ARTIFICIAL INTELLIGENCE AND IMAGING
A TOOL FOR SAFETY AND QUALITY

PR. GUY FRIJA
PARIS-DESCARTES UNIVERSITY
COCIR 2019 BRUSSELS

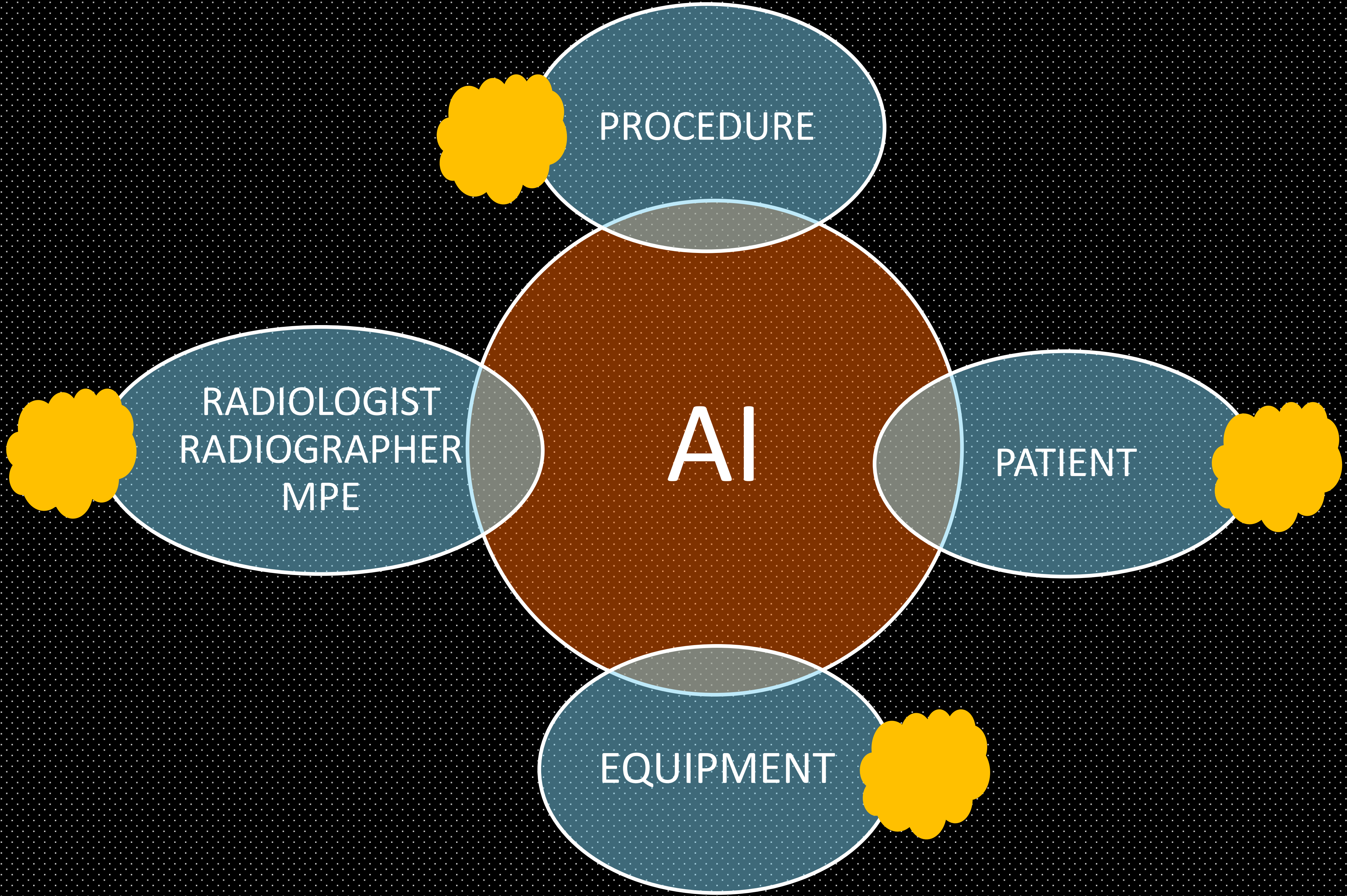
- NOTHING TO DISCLOSE
- SEVERAL COMPANIES ARE MENTIONED FOR PROVIDING EXAMPLES

CLINICAL AI

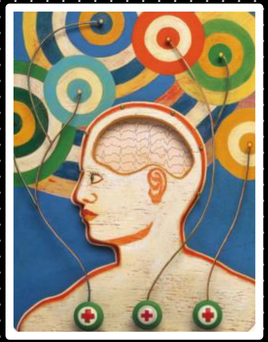
- NICHE APPLICATION
- CHALLENGES WITH DATA
- VALIDATION
- SLOW IMPLEMENTATION

TECHNICAL AI

- ORGANISATION, PROCESSES
- MORE GENERIC
- NON CLINICAL DATA
- FAST IMPLEMENTATION


PROCEDURE
RADIOLOGIST
RADIOGRAPHER
MPE
AI
PATIENT
EQUIPMENT

HOW WILL AI FIT INTO IMAGING SAFETY AND QUALITY

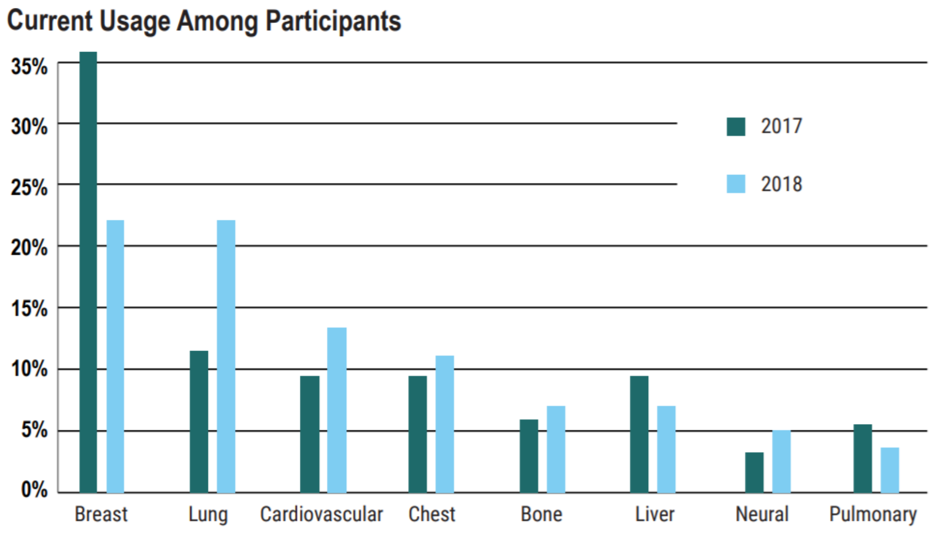


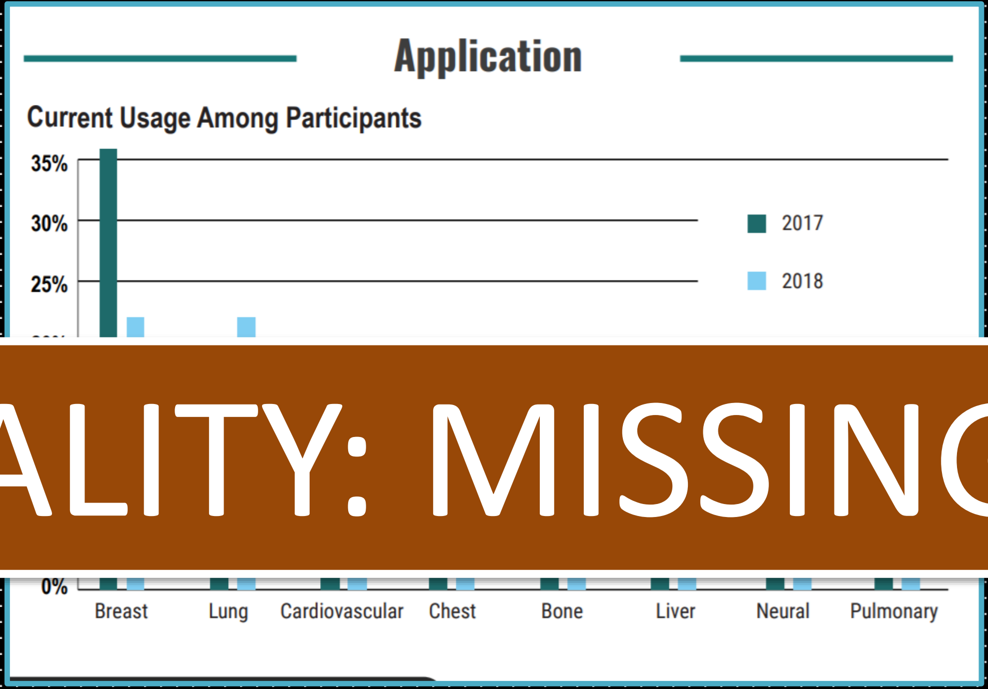
- MAXIMISE PATIENT EXPERIENCE AND MINIMISE RISKS
- IMPROVE ACCURACY AND REDUCE VARIABILITY
- IMPROVE EFFICIENCY, QUALITY AND SAFETY WITHIN THE WORKFLOW

Reaction Data

Machine Learning

Application





SAFETY AND QUALITY: MISSING

Table 3: Survey Results: Priorities for AI in Radiology

Priority	Theme	Focus Area
	Clinical Implementation	Build edge appliance for demonstration purposes with useful AI tools (eg, annotation, anonymization)
	Clinical Implementation	Create a medical version of ImageNet
	Clinical Implementation	Create a sandbox virtual environment for AI integration testing
	Clinical Implementation	Create and prioritize AI use cases
	Clinical Implementation	Host challenge-winning AI models
✓	Data Collection and Curation	Convene a task force to explore standard and best practices on anonymization and annotation strategies
✓	Data Collection and Curation	Promote a standard for data annotation
	Data Collection and Curation	Support the development of an AI-assisted annotation system for imaging datasets
	Education	Create and publish a statement about the potential future of radiology in a world of AI
✓	Education	Define and publish an AI curriculum
✓	Education	Develop an online portal linking to existing AI resources and educational content
✓	Education	Educate scientists, industry representatives, clinical trainees (residents, fellows, and medical students), and the public about AI in radiology
	Education	Expand the National Imaging Informatics Curriculum and Course to include more AI content
	Education	Support an AI fellowship program
	Ethical and Legal Aspects	Create a data-sharing network with an honest broker to ensure diverse training data
	Ethical and Legal Aspects	Create a registry of algorithm failures
	Ethical and Legal Aspects	Define workflows to promote patient safety and reduce medicolegal risks
	Quality and Business Improvement	Create a focused group to define an AI-enabled value framework for quality and business performance
	Quality and Business Improvement	Create performance and quality registry for benchmarking AI accuracy
	Quality and Business Improvement	Create competitions that emphasize solutions to quality and performance challenges (eg, scheduling, protocoling, hanging protocols)
	Research	Create a platform to assist with the development and validation of algorithms
	Research	Recommend policies and best practices around data sharing, algorithm creation, and validation methods in AI

Note.—Activities are grouped by themes and sorted alphabetically by focus area. The top five priority areas selected by summit participants are flagged in the Priority column.


Radiology: Artificial Intelligence

SPECIAL

Fostering a Healthy AI Ecosystem for Radiology: Conclusions of the 2018 RSNA Summit on AI in Radiology

Falgun H. Chokshi, MD, MS • Adam E. Flanders, MD • Luciano M. Prevedello, MD, MPH • Curtis P. Langlotz, MD, PhD

From the Departments of Radiology and Imaging Sciences and Biomedical Informatics, Emory University School of Medicine, 1364 Clifton Rd NE, Atlanta, GA 30322 (F.H.C.); Department of Radiology, Thomas Jefferson University Hospital, Philadelphia, Pa (A.E.F.); Department of Radiology, The Ohio State University Wexner Medical Center, Columbus, Ohio (L.M.P.); and Departments of Radiology and Biomedical Informatics, Stanford University School of Medicine, Stanford, Calif (C.P.L.). Received February 23, 2019; revision requested February 28; revision received March 1; accepted March 4. **Address correspondence to** F.H.C. (e-mail: *falgun.chokshi@emory.edu*).

Conflicts of interest are listed at the end of this article.

Radiology: Artificial Intelligence 2019; 1(2):e190021 • https://doi.org/10.1148/ryai.2019190021 • Content code:

FULL SESSION ON AI AND RADIATION PROTECTION ECR 2019

RADIOLOGIST PERSPECTIVE

WORKFLOW

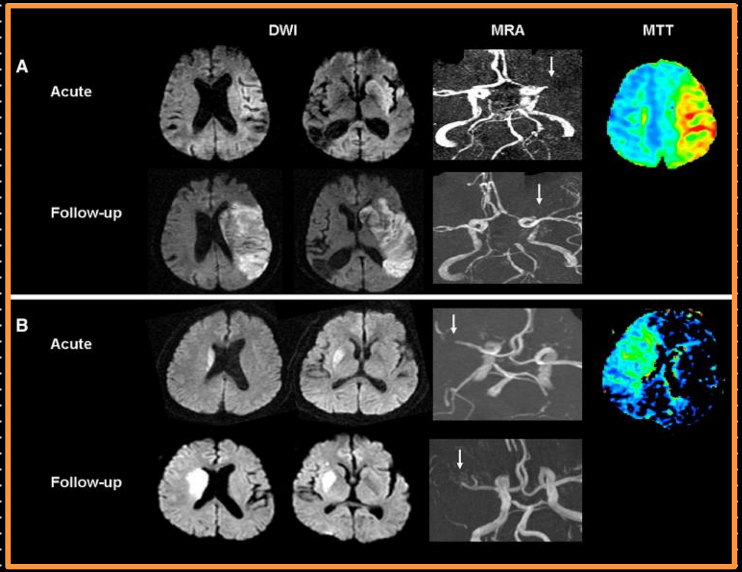
DETECTION

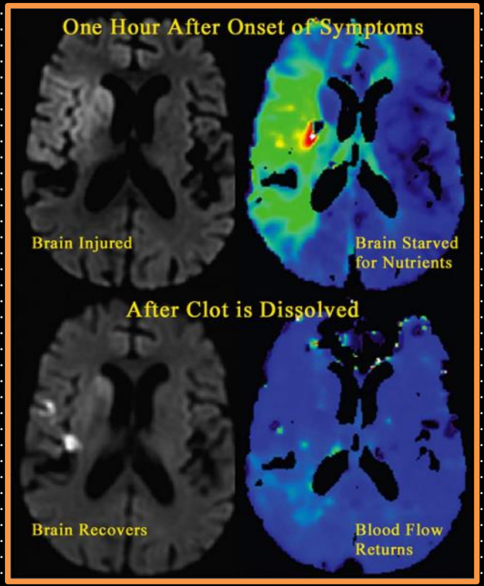
QUANTIFICATION

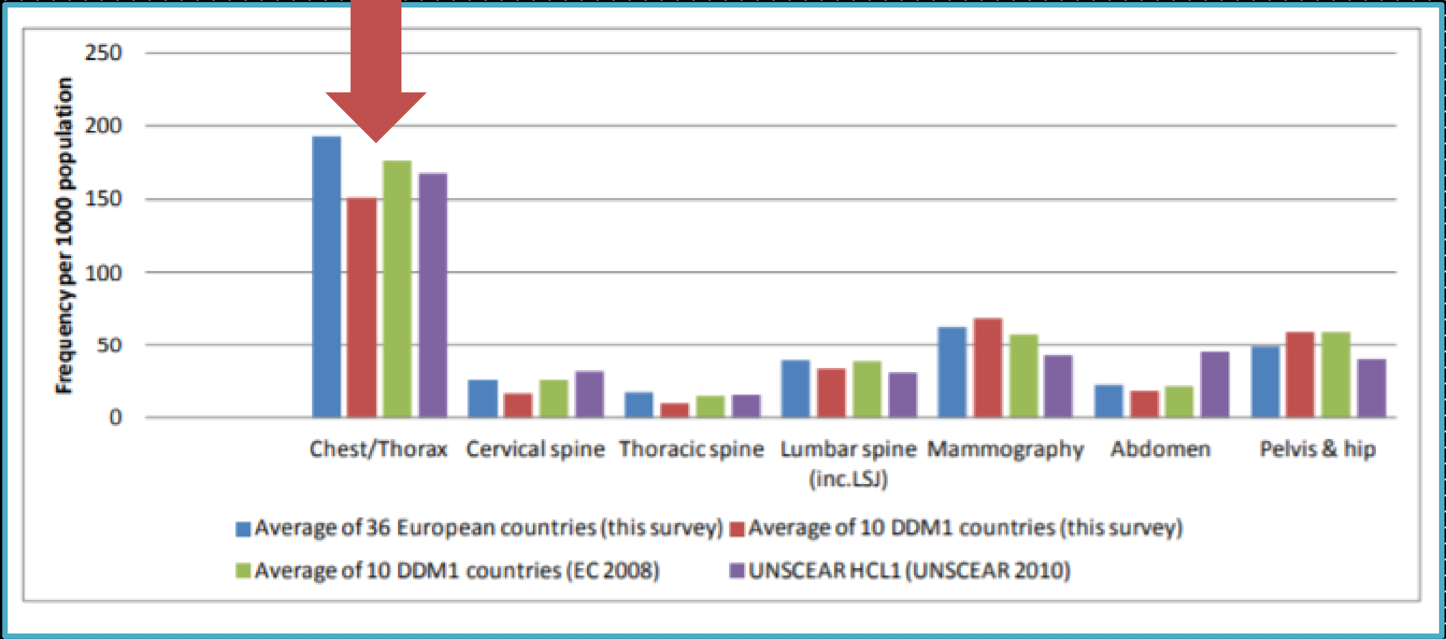
REPORTING

CAPACITY OF THE RADIOLOGIST

- HUGE INCREASE OF NUMBER OF IMAGES
- HUGE INCREASE OF NUMBER OF EXAMINATIONS
- HUGE INCREASE OF INFORMATIONS PER EXAM







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ARTICLE IN PRESS

ORIGINAL ARTICLE

Increasing Utilization of Chest Imaging in US Emergency Departments From 1994 to 2015

Jonathan H. Chung, MD[a], Richard Duszak Jr, MD[b], Jennifer Hemingway, MS[c], Danny R. Hughes, PhD[c,d], Andrew B. Rosenkrantz, MD, MPA[e]

Abstract

Purpose: The aim of this study was to assess national and state-specific changes in emergency department (ED) chest imaging utilization from 1994 to 2015.

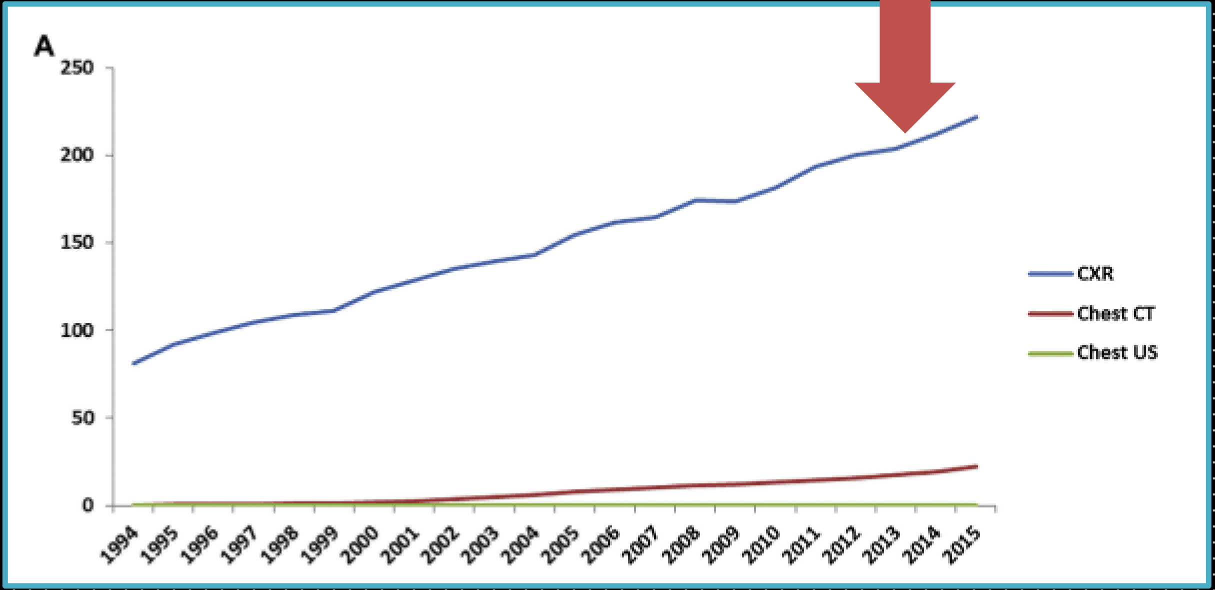
Methods: Using aggregate 100% Medicare Physician/Supplier Procedure Summary Master Files for 1994 to 2015, the annual frequency of chest imaging in Medicare Part B beneficiaries in the ED setting was identified, and utilization was normalized to annual Medicare enrollment as well as annual ED visits. Using individual Medicare beneficiary 5% research-identifiable files, similar determinations were performed for each state.

Results: Between 1994 and 2015, per 1,000 beneficiaries, ED utilization of chest radiography and CT increased by 173% (compound annual growth rate [CAGR] 4.9%) and 5,941.8% (CAGR 21.6%). Per 1,000 ED visits, utilization increased by 81% (CAGR 2.9%) and 3,915.4% (CAGR 19.2%), respectively. Across states, utilization was highly variable, with 2015 radiography utilization per 1,000 ED visits ranging from 82 (Wyoming) to 731 (Hawaii) and CT utilization ranging from 18 (Wyoming) to 76 (Hawaii). Between 2004 and 2015, most states demonstrated increases in the utilization of both radiography (maximal increase of CAGR 11.0% in Vermont) and CT (maximal increase of CAGR 21.0% in Maine). Nonetheless, utilization of radiography declined in four states and utilization of CT in a single state.

Conclusions: Over the past two decades, ED utilization of chest imaging has increased. This was related not only to an increasing frequency of ED visits but also to increasing utilization per ED visit. Across states, utilization is highly variable, but with radiography and CT both increasing, the use of CT seems additive to, rather than replacing, radiography.

Key Words: Thoracic, chest, imaging, CT, radiograph, emergency department

J Am Coll Radiol 2018;■:■-■.



AI 1st READING

Clinical Radiology xxx (2018) 1–5

Contents lists available at ScienceDirect

Clinical Radiology

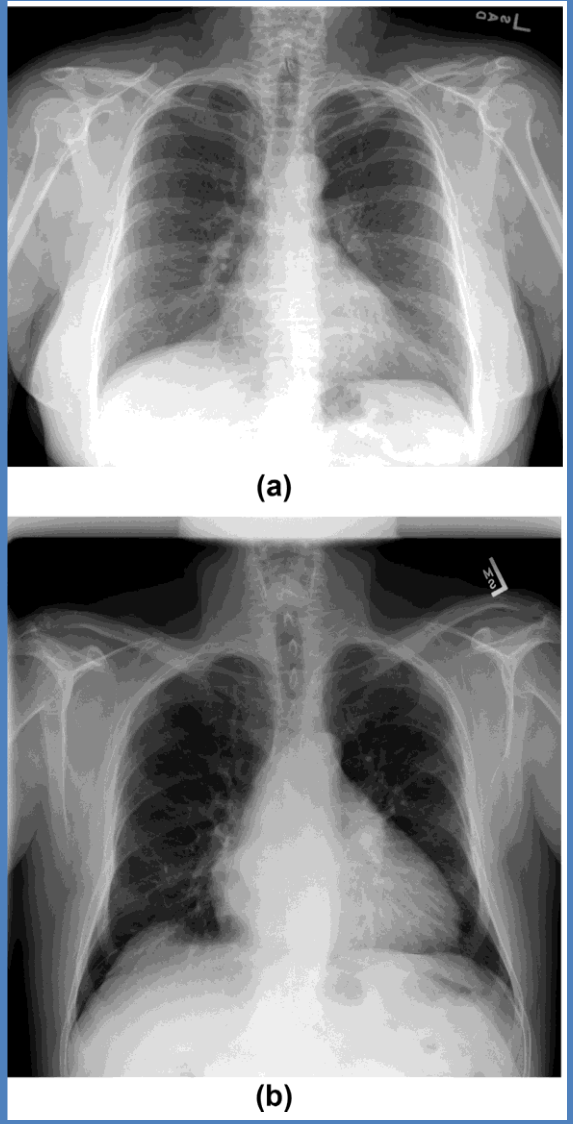
journal homepage: www.clinicalradiologyonline.net

Machine learning “red dot”: open-source, cloud, deep convolutional neural networks in chest radiograph binary normality classification

E.J. Yates[a,*], L.C. Yates[a], H. Harvey[b]

99.8% (95% CI: 99.7–99.9%) and area under the curve (AUC) of 0.98 (95% CI: 0.97–0.99).

CONCLUSION: This study demonstrates the application of a machine learning-based approach to classify chest radiographs as normal or abnormal. Its application to real-world datasets may be warranted in optimising clinician workload.



Radiology

ORIGINAL RESEARCH • THORACIC IMAGING

Assessment of Convolutional Neural Networks for Automated Classification of Chest Radiographs

Jared A. Dunnmon, PhD • Darvin Yi, MS • Curtis P. Langlotz, MD, PhD • Christopher Ré, PhD • Daniel L. Rubin, MD, MS • Matthew P. Lungren, MD, MPH

From the Departments of Computer Science (J.A.D., C.R.), Biomedical Data Science (D.Y., D.L.R.), and Radiology (C.P.L., D.L.R., M.P.L.), Stanford University, 300 Pasteur Dr, Stanford, CA 94305. Received June 13, 2018; revision requested August 7; revision received August 25; accepted September 17. **Address correspondence to** J.A.D. (e-mail: *jdunnmon@cs.stanford.edu*).

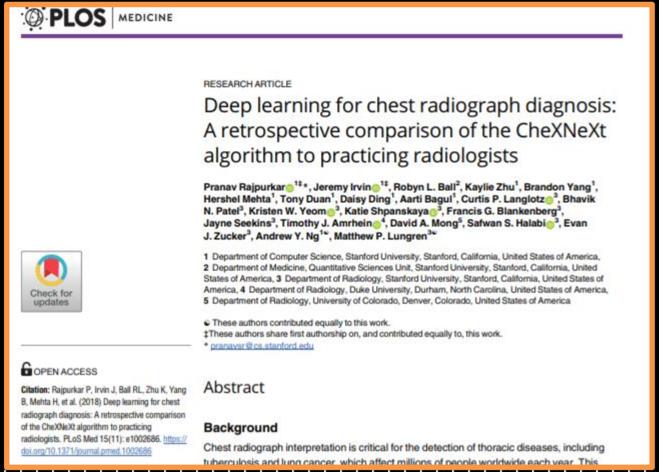
Supported by Stanford DAWN (Google, Intel, Microsoft, NEC, Teradata, VMWare), the Intelligence Community Postdoctoral Research Fellowship Program, the National Institutes of Health (1U01CA187947, 1U01CA190214, U01CA142555), the National Cancer Institute, the Office of Naval Research (N000141712266), the Stanford Center for Artificial Intelligence in Medicine and Imaging, the Defense Advanced Research Projects Agency (FA87501720095), and the Stanford Child Health Research Institute.

Conflicts of interest are listed at the end of this article.

See also the editorial by van Ginneken in this issue.

Radiology 2019; 290:537–544 • https://doi.org/10.1148/radiol.2018181422 • Content code: CH

Conclusion: CNNs trained with a modestly sized collection of prospectively labeled chest radiographs achieved high diagnostic performance in the classification of chest radiographs as normal or abnormal; this function may be useful for automated prioritization of abnormal chest radiographs.



PLOS | MEDICINE

RESEARCH ARTICLE

Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists

Pranav Rajpurkar[1‡*], Jeremy Irvin[1‡], Robyn L. Ball[2], Kaylie Zhu[1], Brandon Yang[1], Hershel Mehta[1], Tony Duan[1], Daisy Ding[1], Aarti Bagul[1], Curtis P. Langlotz[3], Bhavik N. Patel[3], Kristen W. Yeom[3], Katie Shpanskaya[3], Francis G. Blankenberg[3], Jayne Seekins[3], Timothy J. Amrhein[4], David A. Mong[5], Safwan S. Halabi[3], Evan J. Zucker[3], Andrew Y. Ng[1☯], Matthew P. Lungren[3☯]

1 Department of Computer Science, Stanford University, Stanford, California, United States of America, 2 Department of Medicine, Quantitative Sciences Unit, Stanford University, Stanford, California, United States of America, 3 Department of Radiology, Stanford University, Stanford, California, United States of America, 4 Department of Radiology, Duke University, Durham, North Carolina, United States of America, 5 Department of Radiology, University of Colorado, Denver, Colorado, United States of America

☯ These authors contributed equally to this work.
‡These authors share first authorship on, and contributed equally to, this work.
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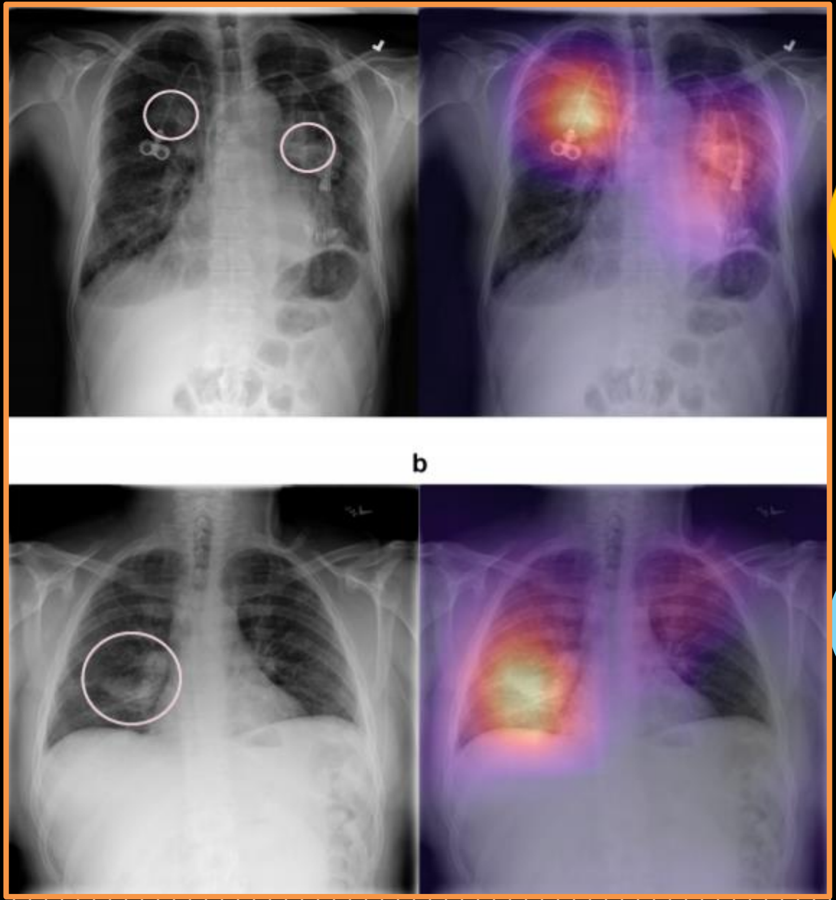
OPEN ACCESS

Citation: Rajpurkar P, Irvin J, Ball RL, Zhu K, Yang B, Mehta H, et al. (2018) Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists. PLoS Med 15(11): e1002686. https://doi.org/10.1371/journal.pmed.1002686

Abstract

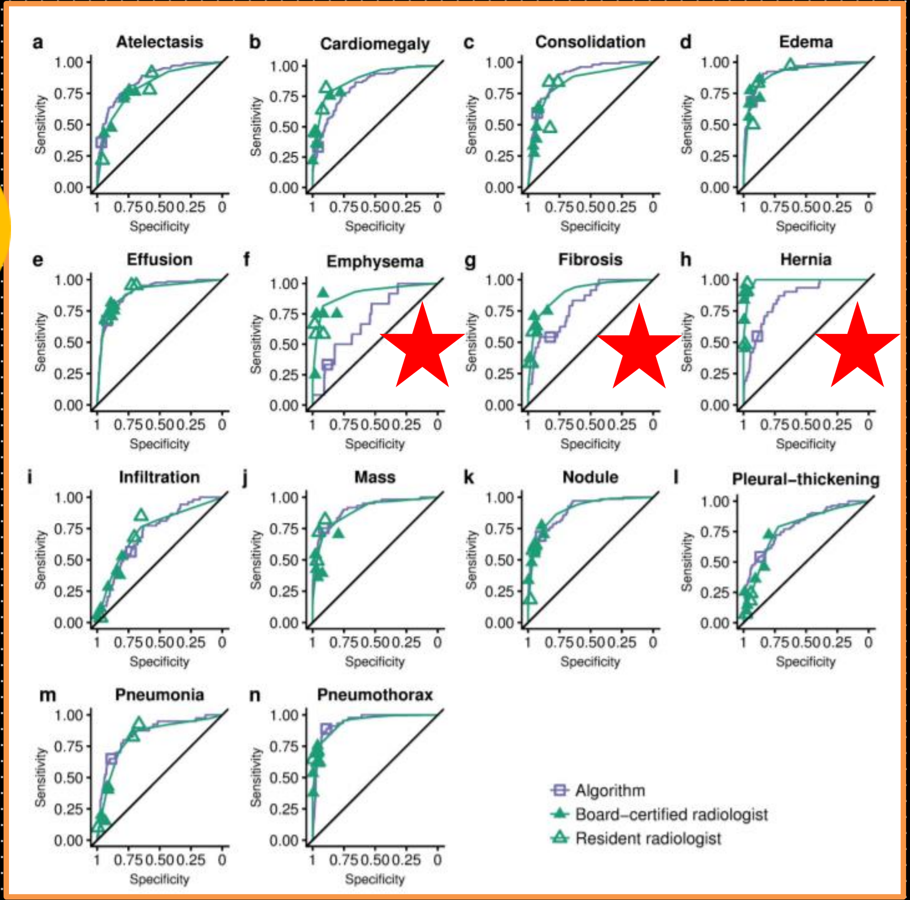
Background

Chest radiograph interpretation is critical for the detection of thoracic diseases, including tuberculosis and lung cancer, which affect millions of people worldwide each year. This



AI 1st
READING

TIME SAVING



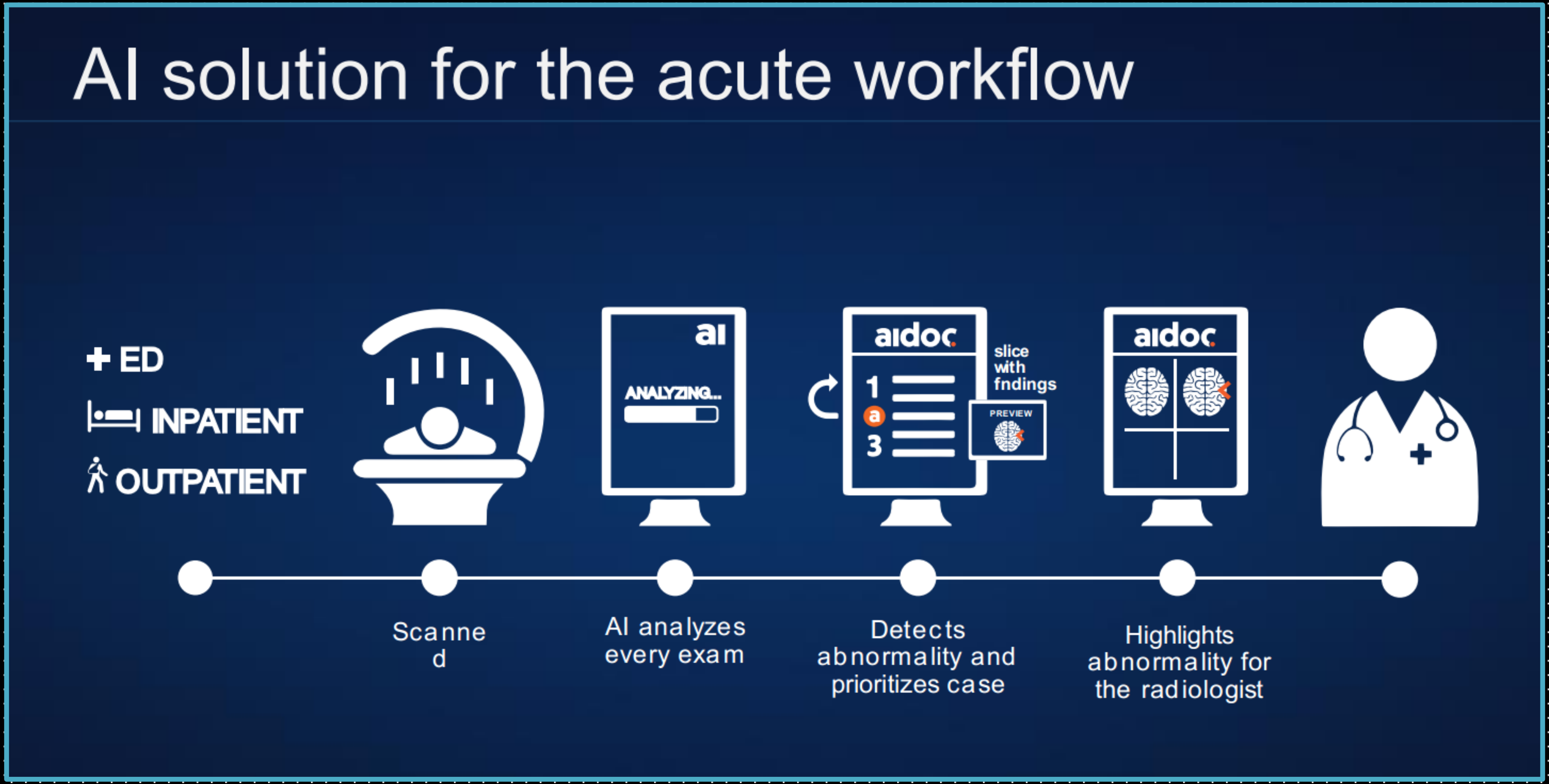
WORKFLOW

URGENT CONDITIONS

PRIORITY LIST

PRIORITY LIST

URGENT CONDITIONS

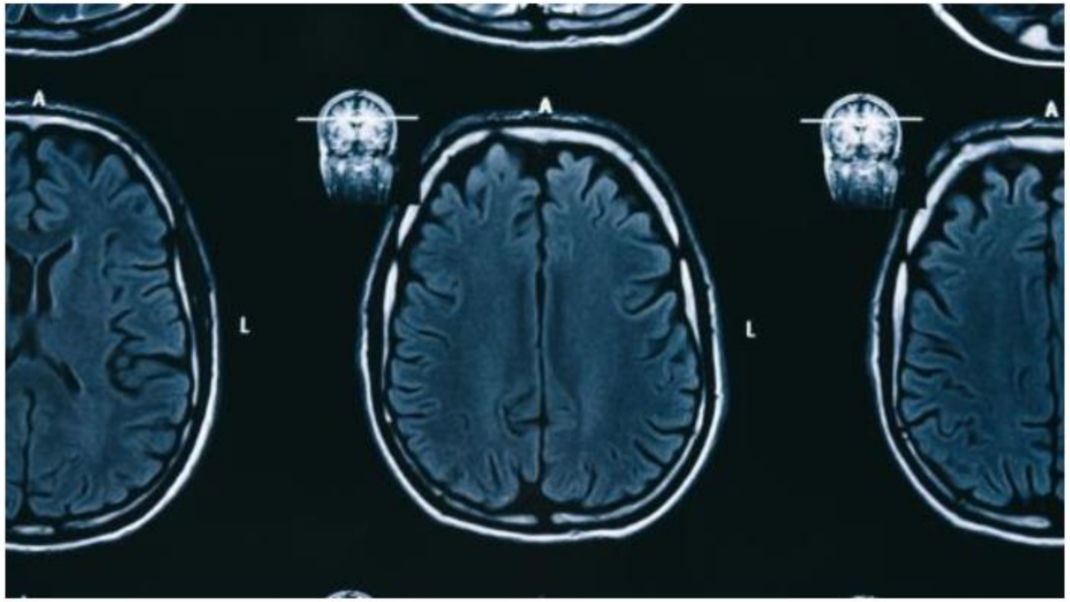


Prioritize

Focus

Radiologists at Belgian hospital adopt Aidoc neuro tool into workflows

January 16, 2019 | *Danielle Brown* | *Imaging*



The radiology department at the Antwerp University Hospital in Belgium has incorporated an Aidoc tool that uses AI to help radiologists make faster diagnoses from CT scans, the university announced Wednesday, Jan. 16.

"Geisinger Health System is leveraging machine learning to speed up the diagnosis of potentially fatal internal head bleeding by **TRAINING COMPUTERS TO ANALYZE COMPUTED TOMOGRAPHY SCANS AND FLAGGING THE MOST URGENT IMAGES** for review by radiologists.

The healthcare organization **HAS REDUCED THE TIME IT TAKES TO DIAGNOSE INTRACRANIAL HEMORRHAGES BY 96 PERCENT,** and as a result the technology has been introduced into its regular clinical workflow".

RADIOLOGIST PERSPECTIVE

WORKFLOW

DETECTION

QUANTIFICATION

REPORTING

LIMITATIONS OF THE RADIOLOGIST

VARIATIONS OF PERFORMANCES FOR A RADIOLOGIST OVER TIME

DIFFERENCES OF PERFORMANCES BTW RADIOLOGISTS FOR THE SAME PROCEDURE

ELSEVIER
Journal of Medical Imaging and Radiation Sciences 47 (2016) 217-220
Journal of Medical Imaging and Radiation Sciences
Journal de l'imagerie médicale et des sciences de la radiation
www.elsevier.com/locate/jmir

Brief Communication

Intraobserver Variability: Should We Worry?

Pete Bridge MSc[a]*, Andrew Fielding PhD[a], Pamela Rowntree FIR[a], and Andrew Pullar MBBS[b]
[a] School of Chemistry, Physics and Mechanical Engineering, Queensland University of Technology, Brisbane, Queensland, Australia
[b] Department of Radiation Therapy, Radiation Oncology Mater Centre, Brisbane, Queensland, Australia

Table 1
Best Reported Kappa for Intraobserver Variability in CT-Based Studies

Paper	Region or Pathology	Task	Kappa (Best Case)
Meirelles 2006	Pleural plaques	Diagnosis	1
Branstetter 2006	Middle ear	Diagnosis	0.99
Tan 2007	Spinal allograft fusion	Classification	0.95
Lee 2009	Ear otosclerosis	Classification	0.94
Brunner 2009	Proximal humerus fractures	Diagnosis	0.91
Panou 2015	Lower limb torsional profile	Evaluation	0.88
Hopyan 2010	Stroke	Diagnosis	0.88
Wattjes 2009	Brain	Classification	0.88
Arduini 2015	Hip muscle	Classification	0.872
Chang 2010	Cervical spine	Evaluation	0.86
Lee 2010	Lung cavitary mass	Evaluation	0.854
Brinjikji 2010	Hemorrhage	Classification	0.8
Ridge 2015	CT pulmonary node	Evaluation	0.792
Hoomweg 2008	Abdominal aortic aneurysm rupture	Diagnosis	0.78
Abul-kasim 2009	Scoliosis screw placement	Evaluation	0.76
Renou 2010	Brain hemorrhage	Classification	0.75
Roll 2011	Calcaneal fractures	Evaluation	0.75
Ozgen 2008	Temporal bone	Evaluation	0.682
De Souza 2012	Neck metastases	Diagnosis	0.66
Bogot 2005	Pulmonary nodule	Evaluation	0.659
Arealis 2014	Bone fractures	Diagnosis	0.65
Bishop 2013	Glenoid bone	Evaluation	0.64
Burkes 2014	Bone fractures	Diagnosis	0.6
Aukland 2006	Chest	Diagnosis	0.54
Carreon 2007	Spine posterolateral fusion	Evaluation	0.48
Van de Velde 2014	Brachial plexus	Outlining	0.45
Stroet 2011	Tibial fractures	Classification	0.45

KAPPA CORRELATION COEFFICIENT

0: AGREEMENT BY CHANCE

1: FULL AGREEMENT

Detection of Breast Cancer with Mammography: Effect of an Artificial Intelligence Support System

Alejandro Rodríguez-Ruiz, MSc • Elizabeth Krupinski, PhD • Jan-Jurre Mordang, MSc • Kathy Schilling, MD • Sylvia H. Heywang-Köbrunner, MD, PhD • Ioannis Sechopoulos, PhD • Ritse M. Mann, MD, PhD

From the Department of Radiology and Nuclear Medicine, Radboud University Medical Center, PO Box 9101, 6500 HB Nijmegen, Geert Grooteplein 10, 6525 GA, Post 766, Nijmegen, the Netherlands (A.R.R., I.S., R.M.M.); Department of Radiology & Imaging Sciences, Emory University, Atlanta, Ga (E.K.); ScreenPoint Medical BV, Nijmegen, the Netherlands (J.J.M.); Lynn Women's Health & Wellness Institute, Boca Raton Regional Hospital, Boca Raton, Fla (K.S.); Referenzzentrum Mammographie Munich, Brustdiagnostik München and FFB, Munich, Germany (S.H.H.); and Dutch Expert Centre for Screening, Nijmegen, the Netherlands (I.S.).
Received June 10, 2018; revision requested July 30; final revision received September 21; accepted September 28.
Address correspondence to R.M.M. (e-mail: *Ritse.Mann@radboudumc.nl*).

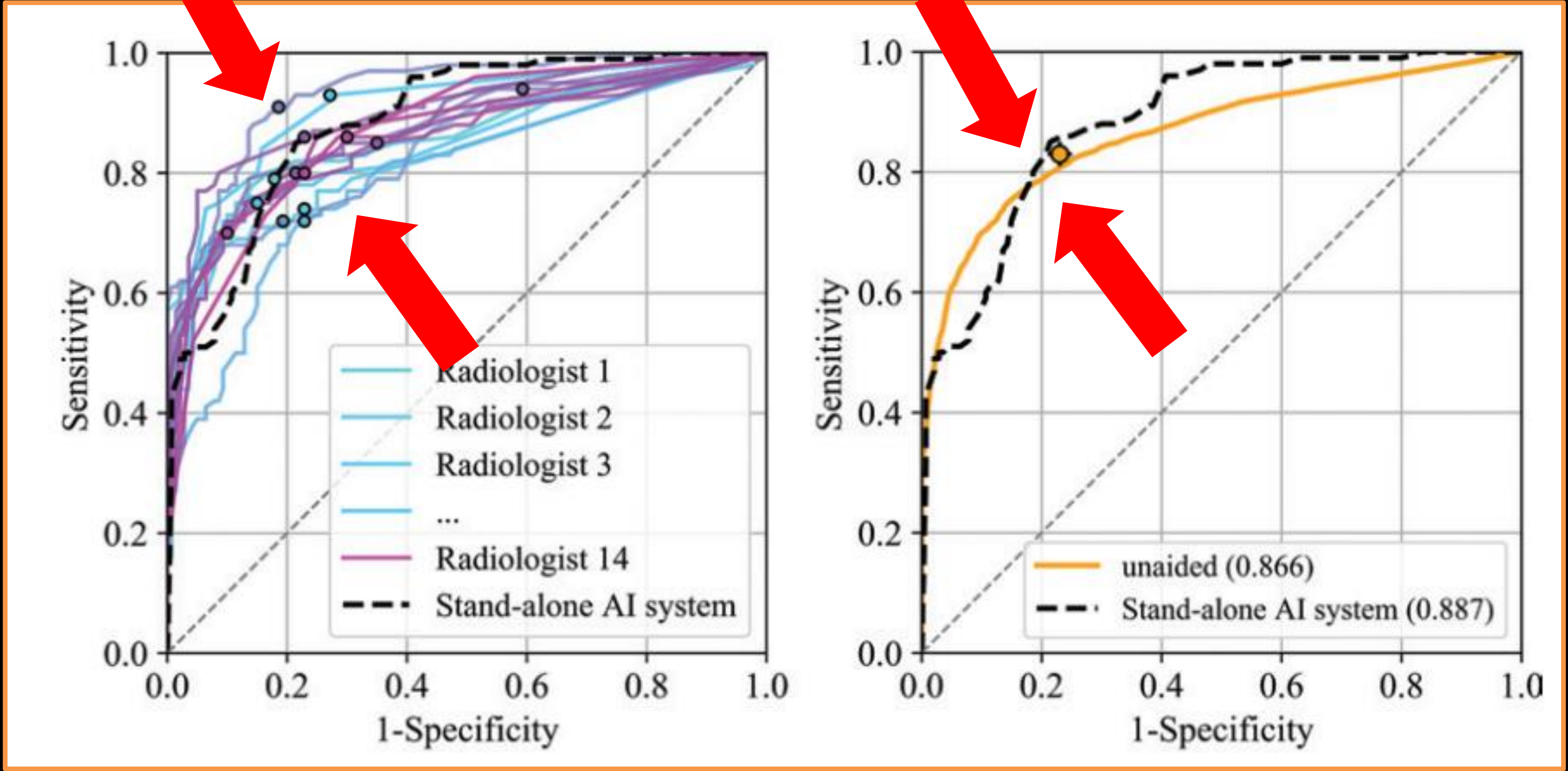
Conflicts of interest are listed at the end of this article.

See also the editorial by Bahl in this issue.

Radiology 2019; 00:1–10 • https://doi.org/10.1148/radiol.2018181371 • Content code: BR

VARIABILITY

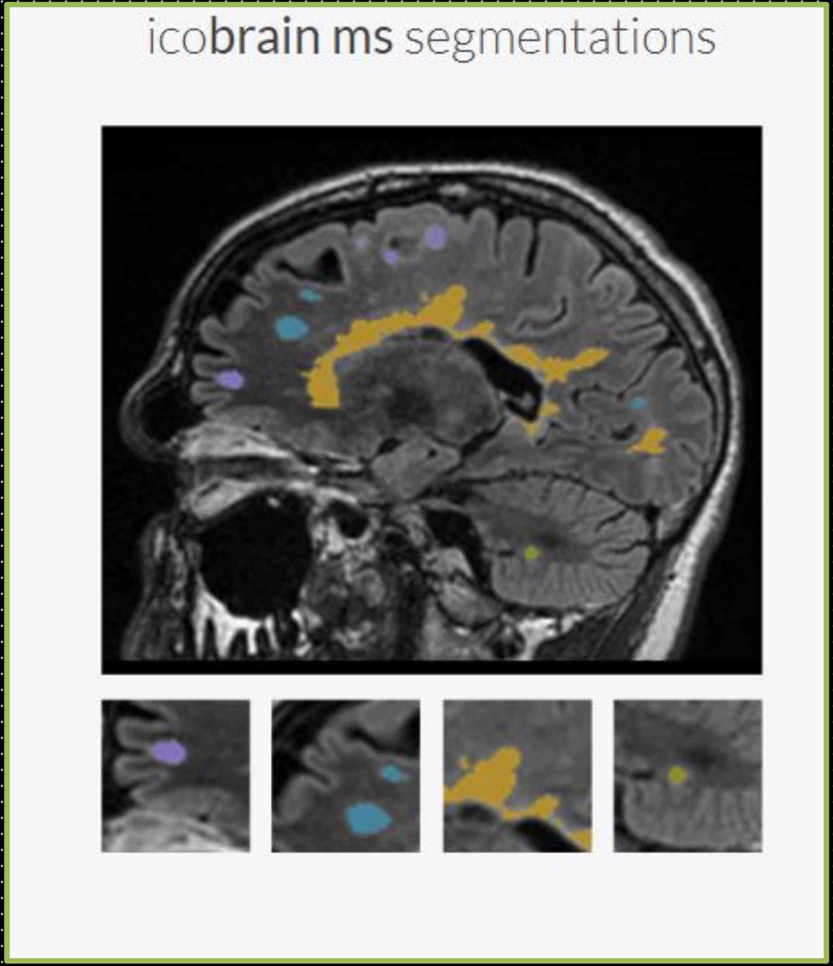
PERFORMANCES



LIMITATIONS OF THE RADIOLOGIST

- QUANTIFICATION TAKES TIME
- F-UP TAKES TIME
- REPEATABILITY IS A KEY ASPECT

icometrix

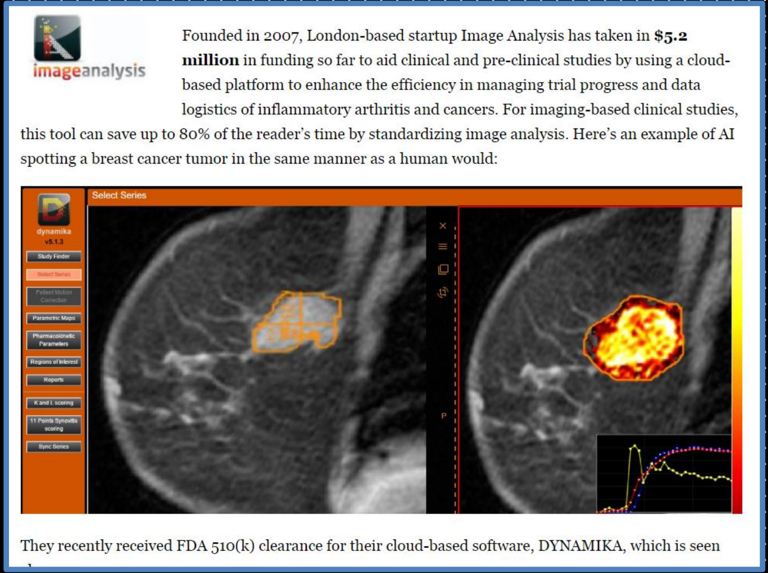


ICOBRAIN QUANTIFIES CLINICALLY RELEVANT BRAIN STRUCTURES IN PATIENTS WITH NEUROLOGICAL DISORDERS SUCH AS

MULTIPLE SCLEROSIS,
DEMENTIA
TRAUMATIC BRAIN INJURY.

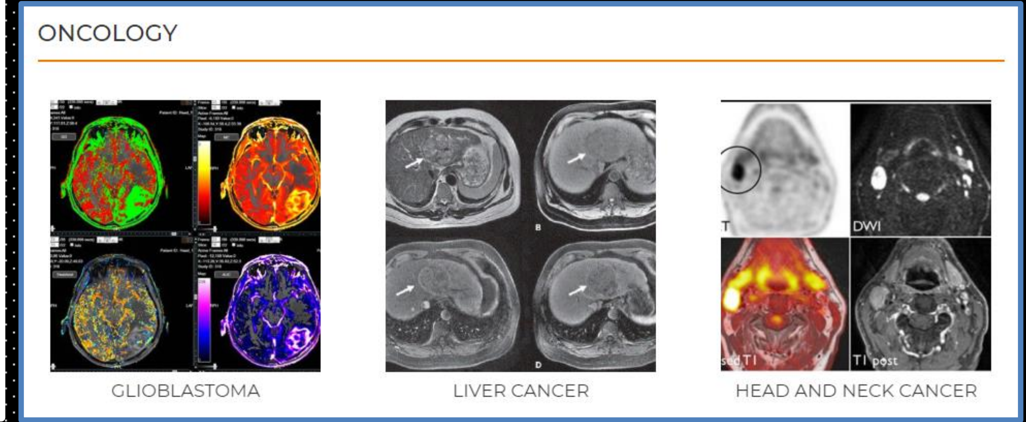
SCORING SYSTEMS

- RECIST 1.1
- IRECIST
- IRRC
- DCE-MRI, TUMOR VASCULARITY BIOMARKERS
- RANO
- MACDONALD CRITERIA
- MACHINE LEARNING TECHNIQUES FOR GRADING OF GBM


imageanalysis

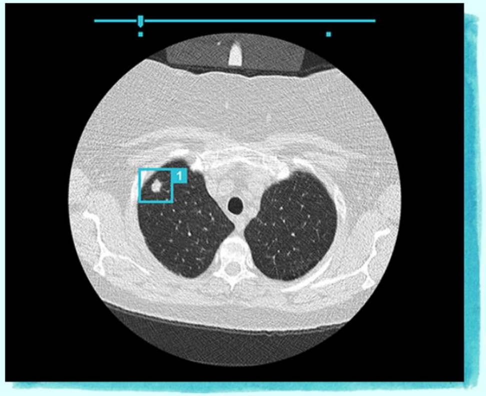
Founded in 2007, London-based startup Image Analysis has taken in **$5.2 million** in funding so far to aid clinical and pre-clinical studies by using a cloud-based platform to enhance the efficiency in managing trial progress and data logistics of inflammatory arthritis and cancers. For imaging-based clinical studies, this tool can save up to 80% of the reader's time by standardizing image analysis. Here's an example of AI spotting a breast cancer tumor in the same manner as a human would:

They recently received FDA 510(k) clearance for their cloud-based software, DYNAMIKA, which is seen



aidence
human sense in artificial intelligence

DETECTION AND QUANTIFICATION OF LUNG NODULES

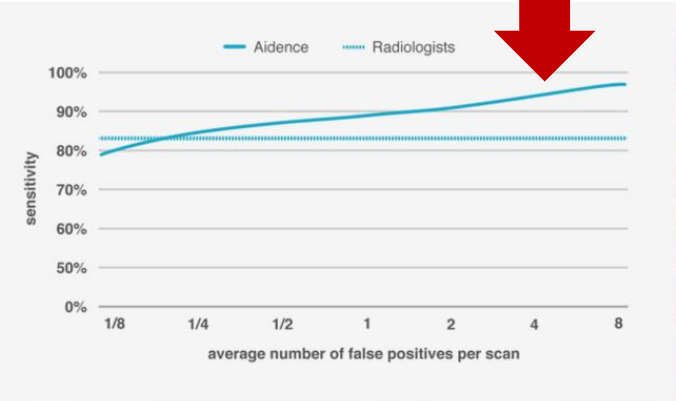


Veye Chest

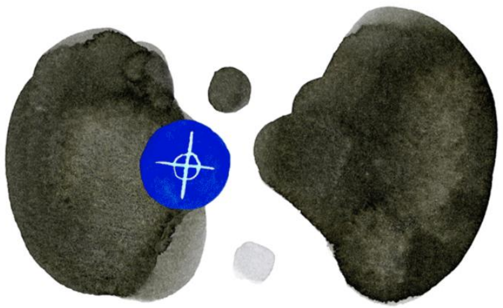
- Veye Chest Detection helps to accurately detect and mark pulmonary nodules
- Veye Chest Reporting automates the quantification of volume, composition, axial diameters and laterality (coming soon)
- Veye Chest Tracking supports you in automatically tracks volume changes over time (coming soon)
- Veye Chest is CE level IIa certified and currently available in Europe

Veye delivers superior accuracy with 90% sensitivity at an average of 1 false-positive per scan

- Veye is trained using over 45,000 chest scans
- Veye is independently validated by radiologists against 900 scans
- Currently, Veye is being validated by the University of Edinburgh



Meet Veye Chest, our highly accurate AI assistant that supports radiologists with detecting, reporting and tracking of pulmonary nodules



AI BENEFITS

- QUANTITY INSTEAD OF FINDING
- IMPROVE DATA RELIABILITY
- IMPROVE DATA COMPARISONS
- IMPROVE DATA STORAGE AND DATA MINING

AI

- DATA BY THE COMPUTER

AI: BETTER PERFORMANCES

- COMPLEX FEATURES
- ADAPTATIVE
- HIGH REPETABILITY

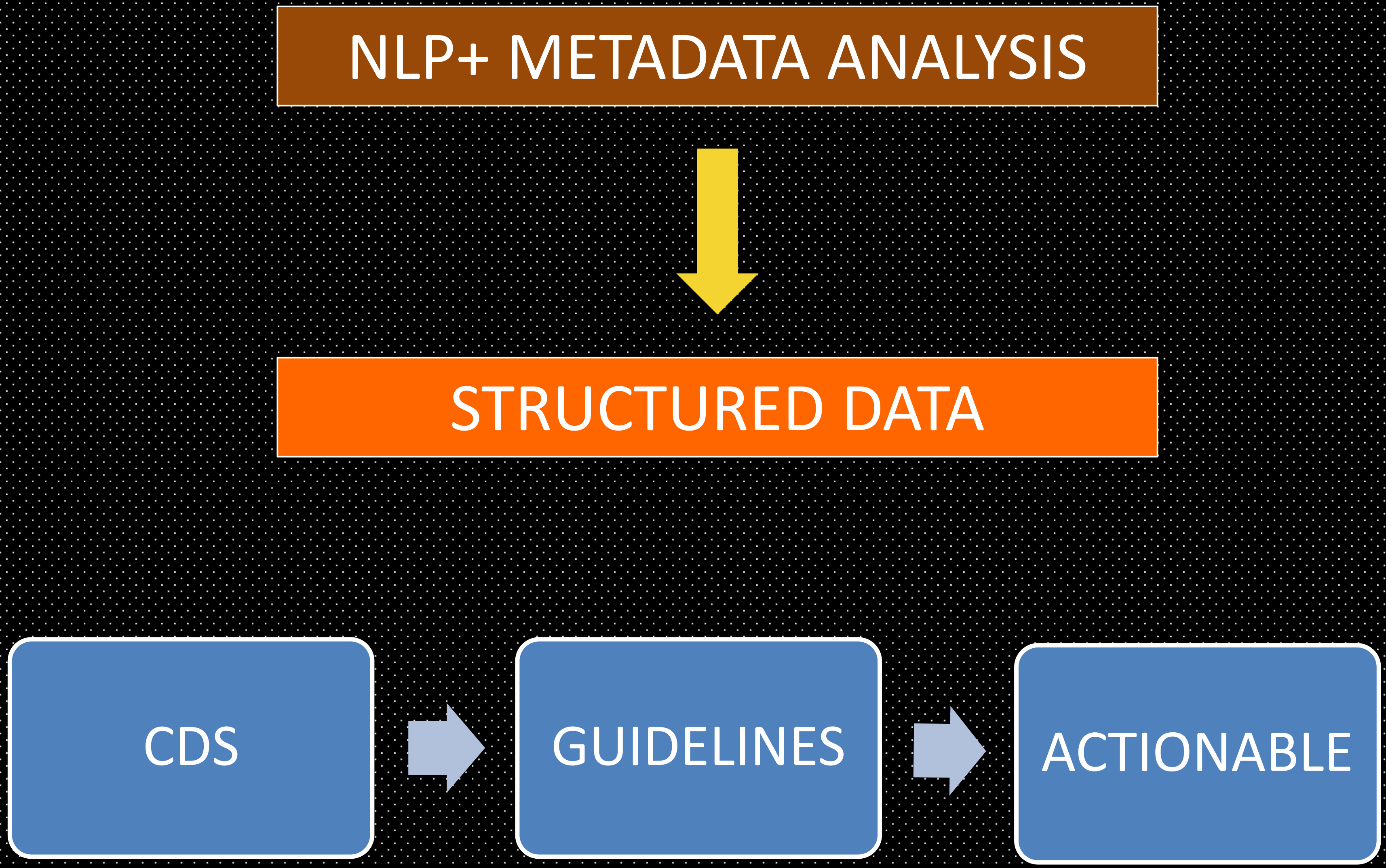
RADIOLOGIST PERSPECTIVE

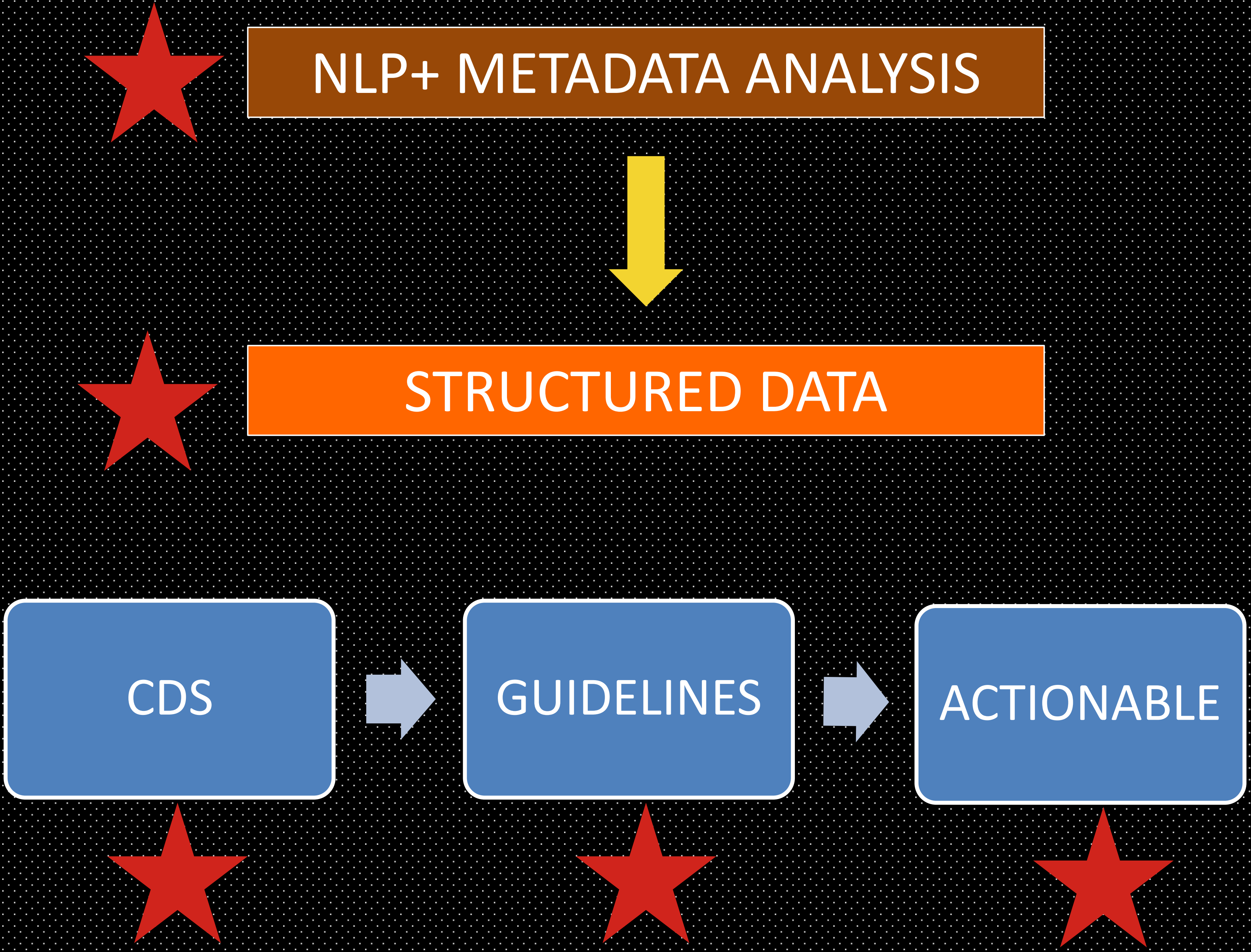
- WORKFLOW
- DETECTION
- QUANTIFICATION
- REPORTING

REPORT LIMITATIONS

- PROSE AND UNSTRUCTURED DATA
- LOW COMPLIANCE WITH RECOMMENDATIONS
- OFTEN NON ACTIONABLE

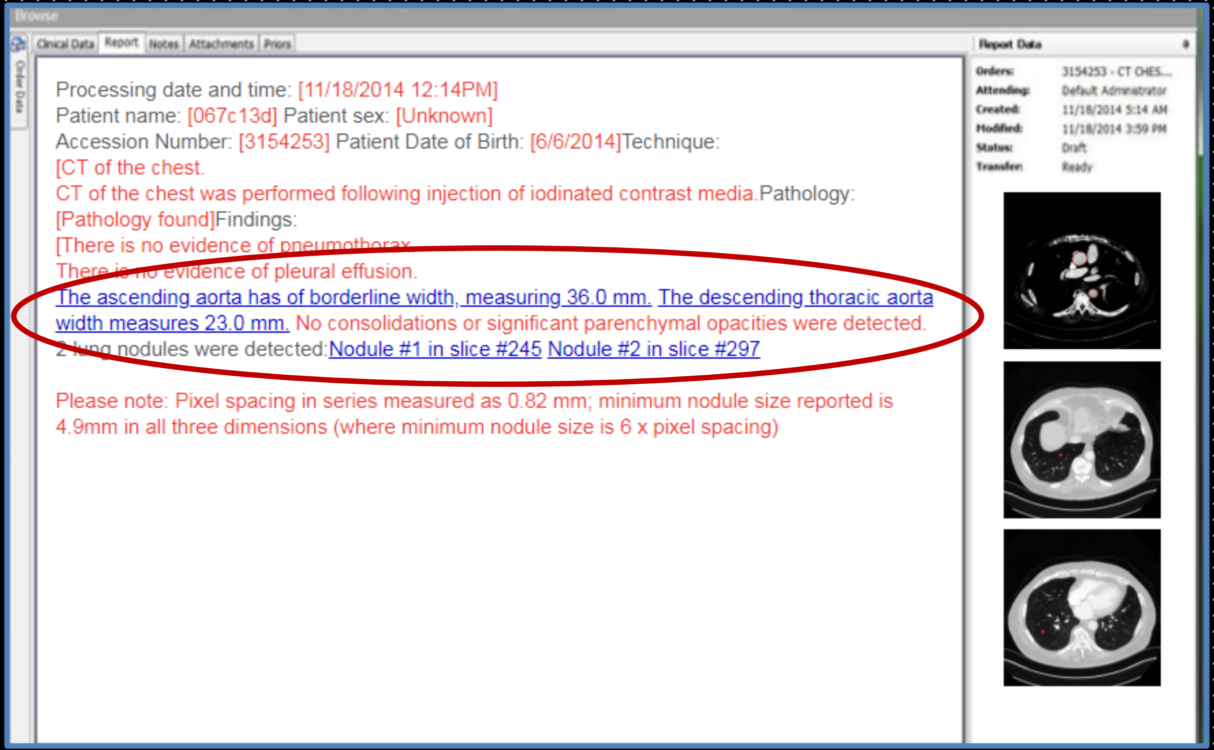
- FLEISCHNER SOCIETY GUIDELINES FOR LUNG NODULES MANAGEMENT AND F-UP
- LOW RATES OF ADHERENCE: **44.7% OF PATIENTS RECEIVED CARE INCONSISTENT** WITH THE FLEISCHNER RECOMMENDATIONS


NLP+ METADATA ANALYSIS
STRUCTURED DATA
CDS
GUIDELINES
ACTIONABLE


NLP+ METADATA ANALYSIS
STRUCTURED DATA
CDS
GUIDELINES
ACTIONABLE

RADLogics Virtual Resident™

Your RADLogics Virtual Resident is a software platform that enables image analysis applications of imaging data associated with CTs, MRIs and X-rays to automatically incorporate their analytics—with key images—into your PACS and reporting system to help radiologists in study review.


Clinical Data | Report | Notes | Attachments | Priors

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CT of the chest was performed following injection of iodinated contrast media.Pathology:
[Pathology found]Findings:
[There is no evidence of pneumothorax.
There is no evidence of pleural effusion.
The ascending aorta has of borderline width, measuring 36.0 mm. The descending thoracic aorta width measures 23.0 mm. No consolidations or significant parenchymal opacities were detected.
2 lung nodules were detected:Nodule #1 in slice #245 Nodule #2 in slice #297

Please note: Pixel spacing in series measured as 0.82 mm; minimum nodule size reported is 4.9mm in all three dimensions (where minimum nodule size is 6 x pixel spacing)

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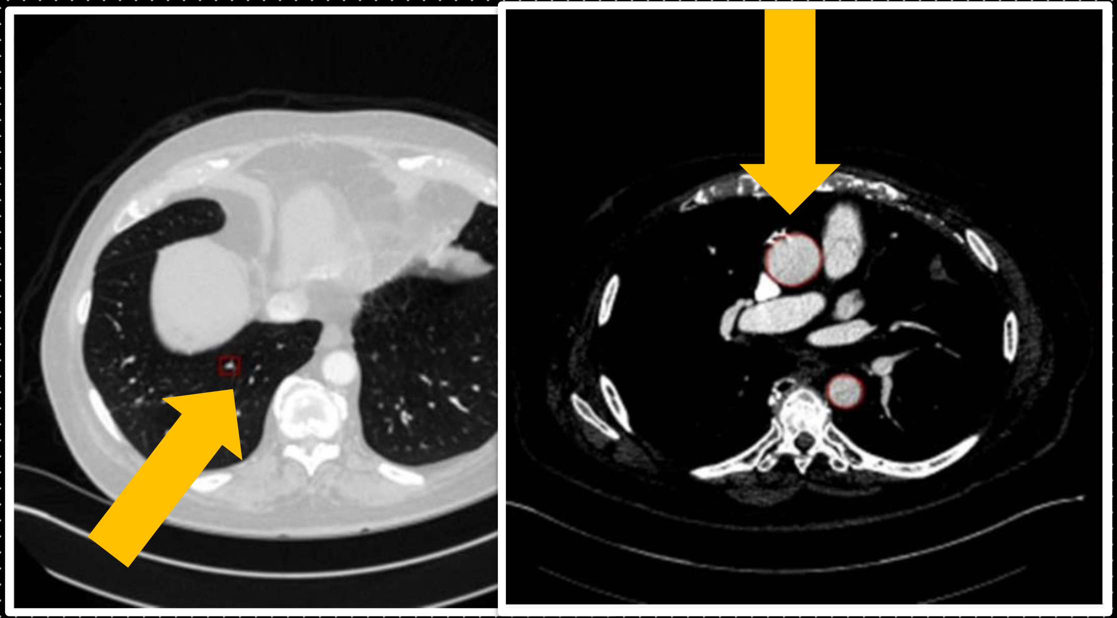


PROCEDURE PERSPECTIVE

- INCONSISTENT PROTOCOL
- OVEREXPOSURE
- FAILURE OF ALERT SYSTEM
- GANTRY POSITIONING ERRORS
- INAPROPRIATE IMAGE QUALITY

AI

AUTOMATION

- NEW CDS ALGORITHMS
- INDIVIDUALISED VS STANDARD PROTOCOLING
- ALERT SYSTEMS
- IMMEDIATE IQ ASSESMENT
- DOSE REDUCTION SOFTWARES

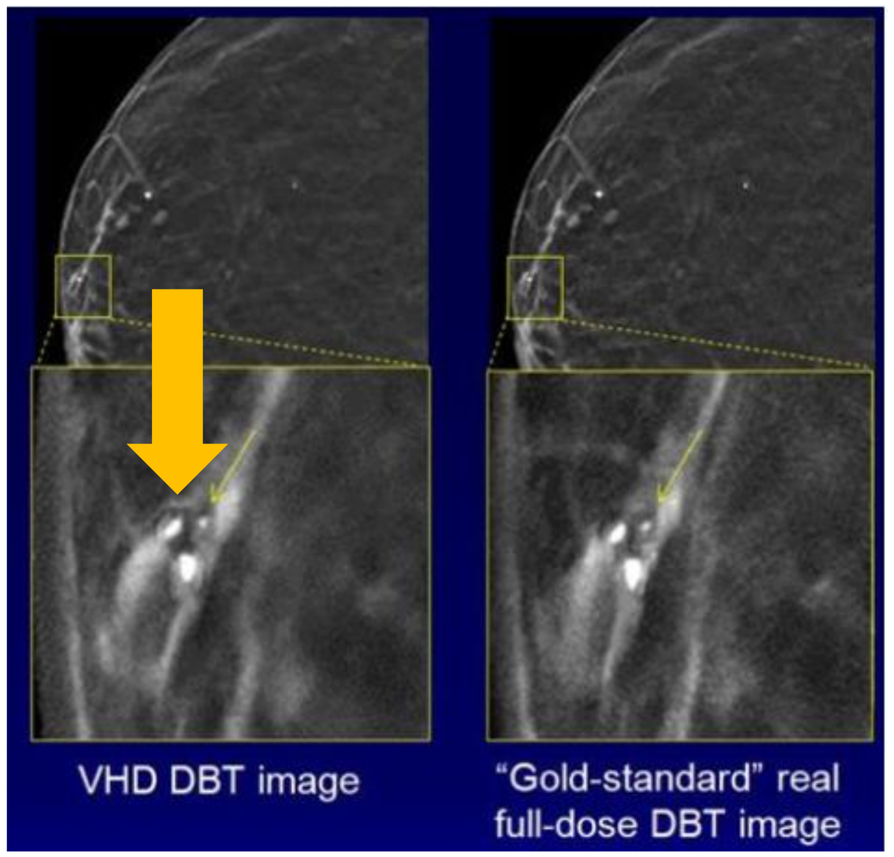
ASSESSMENT OF IMAGE QUALITY

AUTOMATED IMAGE QUALITY EVALUATION OF T_2-WEIGHTED LIVER MRI UTILIZING DEEP LEARNING ARCHITECTURE
ESSES S. ET AL. J. MAGN. RESON. IMAGING 2018;47:723–728

- MEDICAL IMAGE QUALITY ROUTINELY CHECKED
- VISUAL INSPECTION AND PHANTOMS
- POTENTIAL TO INSTANTLY RECOGNIZE, OR PREDICT POOR IMAGE QUALITY ALLOWING TECHNOLOGISTS TO CORRECT SUCH ERRORS BEFORE ENDING THE IMAGING EXAM.

DEEP LEARNING MAY PRODUCE SHARP REDUCTIONS IN DBT DOSE

SPIE MEDICAL IMAGING 2018



Junchi Liu

CONVERT LOW DOSE IMAGES TO VIRTUAL HIGHER-DOSE IMAGES WITH HIGH IMAGE QUALITY

REPRESENTS A 79% DOSE REDUCTION

Research Article
Vol. 8, No. 2 | 1 Feb 2017 | BIOMEDICAL OPTICS EXPRESS 679
Biomedical Optics EXPRESS

Low-dose CT via convolutional neural network

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Abstract: In order to reduce the potential radiation risk, low-dose CT has attracted an increasing attention. However, simply lowering the radiation dose will significantly degrade the image quality. In this paper, we propose a new noise reduction method for low-dose CT via deep learning without accessing original projection data. A deep convolutional neural network is here used to map low-dose CT images towards its corresponding normal-dose counterparts in a patch-by-patch fashion. Qualitative results demonstrate a great potential of the proposed method on artifact reduction and structure preservation. In terms of the quantitative metrics, the proposed method has showed a substantial improvement on PSNR, RMSE and SSIM than the competing state-of-art methods. Furthermore, the speed of our method is one order of magnitude faster than the iterative reconstruction and patch-based image denoising methods.

OCIS codes: (340.7440) X-ray imaging; (100.3190) Inverse problems; (100.6950) Tomographic image processing.

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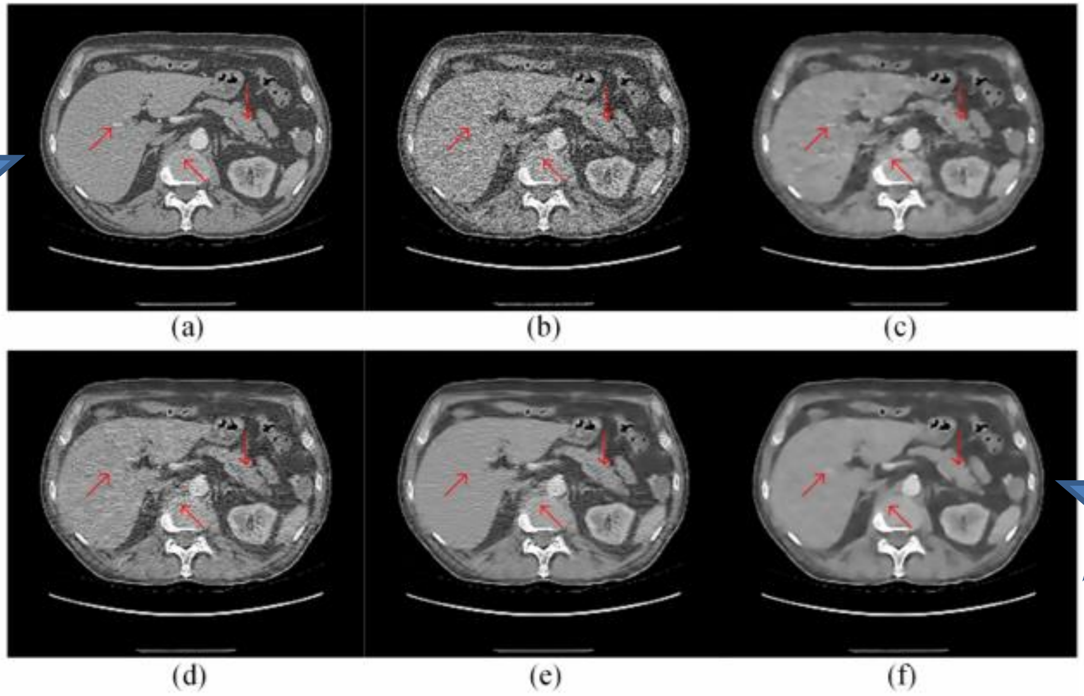
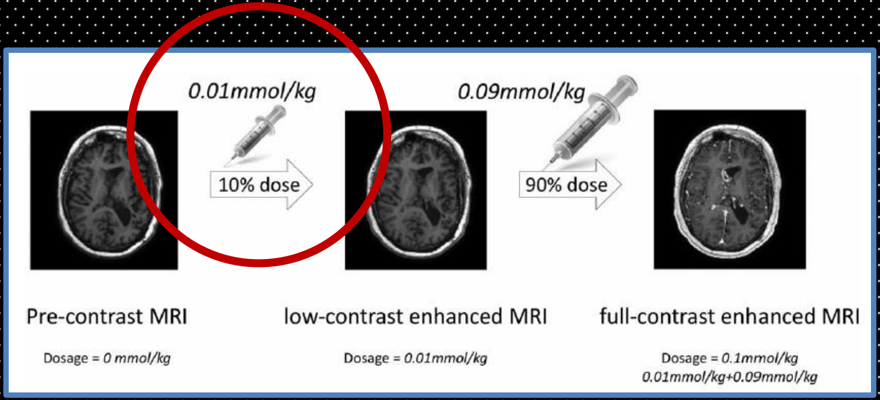


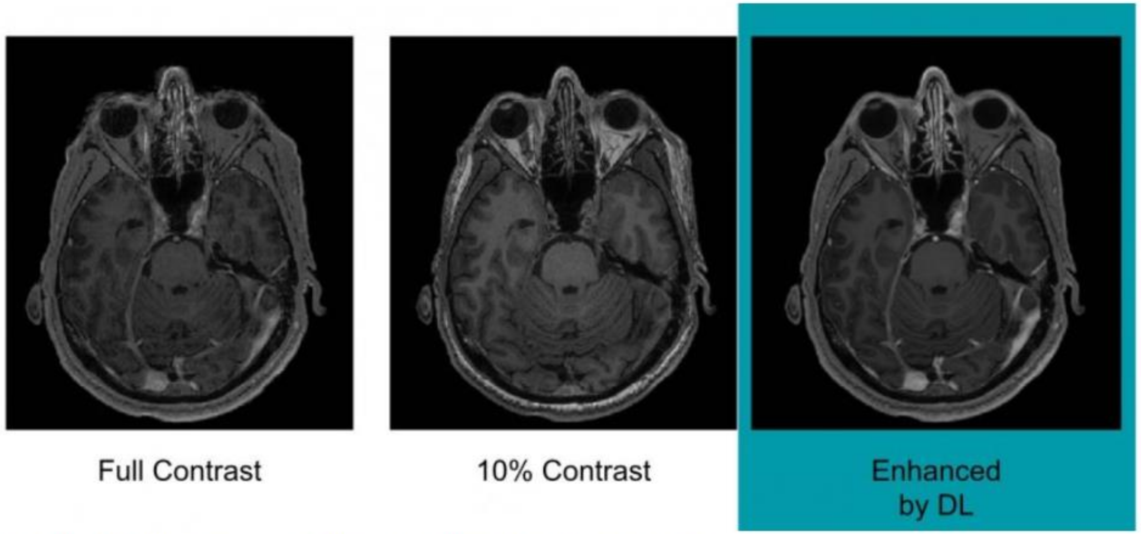
Fig. 3. Results of an abdomen image. (a) Original normal-dose image; (b) the low-dose image; (c) the ASD-POCS image; (d) the KSVD image; (e) the BM3D image; (f) the CNN processed low-dose image.

120 KV 150 mas
80 KV 17 mas

DEEP LEARNING ENABLES REDUCED GADOLINIUM DOSE FOR CONTRAST-ENHANCED BRAIN MRI

E. Gong et al J. MAGN. RESON.IMAGING https://doi.org/10.1002/jmri.2597.





Example of full-dose, 10 percent low-dose and algorithm-enhanced low-dose.

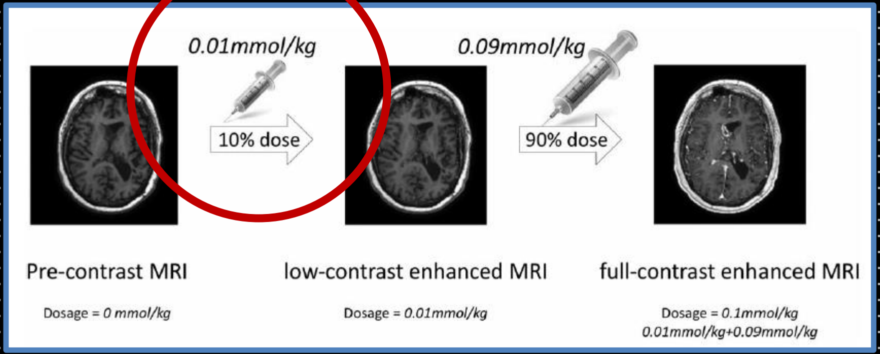
Source: Radiological Society of North America

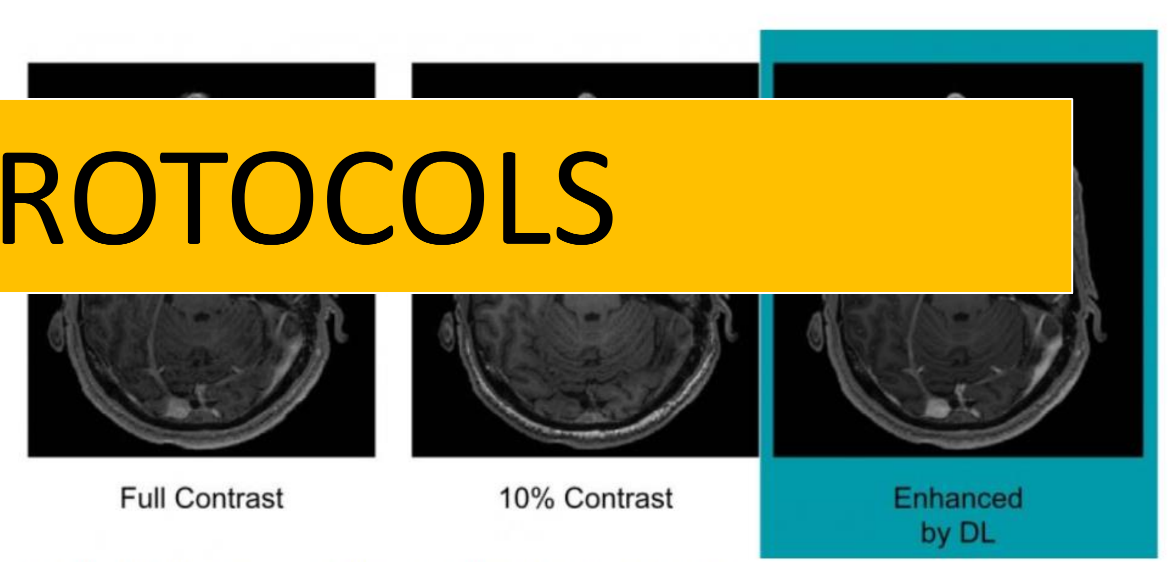
Courtersy of Enhao Gong, Stanford University

AI: SAFE PROTOCOLS

DEEP LEARNING ENABLES REDUCED GADOLINIUM DOSE FOR CONTRAST-ENHANCED BRAIN MRI

E. Gong et al J. MAGN. RESON.IMAGING





Example of full-dose, 10 percent low-dose and algorithm-enhanced low-dose.

Source: Radiological Society of North America

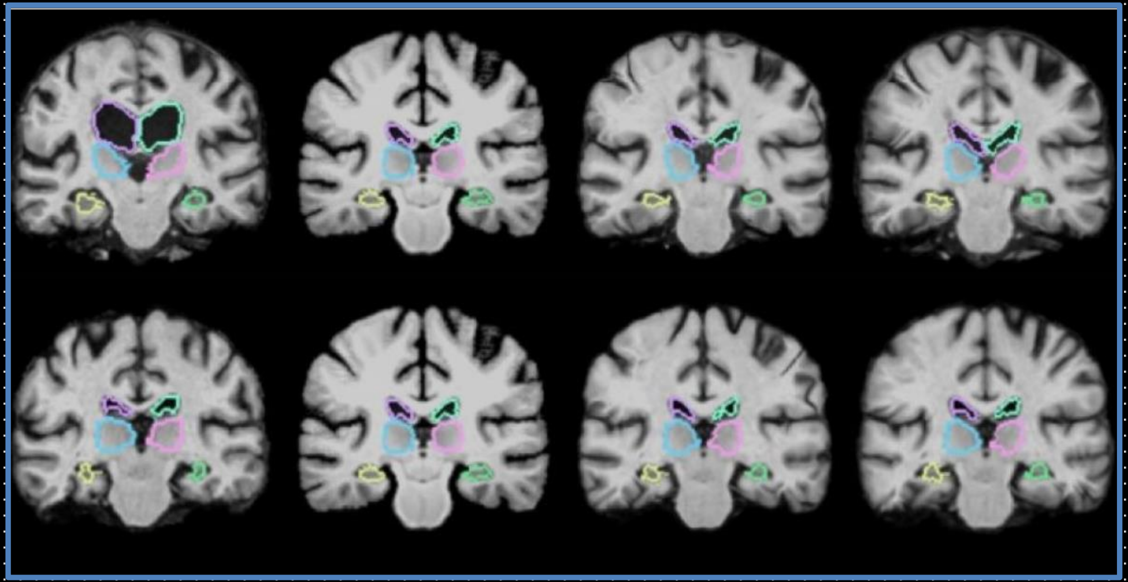
Courtersy of Enhao Gong, Stanford University

PATIENT PERSPECTIVE

AI

EXAMINATION DURATION

VOXELMORPH



MIT RESEARCHERS HAVE DEVELOPED AN ARTIFICIAL INTELLIGENCE-BASED ALGORITHM THAT CAN **REGISTER 3D IMAGES 1,000 TIMES MORE QUICKLY** THAN STANDARD MEDICAL IMAGE REGISTRATION TECHNIQUES

2018

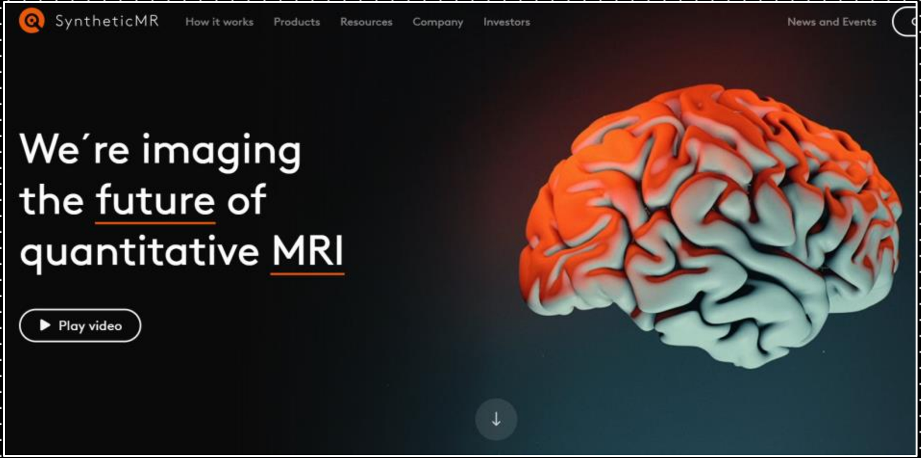
SUBTLE MEDICAL

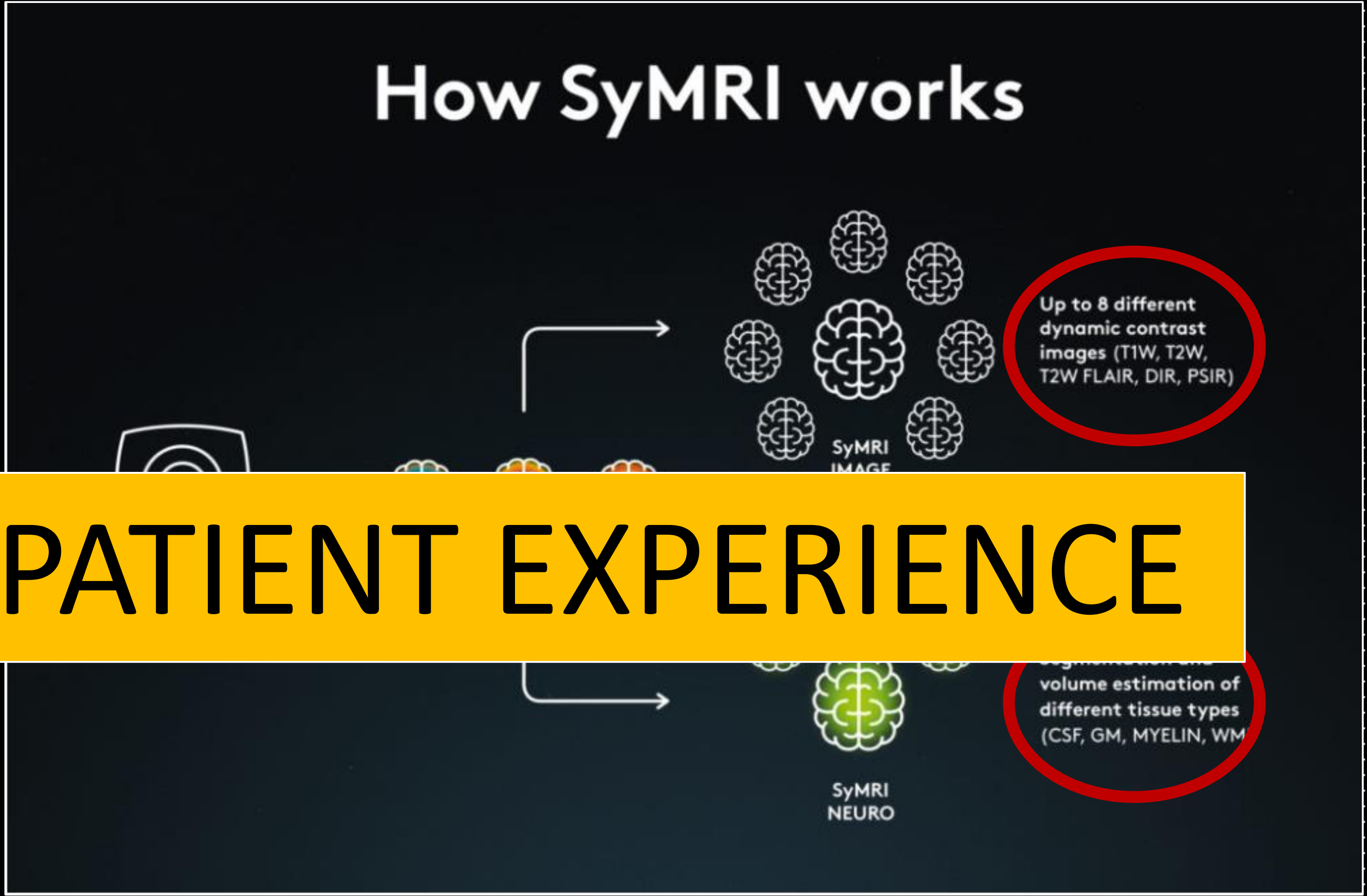
FDA GRANTS CLEARANCE TO AI-POWERED IMAGING SYSTEM

REDUCE THE DURATION OF MRI AND PET SCANS 4X-10X.

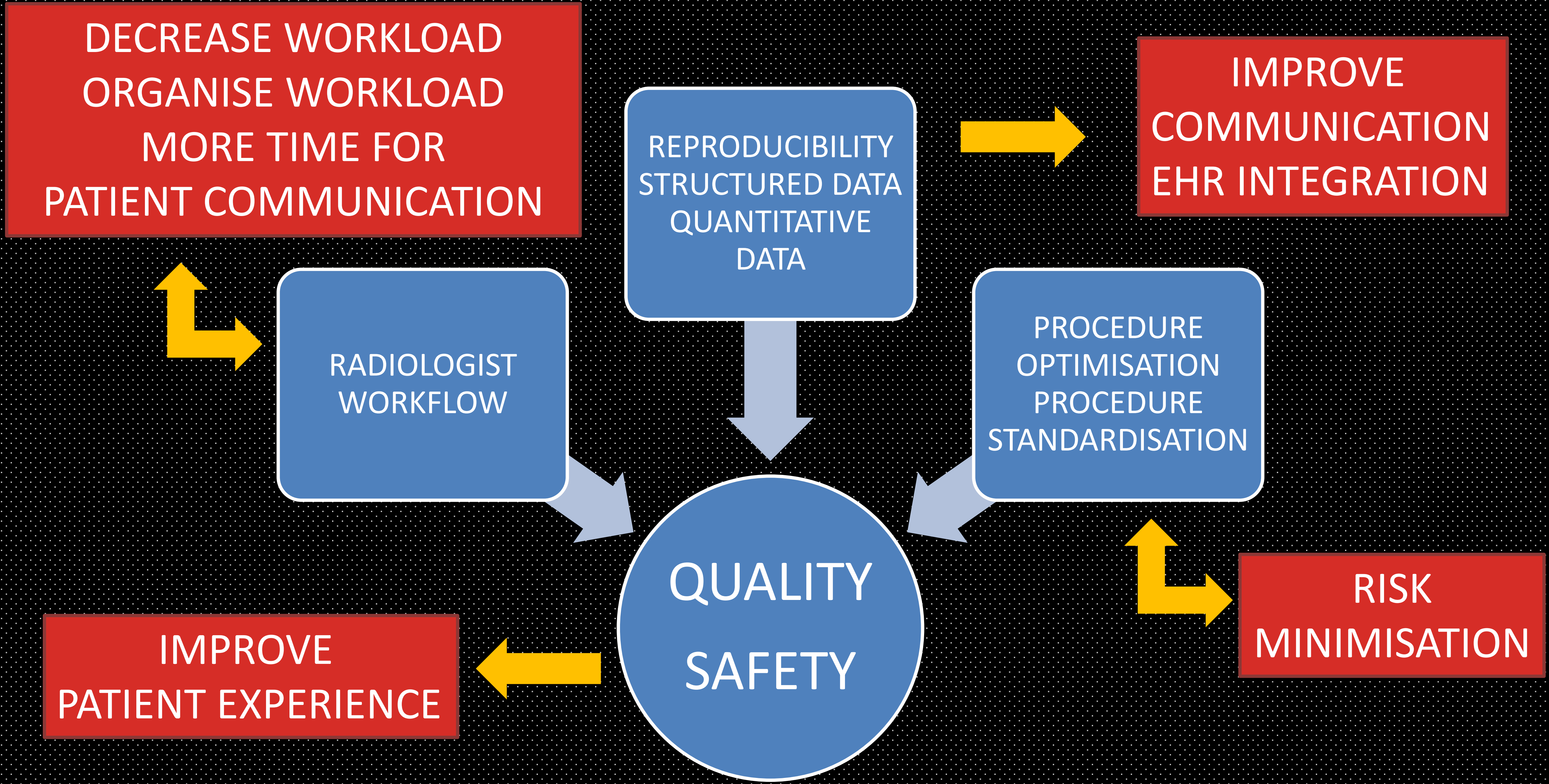
Chen K et al. *Radiology 2018* (in press)

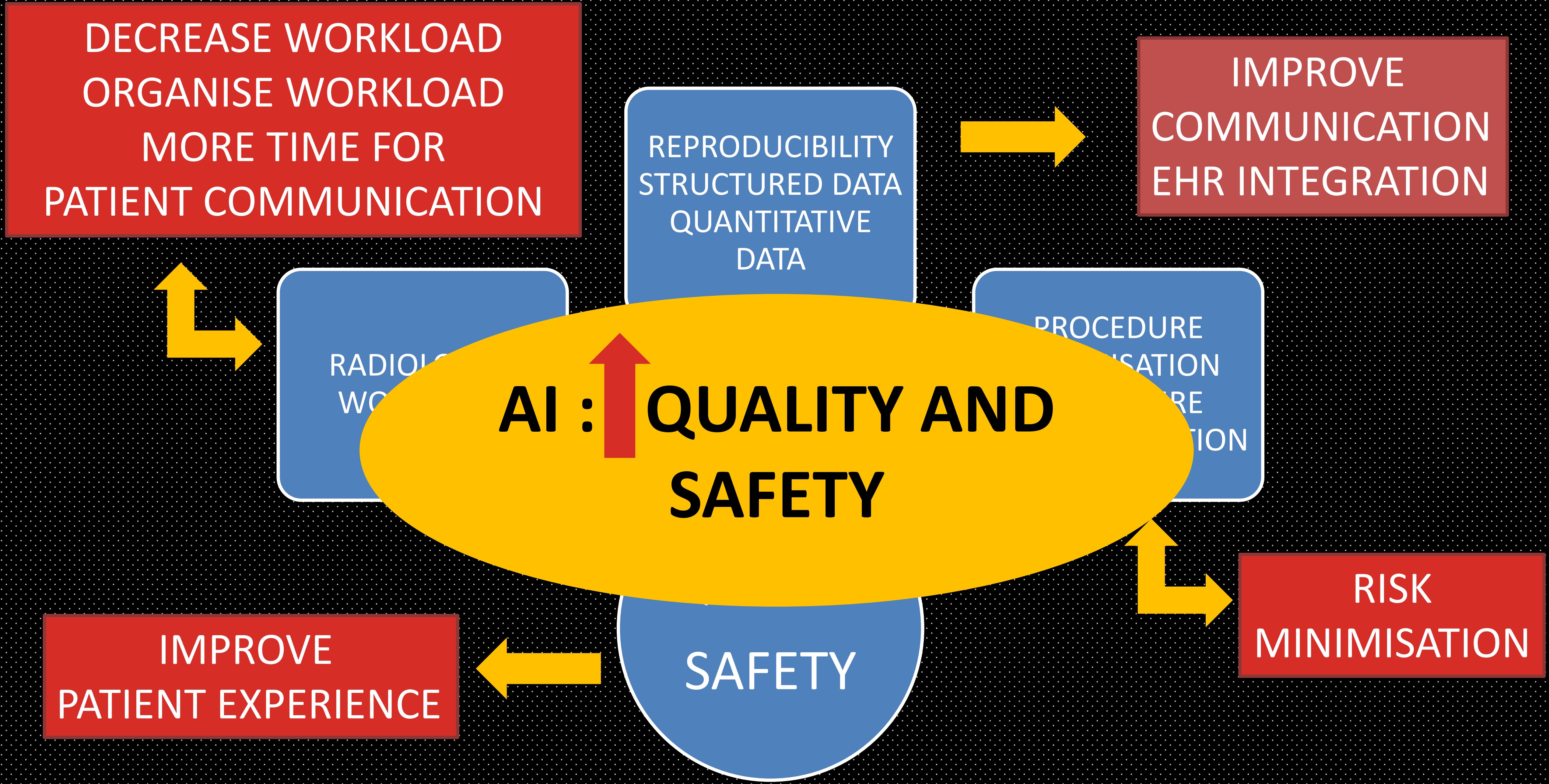
AI: IMPROVE PATIENT EXPERIENCE





ACQUISITION: 6 Min.
POST-PROCESSING : LESS THAN 10 Sec.


DECREASE WORKLOAD
ORGANISE WORKLOAD
MORE TIME FOR
PATIENT COMMUNICATION
REPRODUCIBILITY
STRUCTURED DATA
QUANTITATIVE
DATA
IMPROVE
COMMUNICATION
EHR INTEGRATION
RADIOLOGIST
WORKFLOW
PROCEDURE
OPTIMISATION
PROCEDURE
STANDARDISATION
QUALITY
SAFETY
RISK
MINIMISATION
IMPROVE
PATIENT EXPERIENCE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THANK YOU!!!!!