What reassurances do NHS Clinicians need to Engage with AI?

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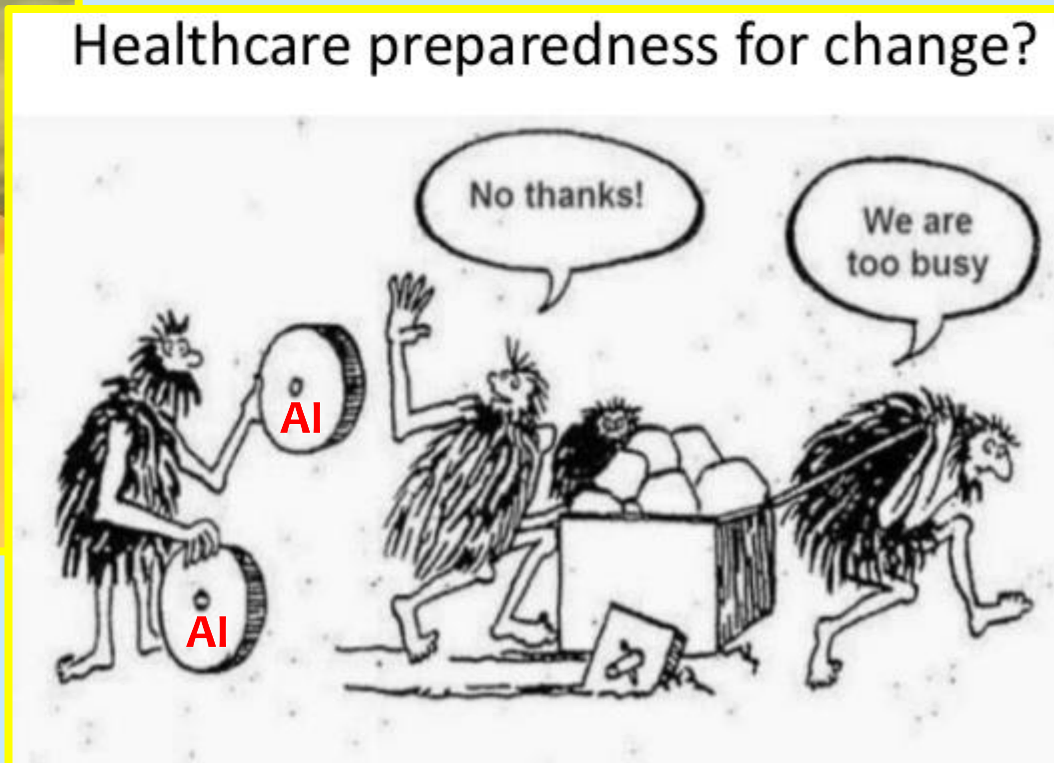
AI will change clinicians' lives

We must welcome AI: helps us, helps patients

- nothing to be scared of

- clinicians are flexible



Reassurances needed

- **integration into normal workflow**
  - radiologists
- **usefulness**
- **accuracy**
  - source data
  - testing and validation data
- **publication**
  - transparency
- **regulation**

AI integration into normal workflow:

A sine qua non:

- **AI products *must* be seamlessly integrated into RIS/PACS/EPR (and radiotherapy planning)**

  - otherwise won’t be used

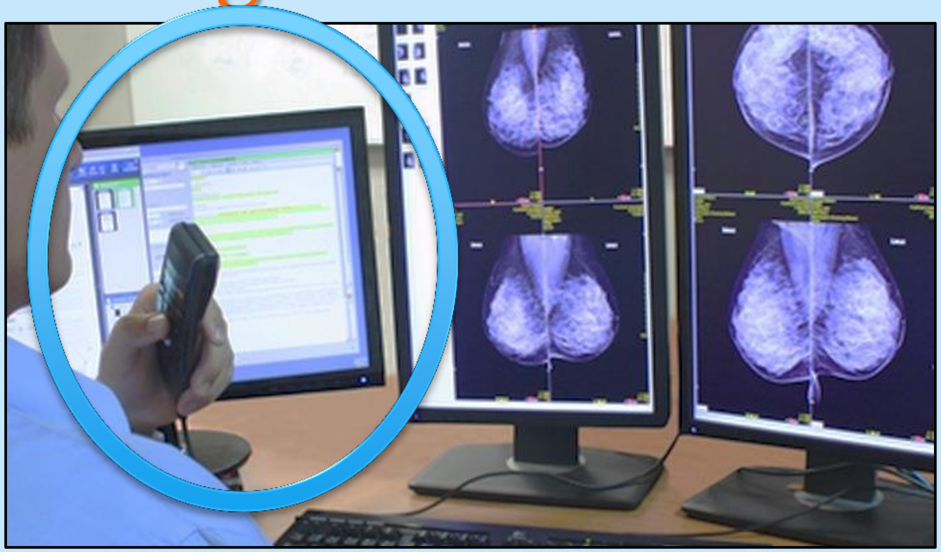
  - cf stand alone MPR/other software, CADs

- **vendor neutral interfacing standards do now exist, so no excuse for not using them**

AI integration into workflow

speech recognition

- **20 years use in radiology reporting**
- **seamlessly integrated into clinical workflow**
- **continues to learn whilst in use**
- natural language processing
- neural networks
- **5% error rate**



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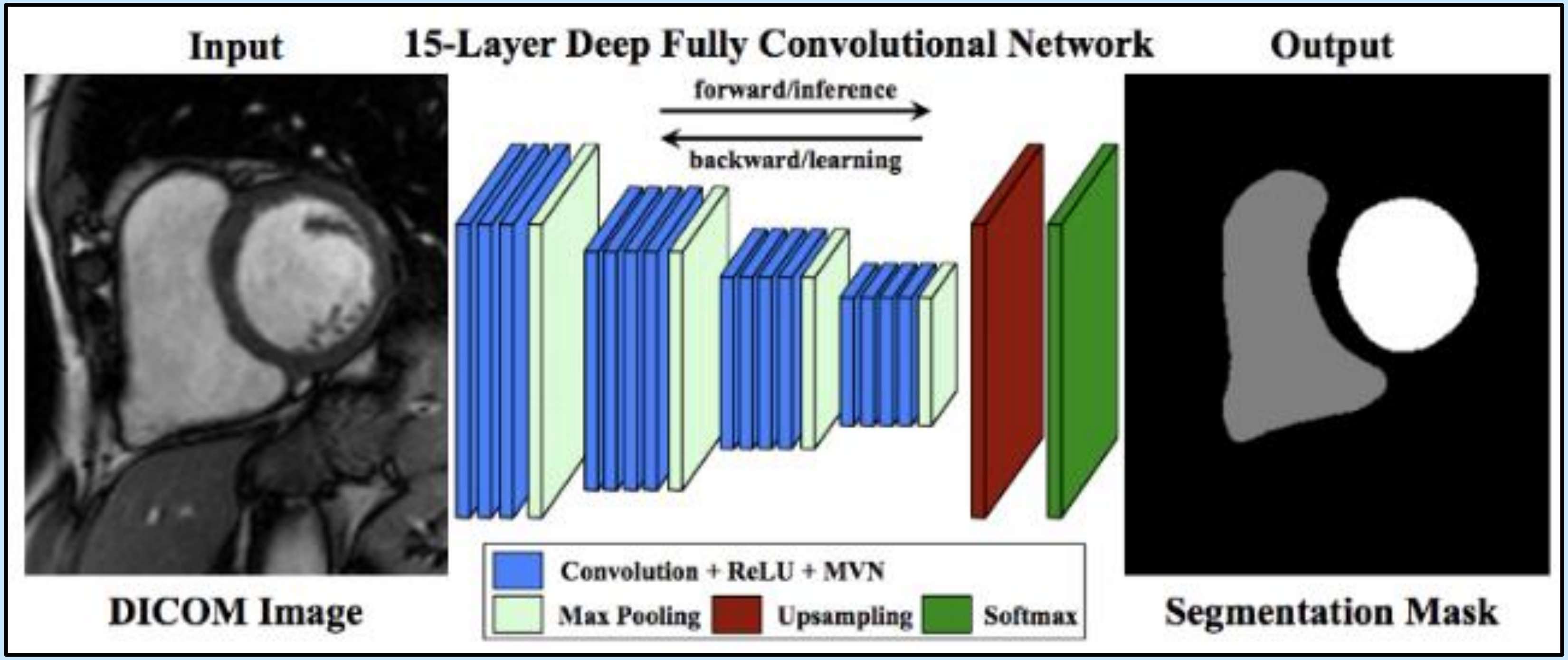
AI usefulness

cardiac MR/CT segmentation

- automated LV and RV segmentation
- removes drudgery

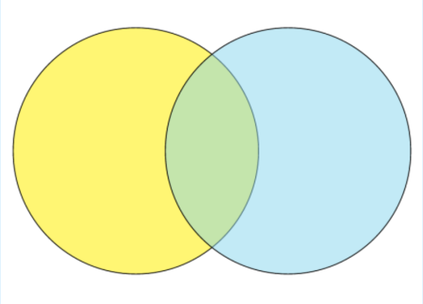


the deep learning in cardiac segmentation:

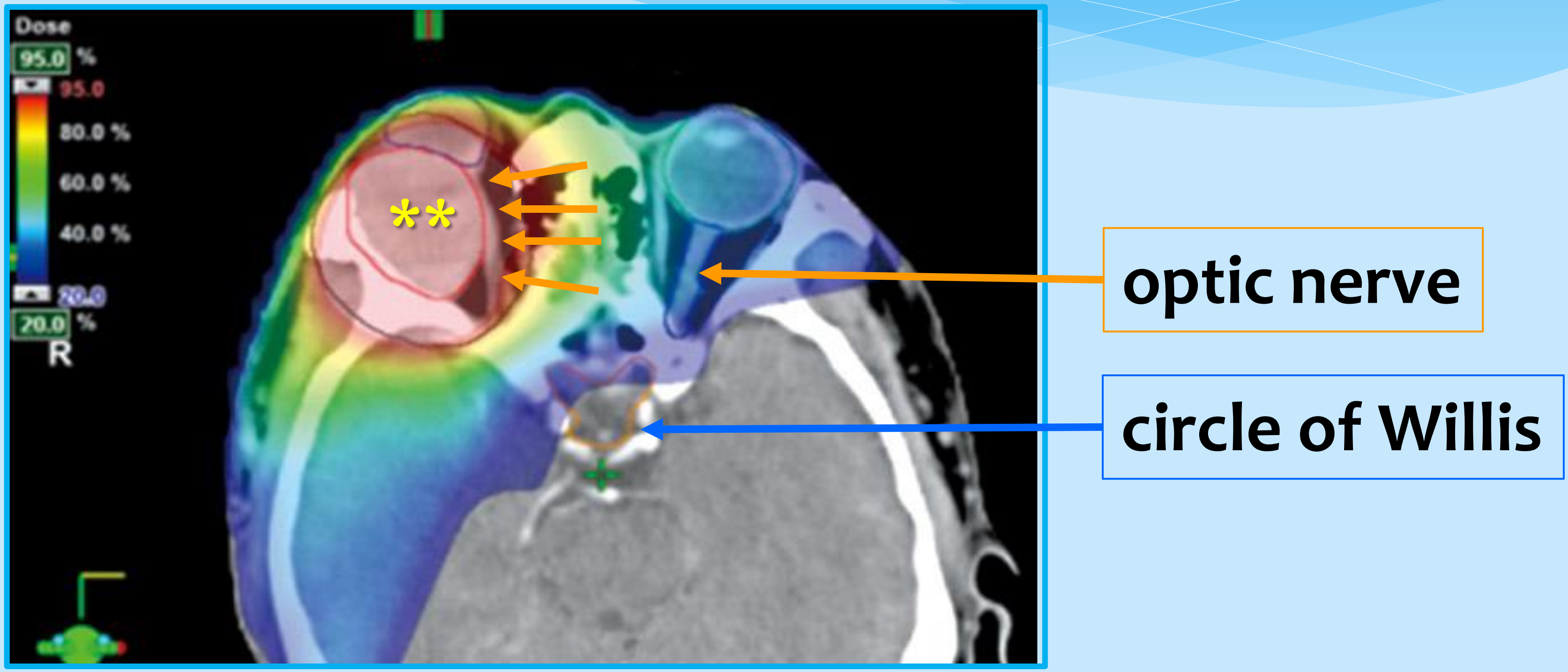
- **utilizes information from adjacent MR slices** (not just single 2D MR slices)
- **employs 'transfer learning' for RV segmentation** (learnt from LV data)
- **has high DICE indices ~ 0.9 (accurate)**

compares AI contour with expert-drawn contour

0= complete mismatch; 1= complete match



AI identification of normal structures in radiotherapy contouring



** = orbital metastasis

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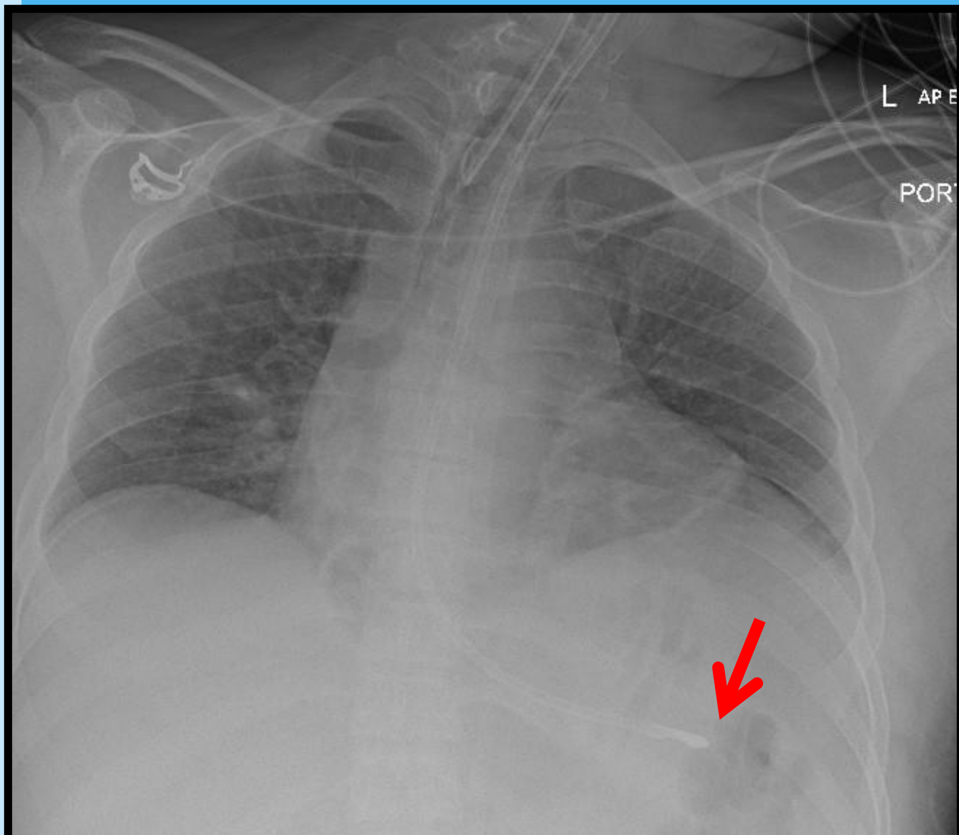
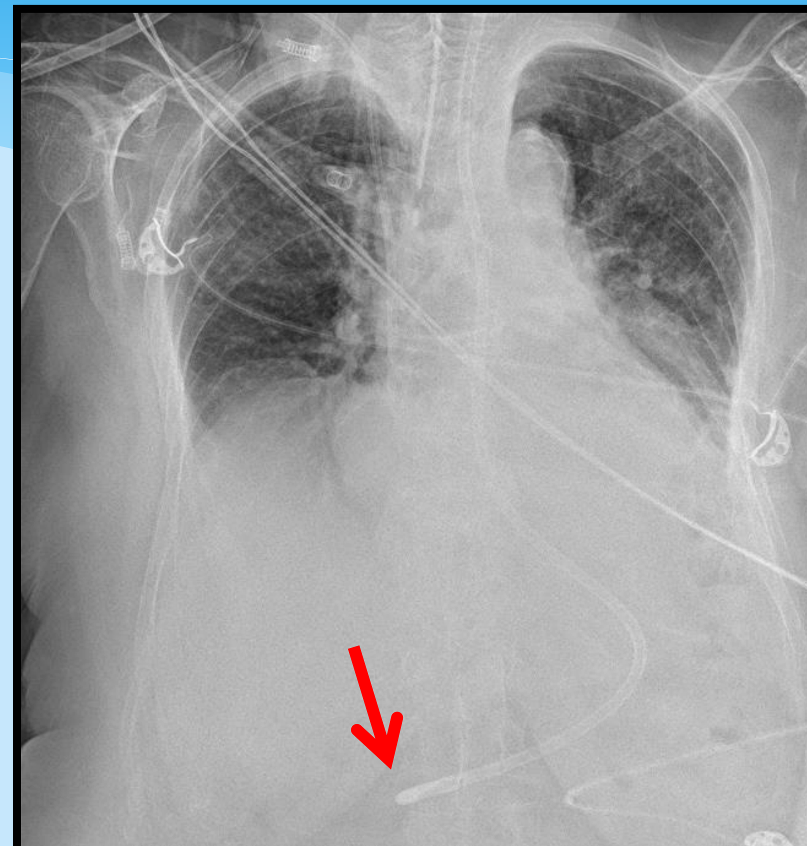
AI accuracy example





nasogastric tube position?

70% accuracy not good enough!

Data requirements

struggle to access sufficiently large datasets

- for training, testing, validating cohorts

- **uniformly acquired** (e.g. imaging protocols)
- **cleaned** (artifacts removed)
- **curated** (annotated) – **need radiologist input**
- **labelled**
- properly **anonymised/pseudoanonymised** with ethical approval/appropriate consent
- **representative:** applicable to patient population

AI expected development solutions

- major change to **unsupervised learning techniques**
  - **discriminative features are learned without explicit labelling**
  - *"generative adversarial networks" "variational autoencoders"*
  - **because lack of radiologists to curate (annotate) the data**
- **data use:**

  shift from processed medical images to **raw acquistion data**
  - advantage: **no loss of information in downsampling** and optimising for human viewers
  - disadvantages:
    - more noise
    - human validation more difficult

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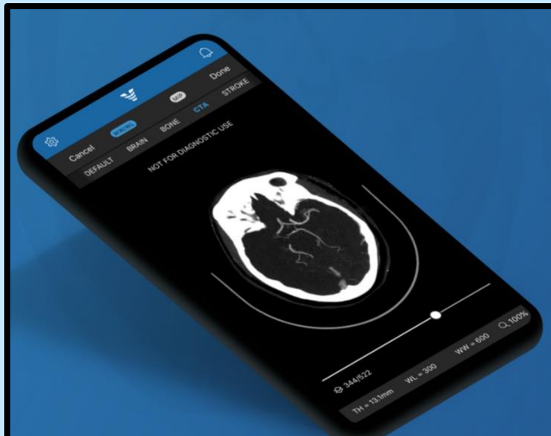
No peer reviewed publication

Thrombotic stroke detection alerts (viz.AI)

- large vessel occlusions, LVOs
- analyses data directly on CT scanner → notifies mobile device of neurorad/stroke physician
- 6 mins (versus 52 mins)
- ***but***: analysed only 300 CTA studies vs 2 neurorads, 90% sensitivity and specificity
- no peer reviewed publication
- yet CE mark / FDA approval



Publication - transparency

- **in reputable peer-reviewed journal**
- **reassurance re:**
  - data used at all stages of AI development
  - methodology
- **fear of “black box” component of deep learning – convolutional neural networks CNN**
  - ?no different from using MRI, a car etc: mechanism of action not fully understood by user
  - ?safe and effective approved drugs: exact mechanism of action unknown

Radiomics research

- **AI recognising complex patterns in imaging data→ automated quantitative assessment**
- AI methods of 'mining' of radiological image data:
  1) predefined engineered features
  - shape
  - intensity
  - texture

  2) automatically learnt features identified by deep learning '*black box*'
- mined radiological imaging data are coupled with data on: - clinical outcomes, genetics, Rx response

Ref: Gillies RJ et al. Radiomics: images are more than pictures, they are data. Radiology, 2016. Vol 278, issue 2

Radiomics research

- **image based precision 'personalised' medicine** in:
  - **diagnosis**
  - **prognosis assessment**
  - **therapy response prediction**

- Published examples:

- ***non small cell lung cancer:*** *histological subtype and biomarkers, disease recurrence, overall survival*
- ***chronic heart failure*** *prognosis from MRI and genetics*
- ***multparametric MR prostate*** *malignancy probability map*
- ***image reconstruction software:*** *artefact correction, better image registration accuracy and motion compensation*

Ref: Hosney Aet al. Artificial intelligence in radiology. Perspectives (2018). Nature Reviews Cancer. 18: 500-510

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Proper AI regulation:

- ❑ **protect the patient and his/her data**
- ❑ **ensure safety of the product: software testing**
  - need **enough data** for testing
  - **access** to these data
  - **standardize** data acquisition and imaging protocols
- ❑ **periodic testing over specific time intervals**
  - deep learning methods **evolve** over time

Proper AI regulation:

- **FDA approval (USA)**
- **CE mark (Europe)**
  - can sell anywhere in Europe
  - < 50% all medical software
- **in Europe – Medical Device Regulation law**
  - becoming EU law (and therefore UK law)
- **International Medical Regulations Forum**
  - seeking global harmonization

- **Who is to blame when AI makes an error?**

AI regulation in the UK

MHRA (medicines and healthcare products regulatory agency)

working with DEAC (devices expert advisory committee)

- a medical device = ‘a thing with a medical purpose’
- health-related software = facilitates clinical decision making / changes patient management

- **medical devices (software) are risk stratified**
  - classes 1, 2a, 2b, 3
  - AI mostly class 2a (2b and 3 implantable)
    - must have a notified body check their technical file and perform post-marketing surveillance
- **RCR (& other Royal Colleges) need to be involved**

an exemplar of AI (deep learning) development

retinal scans – Google DeepMind

optical coherence tomography, OCT (3D retinal images)

- **collaborative project** with Moorfields Eye Hospital
- **huge dataset** 14,884 scans
- **data were:**
  - **cleaned**
  - **curated (annotated)**
- **>94% accuracy** compared with 8 eye experts
- **vendor independent** - this AI technology can be applied to different types of eye scanners

optical coherence tomography (OCT)

ARTICLES
https://doi.org/10.1038/s41591-018-0107-6
nature medicine

Clinically applicable deep learning for diagnosis and referral in retinal disease

Jeffrey De Fauw[1], Joseph R. Ledsam[1], Bernardino Romera-Paredes[1], Stanislav Nikolov[1], Nenad Tomasev[1], Sam Blackwell[1], Harry Askham[1], Xavier Glorot[1], Brendan O'Donoghue[1], Daniel Visentin[1], George van den Driessche[1], Balaji Lakshminarayanan[1], Clemens Meyer[1], Faith Mackinder[1], Simon Bouton[1], Kareem Ayoub[1], Reena Chopra[2], Dominic King[1], Alan Karthikesalingam[1], Cían O. Hughes[1,3], Rosalind Raine[3], Julian Hughes[2], Dawn A. Sim[2], Catherine Egan[2], Adnan Tufail[2], Hugh Montgomery[3], Demis Hassabis[1], Geraint Rees[3], Trevor Back[1], Peng T. Khaw[2], Mustafa Suleyman[1], Julien Cornebise[1,3,4], Pearse A. Keane[2,4*] and Olaf Ronneberger[1,4*]

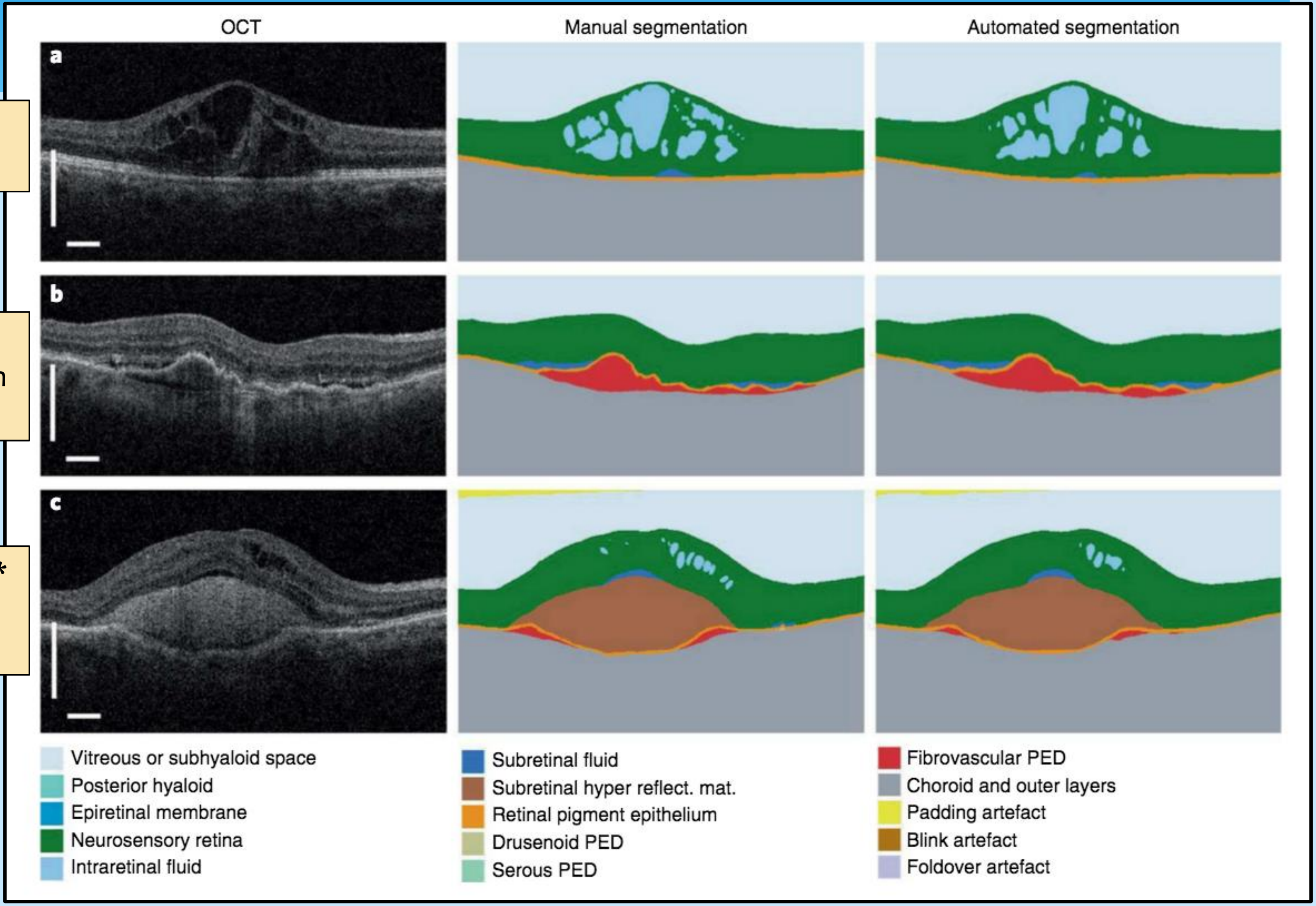
Results have been published: Nature Medicine (2018) 24: 1342–1350

Results of the segmentation network: maps the disease features

diabetic macular oedema

choroidal neovascularization due to AMD*

neovascular AMD* with subretinal haemorrhage



*age-related macular degeneration

Nature Medicine (2018) 24: 1342–1350

- the **classification network** then analyses this segmentation map → **makes diagnoses and referral recommendation, with % confidence figure**
  - **clinician can interrogate each step: transparency**
  - **eliminates the "black box" fear**

- **the need** **1000 OCTs per day at Moorfields**
  - **instant triaging – eliminates delay between scan and Rx**
  - **↓ risk - removes risk of interval sight loss**
    - diabetic eye disease
    - age-related macular degeneration (AMD)

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