Opportunities and Challenges for innovation & Dealing with the Clinical Backlog – Post Covid

SEHTA 2021 MedTech Expo & Conference

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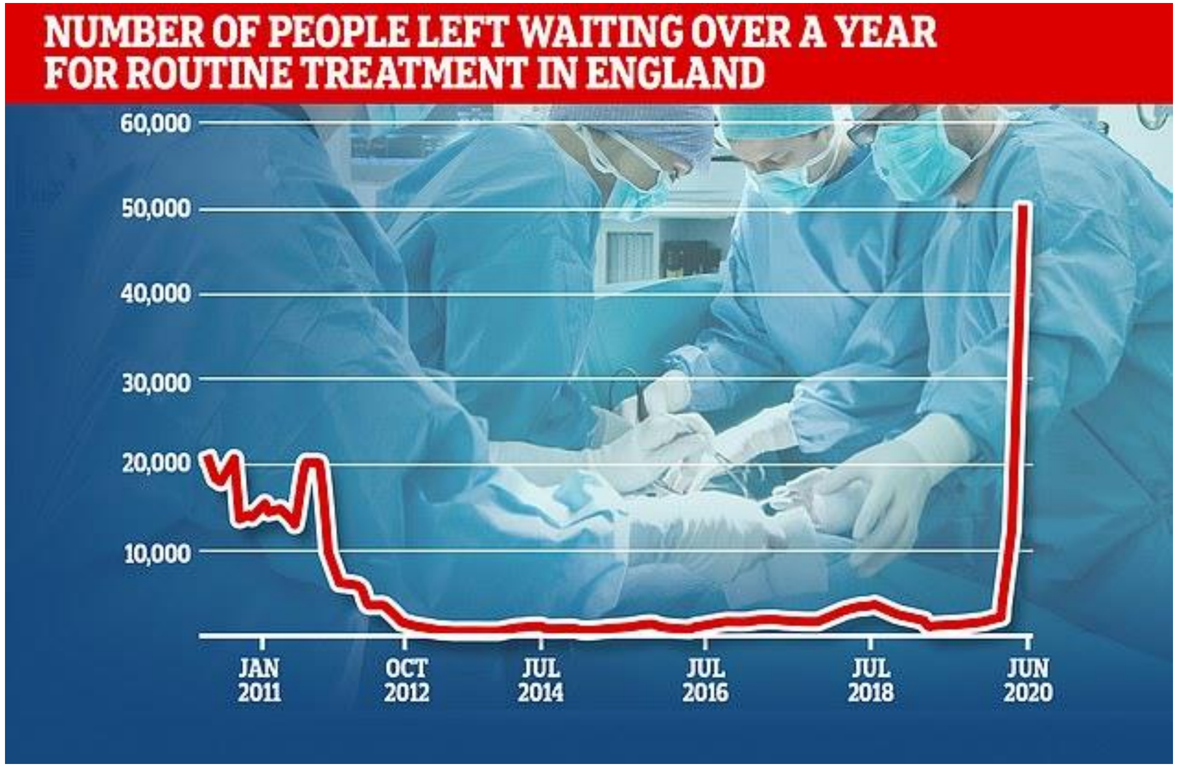
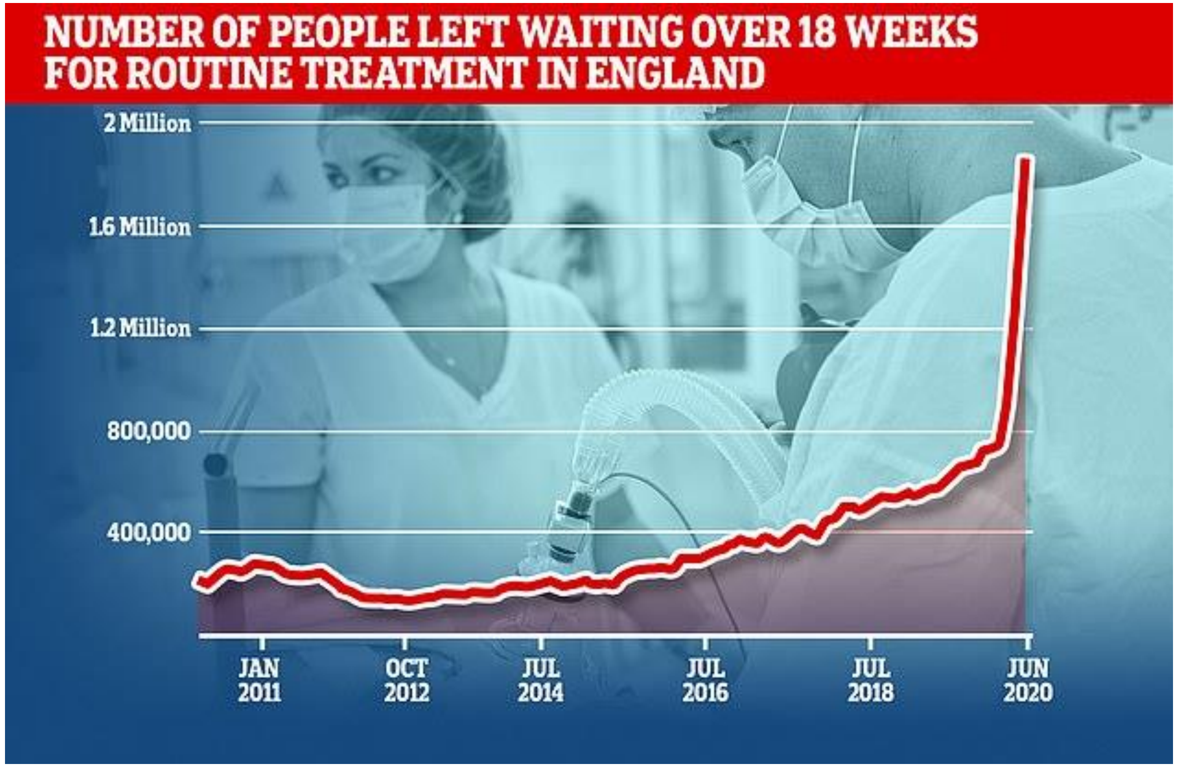
Covid pandemic has left a burning platform for the NHS!!





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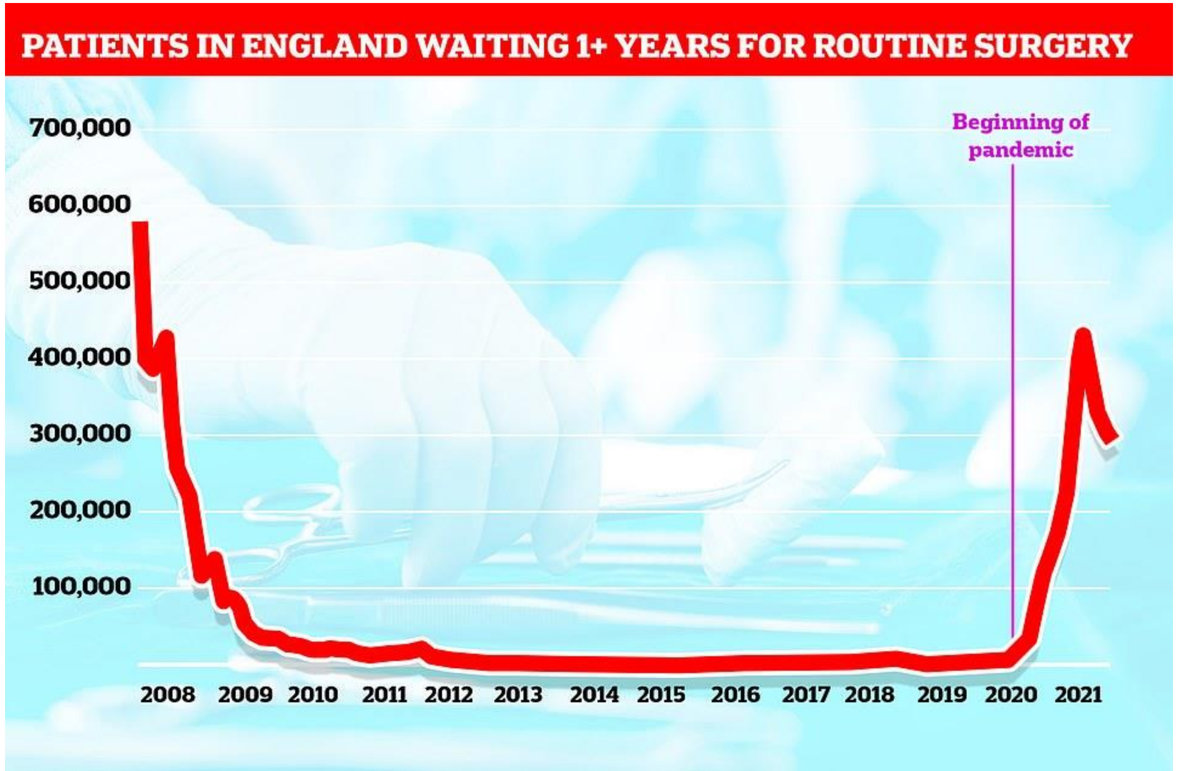
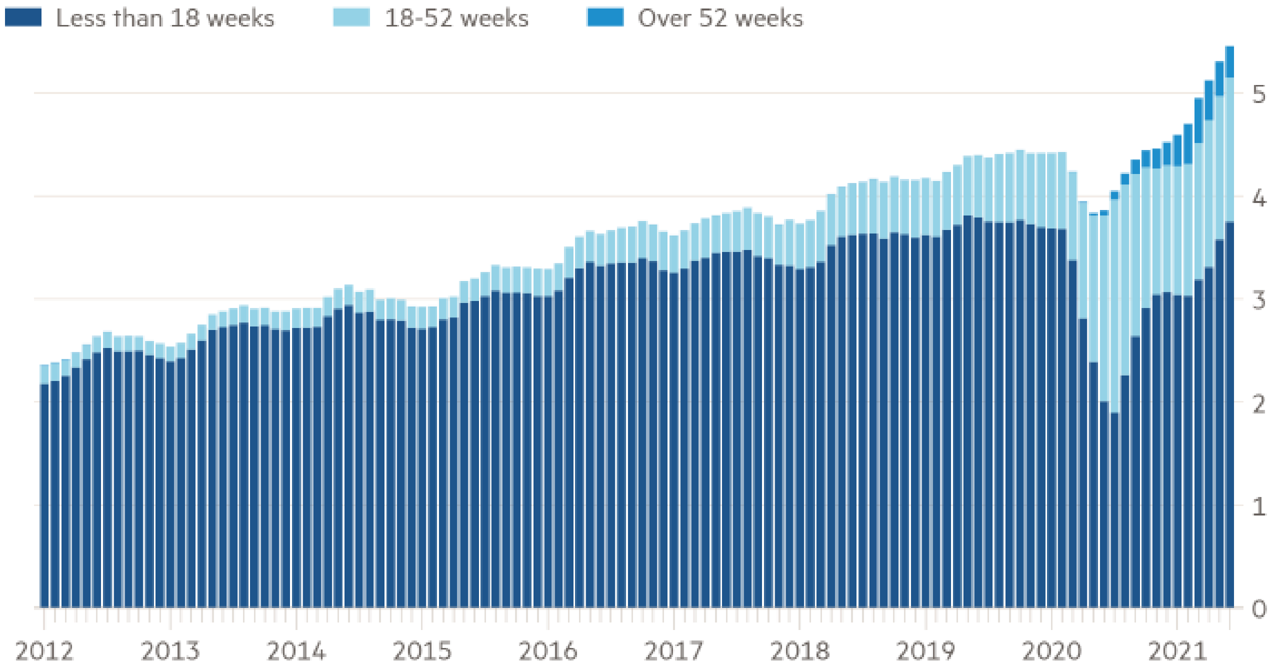


Numbers on NHS waiting lists in England now exceed 5 million

Referred but waiting for treatment, by length of wait (millions)



Source: NHS England

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Examples of innovations being developed by KCL and GST & KCH at London Medical Imaging & AI Centre for Value based Healthcare that could help!

- Triage tool to reduce reporting backlog of brain MRIs - Dr Tom Booth

- Triage tool to help with prostate cancer 28-day diagnostic pathway - Prof Seb Ourselin

- Clinical decision support for patients having cardiac MRIs – Dr Andy King

- Scanning support for antenatal fetal abnormality screening – Prof Jo Hajnal

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Triage tool to reduce reporting backlog of brain MRIs

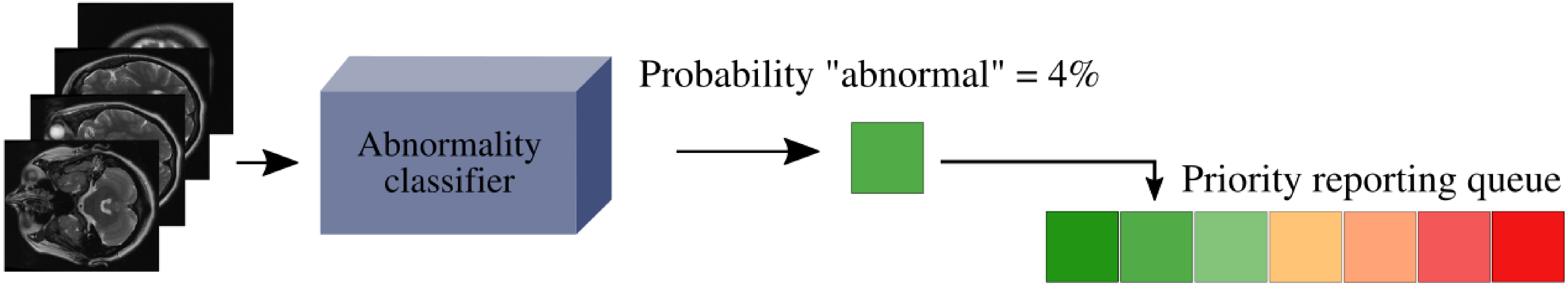
- Growing demand for head MRI examinations + global shortage of radiologists = increase in the time taken to report head MRI scans
- In the UK, reporting times for out-patient brain MRI scans have increased every year since 2012
- Currently, 2% of departments meeting reporting requirements within contracted hours
- ~ 330,000 patients waiting > 30 days to receive radiology report
- These figures were pre-COVID but have now deteriorated further
- For many neurological conditions (e.g., acute stroke, brain tumour, aneurysm…), this delay is leading to poor patient outcomes and increased mortality

Triage tool to reduce reporting backlog of brain MRIs

- A solution to reduce reporting times for abnormal scans is to develop a triage tool to identify abnormalities at the time of imaging, and prioritize the reporting of these scans

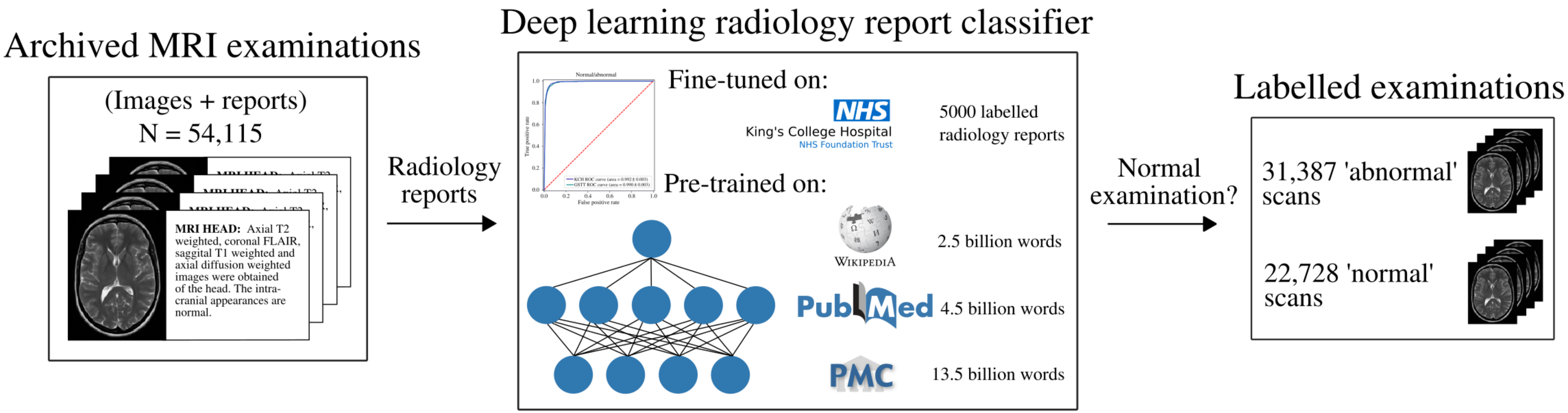
- Computer vision convolutional neural networks show promise for this task

- However, a bottleneck to model development is the difficulty obtaining large, clinically-representative, labelled datasets



Triage tool to reduce reporting backlog of brain MRIs

- 54,115 adult (≥ 18 years) MRI head scans performed at King's College Hospital (KCH) and Guy's and St Thomas' Hospital (GSTT) between 2008-2019 were obtained
- The corresponding radiology reports produced by expert neuroradiologists were also obtained
- Using a validated NLP report classifier, each MRI scan was labelled 'normal' or 'abnormal'
- This labelled dataset was then used to train a computer vision model to distinguish 'normal' or 'abnormal' scans



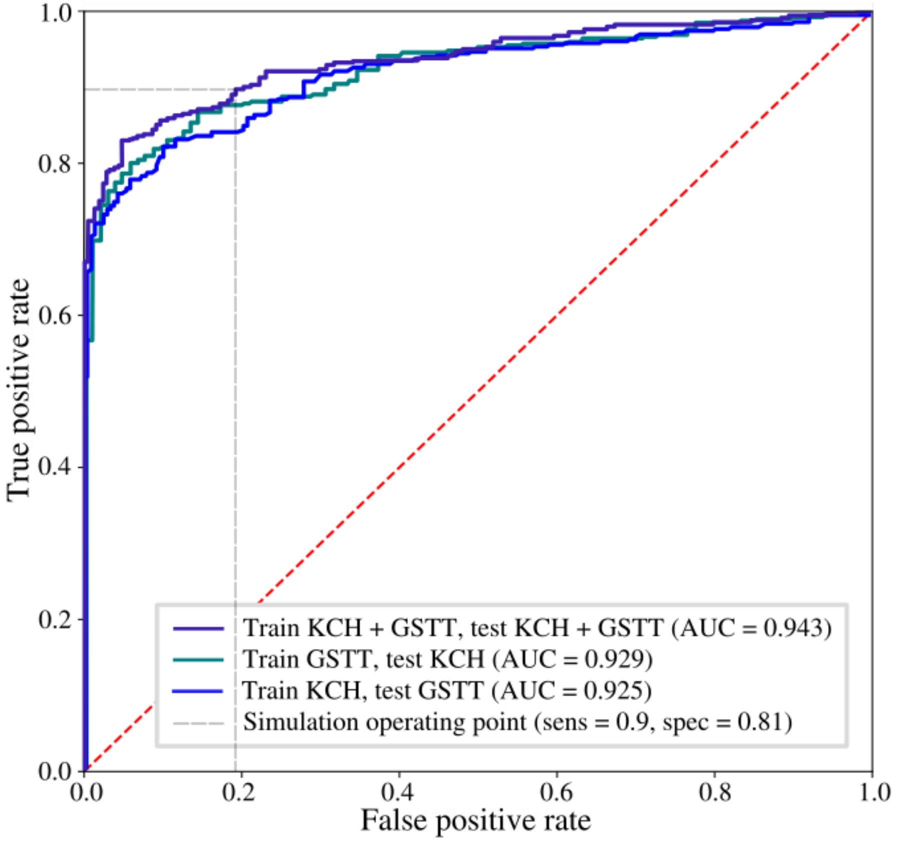
Triage tool to reduce reporting backlog of brain MRIs

- Accurate classification on a test set of 800 images manually labelled by two neuroradiologists (despite 90 classes of morphologically distinct abnormalities)

- Best model (AUC = 0.943) trained and tested on scans pooled from KCH + GSTT

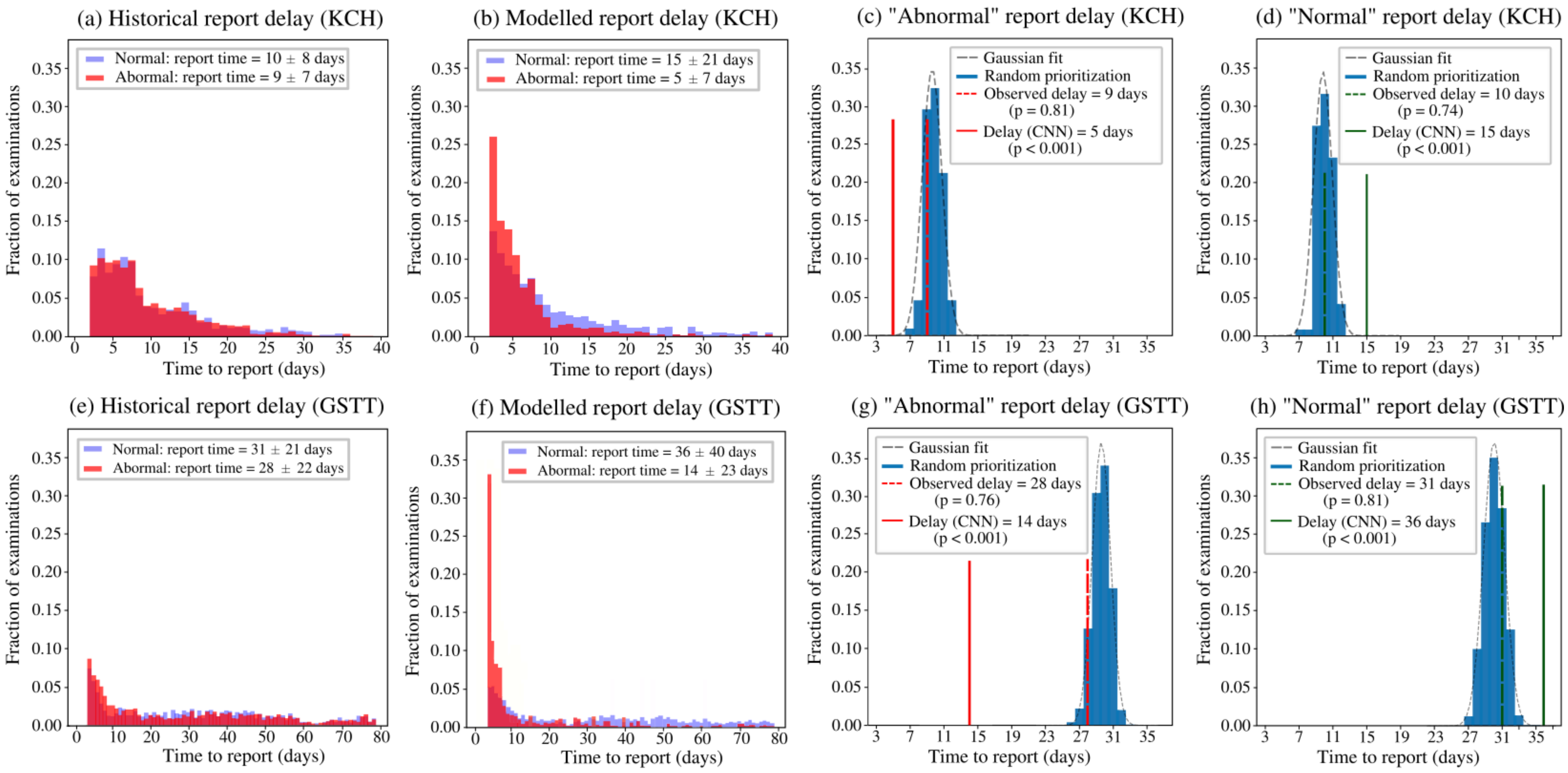
- Models generalised between hospitals (Δ AUC ≤ 0.02)

Train		KCH			GSTT			Pooled		
Test		KCH	GSTT	Pooled	KCH	GSTT	Pooled	KCH	GSTT	Pooled
Model	Baseline	0.921	0.909	0.915	0.903	0.918	0.912	0.925	0.920	0.922
	Noise-corrected	0.941	0.925	0.933	0.929	0.931	0.930	0.946	0.939	0.943

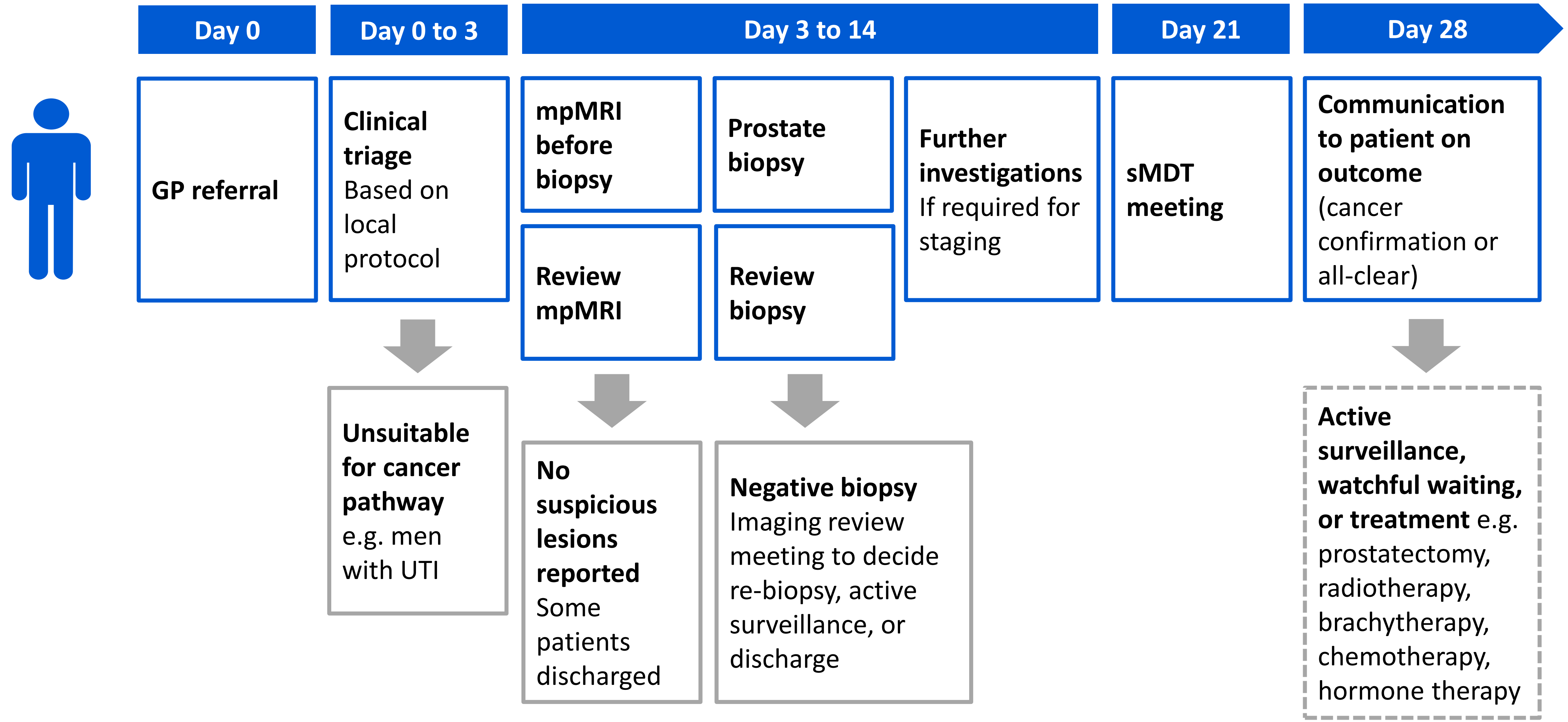


Triage tool to reduce reporting backlog of brain MRIs

- Retrospective simulation study performed using data from 1/1/18–31/12/18
- Reduction in abnormal reporting times (28-14 days GSTT, 9-5 days KCH)



Triage tool to help with prostate cancer 28-day diagnostic pathway

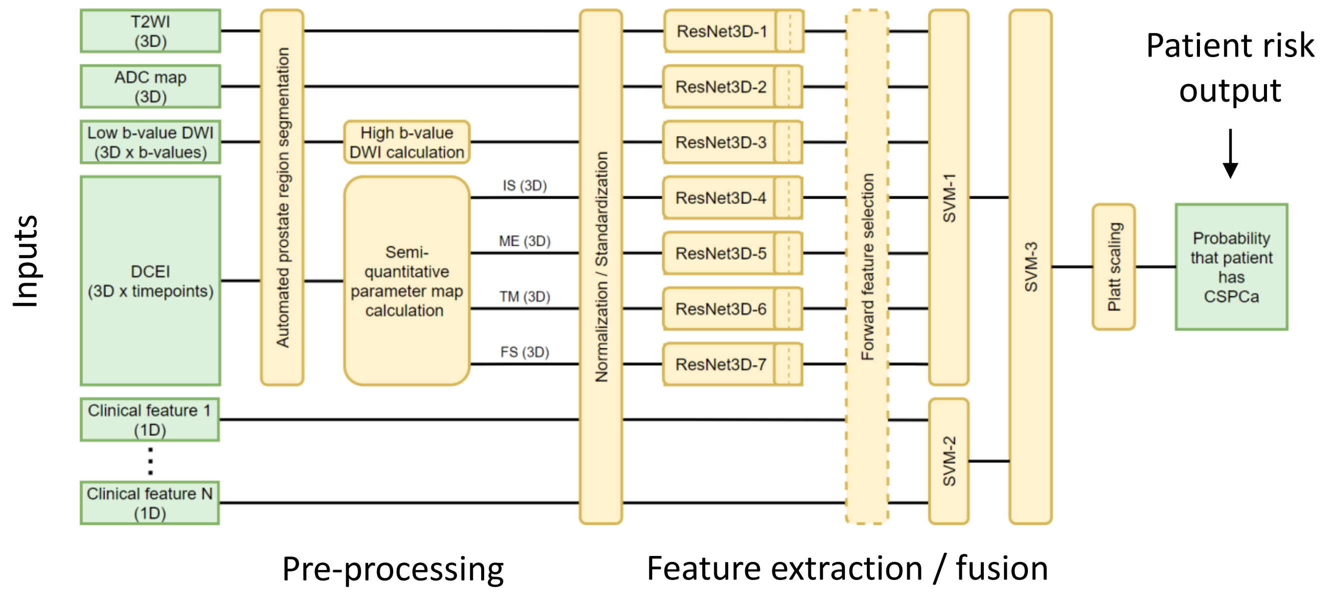


Source: NHS Cancer Programme. *Implementing a timed prostate cancer diagnostic pathway.* April 2018.

Triage tool to help with prostate cancer 28-day diagnostic pathway

Clinical challenge #1:
- Rising case incidence: 12% growth in cases projected in the UK between 2014 and 2035[1].
- Shortfall of clinical radiology consultants: 33% shortfall in the UK in 2020[2].
- MRI-based screening recommended by EAU-EANM-ESTRO-ESUR-SIOG guidelines[3].

Solution: AI-driven triage: Patient Classification Framework (PCF)[4]



Patient classification performance:
- Comparable sensitivity and specificity to an experienced radiologist (>10 years)[4].

Intended clinical use:
- For use following mpMRI collection, and prior to clinical read.
- **Rule out** lowest risk patients who can avoid clinical read / **prioritise** highest risk patients.

Steps to clinical adoption:
- Multicenter validation study.
- Deployment & prospective validation.

[1] www.cancerresearchuk.org/health-professional/cancer-statistics/statistics-by-cancer-type/prostate-cancer

[2] NHS Cancer Clinical Radiology UK workforce census 2020 report

[3] Mottet, N. et al. EAU-EANM-ESTRO-ESUR-SIOG Guidelines on Prostate Cancer—2020 Update. Part 1: Screening, Diagnosis, and Local Treatment with Curative Intent. *Eur. Urol.* **2021**, *79*, 243–262.

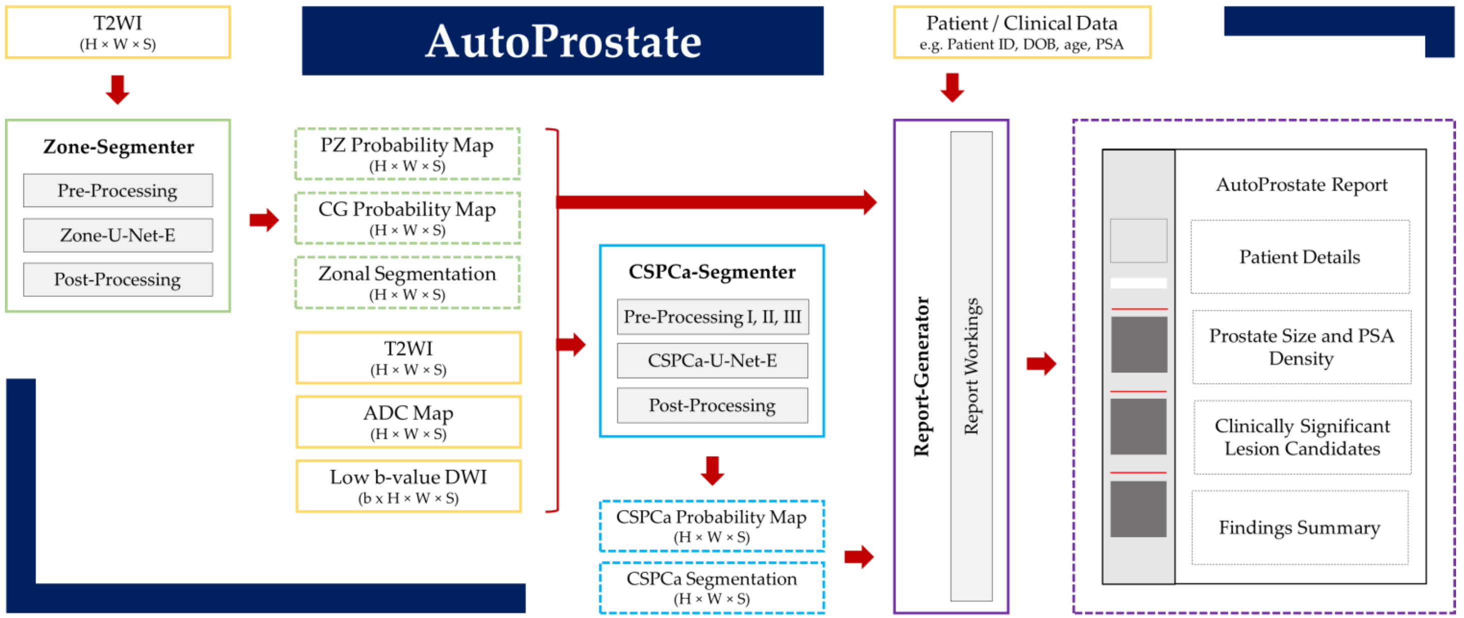
[4] Mehta, P. et al. Computer-aided diagnosis of prostate cancer using multiparametric MRI and clinical features: A patient-level classification framework. *Med. Image Anal.* **2021**, *73*, 102153 .

Triage tool to help with prostate cancer 28-day diagnostic pathway

Clinical challenge #2:

- ~10% of clinically significant cancers missed on mpMRI[1].
- ~50% men undergo an unnecessary biopsy[1].
- High inter-reader variability[1].

Solution: AutoProstate: A Deep Learning-Powered Framework for Automated MRI-Based Prostate Cancer Assessment[2].



Standalone performance:

- Improved prostate volume and prostate-specific antigen density estimation.
- Matched experienced radiologist (>10 years) detection sensitivity.

Intended clinical use:

- **Companion system** for radiologists to improve diagnostic accuracy / reduce variability in diagnosis.

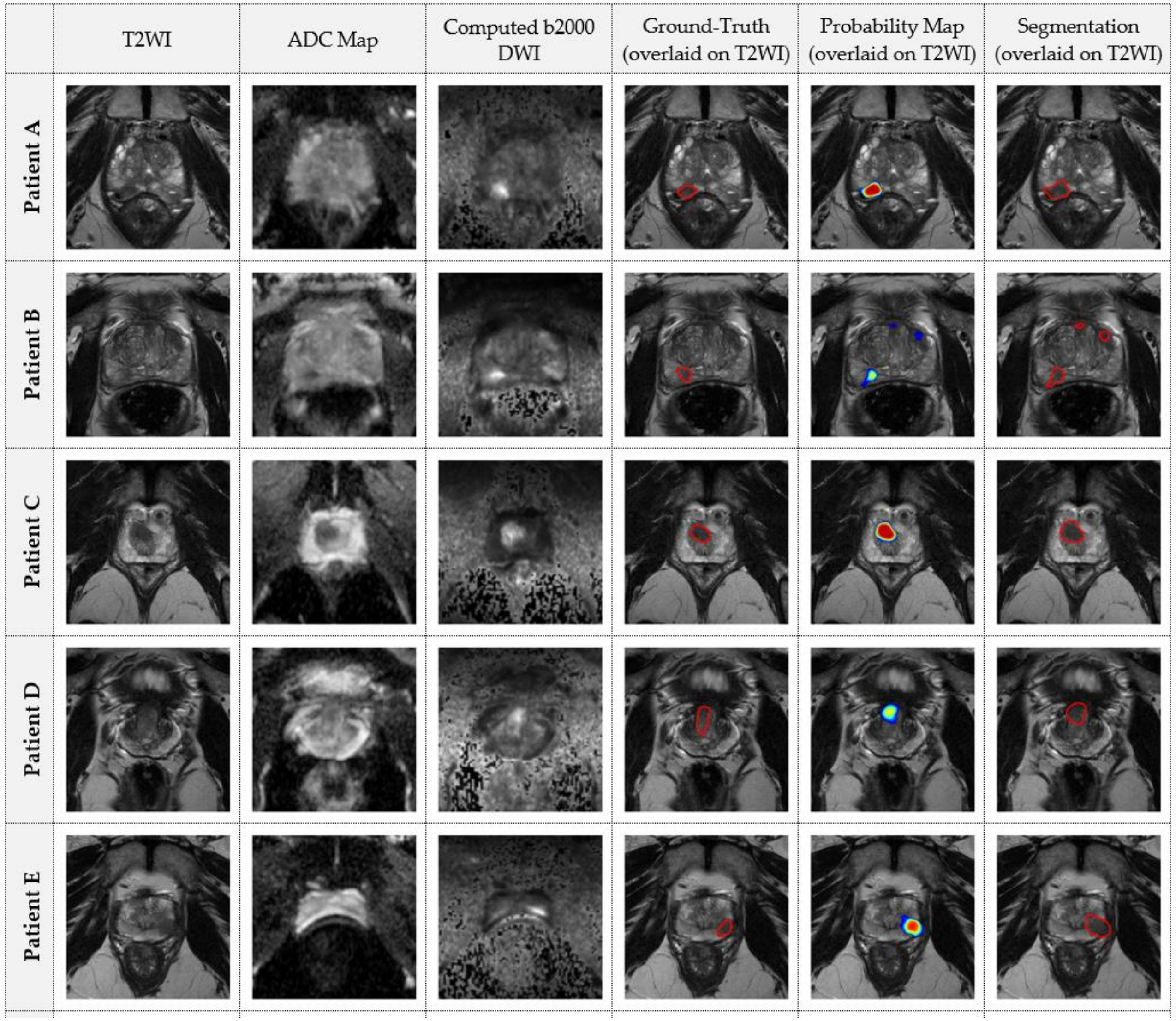
Steps to clinical adoption:

- Multicenter validation study.
- Deployment & prospective validation.

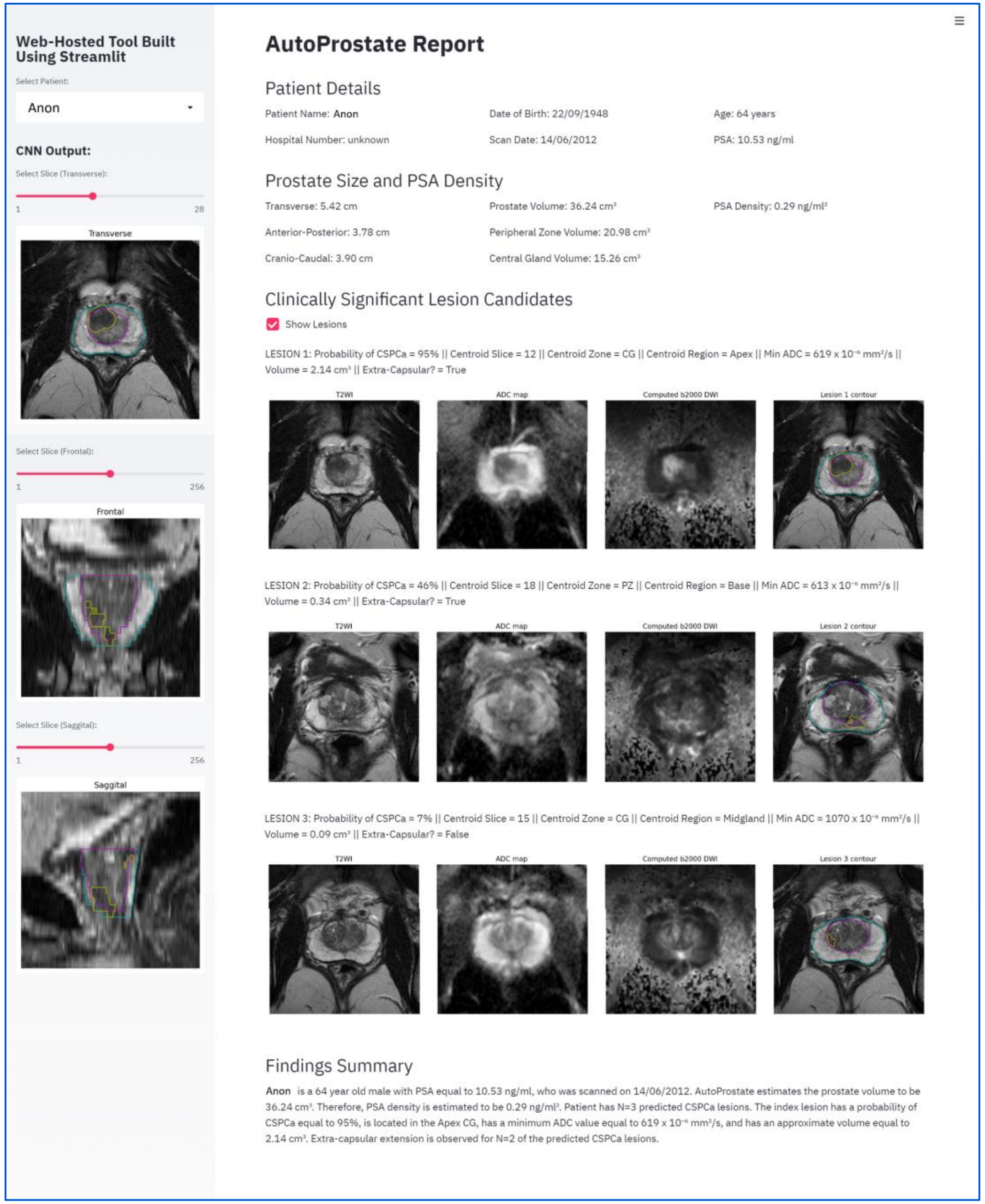
[1]Ahmed, H.U. et al. Diagnostic accuracy of multi-parametric MRI and TRUS biopsy in prostate cancer (PROMIS): a paired validating confirmatory study. *Lancet* **2017**, *389*, 815–822.

[2]Mehta, P. et al. AutoProstate: A Deep Learning-Powered Framework for Automated MRI-Based Prostate Cancer Assessment. *Under review*.

Triage tool to help with prostate cancer 28-day diagnostic pathway



AutoProstate clinically significant prostate cancer lesion segmentations



AutoProstate report for 64-year-old man with a Gleason score 3+4 (significant) tumour in the transition zone

Clinical decision support for patients having cardiac MRIs

AI-based image-selection

Pre-processing QC of images

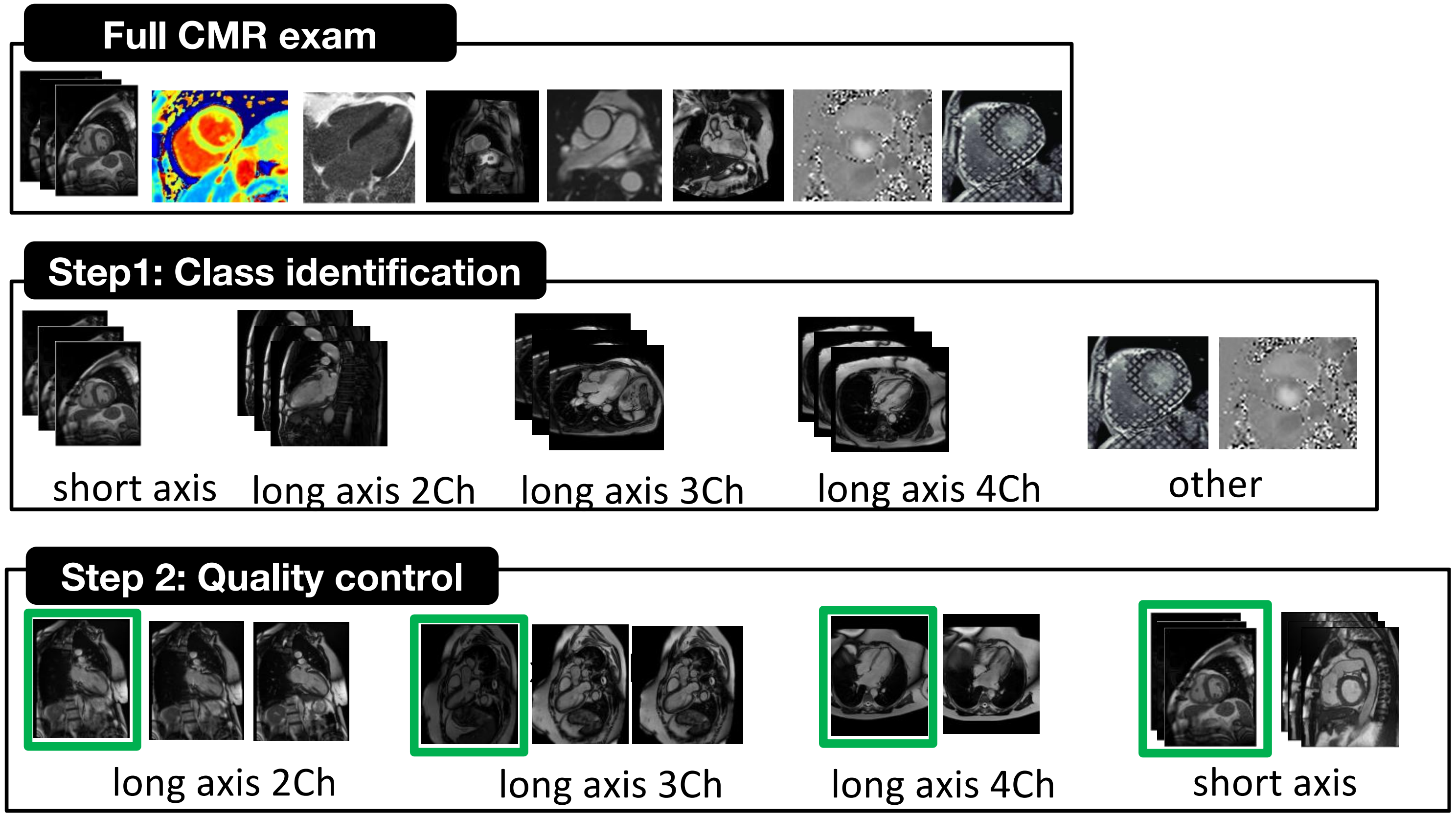
Analysis of CMR
(segmentation, detection, classification)

Post-processing QC

Interpretation to guide clinical decisions
(Reports, Classification, Longitudinal trends)

QC= quality control

Clinical decision support for patients having cardiac MRIs



<u>Step 1 and 2: DenseNet classifier</u>

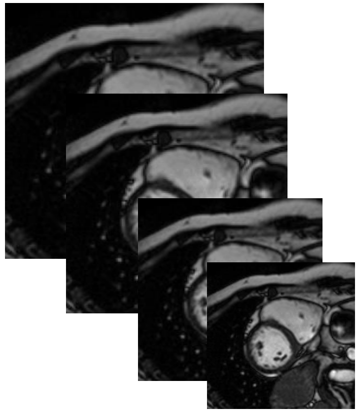
- UKBB & GSTT data
- Validated against experienced CMR cardiologist
- Validation on 400 clinical exams

2-chamber		
BACC	SEN	SPE
90.6	89.7	91.5
3-chamber		
BACC	SEN	SPE
89.2	93.2	85.3
4-chamber		
BACC	SEN	SPE
91.6	89.2	94.5

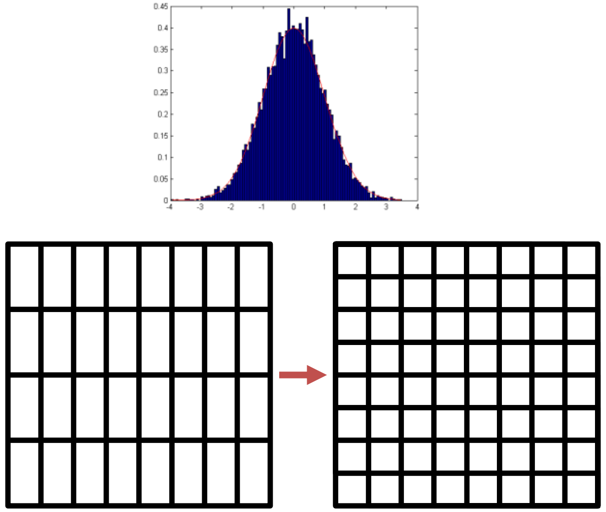
Clinical decision support for patients having cardiac MRIs

nnU-Net framework to segment the short axis and long axis CMR sequences

Input images

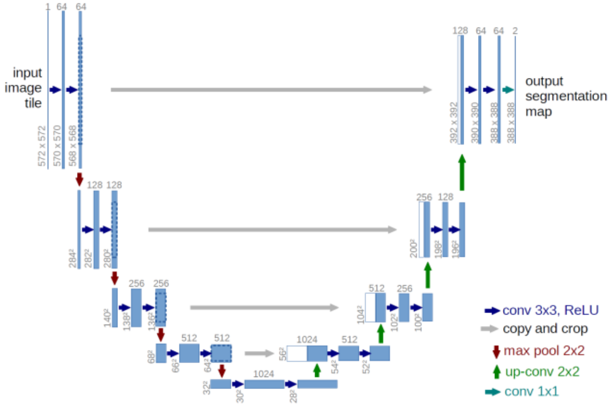


Pre-processing

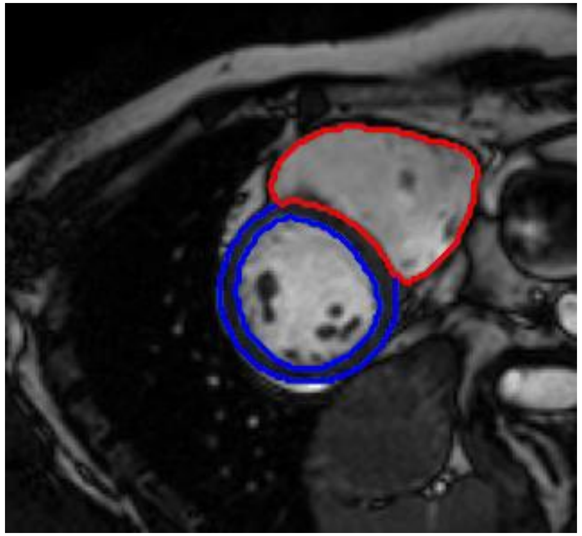


Training (learning)

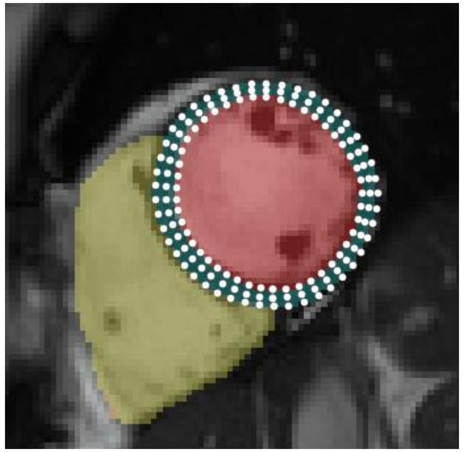
U-Net

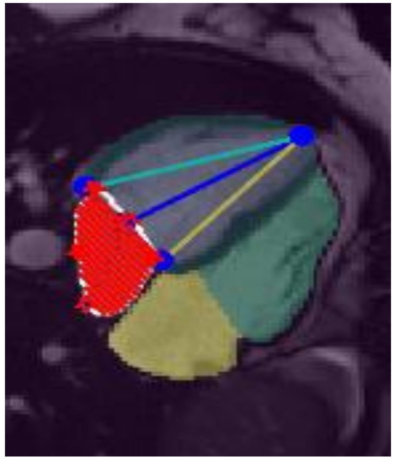


Segmentation



Cardiac function assessment ID XXX			
LV EDV (mL)	170	RV EDV (mL)	178
LV ESV (mL)	75	RV ESV (mL)	83
LV SV (mL)	95	RV SV (mL)	95
LV EF (%)	56	RV EF (%)	47
LV peak ejection rate (mL/s)	473	LV peak circumferential strain (%)	-21
LV peak filling rate (mL/s)	408	LV peak radial strain (mL/s)	+51
LV peak atrial filling rate (mL/s)	155	LV peak 2ch long. strain (%)	-19
LV atrial contribution (mL)	24	LV peak 4ch long. strain (%)	-18



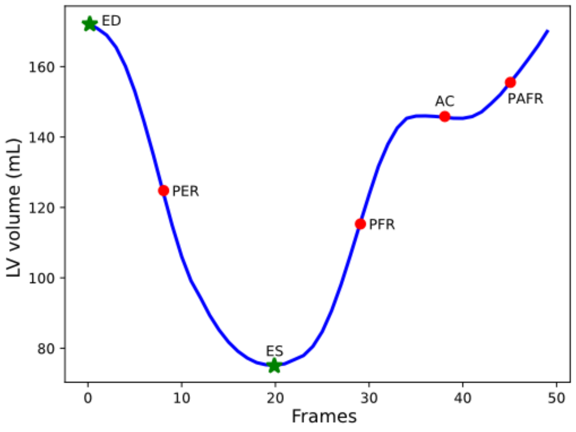


Clinical decision support for patients having cardiac MRIs

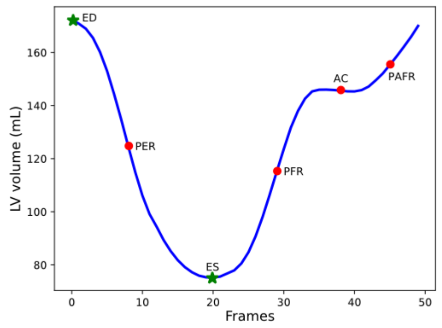
Clinicians use prior knowledge
- Physiological principals
- Expected behaviour

Contraction-relaxation follows certain principles
- Volume Curve
- Strain curves

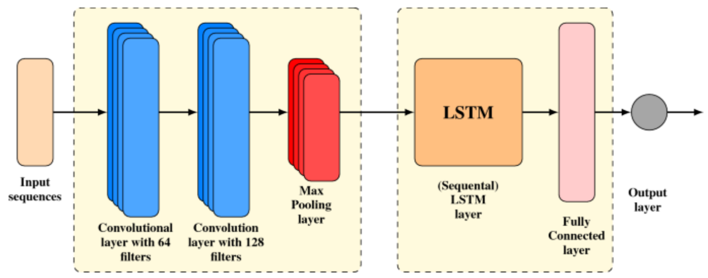
Can we use this knowledge to detect potential errors?



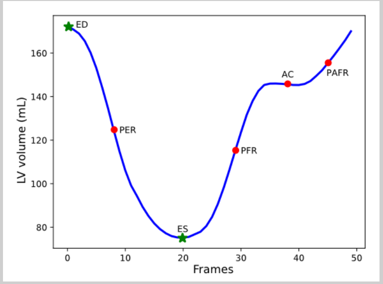
Cardiac Volumes



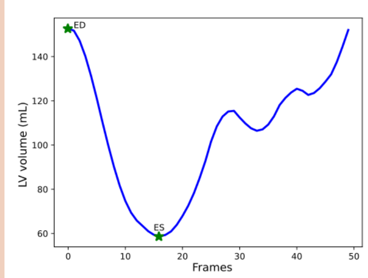
CNN/LSTM network



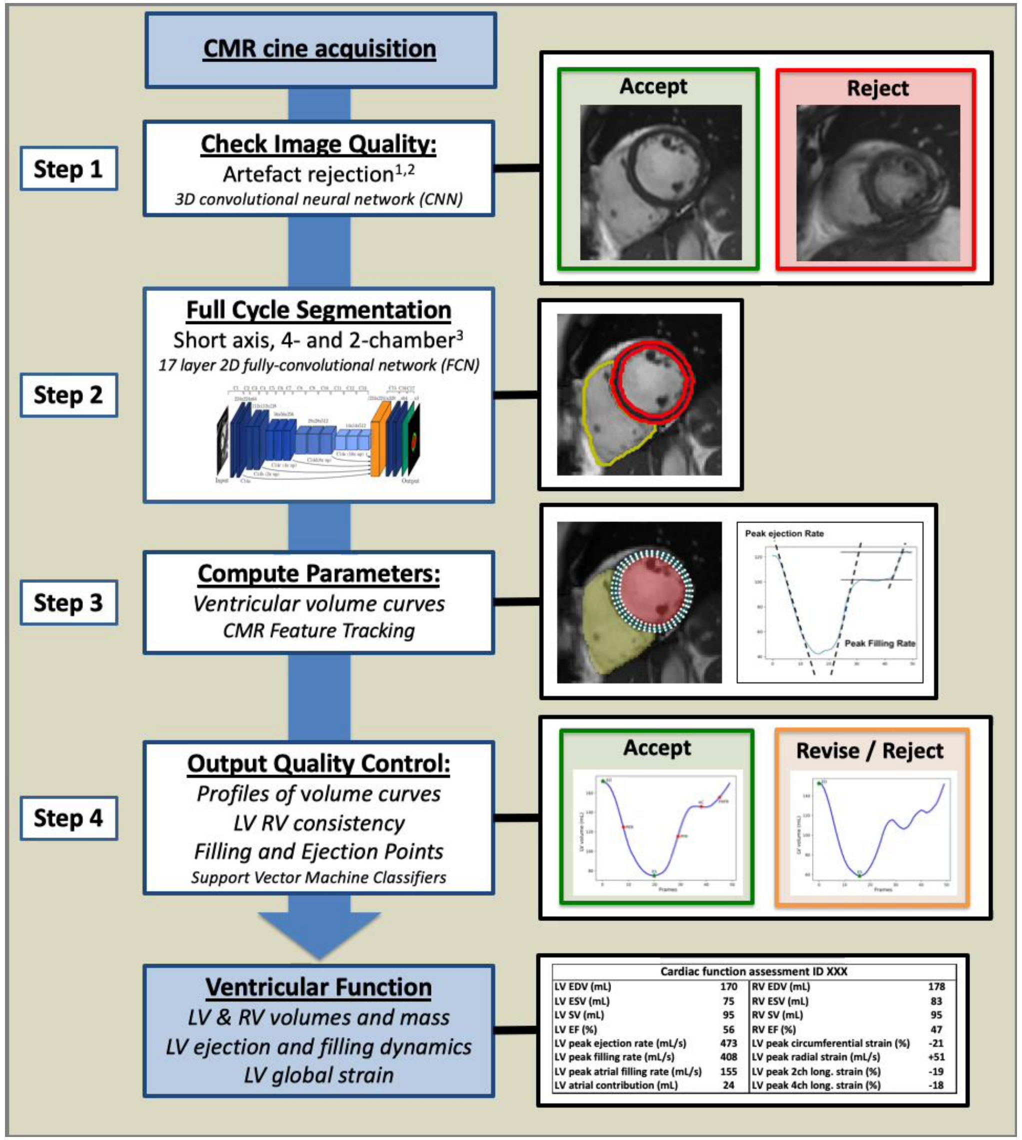
Accept



User revision



Clinical decision support for patients having cardiac MRIs



LV RV segmentation algorithm

- GSTT & UKBB data
- Human-level accuracy[1]
- Limits of agreement vs. man ±6-7 mL

CMR Feature Tracking

- Limits of agreement vs. cvi42: ±4-7%

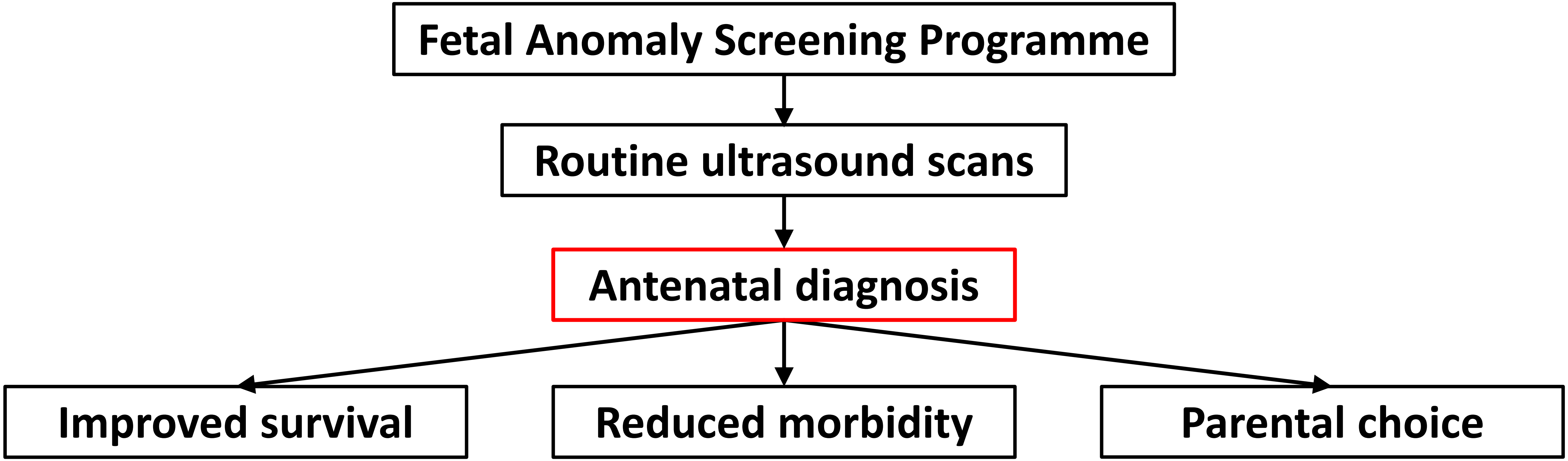
Total image-processing pipeline

- Validated against experienced CMR cardiologist
- 700 cases (500 healthy 200 ischemic CM)
- Sensitivity of detecting errors
  - Volumes 94.99%
  - Strain 93.21%

B. Ruijsink and E. Puyol-Antón, et al. "Fully automated, quality-controlled cardiac analysis from CMR: validation and large-scale application to characterize cardiac function." *JACC: Cardiovascular Imaging* 13.3 (2020): 684-695.

Scanning support for antenatal fetal abnormality screening

Ultrasound-based screening programmes aim to detect fetal anomalies before babies are born



Scanning support for antenatal fetal abnormality screening

- However these screening programmes currently fail to achieve universal detection

- In the UK, ***half*** of babies undergoing surgery for major heart disease are diagnosed only after they are born

- Can AI help improve this?

Heart disease detection rates

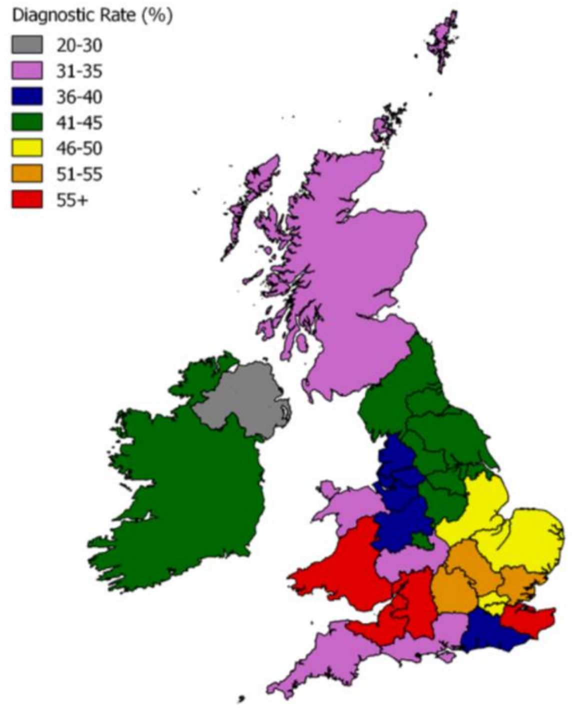
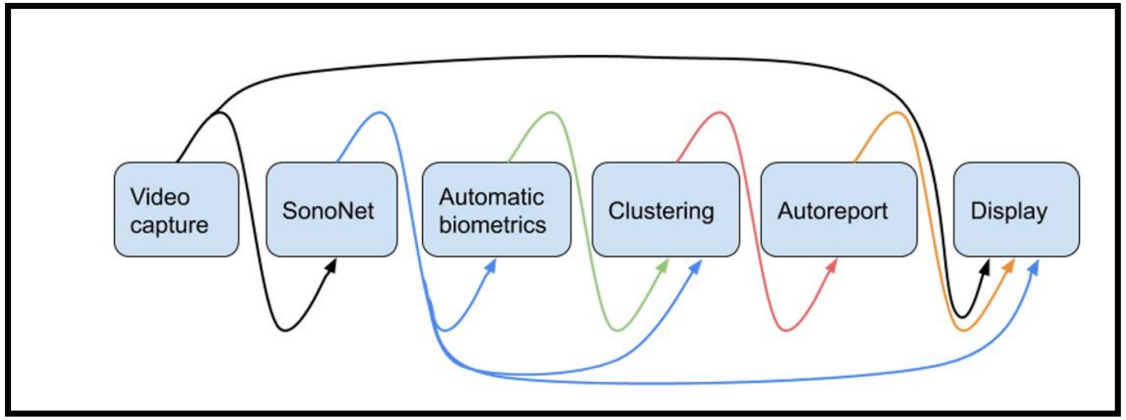


Figure adapted from The National Congenital Heart Disease Audit Website

Scanning support for antenatal fetal abnormality screening

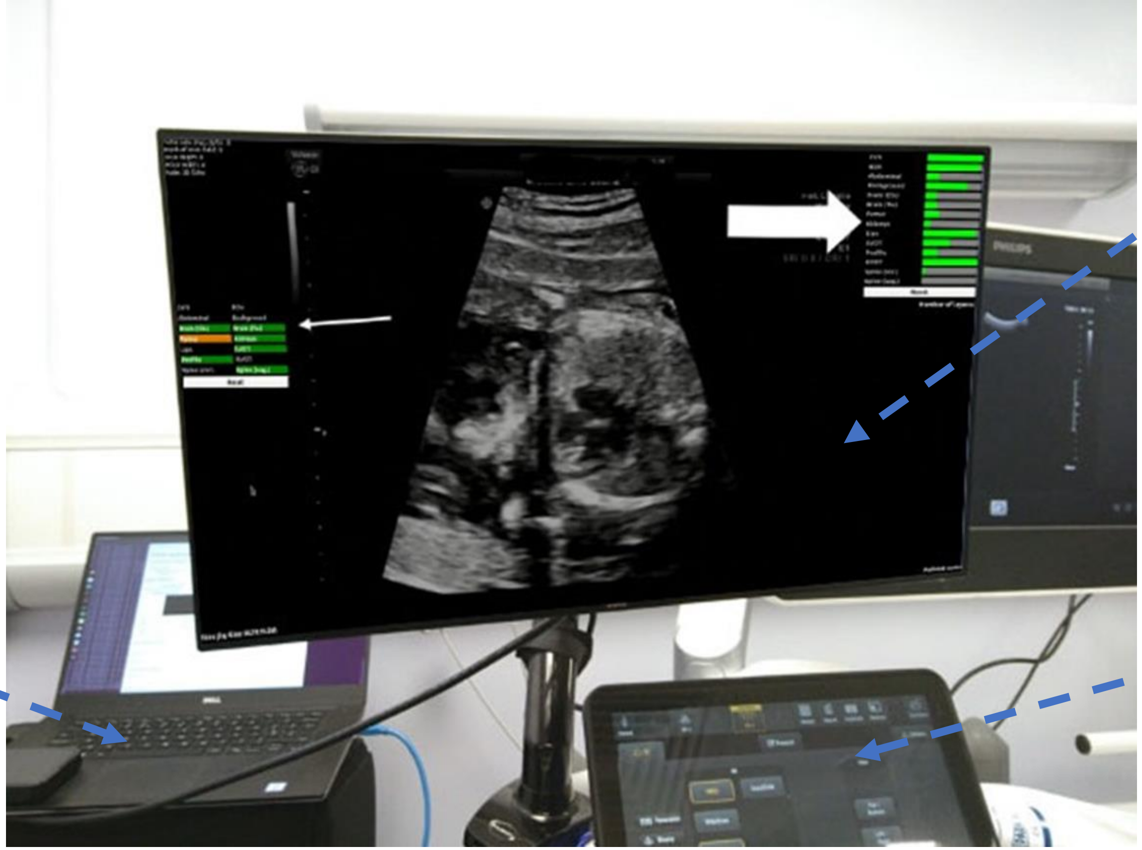
- Several AI models combined into a single, clinically usable tool
- Analyses the stream of ultrasound video in real-time, with feedback to the sonographer

Clinical tool:



Scanning support for antenatal fetal abnormality screening

Additional monitor giving real-time feedback to sonographers

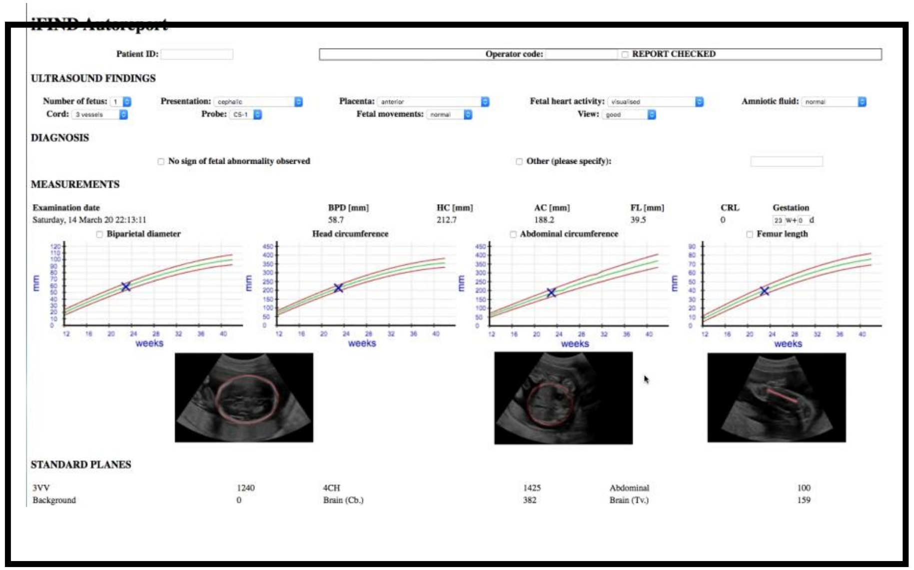


Laptop running AI models

Standard clinical ultrasound machine

Scanning support for antenatal fetal abnormality screening

- 23 pregnant women with healthy fetuses scanned with both AI-assisted and standard manual ultrasound techniques
- Removes need to pause, measure, save images- AI **completely disrupts** the way the scan is performed
- **Automatic report** means that sonographers have a chance to review and assess the automatically saved images and measurements:



Scanning support for antenatal fetal abnormality screening

- **Significant time savings**- average AI scan 14 minutes vs 22 minutes for standard manual scan: more time to focus on important aspects

- Automatic measurement of fetal body size **highly accurate and reproducible**: frees sonographer to concentrate on detecting disease

- Future work: addition of AI to automatically detect fetal disease

Conclusion

- Covid-19 pandemic has left a very large delivery problem for the NHS and **accelerated deployment of healthcare technologies** including AI will need to be part of the solution
- Making **NHS Data available for AI tool development at scale**, “bringing the algorithms to the data” and **empowering NHS Trusts to deploy AI tools** into their day-to-day workflow core to the mission of the London AI centre for Value Based Healthcare
- Enabling **industry, NHS, academic teams to create innovate products** and scale them in the NHS and internationally
- Many clinical pathways are being addressed with a focus on value – **improving outcomes and reducing costs** with strong engagement with NHS commissioners and health economics
- The big challenge remains the readiness of the wider NHS to accept innovative technology into it’s clinical workflow but much is being done to address this challenge.

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