MACHINE LEARNING FOR
MEDICAL IMAGE ANALYSIS

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Discovery & Understanding

Mining of Large Image Databases

Population Modelling

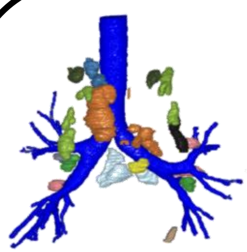
e.g. UK Biobank (>100.000 subjects)

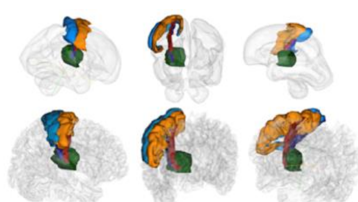
Developing Human Connectome

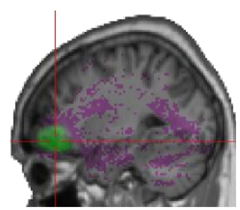
Creating the first map of developing brain connectivity (>1 PB data)

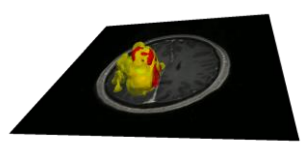
Personalized Medicine & Decision Support

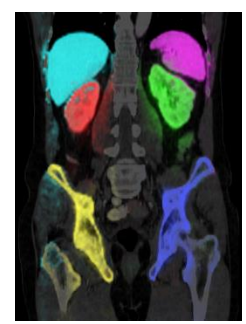
Computer Aided Diagnosis











Quantitative Imaging

e.g. in Cancer, Dementia, Trauma

Anomaly Detection

e.g. Whole-body Imaging

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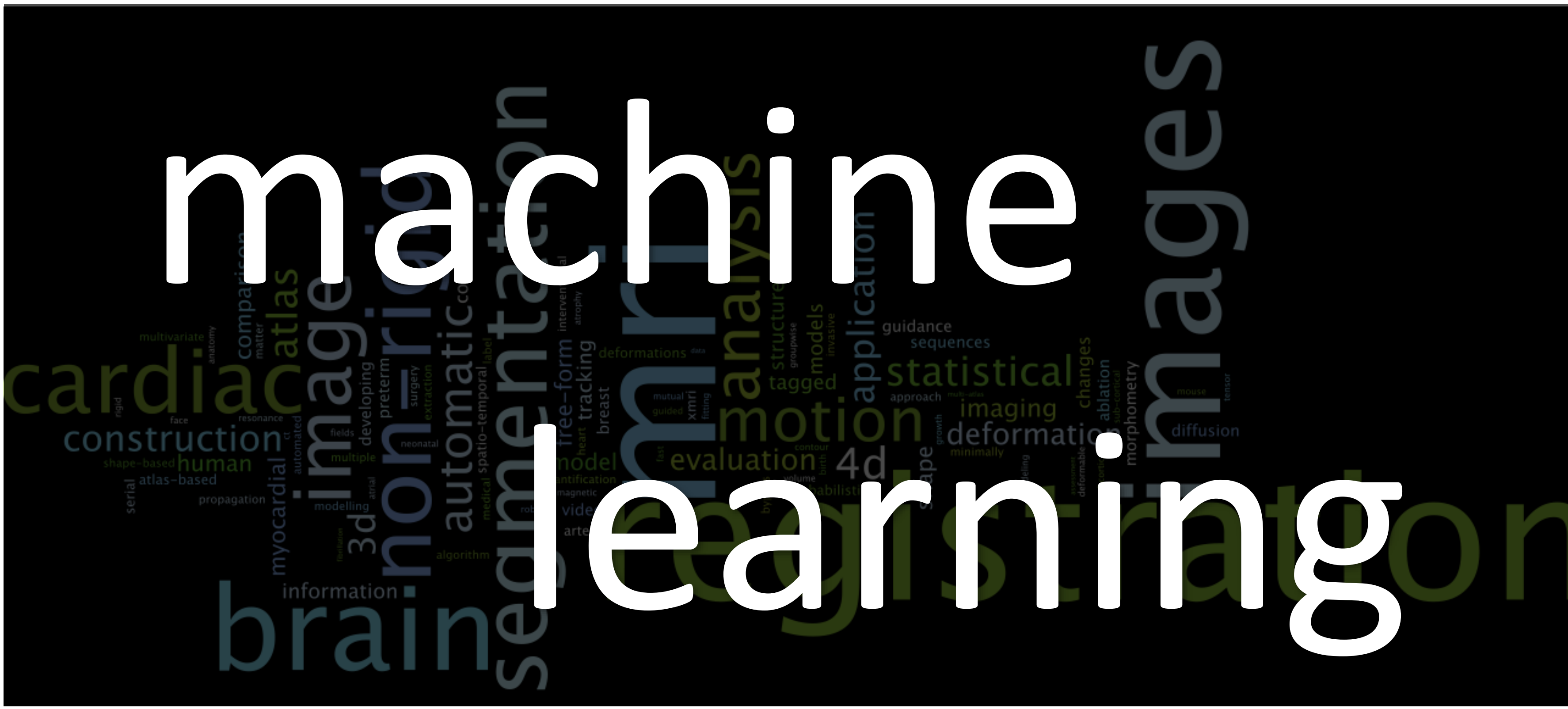
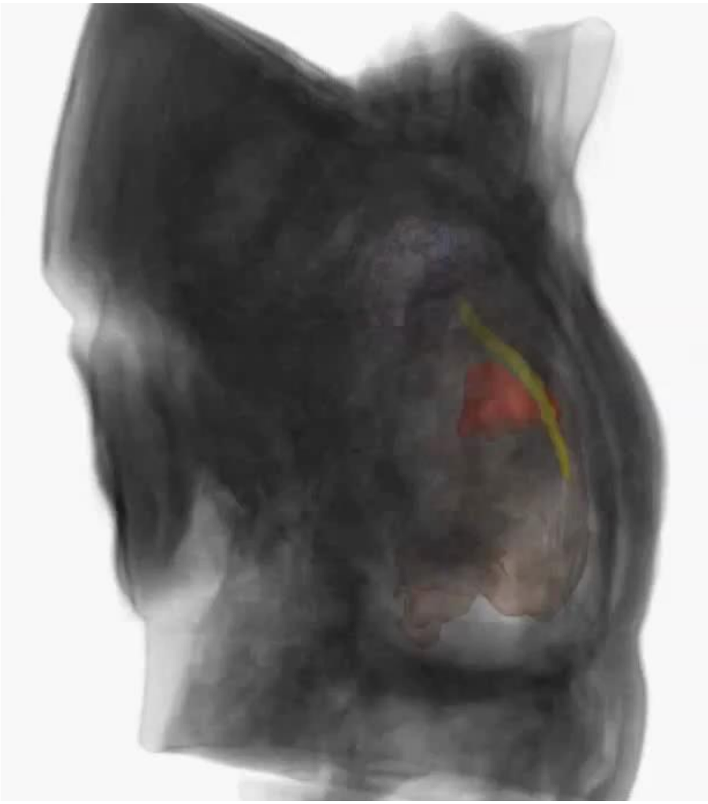
machine learning



Advanced Fetal Imaging & Diagnostics



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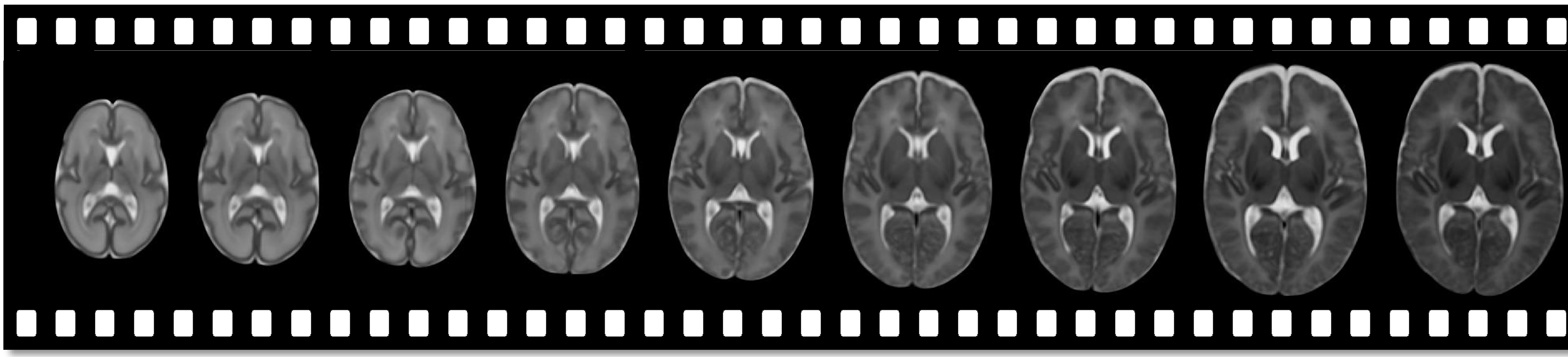
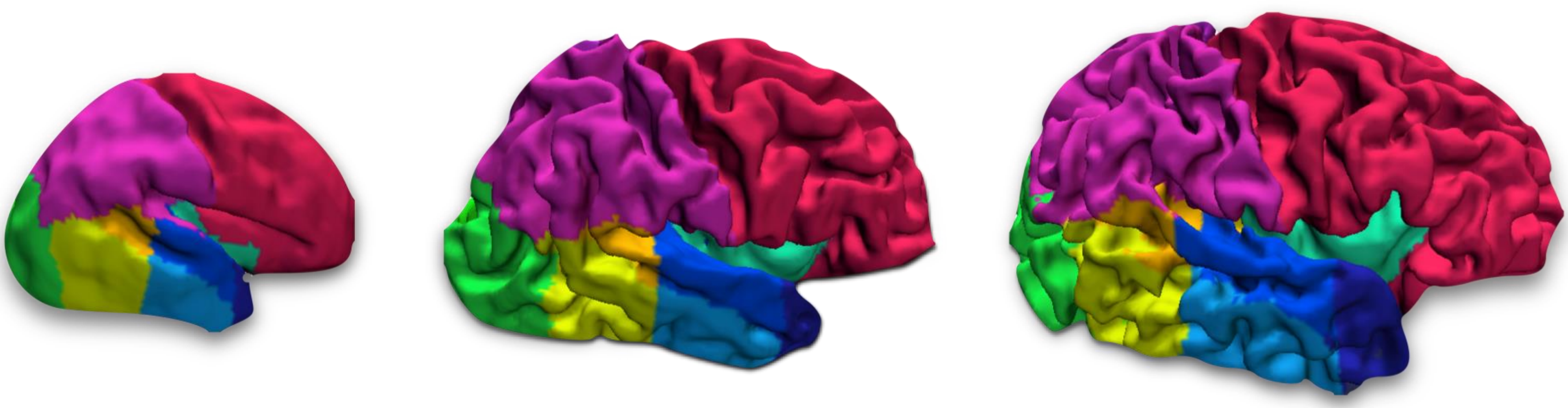
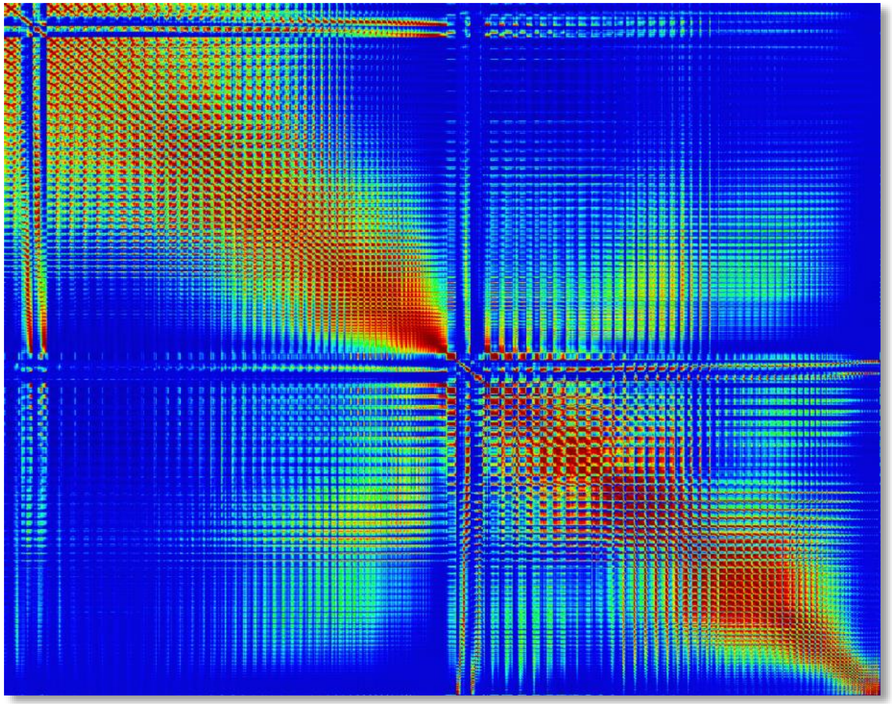
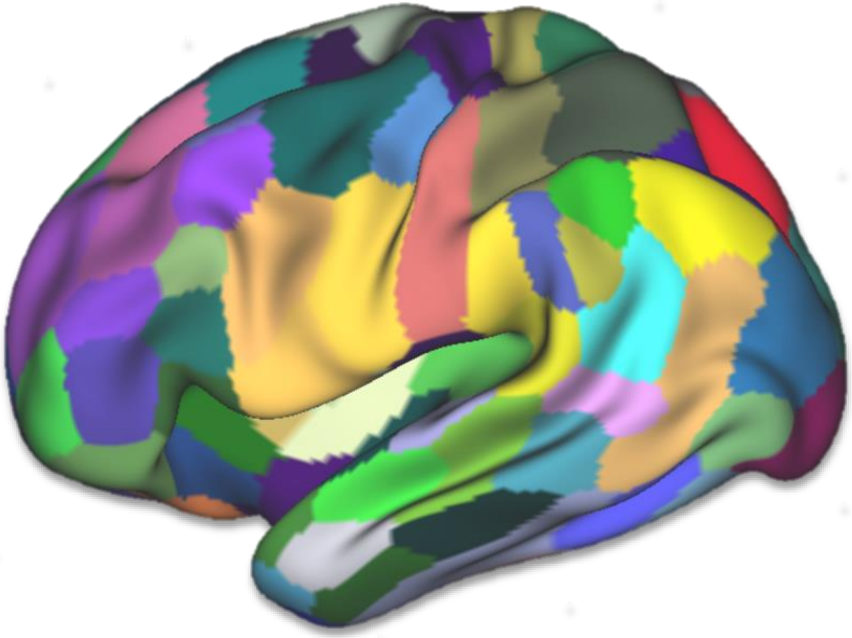
Understanding Brain Development



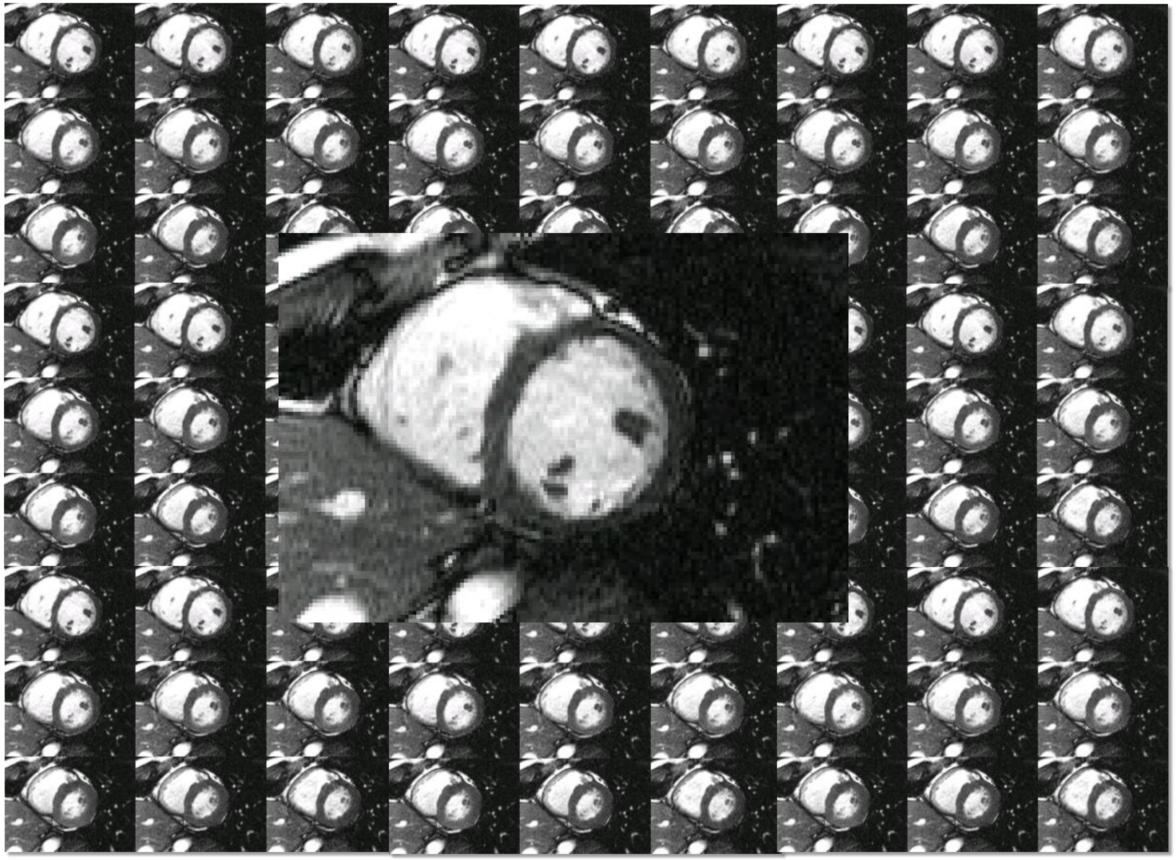


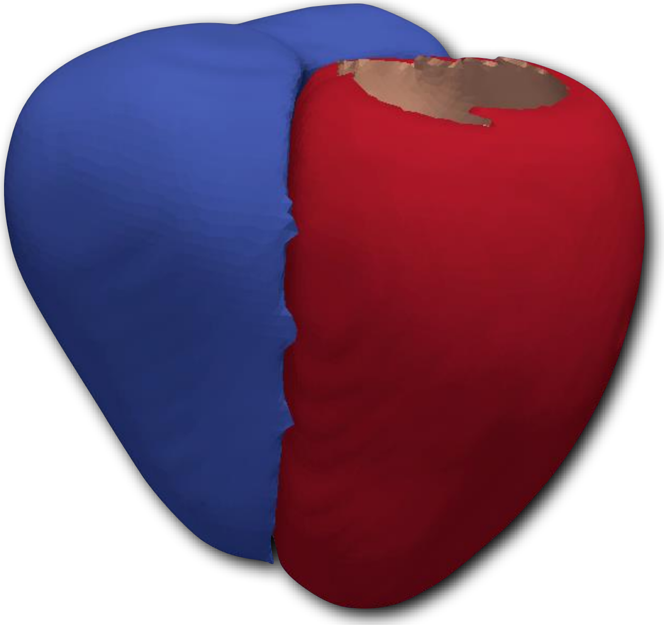
The Developing Human Connectome Project



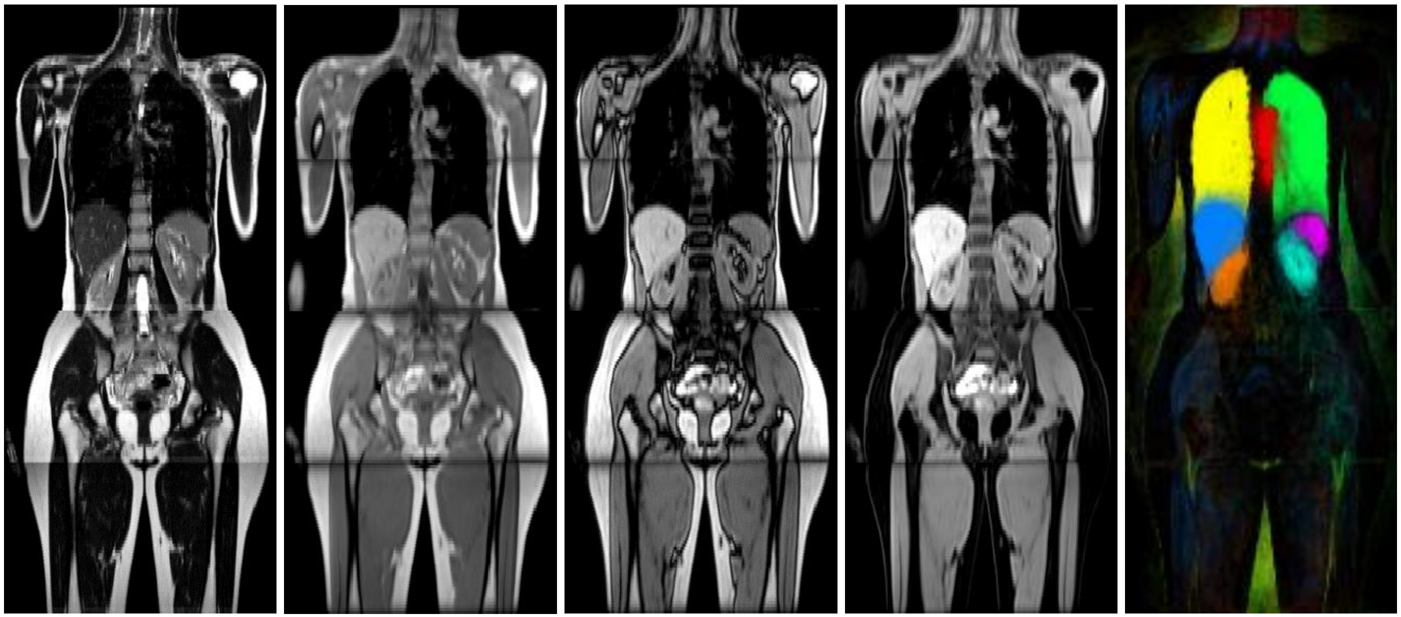


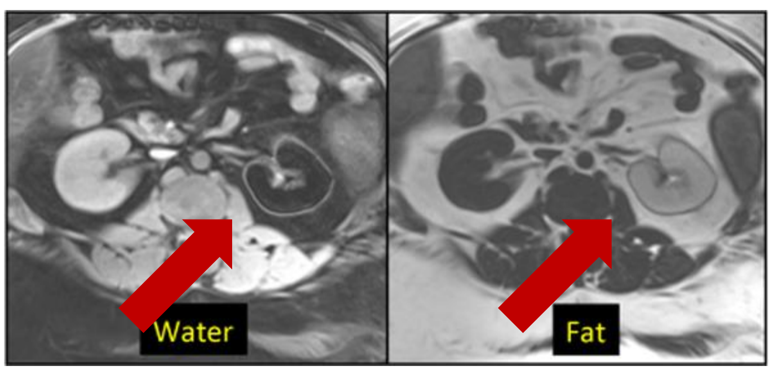
Intelligent Imaging of the Heart

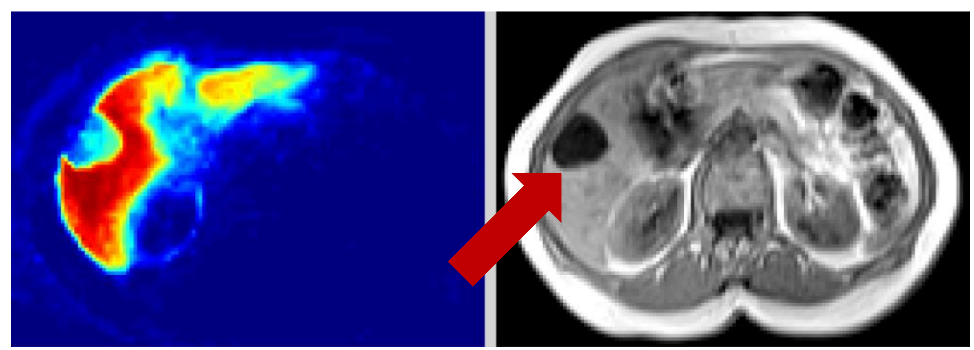




Whole-Body Imaging & Abnormality Detection

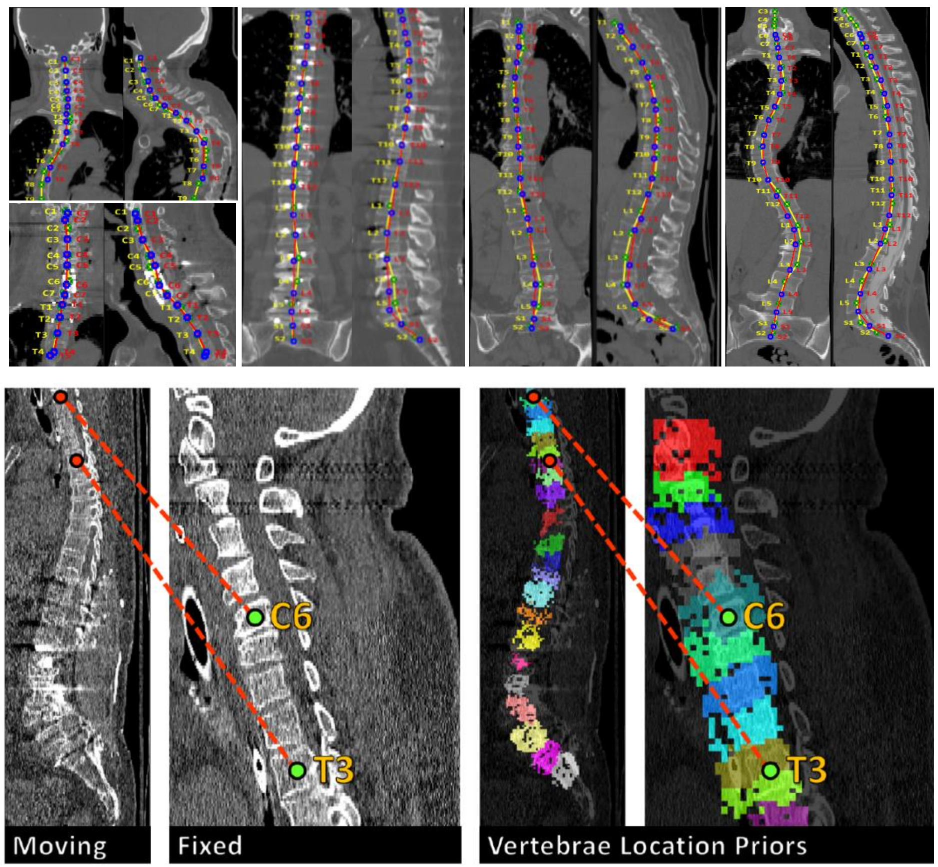




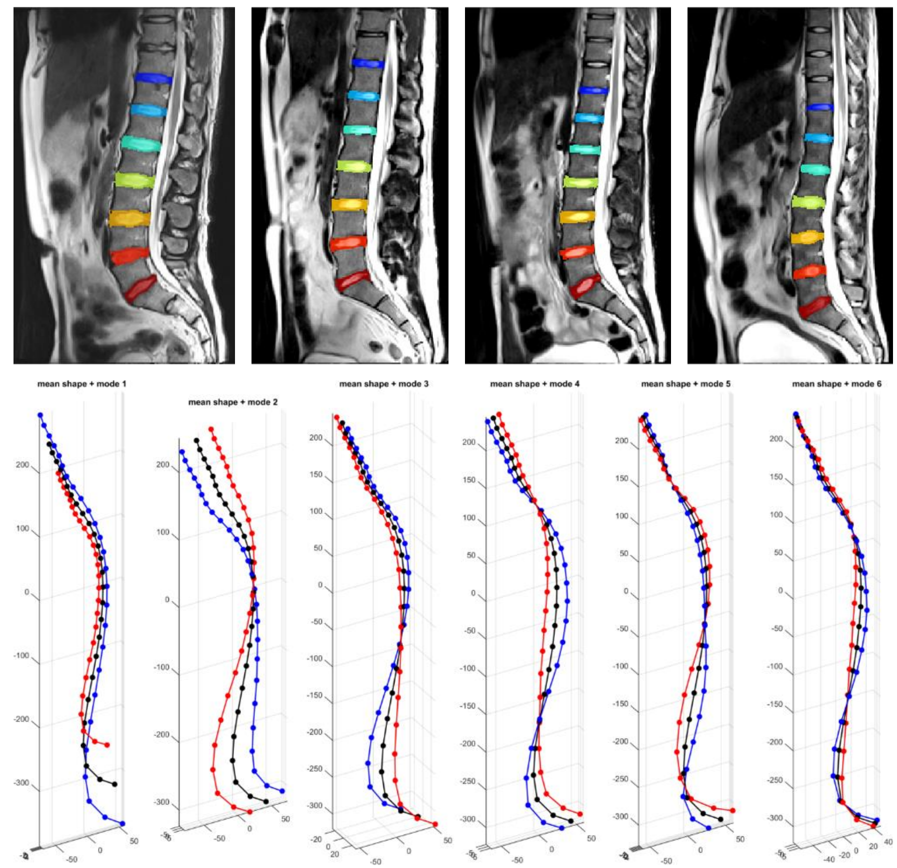


Spine Image Analysis

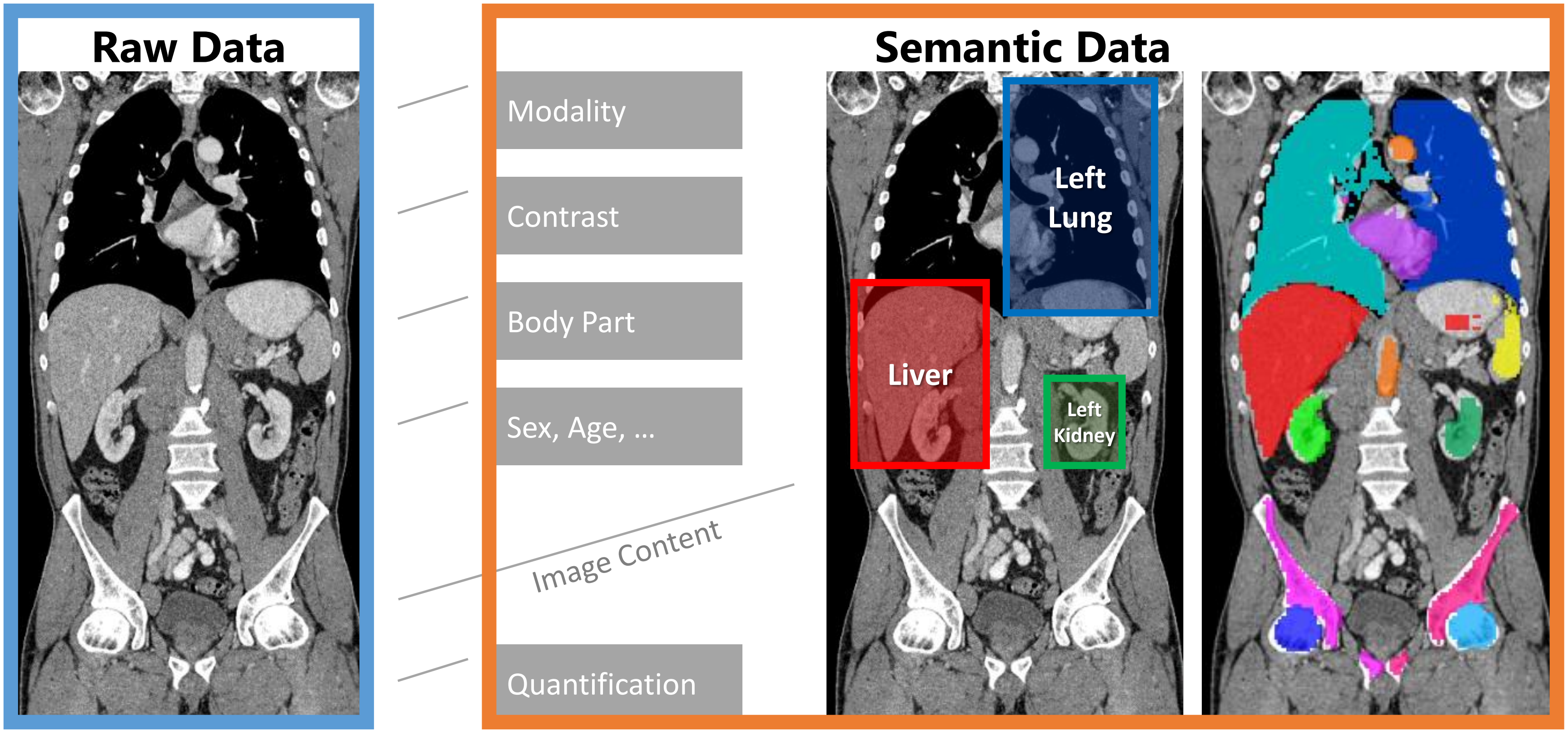
Localization & Registration



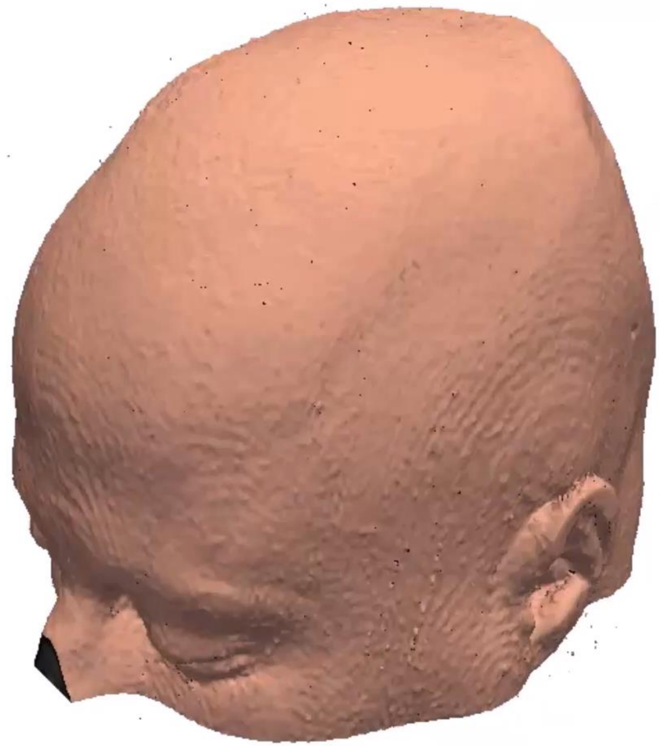
Disc Segmentation & Statistical Models



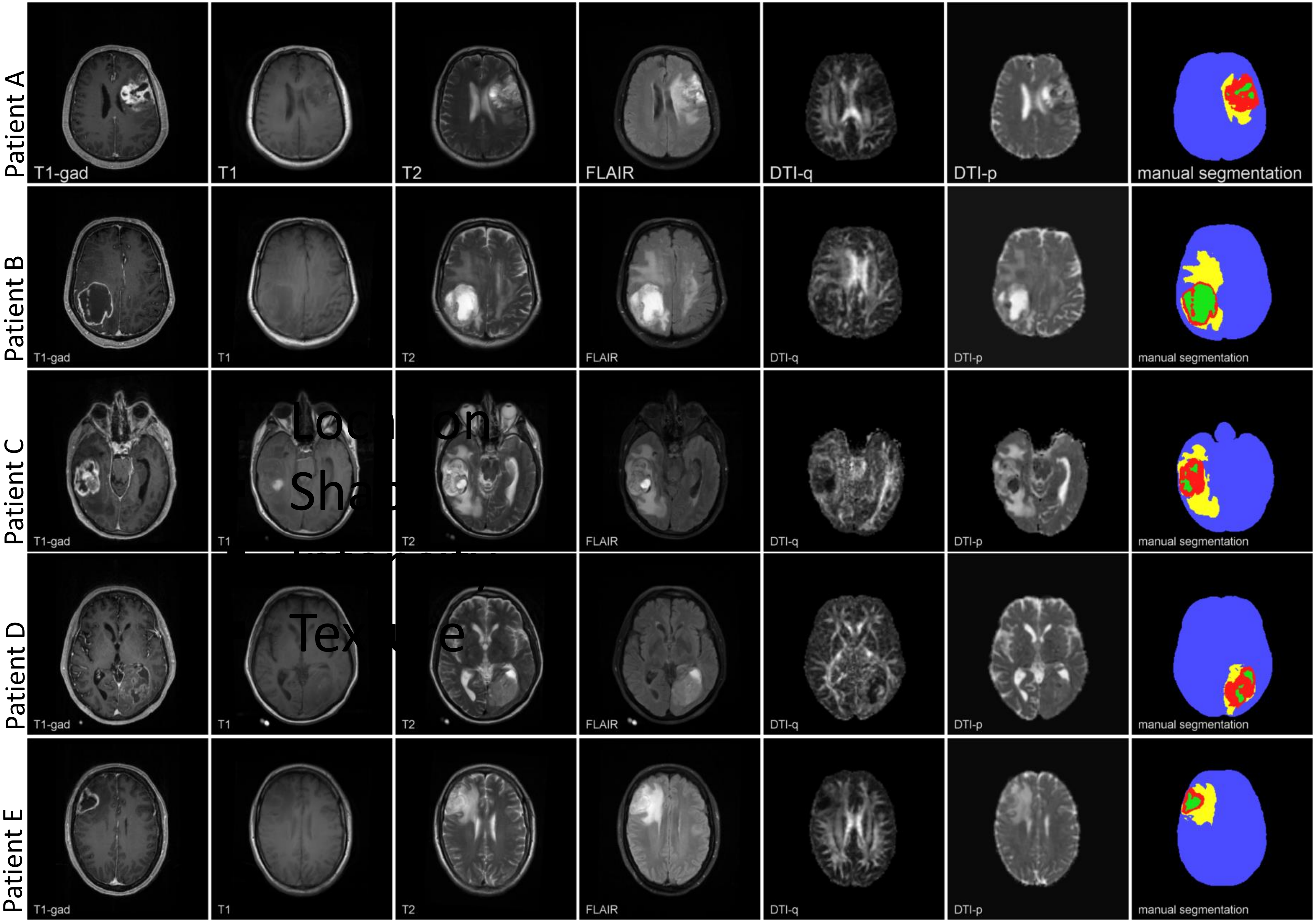
SEMANTIC IMAGING



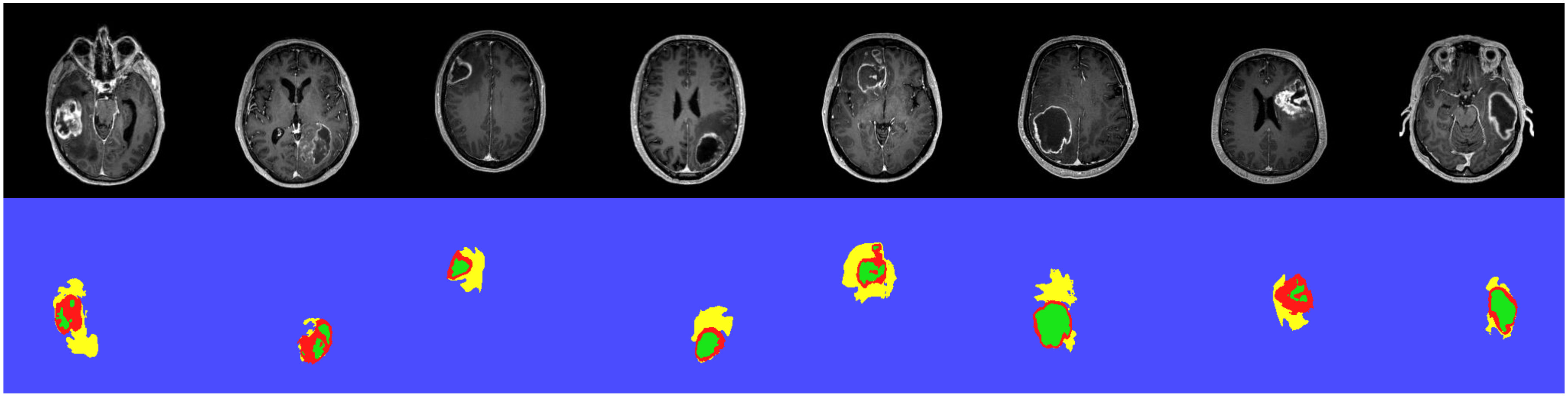
Brain Lesion Segmentation



CHALLENGE: THE INPUT DATA IS VERY HETEROGENEOUS

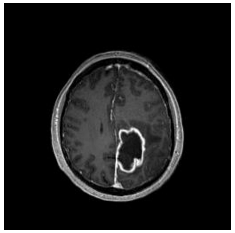


MACHINE LEARNING: TRAINING PHASE



Tumour Tissue Classification

MACHINE LEARNING: TESTING PHASE

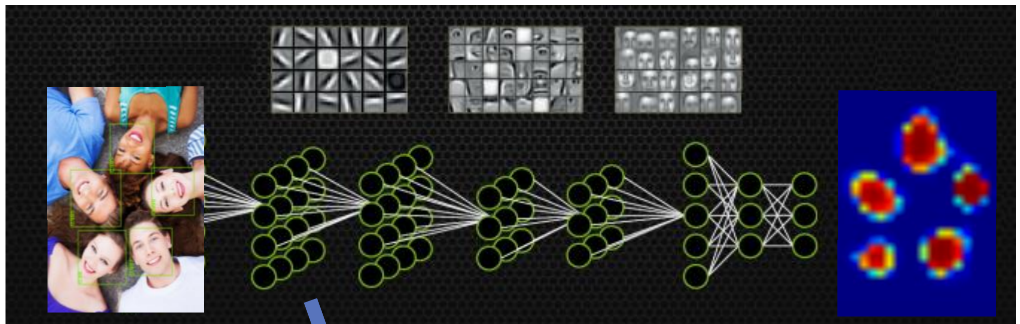


New Patient,
without segmentation

Tumour Tissue Classification

DEEP LEARNING WITH CONVOLUTIONAL NEURAL NETS

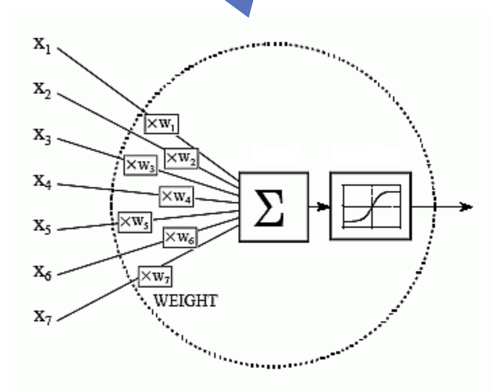
Artificial Neural Networks for Automatic Face Detection



Neuron

Acts as a feature detector.
Its weights determine what pattern activates it.

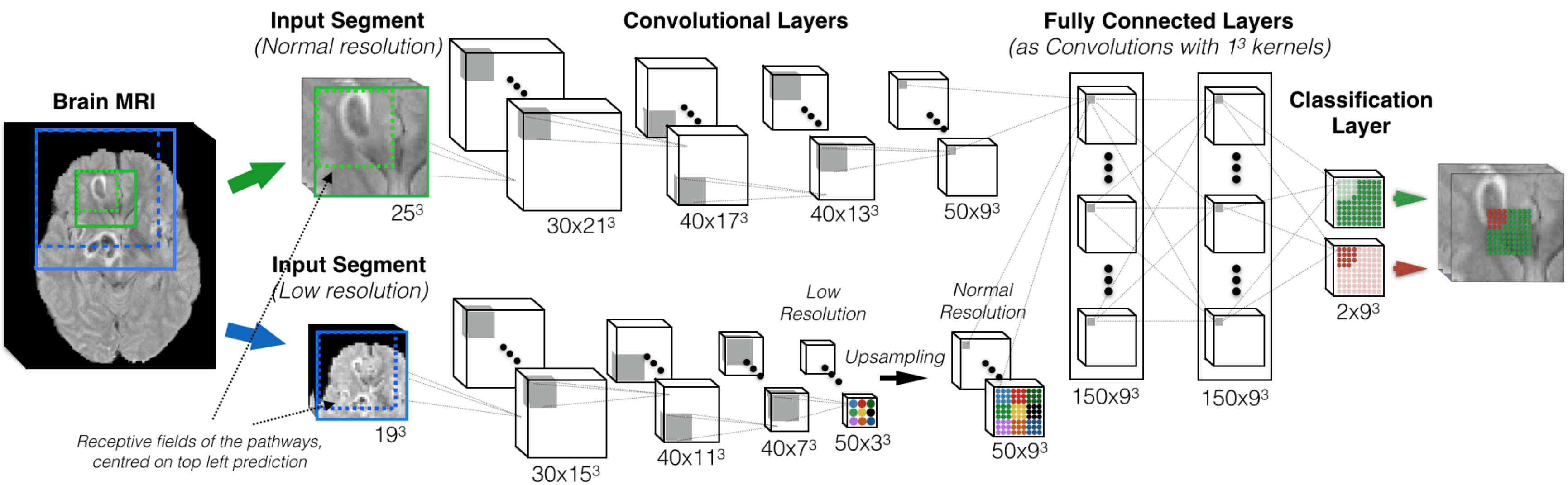
Input
(intensities)



Output
(activation)

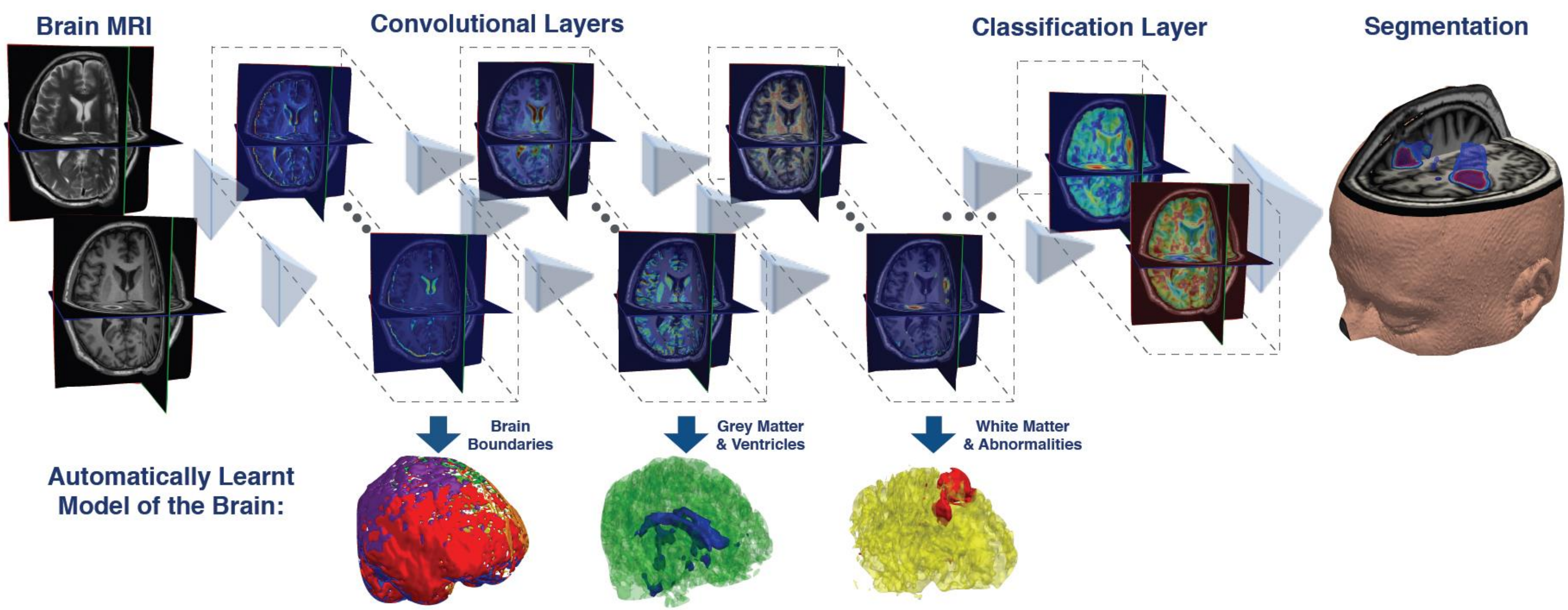
DEEP LEARNING FOR BRAIN LESION SEGMENTATION

Dual Pathway 3D Convolutional Neural Network



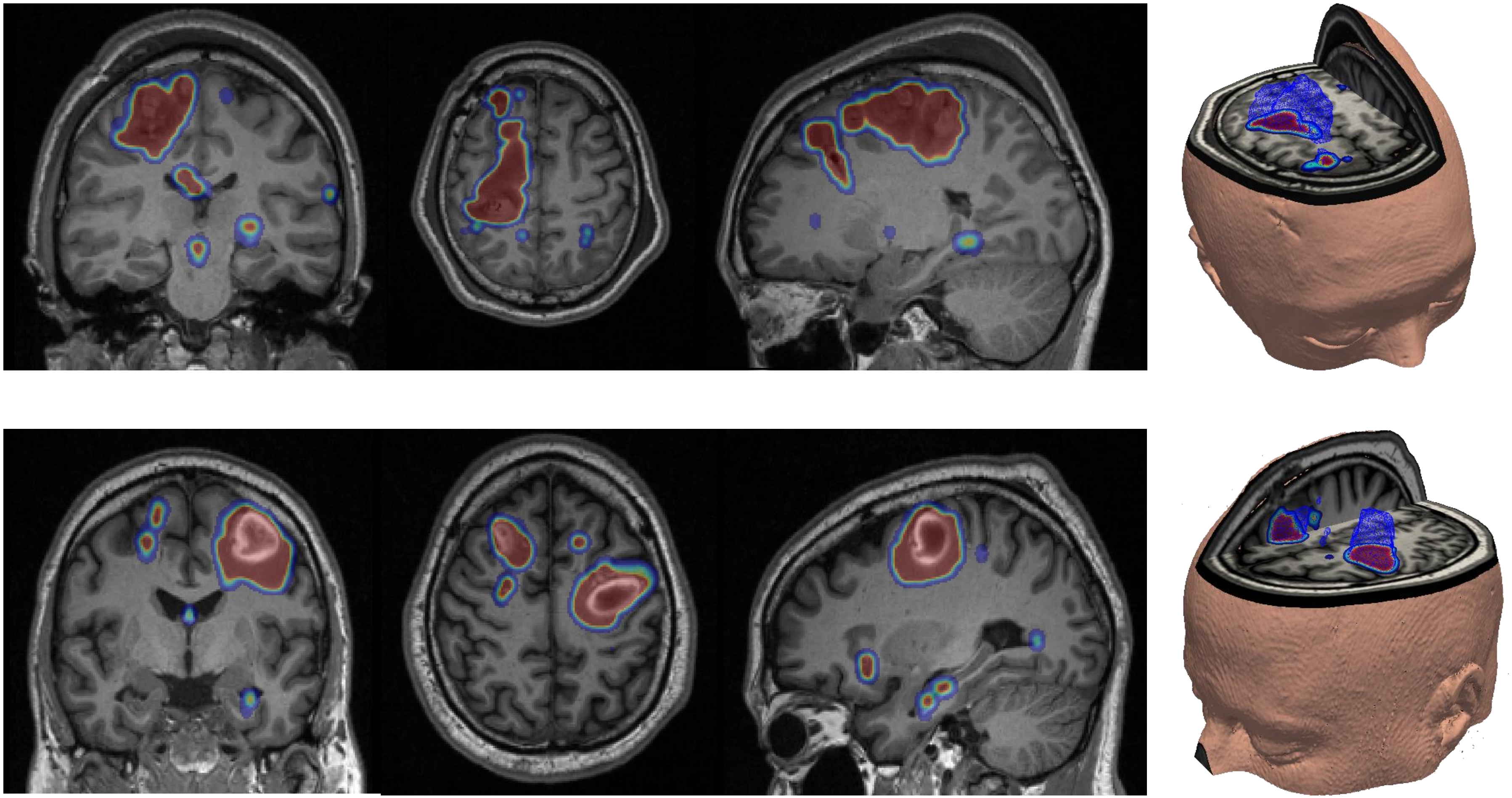
Kamnitsas et al. 2016

Deep Learning for Brain Lesion Segmentation

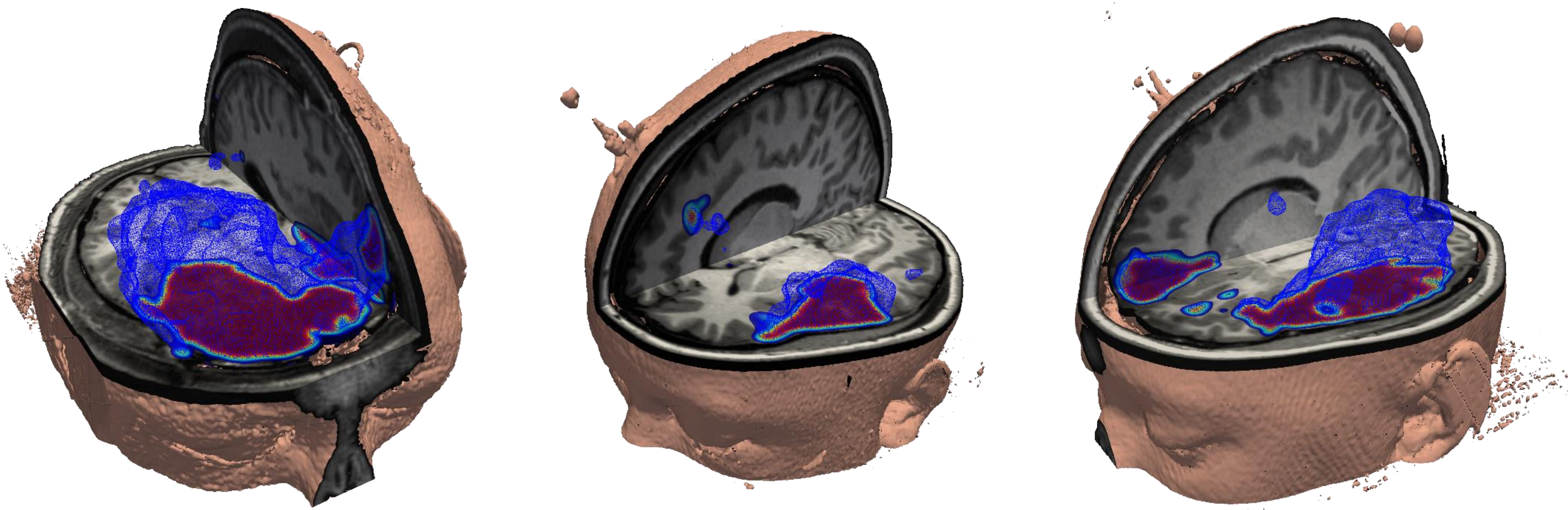


Kamnitsas et al. 2016

Deep Learning for Brain Lesion Segmentation

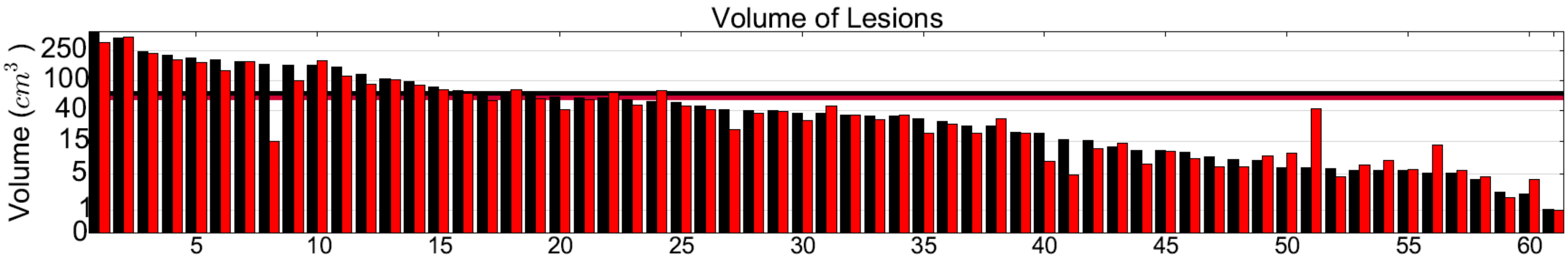


Deep Learning for Brain Lesion Segmentation

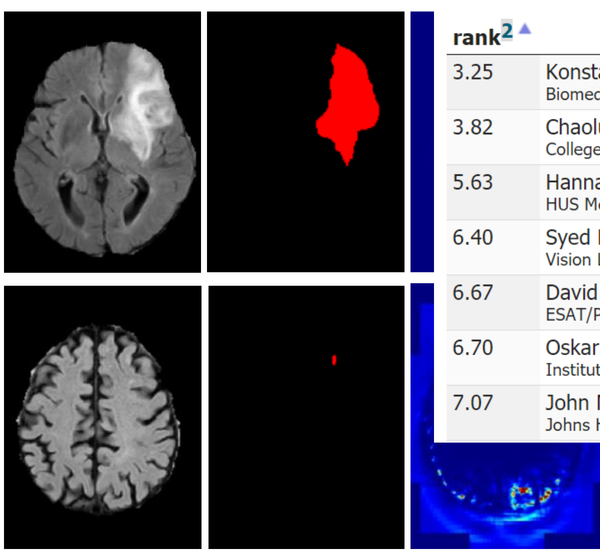


Deep Learning for Brain Lesion Segmentation

- Traumatic Brain Injuries



- Ischemic Stroke Lesions



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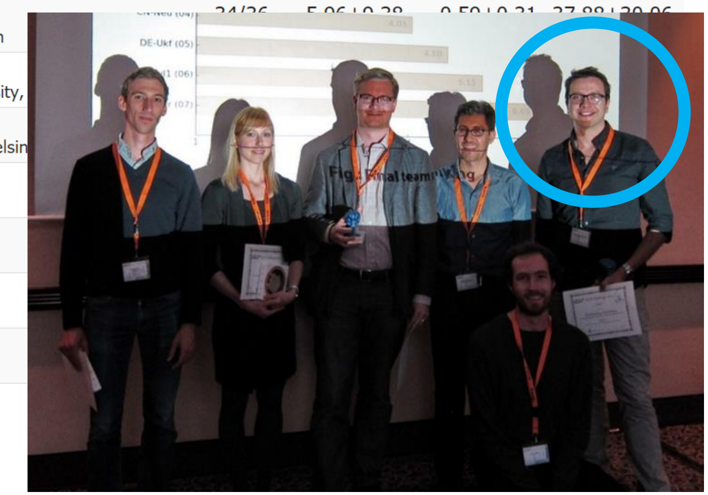
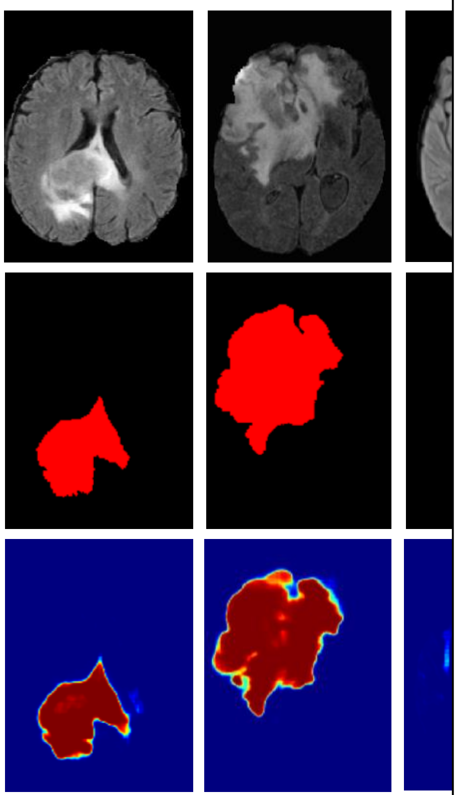


Deep Learning for Brain Lesion Segmentation

- Glioblastoma Brain Tumours



Position	User	Covered Cases	Dice			Positive Predictive Value			Sensitivity		
			complete	core	enhancing	complete	core	enhancing	complete	core	enhancing
1	meier1	3 / 274	0.87 (3)	0.81 (1)	0.83 (1)	0.95 (1)	0.93 (1)	0.87 (1)	0.80 (7)	0.73 (5)	0.81 (1)
2	kamnk1	274 / 274	0.90 (1)	0.75 (3)	0.73 (2)	0.90 (3)	0.86 (3)	0.75 (4)	0.90 (1)	0.72 (6)	0.74 (3)
3	bakas1	186 / 274	0.88 (2)	0.77 (2)	0.68 (4)	0.90 (4)	0.84 (4)	0.68 (6)	0.89 (2)	0.76 (3)	0.75 (2)
4	peres1	274 / 274	0.87 (4)	0.73 (4)	0.68 (3)	0.89 (6)	0.74 (8)	0.72 (5)	0.86 (4)	0.77 (2)	0.70 (6)
5	dvorp1	6 / 274	0.82 (6)	0.65 (8)	0.63 (6)	0.82 (10)	0.78 (6)	0.76 (3)	0.83 (5)	0.66 (9)	0.55 (11)
6	anon1	274 / 274	0.84 (5)	0.67 (6)	0.55 (11)	0.90 (5)	0.76 (7)	0.59 (7)	0.82 (6)	0.68 (7)	0.61 (8)
7	baobs1	20 / 274	0.74 (12)	0.70 (5)	0.63 (5)	0.85 (8)	0.90 (2)	0.79 (2)	0.74 (11)	0.65 (10)	0.58 (10)
8	thirs1	267 / 274	0.80 (7)	0.66 (7)	0.58 (7)	0.84 (9)	0.71 (10)	0.53 (11)	0.79 (8)	0.66 (8)	0.74 (4)
9	peyrj1	274 / 274	0.80 (8)	0.60 (9)	0.57 (9)	0.87 (7)	0.79 (5)	0.59 (9)	0.77 (10)	0.53 (13)	0.60 (9)
10	maieo1	252 / 274	0.75 (10)	0.60	0.56 (10)	0.71 (12)	0.56	0.59 (8)	0.88 (3)	0.81	0.64 (7)

CONCLUSIONS

Significant advances have been made in machine learning for biomedical imaging applications, but…

….mostly when accurate labelled data is available for training

Challenges

- Exploitation of unlabelled and weakly labelled data
- Providing confidence estimates
- Interpretation of results

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Engineering and Physical Sciences Research Council

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SEVENTH FRAMEWORK PROGRAMME

European Commission
Information Society and Media

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IXICO

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European Research Council

wellcome trust

Technology Strategy Board
Driving Innovation

NHS
National Institute for Health Research

action medical research
for children, for life
Charity reg. nos 208701 and SC039284

THE ROYAL SOCIETY

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THANK YOU!