Biomedical Imaging and Genetic (BIG) data analytics for precision medicine

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Quantib (disclosure)

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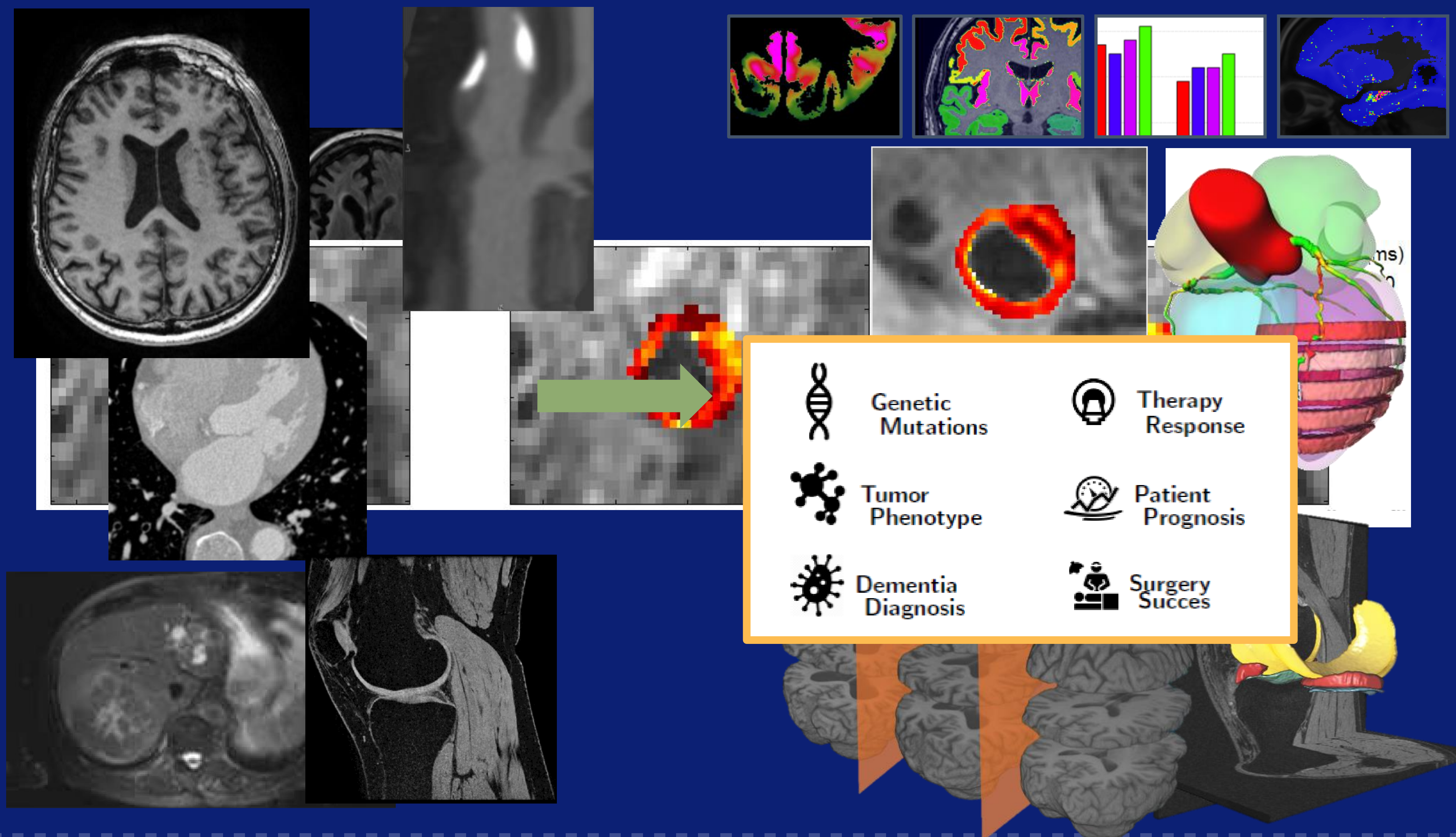

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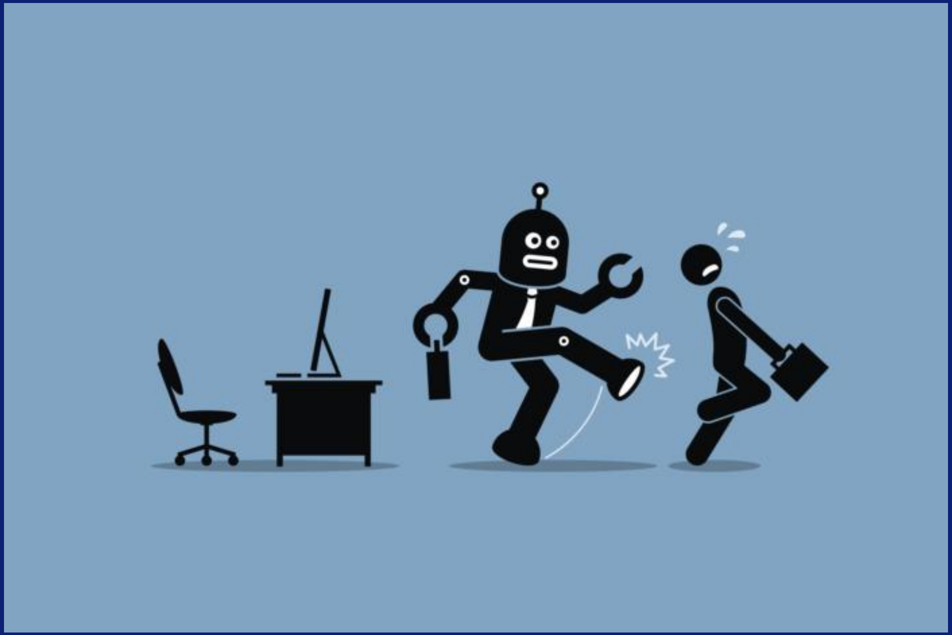
University Medical Center Rotterdam



Olaf Ronneberger @ORonneberger · Nov 6

As of today the U-net arxiv.org/abs/1505.04597 is the most-cited paper in the 21 years history of the #miccai conference (3201 citations according to google scholar scholar.google.co.uk/scholar?hl=en&…). It just overtook the Frangi-filter from 1998 (scholar.google.co.uk/scholar?hl=en&…).

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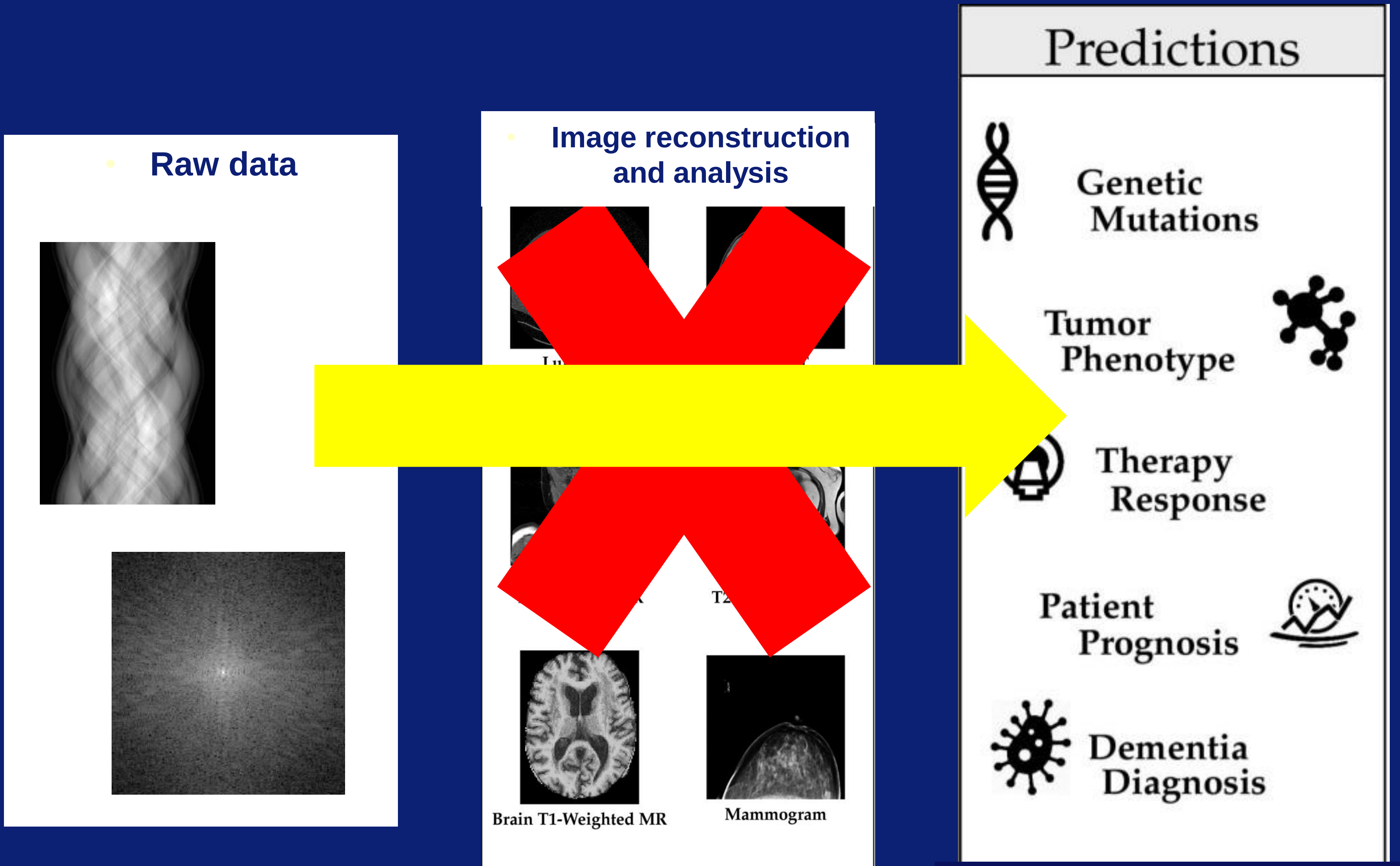
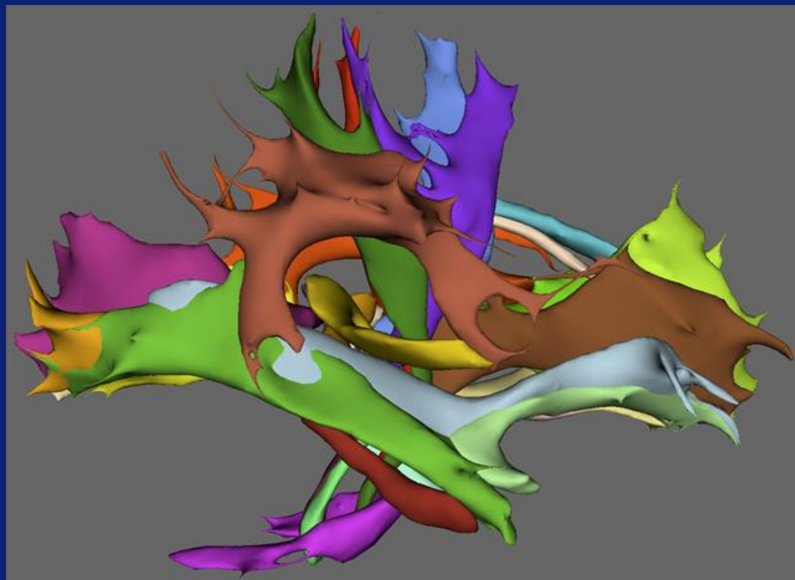
End to end approaches?

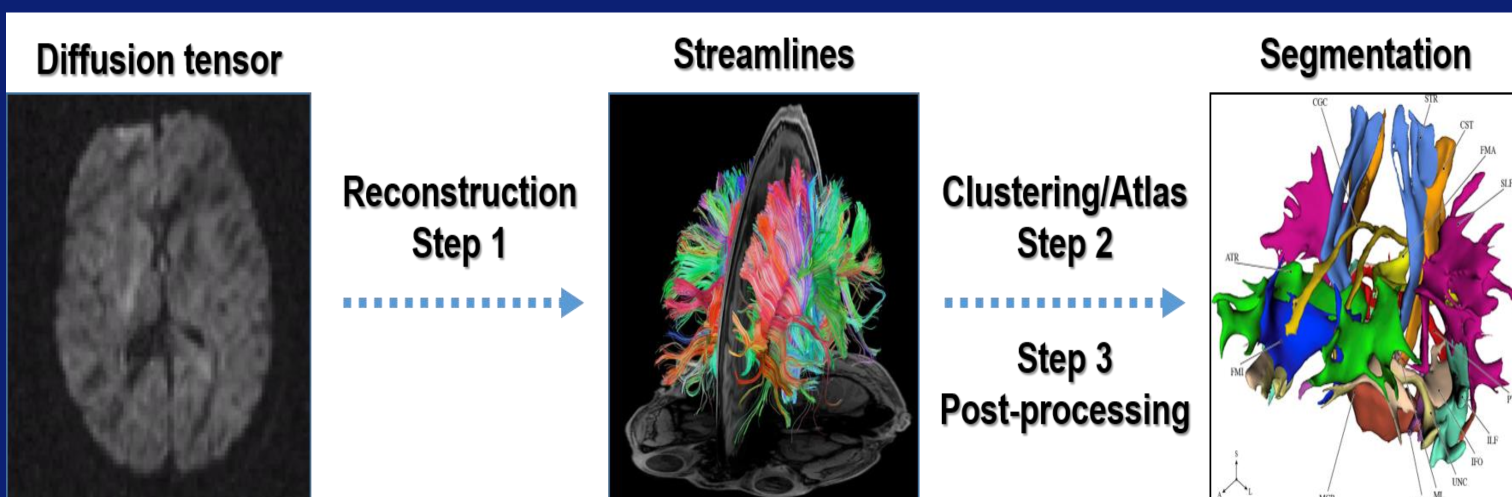


White matter tract segmentation

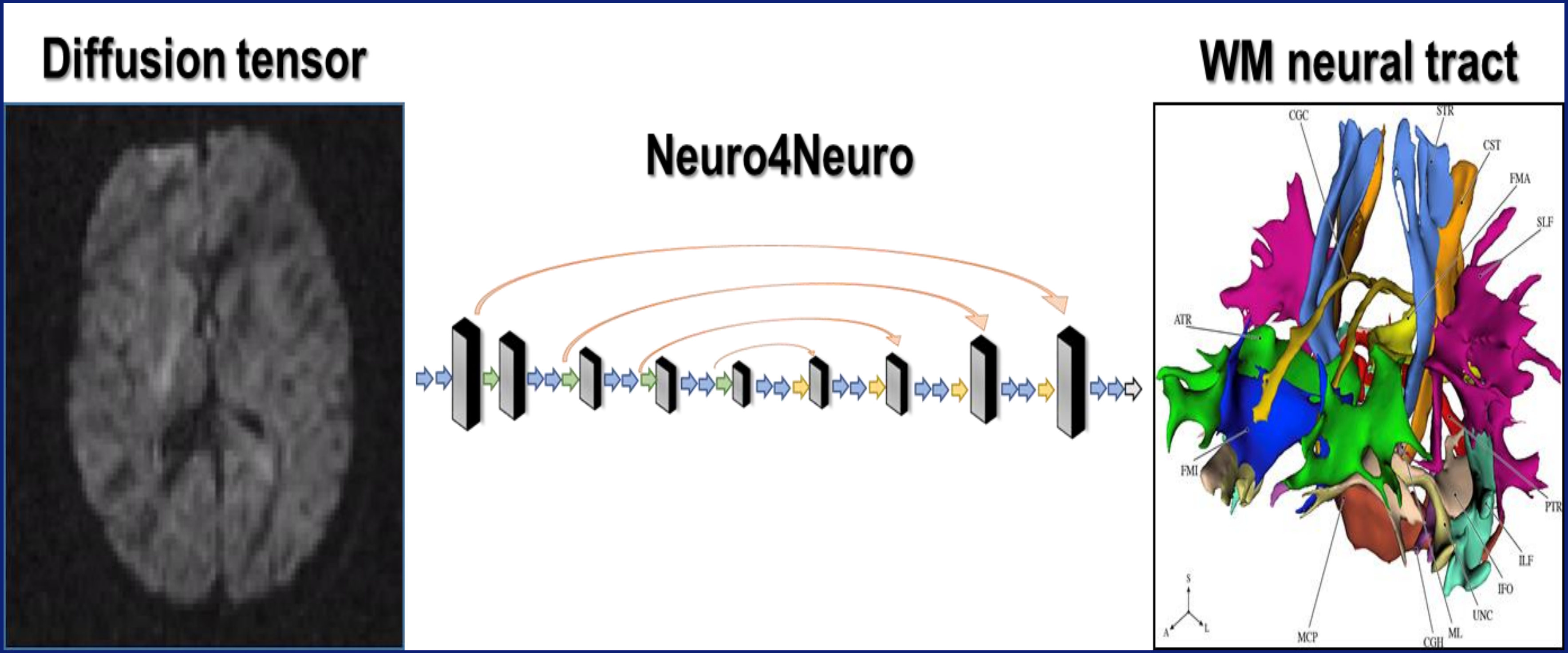


Tractography and atlas-based segmentation

Minutes to multiple hours



White matter tract is now segmented in 0.5 sec

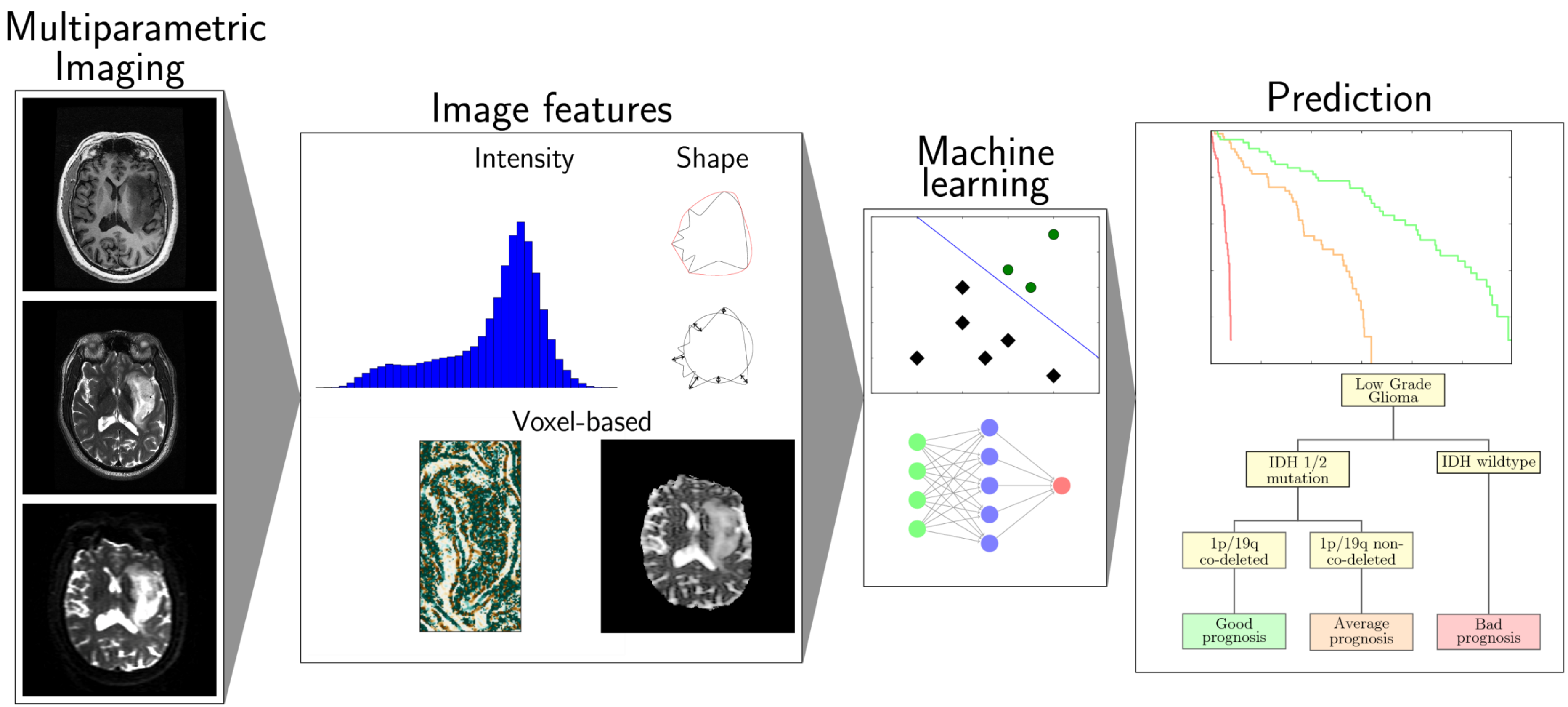


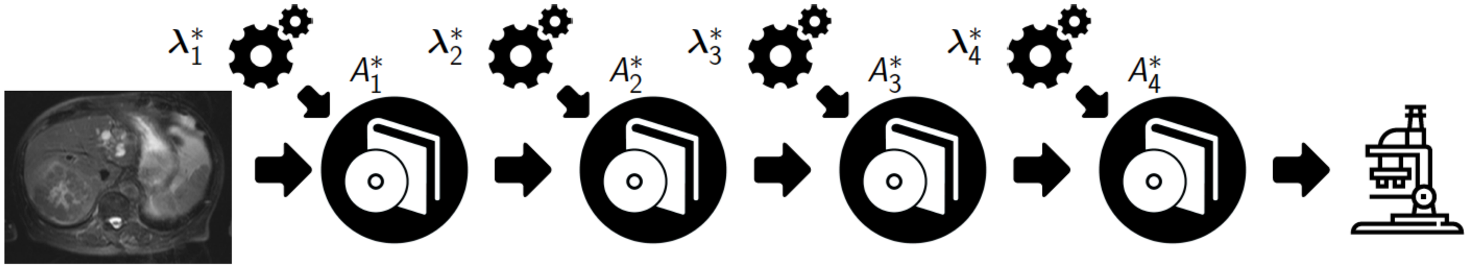
Deep learning network trained and evaluated on more than 9.000 dMRI scans

Bo Li, Esther Bron

Who will be automated?

Radiogenomics: predicting genetic mutation status from non-invasive imaging data





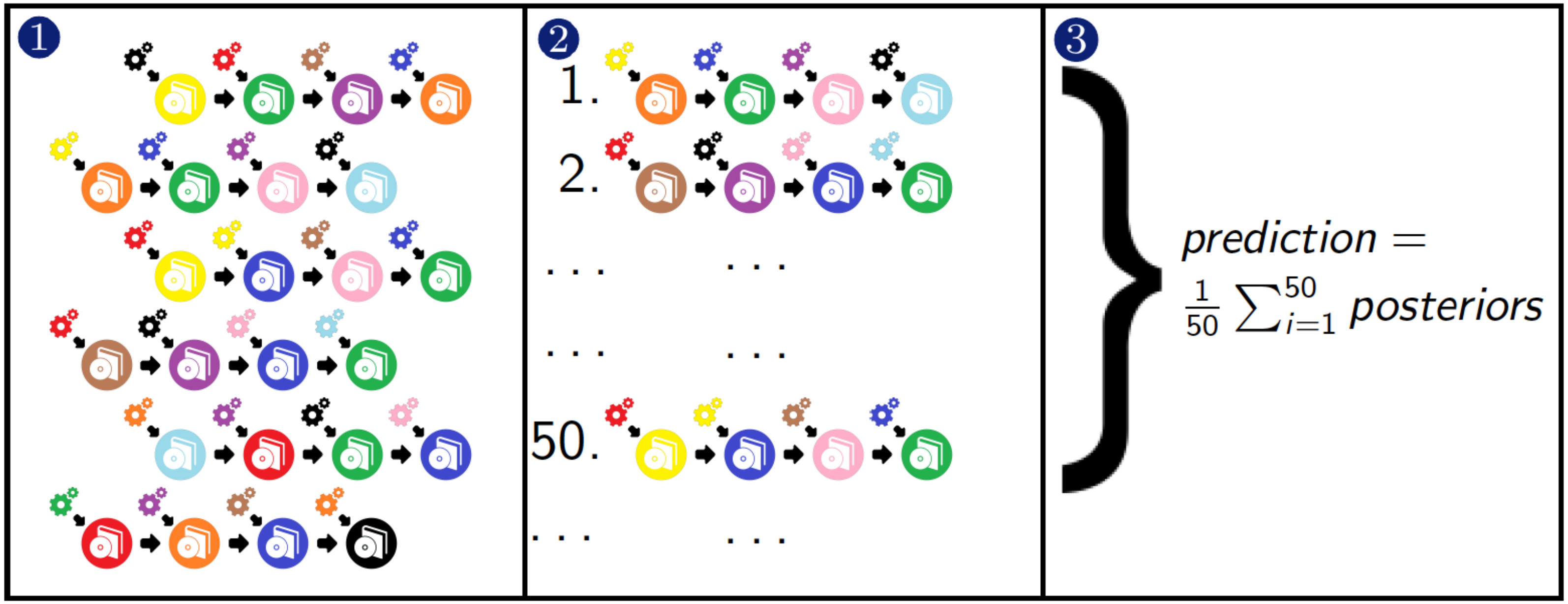
How to find optimal workflow for each application?

- Best algorithm(s) $A^* \in \left\{A^{(1)}, \ldots, A^{(k)}\right\}$ for each step?
- Best (hyper)parameters $\boldsymbol{\lambda}^* \in \left\{\boldsymbol{\Delta}^{(1)}, \ldots, \boldsymbol{\Delta}^{(k)}\right\}$ for each step?

Solution: Combined Algorithm Selection and Hyperparameter optimization problem (CASH). [1]

$$A^*, \boldsymbol{\lambda}^* \in \underset{A^{(j)} \in \mathcal{A}, \boldsymbol{\lambda} \in \boldsymbol{\Delta}^{(j)}}{\operatorname{argmin}} \frac{1}{k} \sum_{i=1}^{k} \mathcal{L}\left(A_{\boldsymbol{\lambda}}^{(j)}, \mathcal{D}_{\text{train}}^{(i)}, \mathcal{D}_{\text{valid}}^{(i)}\right)$$

Automatic radiomic signature optimization

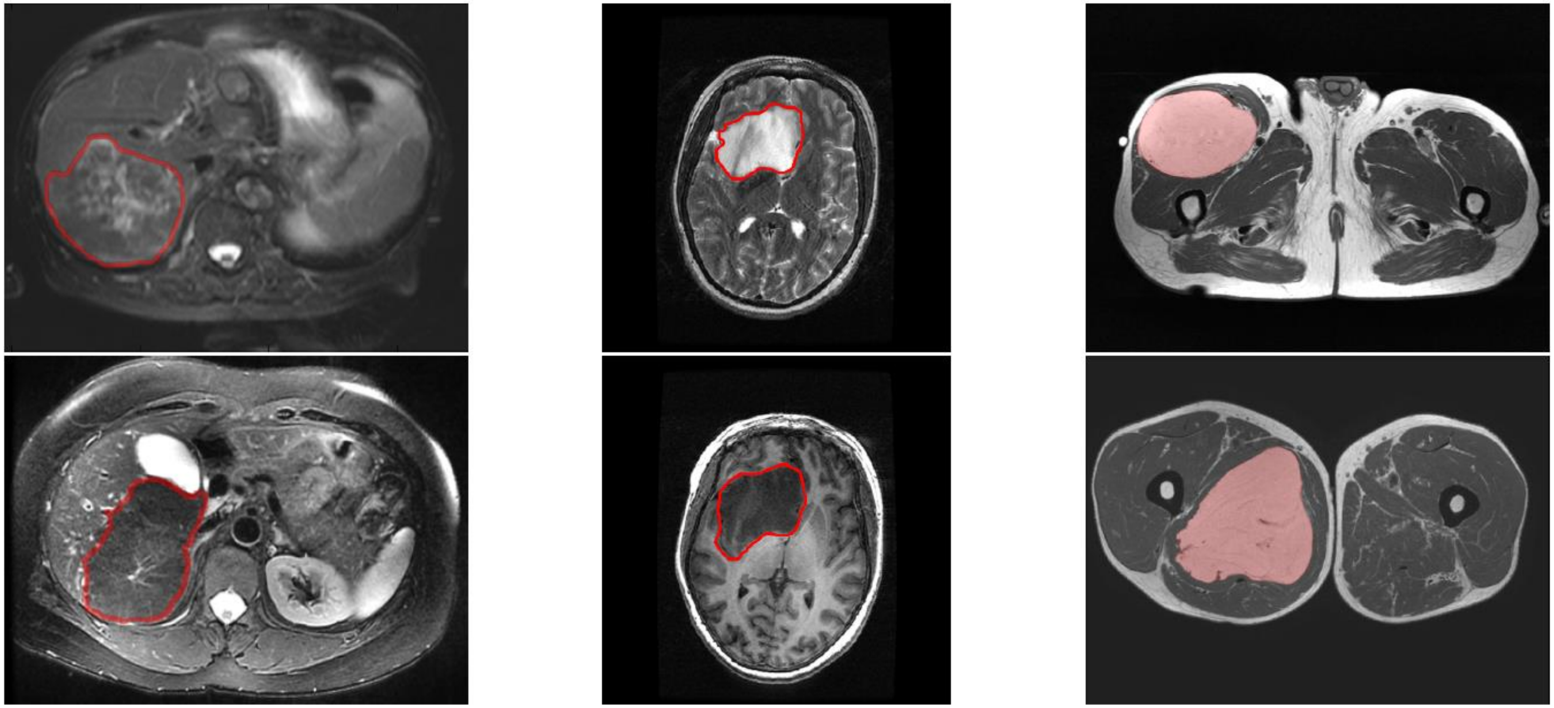


WORC: extension of CASH to radiomics. Solver:

1. Pseudo-randomly generate 100.000 different radiomics workflows.
2. Evaluate and rank the workflows.
3. Create model from ensemble of top 50 workflows.

Martijn Starmans, Stefan Klein et al.

Experiments

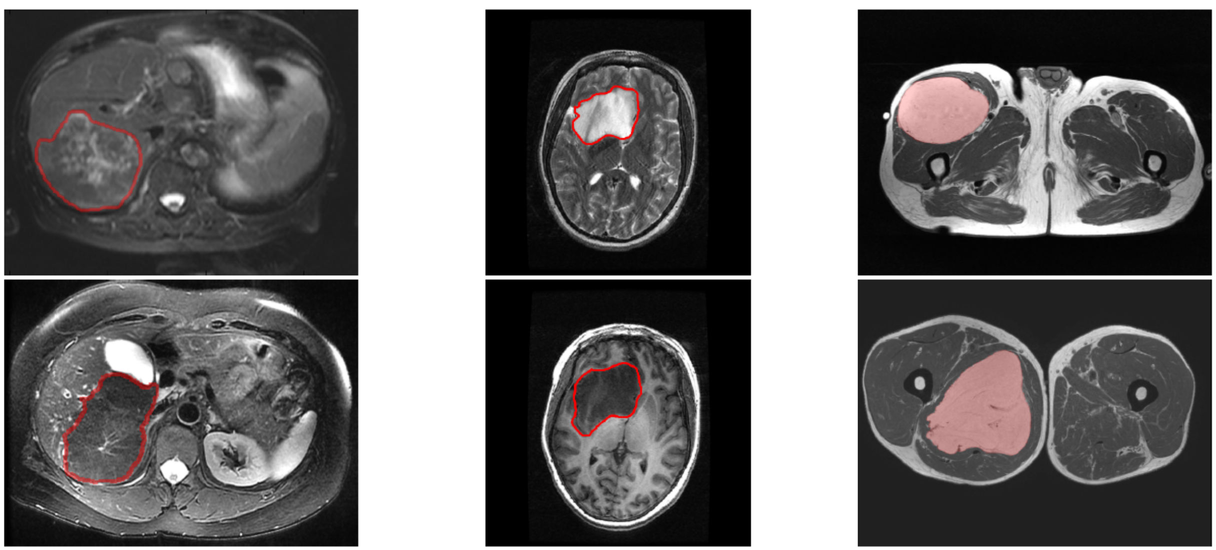


	Liver	Brain	Lipo
Label	Malignant/ Benign	1p19q co-deletion/ no co-deletion	Liposarcoma/ Lipoma
Modality	T2w (FatSat) MR	T2w + T1w MR	T1w MR

Results

Reported as **mean** [95% confidence interval]

	Liver	Brain	Lipo
AUC	**0.93** [0.86, 0.99]	**0.80** [0.74, 0.85]	**0.84** [0.74, 0.93]
F1-score	**0.82** [0.76; 0.91]	**0.76** [0.71, 0.80]	**0.76** [0.66, 0.85]
Sensitivity	**0.74** [0.58, 0.89]	**0.67** [0.58, 0.76]	**0.73** [0.59, 0.86]
Specificity	**0.92** [0.85, 0.98]	**0.79** [0.72, 0.86]	**0.80** [0.67, 0.92]



Totally new imaging biomarkers

Convolutional Neural Network (CNN) Architecture for brain age prediction (trained on 5865 images, tested on 2353)

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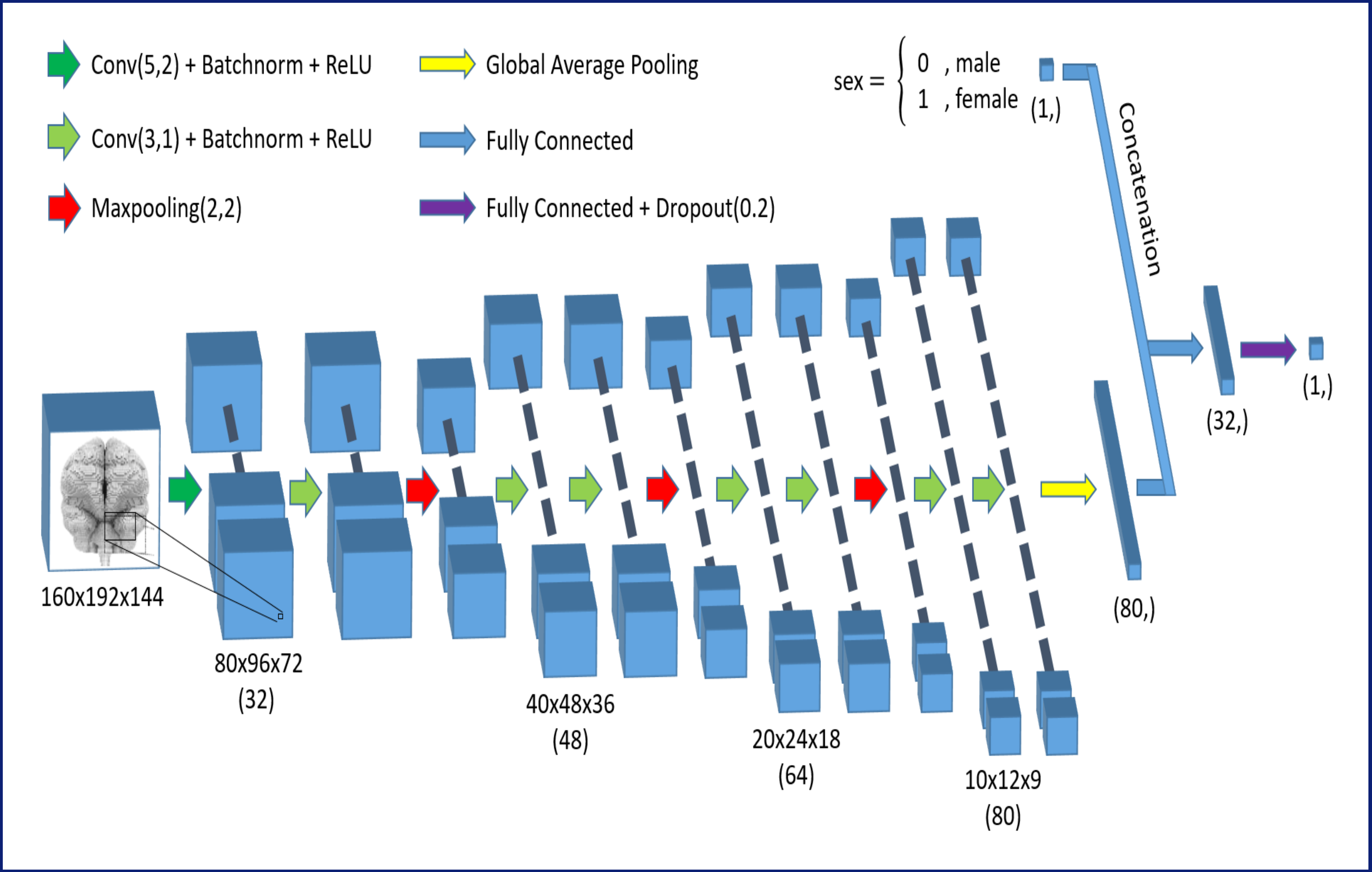
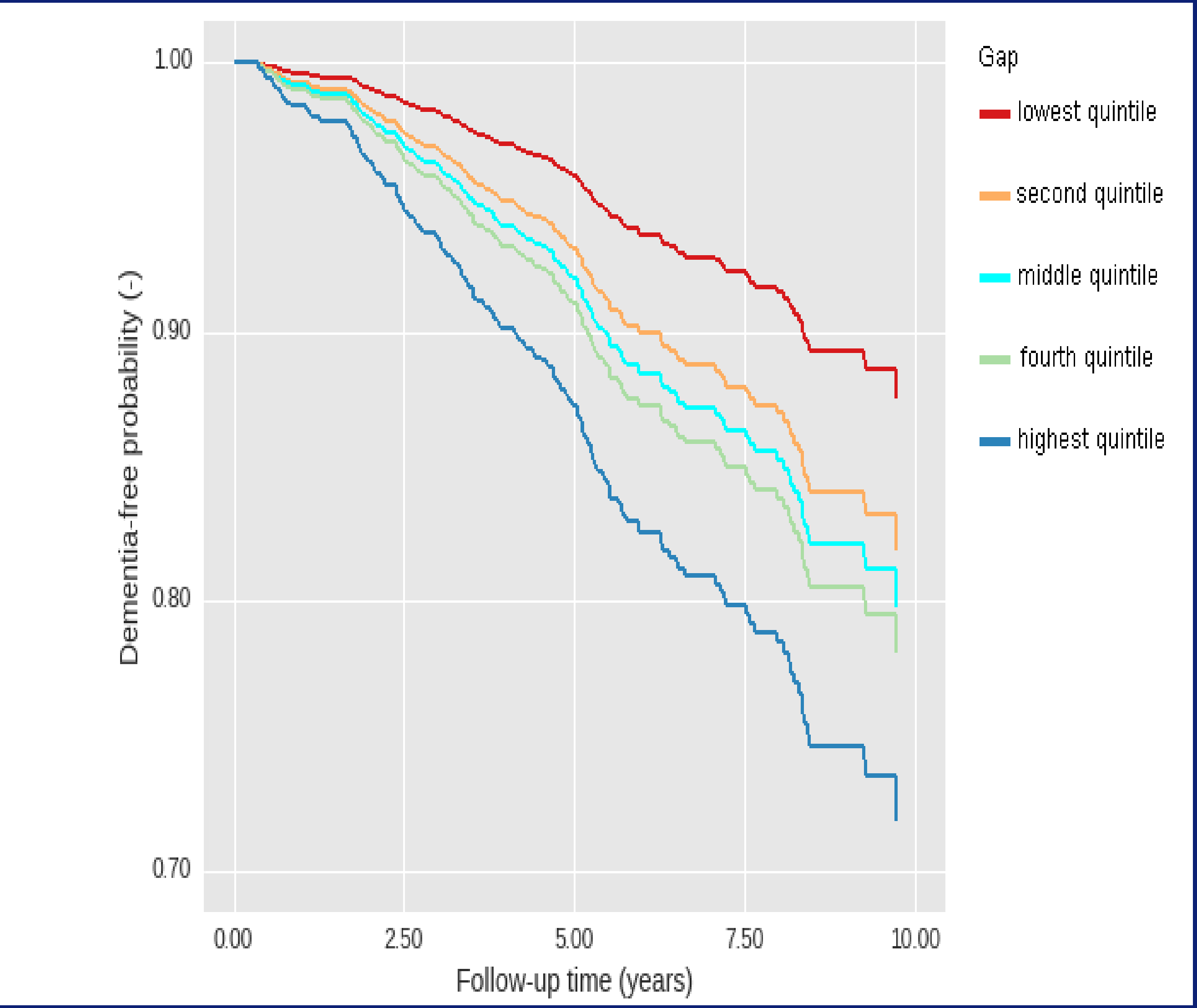
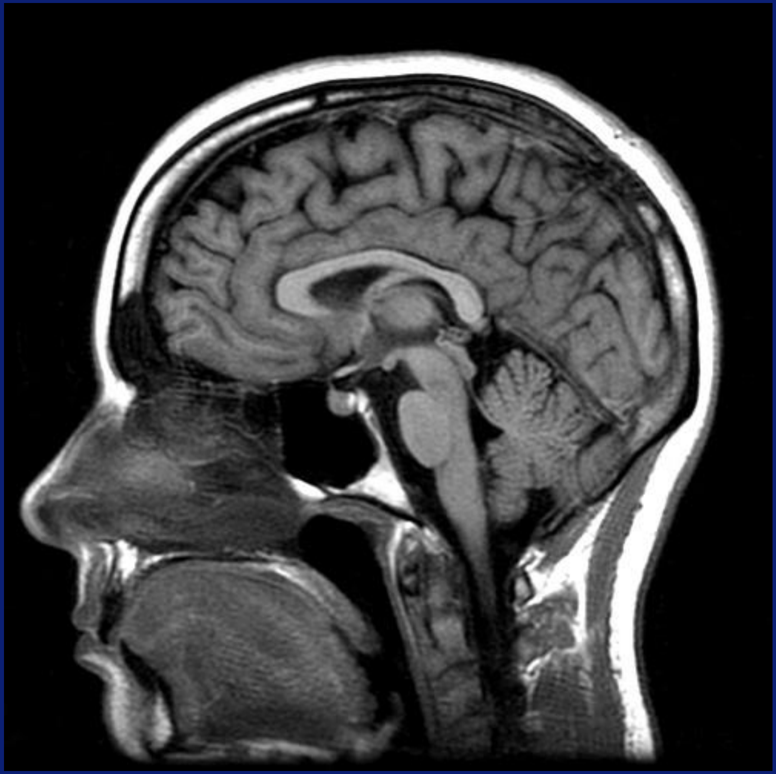


Johnny Wang, Gennady Roshchupkin et al.

Kaplan-Meier curves for new biomarker (delta brain / calendar age)





MRI

Genetics

Population Imaging Genetics

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Risk factors:

Genetic

Blood pressure
Smoking
.....

?

Brain changes:

Hippocampal volume

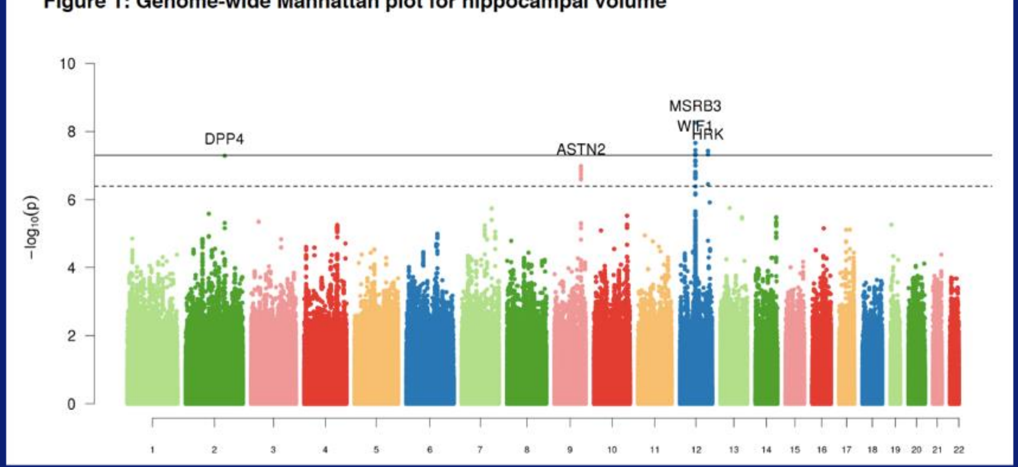
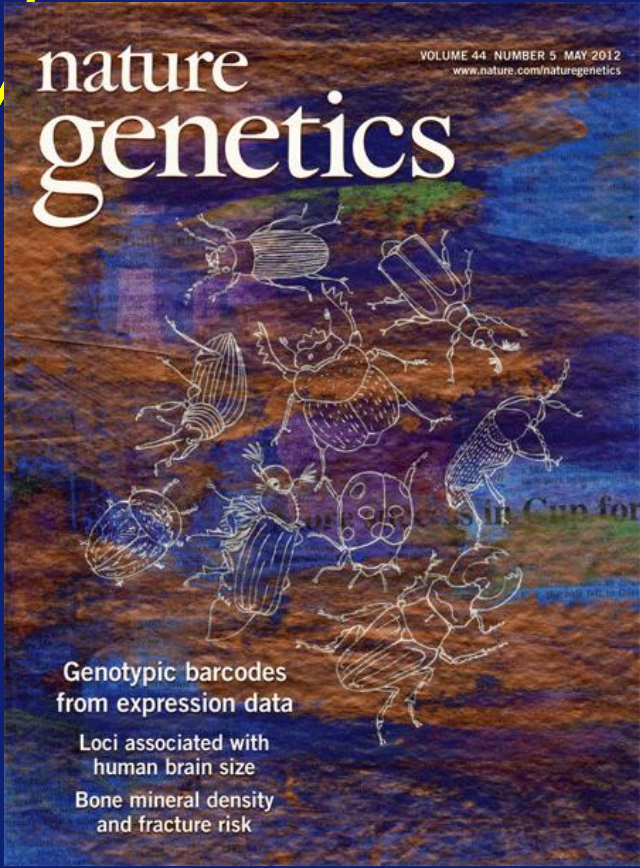
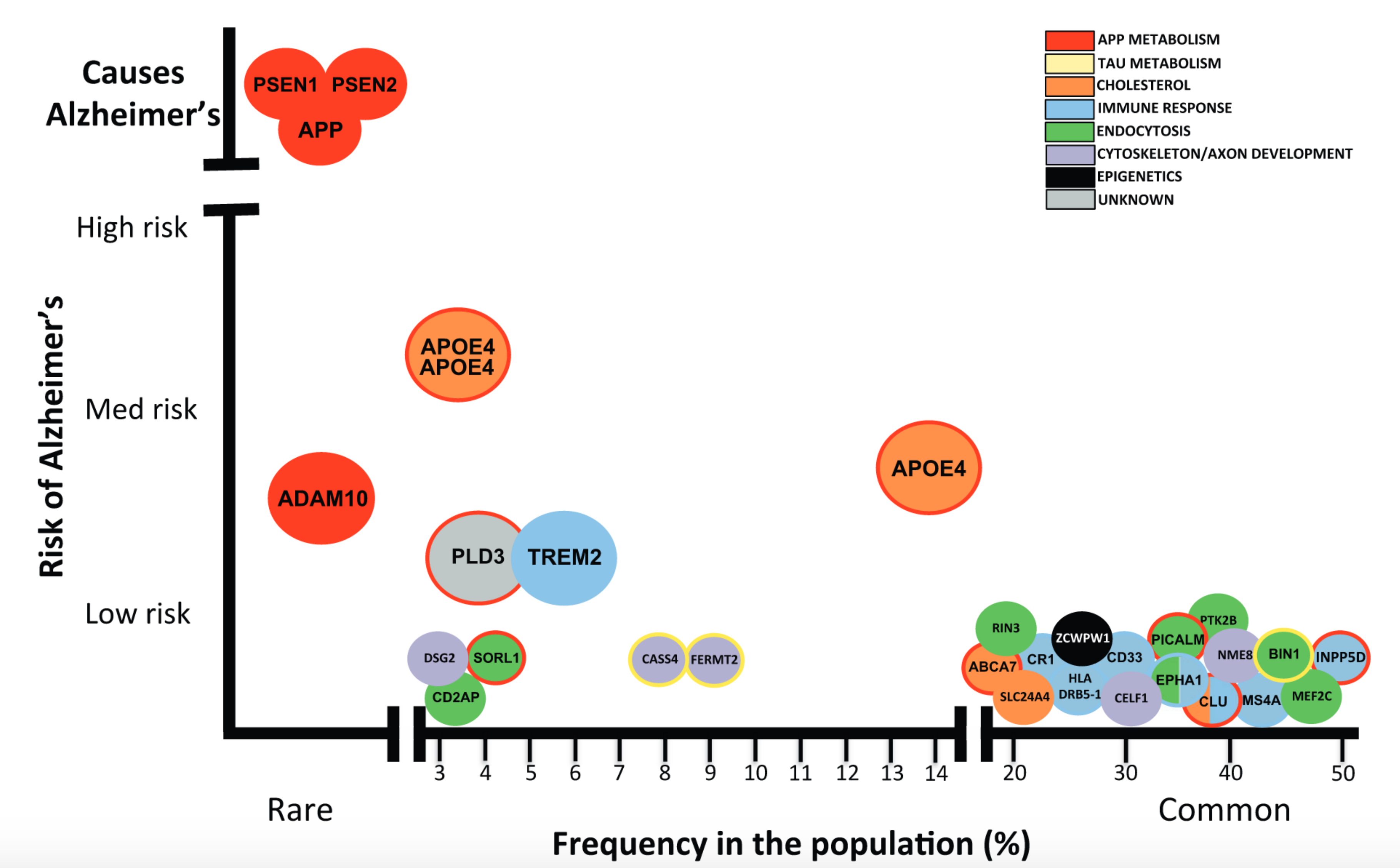


Figure 1: Genome-wide Manhattan plot for hippocampal volume

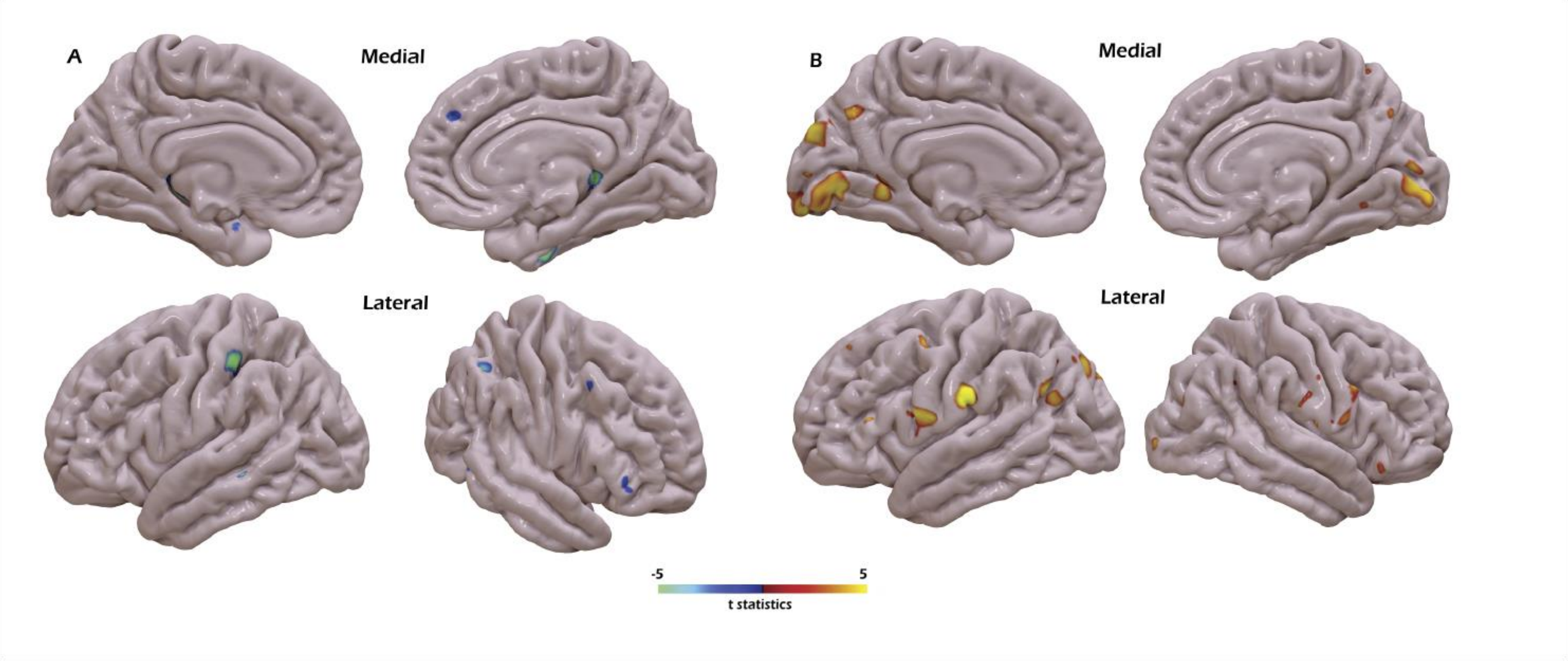


Predicting is not easy … AD risk genes



Imaging genetics: gaining insight

VBM analysis consisted of 4071 nondemented persons with information available on both genome-wide genotyping and MRI data from the population-based Rotterdam Study. The mean age was 64.7 (+/-10.7) years and 2251 (55%) subjects were women.



Roshchupkin et al. Neurobiology of ageing

Some observations

- The current hype in AI in radiology is mostly about image perception

- Potential data driven science is much larger

  - diagnostic and prognostic workflow

  - modeling complex relations between imaging, omics & genetic data

- ** Holy grail questions:

  Find phenotype = f (genotype, environmental factors)

  Predict phenotype (T+1) = f (genotype, environmental factors, phenotype (T)

- Access to good data and clinical knowledge about these data is key

  - we need to adopt FAIR data principles, and

  - build co-creation environments (clinicians, machine learning)

- Still large challenges to address!

MICCAI – ACR / RSNA / ESR collaboration

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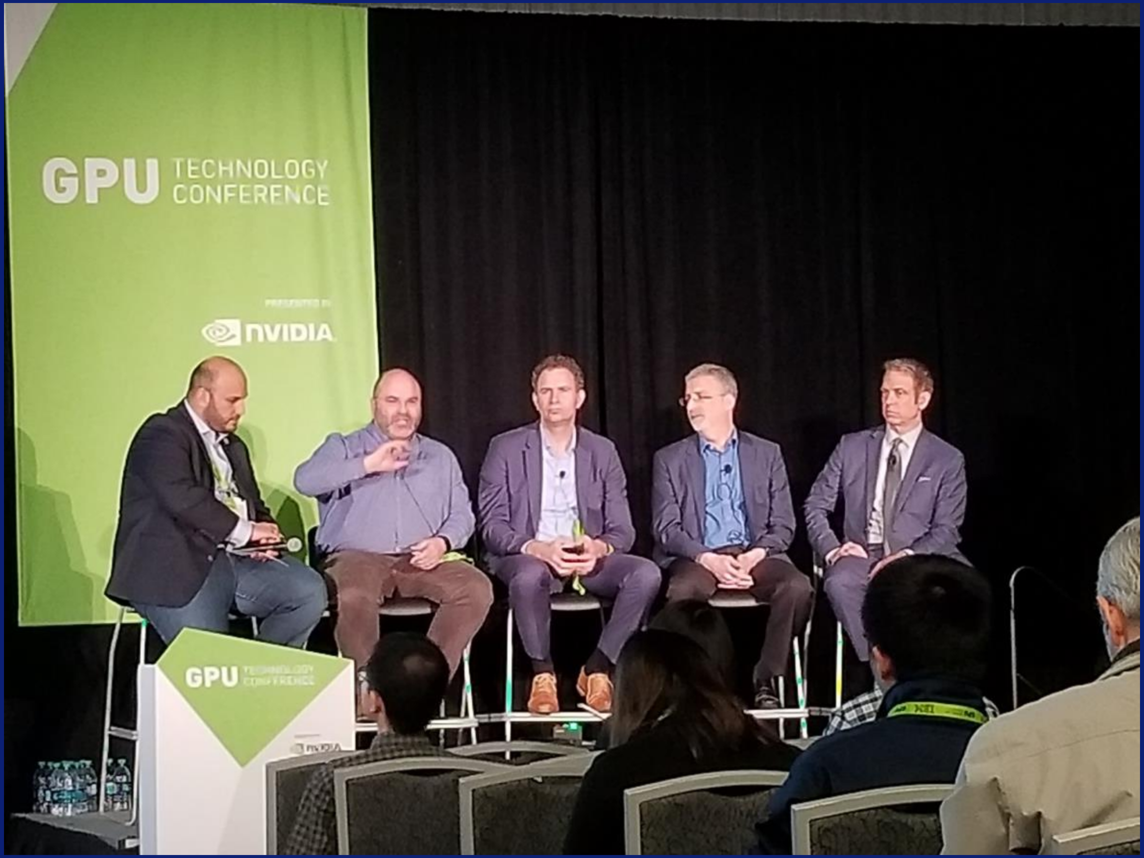
Home / Services / Use Case Directory (TOUCH-AI)

Our TOUCH-AI use cases are scenarios where use of artificial intelligence (AI) may help improve medical imaging care.

They were created to empower AI developers to produce algorithms that are clinically relevant, ethical, and effective. Each use case provides narrative descriptions and flow charts which specify the health care goal of the algorithm, the required clinical input, how it should integrate into the clinical workflow and how it will interface with users and tools.

ACR – MICCAI MoU

“The ACR is creating use cases for imaging AI and will work with MICCAI to leverage this knowledge base in MICCAI's imaging AI competitions."



Acknowledgements

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