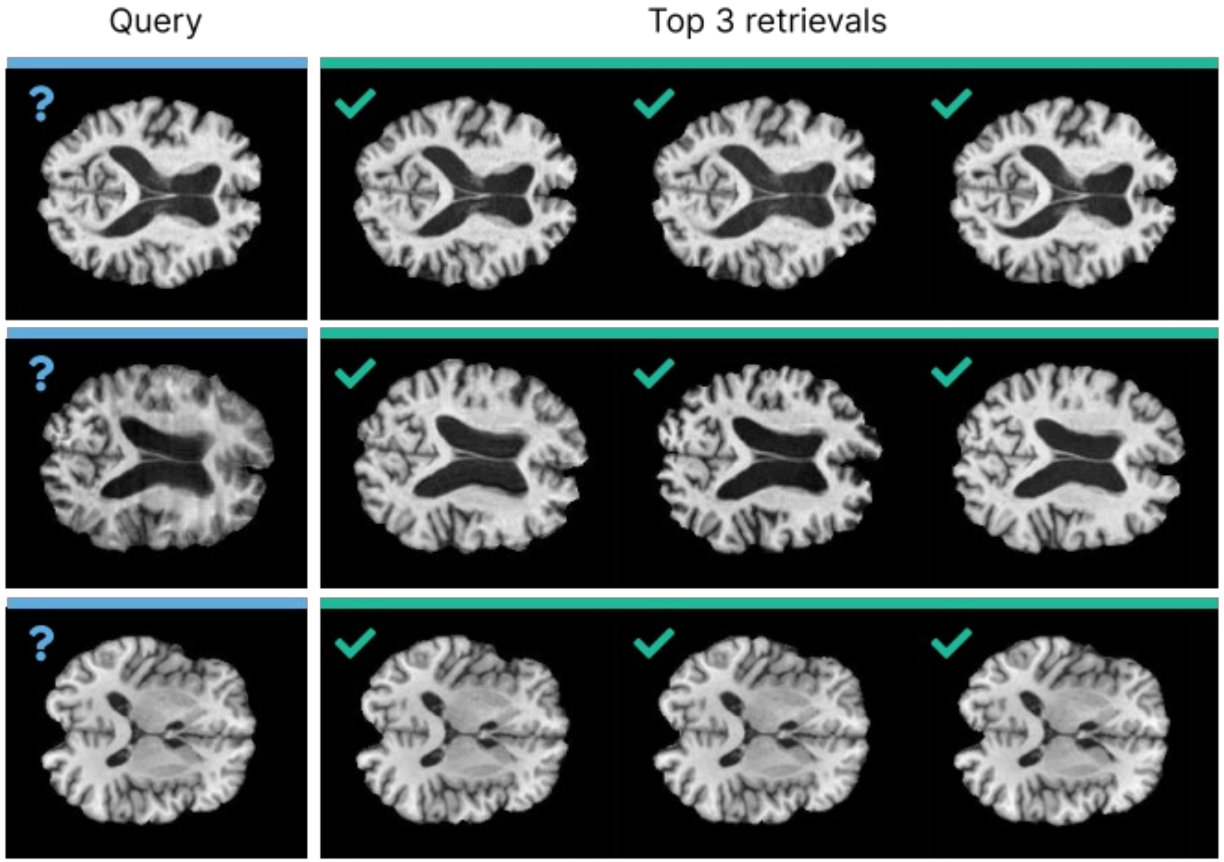
Magnetic Resonance Imaging





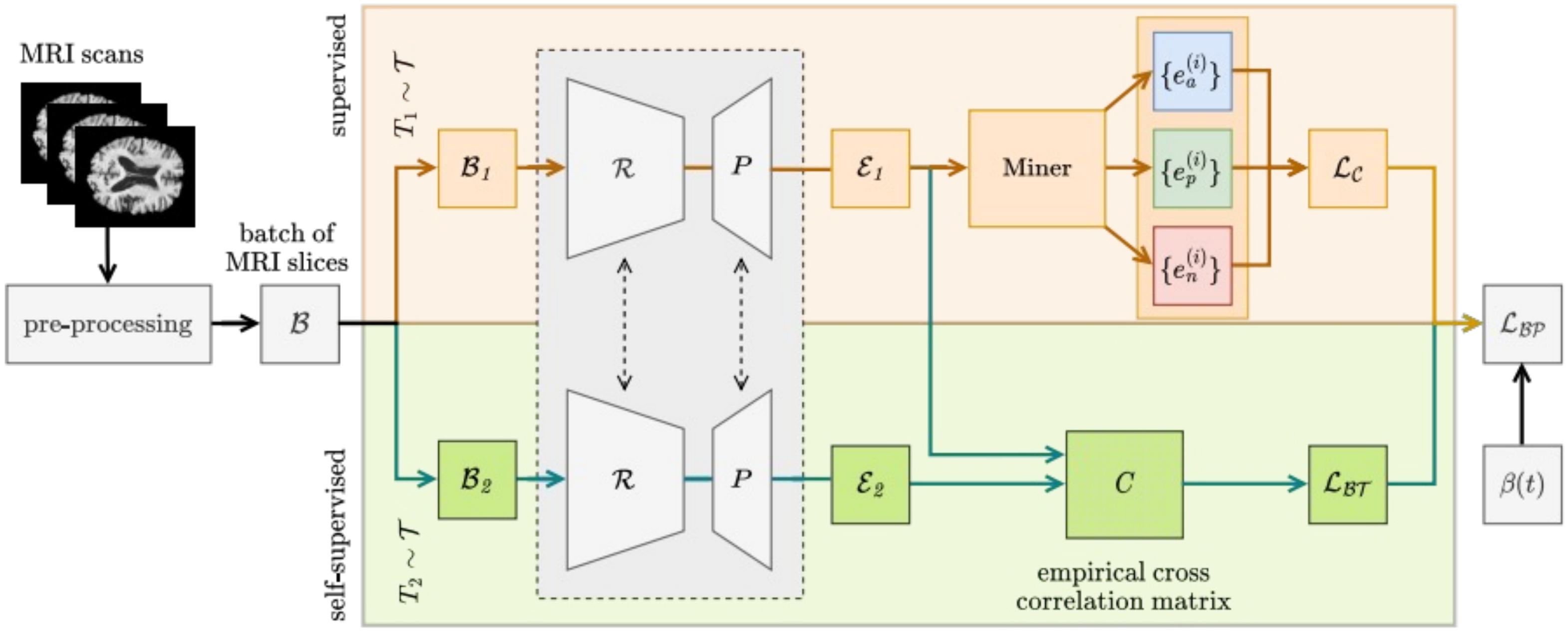
DeepBrainPrint: AI-Powered Medical Imaging Retrieval Framework

- Recent advances in MRI have led to the creation of large datasets
- Difficulty in locating previous scans of the same patient within these datasets
- Re-identification is the process of locating previous scans of the same patient within large datasets



DeepBrainPrint: Proposed Architecture

- Combining **self-supervised** and **supervised** paradigms to create an effective brain fingerprint from MRI scans that can be used for real-time image retrieval



- Introduction of new imaging transformations to improve retrieval robustness in the presence of intensity variations, age, and disease progression in patients.

Puglisi, L., Barkhof, F., Alexander, D.C., Parker, G.J., Eshaghi, A. and **Ravì, D., 2023.** DeepBrainPrint: A Novel Contrastive Framework for Brain MRI Re-Identification. *Accepted at MIDL 2023*

DeepBrainPrint: Experimental Results

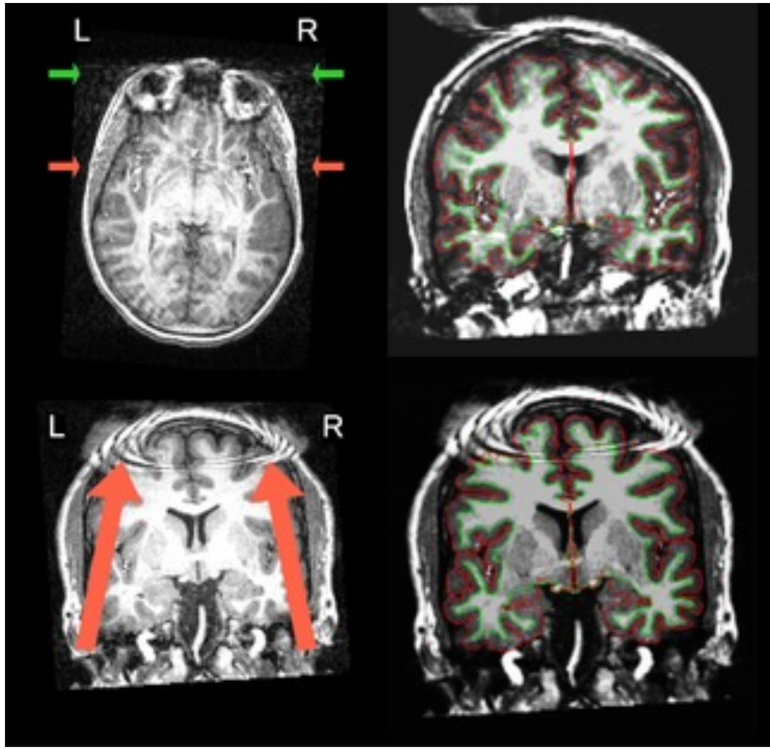
- **Tested on:**
  1. a large dataset of T1-weighted brain MRIs from (ADNI)
  2. a synthetic dataset designed to evaluate retrieval performance with different image modalities

	Settings			ADNI		SYNT-CONTR	
Method	$\widehat{FS}$	$\widehat{SS}$	$\widehat{DT}$	R@3	mAP@3	R@3	mAP@3
SSIM-based [20]	No training			96.89	90.21	76.68	48.86
3D SIFT-Rank [5]	No training			**100.00**	**100.00**	81.77	63.71
Barlow Twins [13]		✓		73.06	45.35	48.70	25.52
Barlow Twins with our transformations		✓	✓	97.41	90.47	92.23	79.62
SimCLR [14]		✓		68.39	38.47	51.30	24.55
SimCLR with our transformations		✓	✓	87.05	67.63	70.98	39.94
NCA [21]	✓		✓	96.89	90.34	72.02	48.10
MLKR [22]	✓		✓	96.37	90.03	72.02	48.07
SoftTriple [9]	✓		✓	98.45	91.97	96.89	87.64
Proxy-NCA [10]	✓		✓	98.45	90.80	94.82	84.86
InfoNCE [11]	✓		✓	96.89	94.04	95.34	86.95
DeepBrainPrint (Proposed)	✓	✓	✓	99.48	95.54	**98.96**	**91.00**

- **Results:**
- Our approach outperforms previous methods, including simple similarity metrics and more advanced deep learning frameworks.

Quality Control System based on Generative AI

- Brain MRI artefacts can impact diagnosis and treatment planning, highlighting the need for quality control.
- Quality control is necessary to ensure each sample meets minimum quality requirements
- Automatic artefact detection methods often require a lot of data
- Scarcity of artefact-containing scans hinders the implementation of machine learning in clinical research



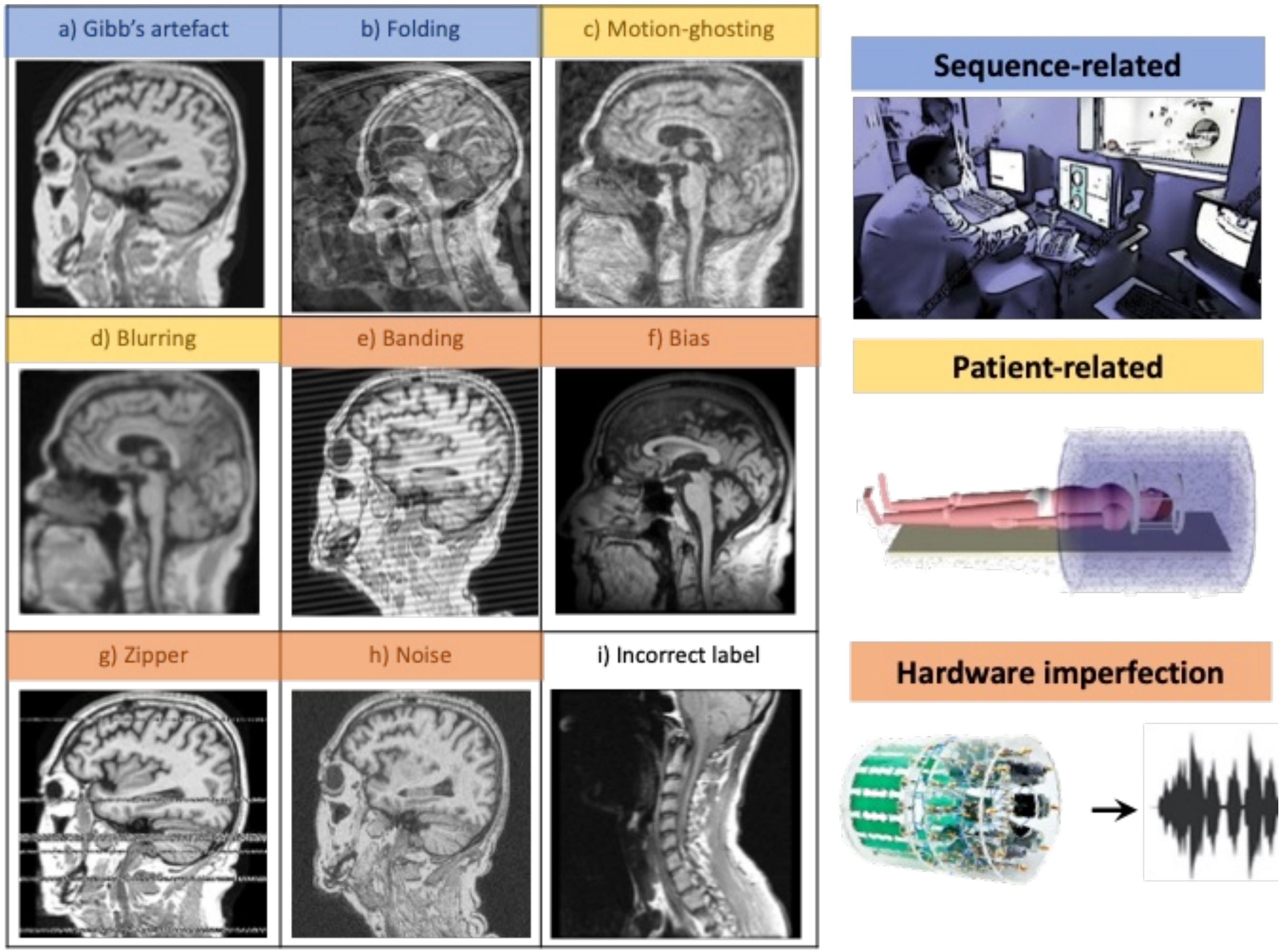
Ravi, D., Barkhof, F., Alexander, D.C., Parker, G.J. and Eshaghi, A**., 2023.** An efficient semi-supervised quality control system trained using physics-based MRI-artefact generators and adversarial training. *Under review at MEDIA 2023*

Proposed method: Artefact Simulations based on Generative AI

- We propose a novel framework based on an **artefact generators** to corrupt brain MRI scans

- We have identified 9 different common artefacts for T1-weighted MRI
  - Hardware imperfection artefacts
  - Patient-related artefacts
  - Sequence-related artefacts
  - Incorrect labelling

- Our AI solution has the advantage of using only artefact-free images with the benefit of requiring limited training labels



Experimental Results: Artefact detection

Approach			Accuracy (%)	F1(%)	F2(%)	Precision(%)	Recall(%)
Features	Classifier	Augm.					
F	PCA-based	✗	83.44 ± 29.29	90.08 ± 35.34	86.35 ± 35.63	97.06 ± 3.03	84.03 ± 35.84
F	Autoencoder	✗	83.33 ± 13.65	90.35 ± 10.84	87.31 ± 13.59	95.92 ± 5.55	85.39 ± 15.21
F	An and Cho (2015)	✗	84.28 ± 16.25	90.61 ± 14.83	87.65 ± 17.37	96.01 ± 5.07	85.78 ± 18.60
F	Zenati et al. (2018)	✗	86.36 ± 17.98	91.84 ± 14.86	88.90 ± 18.77	**97.18 ± 2.47**	87.05 ± 20.72
(Schlegl et al., 2019)	$\mathbf{S_b}$	✗	87.17 ± 11.30	93.00 ± 6.73	91.22 ± 8.80	96.13 ± 4.19	90.07 ± 10.14
(Sadri et al., 2020)	$\mathbf{S_b}$	✗	83.62 ± 22.70	86.00 ± 25.87	84.76 ± 26.11	88.14 ± 25.96	83.96 ± 26.35
(Schlegl et al., 2019)	$\mathbf{S_s}$	✓	87.57 ± 12.94	93.61 ± 8.45	92.47 ± 12.14	95.58 ± 5.15	91.72 ± 14.33
(Sadri et al., 2020)	$\mathbf{S_s}$	✓	92.20 ± 5.29	96.00 ± 2.91	96.30 ± 3.31	95.51 ± 5.35	96.49 ± 4.33
Szegedy et al. (2016)	Szegedy et al. (2016)	✓	92.43 ± 5.19	94.89 ± 4.22	94.94 ± 4.52	94.79 ± 3.56	94.98 ± 4.09
Proposed	Proposed	✓	**94.76 ± 5.36**	**96.37 ± 2.89**	**96.99 ± 1.81**	95.34 ± 5.49	**97.42 ± 2.02**

- Tested on:
  - 1) a large dataset of scans with **artificially-generated artifacts**
  - 2) a real world **multiple sclerosis clinical trial**
- Proposed pipeline outperforms traditional supervised and unsupervised methods
- Data augmentation increases by up to 12.5% on accuracy, F1, F2, precision and recall

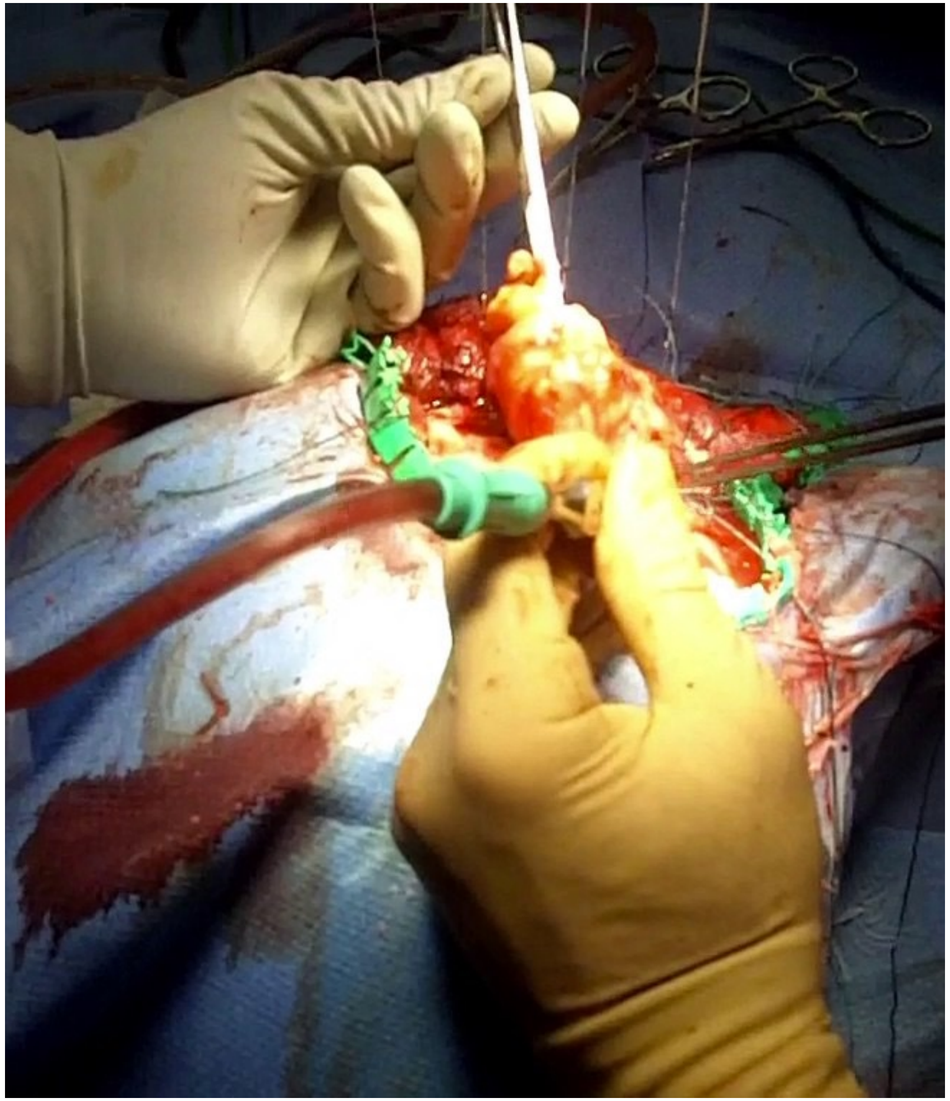
Hyperspectral Imaging: Cancer Detection

Ravi, D., Fabelo, H., Callic, G.M. and Yang, G.Z., 2017. Manifold embedding and semantic segmentation for intraoperative guidance with hyperspectral brain imaging. *IEEE transactions on medical imaging*, *36*(9), pp.1845-1857.

Hyperspectral Imaging: Cancer Detection

- Brain tumours resection is challenging:
  – hard to delineate the exact boundaries

- Current technologies:
  - **MRI/CT**
    not ready yet during surgery
  - **Neuro-navigation**
    plagued by brain shift
  - **Fluorescence techniques**
    based on subjective visual assessment



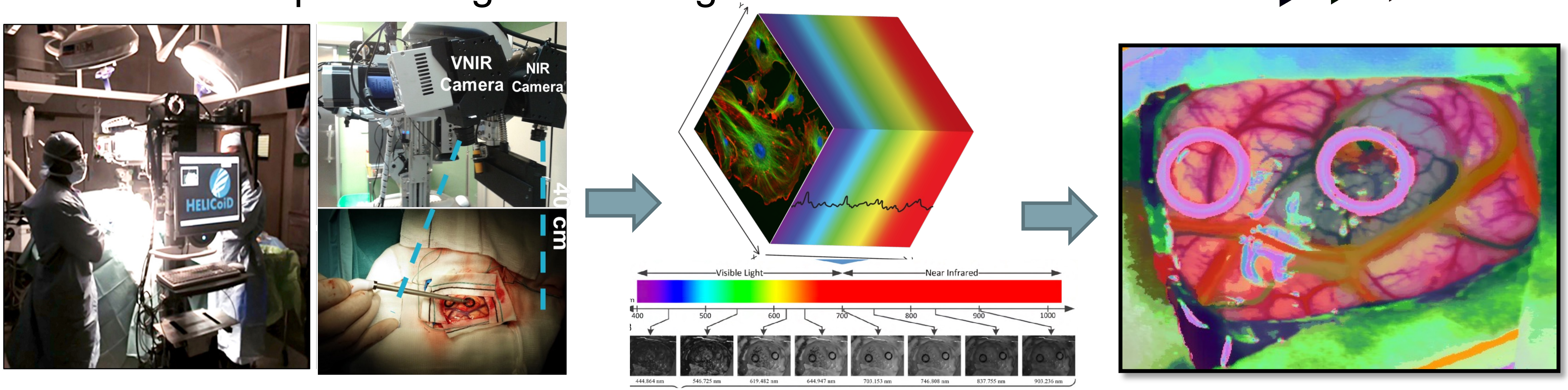
Glioma resection

Intraoperative Tissue Classification: Hyperspectral imaging

- Hyperspectral imaging is a non-ionizing and minimally-invasive sensing technique

- Can differentiate between tissue types in real-time

- The amount of data to analyze is high-dimensional:
  – Its real-time processing is not straightforward



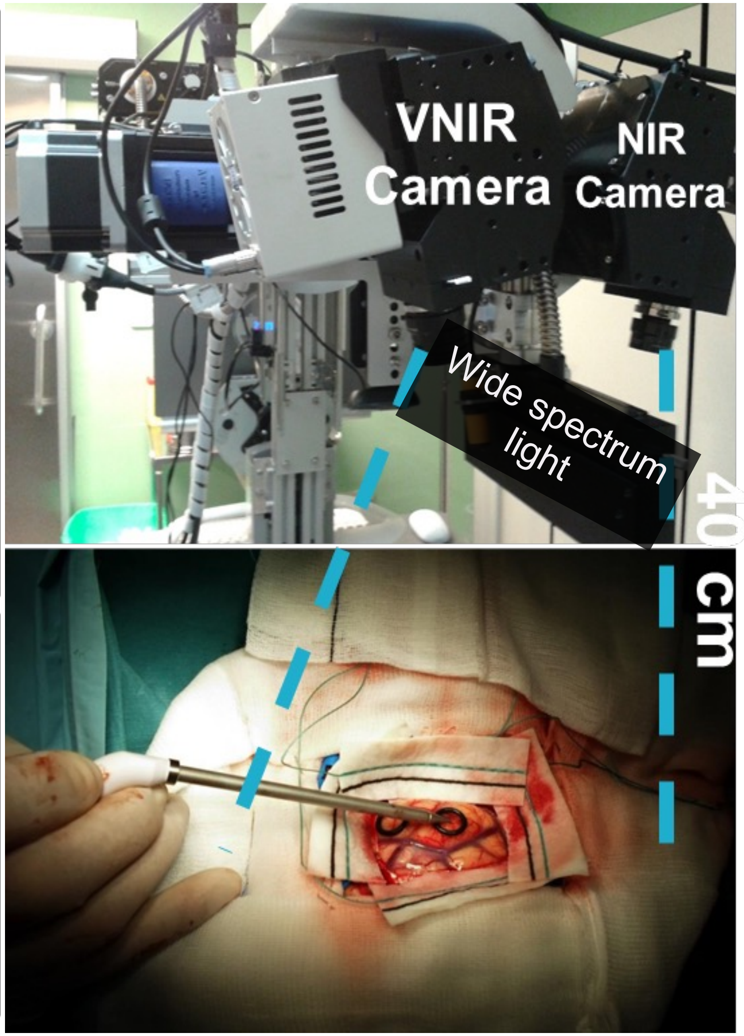
Acquisition System

- VNIR camera
  - 826 spectral bands

400nm 1000nm

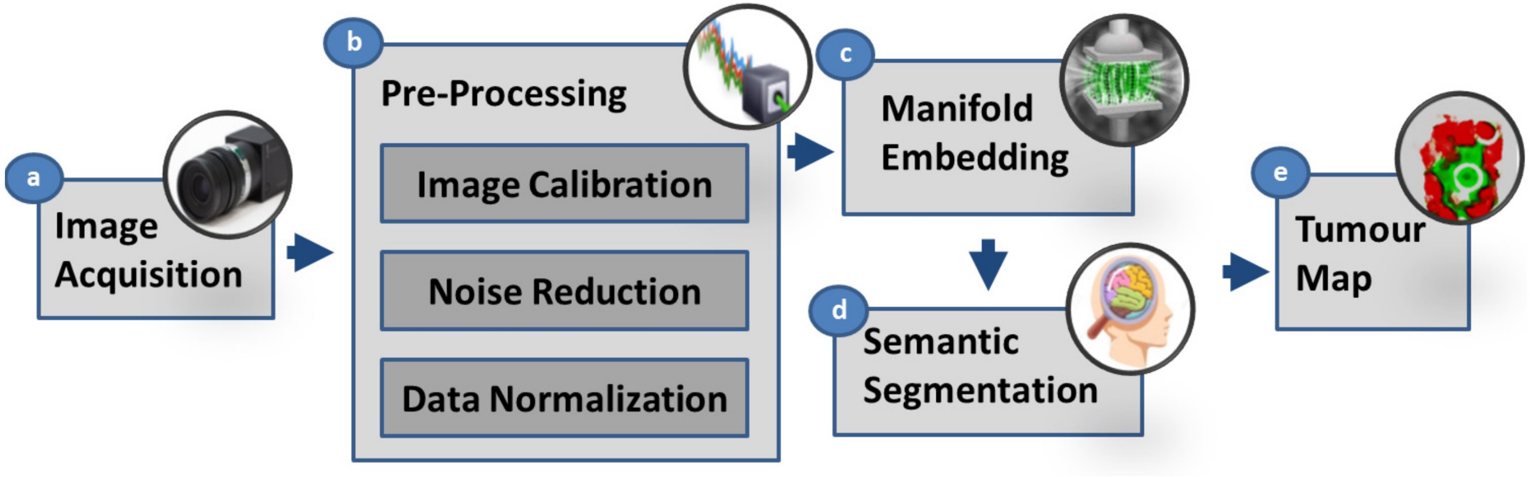
- NIR camera
  - 172 spectral bands

900nm 1700nm



Hyperspectral imaging: Proposed Pipeline

- **Manifold embedding** based on deep learning is used to allow **real-time** processing
- **Semantic segmentation** is used to obtain the tumour map



Ravì, D et al. "Manifold embedding and semantic segmentation for intraoperative guidance with hyperspectral brain imaging." 2017 IEEE TMI

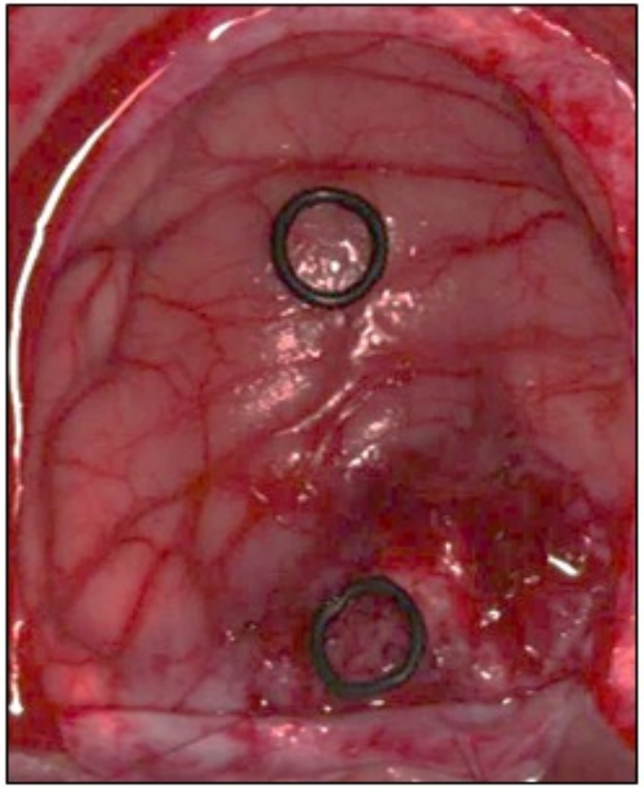
Hyperspectral imaging: Database

- **33 hyperspectral images**
  - in-vivo brain
- **18 different patients**

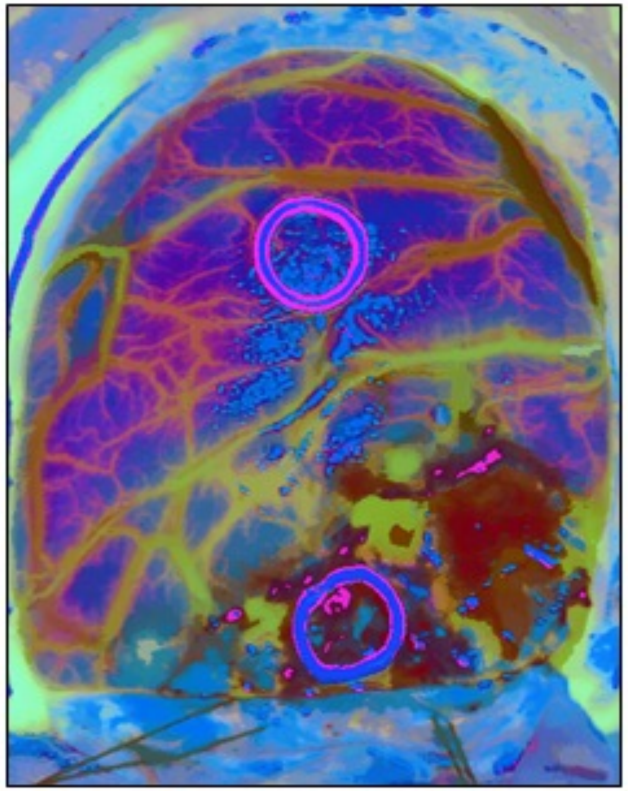
- **Acquisition protocol**:
  1. Two fiducial markers are placed in the brain
  2. Hyperspectral images are acquired
  3. Tissue samples are collected
  4. Pathologic diagnosis is carried out (ground truth)

Description			**Number of Patients**	**Number of Images**
Normal			11	17
Primary	IV Grade	Glioblastoma	8	12
	III Grade	Oligodendroglioma anaplsigo	1	4
	I Grade	Ganglioglioma	1	2
		Meningioma	1	1
Secondary		Lung Carcinoma	2	2
		Lung Adenocarcinoma	1	1
		Renal Carcinoma	1	1
		Breast Meta Carcinoma	1	3

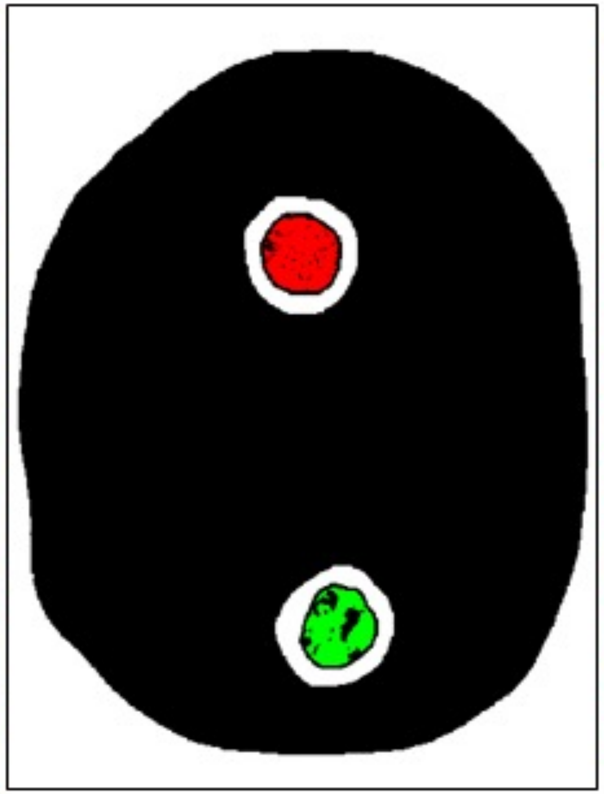
Hyperspectral imaging: Visual Results



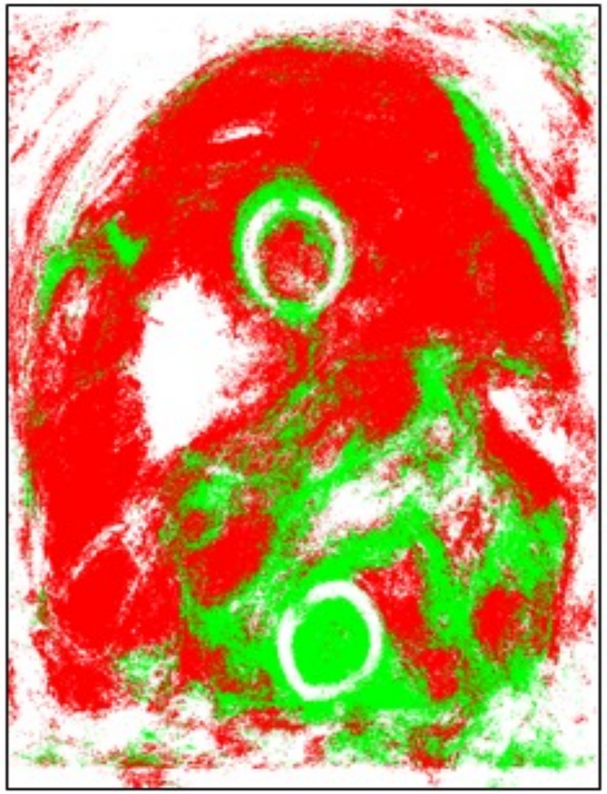
RGB image



Embedded output



Ground truth



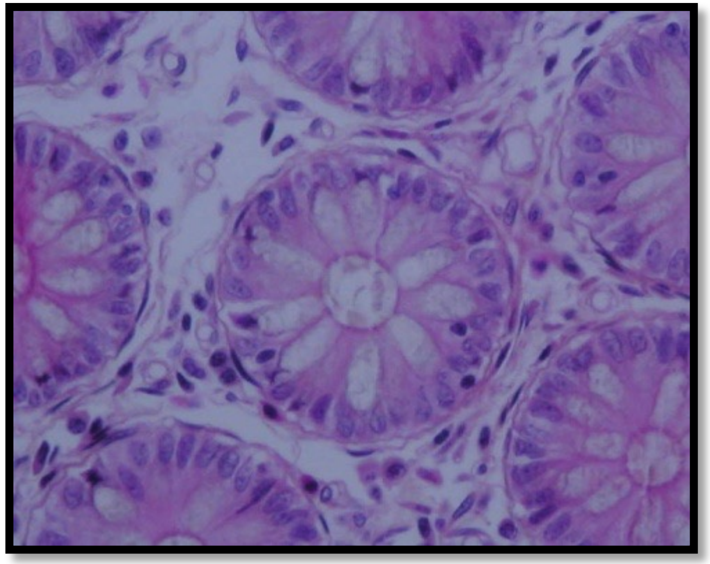
Classification map

Endoscope vs Endomicroscopy

Biopsies

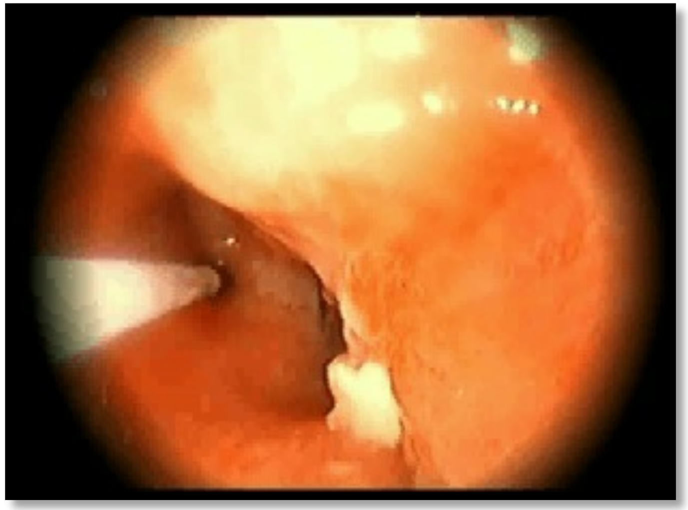
Endoscope

Days or Weeks

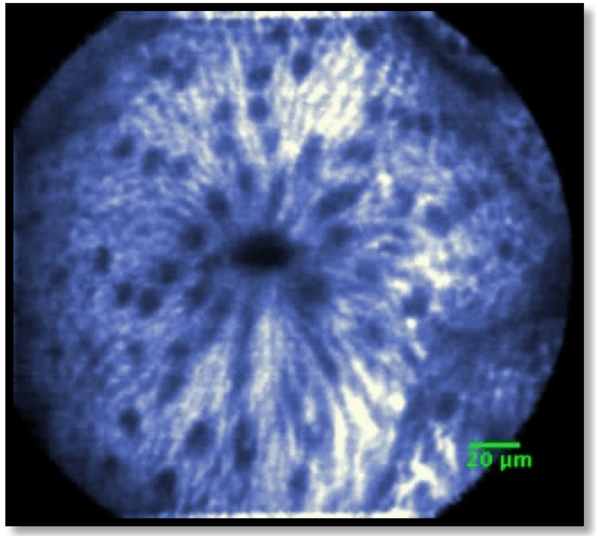


Optical Biopsies

Endomicroscopy

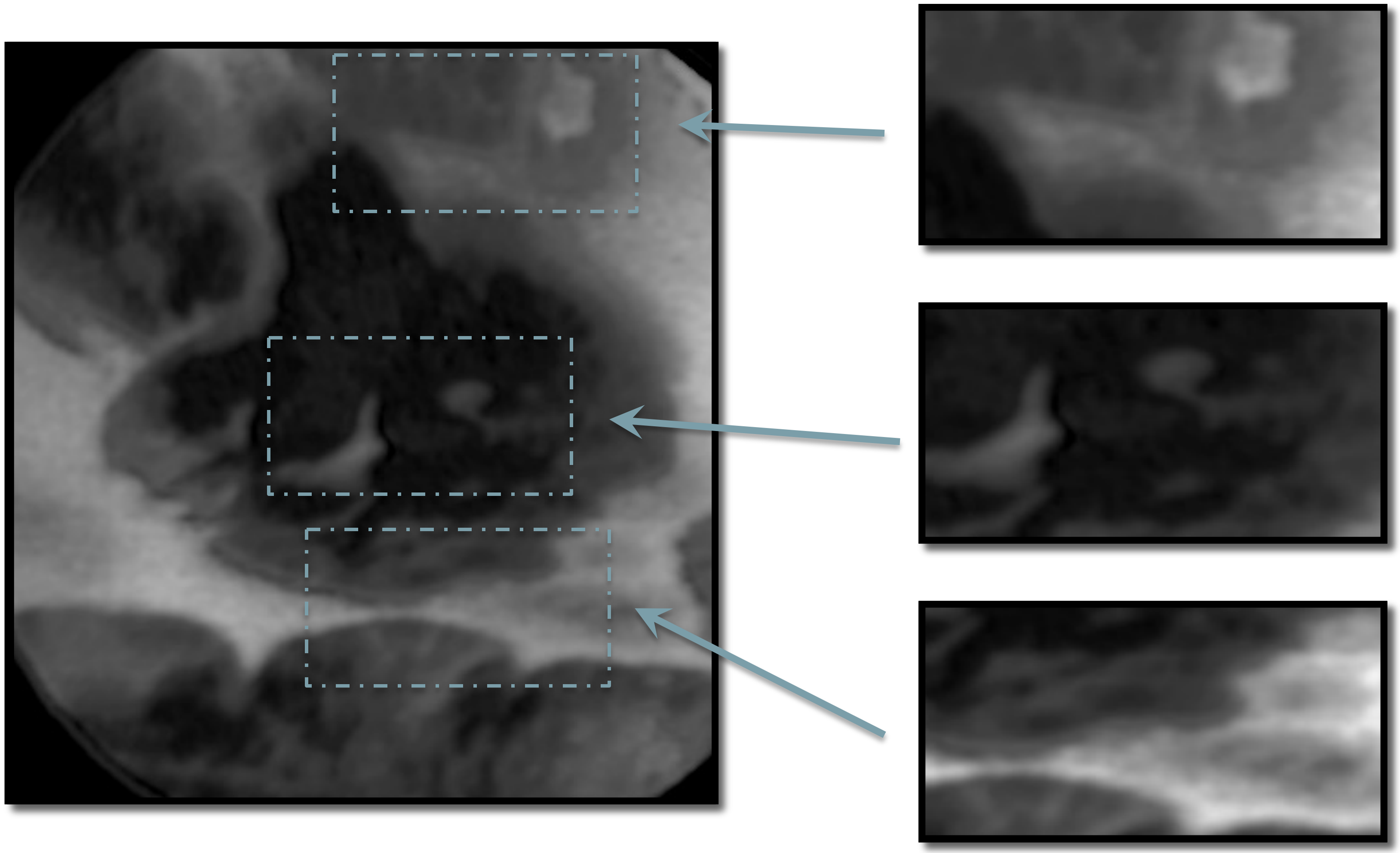


Real-Time



Endomicroscopy Provides Limited Image Quality

- Accurate diagnoses are partially hampered by the low image quality



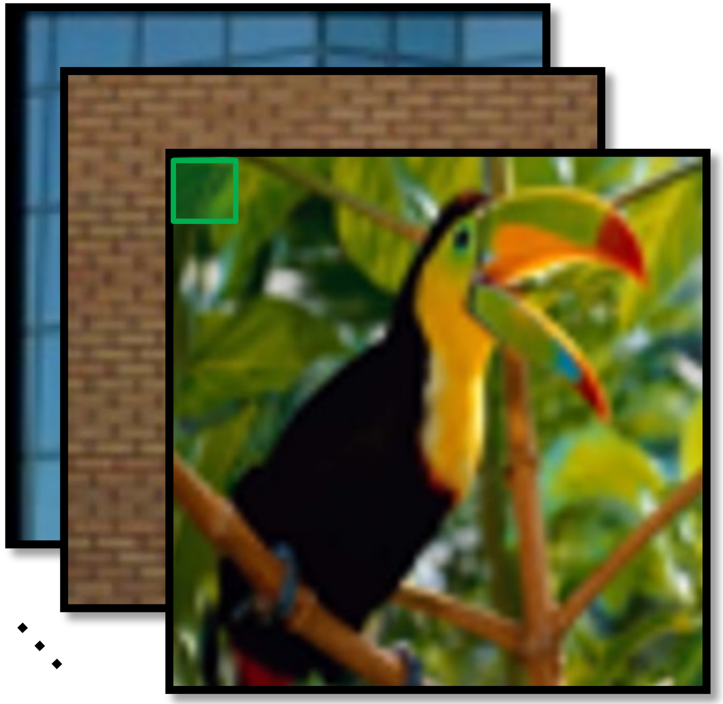
- Noise
- Low contrast
- Lack of details
- Artifacts

Example-Based Super-Resolution

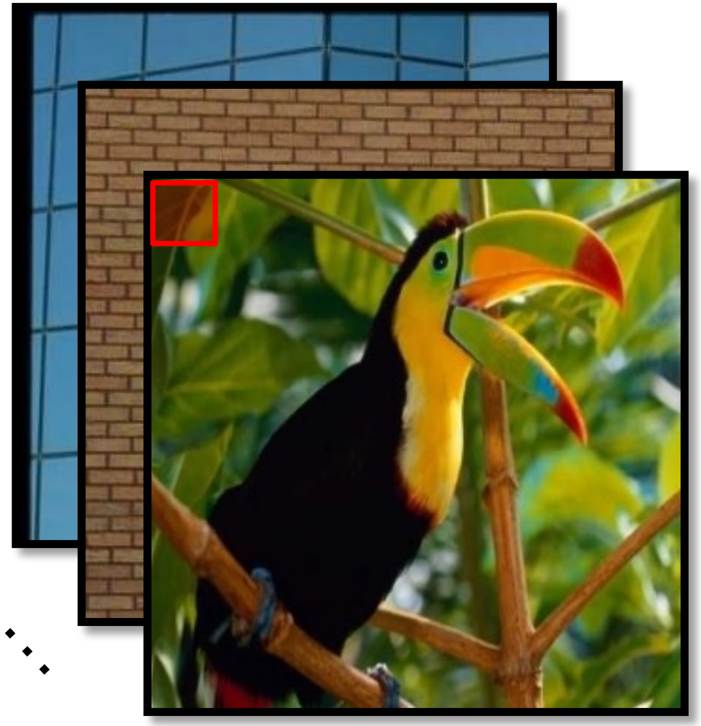
Supervised training

Aligned pairs of LR and HR are required

Designed for natural images

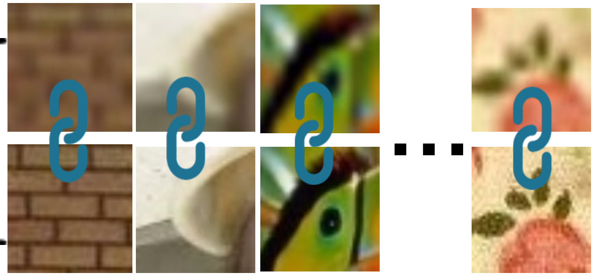


LR images



HR images

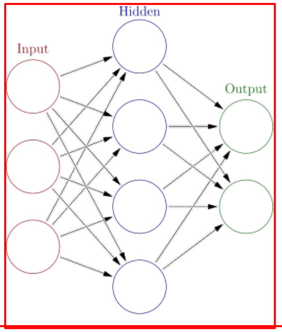
Matching patch-pairs



Feature Extraction (LR)

Feature Extraction (HR)

$$\left\{ \begin{matrix} \mathbf{x}_i \\ \mathbf{y}_i \end{matrix} \right\}_i$$

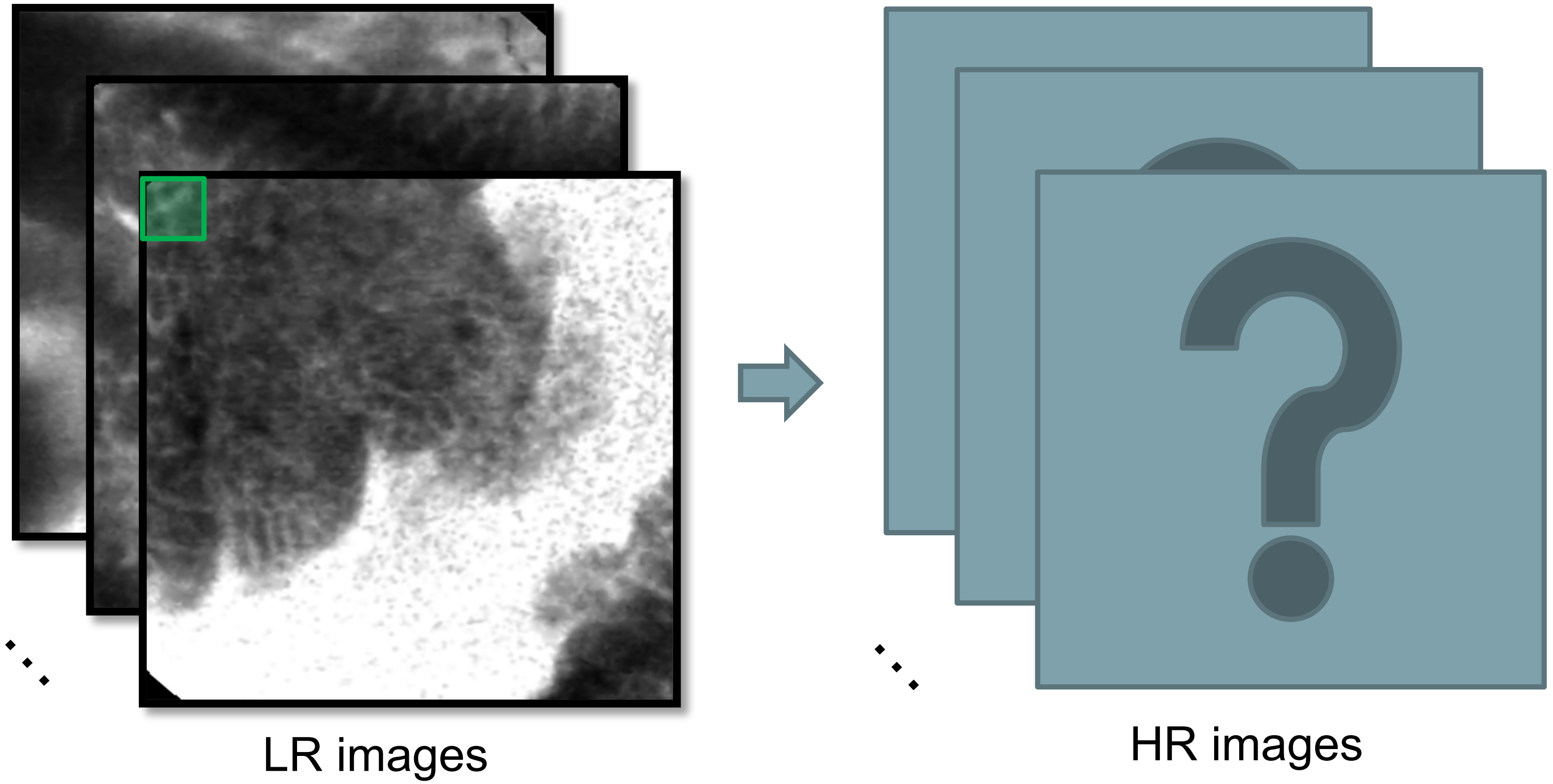


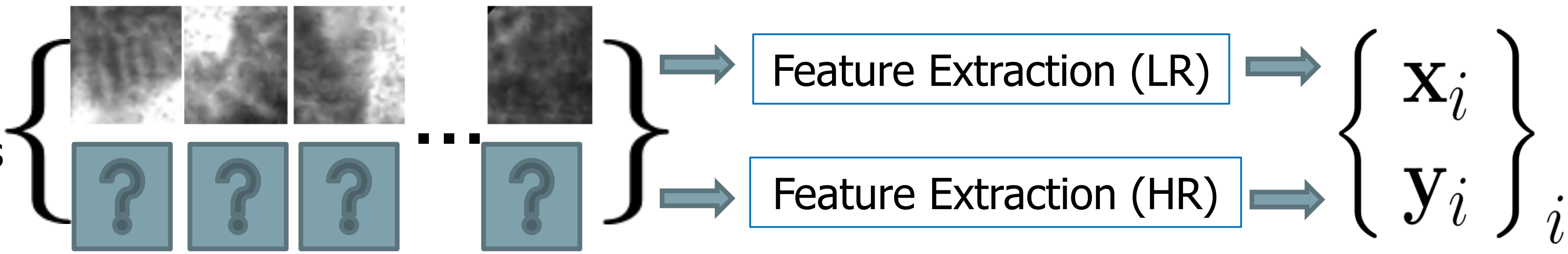
Super-resolving model

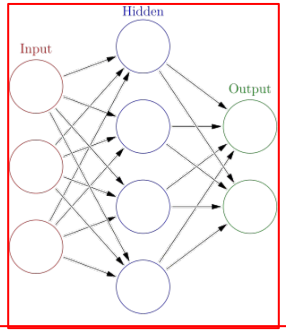
Example-Based Super-Resolution

Lack of paired images in medical imaging

HR are often not available





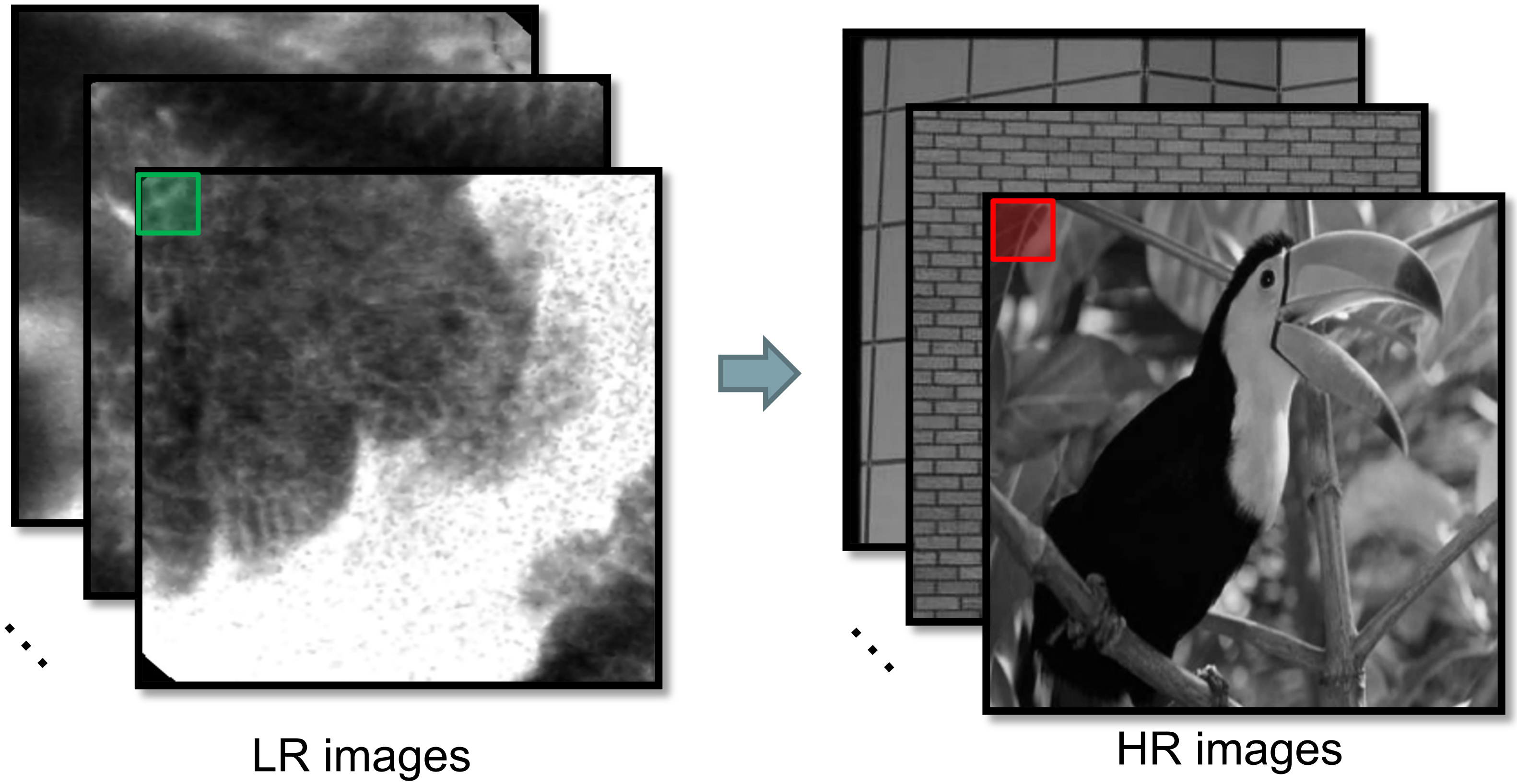


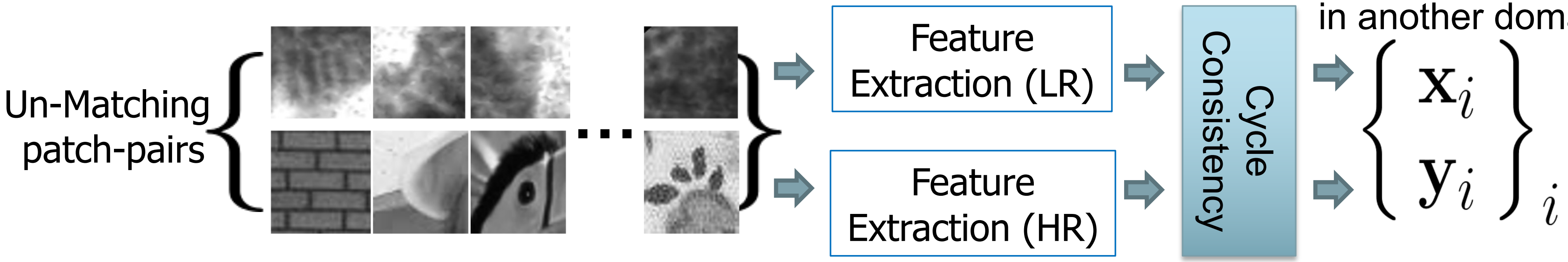
Super-resolving model

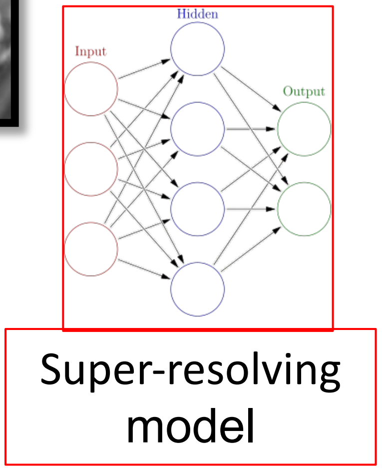
Example-Based Super-Resolution

Use Un-Paired training images

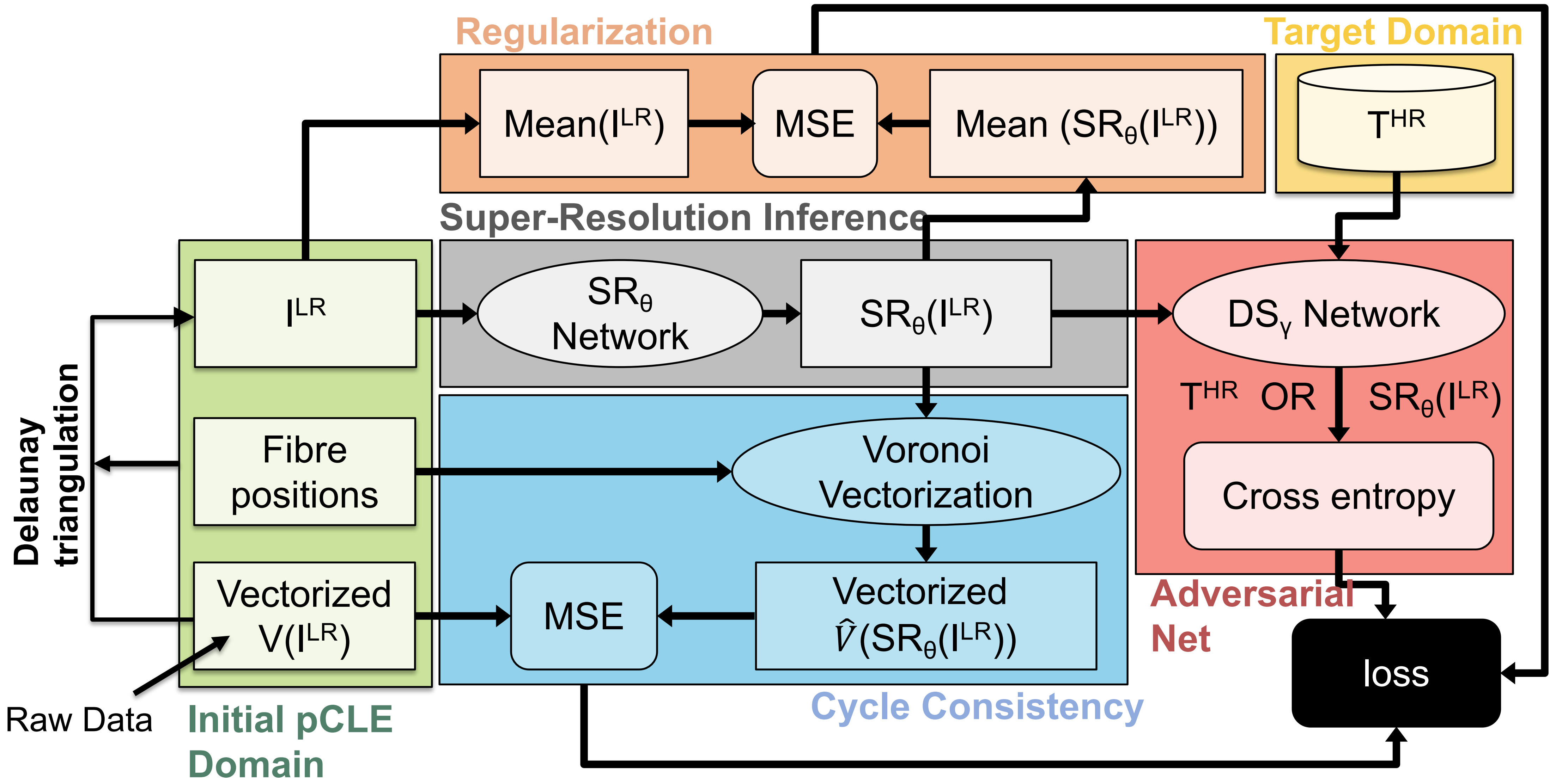
Exploit HR images from another domain



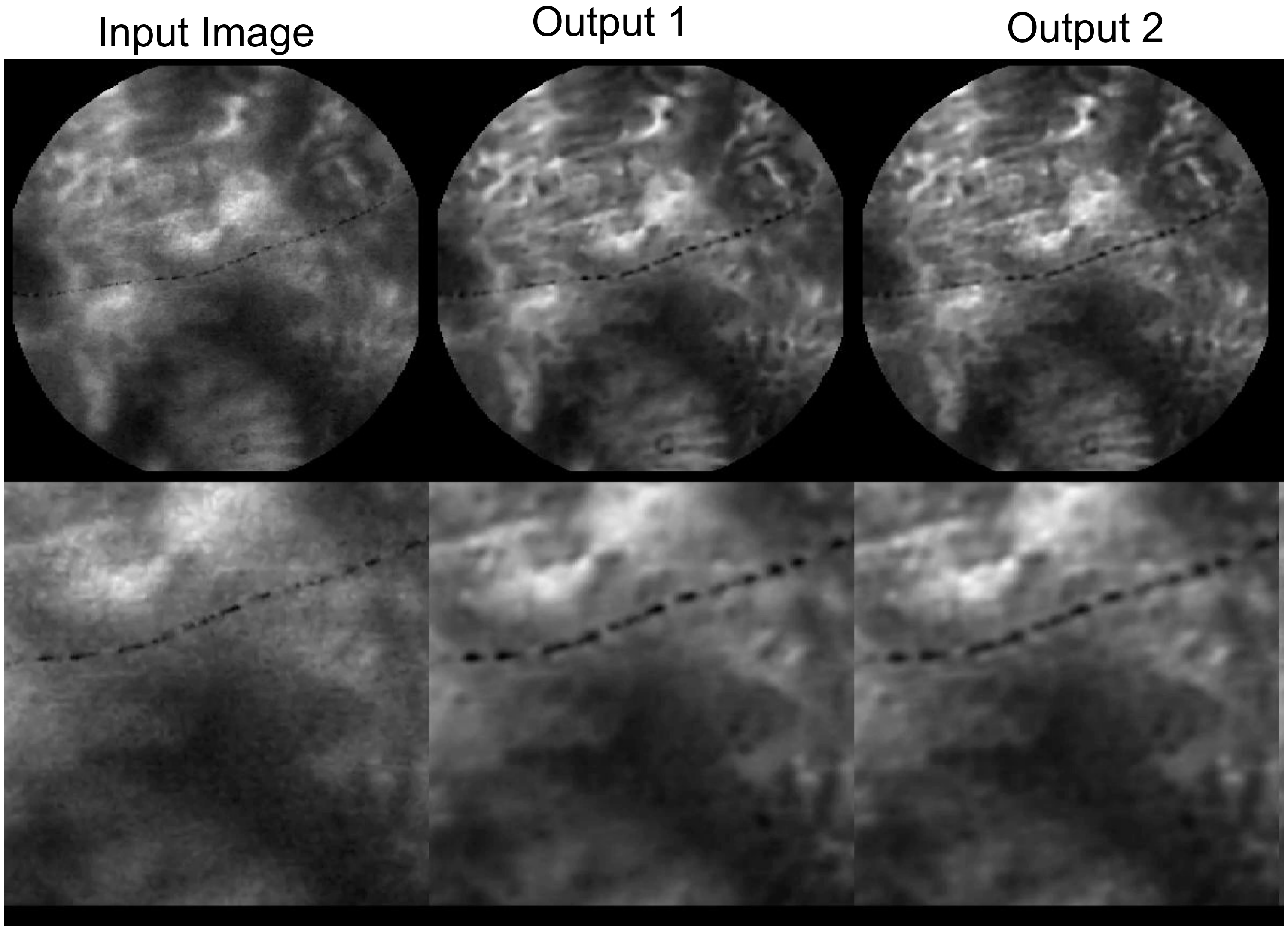




Proposed Pipeline: Adversarial Training with Cycle Consistency

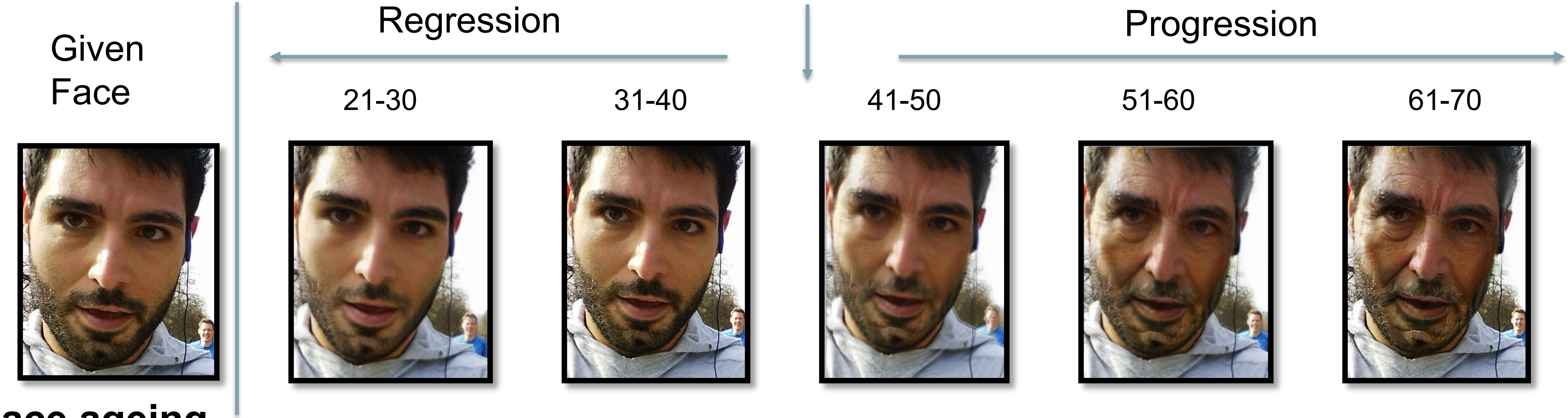


Examples of Super-Resolution in Endomicroscopy Images



Ravì, D., Szczotka, A. B., Pereira, S. P., & Vercauteren, T. (2019). Adversarial training with cycle consistency for unsupervised super-resolution in endomicroscopy. *Medical image analysis*, *53*, 123-131.

Image-Based Disease Progression Modelling



Face ageing

Can we use similar technology + **biological constraints**

to predict **ageing and disease progression** in specific organs?

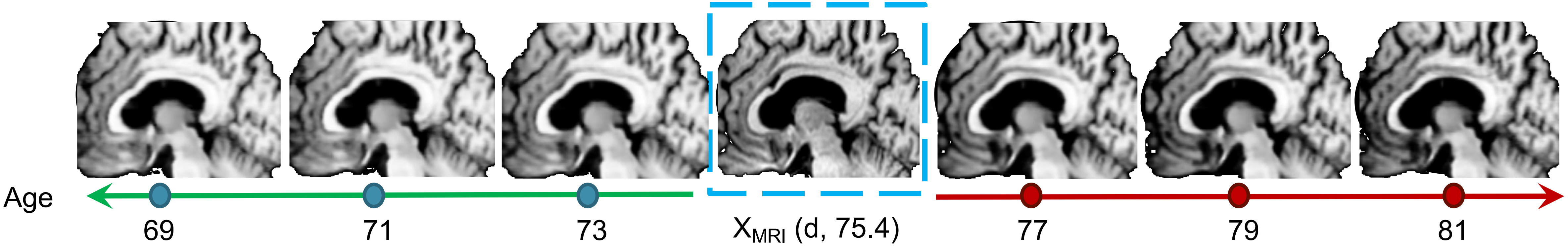
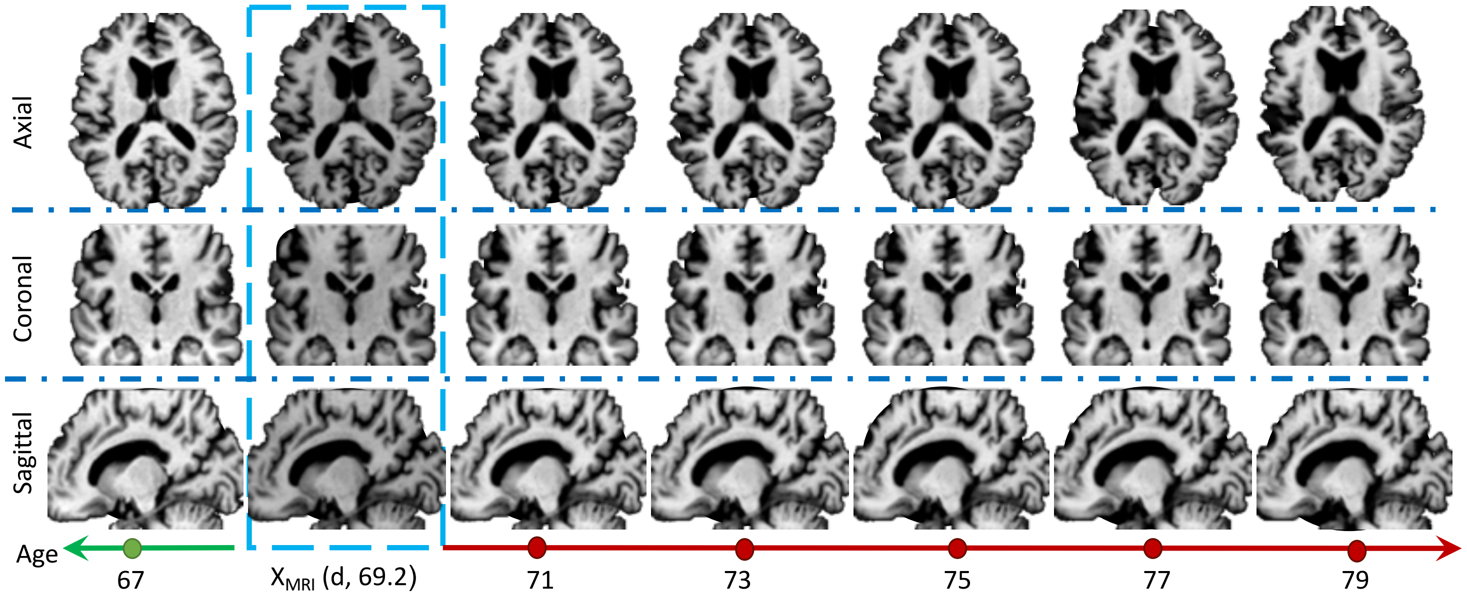
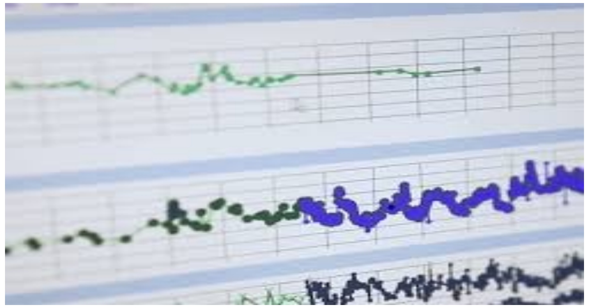


Image-Based Disease Progression Modelling





Predict patient **outcomes**

- **Aims:**
  - Learn and simulate **disease progression** in MRI
- **Challenges:**
  - High dimensional problem (3D ➞ 3D+time)
  - High-resolution images
  - Subject-specific prediction

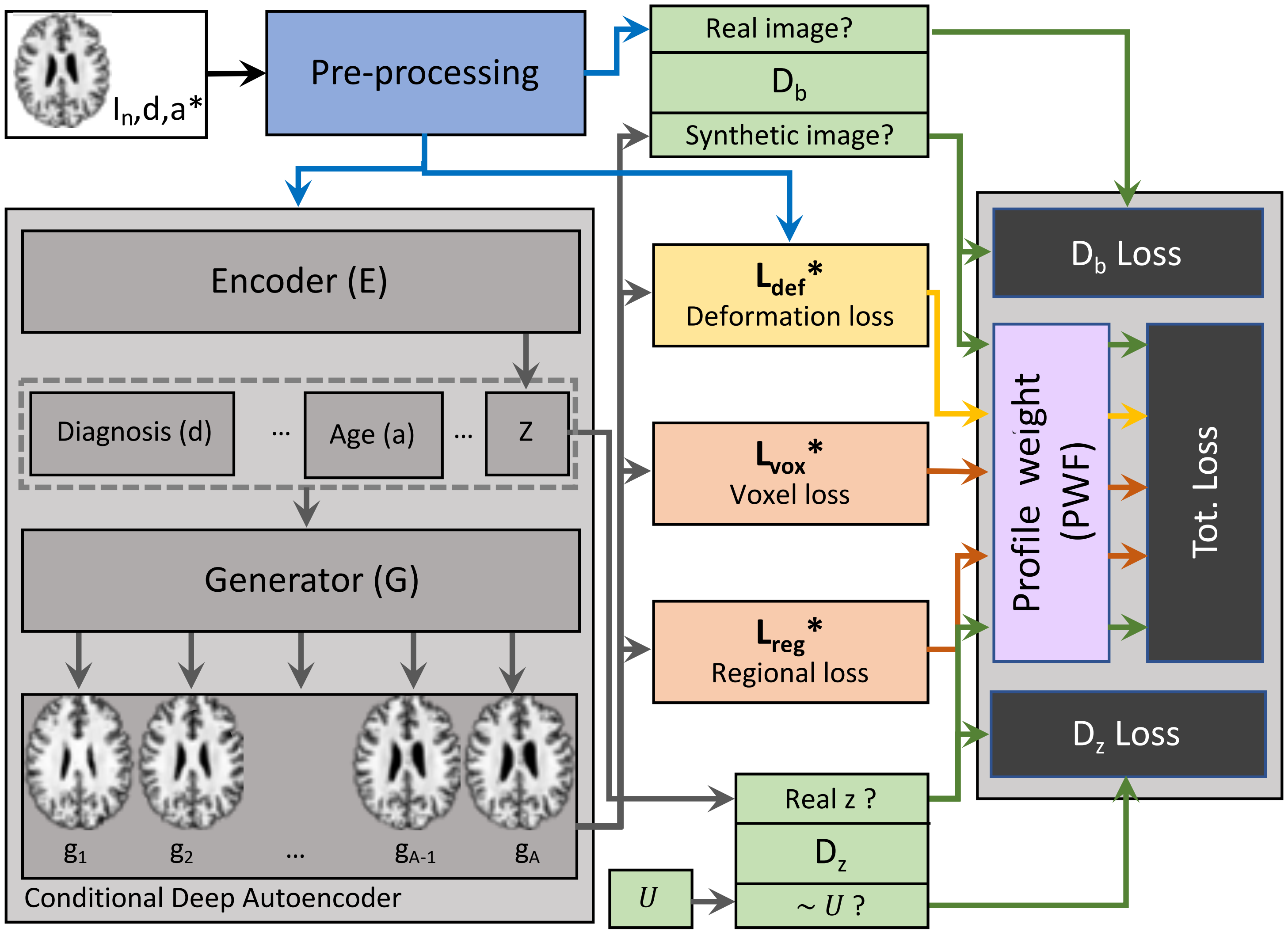
Motivations:

1. Privacy / data augmentation
2. Improve **personalized treatments**
3. **Select patients** in clinical trials
4. Validate other hypothetical models

Ravi, D., et al. "Degenerative Adversarial NeuroImage Nets for 4D Simulations: Application in Longitudinal MRI." *MedIA 2021*

What is DANI-Net Able to Model?

1. **Deformations** that preserve individuality
2. **Realistic brain structures**
3. **Conditioning** on different diagnosis
4. **Temporal smoothing**
5. Mimic **biological constraints** (atrophy, volume shrinking)

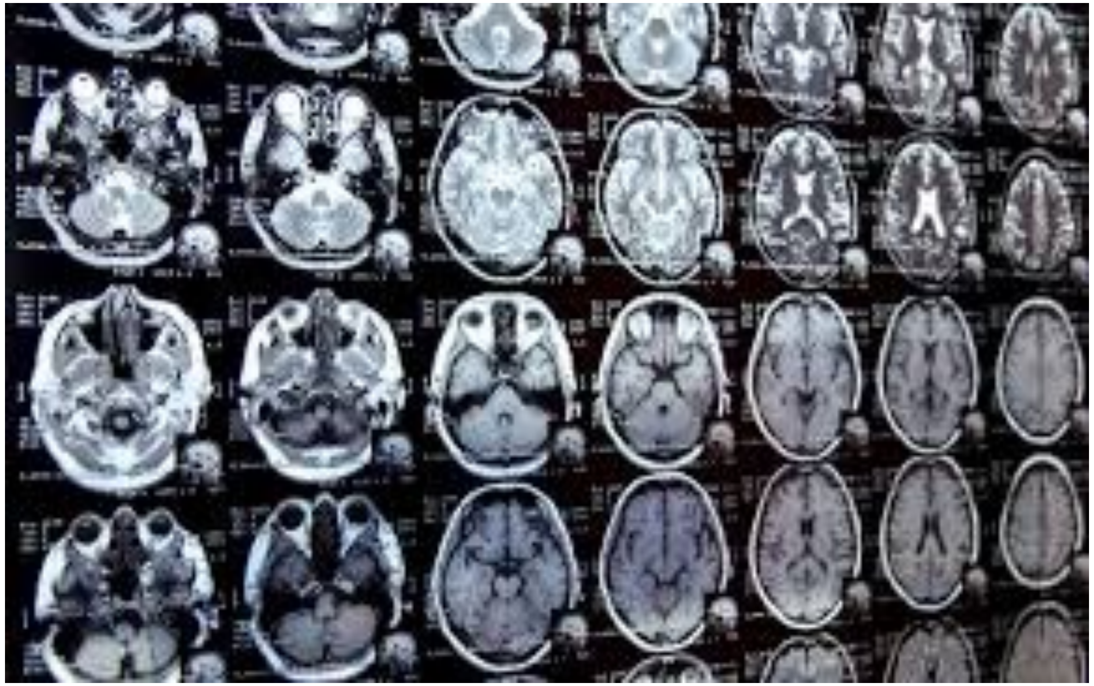


Ravi D., **et al.** Degenerative Adversarial NeuroImage Nets: Generating Images that Mimic Disease Progression, MICCAI, 2019

Image-Based Disease Progression Modelling: Dataset

ADNI Alzheimer's Disease Neuroimaging Initiative

- 12386 T1-weighted MRI (1mm)
- 1216 patients (aged between 63 to 87)
- 3 different diseases + normal ageing



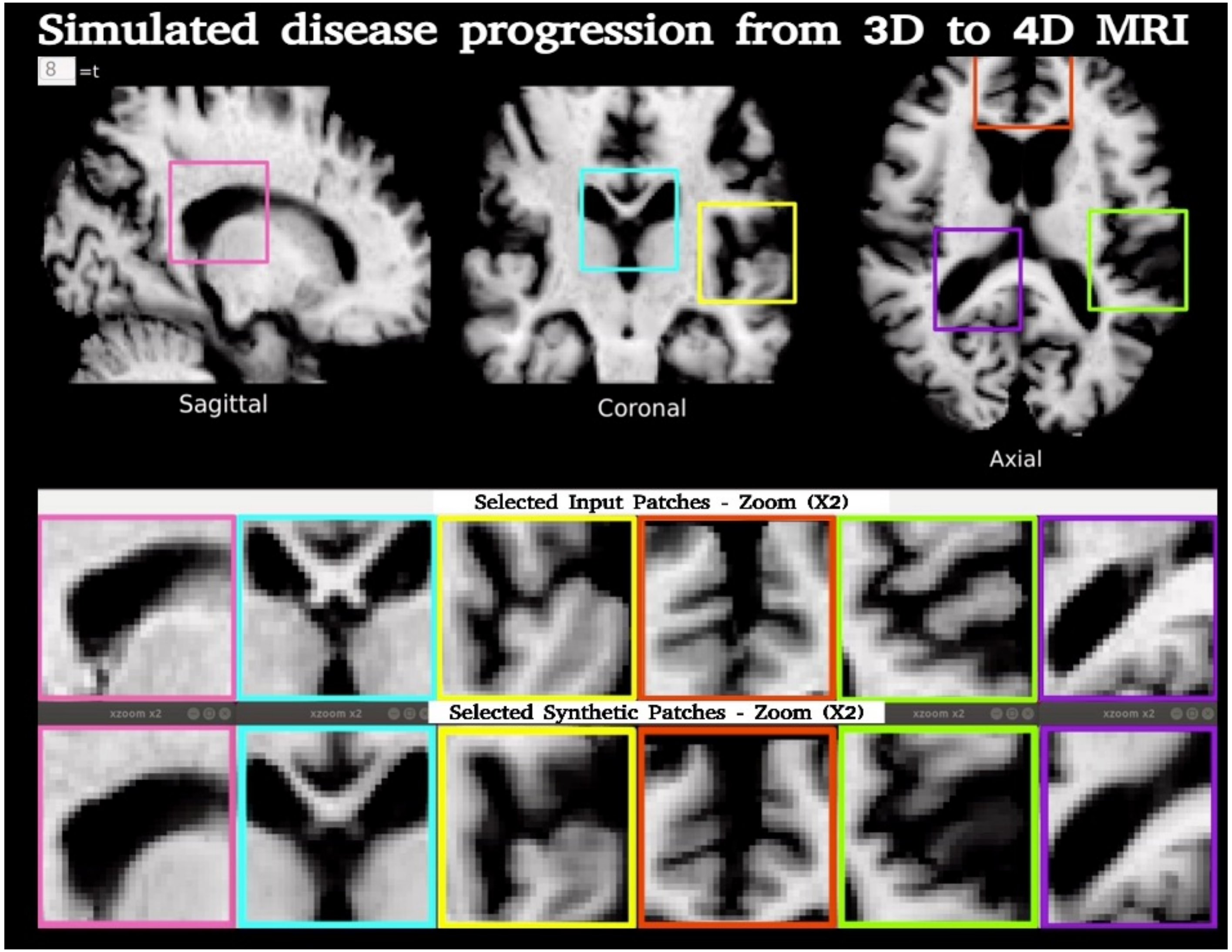
- Training: 80%
- Test: 10%
- Validation: 10%

- Training Time: 2 days on HPC with 50 GPUs

Image-Based Disease Progression Modelling 4D-Simulation

- **Visual assessment**
  - No artefacts
  - High-resolution
  - Subject-specific

- **Quantitative Analyses**
  - Volumetric comparison with the real follow-up
  - 6 brain regions considered
  - Comparison against traditional regional expansion regressors



Ravi, D., et al. "Degenerative Adversarial NeuroImage Nets for 4D Simulations: Application in Longitudinal MRI." *submitted at MedIA 2021*

Smart Sensing

Applications

Patient monitoring

Wellbeing

Diseases status change

Sports

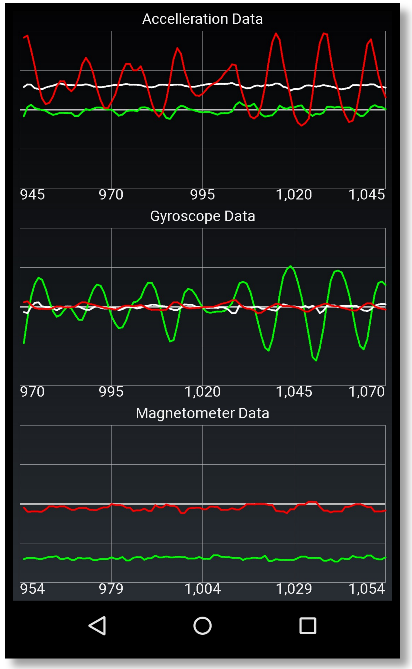
Wearable and implantable sensors

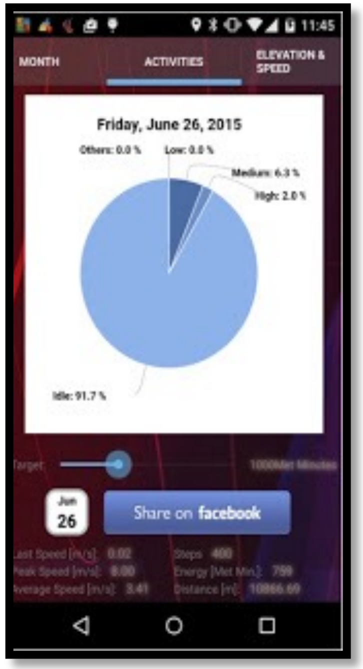
Challenges:

- **Dance data (50Hz)**
- **Continues data (entire day)**

Smart Sensing: Patient Monitoring using Smartphone

Available sensors:
- Camera
- Inertial sensors
- GPS
- Audio
- Proximity
- Barometer





- **Examples of what we can measure:**
  - Human activity recognition and location tracking
  - Image and voice recognition
- **Possible external Bluetooth devices**:
  - sweat sensors, pollution sensor, gait, ECG, blood pressure, actigraphy

Smart Sensing: Real-time food intake monitoring

- Motivations:
  - Traditional methods based on **questionnaires are unreliable**
- Proposed solution:
  - **Automatically** food intake detection using **egocentric cameras**

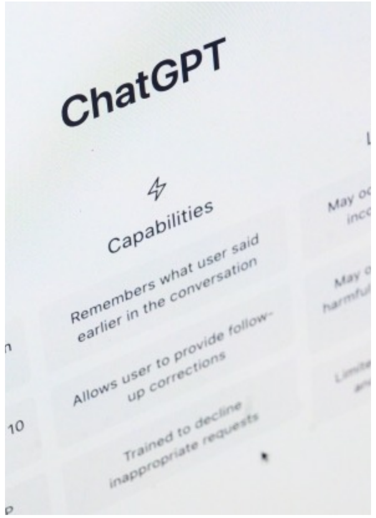
D. Ravì, B. Lo, G-Z Yang, "Real-time Food Intake Classification and Energy Expenditure Estimation on a Mobile Device", IEEE Body Sensor Networks (BSN) 2015

Can ChatGPT Be a Doctor? Bot Passes Medical Exam

- The newest version of ChatGPT **passed the US medical licensing exam** with flying colors

- Diagnosed a 1 in 100,000 condition in seconds

- A doctor and Harvard computer scientist says GPT-4 has better clinical judgment than "many doctors”
    - The chatbot can diagnose rare conditions "just as I would," he said.



Conclusion, Limitation and Challenges

- **AI in Medical Imaging emerges as a vital field in healthcare**

- There are still numerous challenges to overcome in the field:
  1. The need for large labelled and expensive training datasets
  2. Data Sharing and Privacy concerns -> **federated learning**
  3. Unbalanced datasets -> **generative models and data augmentation**
  4. The lack of interpretability models -> **X-AI**
  5. Overfitting and generalization -> **domain adaptation**
  6. Regulation of AI in healthcare

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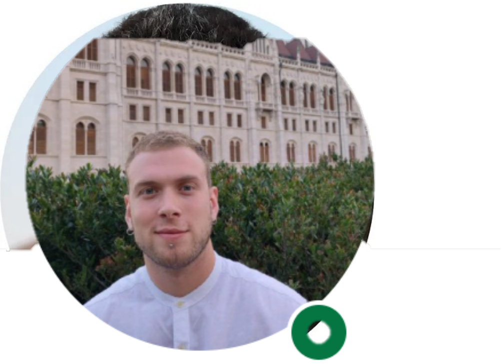

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Questions??

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http://www.homepages.ucl.ac.uk/~rmaprav/

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