Artificial Intelligence in medical imaging

Professor Daniel Rueckert, FREng, FIEEE
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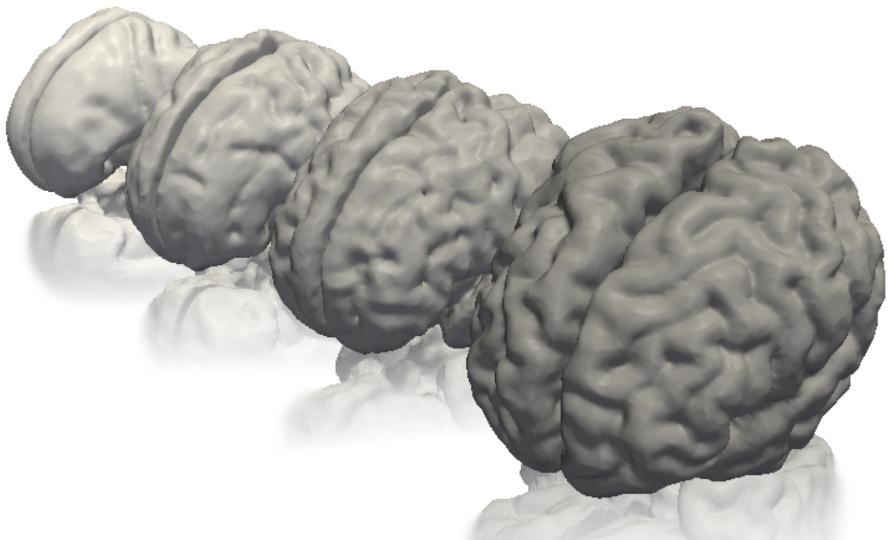
Department of Computing
Imperial College London, UK



Artificial Intelligence is everywhere!

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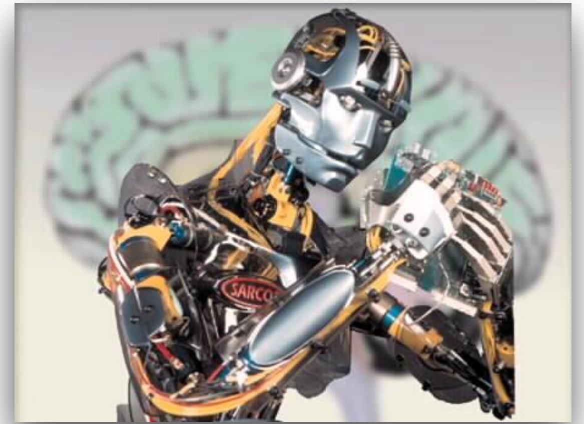


Robotics

Autonomous navigation

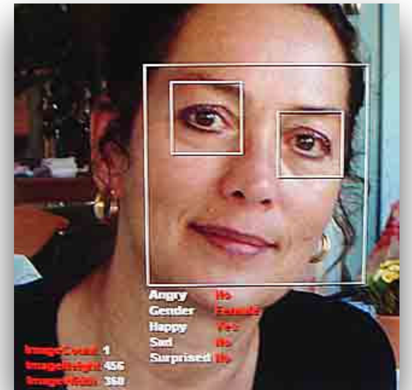


Image and speech understanding

Artificial Intelligence:
A lot has happened over the last 40 years

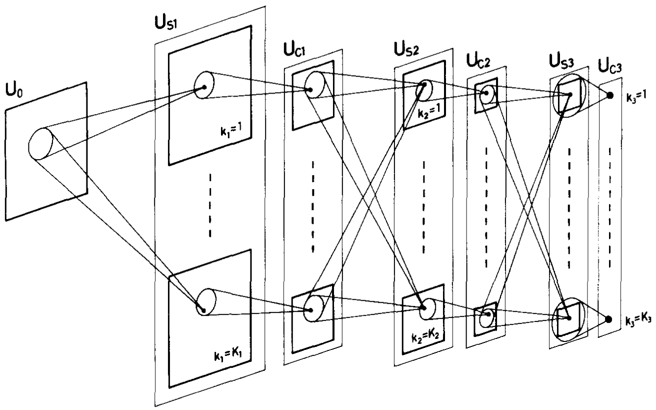
Biol. Cybernetics 36, 193–202 (1980)

Biological Cybernetics

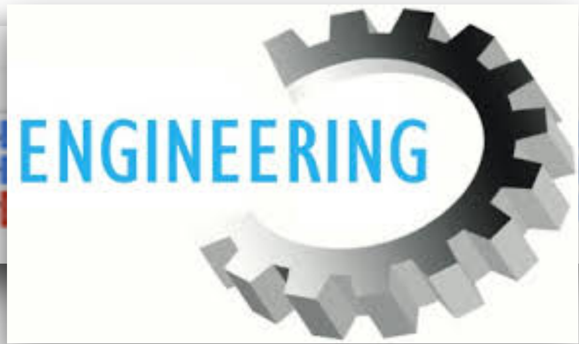
Neocognitron: A Self-organizing Neural Network Model for a Mechanism of Pattern Recognition Unaffected by Shift in Position

Kunihiko Fukushima
NHK Broadcasting Science Research Laboratories, Kinuta, Setagaya, Tokyo, Japan

K. Fukushima, 1980



Compute power
(GPUs)



Engineering

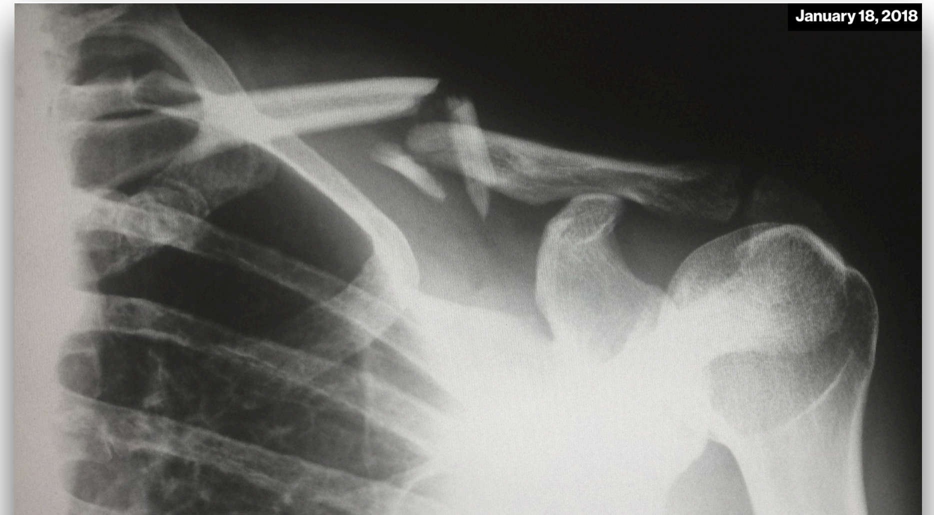
C. Szegedy, CVPR 2015

Data

What about AI in Medicine or Radiology?

AI In Medicine: Rise Of The Machines (Forbes, 2017)

MIT Technology Review



AI Is Continuing Its Assault on Radiologists

A new model can detect abnormalities in x-rays better than radiologists—in some parts of the body, anyway.

THE NEW YORKER

APRIL 3, 2017 ISSUE

A.I. VERSUS M.D.

What happens when diagnosis is automated?

By Siddhartha Mukherjee

Should we worry about AI?

“They should stop training radiologists now.”
Geoffrey Hinton (godfather of deep learning) in 2017

"To the question, will AI replace radiologists, I say the answer is no…”

“… but radiologists who do AI will replace radiologists who don’t."
Curtis Langlotz in 2017


RSNA News

Machine Learning Plays Central Role at RSNA 2017

BY MIKE BASSETT

November 1, 2017

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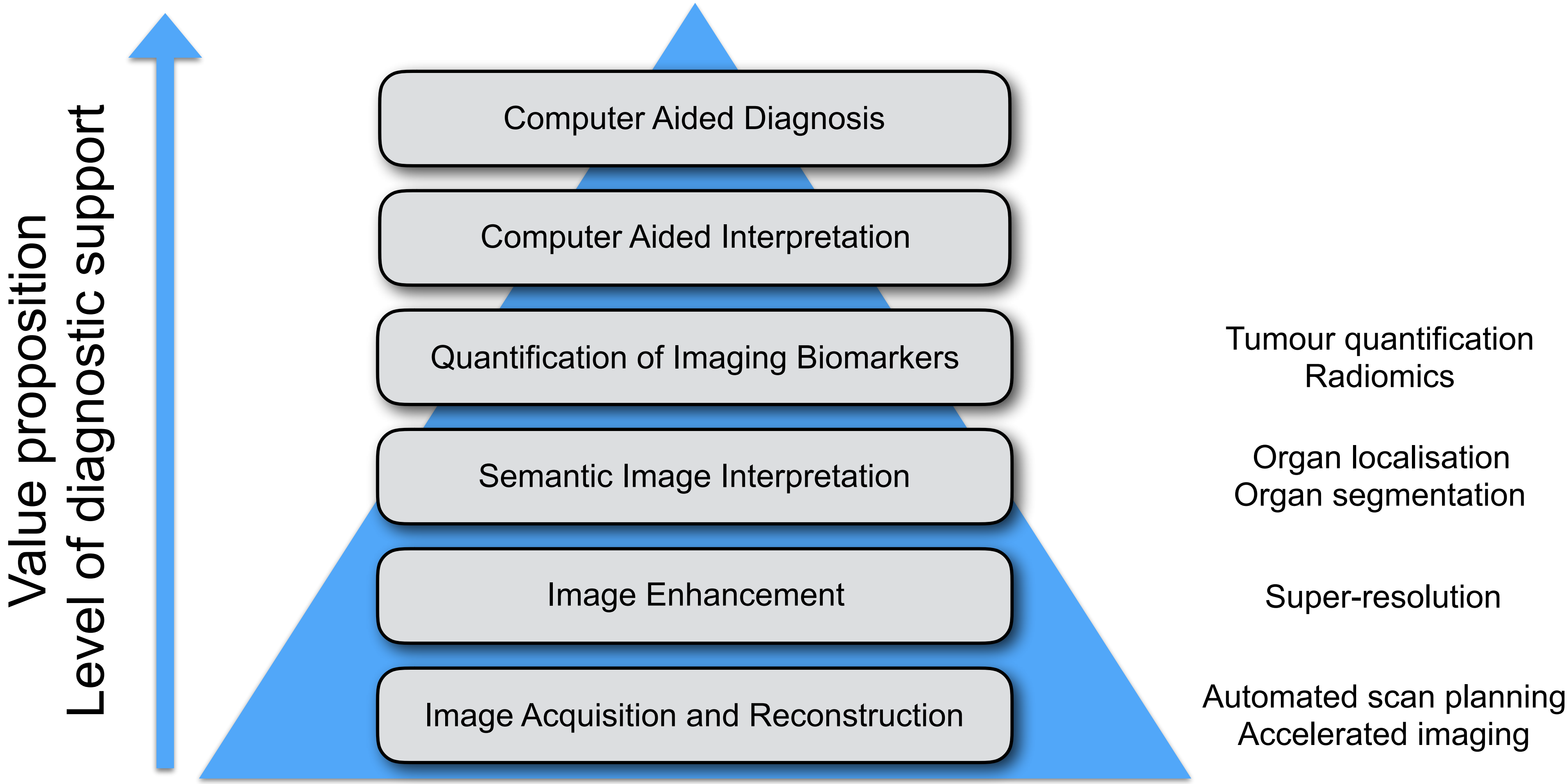
Langlotz

Machine Learning (ML) and the role it will play in the future of radiology will be central to a broad scope of programming at RSNA 2017.

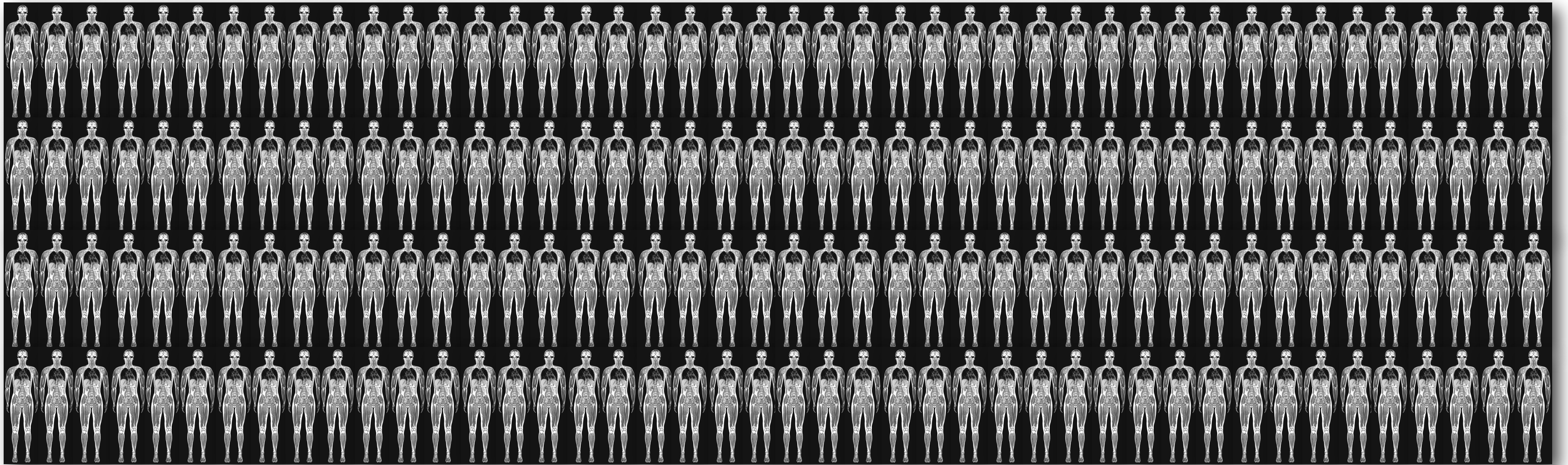
AI in Medical Imaging: Opportunities



AI in Medical Imaging: Opportunities

- Machine learning techniques are starting to reach levels of human performance in challenging visual tasks
- Big data is slowly arriving in medical imaging

UK Biobank will provide large-scale imaging data from 100,000 subjects



AI in Medical Imaging: Opportunities

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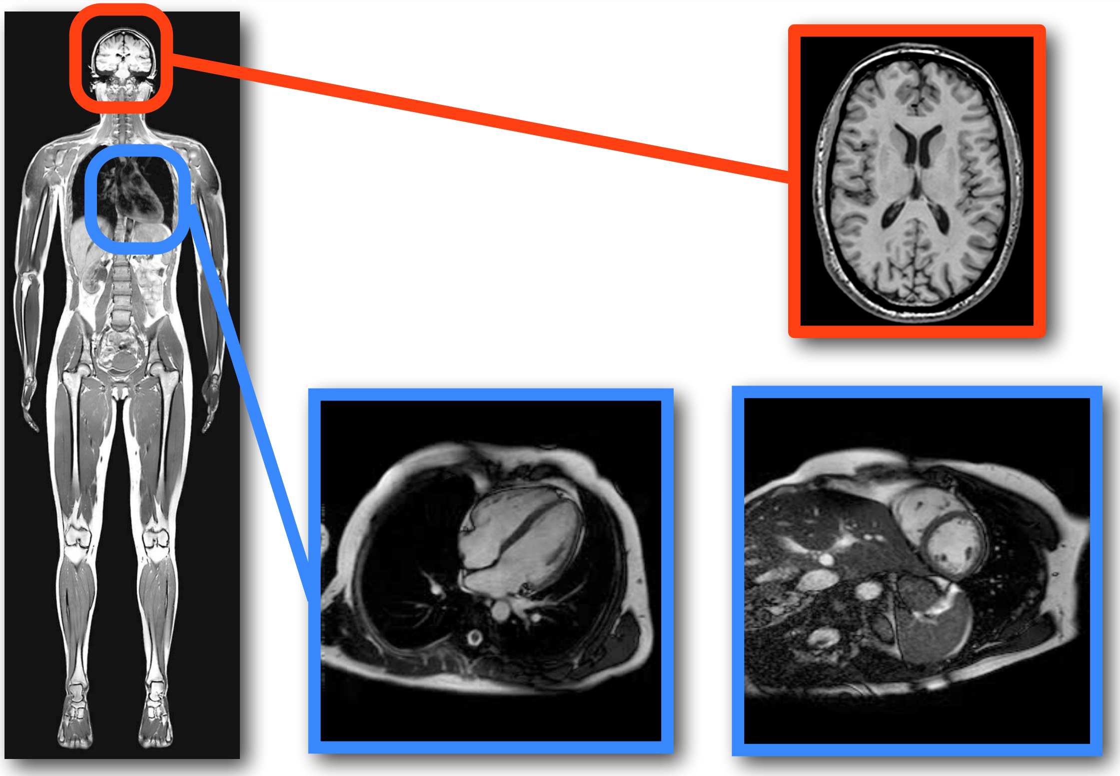


+

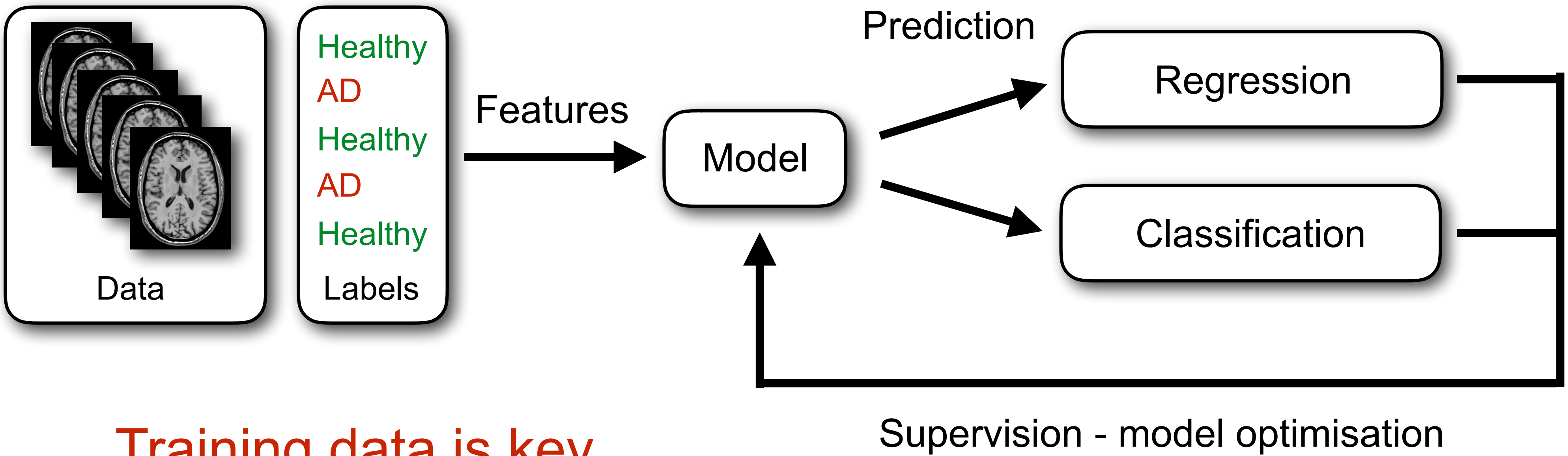
Lifestyle

Genetics

Clinical records

AI in Medical Imaging: Challenges

- AI or machine learning can be classified into:
  - Unsupervised approaches
  - Supervised approaches (most successful to date)



Training data is key

AI in Medical Imaging: Challenges

- How to obtain training data?
- Training data is expensive:
  - manpower, cost, time
  - years of training and expertise required
- Training data is imperfect:
  - training data may be wrongly labelled, e.g. for diseases such as Alzheimer's confirmation requires pathology (difficult and costly to obtain)

Crowdsourcing

Experts

More importantly, radiology tasks are not simple classification tasks but far more complex

Overview

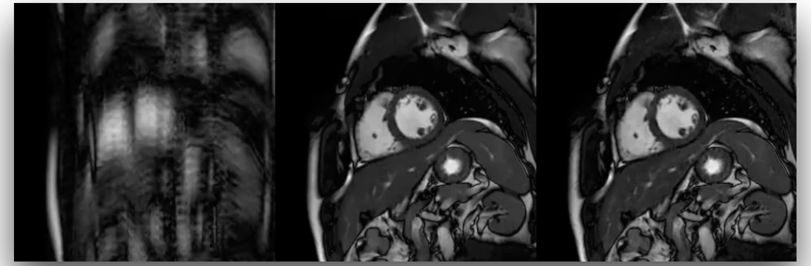


Image reconstruction

Abdominal View
Confidence: 98%

Image classification

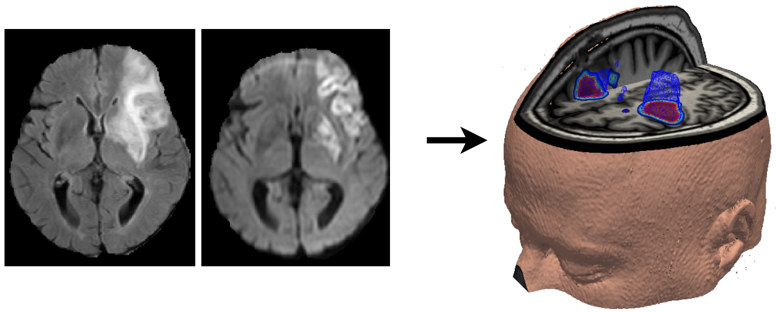
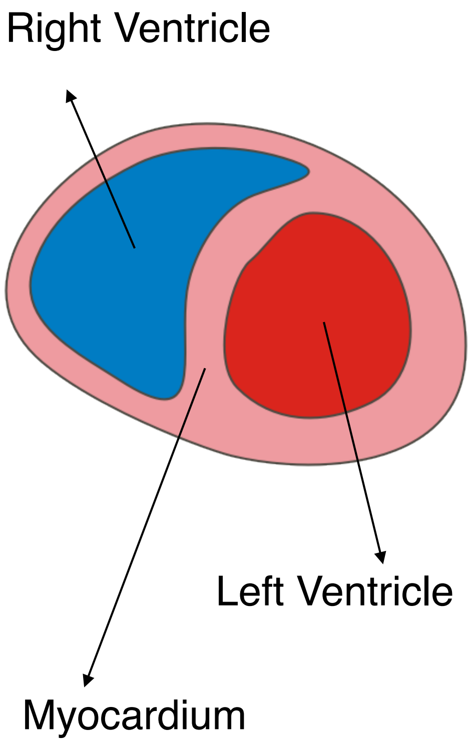


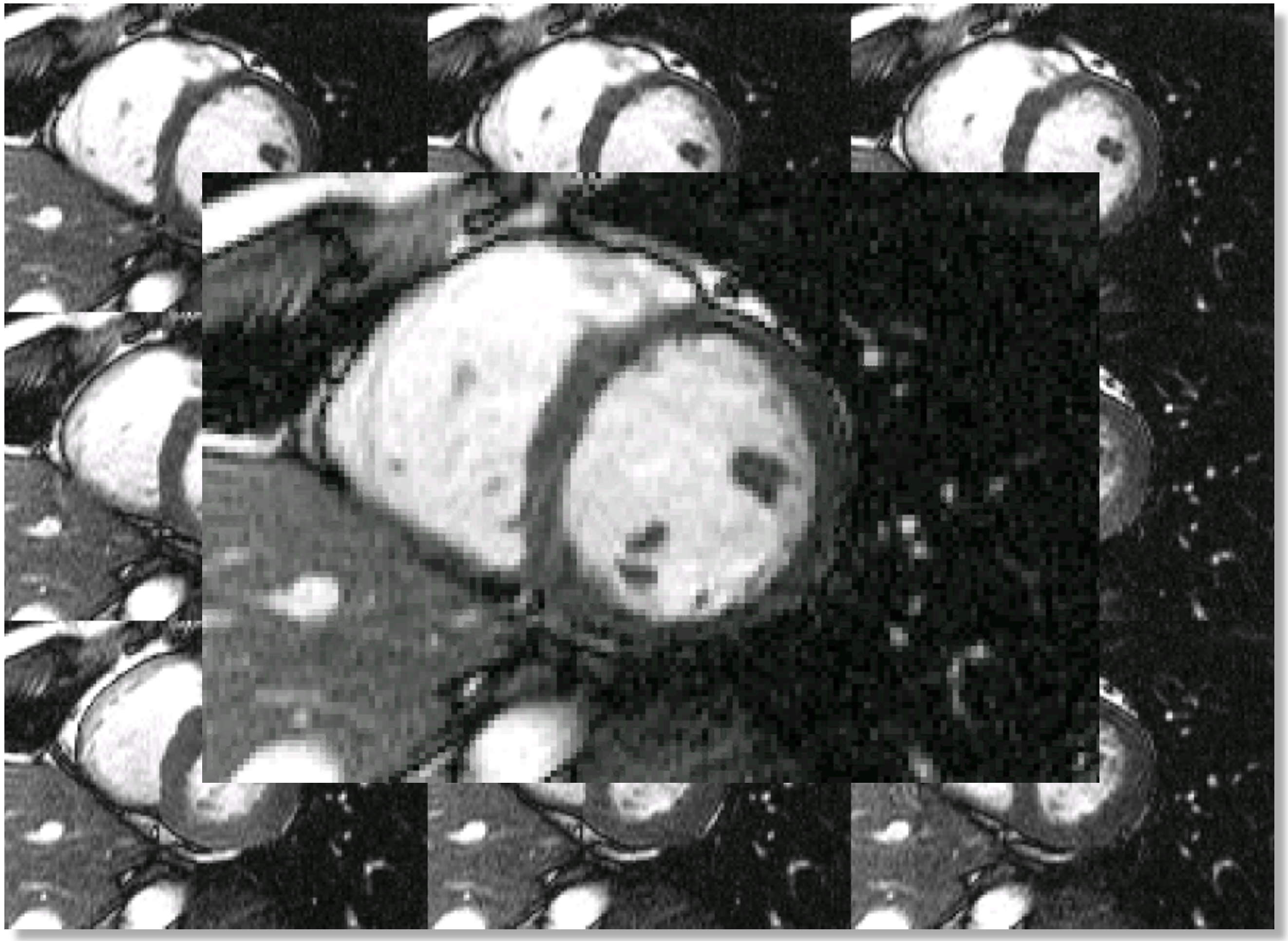
Image segmentation

MR image acquisition: Challenges

- Magnetic Resonance Imaging (MRI)
  - MRI acquisition is inherently a slow process
  - Slow acquisition is
    - ok for static objects (e.g. brain, bones, etc)
    - problematic for moving objects (e.g. heart, liver, fetus)
  - Options for MRI acquisition:
    - real-time MRI: fast, but 2D and relatively poor image quality
    - gated MRI: fine for period motion, e.g. respiration or cardiac motion but requires gating (ECG or navigators) leading to long acquisition times (30-90 min).

Example: Cardiac imaging



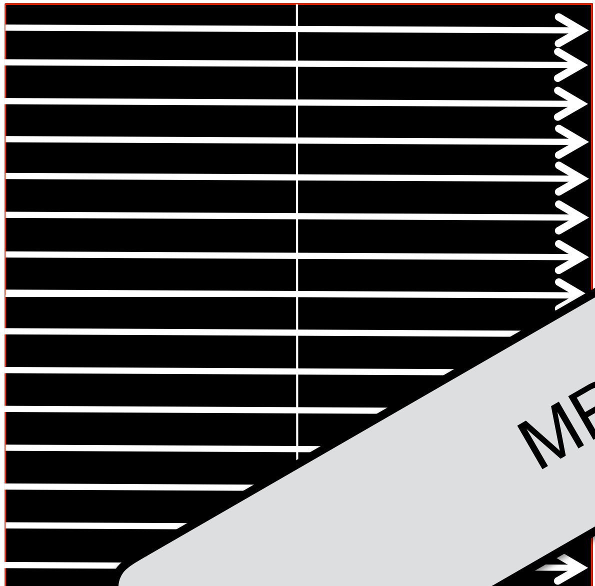


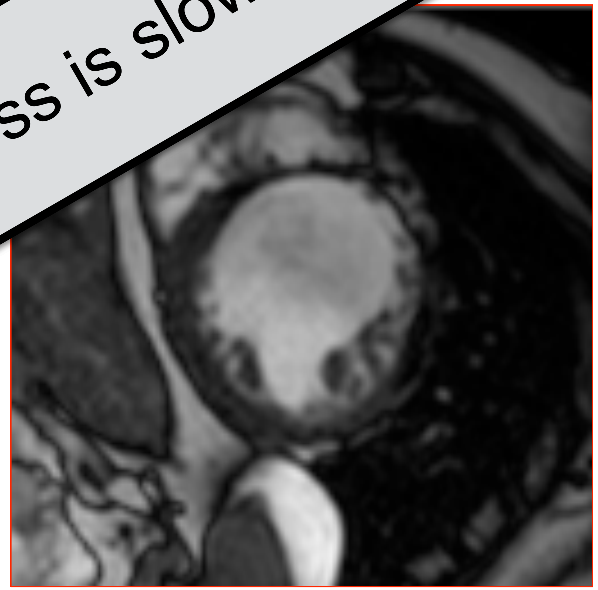
MR full acquisition

- MRI acquisition is performed in k-space by sequenti
  traversing sampling trajectories.

K-space

t = 0

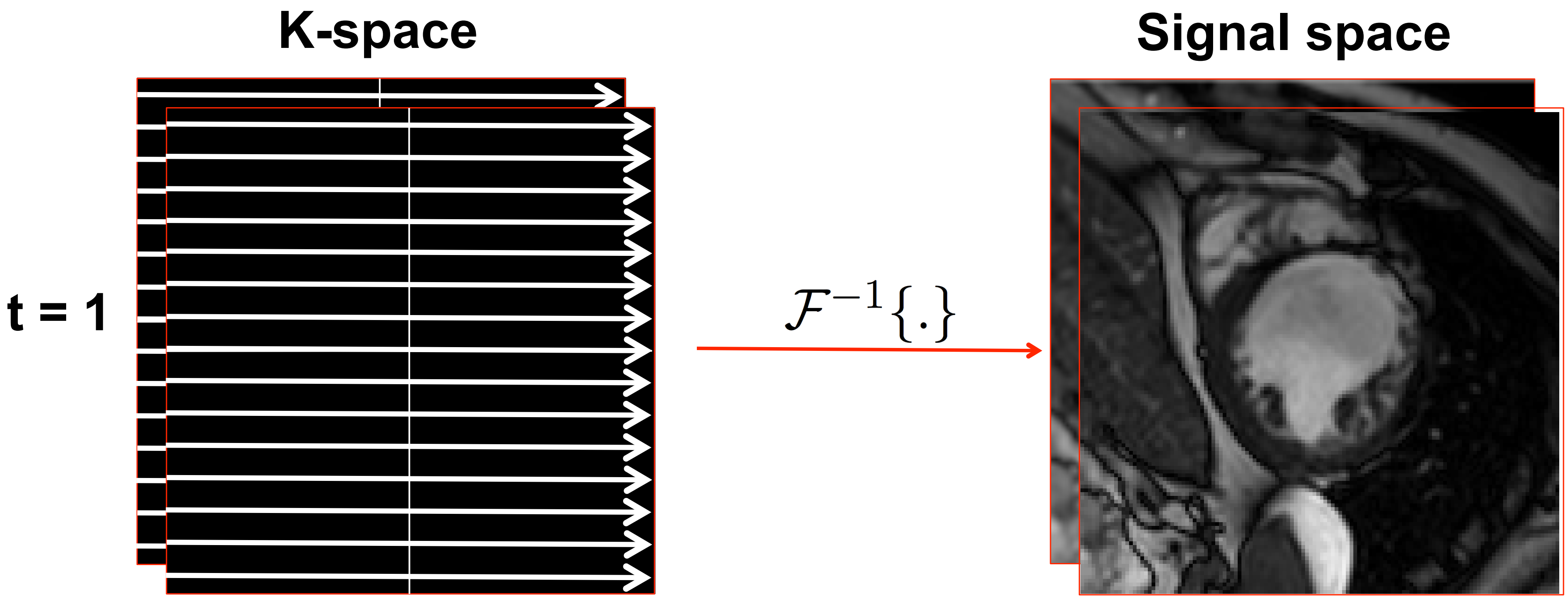




MR acquisition process is slow

MR full acquisition

- MRI acquisition is performed in k-space by sequentially traversing sampling trajectories.



MR full acquisition

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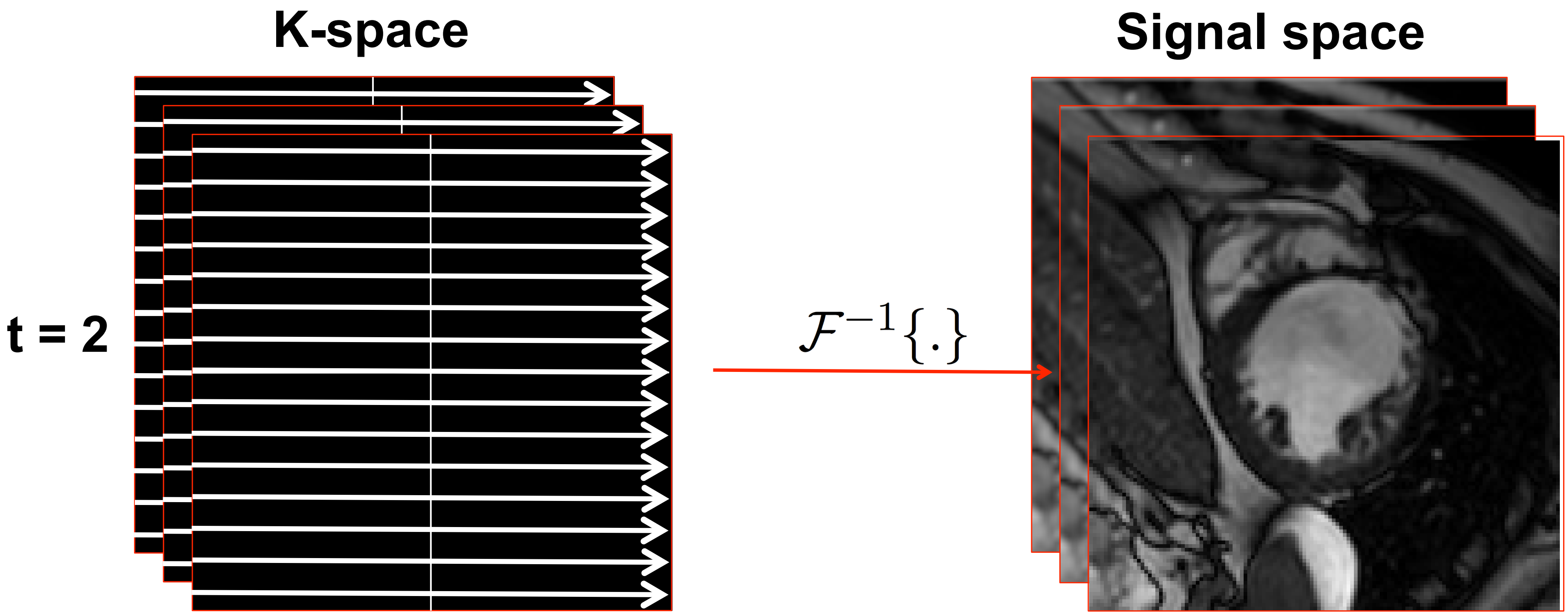

MR full acquisition

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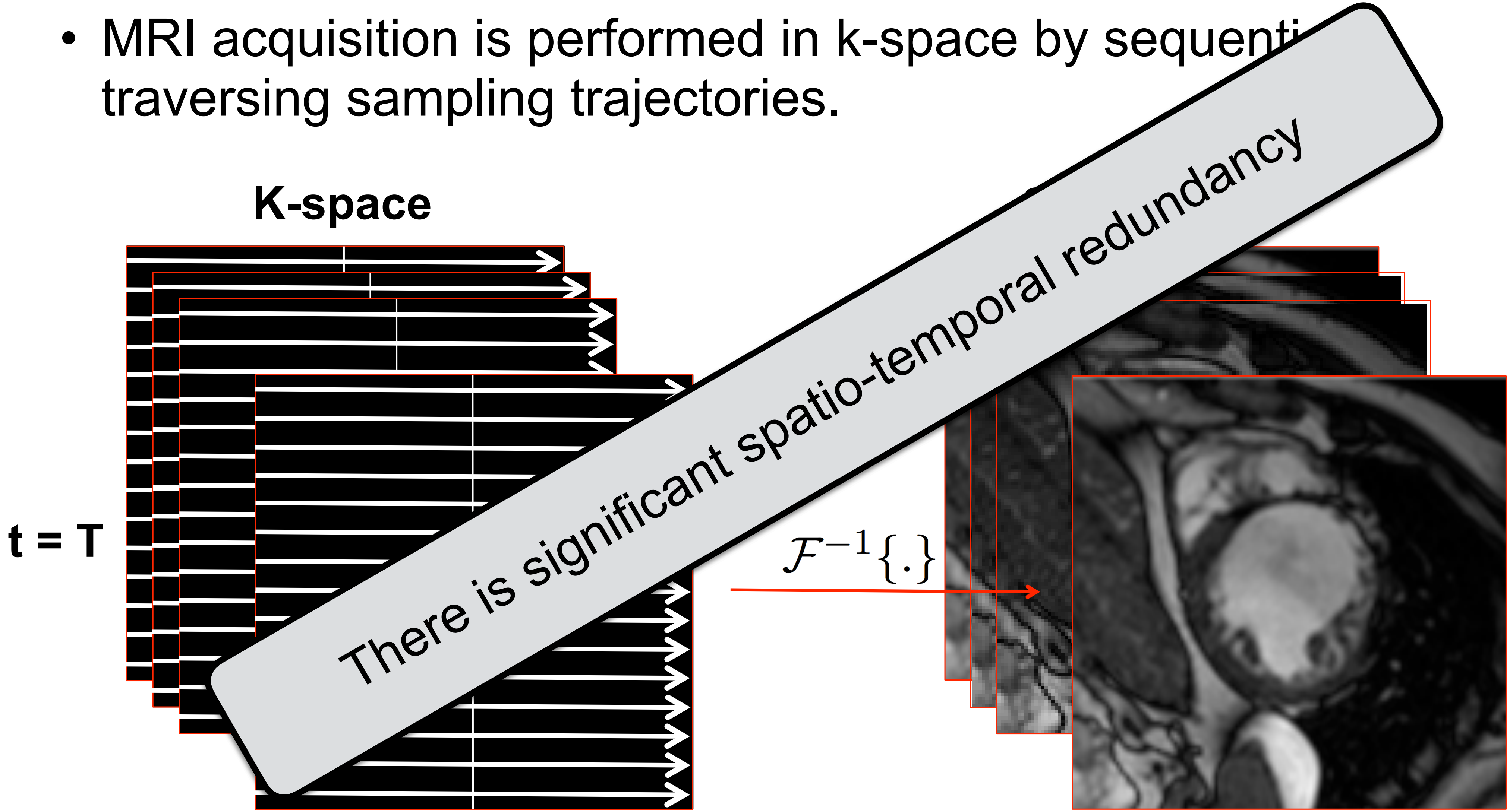


K-space undersampling

- Acquiring a fraction of k-space **accelerates** the process but introduces **aliasing** in signal space.

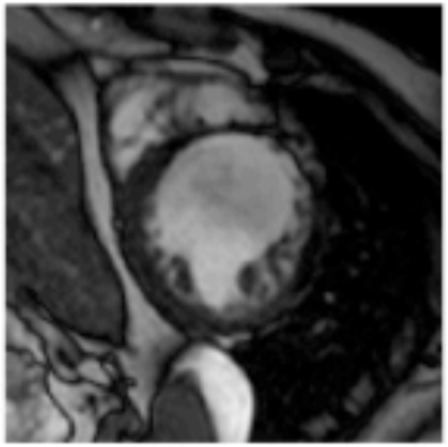
K-space undersampling

- Acquiring a fraction of k-space **<u>accelerates</u>** the process but introduces **<u>aliasing</u>** in signal space.

K-space **Signal space**

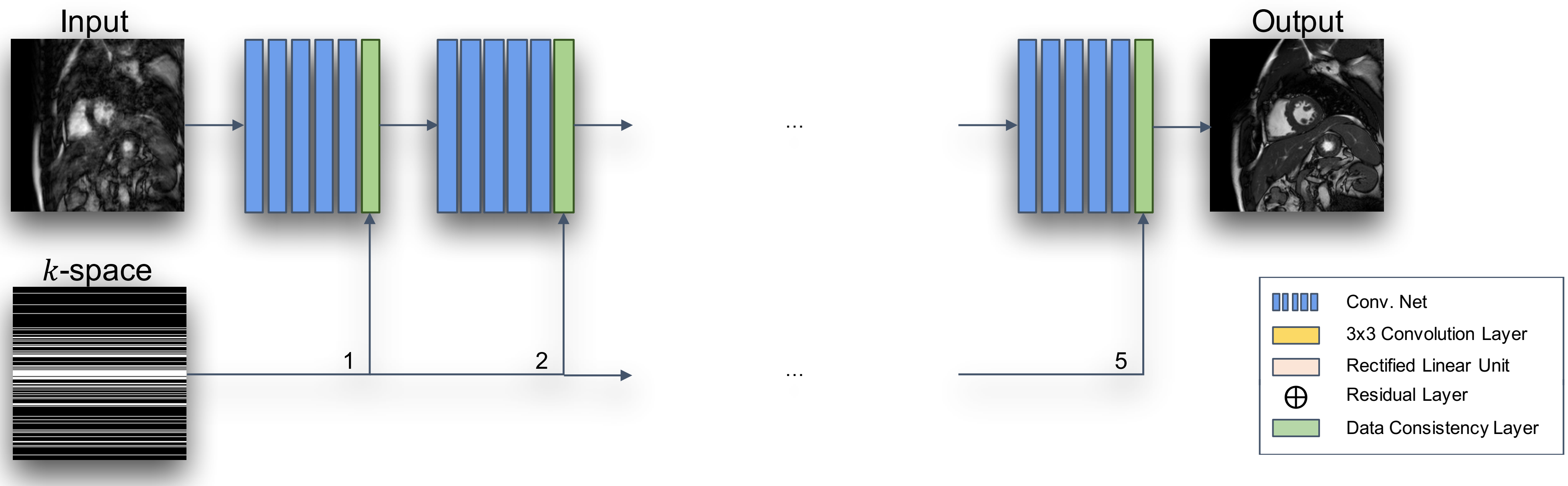
Full sampling (slow)

$\mathcal{F}^{-1}\{.\} \longrightarrow$



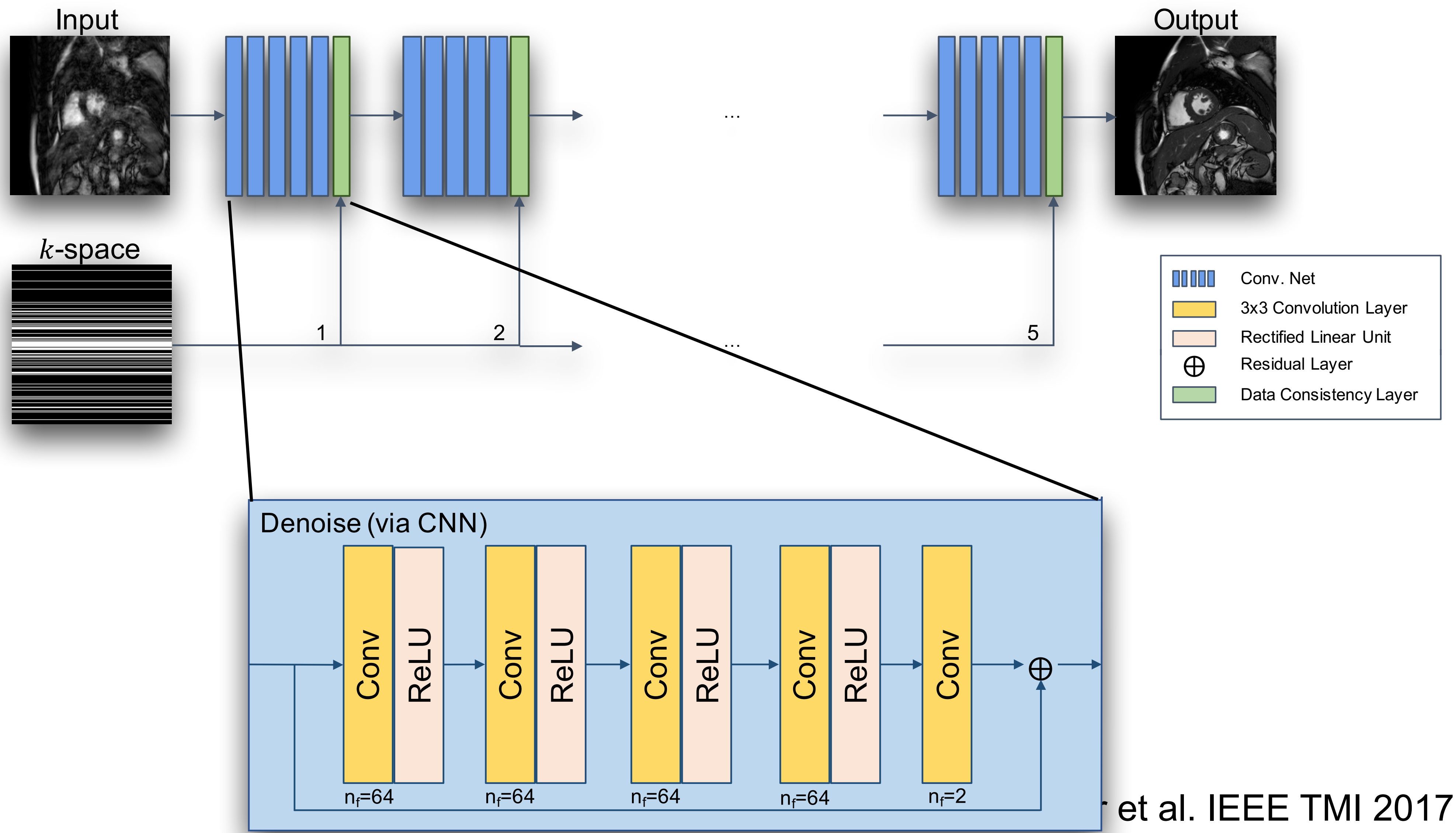
$\mathbf{x}_f$

Deep Cascade of CNNs for MRI Reconstruction



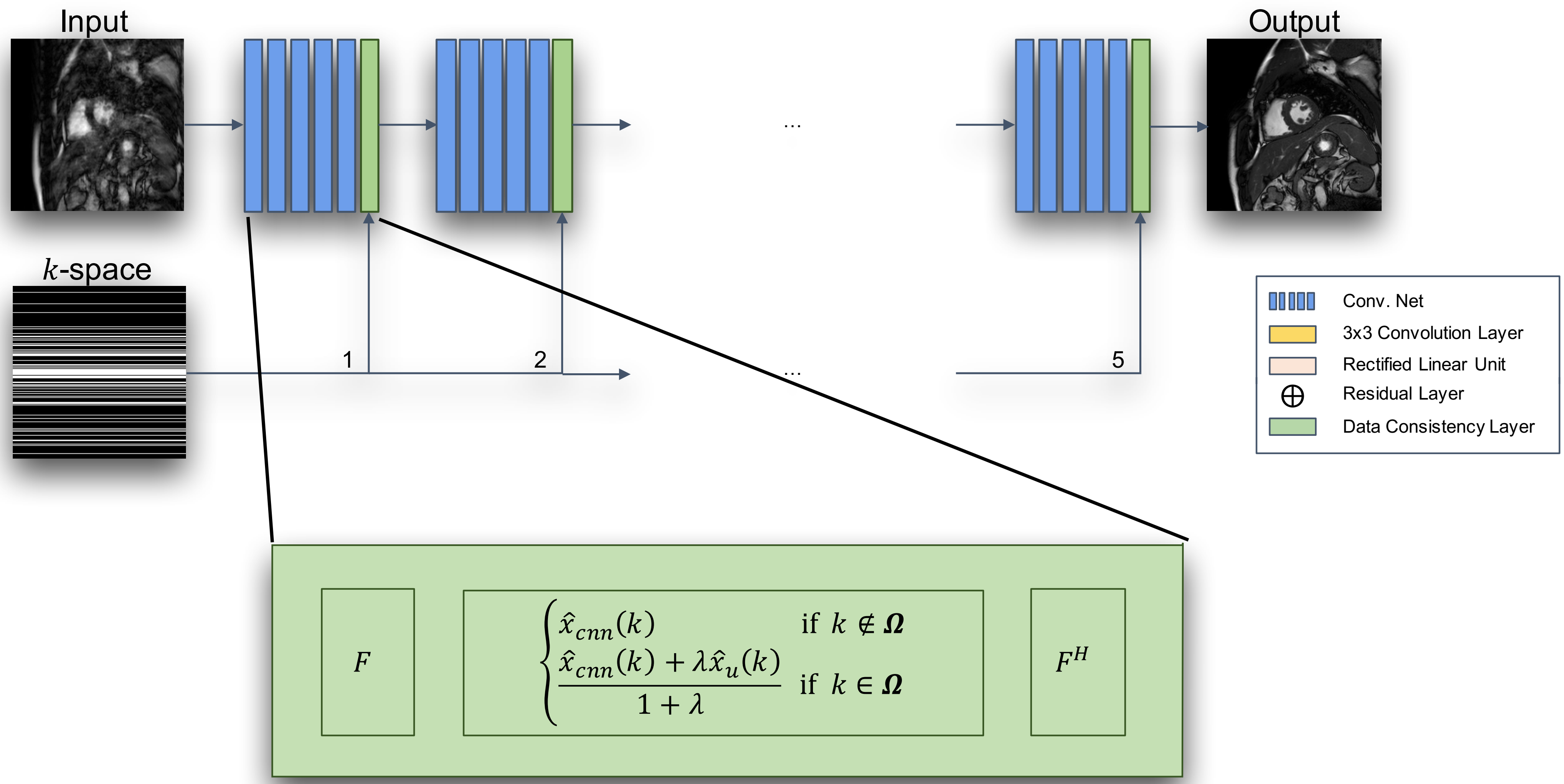
Schlemper et al. IEEE TMI 2017

Deep Cascade of CNNs for MRI Reconstruction



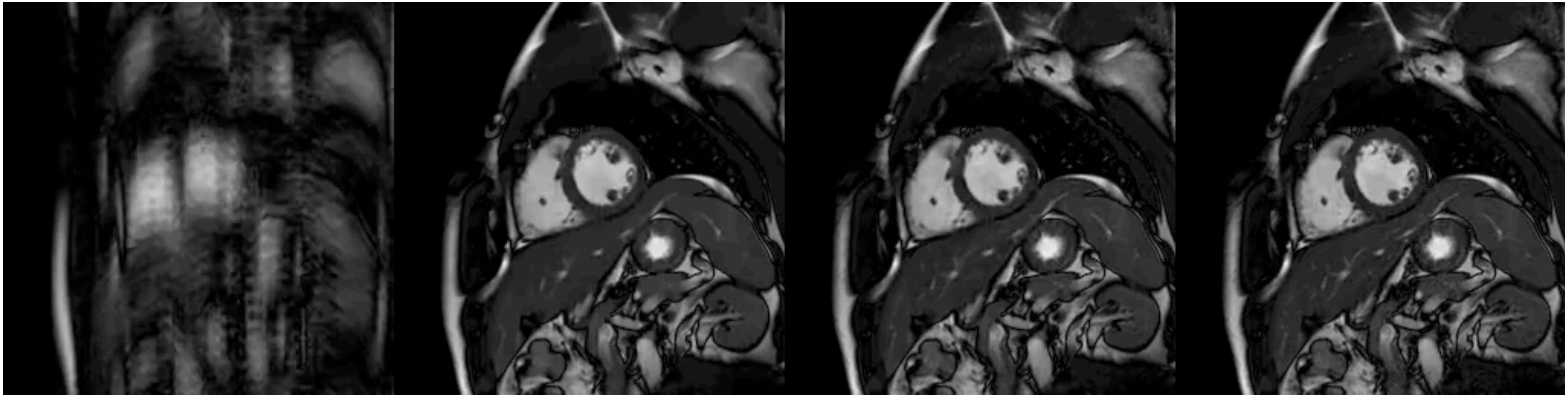
r et al. IEEE TMI 2017

Deep Cascade of CNNs for MRI Reconstruction



Schlemper et al. IEEE TMI 2017

Magnitude reconstruction (6-fold)

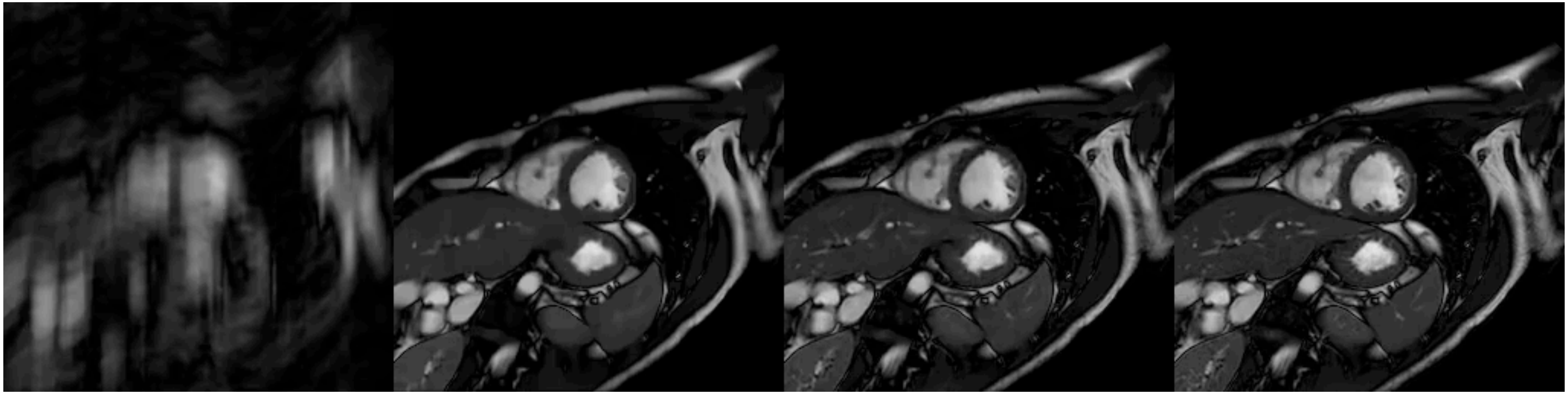


(a) 6x Undersampled (b) DLTG (c) CNN (d) Ground Truth

Reconstructions using ML

Schlemper et al. IEEE TMI 2017

Magnitude reconstruction (11-fold)



(a) 11x Undersampled **(b) DLTG** **(c) CNN** **(d) Ground Truth**

Reconstructions using ML

Schlemper et al. IEEE TMI 2017

Overview

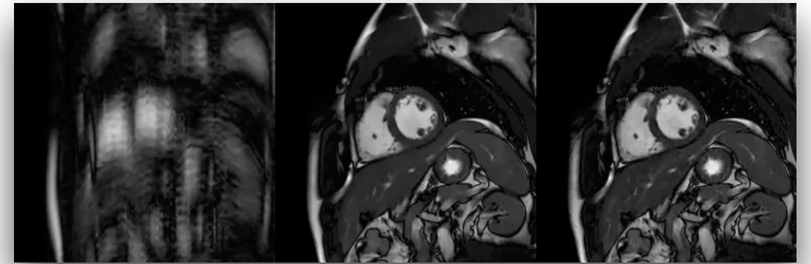


Image reconstruction

Image classification

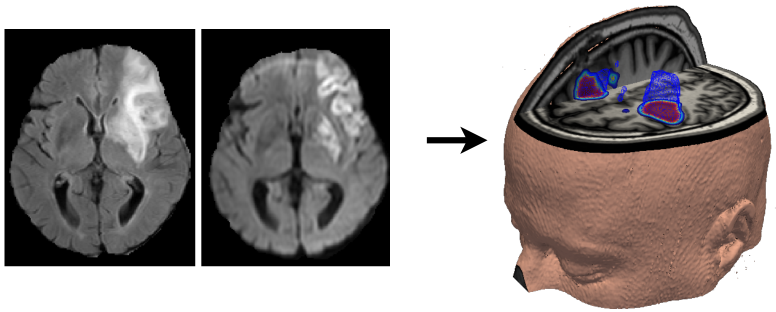


Image segmentation

Automatic Standard Scan Plane Detection

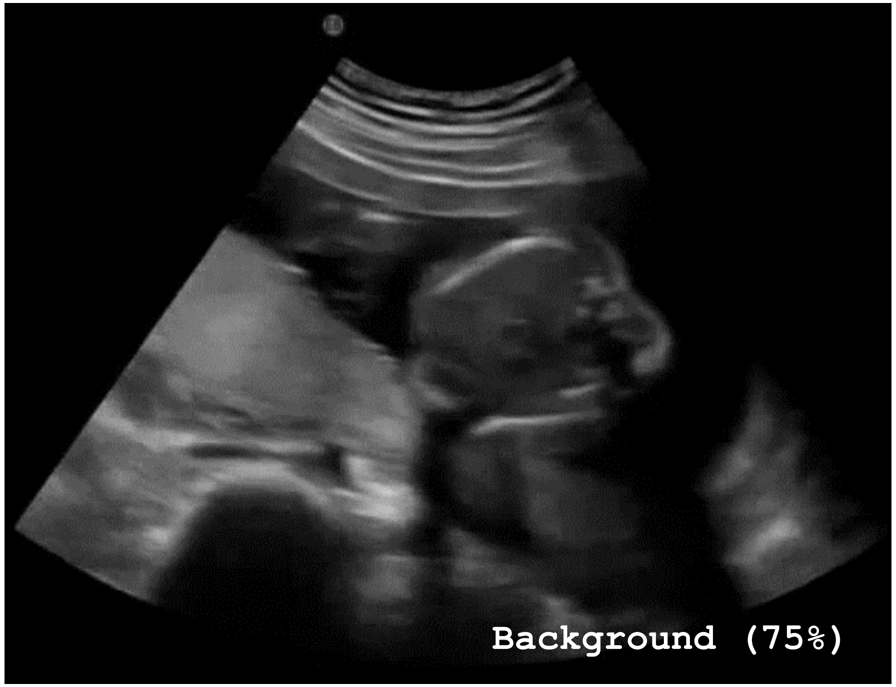
Abdominal View
Confidence: 98%

Lips View
Confidence: 96%

Goal: Do this in real-time on images straight from US machine

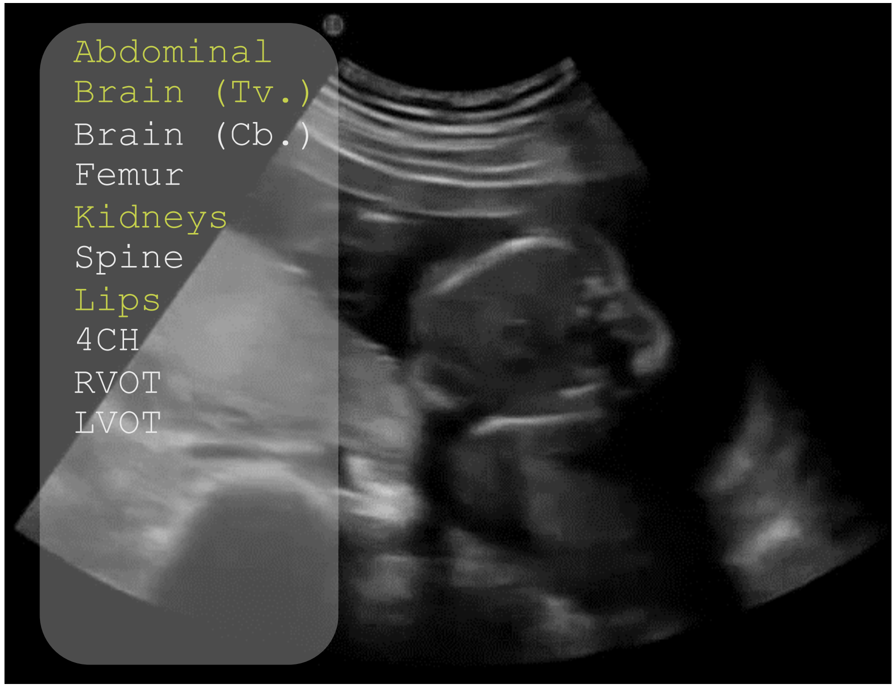
Automatic Standard Scan Plane Detection

- Potential applications:
  - Guidance: Assist inexperienced sonographers



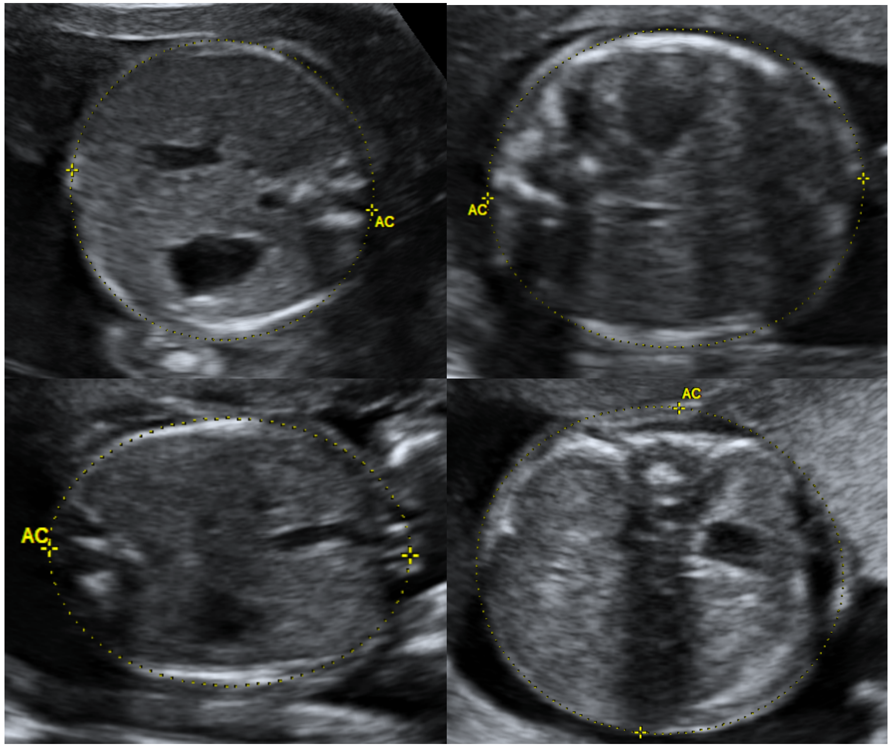
Automatic Standard Scan Plane Detection

- Potential applications:
  - Guidance: Assist inexperienced sonographers
  - Convenience: Automatically make a check list of visited planes



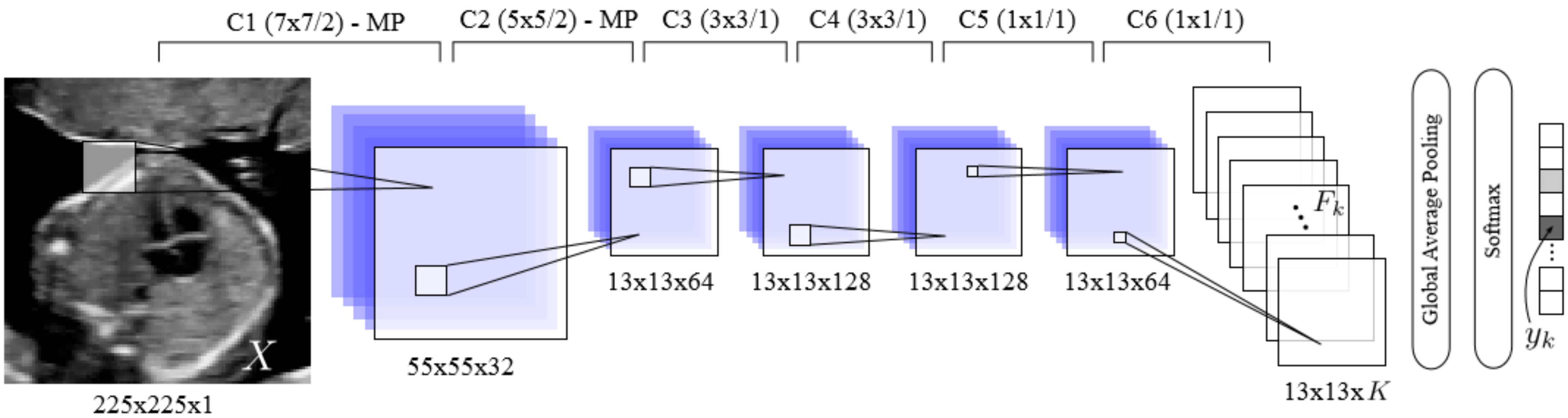
Automatic Standard Scan Plane Detection

- Potential applications:
  - Guidance: Assist inexperienced sonographers
  - Convenience: Automatically make a check list of visited planes
  - Reproducibility: Reduce variability between operators



Automatic Standard Scan Plane Detection: Method

- Fully convolutional neural network:



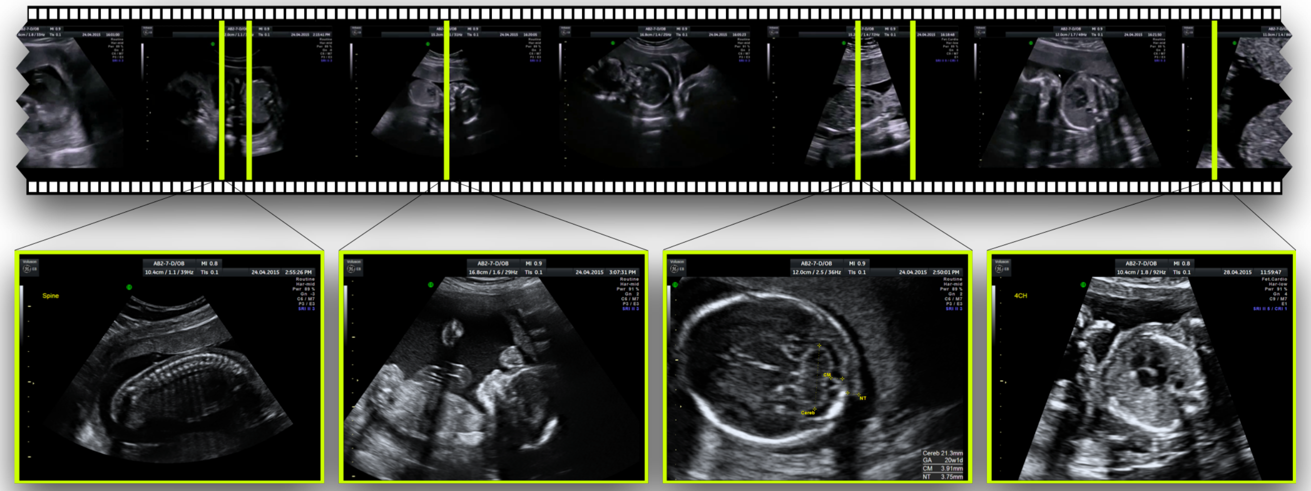
  - Very fast
  - Very accurate

C. Baumgartner et al. MICCAI 2016, IEEE-TMI 2017

Automatic Standard Scan Plane Detection: Data

- We use very large 2D ultrasound dataset consisting of ***images*** of standard views and ***videos***

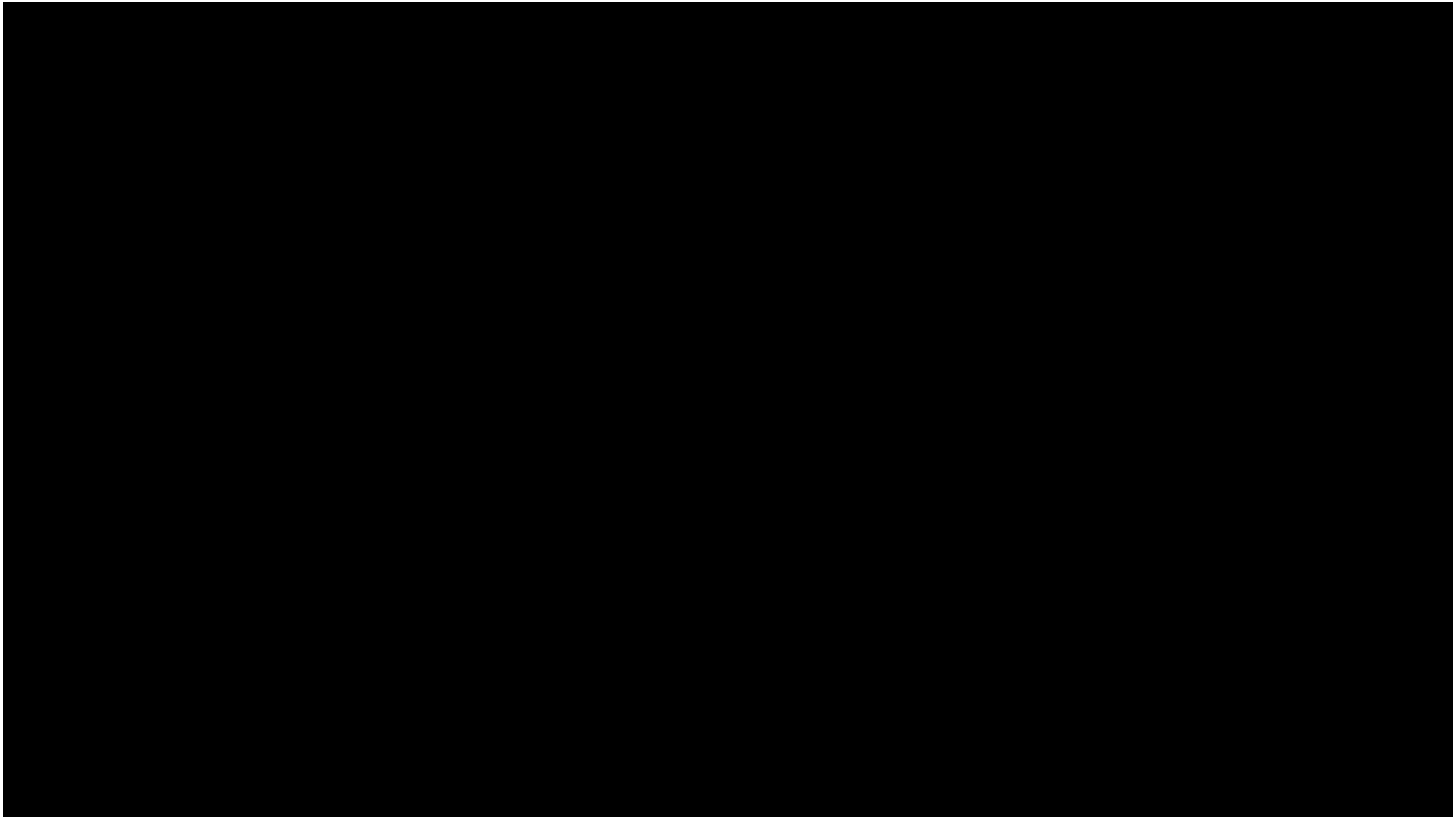
Video of fetal ultrasound examination (typically 20 minutes, 30'000 frames)



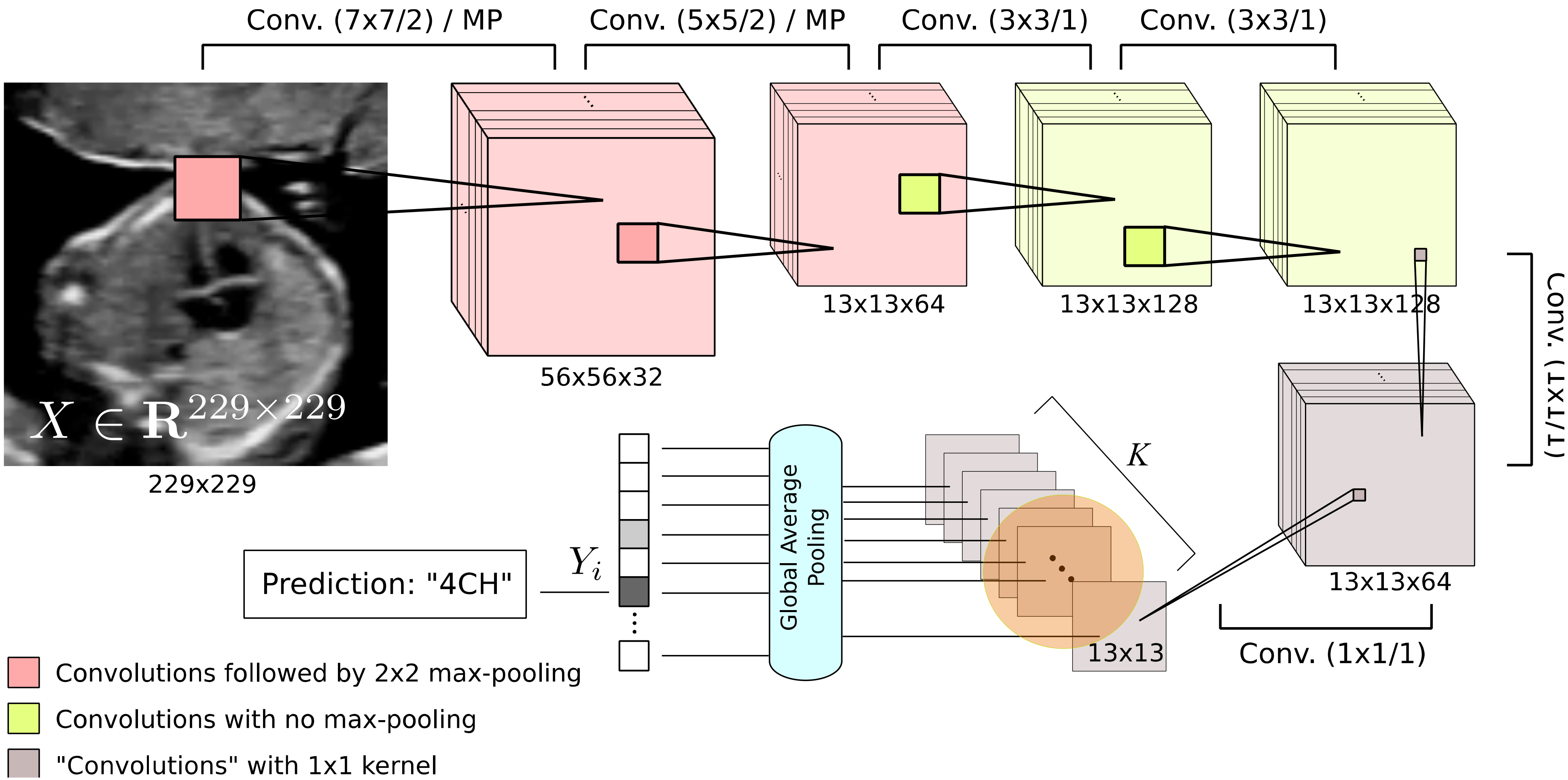
Annotated "freeze frames" saved by operator (typically 30 images)

- Data from
  - 2700 patients
  - Between 1200 and 4800 images for each standard plane

Demo



Automatic Standard Scan Plane Detection: Localisation

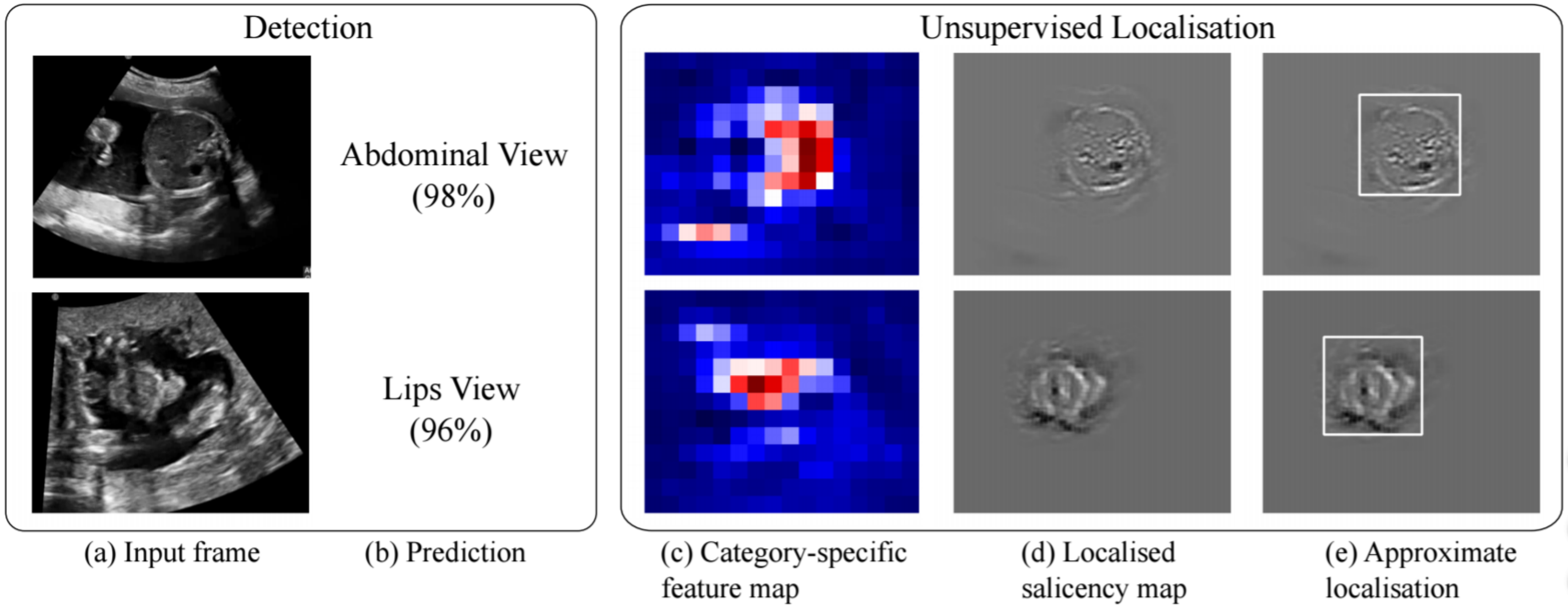


Localisation is (almost) for free in this framework!

C. Baumgartner et al. MICCAI 2016, IEEE-TMI 2017

Automatic Standard Scan Plane Detection: Localisation

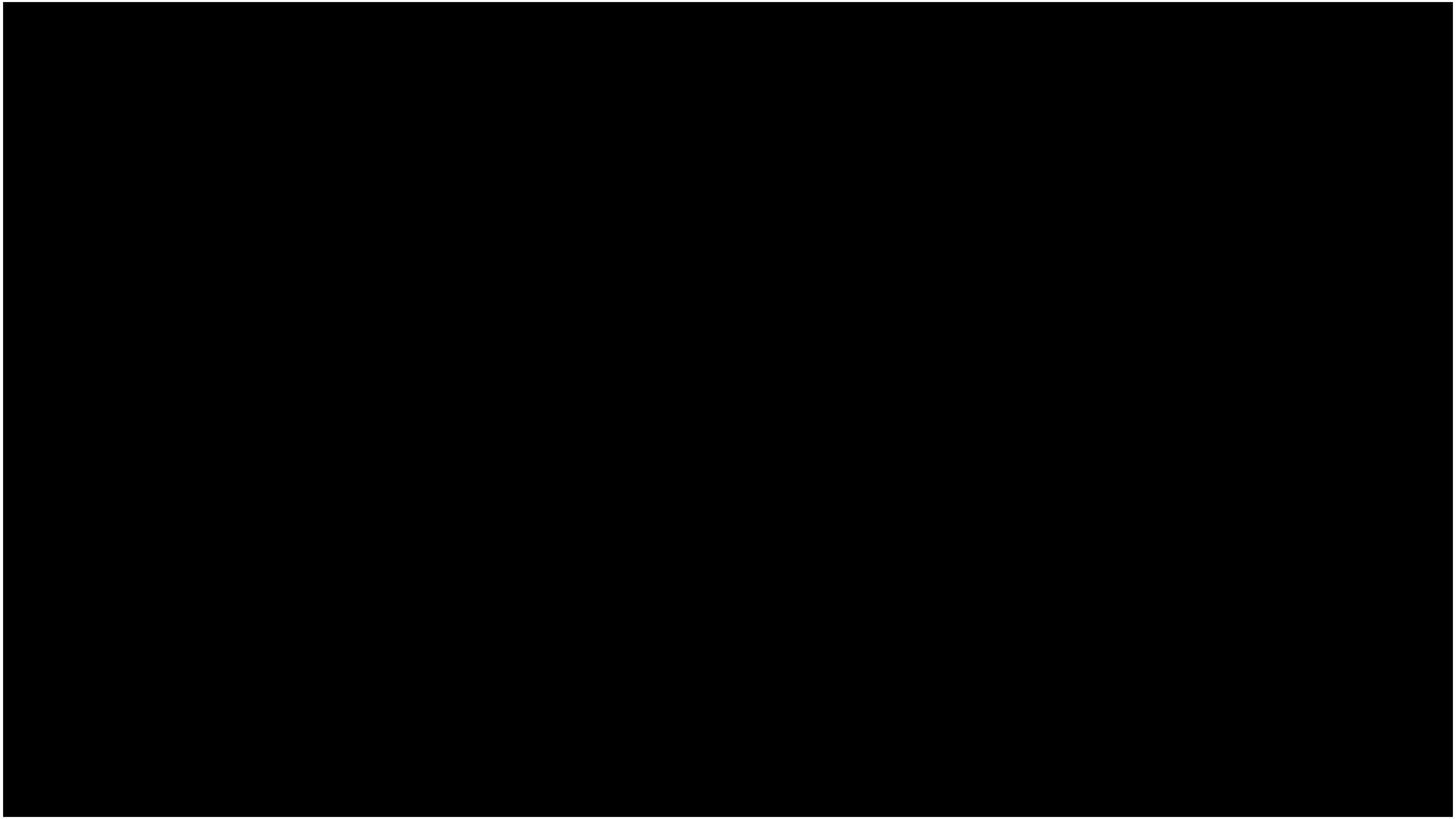
- Can also identify which regions of a frame caused it to make a particular prediction



- This can be used for localisation of the fetal anatomy without having bounding boxes for training

C. Baumgartner et al. MICCAI 2016, IEEE-TMI 2017

Demo



Overview

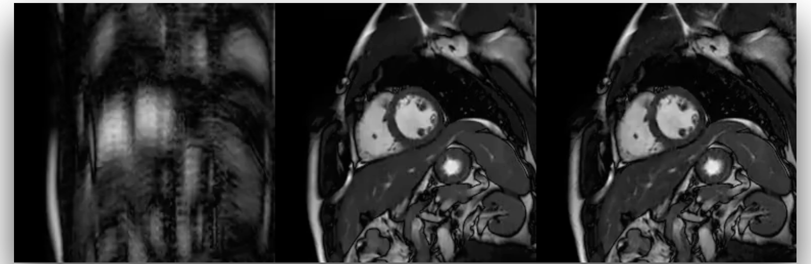


Image reconstruction

Abdominal View
Confidence: 98%

Image classification

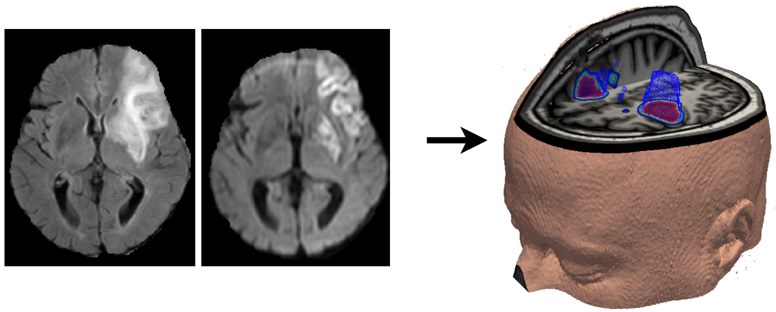


Image segmentation

Convolutional Neural Networks for Image Segmentation

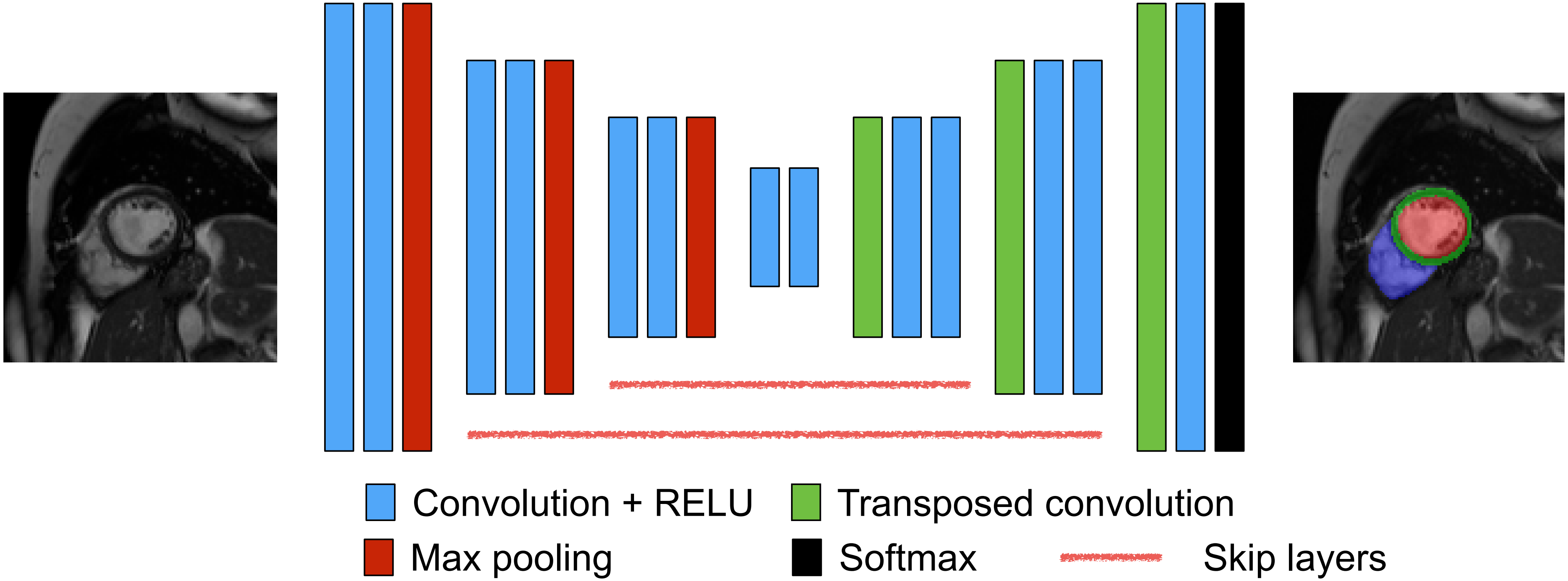


Image segmentation as a machine learning problem

- Fully connected networks (Long et al., 2015)
- Manual annotations of **4,872 subjects** (QMUL/Oxford) with **93,128 pixelwise annotated 2D images** slices
- Divided into training/validation/test: 3,972/300/600

Petersen *et al. Journal of Cardiovascular Magnetic Resonance* (2017) 19:18
DOI 10.1186/s12968-017-0327-9

Journal of Cardiovascular Magnetic Resonance

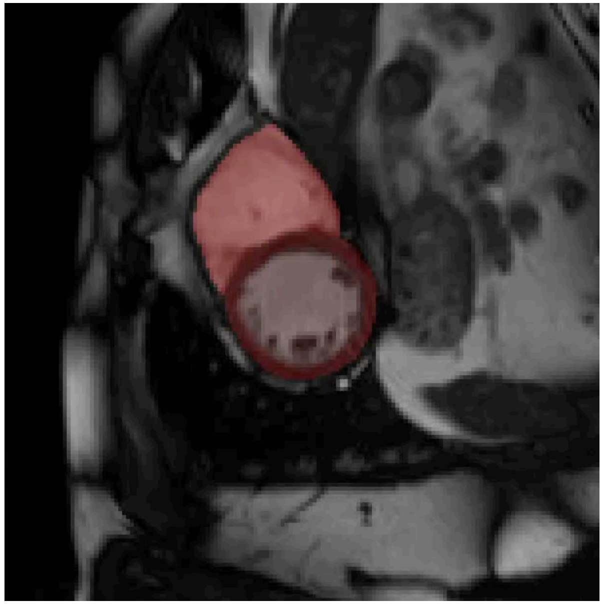
RESEARCH Open Access

CrossMark

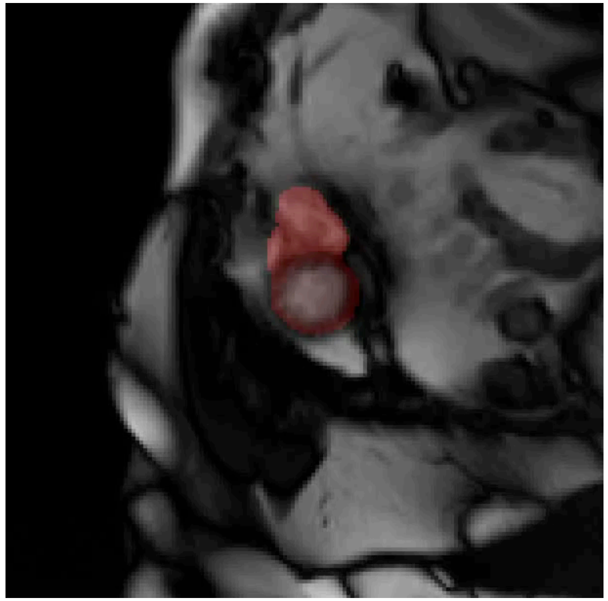
Reference ranges for cardiac structure and function using cardiovascular magnetic resonance (CMR) in Caucasians from the UK Biobank population cohort

Steffen E. Petersen[1*], Nay Aung[1], Mihir M. Sanghvi[1], Filip Zemrak[1], Kenneth Fung[1], Jose Miguel Paiva[1], Jane M. Francis[2], Mohammed Y. Khanji[1], Elena Lukaschuk[2], Aaron M. Lee[1], Valentina Carapella[2], Young Jin Kim[2,3], Paul Leeson[2], Stefan K. Piechnik[2] and Stefan Neubauer[2]

SA, basal

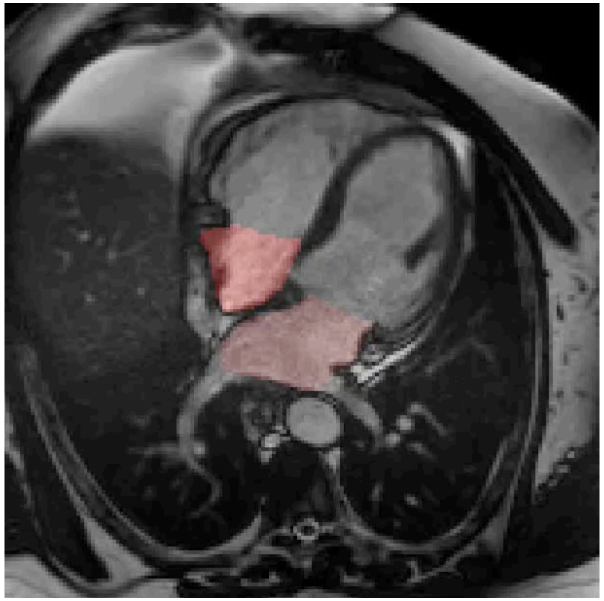


SA, mid-ventricular



SA, apical

LA, 2 chamber



LA, 4 chamber

Evaluation of segmentation accuracy
Comparison to expert observers

(a) Absolute difference

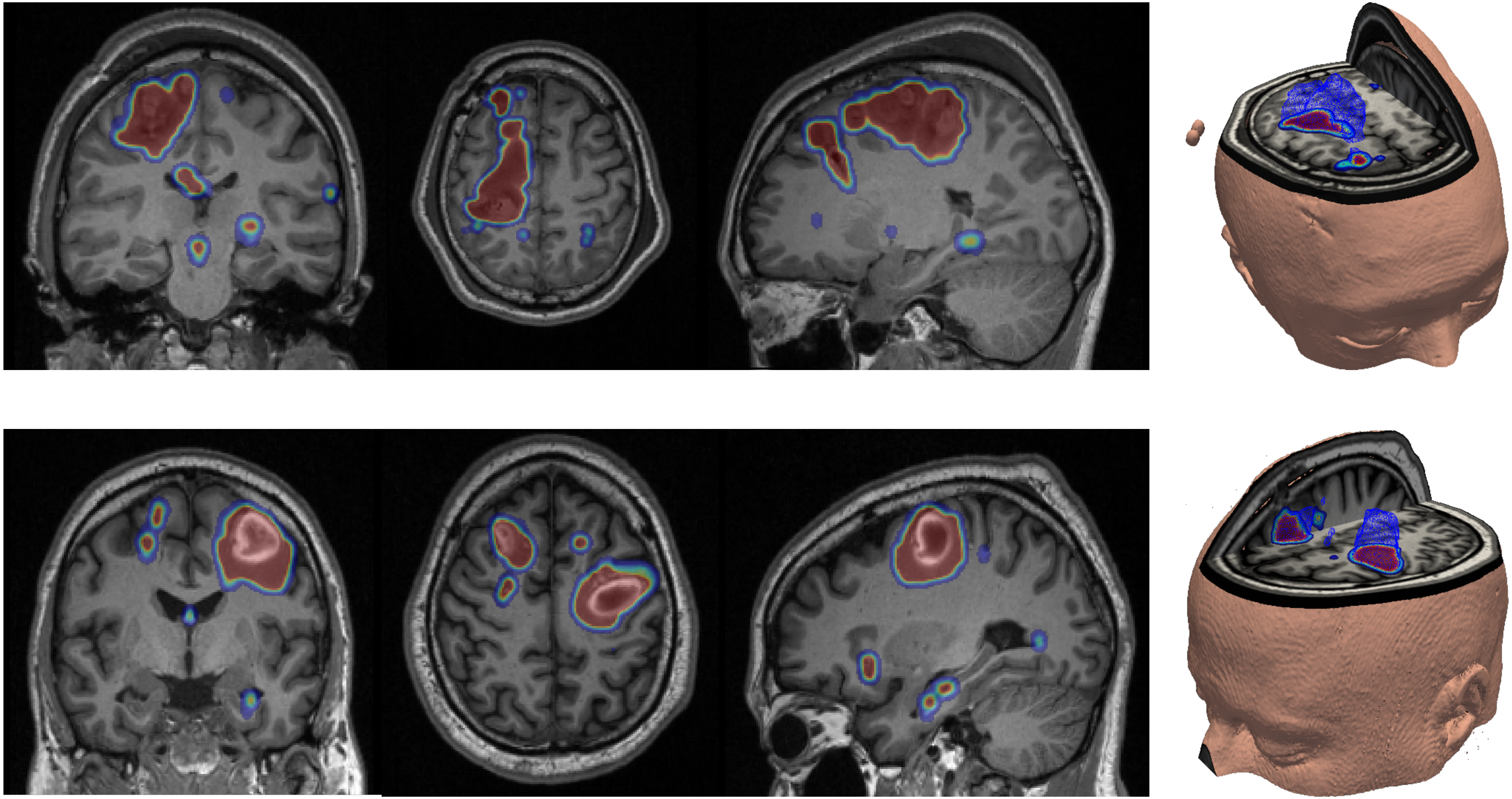
	Auto vs Man (n = 600)	O1 vs O2 (n = 50)	O2 vs O3 (n = 50)	O3 vs O1 (n = 50)
LVEDV (mL)	$6.1_{\pm 5.3}$	$6.1_{\pm 4.4}$	$8.8_{\pm 4.8}$	$4.8_{\pm 3.1}$
LVESV (mL)	$5.3_{\pm 4.9}$	$4.1_{\pm 4.2}$	$6.7_{\pm 4.2}$	$7.1_{\pm 3.8}$
LVM (gram)	$6.9_{\pm 5.5}$	$4.2_{\pm 3.2}$	$6.6_{\pm 4.9}$	$6.5_{\pm 4.8}$
RVEDV (mL)	$8.5_{\pm 7.1}$	$11.1_{\pm 7.2}$	$6.2_{\pm 4.6}$	$8.7_{\pm 5.8}$
RVESV (mL)	$7.2_{\pm 6.8}$	$15.6_{\pm 7.8}$	$6.6_{\pm 5.5}$	$11.7_{\pm 6.9}$

(b) Relative difference

	Auto vs Man (n = 600)	O1 vs O2 (n = 50)	O2 vs O3 (n = 50)	O3 vs O1 (n = 50)
LVEDV (%)	$4.1_{\pm 3.5}$	$4.2_{\pm 3.1}$	$6.3_{\pm 3.3}$	$3.4_{\pm 2.2}$
LVESV (%)	$9.5_{\pm 9.5}$	$6.8_{\pm 7.5}$	$12.5_{\pm 8.5}$	$11.7_{\pm 5.1}$
LVM (%)	$8.3_{\pm 7.6}$	$4.4_{\pm 3.3}$	$6.0_{\pm 3.7}$	$6.7_{\pm 4.6}$
RVEDV (%)	$5.6_{\pm 4.6}$	$8.0_{\pm 5.0}$	$4.2_{\pm 3.1}$	$5.7_{\pm 3.6}$
RVESV (%)	$11.8_{\pm 12.2}$	$30.6_{\pm 15.5}$	$10.9_{\pm 8.3}$	$16.9_{\pm 9.2}$

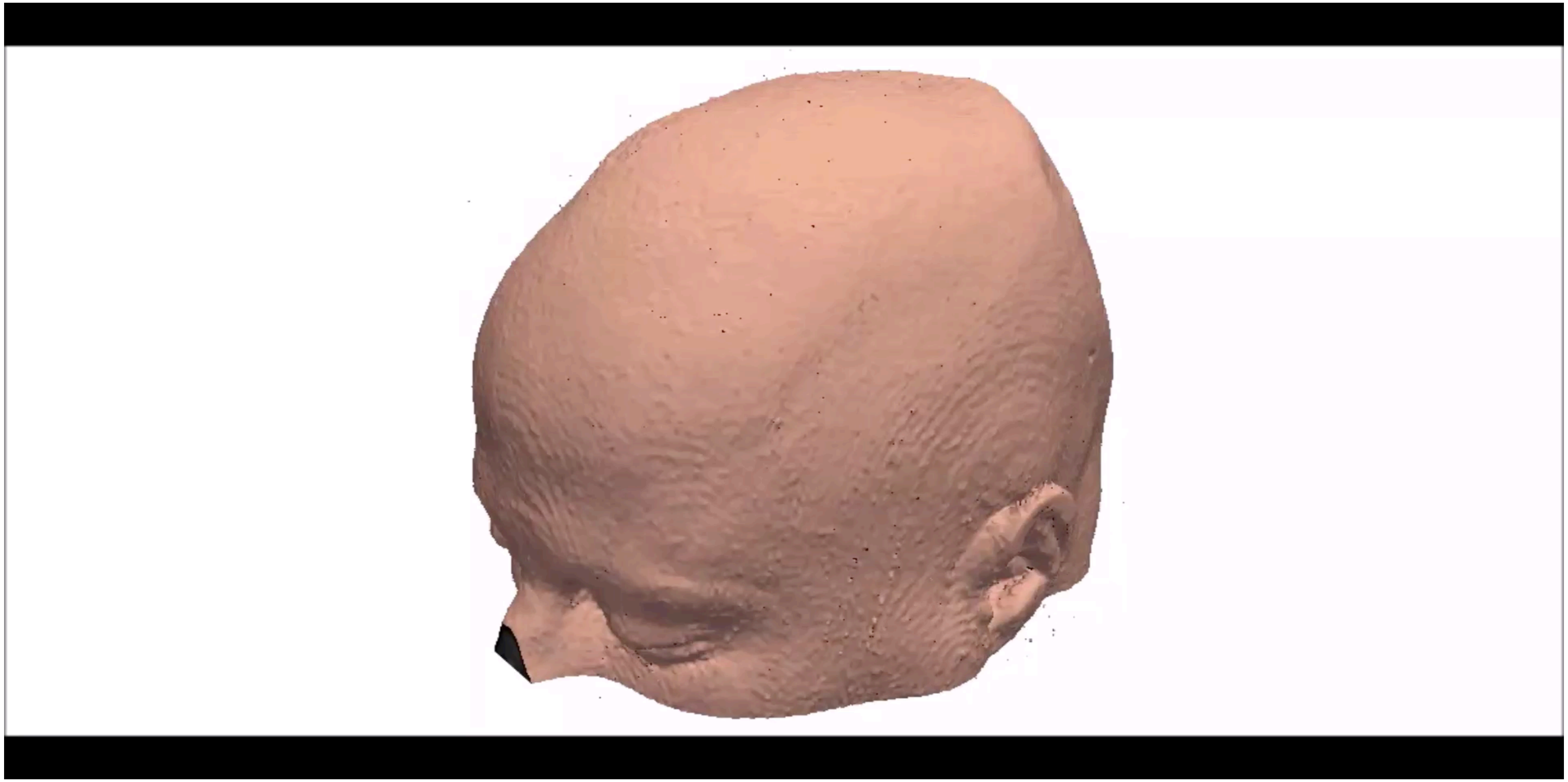
Automated Manual

DeepMedic in Action



K. Kamnitsas et al. Medical Image Analysis, 2016

DeepMedic in Action



K. Kamnitsas et al. Medical Image Analysis, 2016

Practical challenges in many AI scenarios: Deployment in the clinic

- AI-based solutions often degrade when deployed in clinical scena
- This is caused by differe between training a
  - different s
  - sc
- or
  feasible
  s

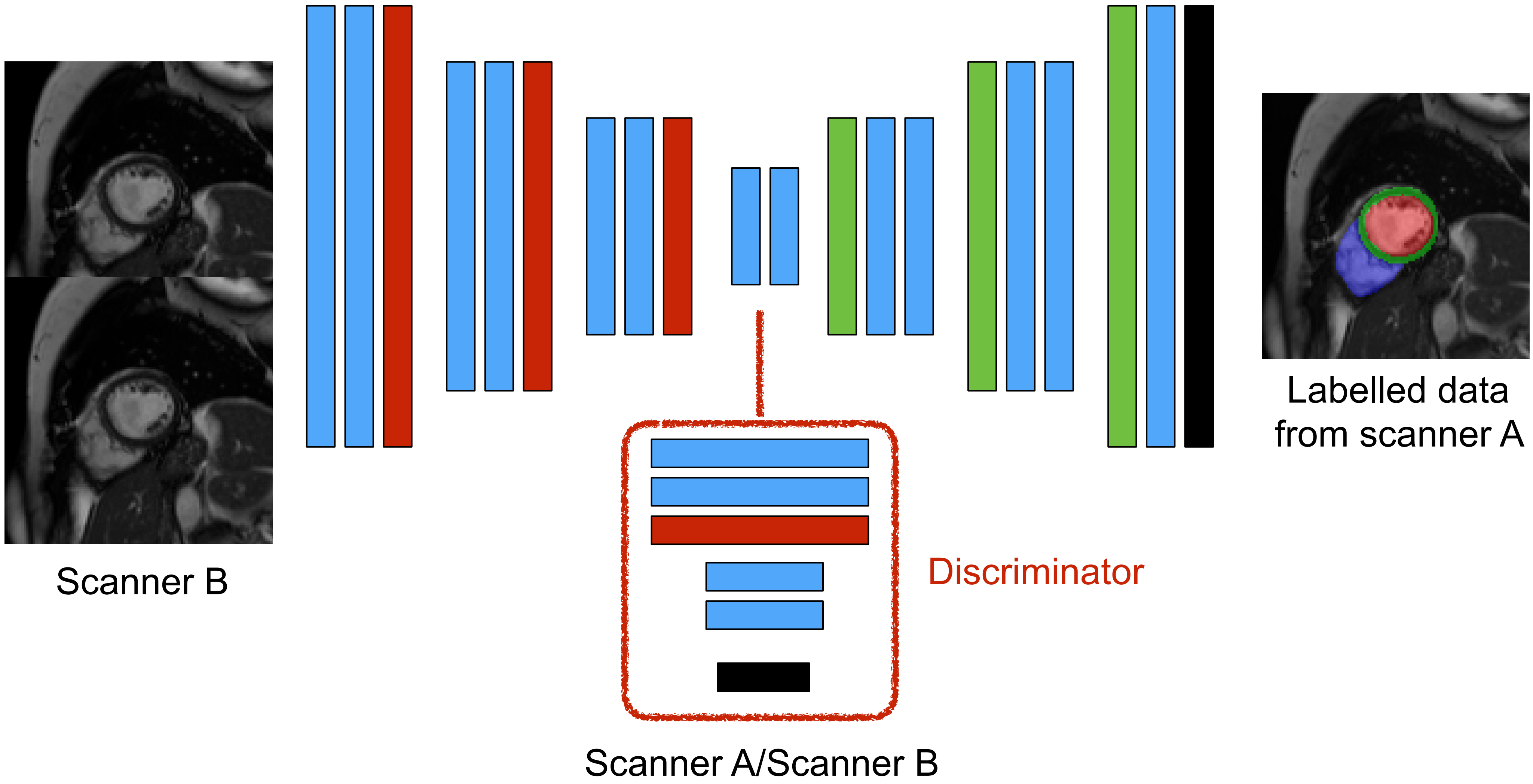
Transfer learning problem

Philips

ns

GE

Transfer learnings for CNNs
Using adversarial learning



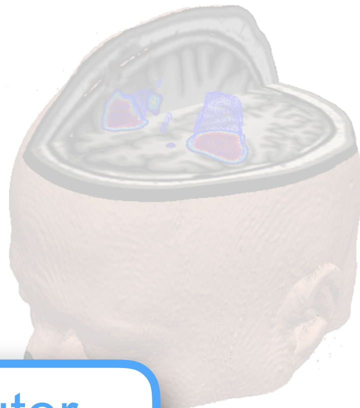
K. Kamnitsas et al. IPMI 2017, arXiv:1612.08894

Summary and Conclusions

- AI already plays a crucial role in
  - Image acquisition and reconstruction

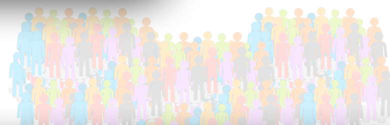
Validation is challenging

- Applications of AI in computer-aided detection and decision support have been limit



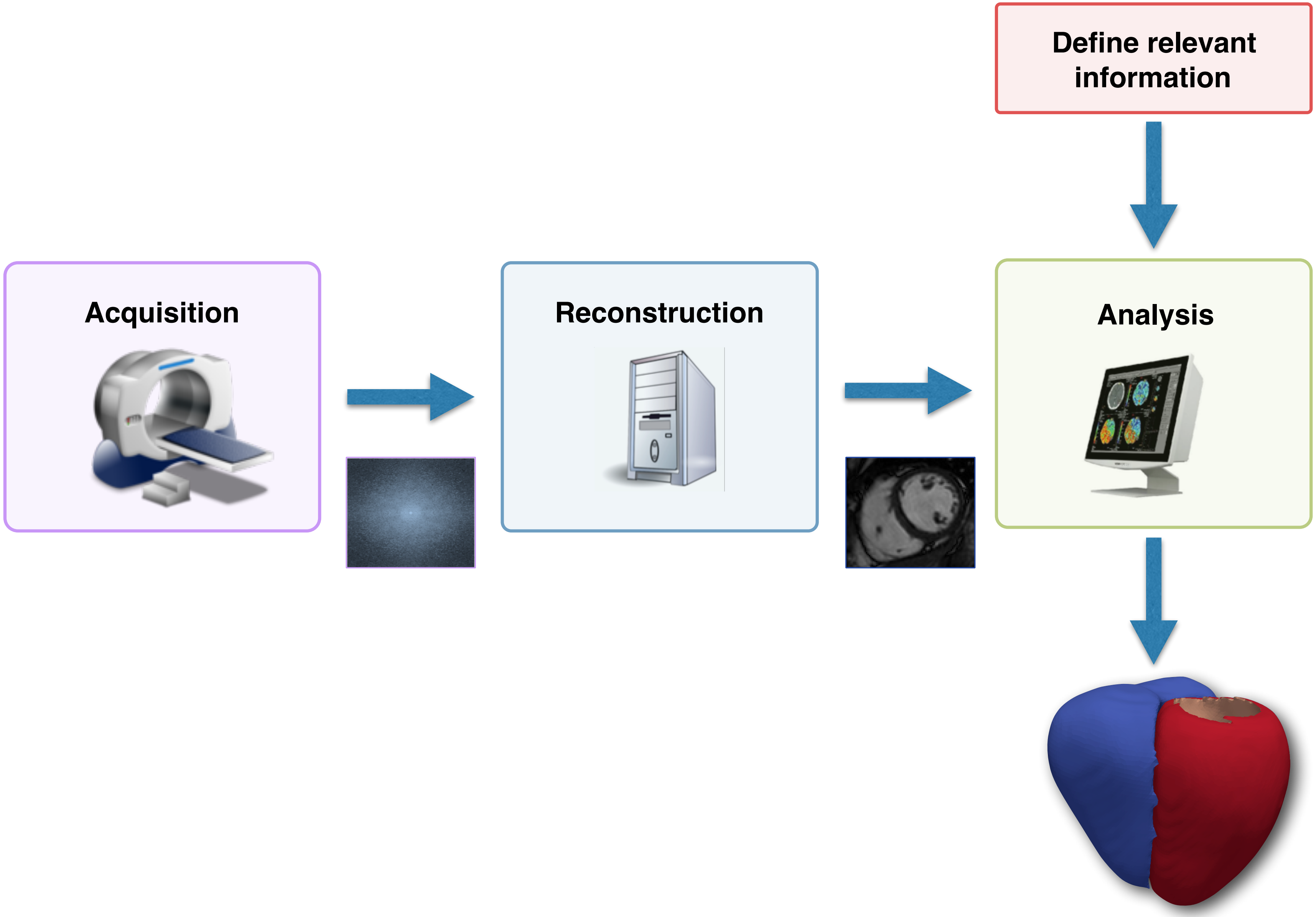
Requires collaboration between computer scientists, engineers and clinicians

- Truly intelligent computer-aided diagnosis requires
  - Learning from unlab population data
  - Integration of imaging and non-imaging information, e.g. clinical records and genetics



Optimisation of imaging pipeline with respect to clinically useful information

Current state-of-the-art

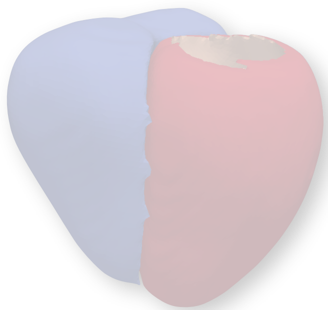


Future: End-to-end optimisation of entire imaging pipeline via deep learning

Define relevant information

Acqui

End-to-end optimisation of acquisition, reconstruction, analysis & interpretation via deep learning



Future: End-to-end optimisation of entire imaging pipeline via deep learning

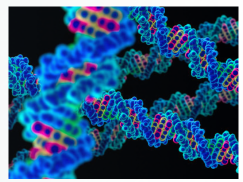
End-to-end optimisation of acquisition, reconstruction, analysis & interpretation via deep learning

Big data (population data)

biobank uk

Dementias Platform UK
Medical Research Council

Multi-modal data



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PredictND

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