

Data Mining and Machine Learning for Integrated CDS

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Radiology Forces

Pros

- Revenue center profit margin
- Value and volume
- Outpatient focus
- Fast and efficient
- Technological advances
- Constant modality innovation
- New indications
- IR new treatments (cancer)
- IT rich and driven
- EHR availability
- Data rich
- Research opportunity
- Subspecialization
- Networks
- Actionable Reporting

Cons

- Busy and burned out
- Too much data (10X # images)
- 24/7 expectations
- Turf
- Cost center (PHM)
- Research \$ less
- No major new modalities (PET/MR 7T)
- Variation and waste
- Quality and Safety
- Peer learning
- Research \$ less
- Leadership
- Subspecialization networks
- Service business
- Actionable reporting

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Artificial Intelligence and Machine Learning

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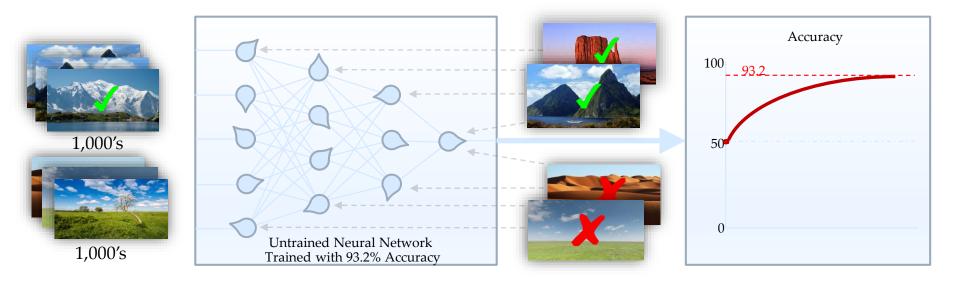
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So what is Machine-Deep Learning?

DATA SCIENCE

TRAINING ARTIFICIAL NEURAL NETWORKS

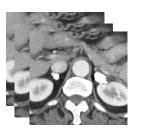




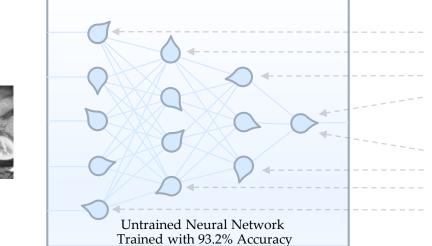
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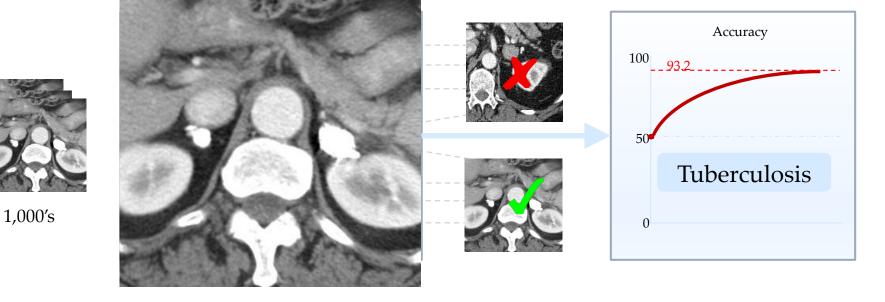
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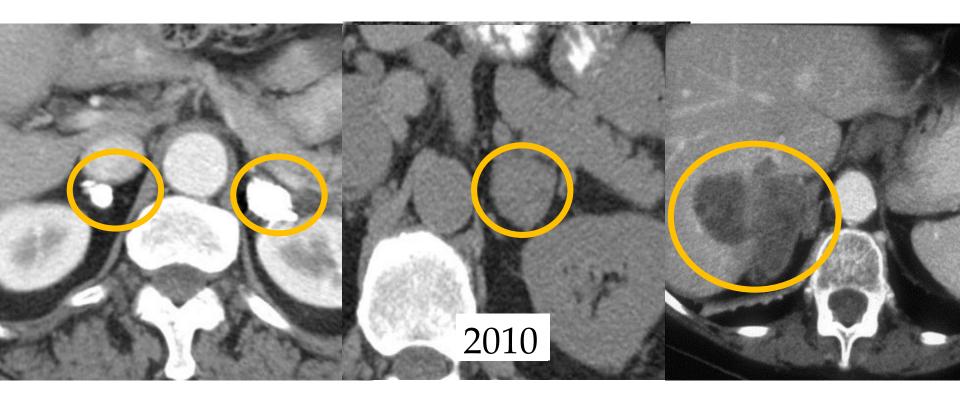
Machine Learning in Radiology

DATA SCIENCE

TRAINING ARTIFICIAL NEURAL NETWORKS



So what does this mean for Radiology?



Adenoma

Metastasis

Predictions for ML in medicine – 3 paradigms

- 1. Improved prognostic prediction
- 2. Machine learning will displace much of the work of radiologists and anatomical pathologists. These physicians focus largely on interpreting digitized images, which can easily be fed directly to algorithms instead. Massive imaging data sets, combined with recent advances in computer vision, will drive rapid improvements in performance, and machine accuracy will soon exceed that of humans. Indeed, radiology is already partway there: algorithms can replace a second radiologist reading mam-mogram and will soon exceed human accuracy.
- 3. Diagnostic accuracy and reduction of error



Doom and Gloom

Catalogue of fears

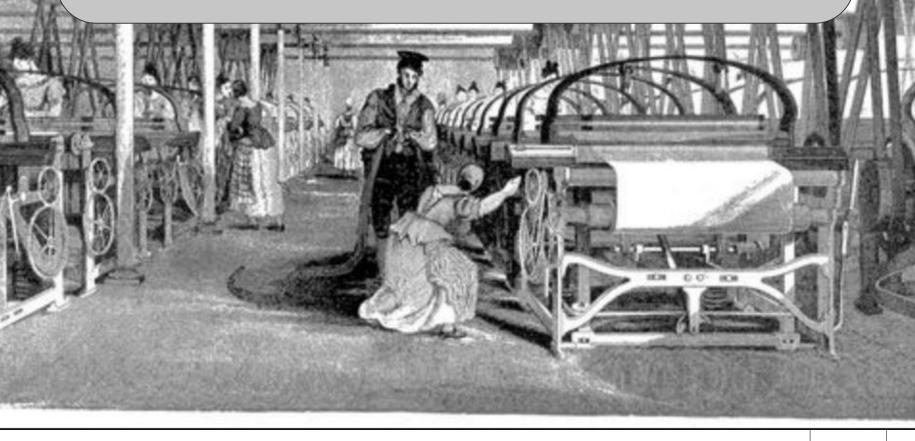
Probability of computerisation of different occupations, 2013 (1 = certain)

Job	Probability
Recreational therapists	0.003
Dentists	0.004
Athletic trainers	0.007
Clergy	0.008
Chemical engineers	0.02
Editors	0.06
Firefighters	0.17
Actors	0.37
Health technologists	0.40
Economists	0.43
Commercial pilots	0.55
Machinists	0.65
Word processors and typists	0.81
Real-estate sales agents	0.86
Technical writers	0.89
Retail salespeople	0.92
Accountants and auditors	0.94
Telemarketers	0.99

Source: "The Future of Employment: How Susceptible are Jobs to Computerisation?", by C. Frey and M. Osborne (2013)

- Experts warn that "the substitution of machinery for human labor" may "render the population redundant". They worry that "the discovery of this mighty power" has come "before we knew how to employ it rightly".
- But these are in fact the words of commentators discussing mechanization and steam power two centuries ago. Back then the controversy over the dangers posed by machines was known as the "machinery question".

In America during the 19th century the amount of coarse cloth a single weaver could produce in an hour increased by a factor of 50, and the amount of labor required per yard of cloth fell by 98%. This made cloth cheaper and increased demand for it, which in turn created more jobs for weavers: their numbers quadrupled between 1830 and 1900





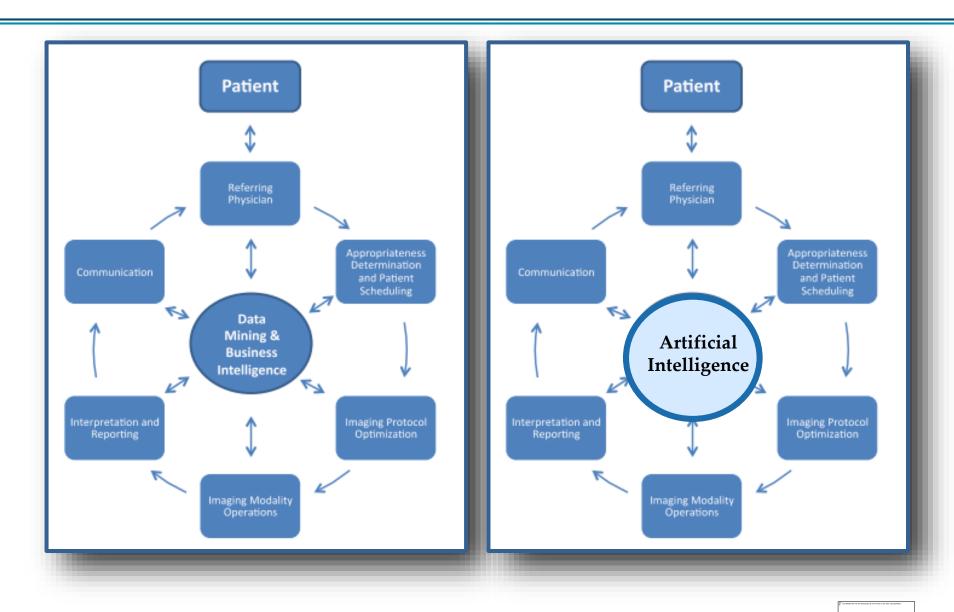
Average number of tellers fell from 20 per branch in 1988 to 13 in 2004. But that reduced the cost of running a bank branch, allowing banks to open more branches in response to customer demand. The number of urban bank branches rose by 43% over the same period

Mistaken Analysis – Misguided Interpretation

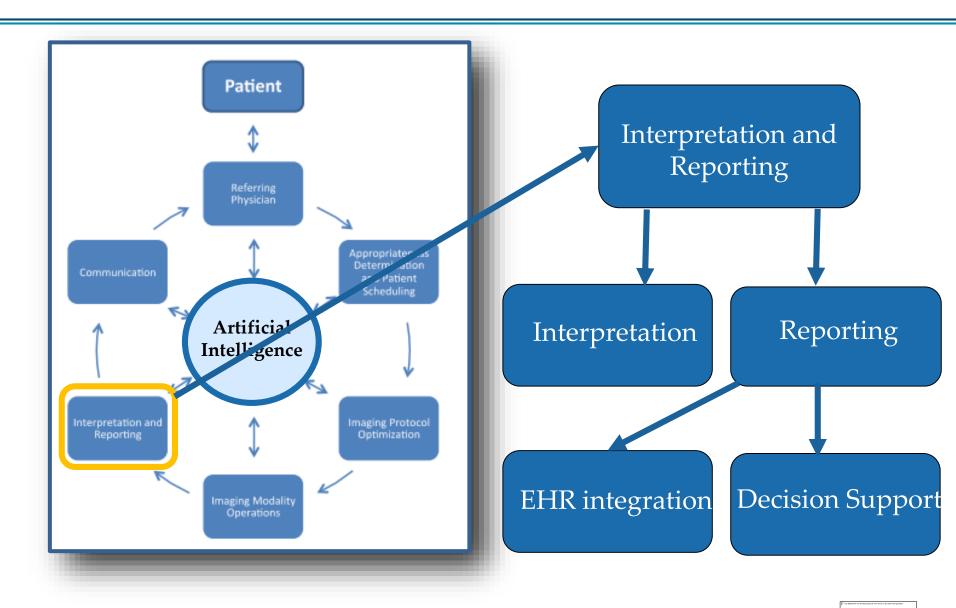
- More jobs or less jobs with computers?
- "lump of labor" fallacy.
- "This notion that there's only a finite amount of work to do, and therefore that if you automate some of it there's less for people to do, is just totally wrong,". Those sounding warnings about technological unemployment "basically ignore the issue of the economic response to automation"
- So more work, but probably different types of work
- We will have to adjust
- AI will likely impact each activity in the imaging value chain



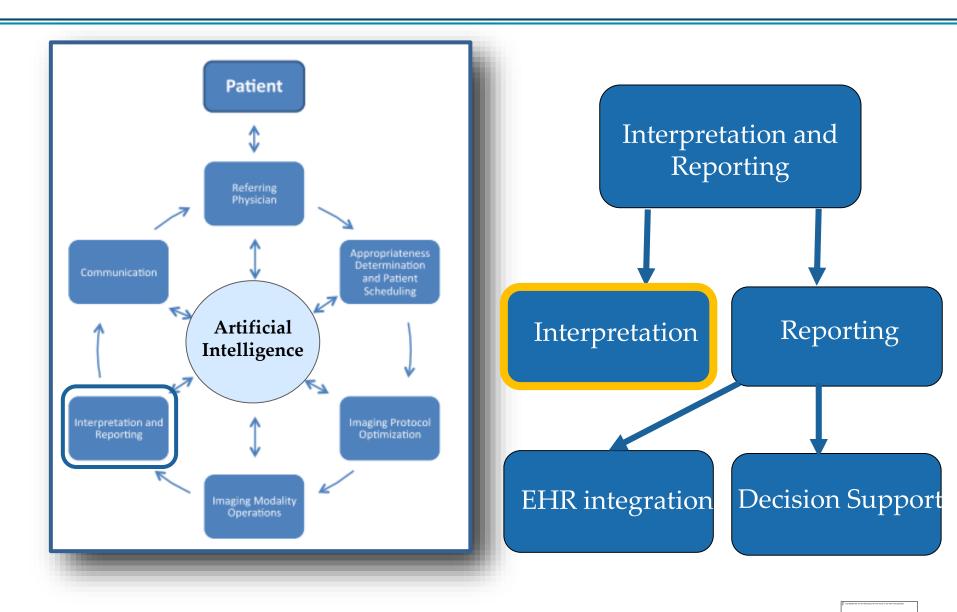
Imaging Value Chain – JACR 2015



Imaging Value Chain

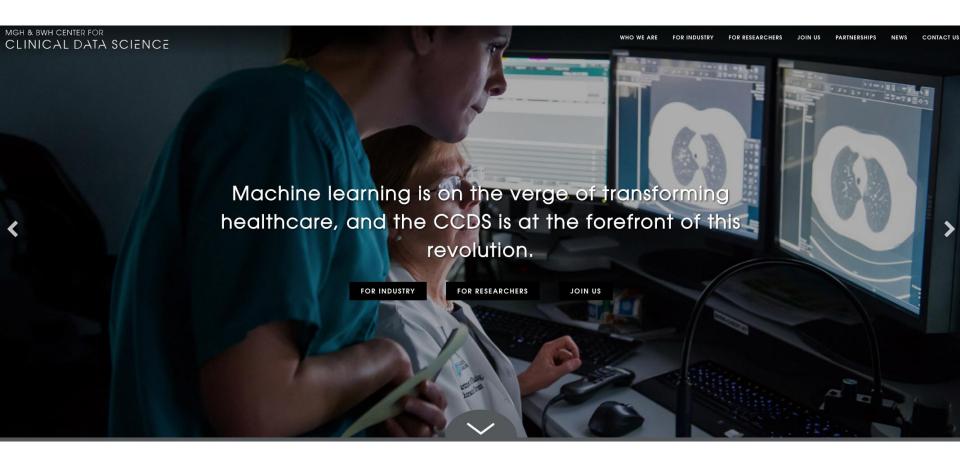


Imaging Value Chain

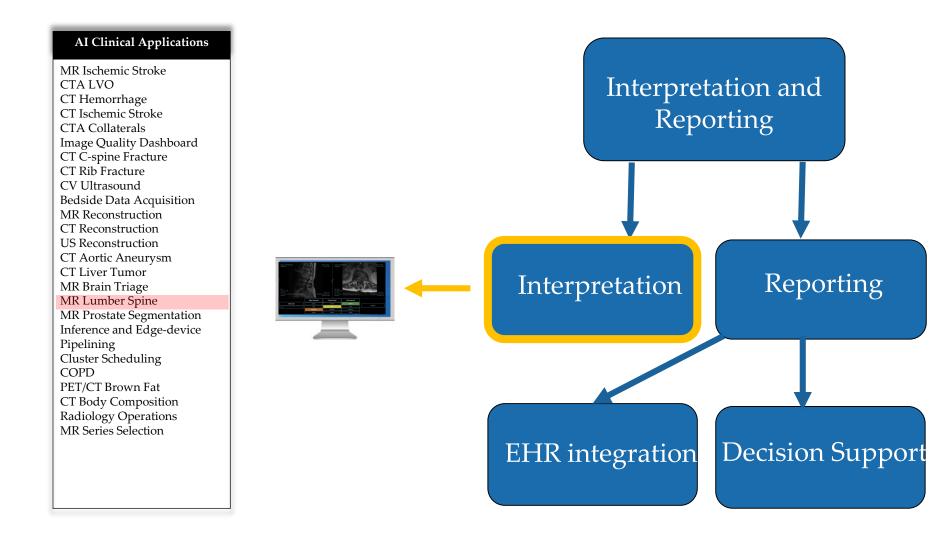


18

MGH & BWH Clinical Data Science



Imaging Value Chain



SIGNIFICANT FINDINGS BY LEVEL:

T12-L1:Unremarkable.

L1-2: Unremarkable.

L2-3: There is disc bulge, mild facet arthropathy bilaterally as well as a left foraminal/extraforaminal disc protrusion resulting in mild spinal canal stenosis, as well as mild right and moderate left neural foraminal stenosis.

L3-4: There is bilateral facet arthropathy, prominence of the epidural fat, as well as a left foraminal/extraforaminal disc protrusion without significant neural foraminal. There is mild spinal canal stenosis.

L4-5: There is a bulging disc, prominence of the epidural fat, as well as bilateral facet arthropathy with mild left and mild-moderate right neural foraminal stenosis. There is mild spinal canal stenosis.

L5-S1: There is bilateral facet arthropathy as well as disc uncovering and prominence of the epidural fat, which results in severe right and moderate left neural foraminal stenosis.

Localization



Stenosis Grading



T12-L1	0	0	0
L1-2	0	0	0
L2-3	1	1	3
L3-4	1	0	0
L4-5	1	2	1
L5-S1	0	5	3
No stenosis			Severe
0 1	2	3 4	5

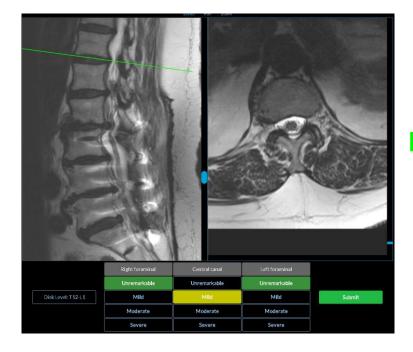
Machine Learning: Lumbar Spine MRI Interpretation Algorithm



Courtesy Keith Dreyer

One-Click Results Integration into Reporting Software

PACS Viewer Integration



Reporting Software

SIGNIFICANT FINDINGS BY LEVEL:

T12-L1:There is mild spinal canal stenosis. There is no significant left foraminal stenosis and there is mild right foraminal stenosis.

L1-2: There is moderate spinal canal stenosis. There is mild left and right foraminal stenosis.

L2-3: There is severe central spinal canal and left and right foraminal stenosis.

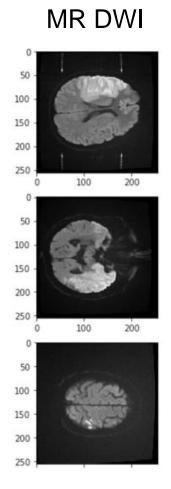
L3-4: There is no significant spinal canal stenosis. There is moderate left foraminal stenosis and there is no significant right foraminal stenosis.

L4-5: There is mild central spinal canal and left and right foraminal stenosis.

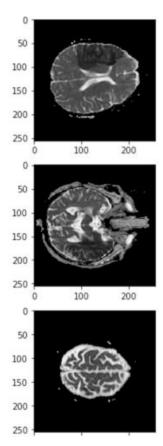
L5-S1: There is mild spinal canal stenosis. There is mild left foraminal stenosis and there is moderate right foraminal stenosis.

IMPRESSION:

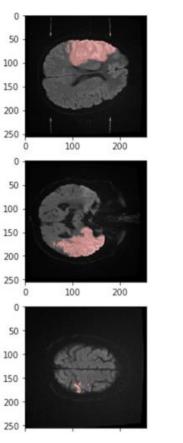
Stoke Detection and Outcomes

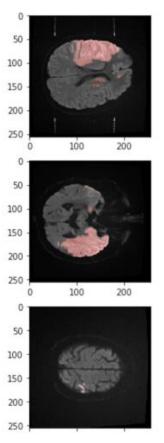


MR ADC



Machine Learning

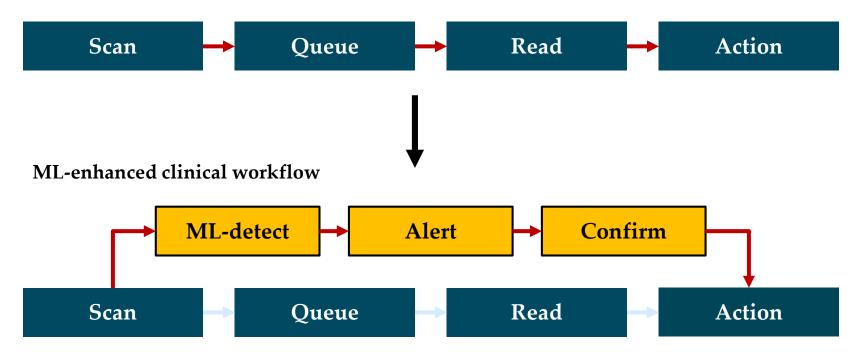




Courtesy Mark Michalski

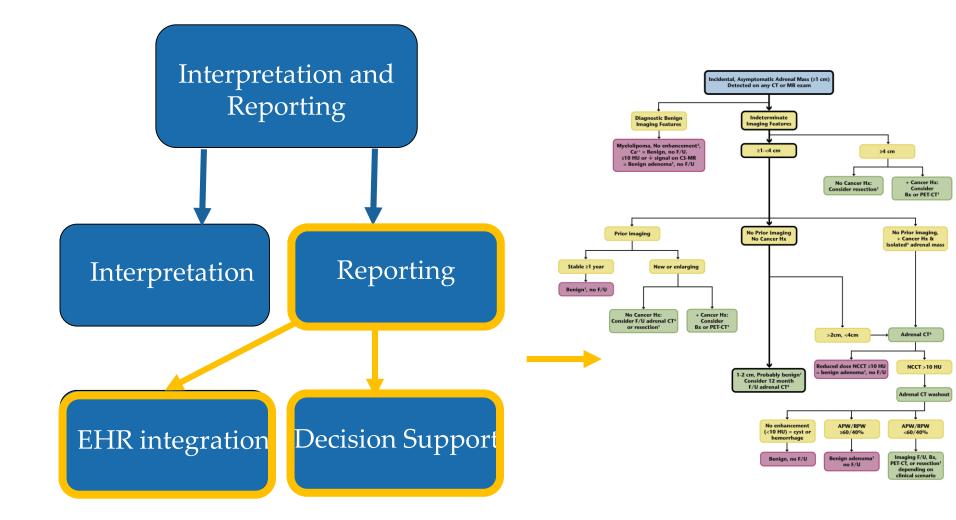
Stroke Detection Workflow

Current clinical workflow



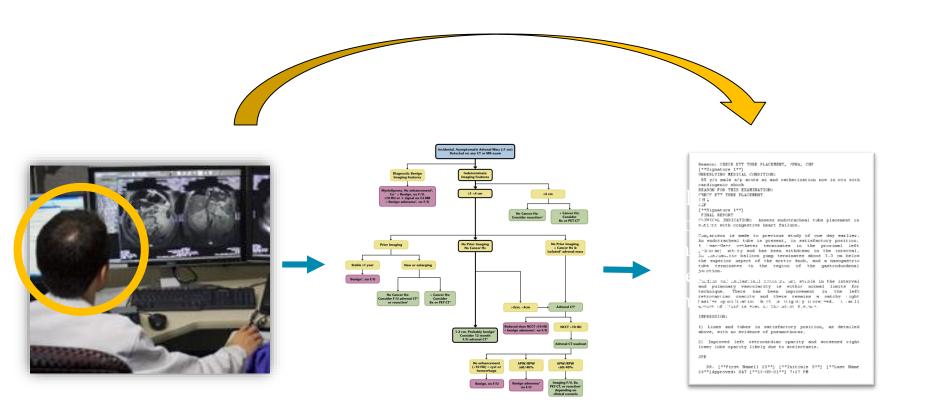
- Reduces time to action for stroke victims, especially in incidental findings
- Enables MGH/BWH to more effectively read scans from other hospitals, especially at night

Actionable Reporting



Mayo-Smith et al., JACR 2017

Actionable Reporting



Imaging Data

Best practice algorithm

Actionable Radiology Report

Computer Assisted Decision Support

 Patient:
 74F

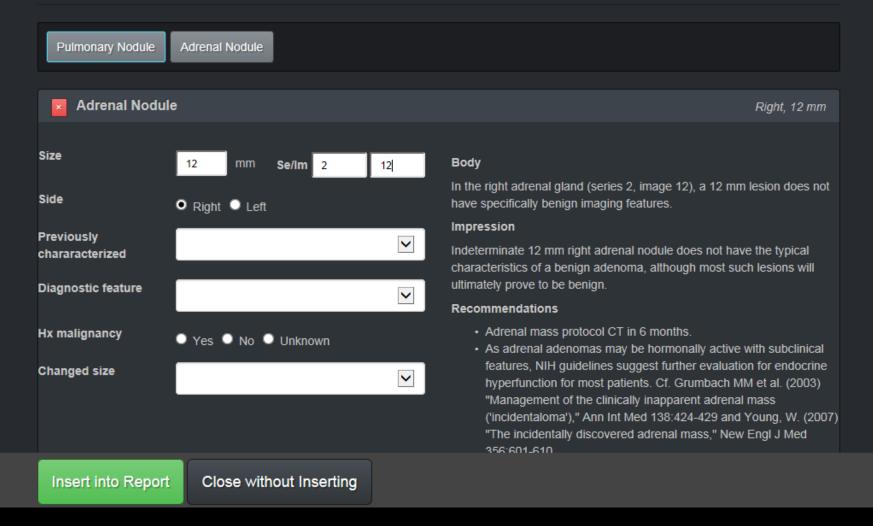
 Exam: CTABPW (
)

 Completed:
 2013-12-02T

Pulmonary Nodule	Adrenal Nodule
Adrenal Nodul	e
Size	mm Se/Im
Side	
Side	Right
Previously	
chararacterized	
Diagnostic feature	
Diagnostic leature	
Hx malignancy	
The mangnancy	Yes No Unknown
Changed size	

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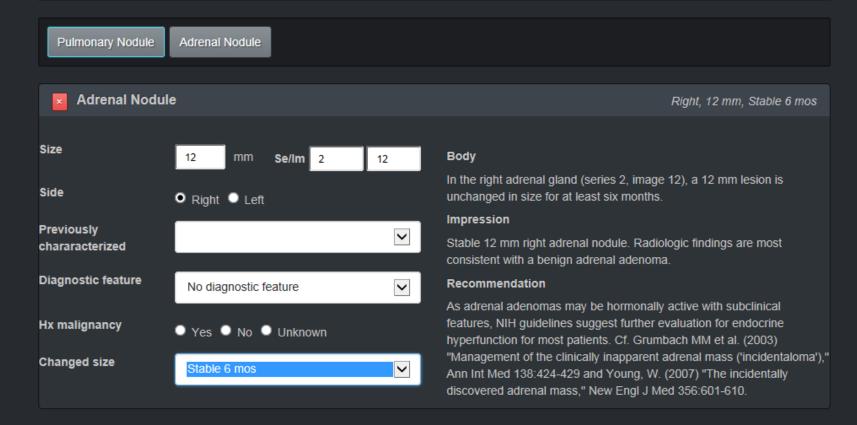
Patient: 74F Exam: CTABPW () Completed: 2013-12-02T



 Patient:
 74F

 Exam: CTABPW (
)

 Completed:
 2013-12-02T



Insert into Report Close without Inserting

Computer Assisted Reporting: Adrenal

Scans were continued into the pelvis to evaluate the entire GI tract.

COMPARISON: 9/15/2012

FINDINGS: LOWER THORAX: Lung bases are clear.

HEPATOBILIARY: No focal hepatic lesions. No biliary ductal dilatation. SPLEEN: No splenomegaly. PANCREAS: No focal masses or ductal dilatation.

ADRENALS:

In the right adrenal gland (series 2, image 12), a 12 mm lesion is unchanged in size for at least six

months. KIDNEYS/URETERS: No hydronephrosis, stones, or solid mass lesions. PELVIC ORGANS/BLADDER: Unremarkable.

PERITONEUM / RETROPERITONEUM: No free air or fluid. LYMPH NODES: No lymphadenopathy. VESSELS: Unremarkable.

GI TRACT: No distention or wall thickening.

BONES AND SOFT TISSUES: Unremarkable.

IMPRESSION:

Stable 12 mm right adrenal nodule. Radiologic findings are most consistent with a benign adrenal adenoma.

RECOMMENDATION:

As adrenal adenomas may be hormonally active with subclinical features, NIH guidelines suggest further evaluation for endocrine hyperfunction for most patients. Cf. Grumbach MM et al. (2003) "Management of the clinically inapparent adrenal mass ('incidentaloma')," Ann Int Med 138:424-429 and Young, W. (2007) "The incidentally discovered adrenal mass," New <u>Engl</u> J Med 356:601-610.

Standardized Common Lexicon Compliant Data minable Referrer buy-in Recommendation portal

Computer Assisted Reporting

Lu, et al. JACR 2016

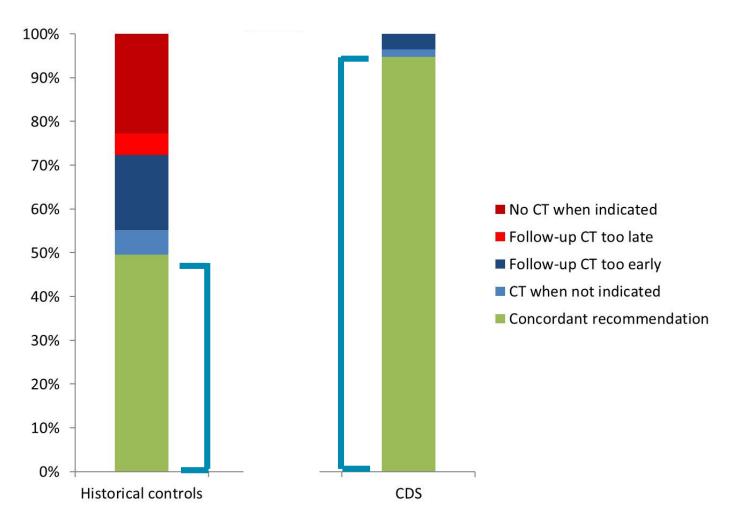
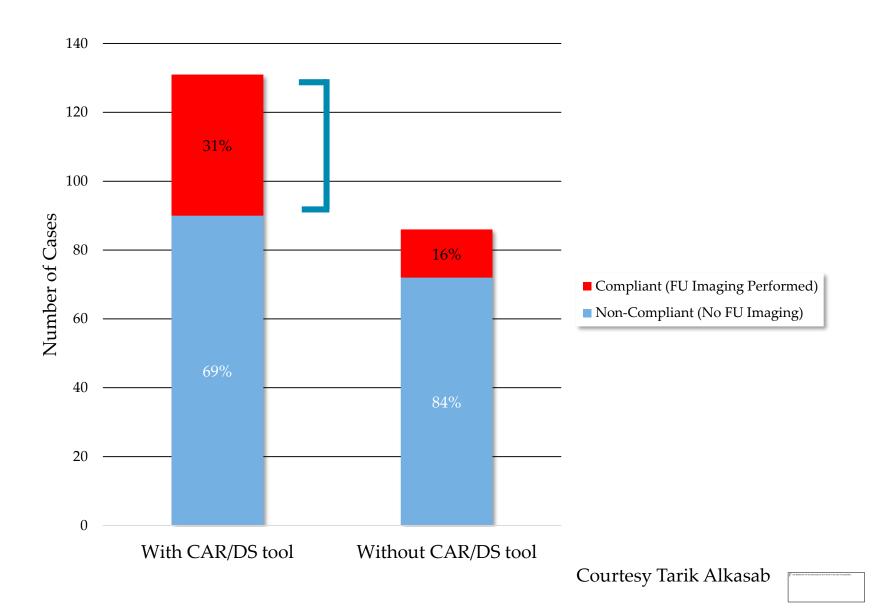


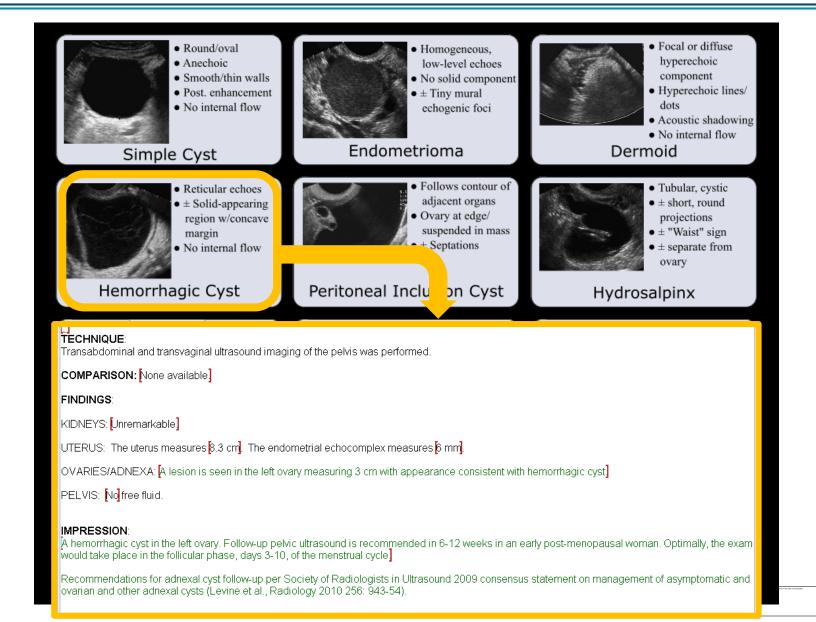
Figure 1: Percentage with guidelines-concordant recommendation for follow-up CT. The clinical decision support (CDS) group was significantly more likely to have a concordant recommendation than the non-CDS and pre-intervention historical controls (both with p < 0.01).

Compliance with FU Imaging Recommendations for Conventional Reports and CAR/DS Reports

Incidental Adrenal Nodules on Abdominal CTs (n=217 cases)



Computer Assisted Reporting: Ovarian Cysts



The Data Divide – EHR Integration



Radiomic Data

Beason: CHICK HIT THE PLACEMENT, 7984, CHF ("Signature 1") UNDERLYING REDCAL CONDITION: 05 70 main a fly arute m and catherization now in ccu with excalingenic shock REGORING THE FLANDATION: CHECK ETT THE FLANDATION: CHECK ETT THE FLANDATION: CHECK ETT THE FLANDATION: 7984

7PNA CHF [**Signature 1**] FINAL REPORT CLINICAL INDICATION: Assess endotracheal tube placement in patient with congestive heart failure.

Comparison is made to previous study of one day earlier. An emborracheal tube is present, in astifactory position. University of the second state of the superior and state of the superior append of the arctic knob, and a narogastric tube tremsinates in the region of the gastroduodenal junction.

Cardiac and mediatinal contours are stable in the interval and pulmany varenlative is within surmal limits for technique. There has been improvement in the left retrocardiac opacity and there remains a patchy right basiler opacification which is pightly increased. A small amount of fluid is seen in the surner fissure.

IMPRESSION:

 Lines and tubes in satisfactory position, as detailed above, with no evidence of pneumothorax.

 Improved left retrocardiac opacity and worsened right lower lobe opacity likely due to atelectasis.
 JPE

DR. [**First Name11 25**] [**Initials 5**] [**Last Name 26**]Approved: SAT [**13-09-01**] 7:27 PM

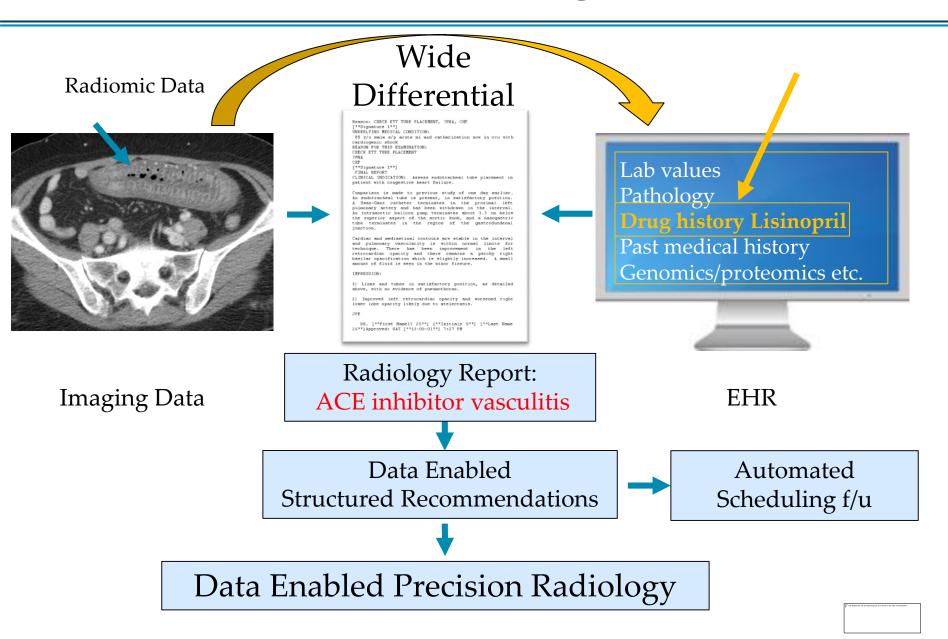
Actionable Report

Lab values Pathology Drug history Past medical history Genomics/proteomics etc.



EHR

The Data Divide – EHR Integration





Artificial Intelligence and Machine Learning SA-CME in Radiology: Opportunities, Challenges, Pitfalls, and Criteria for Success

James H. Thrall, MD, Xiang Li, PhD, Quanzheng Li, PhD, Cinthia Cruz, MD, Synho Do, PhD, Keith Dreyer, DO, PhD, James Brink, MD

Credits awarded for this enduring activity are designated "SA-CME" by the American Board of Radiology (ABR) and qualify toward fulfilling requirements for Maintenance of Certification (MOC) Part II: Lifelong Learning and Self-assessment. To access the SA-CME activity visit https://3s.acr.org/Presenters/CaseScript/CaseView?CDId=0GSf930sE7s%3d.

Abstract

Worldwide interest in artificial intelligence (AI) applications, including imaging, is high and growing rapidly, fueled by availability of large datasets ("big data"), substantial advances in computing power, and new deep-learning algorithms. Apart from developing new AI methods per se, there are many opportunities and challenges for the imaging community, including the development of a common nomenclature, better ways to share image data, and standards for validating AI program use across different imaging platforms and patient populations. AI surveillance programs may help radiologists prioritize work lists by identifying suspicious or positive cases for early review. AI programs can be used to extract "radiomic" information from images not discernible by visual inspection, potentially increasing the diagnostic and prognostic value derived from image datasets. Predictions have been made that suggest AI will put radiologists out of business. This issue has been overstated, and it is much more likely that radiologists will beneficially incorporate AI methods into their practices. Current limitations in availability of technical expertise and even computing power will be resolved over time and can also be addressed by remote access solutions. Success for AI in imaging will be measured by value created: increased diagnostic certainty, faster turnaround, better outcomes for patients, and better quality of work life for radiologists. AI offers a new and promising set of methods for analyzing image data. Radiologists will explore these new pathways and are likely to play a leading role in medical applications of AI.

Key Words: Artificial intelligence, machine learning, opportunities, challenges, pitfalls

J Am Coll Radiol 2018;15:504-508. Copyright © 2017 American College of Radiology

Why AI in Radiology?

- VALUE
- Medicine should always be about better value for patients
- Outcomes cost effective
- Too much variation with humans
- Convergence: Massive data, new computing power and new deep learning algorithms
- New knowledge extraction of new and better information
- Information the human eye can't see (pixel biopsies)
- Increased diagnostic certainty, faster turnaround, better outcomes for patients,
- Better quality of work life for radiologists
- Peer Review



Standardization

- AI imaging research would benefit from:
 - (1) national and international image sharing networks,

(2) **reference datasets** of proven cases against which AI programs can be tested and compared (protocol and and language variation)

(3) criteria for standardization and optimization of imaging protocols for use in AI applications

(4) a common lexicon for describing and reporting AI applications

Thrall IH

IACR March 2018

• Standards still need to be developed that address curation of images

Workflow

- DS and protocol optimization –shorter scan times tailored to particular patient
- Real-time scanning management and patient flow
- Technologist tasks (body part separation)
- Prioritization of case urgency optimization of work lists stroke/PE (while on table)
- Pre-analysis of cases in high-volume applications where observer fatigue may be a factor (screening)
- Improving the quality of reconstructed images.
- Radiomics mathematical imaging phenotype

However – before we get ahead of ourselves, there is a lot of hype Brink JA JACR March 2018

Thrall JH JACR March 2018 Machine learning is not a magic device that can spin data into gold, though many news releases would imply that it can. Instead, it is a natural extension to traditional statistical approaches. Machine learning is a valuable and increasingly necessary tool for the modern health care system. Considering the vast amounts of information a physician may need to evaluate³—such as the patient's personal history, familial diseases, genomic sequences, medications, activity on social media, admissions to other hospitals—deriving insight to guide clinical decision may be an overwhelming task for any one person. As more control is ceded to algorithms, it is important to note that these new algorithmic decision-making tools come with no guarantees of fairness, equitability, or even veracity. Although we are reluctant to repeat the cliché, even with the best machine learning algorithms the maxim of "garbage in, garbage out" remains true. Whether an algorithm is high or low on the machine learning spectrum, best analytic practices must be used to ensure that the end result is robust and valid. This is especially true in health care because these algorithms have the potential to affect the lives of millions of patients.



Data Mining and Machine Learning for Integrated CDS







