

Big Data, ML & AI in Diagnostics

Dr Vidur Mahajan, MBBS, MBA
Chief Executive Officer, CARPL.ai

Big data, ML & AI – are they just the same thing?

Big Data

Infinitely large data that cannot be analysed using traditional data processing techniques

Machine Learning

When machines learn to perform tasks, or learn insights from data

Artificial Intelligence

When the learned tasks emulate human cognition, or even surpass it

AI IS WHATEVER MACHINES CAN'T DO YET
- Wikipedia

Automation in Diagnostics



Thyrocare's Lab

Automation in Diagnostics – Pathology & Lab Medicine

Pathology & Lab Medicine has
scaled exponentially
due to robotics and automation

Pathologists sign out
1000s of tests per day

Only review '**edge**' or
'**abnormal**' tests –
rest auto-reported

Democratisation of
blood testing

What about Radiology?

Radiology clinical flow has remained
largely unchanged for the
past several decades

Yes, **PACS and digitization** have
come

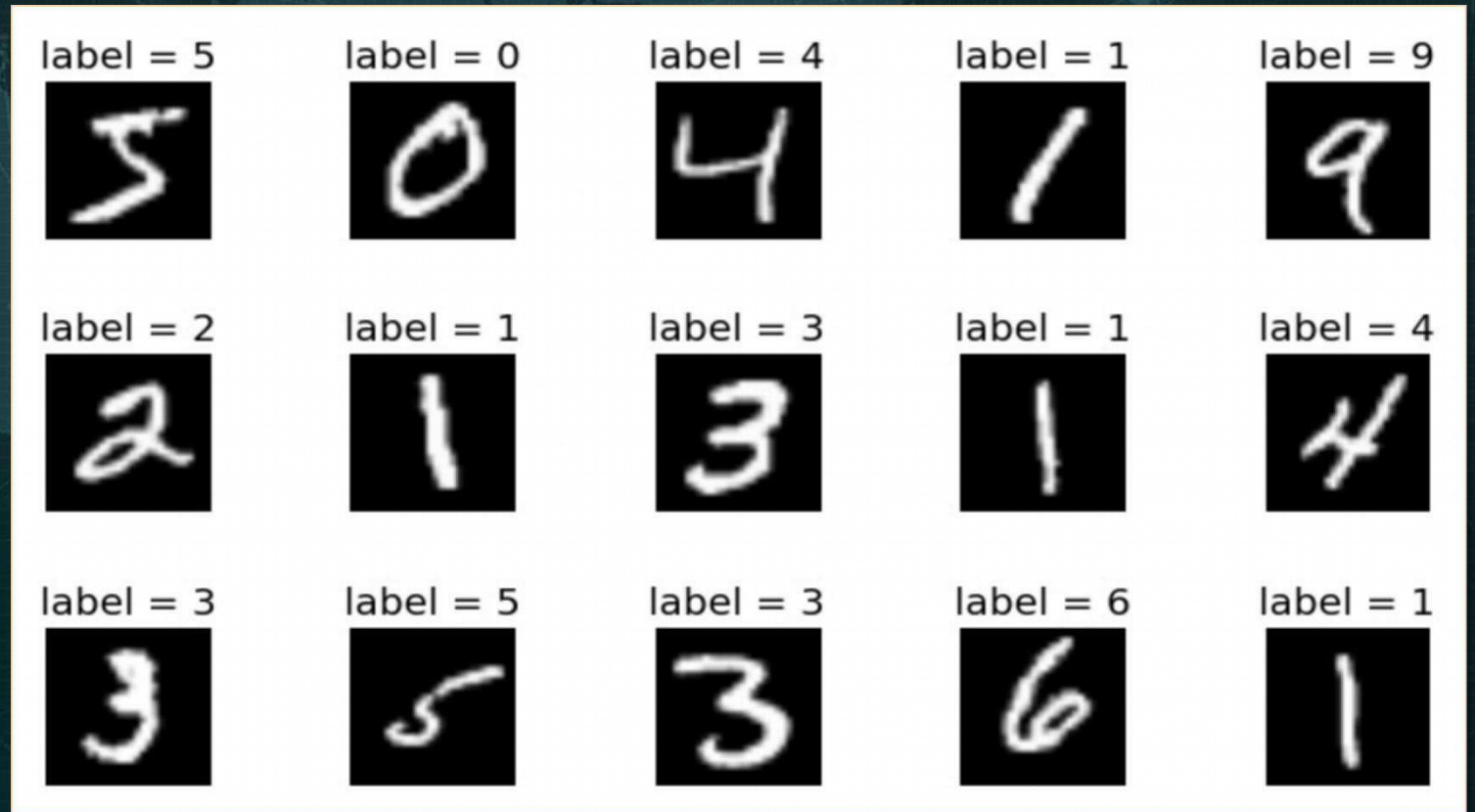
Radiologists still **“see”**
all scans

Even though it is a
“fixed cost” business

Deep Learning is transforming the world of radiology!

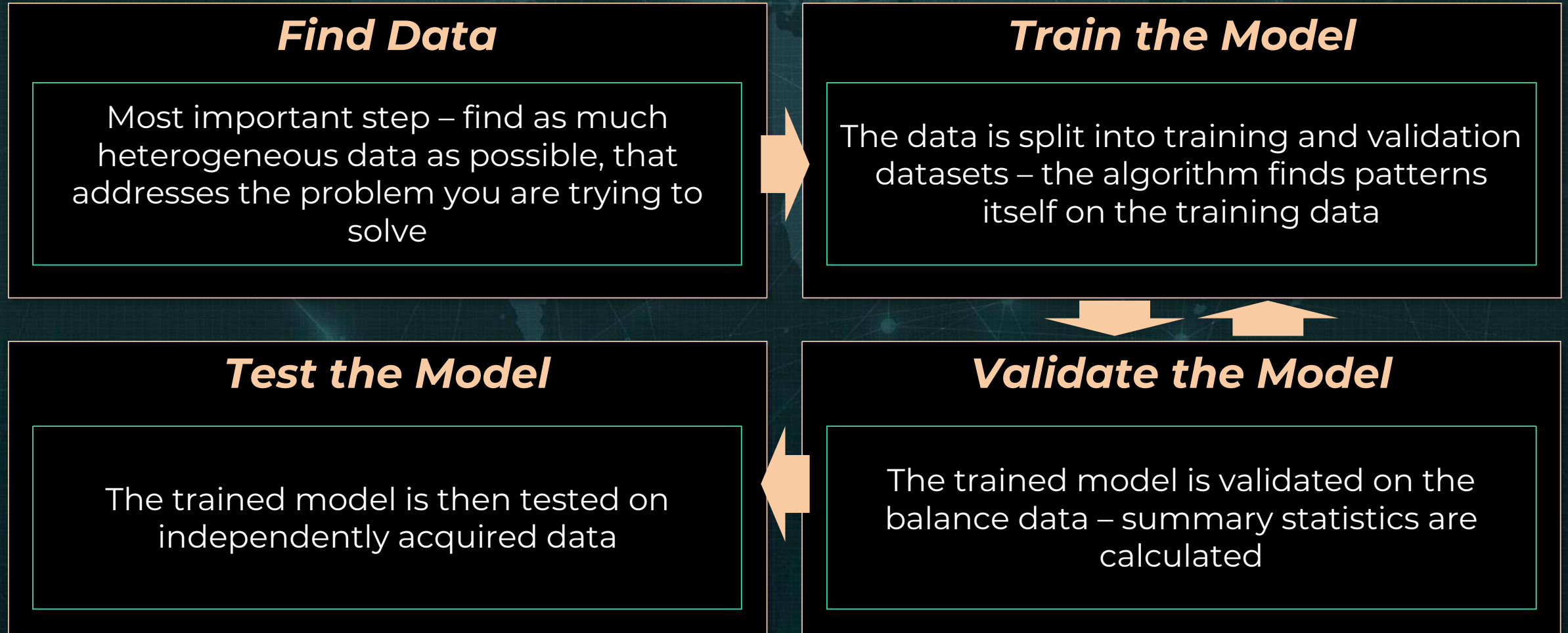
What is Deep Learning? Supervised Learning?

- Traditional technique – most healthcare AI is focused on this
- Labour intensive – “Ground Truth” is vital
- Involves “feeding” labelled data into algorithms so that patterns in the data are recognised
- For example – Facebook’s face detection only works once enough pictures of people are tagged by users

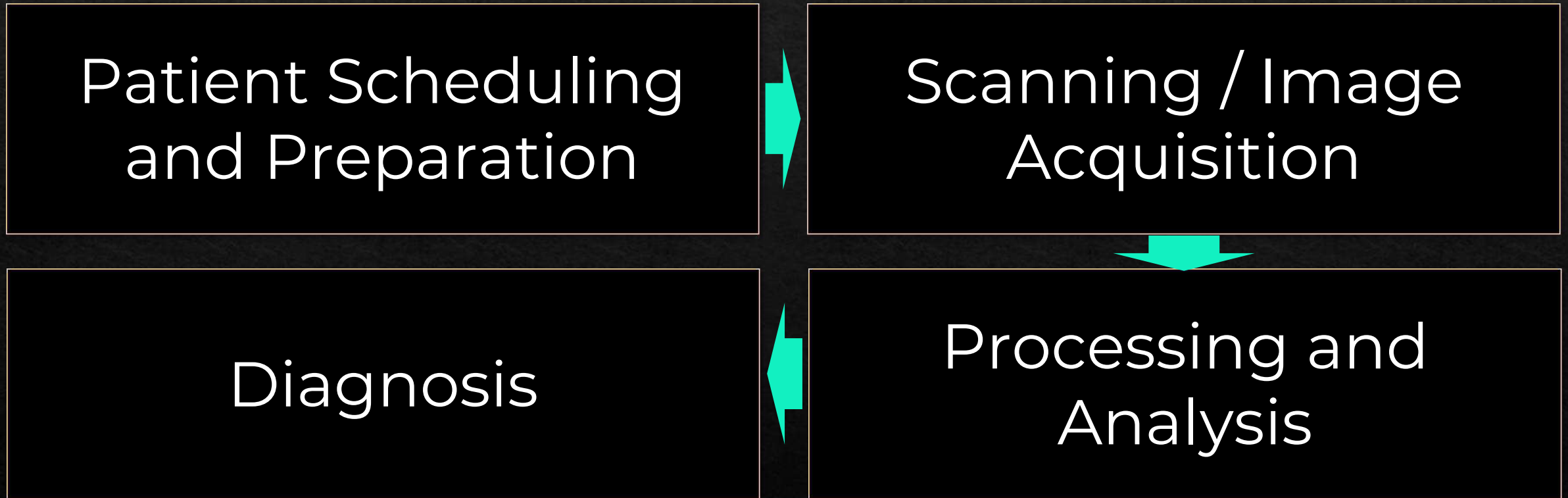


EMNIST Dataset for Digits

How is an AI algorithm created?



SOME EXAMPLES FROM RADIOLOGY



SOME EXAMPLES FROM RADIOLOGY

Patient Scheduling
and Preparation

Scanning / Image
Acquisition

Diagnosis

Processing and
Analysis

PRE-SCANNING: PREDICTING PATIENT WAIT TIMES!

[J Am Coll Radiol](#). 2018 Sep;15(9):1310-1316. doi: 10.1016/j.jacr.2017.08.021. Epub 2017 Oct 24.

Machine Learning for Predicting Patient Wait Times and Appointment Delays.

[Curtis C](#)¹, [Liu C](#)¹, [Bollerman TJ](#)¹, [Pianykh OS](#)².

Author information

- 1 Department of Radiology, Massachusetts General Hospital, Boston, Massachusetts.
- 2 Department of Radiology, Massachusetts General Hospital, Boston, Massachusetts. Electronic address: opianykh@mgh.harvard.edu.

Abstract

Being able to accurately predict waiting times and scheduled appointment delays can increase patient satisfaction and enable staff members to more accurately assess and respond to patient flow. In this work, the authors studied the applicability of machine learning models to predict waiting times at a walk-in radiology facility (radiography) and delay times at scheduled radiology facilities (CT, MRI, and ultrasound). In the proposed models, a variety of predictors derived from data available in the radiology information system were used to predict waiting or delay times. Several machine-learning algorithms, such as neural network, random forest, support vector machine, elastic net, multivariate adaptive regression splines, k-th nearest neighbor, gradient boosting machine, bagging, classification and regression tree, and linear regression, were evaluated to find the most accurate method. The elastic net model performed best among the 10 proposed models for predicting waiting times or delay times across all four modalities. The most important predictors were also identified.

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PRE-SCANNING: WILL THE PATIENT SHOW UP?

npj | Digital Medicine

www.nature.com/npjdigitalmed

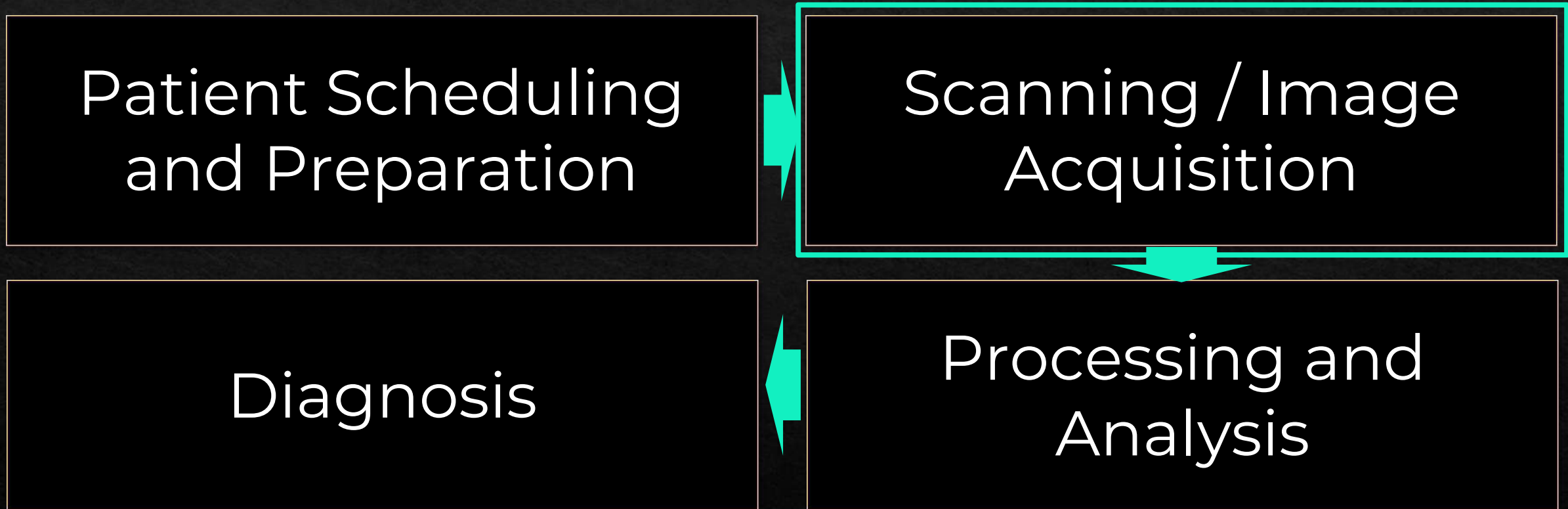
ARTICLE OPEN

Predicting scheduled hospital attendance with artificial intelligence

Amy Nelson¹, Daniel Herron², Geraint Rees^{3,4,5}  and Parashkev Nachev¹

Failure to attend scheduled hospital appointments disrupts clinical management and consumes resource estimated at £1 billion annually in the United Kingdom National Health Service alone. Accurate stratification of absence risk can maximize the yield of preventative interventions. The wide multiplicity of potential causes, and the poor performance of systems based on simple, linear, low-dimensional models, suggests complex predictive models of attendance are needed. Here, we quantify the effect of using complex, non-linear, high-dimensional models enabled by machine learning. Models systematically varying in complexity based on

SOME EXAMPLES FROM RADIOLOGY

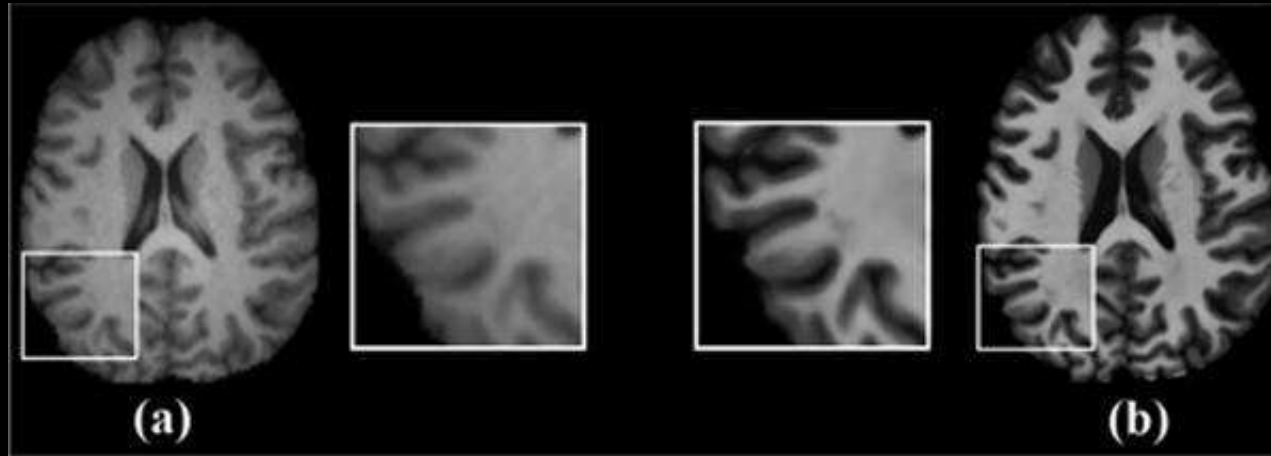


Automation of the MR protocoling process

The screenshot displays the AIRx™ software interface, which is used for automating MR slice prescription. The interface is divided into two main sections: 'Patient' and 'Exam'. The 'Patient' section contains a list of patient names, with 'John' and 'Doe' visible. A mouse cursor is hovering over the 'John' button. The 'Exam' section contains a list of exam types, represented by empty rectangular boxes. The interface is designed to streamline the selection of patients and exams for MR imaging.

AIRx™: Intelligent MR slice prescription developed by GE

Reconstruction of 7T-Like Images From 3T MRI

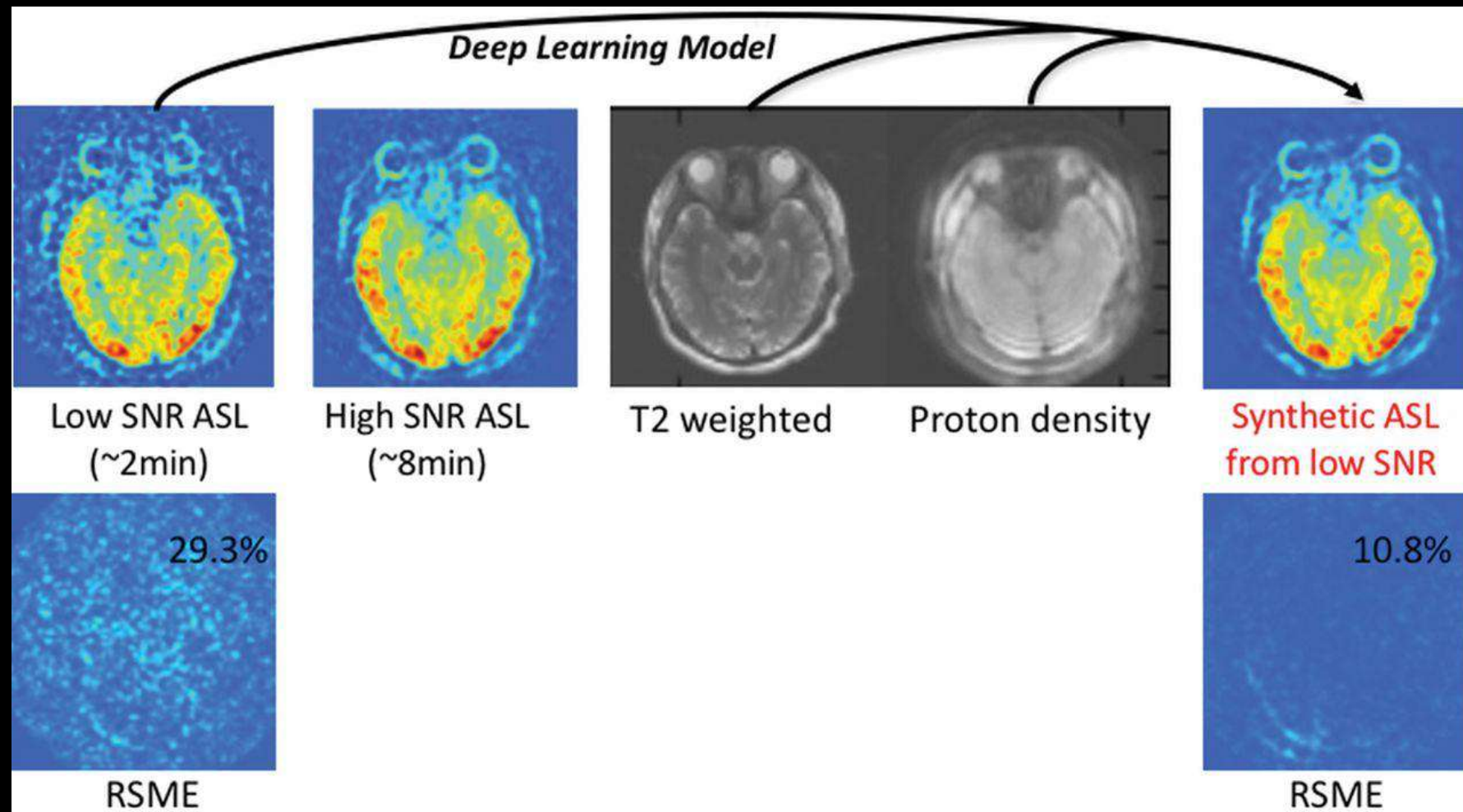


Axial views of (a) 3T MRI and (b) 7T MRI of the same subject, together with the zoomed regions. 7T MRI shows better anatomical details and tissue contrast compared to 3T MRI.



Deep learning based Reconstruction results for a brain region

Improving the SNR of ASL MR using deep learning



Gong E, Pauly J, Zaharchuk G. Proceedings of the Annual Meeting of the International Society for Magnetic Resonance in Medicine, Honolulu, Hawaii. April 22-27, 2017

Deep Learning Based Image Recon for Low Dose CT

FDA Clears GE's Deep Learning Image Reconstruction Engine

Engine provides TrueFidelity CT images for Revolution, Revolution Apex CT systems; FDA also clears trio of CT applications



April 19, 2019 – GE Healthcare has received 510(k) clearance from the U.S. Food and Drug Administration (FDA) of its Deep Learning Image Reconstruction engine on the new Revolution Apex **computed tomography (CT)** device. The engine has also been approved as an upgrade to GE's Revolution CT system in the United States.

Synthetic PET – Generate PET Images from CT

Synthetic PET Generator: A Novel Method to Improve Lung Nodule Detection by Combining Outputs from a Pix2pix Conditional Adversarial Network and a Convolutional Neural Network Based Malignancy Probability Estimator

V Venugopal¹, MD, New Delhi, India; A Chunduru², MENG; S Vaidya², BEng, MENG;
V Mahajan¹, MBA, MBBS; H Mahajan¹, MD, MBBS

¹Centre for Advanced Research in Imaging, Neurosciences and Genomics, New Delhi

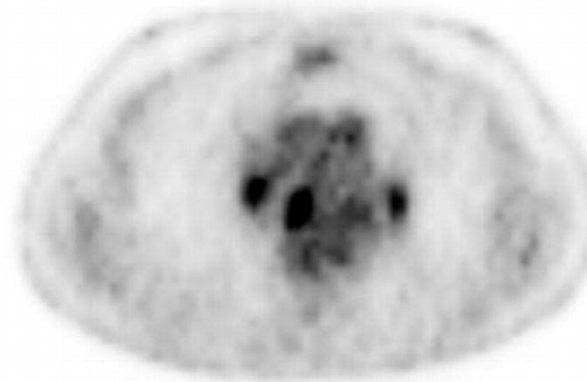
²Predible Health, Bangalore

A better lung nodule characterisation tool using ‘Synthetic PET’?

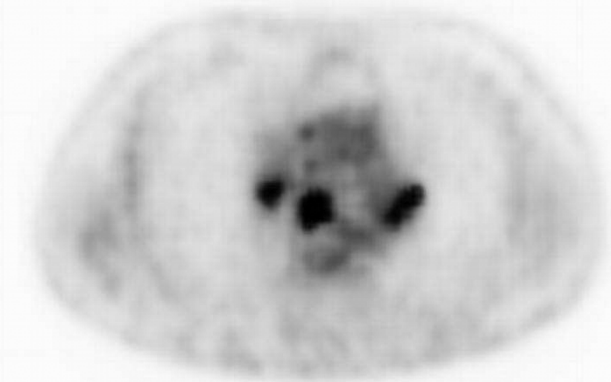
Synthetic PET – Generate PET Images from CT



Input CT Image

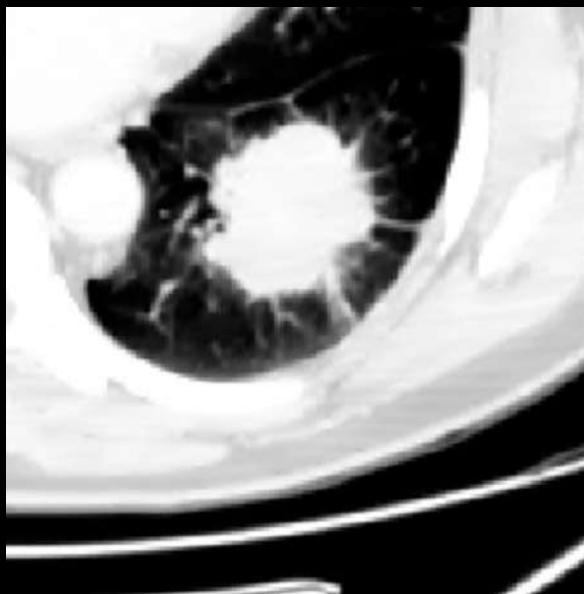


True PET

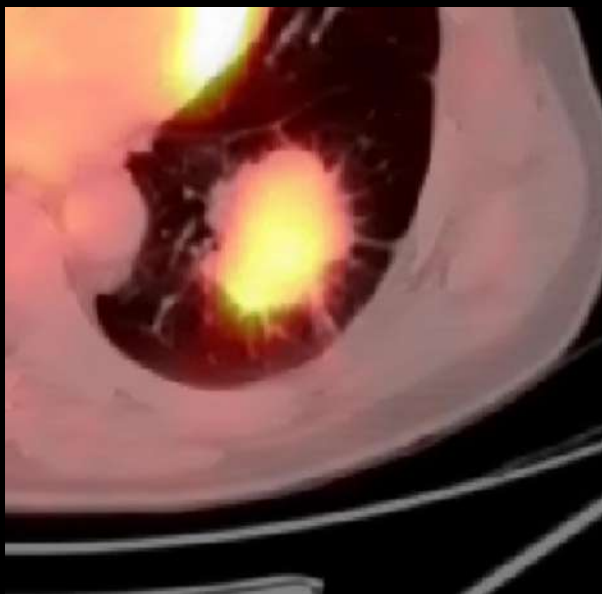


Synthetic PET

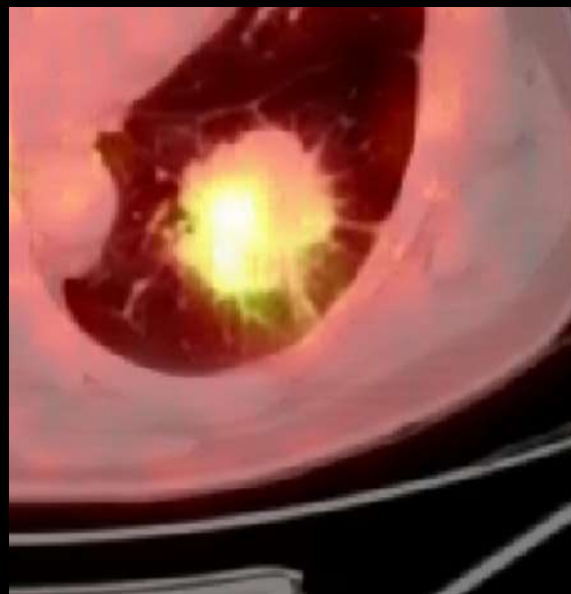
Presented at RSNA 2018



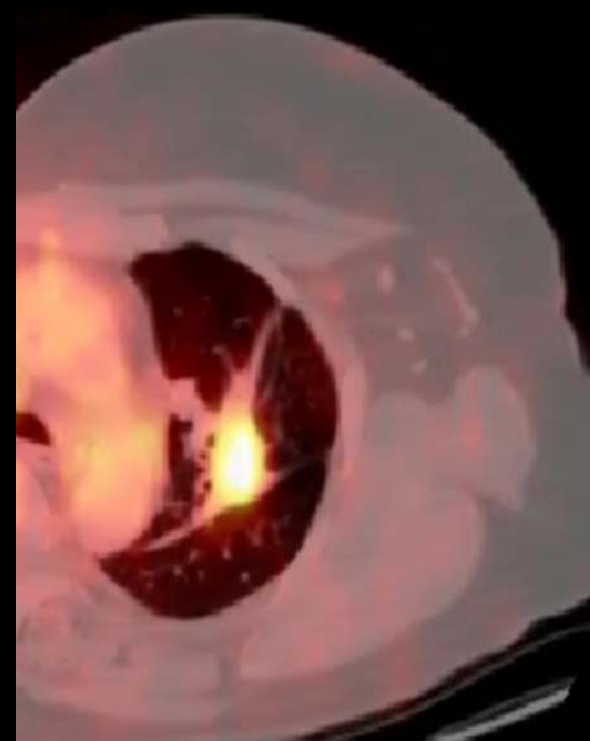
CT input

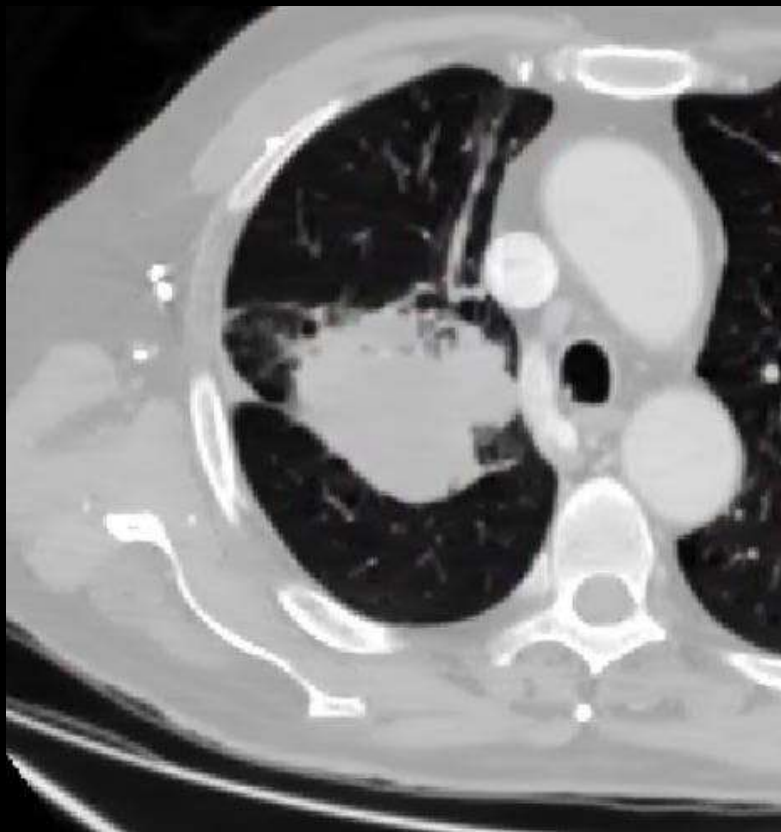


PET overlay



Synthetic PET overlay

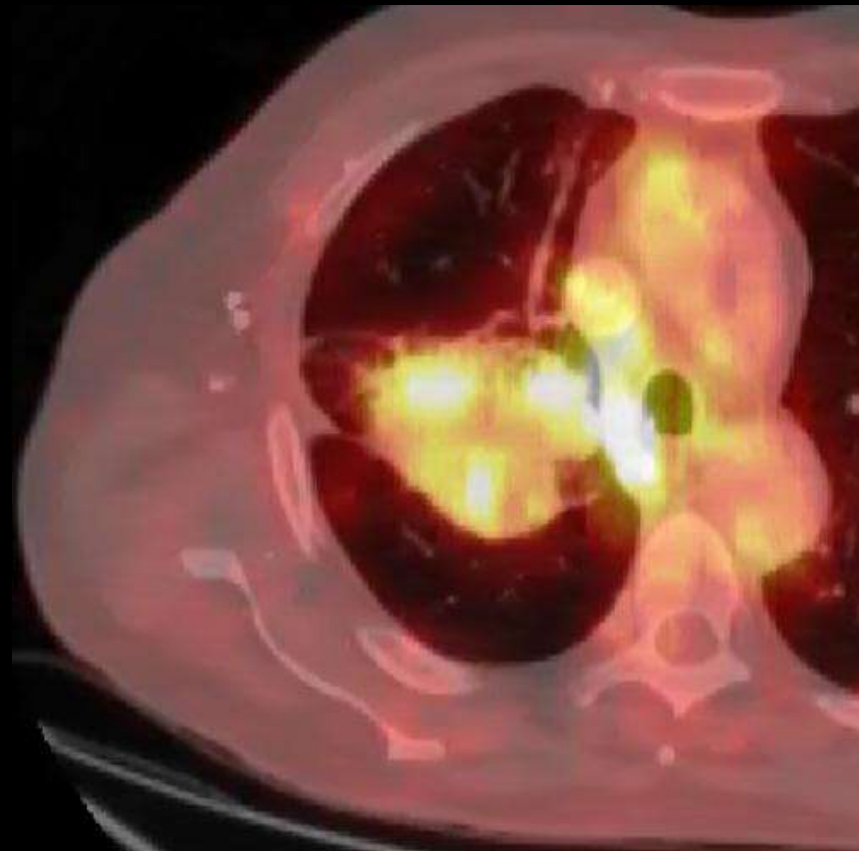




CT input



PET overlay



Synthetic PET overlay

SCANNING: CREATING VIRTUAL MRI!

VIGANIT™: Towards Virtual MR Imaging – Predicting T1- and Diffusion-Weighted Brain Images from T2-Weighted MR Images Using Convolutional Neural Networks

Mahajan V¹, Venugopal V¹, Upadhyay A², Venkatraman A²

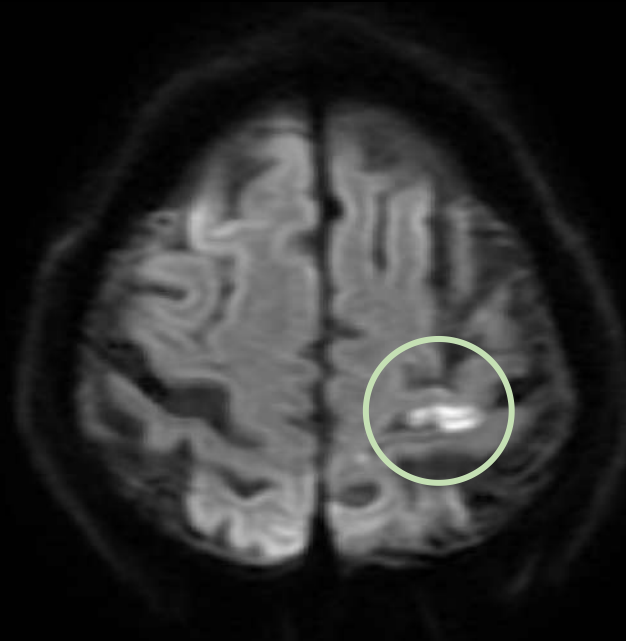
¹Centre for Advanced Research in Imaging, Neurosciences and Genomics, New Delhi

²TriOcula Inc, Bangalore

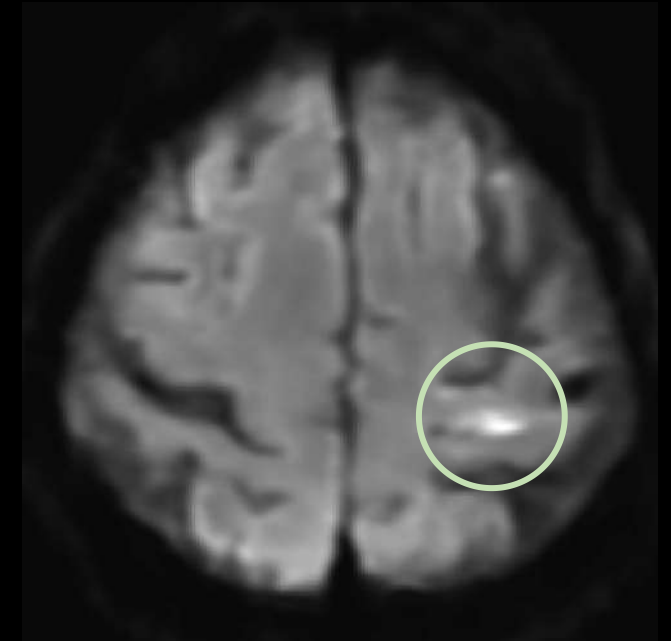
EXAMPLE OF VIRTUAL MRI PERFORMING AS WELL AS REAL MRI



Input T2W Image

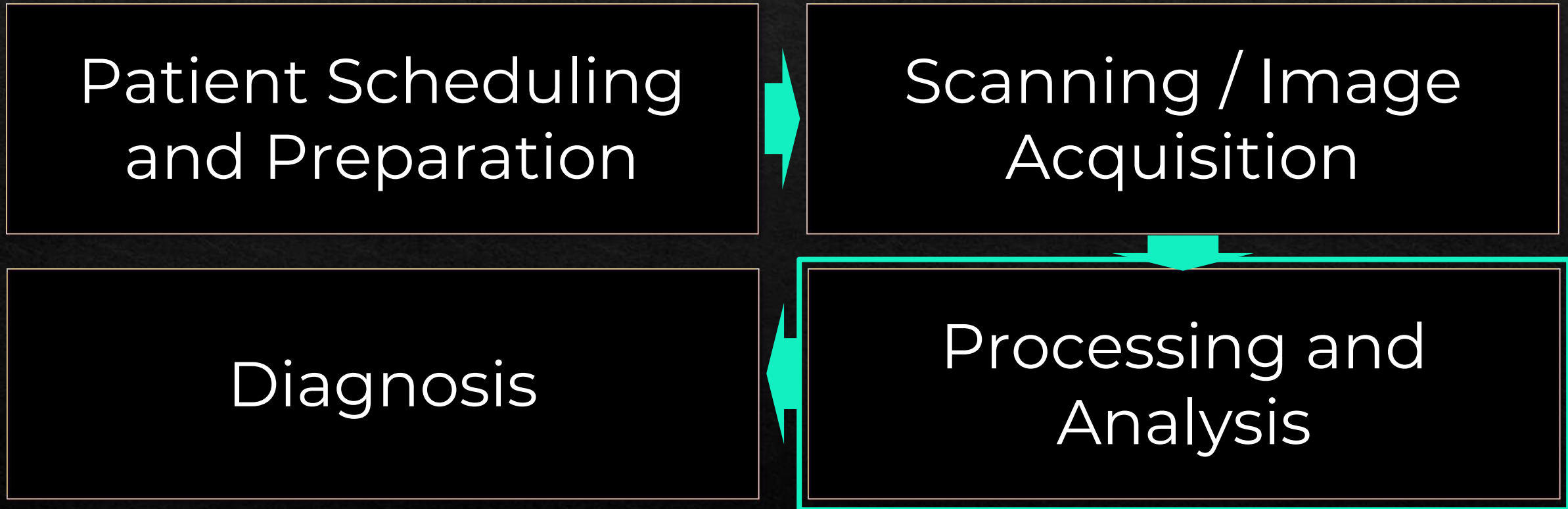


True Diffusion Image

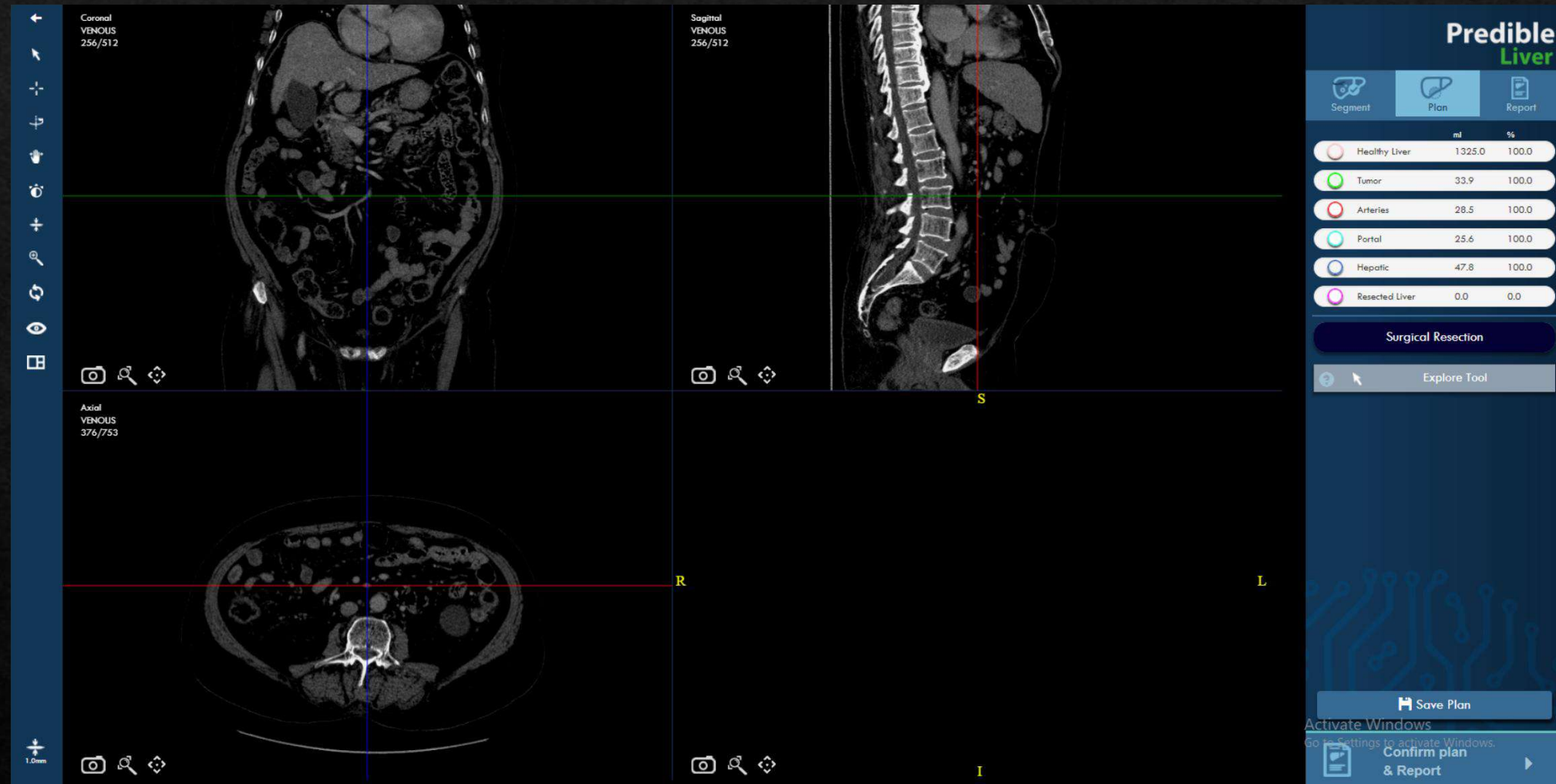


Virtual Diffusion Image

THE RADIOLOGY WORKFLOW

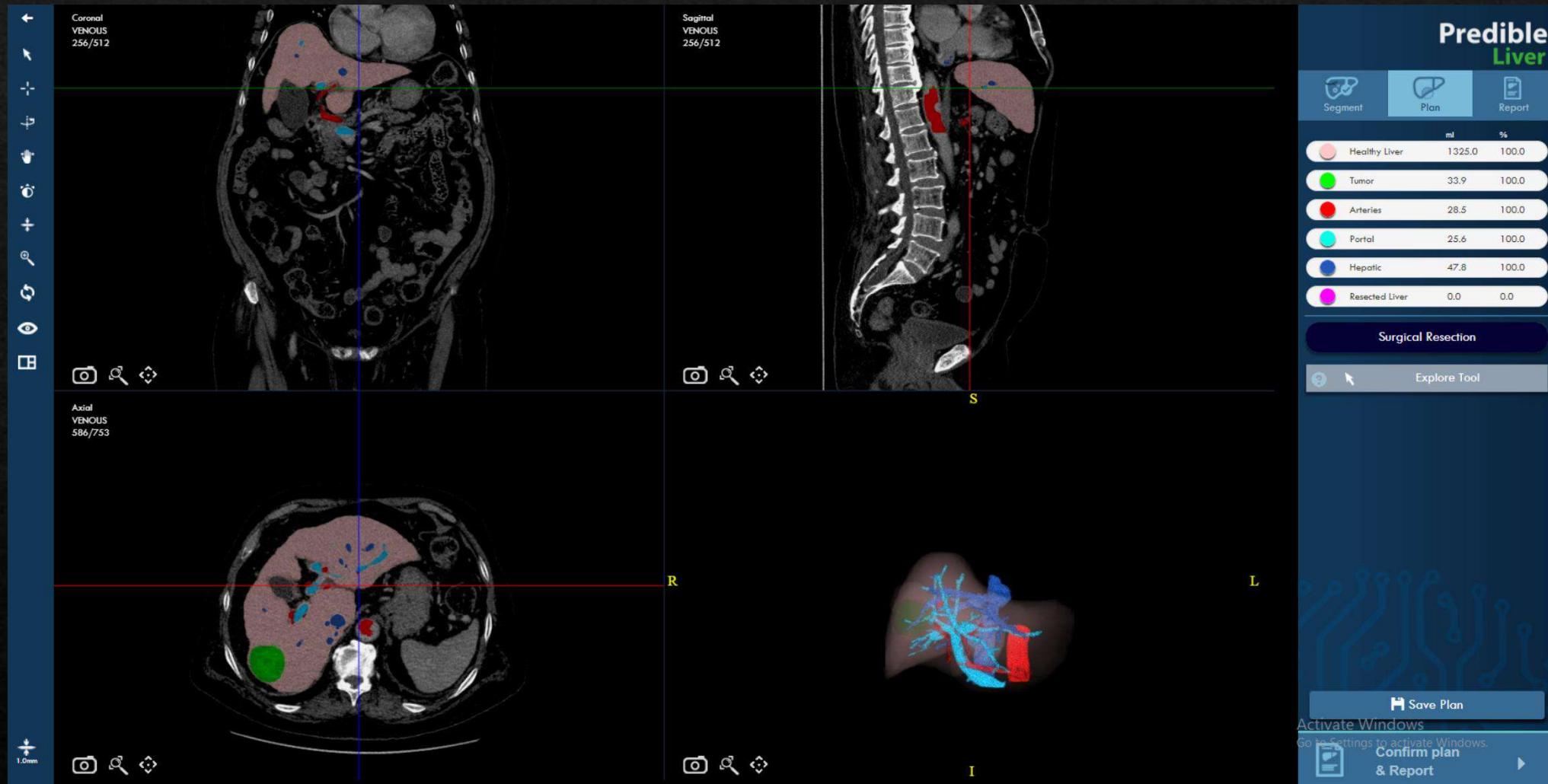


POST-PROCESSING: AUTOMATED LIVER, VESSELS AND TUMOUR SEGMENTATION



Poster at ECR 2019

POST-PROCESSING: AUTOMATED LIVER, VESSELS AND TUMOUR SEGMENTATION



Automated Lumbar Spinal Canal Stenosis Detection

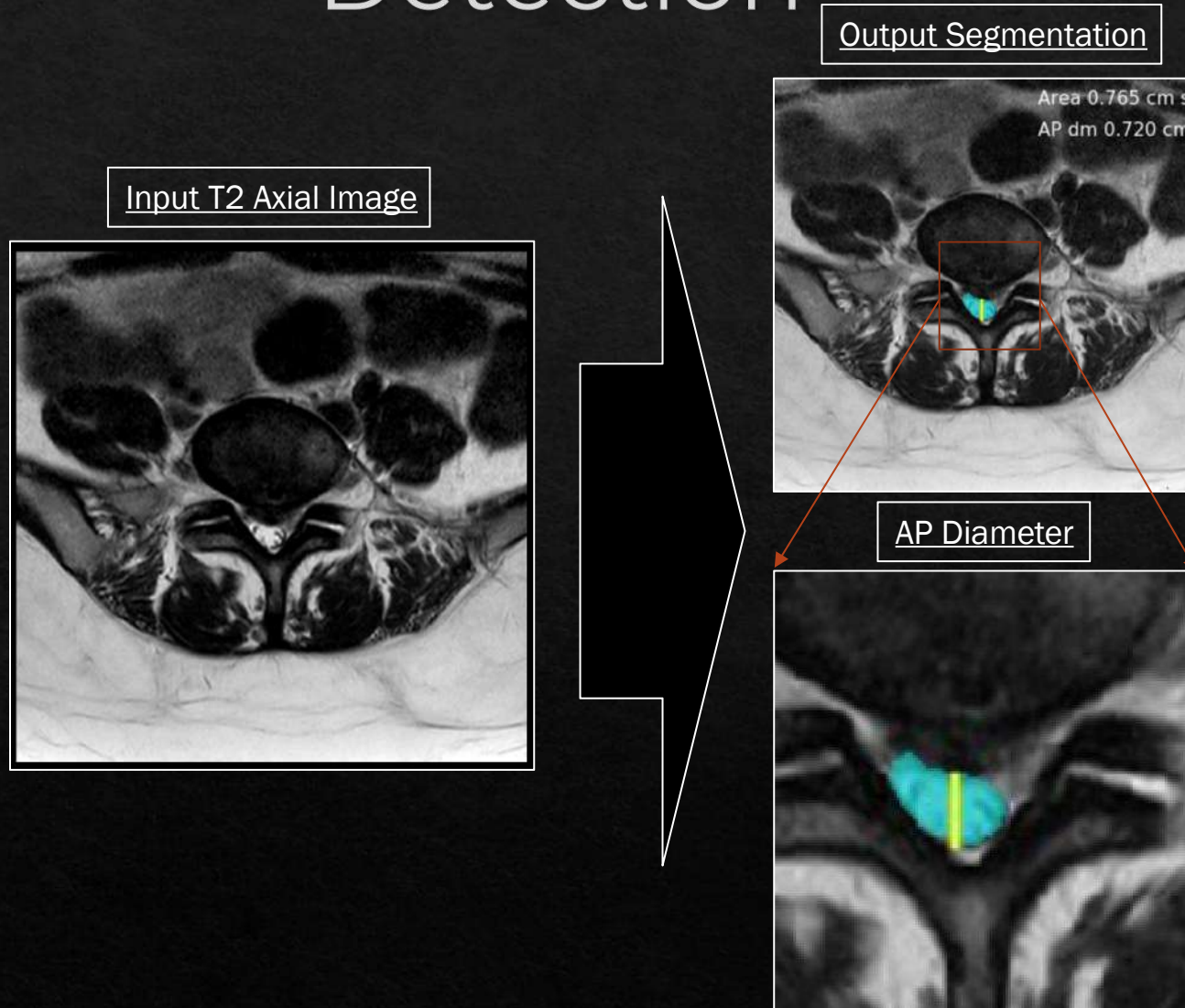
Development and Validation of a Deep Learning Based Automated Lumbar Spinal Canal Segmentation and Measurement Tool

Mahajan V¹, Venugopal V¹, ¹Mahajan H, ²Gupta S, ²Goyal A

¹Centre for Advanced Research in Imaging, Neurosciences and Genomics, New Delhi

²Imago Inc, Gurugram

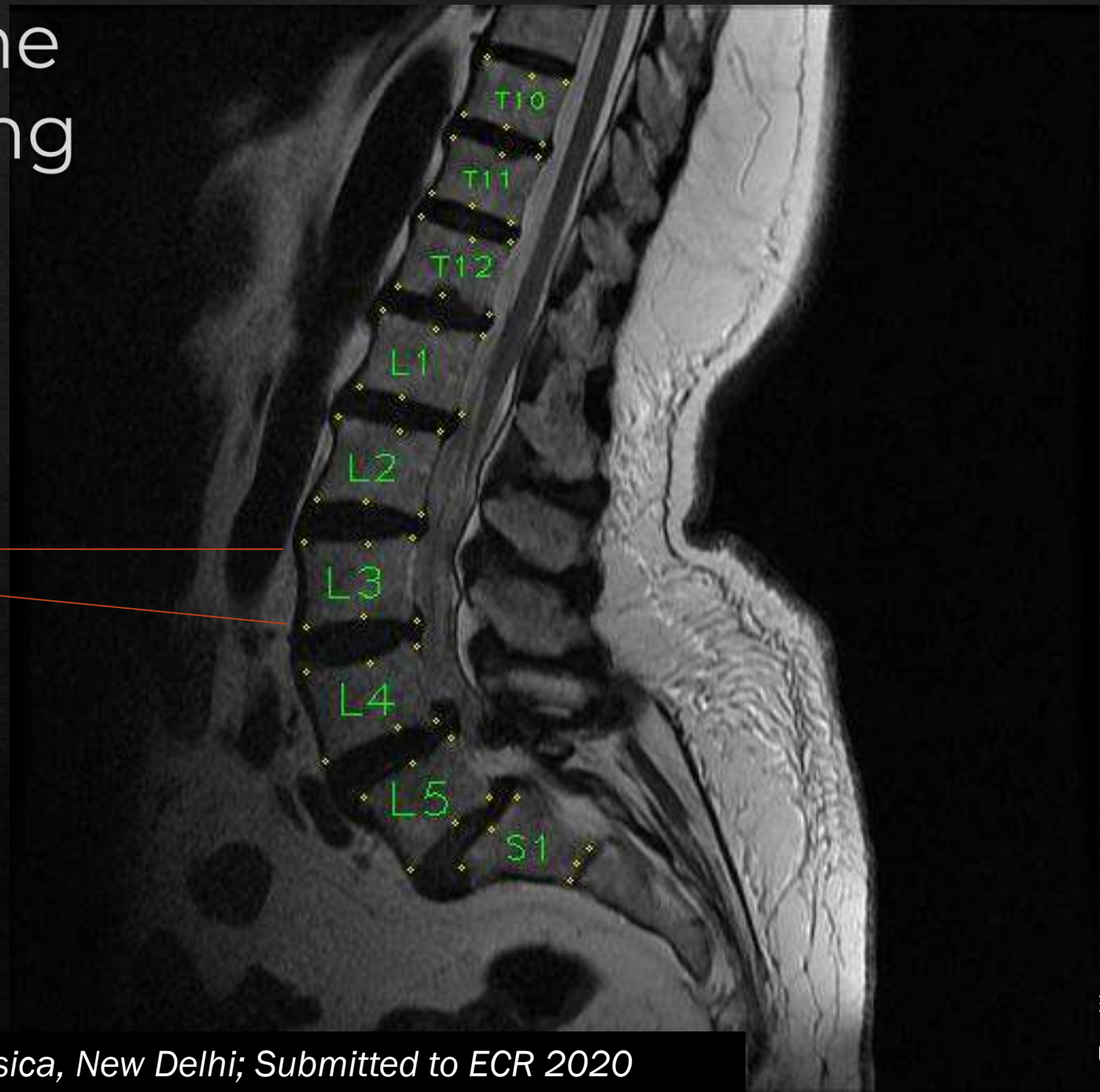
Automated Lumbar Spinal Canal Stenosis Detection



Under development; presented at ECR 2019

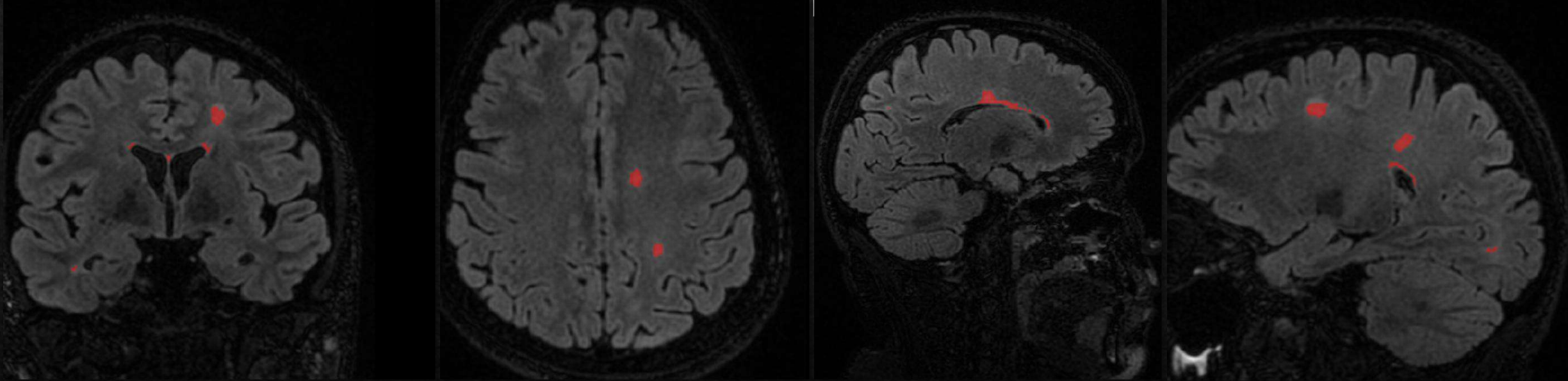
Automated spine MRI analysis using AI

Automated detection of key vertebral points leads to detailed analysis like spinal canal diameter, listhesis, fractures etc.



Developed by Synapsica, New Delhi; Submitted to ECR 2020

Automated segmentation of White Matter Lesions



Lesion number	87		
Total Lesion Volume [mL]	6.7727	Dominant Lesion Volume [mL]	2.5736
Total Relative Volume [%]	0.5094	Dominant Volume / Total [%]	37.9988
Mean Lesion Volume [mL]	0.0778	Dominant Volume / Total IC [%]	0.1935
Mean Lesion Area [mm ²]	19.1161	Entropy [ua]	1.1275
Dissemination [cm]	11.5341	BPF [%]	76.861

Reproducible, accurate results with zero effort

In collaboration with QUIBIM, Spain

SOME EXAMPLES FROM RADIOLOGY

Patient Scheduling
and Preparation

Scanning / Image
Acquisition

Diagnosis

Processing and
Analysis

AI algorithms are acting as 'triaging' tools



SiIM

Pneumothorax Detection and Localization in X-Ray Images Given Richer Annotation Information

Qian Zhao PhD¹, Min Zhang PhD¹, Gopal Avinash PhD¹,
Vasanth Venugopal MD², Vidur Mahajan MBBS²

¹ GE Healthcare, Milwaukee, WI, USA
² CARING, Mahajan Imaging, New Delhi, INDIA

 #CMIMI18

Brainstorming, annotation, validation – all done at CARING, New Delhi

Automated detection of critical findings on NCCT Head

THE LANCET

ARTICLES | [ONLINE FIRST](#)

Deep learning algorithms for detection of critical findings in head CT scans: a retrospective study

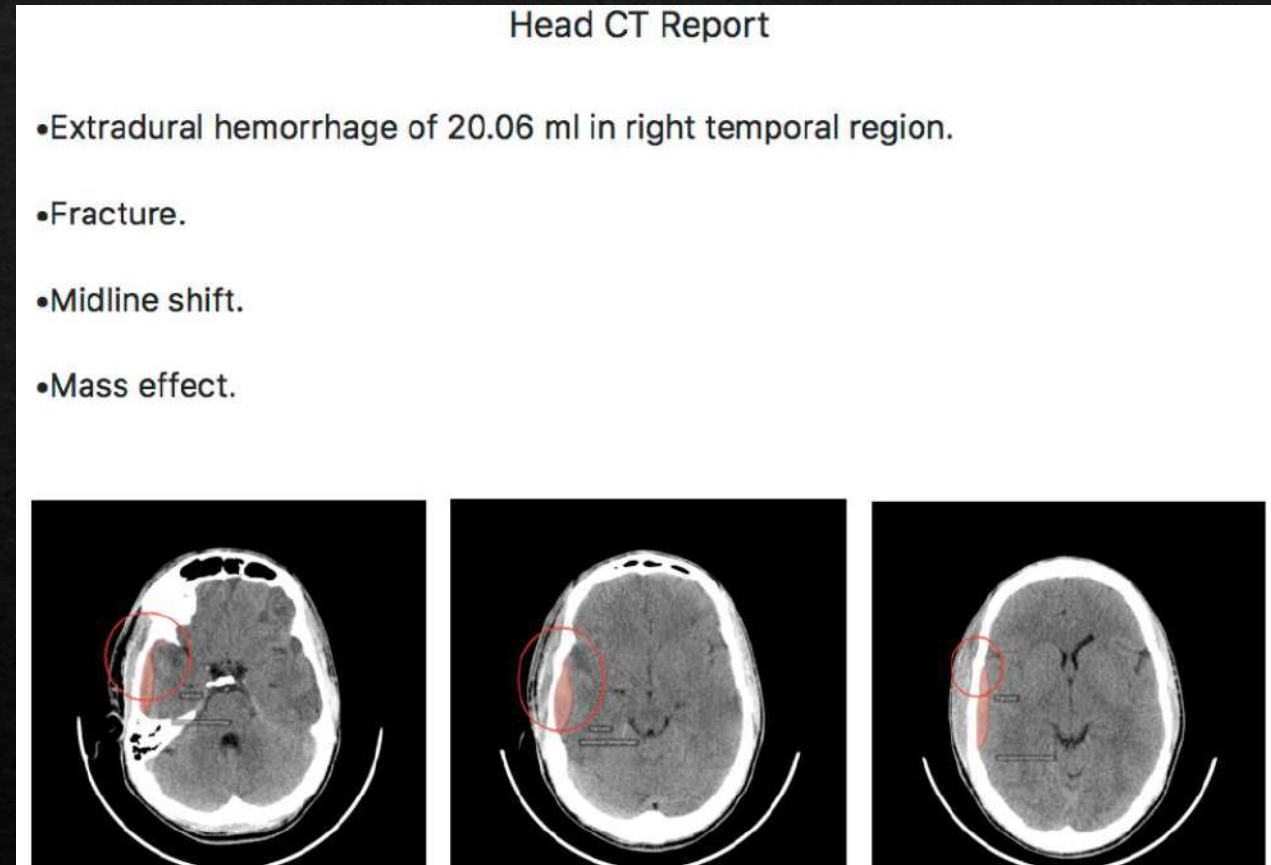
[Sasank Chilamkurthy, BTech](#)   • [Rohit Ghosh, BTech](#) • [Swetha Tanamala, MTech](#) • [Mustafa Biviji, DNB](#) • [Norbert G Campeau, MD](#) • [Vasanth Kumar Venugopal, MD](#) • [Vidur Mahajan, MBA](#) • [Pooja Rao, PhD](#) • [Prashant Warier, PhD](#) • [Show less](#)

Published: October 11, 2018 • DOI: [https://doi.org/10.1016/S0140-6736\(18\)31645-3](https://doi.org/10.1016/S0140-6736(18)31645-3) •



Automated detection of critical findings on NCCT Head

- ◇ Training dataset of >3L scans
- ◇ Validation on 490 scans
- ◇ Area Under Curve
 - ◇ Intra-Cranial Bleed: 0.94
 - ◇ Fractures: 0.96
 - ◇ Midline Shift: 0.97
 - ◇ Mass Effect: 0.92
- ◇ Automated report generation





All types of intracranial bleeds detected by this Algorithm



Cranial fracture

Detects fractures, localizes them with a bounding box on the image, and names the cranial bone(s) affected.



Midline shift

Detects and quantifies midline shift on head CT scans.

But, AI needs to be validated with caution: Acute MCA infarct mis-labelled as intra-cranial bleed

- ◆ FDA currently does not go deep into functioning of such algorithms
- ◆ Onus of validating remains with user
- ◆ Developers only need to show comparison with existing workflow

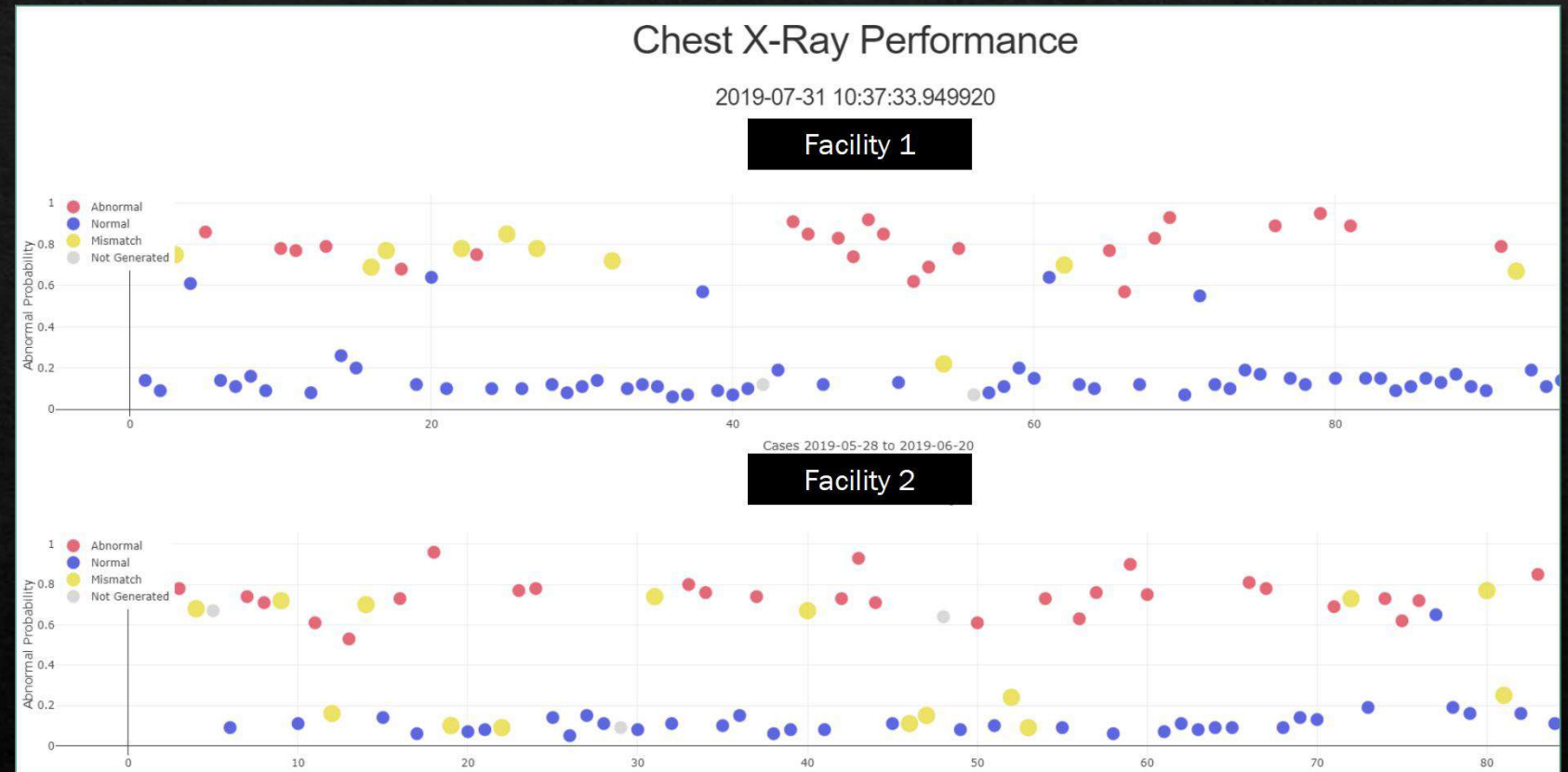


Triaging Leads to Case Prioritization

Priority	STAT	Patient Name	Patient MRN	Modality	Study Time	Hospital Location	Procedure

AI based QA system: AI reads every scan in tandem with radiologists and highlights 'mismatches'...

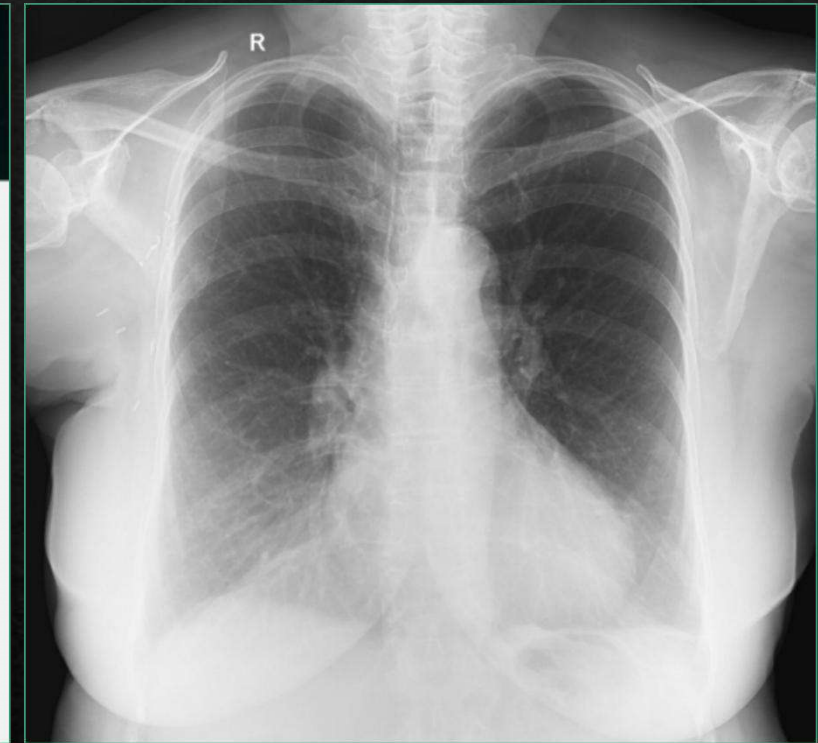
A live dashboard monitors AI performance vs radiologists, marking out 'mismatches' (yellow)



Currently deployed at CARING, Mahajan Imaging

...and a 2nd radiologist acts as an arbitrator

Mismatches				
ostID	RAD Report	AI Report	AI Probability	Who is more Accurate? (Select One)*
SHH706190	DATE:7/29/2019 Investigation_Name:X-RAY CHEST PA VIEW ReportStatus:Abnormal TestReport: DIGITAL X-RAY CHEST-PA VIEW Clinical profile: Routine check-up. The lung fields are clear with no evidence of any parenchymal lesion. Both domes of diaphragm costophrenic angles and hila appear normal. The cardiac shadow appears normal. Radio-opaque density of surgical staples are noted in right axillary region. Comparison has been made with previous x-ray dated 19.01.2019 there is no obvious interval change and no new lesion is seen. Dr. Manu Malhotra Chawla DMRD DNB DMC	Atelectasis; BluntedCP; Cardiomegaly; Consolidation; Fibrosis; Opacity;	0.68	Select Comments: SUBMIT



The arbitrator has access to a portal where she/he can define who was right – AI or radiologist

CARING experience of using AI-based QA

AI Impact – 12 wrong reports avoided by AI

708 'normal' cases re-read by AI



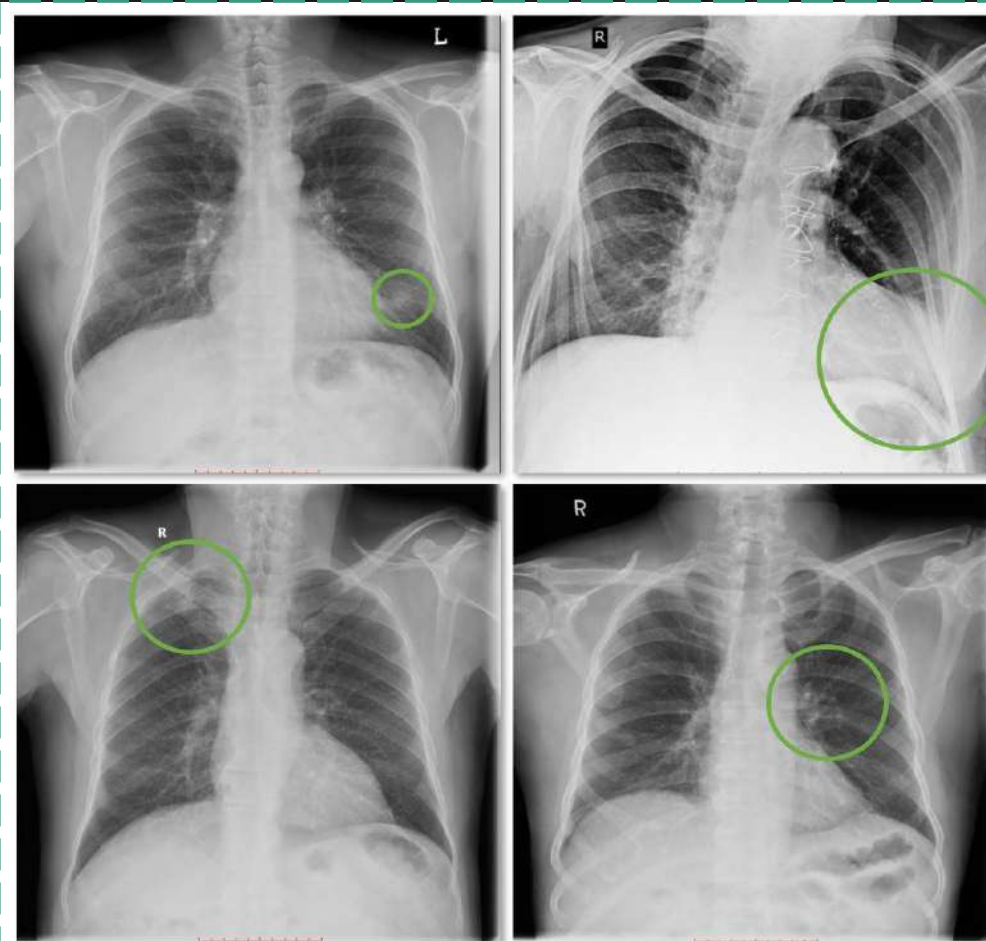
46 cases labelled as 'abnormal' by AI



*46 cases re-read by arbitrator
(radiologist)*



*12 cases with truly missed findings
detected*



4 cases with opacities, correctly identified by AI during Quality Review, missed by radiologist

Automated lung nodule detection and characterization

Radiologist level performance in Nodule characterization by Convolutional Neural Networks and Noisy-OR Gate based deep learning system

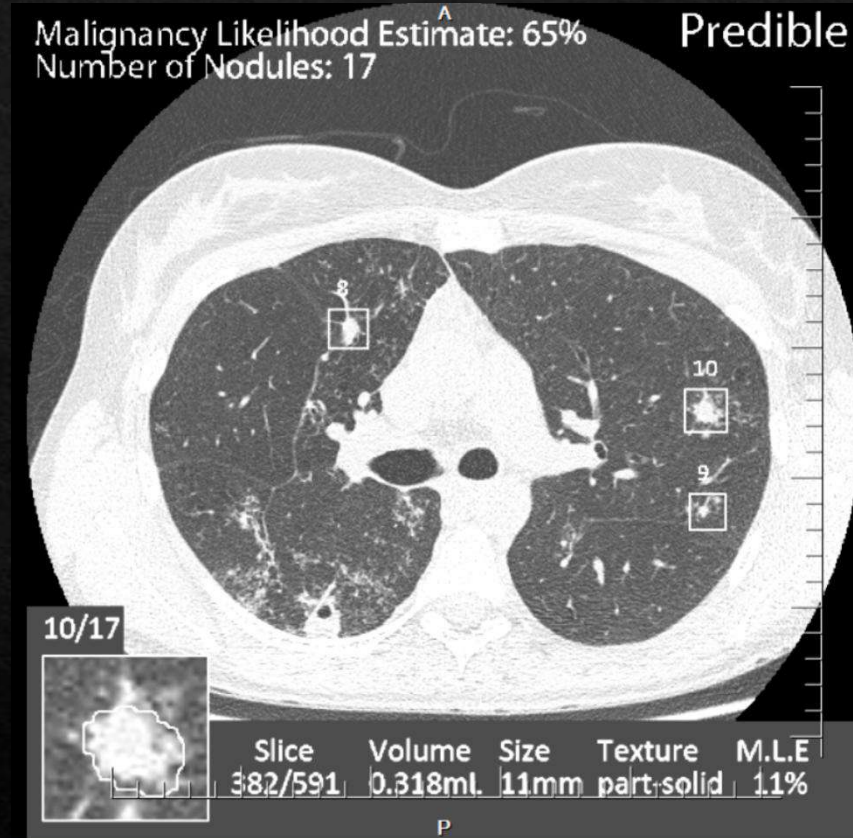
Venugopal V¹, Mahajan V¹, ¹Mahajan H, ²Vaidhya S, ²Chunduru A

¹Centre for Advanced Research in Imaging, Neurosciences and Genomics, New Delhi

²Predible Health, Bangalore

Lung nodules can be automatically detected and characterised to be benign or malignant by AI

- *Nodules are detected and saved as secondary capture, viewable by radiologists.*
- *Acts as a double reader, making sure no nodules are missed, improving quality of reporting*



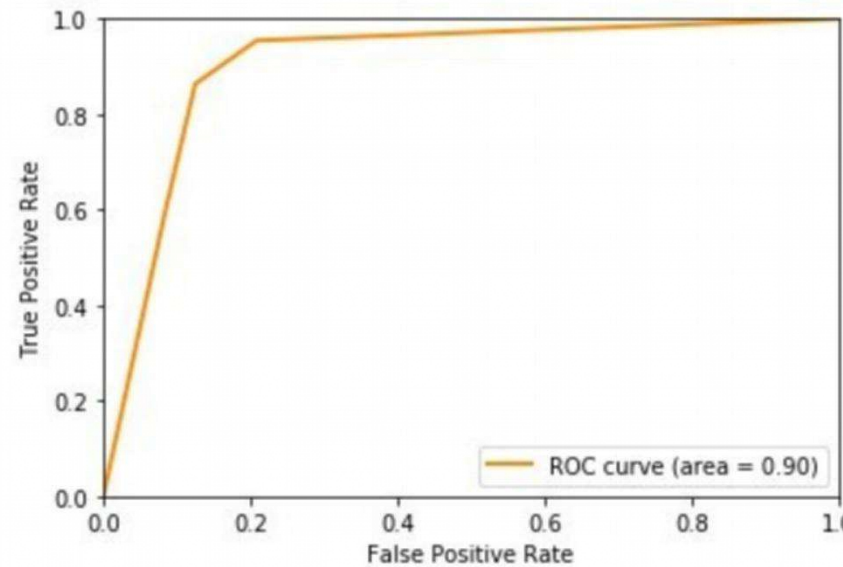
Malignancy Likelihood Estimate: 66%
Number of nodules: 17

Predible

ID	Slice	Volume	Size	Texture	M.L.E.
4	312	0.106mL	10mm	solid	4%
6	361	0.288mL	10mm	part-solid	28%
8	377	0.14mL	10mm	solid	8%
9	379	0.03mL	9mm	solid	4%
10	380	0.318mL	11mm	part-solid	11%
12	418	0.34mL	10mm	solid	7%
13	419	0.308mL	10mm	part-solid	6%
15	434	0.259mL	8mm	solid	5%
16	443	3.373mL	30mm	solid	9%
17	473	1.061mL	10mm	part-solid	5%

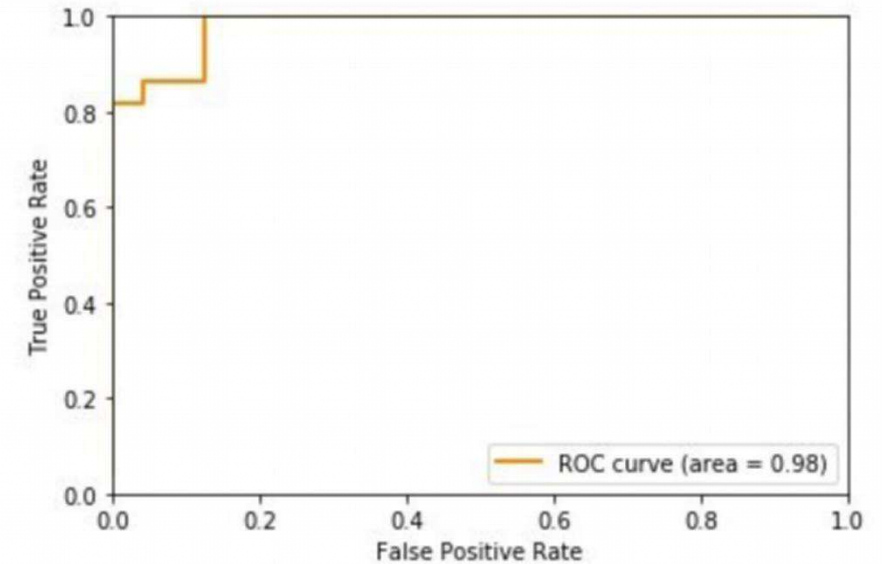
The AI out-performed three senior radiologists on nodule characterisation vs biopsy

While extensive studies are required to determine the clinical utility of AI, especially as it relates to characterising nodules, initial results are very encouraging...



ROC on radiologists average score

Radiologist Accuracy
77-78%



ROC on AI

AI Accuracy
84-87%

Automated Normal vs Abnormal Chest X-Ray Classification

Automated classification of chest X-rays as normal/abnormal using a high-sensitivity deep learning algorithm

V. Venugopal¹, M. Tadepalli², B. Reddy², A. Modi², S. Gupta¹, P. Warier², P. Rao², H. Mahajan¹, V. Mahajan¹

¹Centre for Advanced Research in Imaging, Neurosciences and Genomics, New Delhi

²Qure.ai, Mumbai

Presented at ECR 2019

DIAGNOSIS: AUTOMATIC GENERATION OF CHEST X-RAY REPORTS

[← Back to SSG06](#)

Can AI Generate Clinically Appropriate X-Ray Reports? Judging the Accuracy and Clinical Validity of Deep Learning-Generated Test Reports as Compared to Reports Generated by Radiologists: A Retrospective Comparative Study

Tuesday 11:40-11:50 AM | SSG06-08 | Room: [S406A](#)



PARTICIPANTS:

[Vasanthakumar Venugopal, MD](#) New Delhi, India (**Presenter**)

Disclosure: Consultant, CARING Research collaboration, General Electric Company Research collaboration, Koninklijke Philips NV Research collaboration, Qure.ai Research collaboration, Predible Health Research collaboration, Oxipit.ai Research collaboration, Synapsica Research collaboration, Quibim

[Vidur Mahajan, MBBS](#) New Delhi, India

Disclosure: Researcher, CARING Associate Director, Mahajan Imaging Research



AI doesn't hedge when reporting on chest x-rays

By Erik L. Ridley, AuntMinnie staff writer

November 4, 2019 --

Tuesday, December 3 | 11:40 a.m.-11:50 a.m. | SSG06-08 | Room S406A

In this presentation, researchers from India will describe how a deep-learning algorithm shows potential for producing accurate reports of chest radiographs.

The researchers set out to study the effects of artificial intelligence (AI) for reducing hedging in radiology reports, according to presenter Dr. Vasanth Venugopal of Mahajan Imaging in New Delhi.

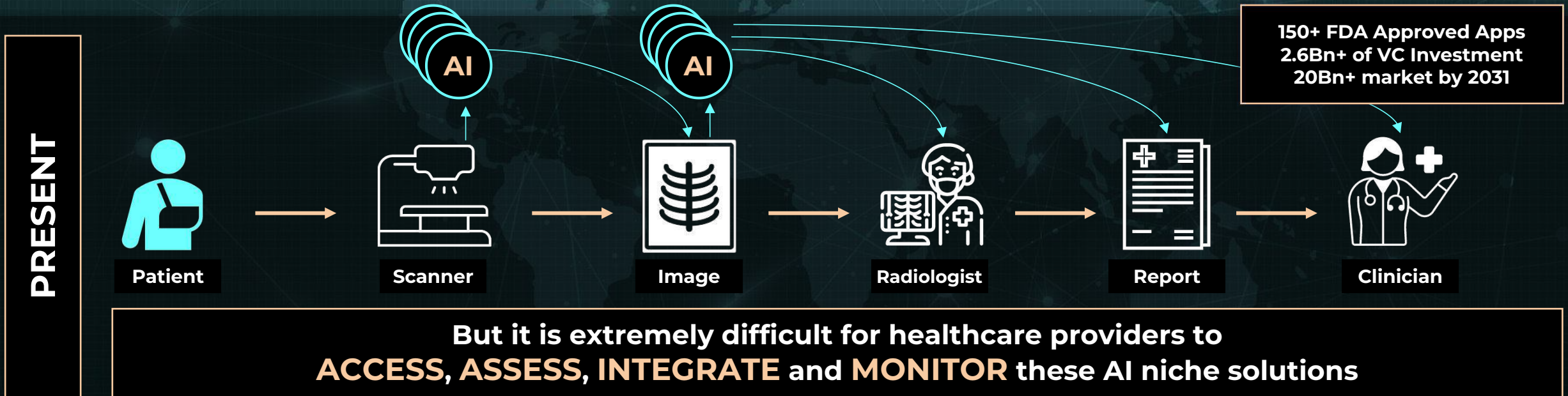
"We choose to investigate this area as we are encountering serious deficiencies in patient management due to defensive practice where the clinical opinions are influenced by perceived legal threats," Venugopal told *AuntMinnie.com*.

Using a commercial deep-learning algorithm (ChestEye, Oxipit) on nearly 300 chest radiographs acquired at their institution, the researchers found that the software generated reports that were as accurate as the radiologists' reports in nearly 80% of the cases and were more accurate in 5% of the exams.



All AI companies at RSNA 2021

These AI algorithms are all coming into the workflow in a fragmented manner....



NICHE SOLUTIONS
Body part x modality x disease

INCREMENTAL
10%, 20% gains

GENERALISABILITY
Does it work?

What if...

What if we could create **radiology's 'lab medicine' moment** – one rad signs out 1000s of reports?

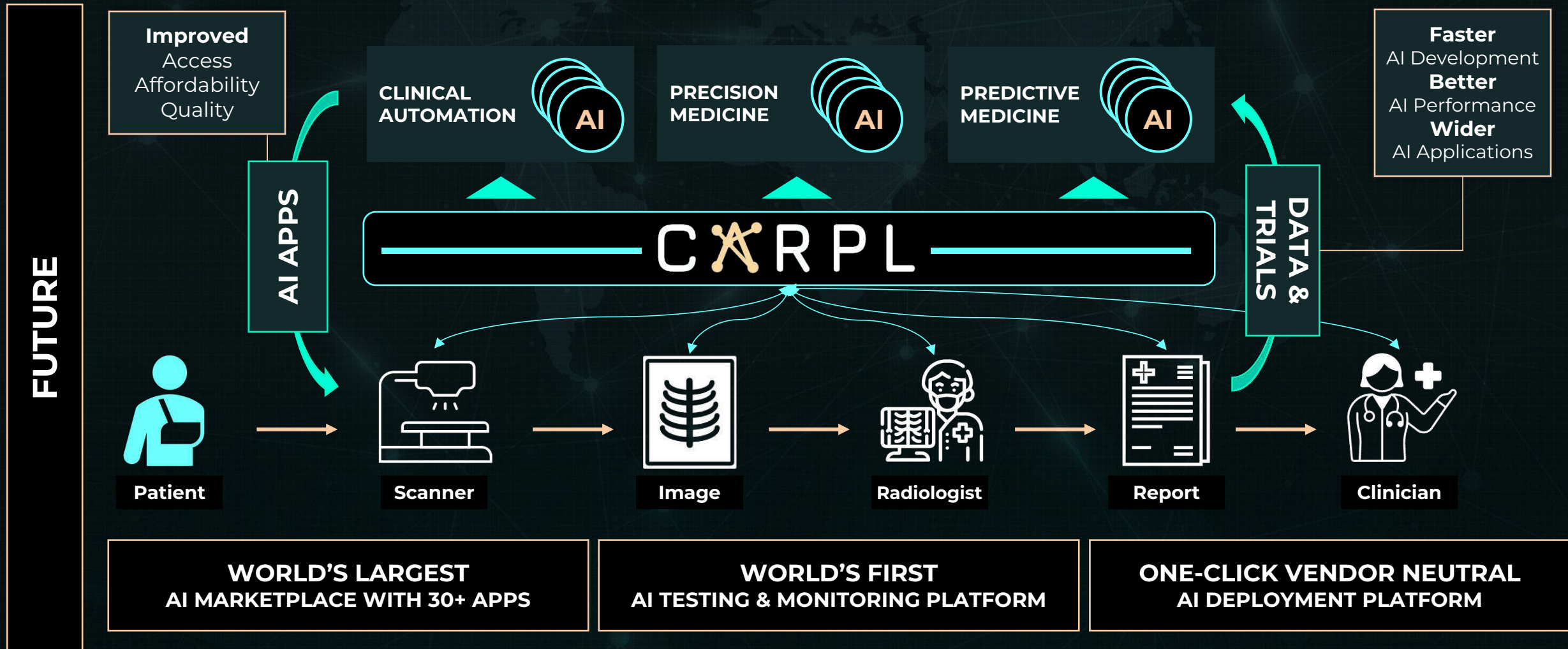
Multiple AI systems
on the same study?

**Near 0 switching
cost** between AI
systems?

**Algorithm (reagent)
rental** business
models?

CARPL – the unifying platform for radiology automation

The world's first vendor neutral testing and deployment platform for radiology AI



Developer Ecosystem



Provider Ecosystem



Health Tech Ecosystem



Clinical automation is just ONE piece!

Outcomes Prediction!
Precision Medicine!
Radio-genomics!

Things clinicians can't do..

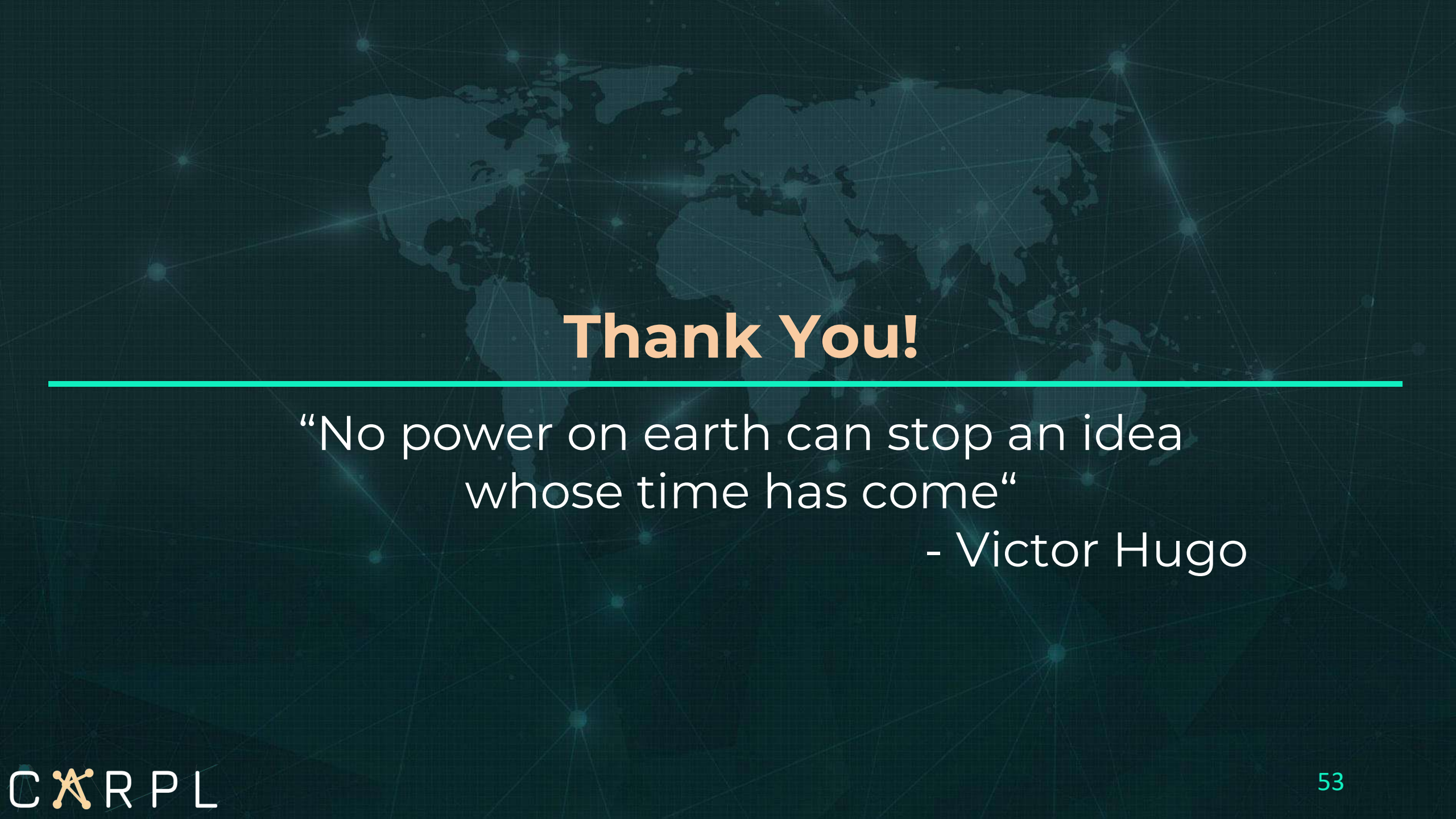
What does this mean for diagnostics?

A new field is emerging!
INTEGRATED DIAGNOSTICS!

Digital Backbone

Learn about AI

Friend not foe!

A dark teal background featuring a faint world map. Overlaid on the map is a network of glowing blue dots connected by thin, light blue lines, creating a global connectivity theme.

Thank You!

“No power on earth can stop an idea
whose time has come”
- Victor Hugo