Medicine powered by AI

06/04/19

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AI Scientist

AI Research Team
Canon Medical Research Europe

Canon Medical Research Europe

1994
Company Founded by two University of Edinburgh Graduates

1999
Started working with Toshiba

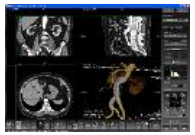
2001
1st Ultrasound product for Toshiba

2003
1st Technology Framework R&D for Toshiba

2009
Acquired by Toshiba

2011
R&D Grant from Scottish Govt

2018
Rebranded as a Canon Medical Research



Global R&D Organisation

Canon Medical Systems Corporation

Edinburgh

Marseille

Dailan

Beijing

Nasu & Yokohama

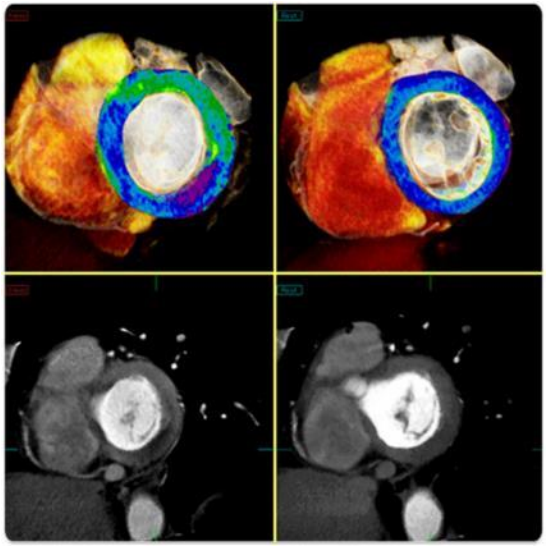
Minneapolis

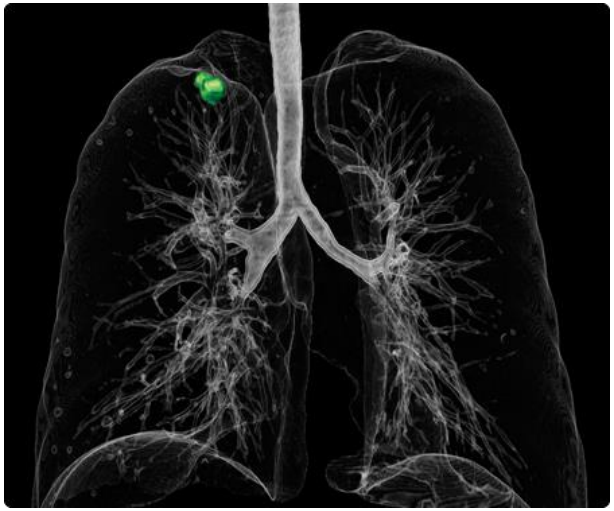
Chicago

Waterloo

R&D Collaboration in Action

Visualisation





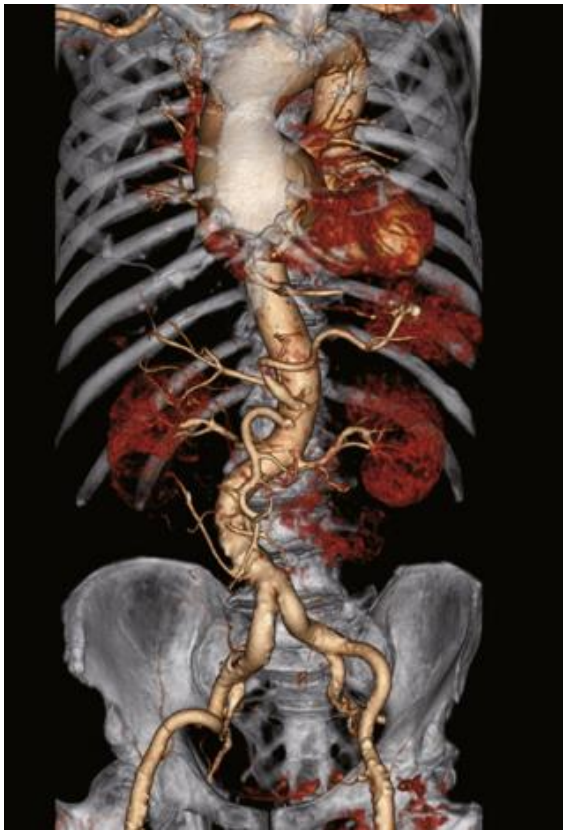
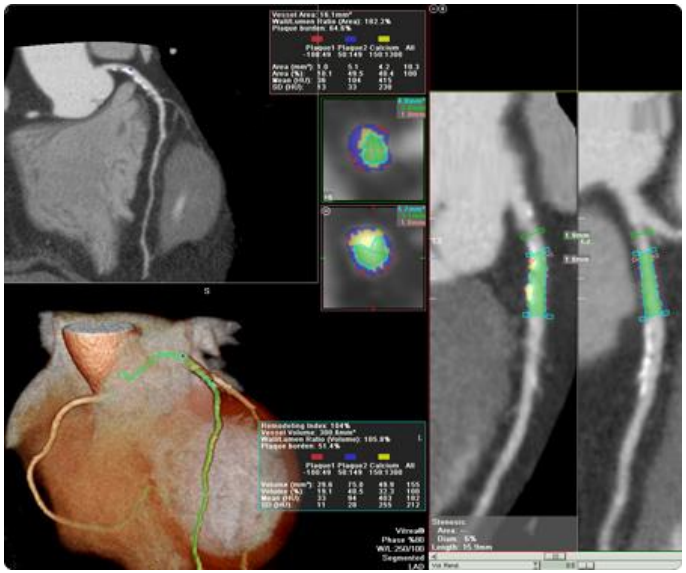
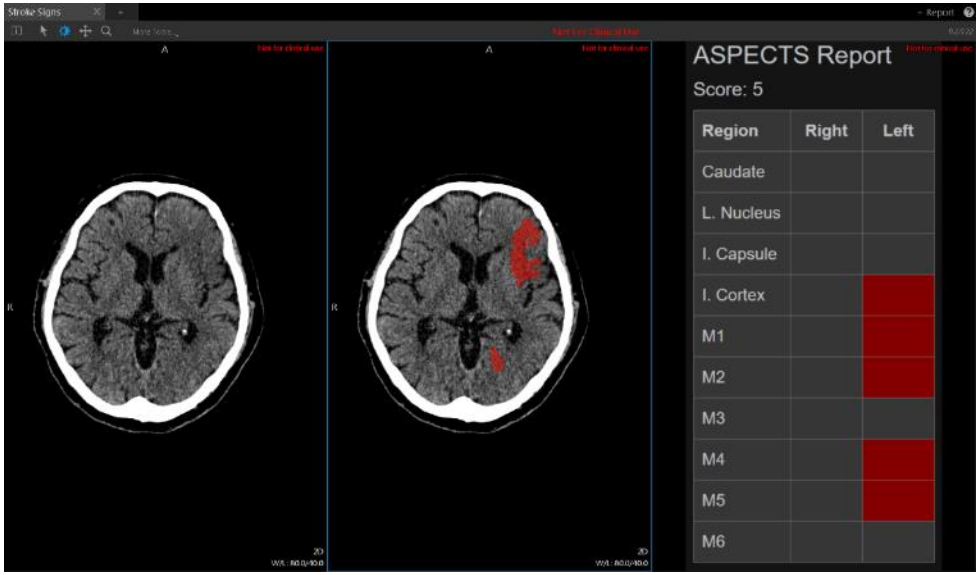
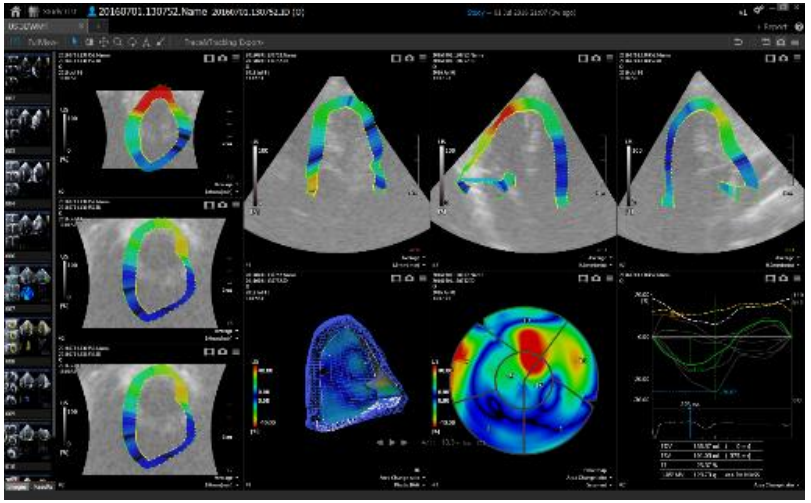


Image Analysis



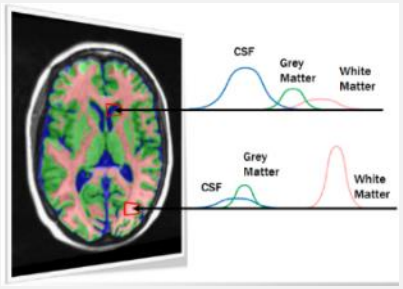




AI at Canon

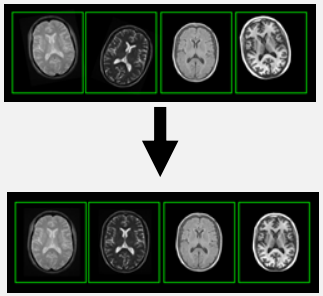
2009: GM/WM/CSF tissue classification in MR Brain

Gaussian mixture model



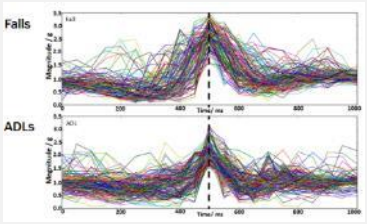
2015: Image registration

Fully convolutional NN



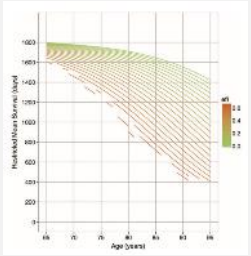
2015: Fall detection from accelerometer

1D Neural Network



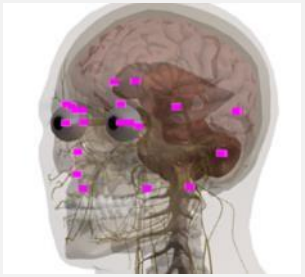
2018: Frailty measurement from coded medical data

Gradient boosting classifier



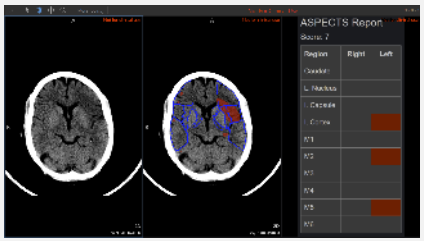
2012: Anatomical landmark detection

Random forest (product), Fully convolutional NN (R&D)



2016: Stroke signs detection

Fully convolutional NN



2017: Rule-based information retrieval

Rule-based with ontologies

2019: Natural language inference for healthcare text

Transformer NN

Canon

iCAIRD

The Industrial Centre for Artificial Intelligence Research in Digital Diagnostics

Alison Murray
Professor of Radiology, Director of SINAPSE, University of Aberdeen, NHS Grampian

Peter Hamilton
Leader Image Analytics, Philips Digital Pathology Solutions, Hon Professor of Tissue Imaging, QUB, Belfast

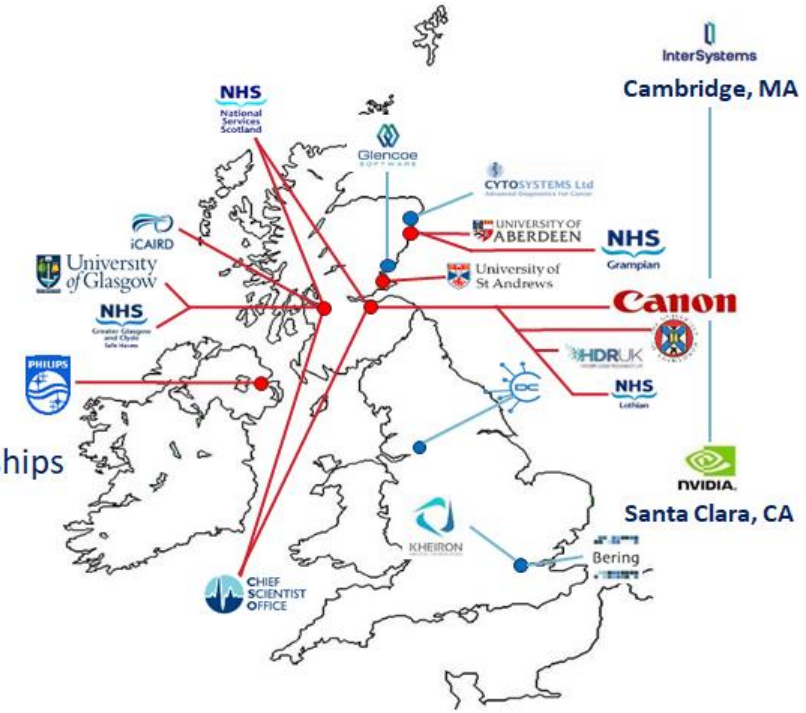
Andy Smout
Vice President Research, Canon Medical, Edinburgh

Colin McCowan
Professor of Health Informatics, University of Glasgow and Glasgow Safe Haven

David Harrison
Professor of Pathology, Universities of St Andrews & Edinburgh, NHS Lothian

Key features

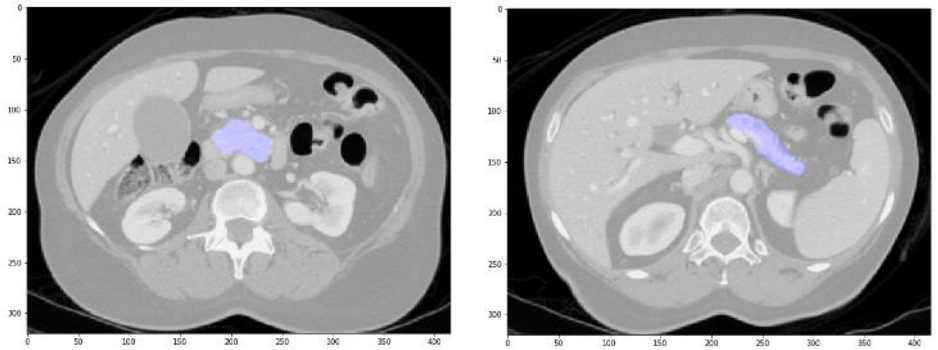
- Tried & tested partnerships
- NHS NSS Board
- Safe havens & HDRUK
- SINAPSE
- National PACS
- Direct link to clinicians



Read more

The biggest challenge in medical AI

[Wikimedia]



[Medical Decathlon]

#{Pictures of cats}>>#{Labelled medical scans}

Google 'betrays patient trust' with DeepMind Health move

Moving healthcare subsidiary into main company breaks pledge that 'data will not be connected to Google accounts'

[Guardian]

SCIENCE

IT'S EASIER TO DONATE YOUR BODY TO SCIENCE THAN YOUR MEDICAL RECORDS

Handing over your digital health data is still nearly impossible

[The Verge]

Jury of citizens ponder tricky question about health records

To what extent should patients control access to patient records?

It's a difficult question that is at the heart of the public controversy which arose in 2014 around care data and the "selling" of hospital records to private companies. Researchers, epidemiologists, managers and many others rely on getting access to detailed information in patient records to improve the effectiveness and safety of future health services. But many people feel uneasy about others delving into their patient record, even if it is for a good cause.

[Health e-Research Centre]

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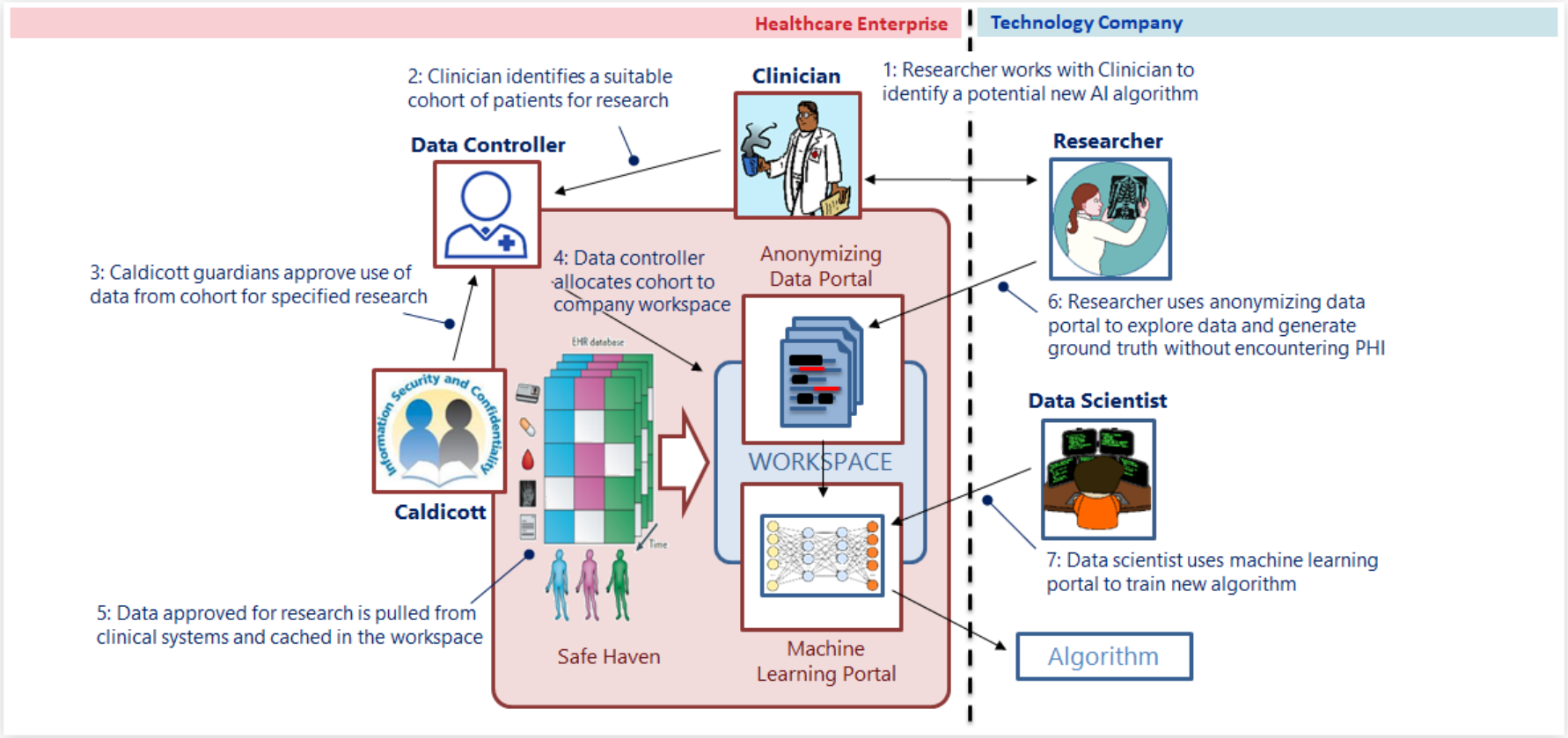
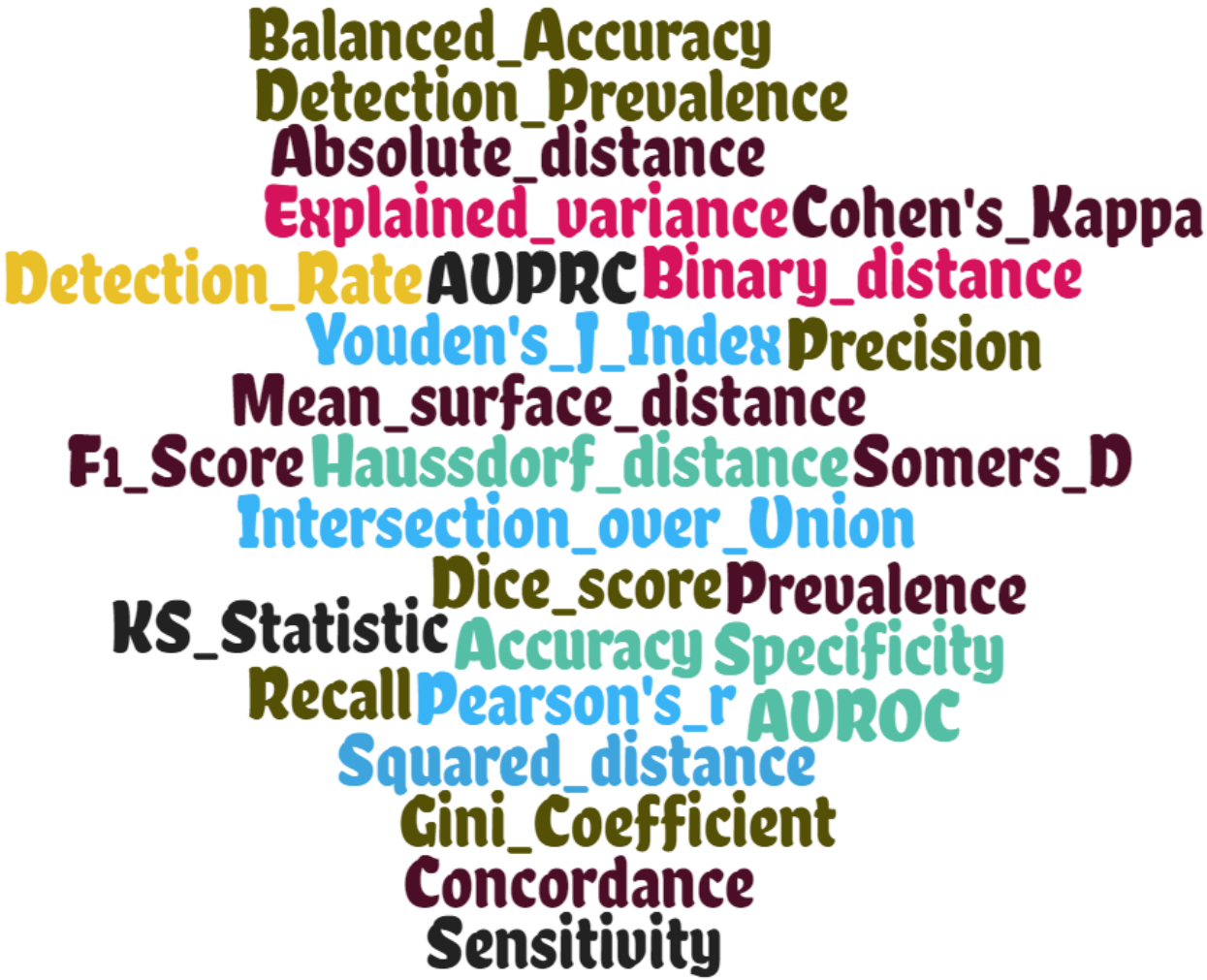
SHAIP

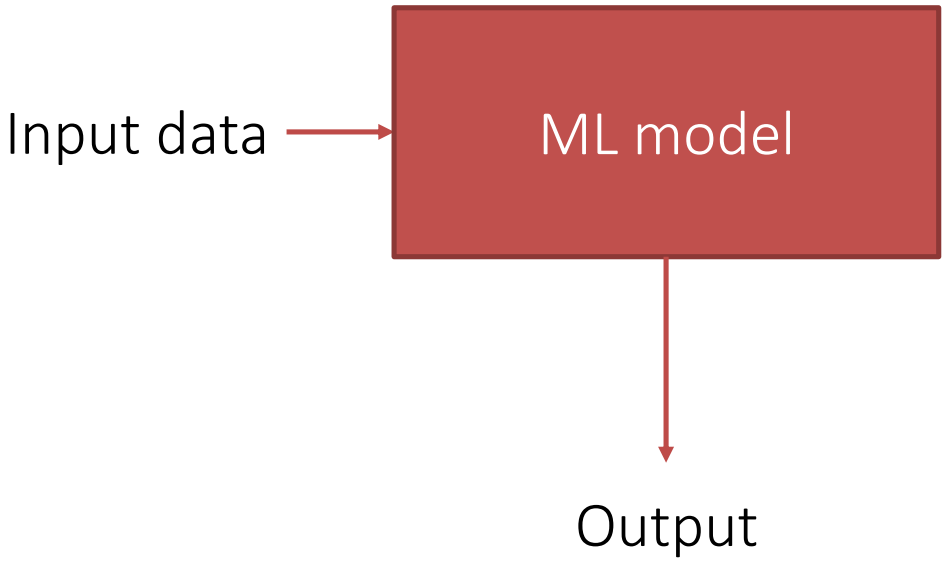
Save Haven AI Platform



The ~~science~~ art of measuring performance

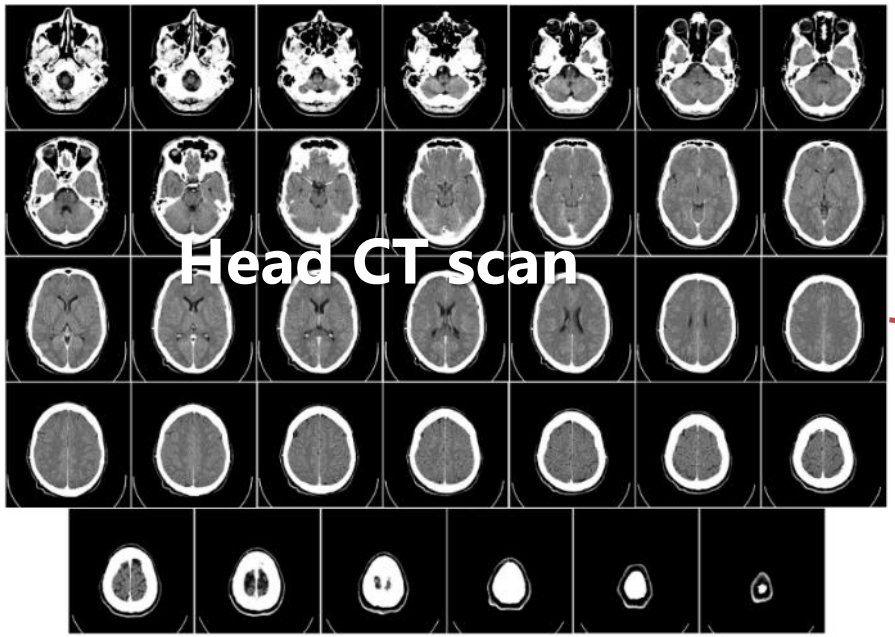


Note



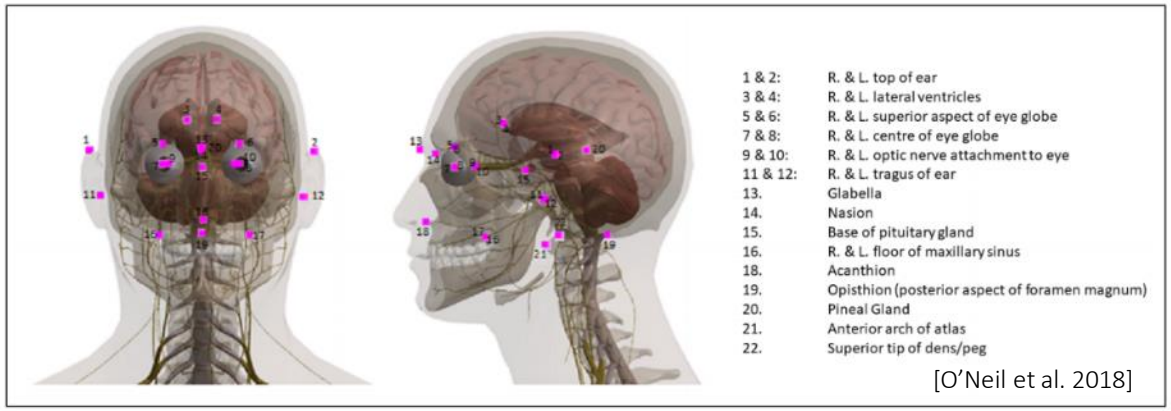
How good is good enough?

- Prediction of landmark (x,y,z) coordinates



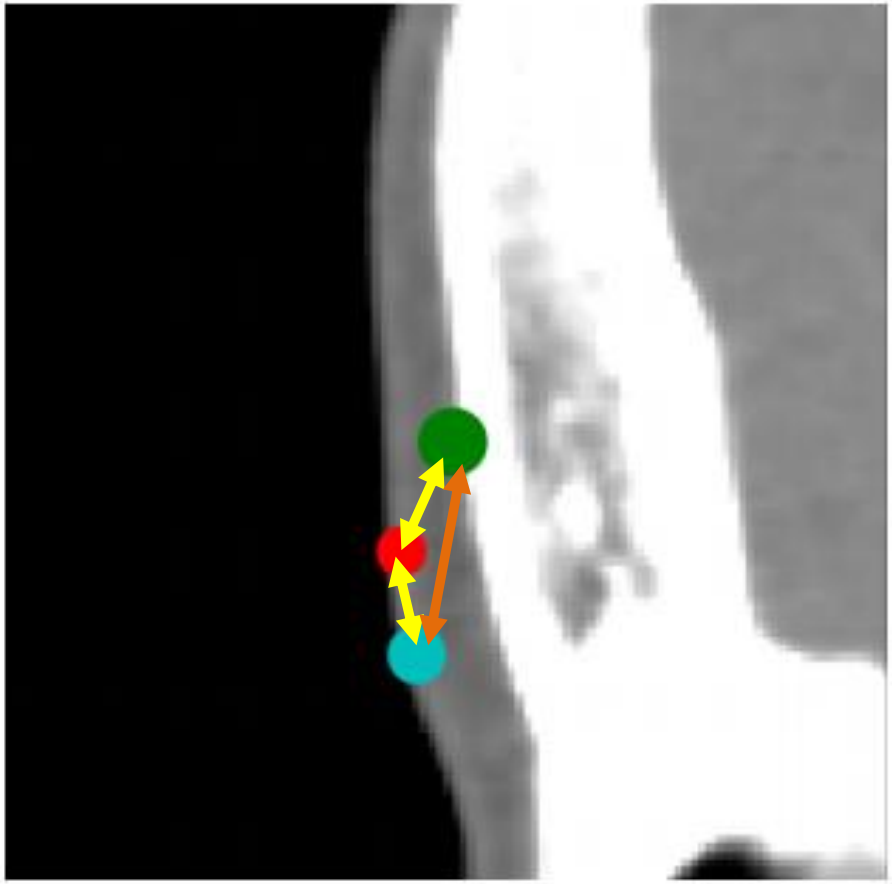
ML model

[Radiology Dept, Uppsala University Hospital]



[O'Neil et al. 2018]

How good is good enough?

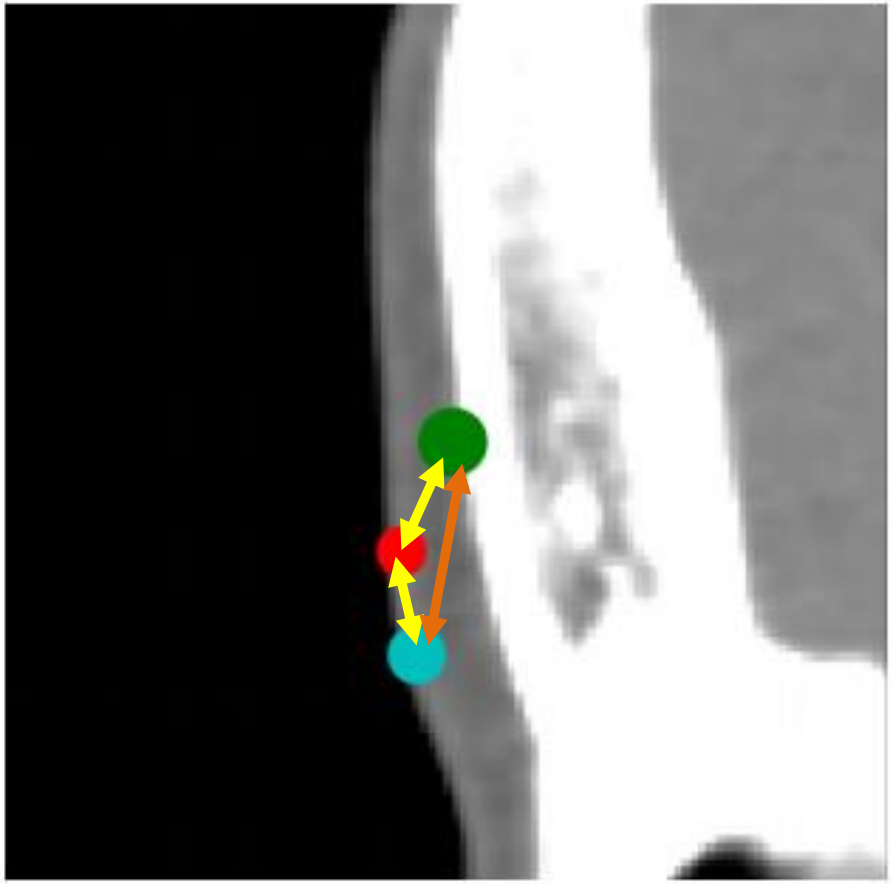


[O'Neil et al. 2018]

Metric: How far were we from the landmark in mm

When can we say we're doing as well as a radiologist?
1mm away?
0.5mm away?

How good is good enough?



[O'Neil et al. 2018]

Metric: How far were we from the landmark in mm

Green and blue are 2 different specialist annotators, red is the model.

How good is good enough?

- To be as good as a difference between 2 humans completing the same task

Method	Reference							
	Observer A				Observer B			
	Mean	Median	Max	%	Mean	Median	Max	%
Observer A	-	-	-	-	2.20	1.49	9.27	11.0
Observer B	2.20	1.48	9.27	11.0	-	-	-	-
Pass 0 (4mm)								
DF	4.47	4.03	11.54	50.4	4.58	4.14	11.28	49.2
DF (+HOG)	4.25	3.91	10.07	47.7	4.36	3.92	9.86	46.5
FCN	3.38	2.65	12.20	21.6	3.52	2.71	12.15	23.7
FCN + Atlas Correction	3.03	2.53	10.45	16.1	3.31	2.62	10.89	21.6
Pass 1 (2mm)								
DF	3.59	2.85	13.73	26.6	3.83	3.02	13.59	27.6
DF (+HOG)	3.30	2.88	**9.77**	24.9	3.47	2.84	**9.69**	26.9
FCN	2.93	1.50	19.08	12.2	3.42	1.84	20.93	17.5
FCN + Atlas Correction	**2.29**	**1.49**	11.41	10.8	**2.77**	**1.78**	12.26	**16.1**
Alternative: Pass 0 (2mm) + Atlas Correction								
FCN	2.55	1.55	15.08	**10.3**	3.10	1.92	15.38	17.5

- Read further details in the paper:

Alison Q. O'Neil, Antanas Kascenas, Joseph Henry, Daniel Wyeth, Matthew Shepherd, Erin Beveridge, Lauren Clunie, Carrie Sansom, Evelina Seduikyte Keith Muir, Ian Poole (2018).

Attaining human-level performance with atlas location autocontext for anatomical landmark detection in 3D CT data

The European Conference on Computer Vision (ECCV) Workshops, 2018

Which metric?

- Multi-label classification task (non-exclusive labels)

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Hospital discharge summary

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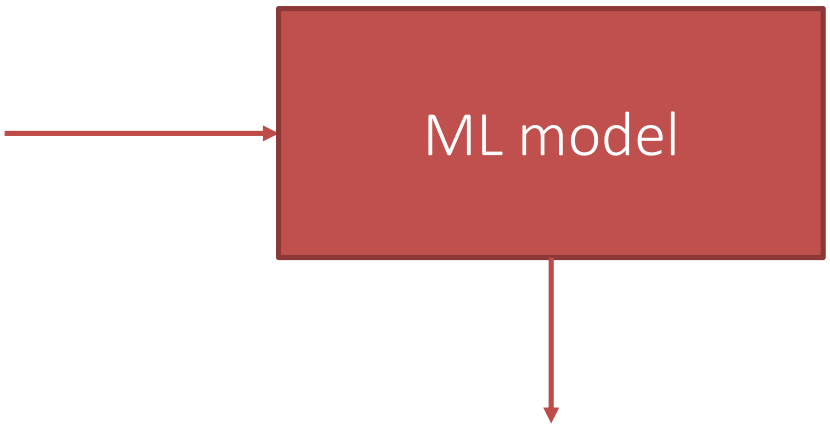

	hypertension	lung cancer	diabetes	coronary artery disease
John	1	0	1	1
Ewan	0	1	1	0

~9,000 labels, 10-50 ‘1’s per patient

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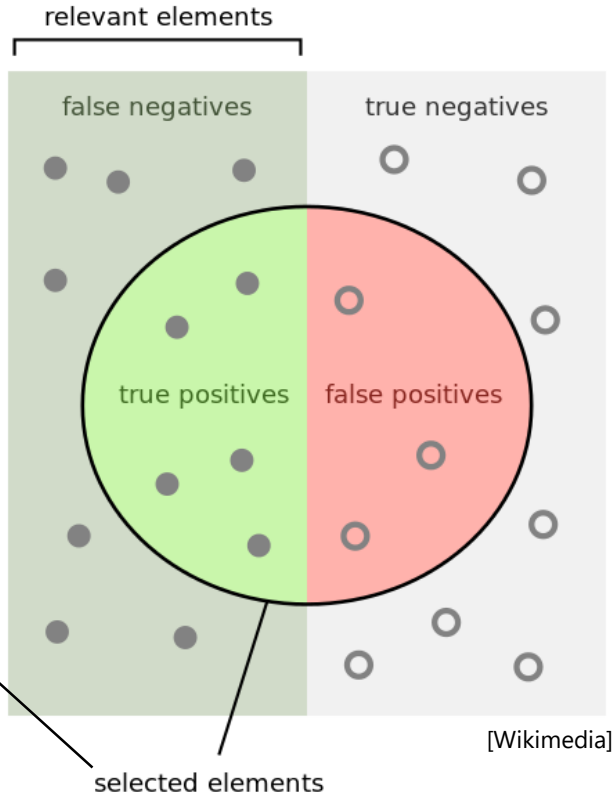
Which metric?

- Predictions for one disease:

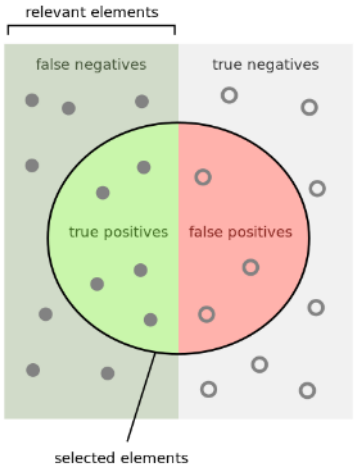
	True	Predicted
Thomas	1	0.95
Caroline	1	0.88
Sarah	0	0.65
Mike	1	0.62
Dave	1	0.48
Michelle	0	0.43
Anna	0	0.26
Alex	0	0.25
George	1	0.22
Emily	0	0.03
Kate	0	0.01



[Wikimedia]

Which metric?

- Accuracy + AUC (Area under the ROC curve)

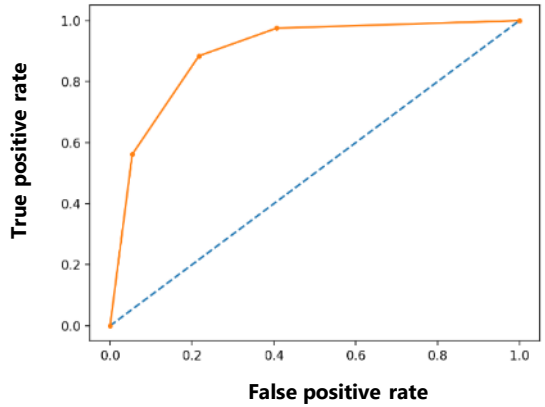


Accuracy

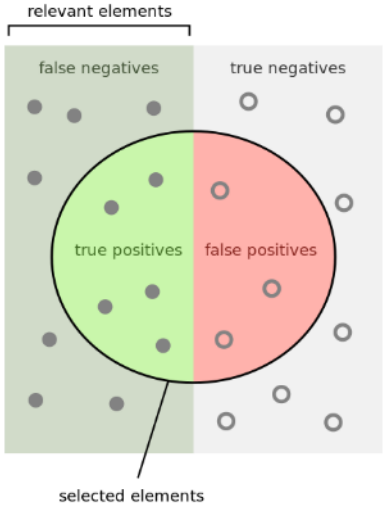
Recall
Sensitivity
True positive rate
Hit rate

Specificity
True negative rate

Fall-out
False positive rate



- Precision, Recall, F1 + AUPRC (Area under the precision-recall curve)



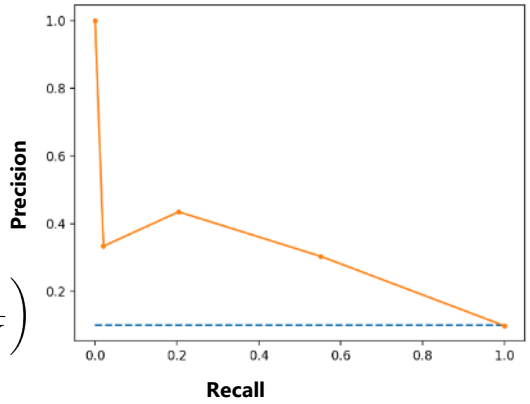
How many selected items are relevant?

Precision
Positive predictive value

How many relevant items are selected?

Recall
Sensitivity
True positive rate
Hit rate

$$F_1 = \left(\frac{\mathrm{recall}^{-1} + \mathrm{precision}^{-1}}{2}\right)^{-1} = \left(\frac{2TP}{2TP + FP + FN}\right)$$



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How to average

	hypertension	coronary artery disease	…	Jaw dislocation	Struck by a lightning
John	1 0.89	0	…	1	0
Ewan	1 0.78	1	…	0	0
Alice	0 0.12	0		0	0
…					
Total cases	10,000	3,000	…	10	2

How to average

	hypertension	coronary artery disease	…	Jaw dislocation	Struck by a lightning
John	1 0.89 TP	0	…	1	0
Ewan	1 0.78 TP	1	…	0	0
Alice	0 0.12 TN	0		0	0
…					
Total cases	10,000	3,000	…	10	2
F1 score	0.85	0.7		0.2	0.0

true prediction

$$F_1(hypertension) = \left(\frac{\text{recall}^{-1}+\text{precision}^{-1}}{2}\right)^{-1} = \left(\frac{2TP}{2TP+FP+FN}\right) = 0.85$$

How to average

	hypertension	coronary artery disease	…	Jaw dislocation	Struck by a lightning
Total cases	10,000	3,000	…	10	2
F1 score	0.85	0.7		0.2	0.0

$$F_1(all) = \frac{0.85+0.7+\ldots+0.2+0}{N_{labels}} = 0.088$$

← [Mullenbach et al. 2018]

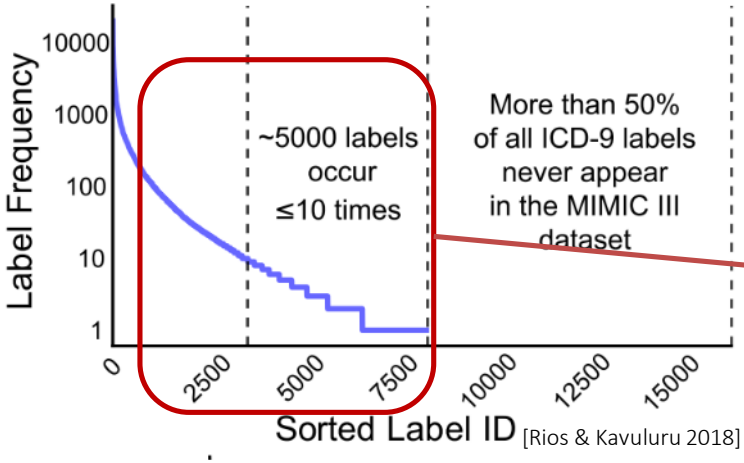
How to average

	hypertension	coronary artery disease	...	Jaw dislocation	Struck by a lightning
Total cases	10,000	3,000	...	10	2
F1 score	0.85	0.7		0.2	0.0

$$F_1(all) = \frac{0.85+0.7+\ldots+0.2+0}{N_{labels}} = 0.088$$

[Mullenbach et al. 2018]

Hard to perform well on rare labels



[Rios & Kavuluru 2018]

Majority of labels are rare (<100 positive examples)

How to average

	hypertension	coronary artery disease	...	Jaw dislocation	Struck by a lightning
John	1 0.89 TP	0 0.55 FP	...	1 0.75 TP	0 0.01 TN
Ewan	1 0.78 TP	1 0.48 FN	...	0 0.34 TN	0 0.02 TN
Alice	0 0.12 TN	0 0.05 TN		0 0.62 FP	0 0.01 TN
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Total cases	10,000	3,000	...	10	2

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macro

[Mullenbach et al. 2018]

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- Maybe we should've picked accuracy instead…

Conclusion

- Think about the use case!
- (here we don't know how good/consistent human annotators are)
- Want to learn more about state-of-the-art deep learning solutions for ICD coding of hospital discharge summaries:
  - Mullenbach, J., Wiegreffe, S., Duke, J., Sun, J., & Eisenstein, J. (2018). **Explainable Prediction of Medical Codes from Clinical Text.** *Proceedings Of NAACL-HLT 2018*, 1101–1111.

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