The Impact of Deep Learning on Radiology

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Disclosure

- Patent royalties from iCAD
- Research support from Ping An
- Software licenses to Imbio, Zebra Med.

Disclaimer

- Opinions discussed are mine alone and do not necessarily represent those of NIH or DHHS.

Overview

- Background
- Radiology imaging applications
- Data mining radiology reports and images
- Challenges and pitfalls

We've Entered the Deep Learning Era

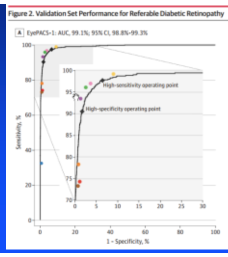
- Hand-crafted features less important
- Large annotated datasets more important
- Impact: More and varied researchers can contribute, accelerating pace of progress

Deep Learning

- Convolutional neural networks (ConvNets)
- An improvement to neural networks
- More layers permit higher levels of abstraction
- Similarities to low level vision processing in animals
- Marked improvements in solving hard problems like object recognition in pictures

JAMA | Original Investigation | INNOVATIONS IN HEALTH CARE DELIVERY

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

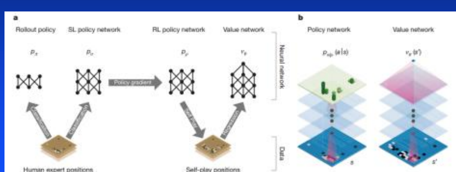


Gulshan et al., JAMA 2016

ARTICLE

doi:10.1038/nature16961

Mastering the game of Go with deep neural networks and tree search



Silver et al., Nature 2016

Deep Learning Improves CAD

Dataset	# Patients	# Targets
sclerotic lesions	59	532
lymph nodes	176	983
colonic polyps	1,186	252

Dataset	Sensitivity[1]	Sensitivity[2]	AUC[1]	AUC[2]
sclerotic lesions	57%	70%	n/a	0.83
lymph nodes	43%	77%	0.76	0.94
colonic polyps(>=6mm)	58%	75%	0.79	0.82
colonic polyps(>=10mm)	92%	98%	0.94	0.99

Summers et al. Gastroenterology 2005; Roth et al. IEEE TMI 2015

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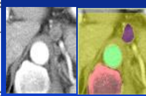

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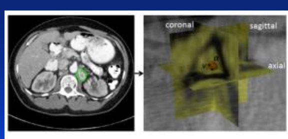
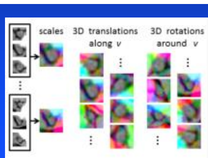
Hua, Liu, Summers et al. ARRS 2012; Roth et al. IEEE TMI 2015





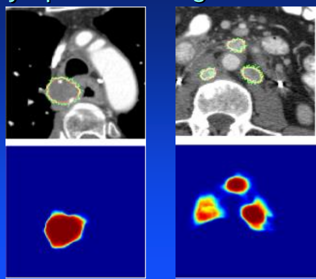
- 90 CTs with 388 mediastinal LNs
- 86 CTs with 595 abdominal LNs
- Sensitivities 70%/83% at 3 FP/vol. and 84%/90% at 6 FP/vol., respectively

H Roth et al., MICCAI 2014

- Deeper CNN model performed best
- GoogLeNet for mediastinal LNs
- Sensitivity 85% at 3 FP/vol.

HC Shin et al., IEEE TMI 2016

Lymph Node Segmentation

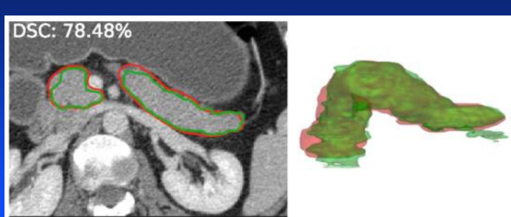


I Nogues et al. RSNA 2016

Lymph Node CT Dataset

- doi.org/10.7937/K9/TCIA.2015.AQIIDCNM
- TCIA CT Lymph Node
- 176 scans, 58 GB
- Also: annotations, candidates, masks

Pancreas CAD using CNN

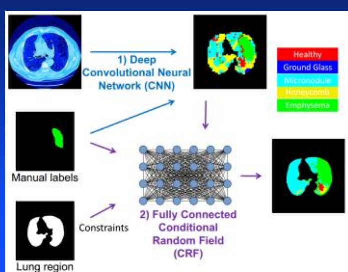


H Roth et al., MICCAI 2016

Pancreas CT Dataset

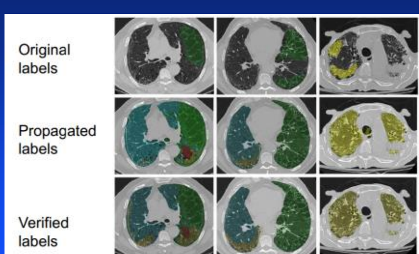
- doi.org/10.7937/K9/TCIA.2016.tNB1kqBU
- TCIA CT Pancreas
- 82 scans, 10 GB

Segmentation Label Propagation



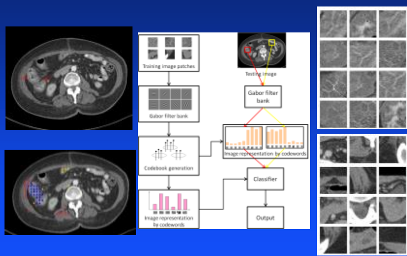
Gao et al. IEEE ISBI 2016

Segmentation Label Propagation



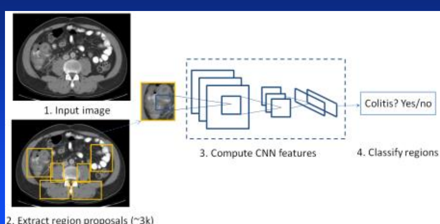
Gao et al. IEEE ISBI 2016

Colitis CAD



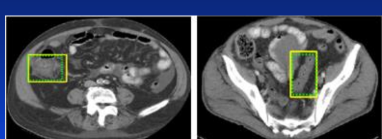
Wei et al. SPIE, ISBI 2013

Colitis CAD



J Liu et al. SPIE Med Imaging 2016

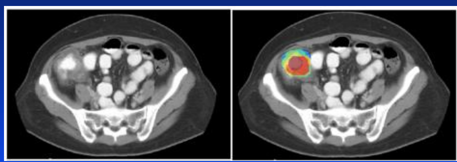
Colitis CAD



- 26 CT scans of patients with colitis
- 260 images
- 85% sensitivity at 1 FP/image

J Liu et al. SPIE Med Imaging and ISBI 2016

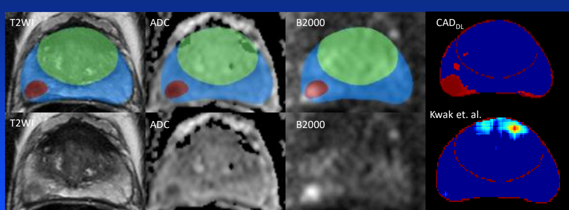
Colitis CAD



- 80 CT scans of patients with colitis
- 80 controls
- 93.7% sensitivity and 95.0% specificity

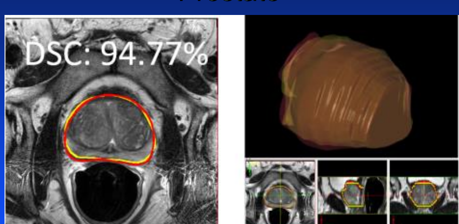
J Liu et al. Medical Physics 2017

Prostate



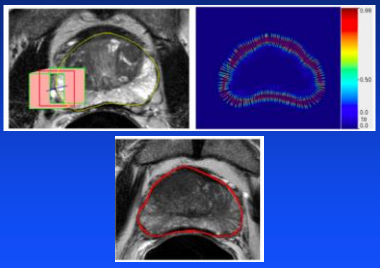
Tsehay et al. SPIE MI 2017

Prostate



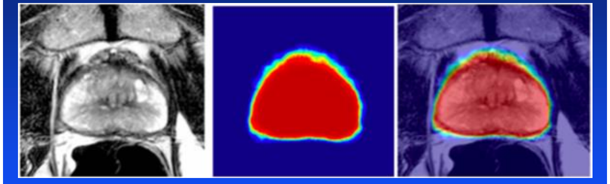
Cheng et al. SPIE MI 2017

Prostate



Cheng et al. JMI 2017

Prostate



Cheng et al. JMI 2017

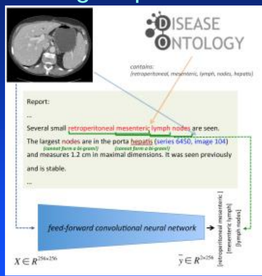
Prostate

Table 2 Quantitative comparisons between proposed method and other notable methods from the literature.

Methods	DSC + Std. dev (%)	HDRFDIST (mm)	AVGDIST (mm)	Images	Evaluation	Trim (α:0.95)
Klein et al.[1]	84.40 ± 3.10	10.20 ± 2.60	2.50 ± 1.40	50	Leave-one-out	Yes
Toth and Madabhushi[4]	87.66 ± 4.97		1.51 ± 0.78	108	Fivefold validation	Yes
Liao et al.[7]	86.70 ± 2.20	8.20 ± 2.50	1.90 ± 1.60	30	Leave-one-out	Yes
Guo et al.[8]	87.10 ± 4.20	8.12 ± 2.89	1.66 ± 0.49	66	Twofold validation	Yes
Milletari et al.[9]	86.90 ± 3.30	5.71 ± 1.20		Promise 12(80)	Train:50, test:30	Yes
Yu et al.[10]	89.43	**5.54**	1.95	Promise 12(80)	Train:50, test:30	Yes
Korsager et al.[20]	88.00 ± 5.00		1.45 ± 0.41	67	Leave-one-out	Yes
Chilali et al.[21]	81.78 ± 5.86	13.52 ± 7.87	3.00 ± 1.50	Promise 12(80)	Train:50, test:30	Yes
HNNmri+ced	**89.77 ± 3.29**		**0.16 ± 0.08**	250	Fivefold validation	No

Cheng et al. JMI 2017

Data Mining Reports & Images



HC Shin et al. CVPR 2015

Data Mining Reports & Images

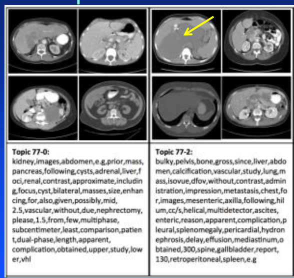
- Trained on 216,000 key images (CT, MR, …)
- 169,000 CT images
- 60,000 patient scans
- Recall-at-K, K=1 (R@1 score)) was 0.56

HC Shin et al. CVPR 2015 & JMLR 2016

Data Mining Reports & Images

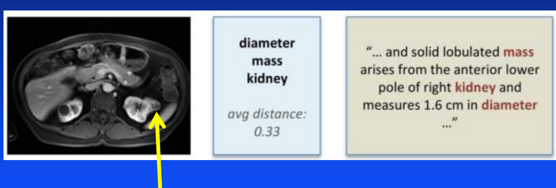
HC Shin et al. CVPR 2015 & JMLR 2016

Topic: Metastases



HC Shin et al. CVPR 2015 & JMLR 2016

Data Mining Reports & Images



HC Shin et al. CVPR 2015 & JMLR 2016

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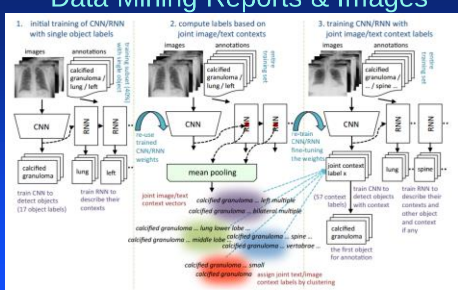

HC Shin et al. CVPR 2016

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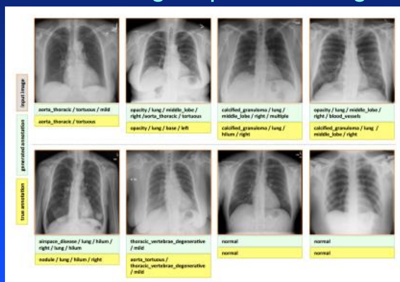

HC Shin et al. CVPR 2016

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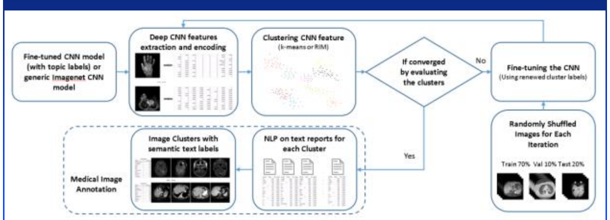
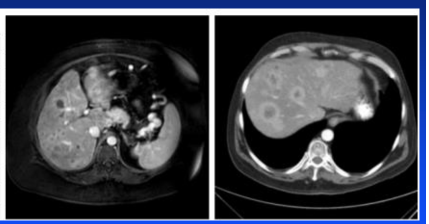


X Wang et al. WACV 2017

Data Mining Reports & Images

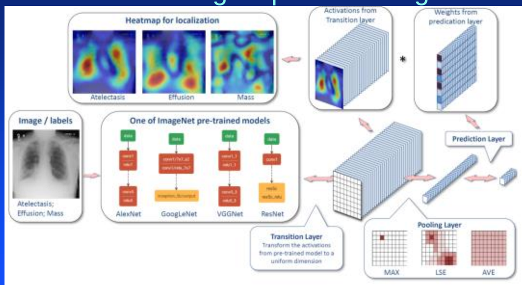
Cluster #23

Word	Frequency
liver	524
abdomen	337
enhancement	217
mass	198
lesion	168
lobe	161
adenopathy	119
lesions	109
segment	58
bulky	45



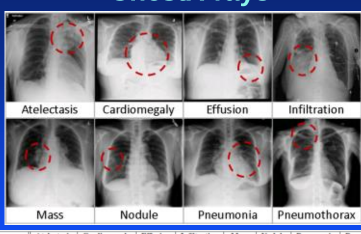
X Wang et al. WACV 2017

Data Mining Reports & Images



X Wang et al. CVPR 2017

ChestX-ray8



T(IoBB)	Atelectasis	Cardiomegaly	Effusion	Infiltration	Mass	Nodule	Pneumonia	Pneumothorax
T(IoBB) = 0.1								
Acc.	0.7277	0.9931	0.7124	0.7886	0.4352	0.1645	0.7500	0.4591
AFP	0.0823	0.0487	0.0589	0.0426	0.0691	0.0630	0.0691	0.0264

X Wang et al. CVPR 2017

Challenges and Pitfalls

- Network architectures are complex
- Well-annotated large datasets are few
- Rapidly evolving hardware & software

Approaches

- Aggregate entire PACS image collections from multiple institutions
- Use the radiologist reports as annotations
- Transfer learning from other trained datasets

Gastrointestinal Imaging • Review

Progress in Fully Automated Abdominal CT Interpretation

Ronald M. Summers[1]

OBJECTIVE. Automated analysis of abdominal CT has advanced markedly over just the last few years. Fully automated assessment of organs, lymph nodes, adipose tissue, muscle, bowel, spine, and tumors are some examples where tremendous progress has been made. Computer-aided detection of lesions has also improved dramatically.

CONCLUSION. This article reviews the progress and provides insights into what is in store in the near future for automated analysis for abdominal CT, ultimately leading to fully automated interpretation.

AJR 2016; 207:67–79

IEEE TRANSACTIONS ON MEDICAL IMAGING, VOL. 35, NO. 5, MAY 2016 1153

Guest Editorial

Deep Learning in Medical Imaging: Overview and Future Promise of an Exciting New Technique

Hayit Greenspan, *Guest Editor*

Bram van Ginneken, *Guest Editor*

Ronald M. Summers, *Guest Editor*

Conclusions

- Deep learning leading to large improvements in CAD and segmentation
- Pace of deep learning technology exceptionally fast
- Big data permit new advances
- Interest in deep learning and big data in radiology image processing is soaring

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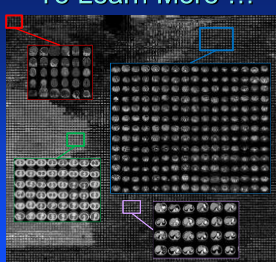
  - ISTP
  - IRTA
  - BESIP
  - CRTP

To Learn More …



www.cc.nih.gov/drd/summers.html

X Wang et al. RSNA 2016