Artificial Intelligence to Enhance Radiology Image Interpretation

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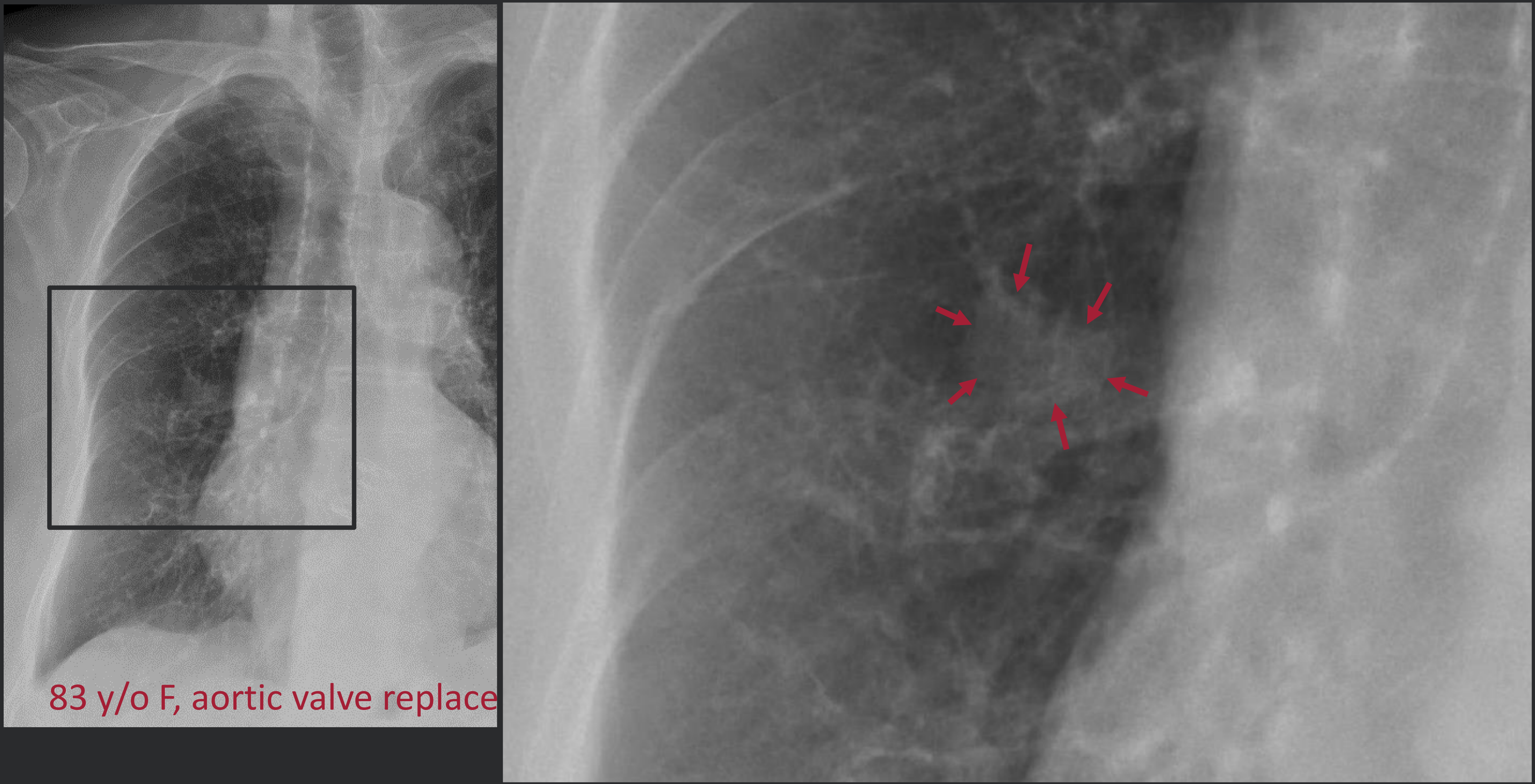
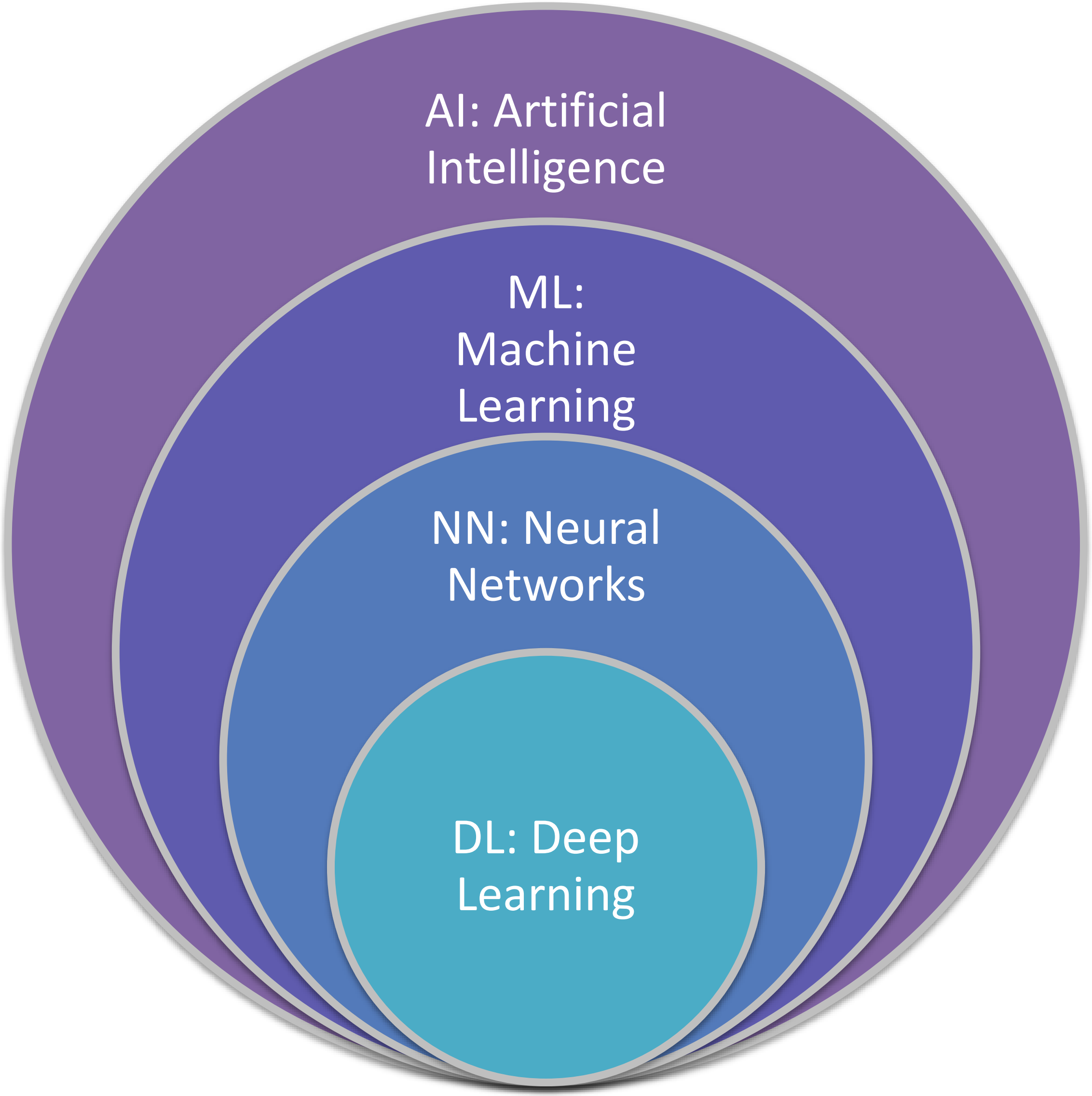
Stanford | MEDICINE


83 y/o F, aortic valve replace

Disclosures

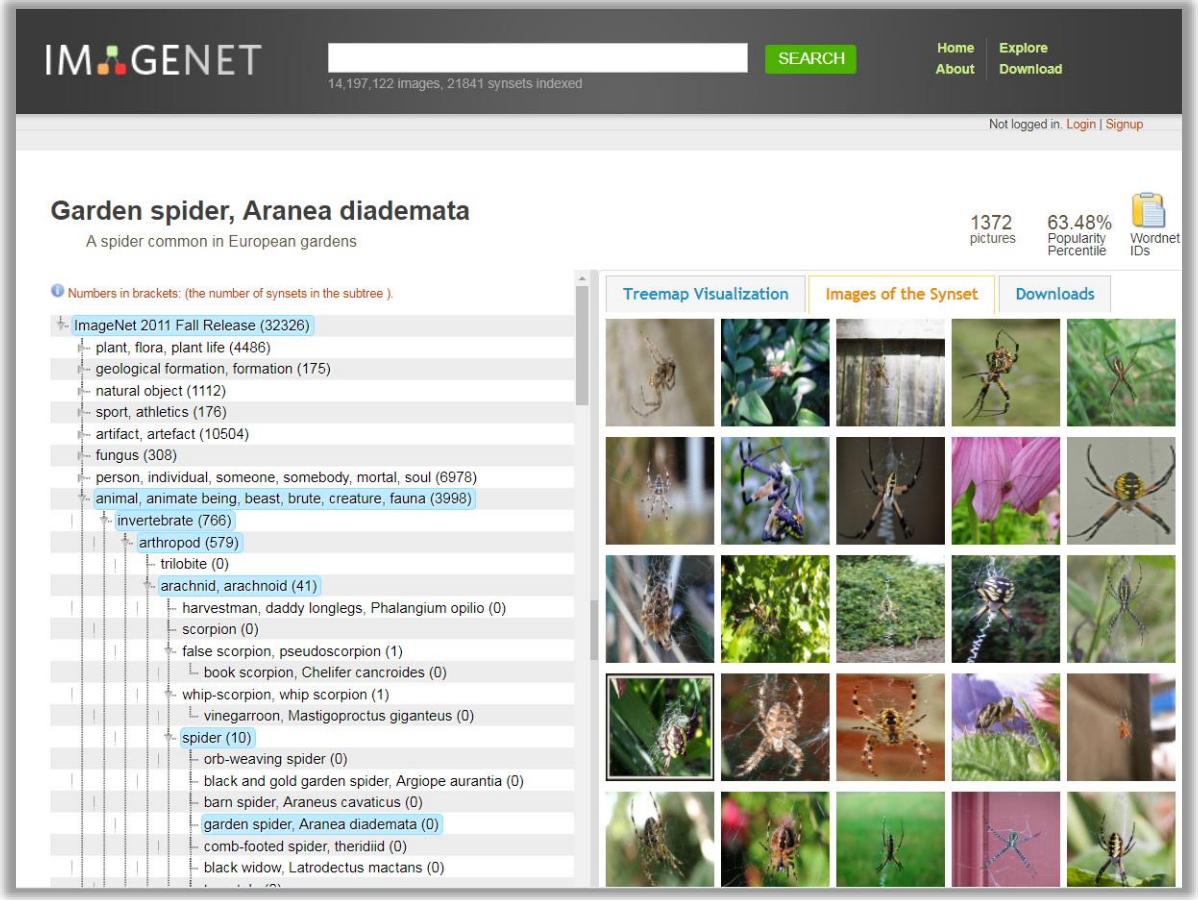
- Board of directors, Radiological Society of North America
- Advisory board, Nuance Communications
- Shareholder and advisor, whiterabbit.ai
- Shareholder and advisor, Nines.ai
- Research support from:
  - Google
  - Siemens
  - GE Healthcare
  - Philips

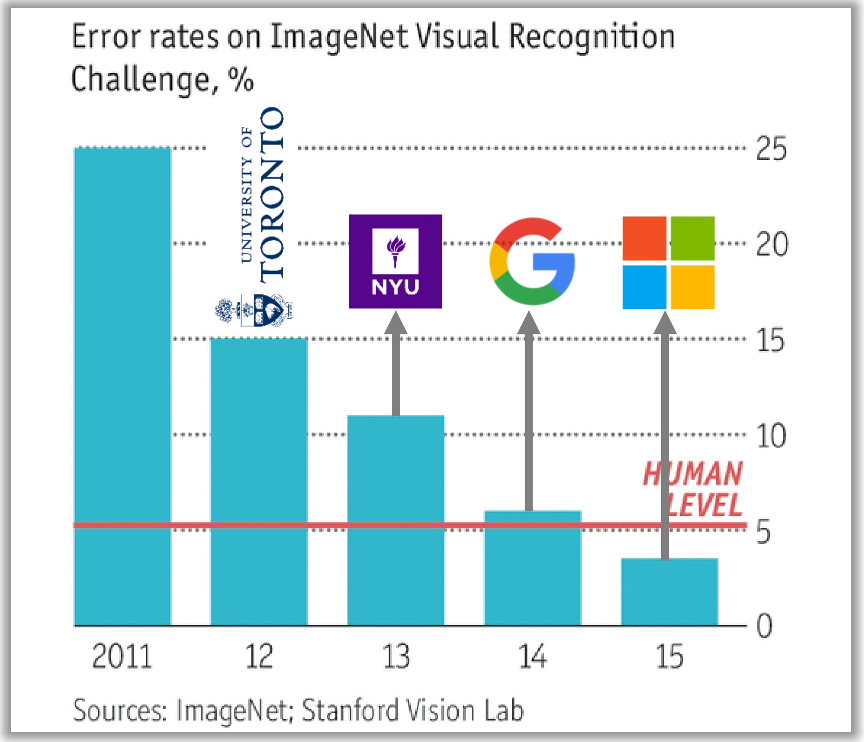


Definitions

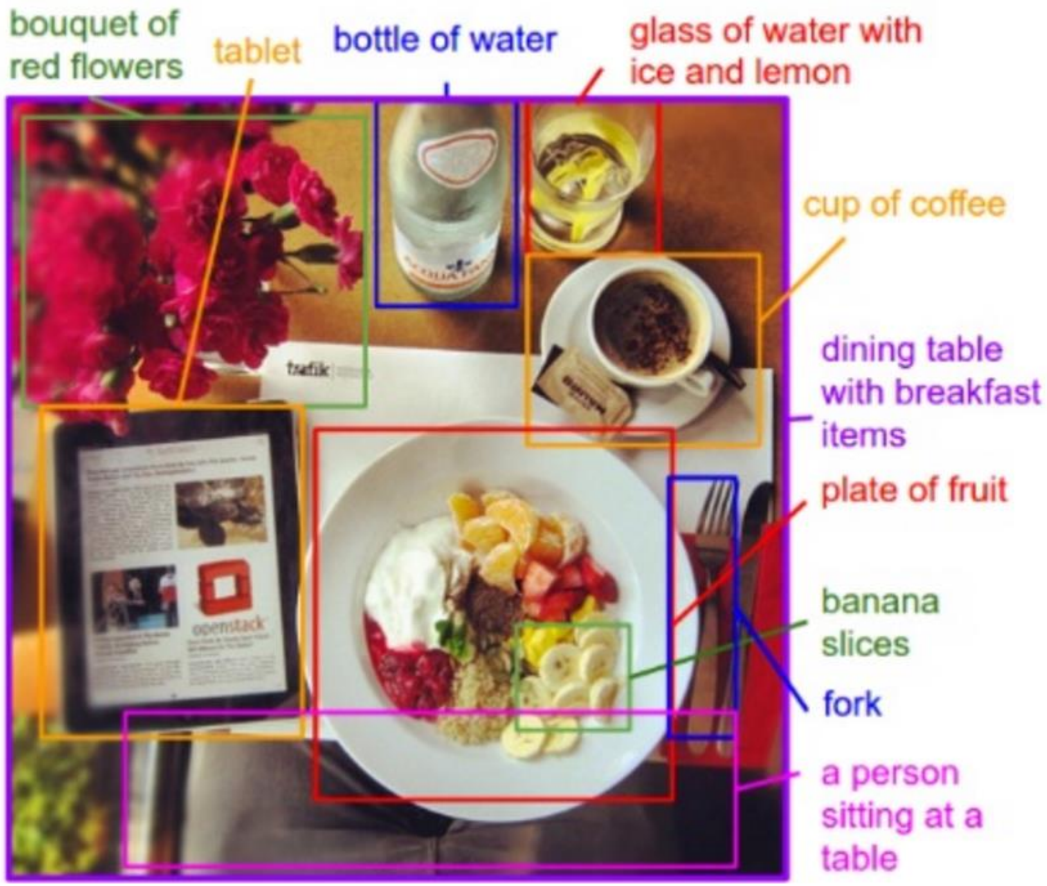
- AI: When computers do things that make humans seem intelligent
- ML: Rapid automatic construction of detectors and classifiers from data
- NN: New and extremely powerful “black box” form of machine learning

ImageNet

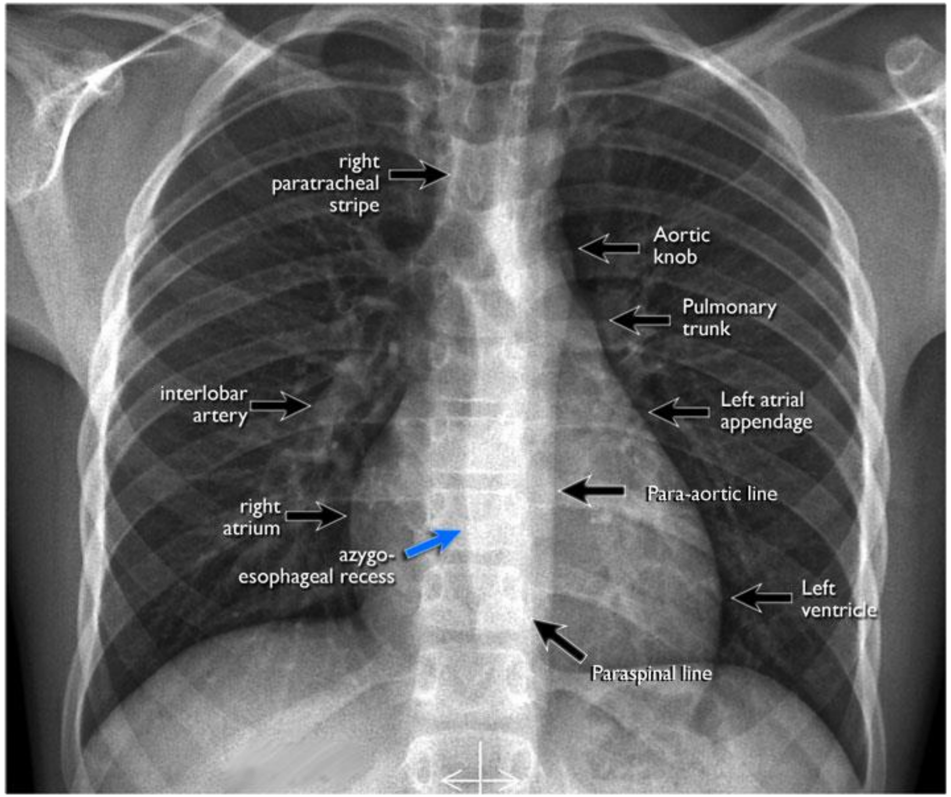




- Russakovsky O, Deng J, Su H, et al. ImageNet Large Scale Visual Recognition Challenge. Int J Comput Vis. 2015;115(3):211-252.
- https://www.economist.com/news/special-report/21700756-artificial-intelligence-boom-based-old-idea-modern-twist-not
- http://karpathy.github.io/2014/09/02/what-i-learned-from-competing-against-a-convnet-on-imagenet/



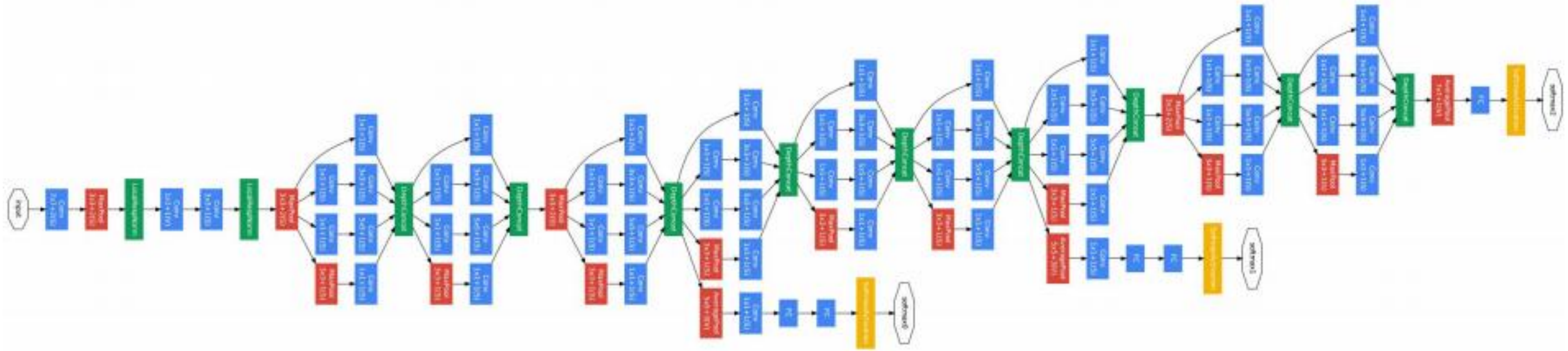
Karpathy, Andrej & Li, Fei Fei. Deep Visual-Semantic Alignments for Generating Image Descriptions, CVPR, 2015



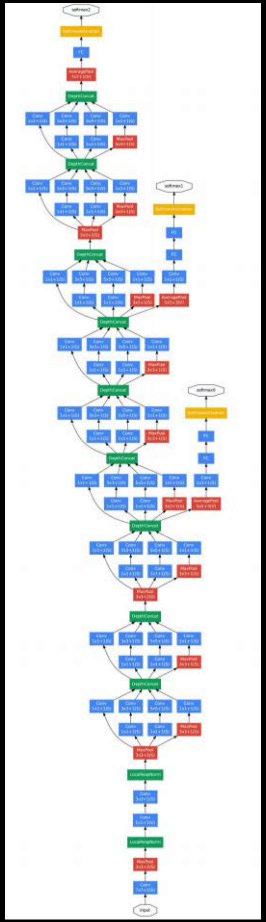
http://www.radiologyassistant.nl/

“Deep” Neural Networks: Tens of Millions of Parameters

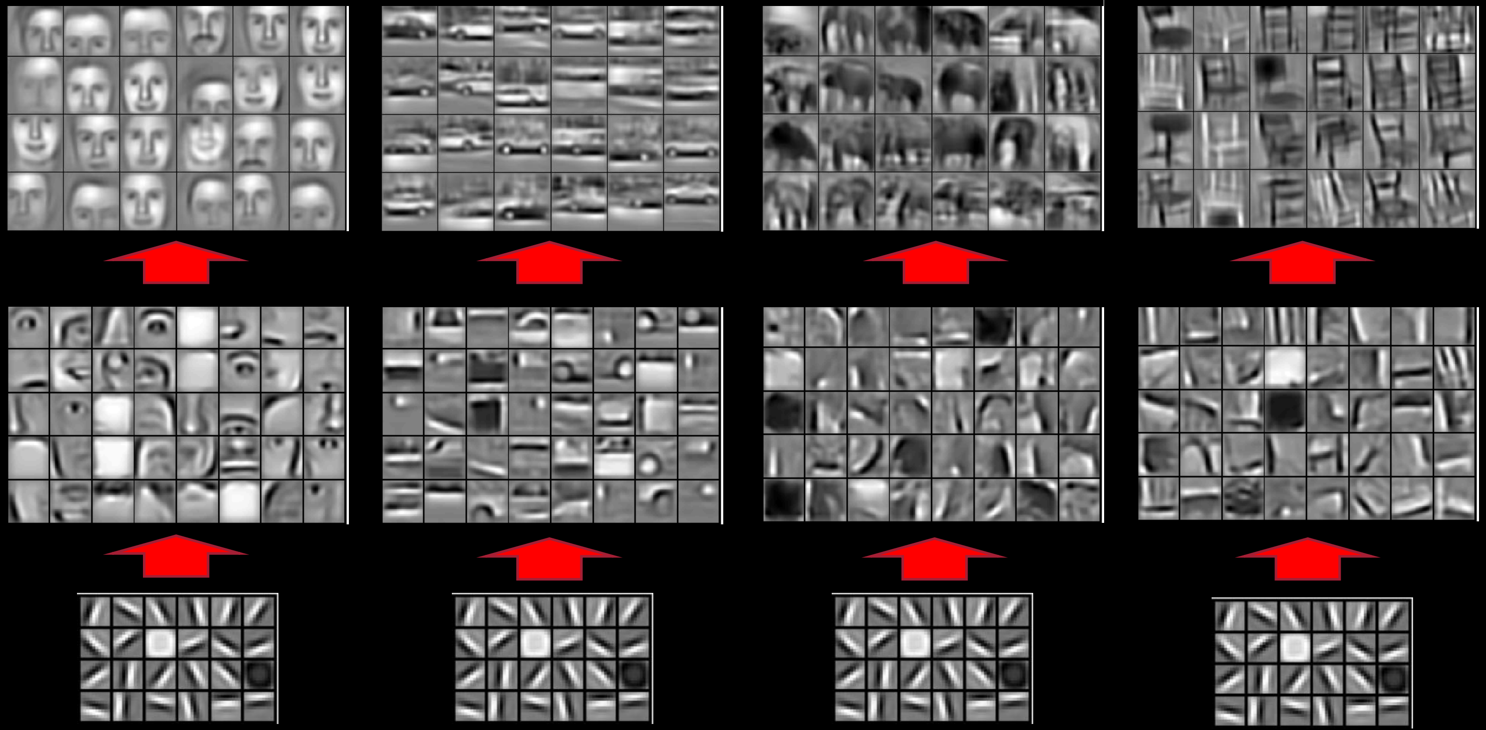
The Inception Architecture (GoogLeNet, 2014)

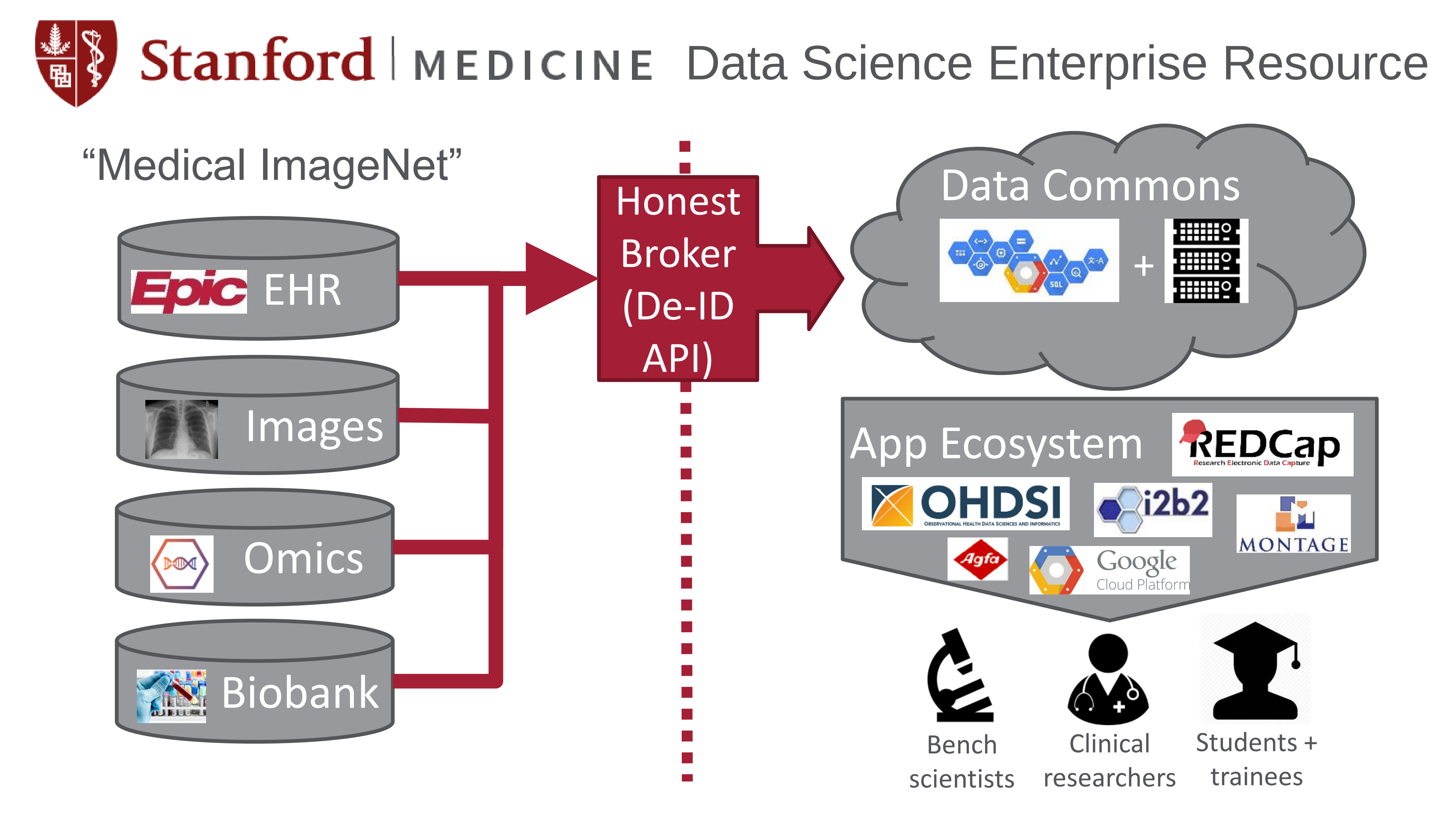


Learning Object Recognition

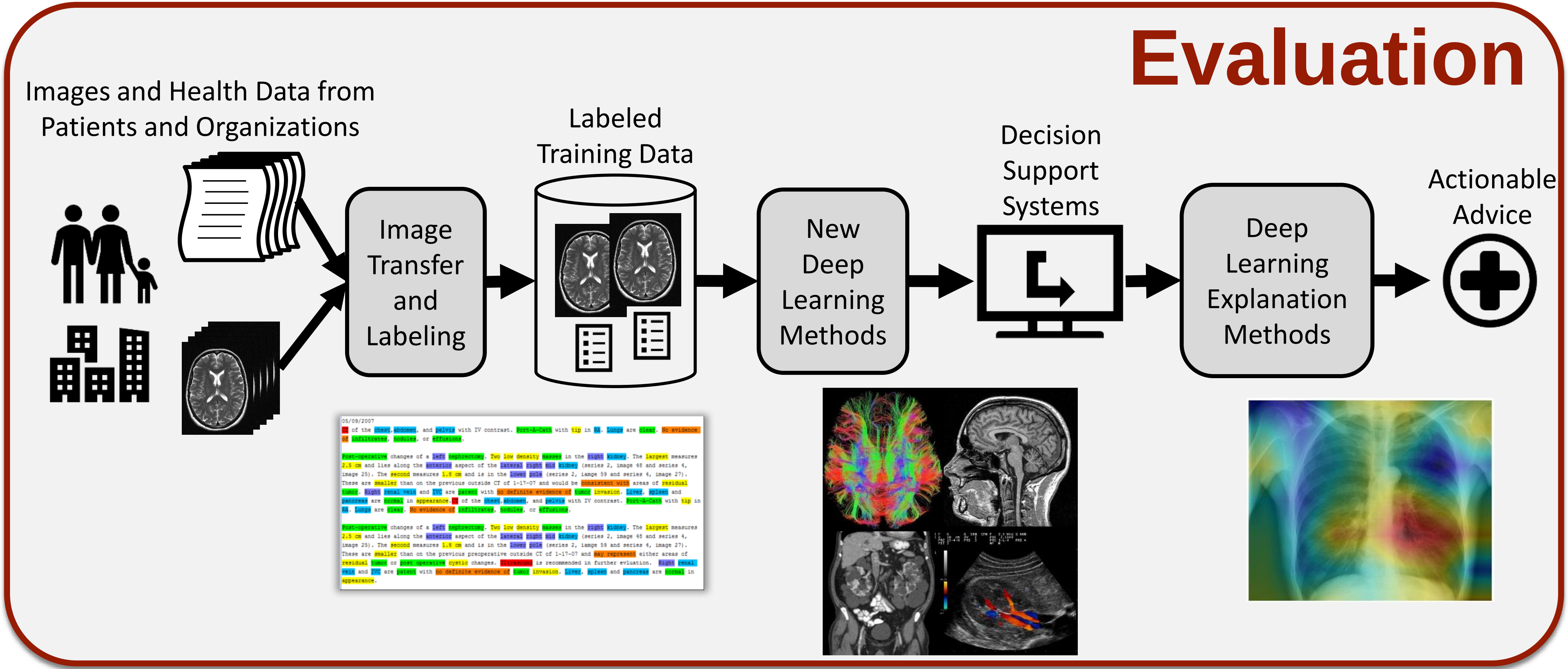


Faces Cars Elephants Chairs




Stanford | MEDICINE
Data Science Enterprise Resource
"Medical ImageNet"
Epic EHR
Images
Omics
Biobank
Honest Broker (De-ID API)
Data Commons
+
App Ecosystem
REDCap
Research Electronic Data Capture
OHDSI
OBSERVATIONAL HEALTH DATA SCIENCES AND INFORMATICS
i2b2
MONTAGE
Agfa
Google Cloud Platform
Bench scientists
Clinical researchers
Students + trainees

Deep Learning Research in Radiology



Cohort Selection and Image Labeling

Sorting
Date Ascending
Date Descending
Relevance
Random

Modality
CR CT DF DX
MG MR NM OT
PT RF SC US XA

@impression tension pneumothorax | Search

92 reports in 0.027 seconds | Advanced Search

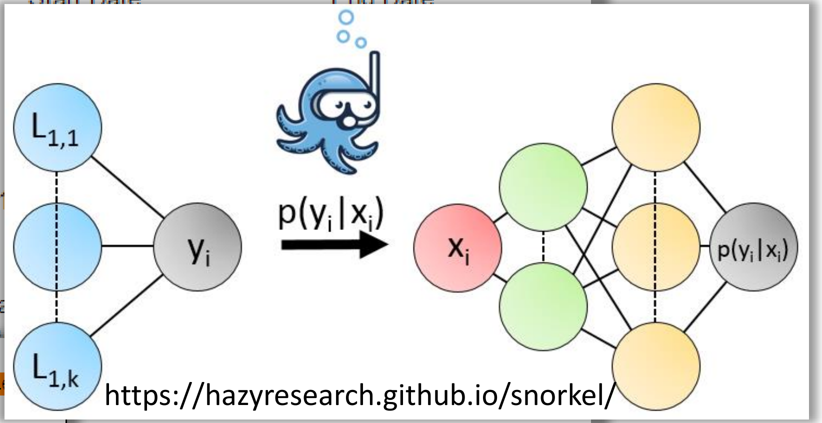
- DXCH1 (Chest 1 View) POR/SCHNOW - 201

RADIOGRAPHIC EXAMINATION OF THE CHEST: 10/4/2016 7:00 AM, 1
8:57 AM, 10/4/2016 6:30 AM, 10/4/2016 5:42 AM, 10/4/2016 5:39 AM

CLINICAL HISTORY: 26 years of age, Male, history of MRSA pneumonia

Start Date: End Date:

-04



05/09/2007
CT of the chest,abdomen, and pelvis with IV contrast. Port-A-Cath with tip in RA. Lungs are clear. No evid
of infiltrates, nodules, or effusions.

Post-operative changes of a left nephrectomy. Two low density masses in the right kidney. The larges
2.5 cm and lies along the anterior aspect of the lateral right mid kidney (series 2, image 48 and se
image 25). The second measures 1.8 cm and is in the lower pole (series 2, iamge 59 and series 4, ima
These are smaller than on the previous outside CT of 1-17-07 and would be consistent with areas of r
tumor. Right renal vein and IVC are patent with no definite evidence of tumor invasion. Liver, splee
pancreas are normal in appearance.CT of the chest,abdomen, and pelvis with IV contrast. Port-A-Cath
RA. Lungs are clear. No evidence of infiltrates, nodules, or effusions.

Post-operative changes of a left nephrectomy. Two low density masses in the right kidney. The larges
2.5 cm and lies along the anterior aspect of the lateral right mid kidney (series 2, image 48 and se
image 25). The second measures 1.8 cm and is in the lower pole (series 2, iamge 59 and series 4, ima
These are smaller than on the previous preoperative outside CT of 1-17-07 and may represent either a
residual tumor or post operative cystic changes. Ultrasound is recommended in further evluation. Ri
vein and IVC are patent with no definite evidence of tumor invasion. Liver, spleen and pancreas are
appearance.

Hassanpour, S & Langlotz, CP. *Artif Intell Med 23(1)*:84-9, 2016.

Radiology

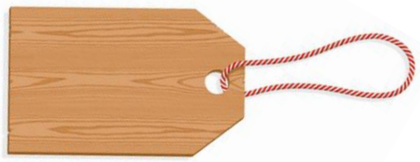
Deep Learning to Classify Radiology Free-Text Reports[1]

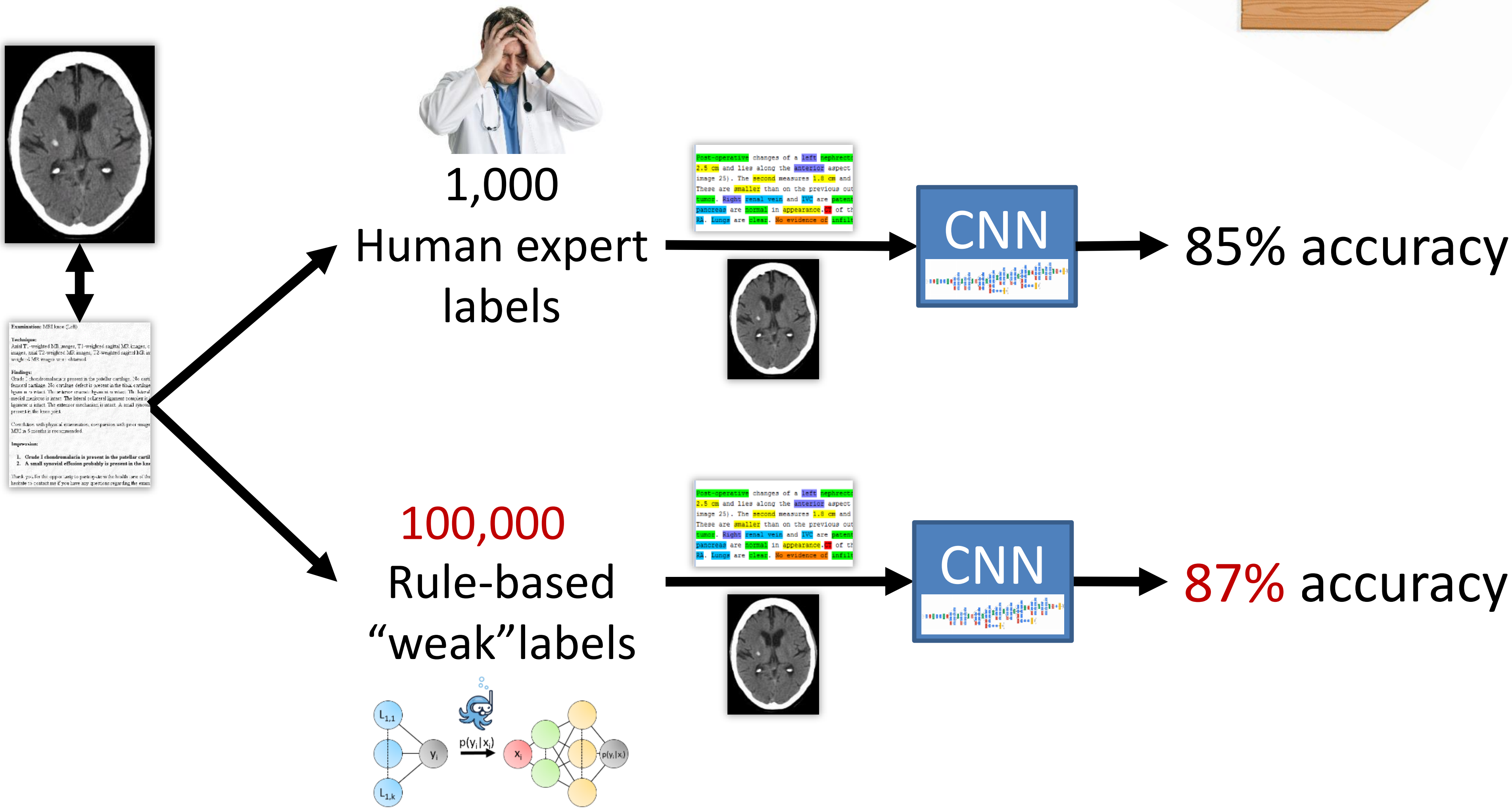
Matthew C. Chen, MS
Robyn L. Ball, PhD
Lingyao Yang, PhD
Nathaniel Moradzadeh, MD
Brian E. Chapman, PhD
David B. Larson, MD, MBA
Curtis P. Langlotz, MD, PhD
Timothy J. Amrhein, MD
Matthew P. Lungren, MD, MPH

Purpose: To evaluate the performance of a deep learning convolutional neural network (CNN) model compared with a traditional natural language processing (NLP) model in extracting pulmonary embolism (PE) findings from thoracic computed tomography (CT) reports from two institutions.

Materials and Methods: Contrast material–enhanced CT examinations of the chest performed between January 1, 1998, and January 1, 2016, were selected. Annotations by two human radiologists were made for three categories: the presence, chronicity, and location of PE. Classification of perfor-

The Power of Weak Labeling

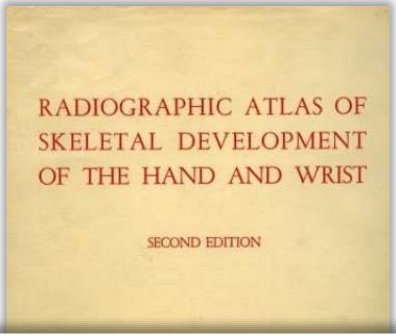




Radiology

Performance of a Deep-Learning Neural Network Model in Assessing Skeletal Maturity on Pediatric Hand Radiographs[1]

David B. Larson, MD, MBA
Matthew C. Chen, MS
Matthew P. Lungren, MD, MPH
Safwan S. Halabi, MD
Nicholas V. Stence, MD
Curtis P. Langlotz, MD, PhD



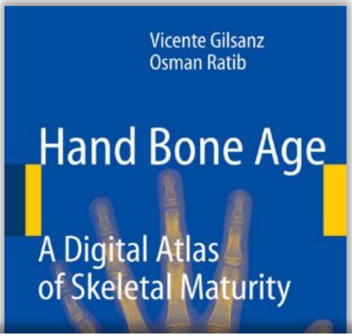


Table 2

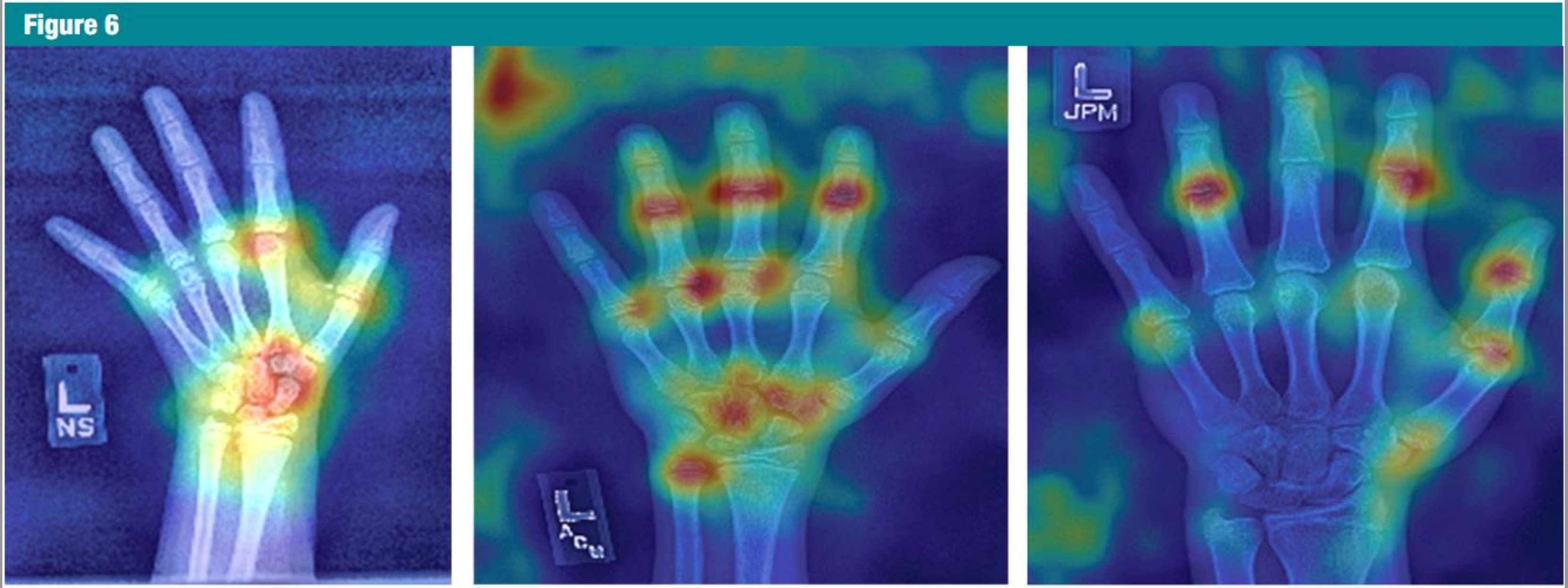
Summary Statistics of Paired Interobserver Difference between Bone Age Estimate of Each Reviewer and Mean of the Other Three Human Reviewers' Estimates, Compared with That of Model

Variable	Clinical Report	Reviewer 1	Reviewer 2	Reviewer 3	Mean
MAD					
Reviewer	0.65	0.55	0.53	0.69	0.61
Model	0.51	0.53	0.53	0.53	0.52
P value (paired *t* test)	<.01	.50	.99	<.01	

Note.—Unless otherwise noted, data are expressed as years. The authors of the clinical report were treated collectively as a single reviewer.

https://doi.org/10.1148/radiol.2017170236

Saliency Maps

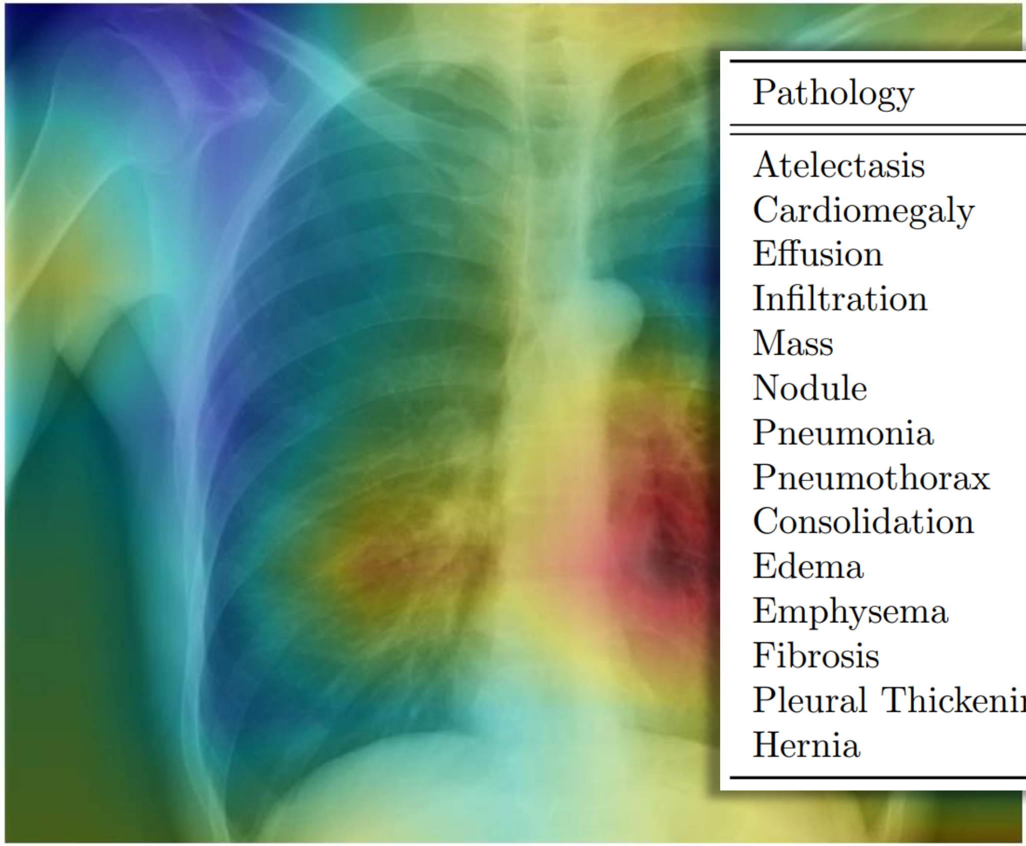


a. b. c.

Figure 6: Original image with superimposed saliency map for sample hand radiographic images in three male patients age 4 years (**a**), 15 years (**b**), and 17 years (**c**).

Machine learning enables systems tailored to local demographics.

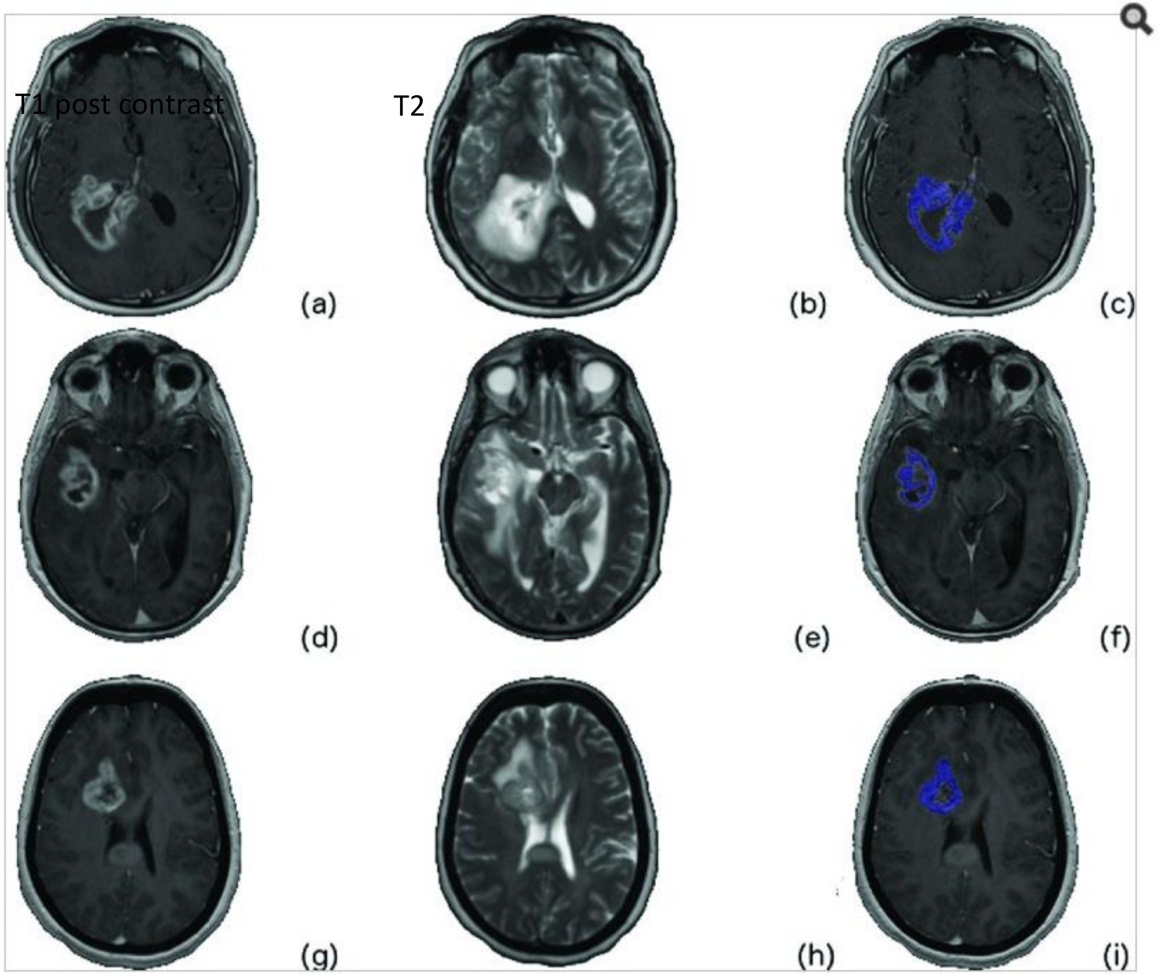
Expert-Level Chest Radiograph Interpretation



Pathology	Wang et al. (2017)	Yao et al. (2017)	CheXNet (ours)
Atelectasis	0.716	0.772	**0.8209**
Cardiomegaly	0.807	0.904	**0.9048**
Effusion	0.784	0.859	**0.8831**
Infiltration	0.609	0.695	**0.7204**
Mass	0.706	0.792	**0.8618**
Nodule	0.671	0.717	**0.7766**
Pneumonia	0.633	0.713	**0.763**
Pneumothorax	0.806	0.841	**0.893**
Consolidation	0.708	0.788	**0.7939**
Edema	0.835	0.882	**0.8932**
Emphysema	0.815	0.829	**0.9260**
Fibrosis	0.769	0.767	**0.8044**
Pleural Thickening	0.708	0.765	**0.8138**
Hernia	0.767	0.914	**0.9387**

Matt Lungren, MD, MPH and Andrew Ng, PhD. https://arxiv.org/abs/1711.05225

Radiogenomics

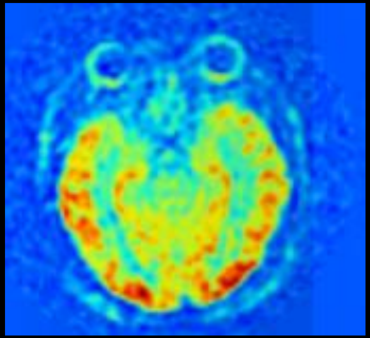


Features (Az=0.72):

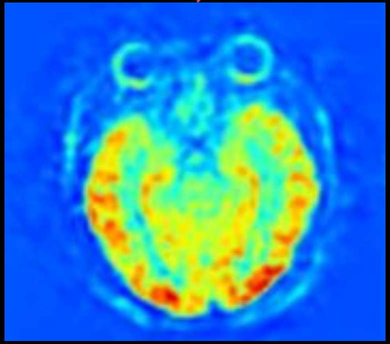
- Gray level nonuniformity
- Run length non uniformity
- Cluster prominence
- Haralick correlation
- Cluster shade
- Inertia
- Inverse difference moment
- Long run low gray level emphasis

Korfiatis, P et al. Med Phys. 2016 Jun; 43(6): 2835–2844.

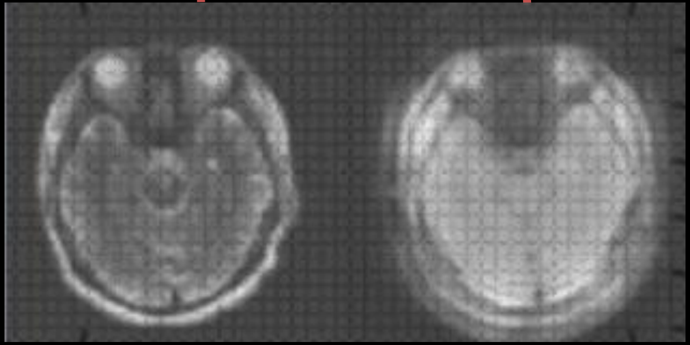
Deep Learning to Improve MRI Image Quality



High SNR ASL

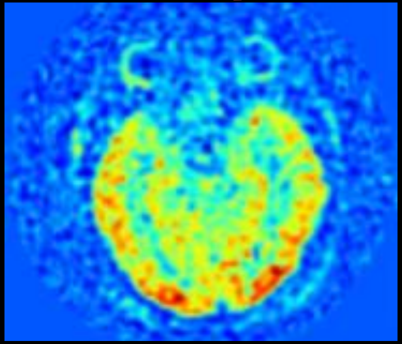


Synthetic ASL

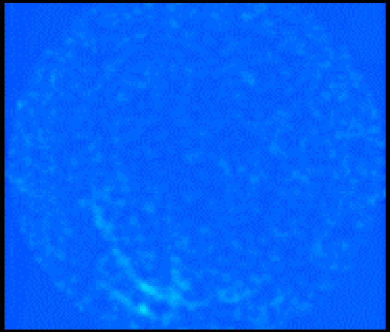


T2 weighted Proton density

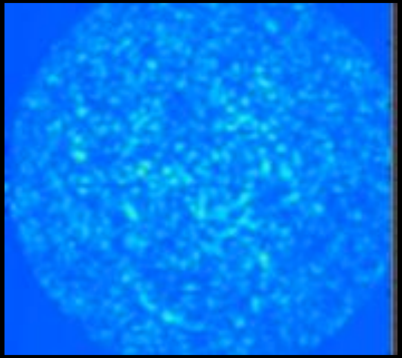
for regularized de-noising



Low SNR ASL



Difference map
vs High SNR

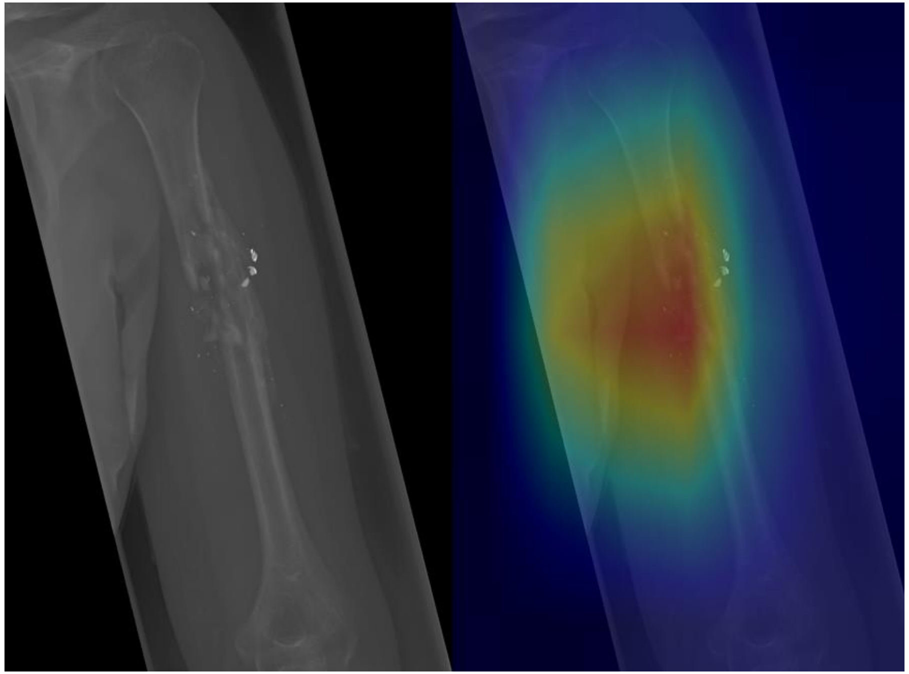


Difference map
vs High SNR

Enhao Gong
John Pauly
Greg Zaharchuk
Stanford EE &
Neuroradiology

AI in Medical Imaging Opportunities

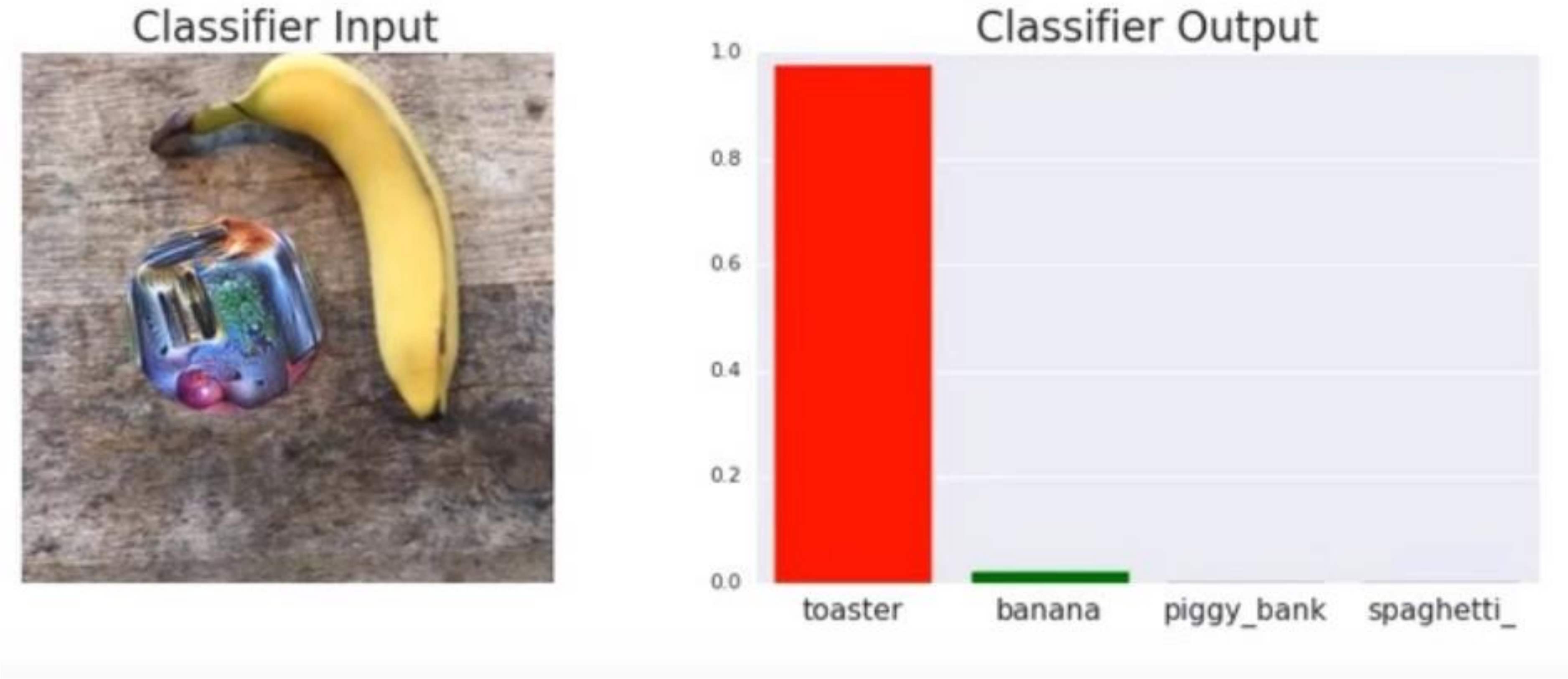
- Efficient image creation
- Image quality control
- Imaging triage
- Computer-aided detection
- Computer-aided classification
- Radiogenomics



These are not stop signs?

Robust Physical-World Attacks on Machine Learning Models, Evtimov et al. https://arxiv.org/abs/1707.08945

Everything is a toaster.



https://gizmodo.com/this-simple-sticker-can-trick-neural-networks-into-thin-1821735479

Conclusions

1. Machine learning will revolutionize clinical imaging practice
   a. Radiologists and pathologists must be trained how to use these new systems
2. Machine learning methods are needed for complex health data
   a. Automated labeling
   b. New machine learning model structures
   c. Explanation and other forms of model transparency
3. Data-driven cancer care organizations will thrive
   a. Data linked across types: EHR, genomics, clinical imaging
   b. Learning cancer systems deliver care with precision
4. Sharing of training data sets will accelerate progress
   a. Subset of cases with high-quality labels for validation

Thank You

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