The Impact of Deep Learning on Radiology

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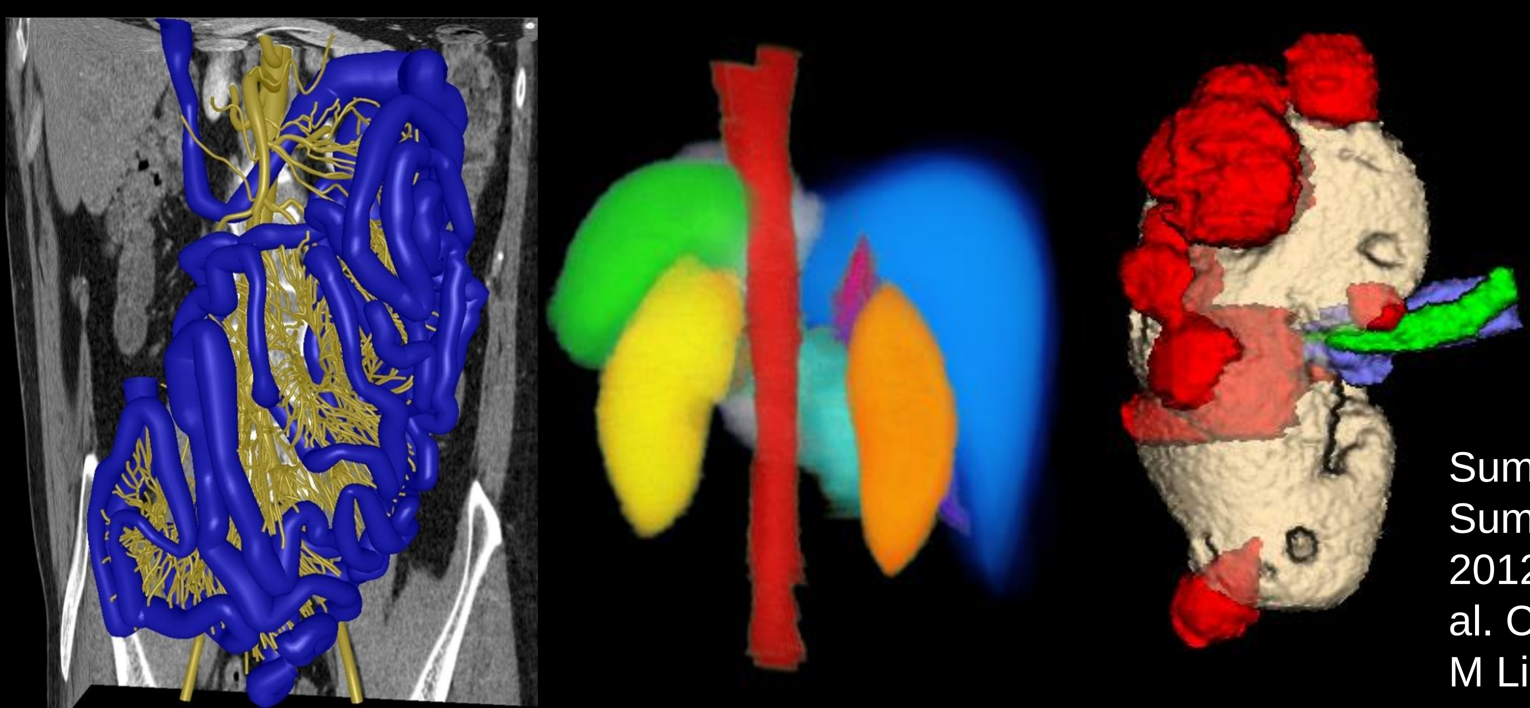
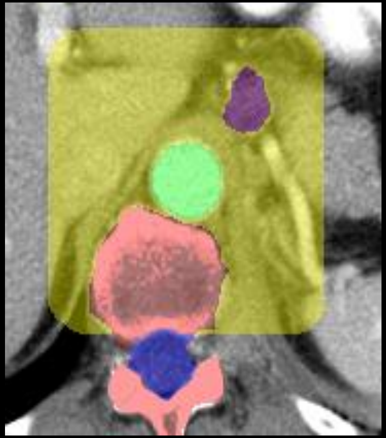
Disclosures

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

Overview

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



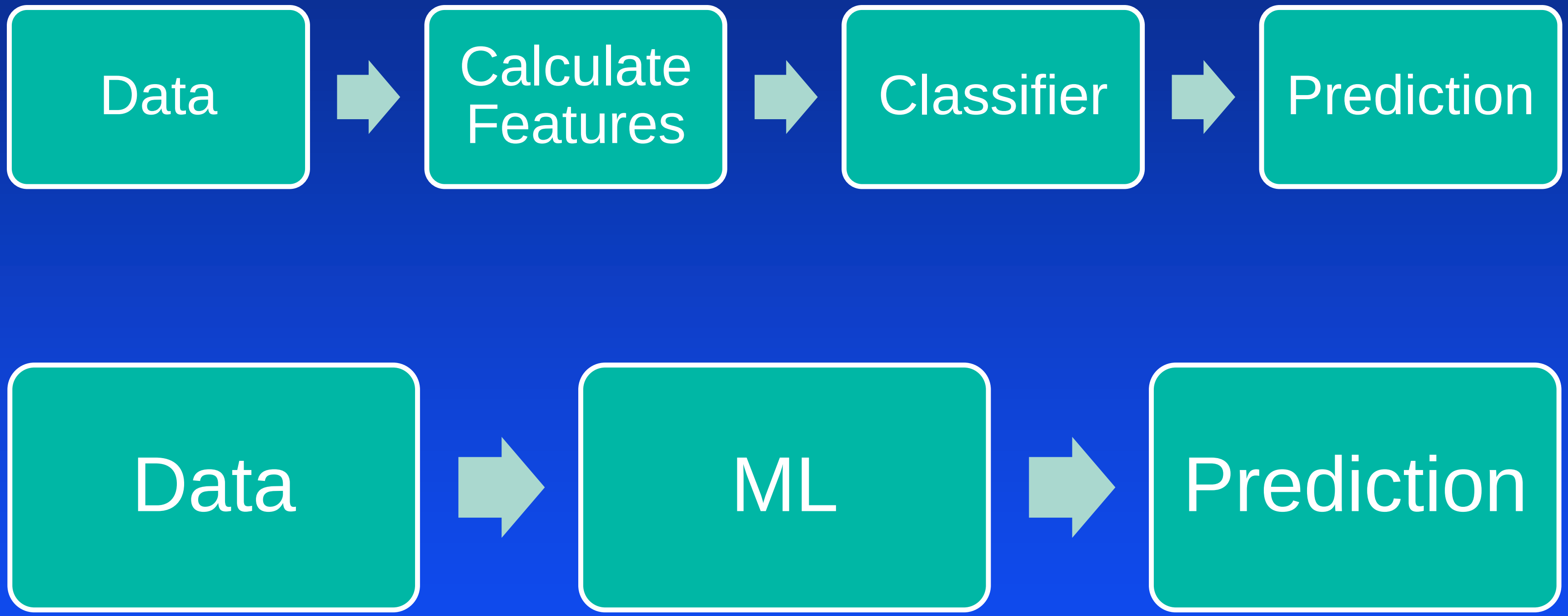


Summers et al. Gastroenterology 2005; Summers et al. JCAT 2011; Hua et al. ARRS 2012; Zhang et al. ISBI 2012; Jiamin Liu et al. CMIG 2014; Images courtesy NIH CIPS, M Linguraru, J Yao

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

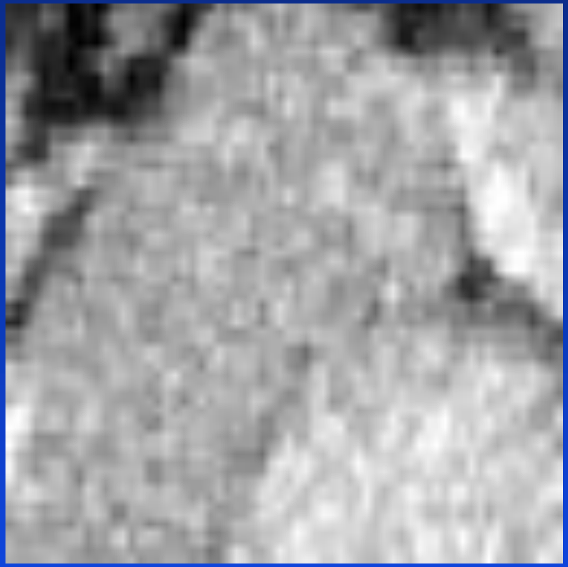
Two Paradigms for Learning



Deep Learning

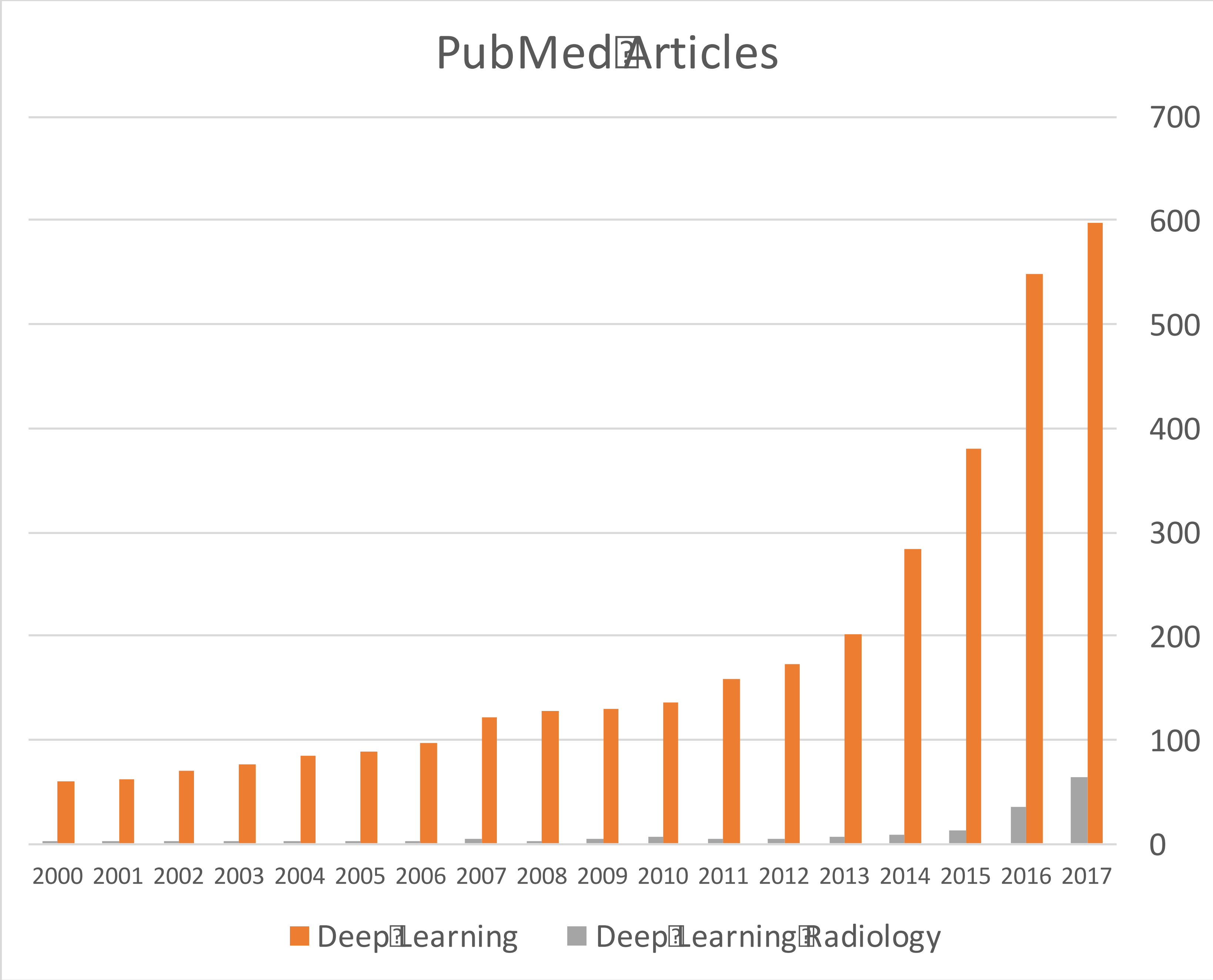
- Convolutional neural networks (ConvNets, CNNs)
- An improvement to neural networks
- More layers permit higher levels of abstraction
- Similarities to low level vision processing in animals
- Marked improvements in solving hard problems like object recognition in pictures

Deep Learning



- GPU acceleration
- Data augmentation
- Numerous software platforms (TensorFlow, Caffe, MatConvNet)
- Functional components (LSTM, DropOut, Softmax, Max-Pooling, ReLu)
- Widely-used networks (AlexNet, VGG, GoogLeNet, ResNet, U-Net)

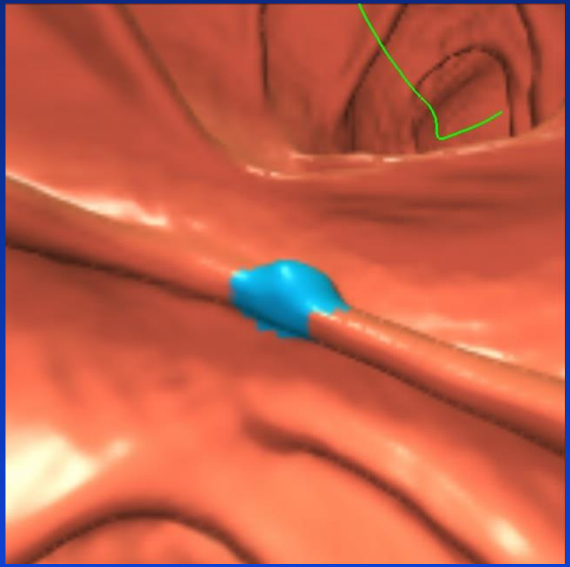
Roth et al. RSNA 2015



PubMed Articles
700
600
500
400
300
200
100
0
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
Deep Learning
Deep Learning Radiology

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

Deep Learning Improves CAD

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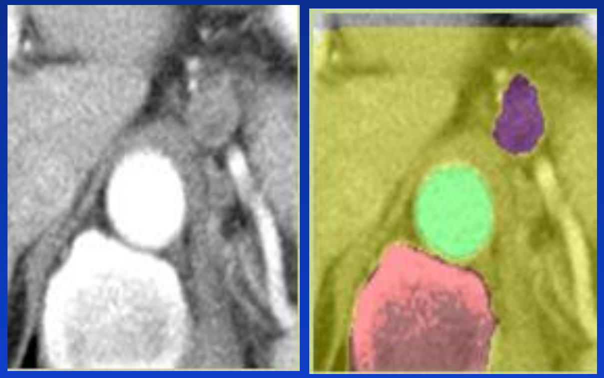

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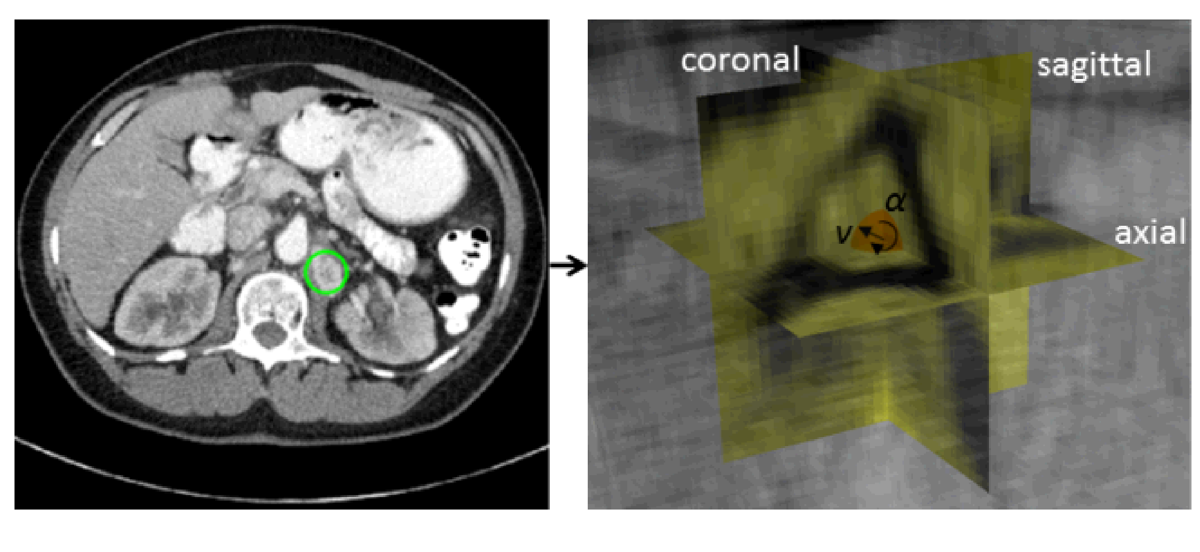
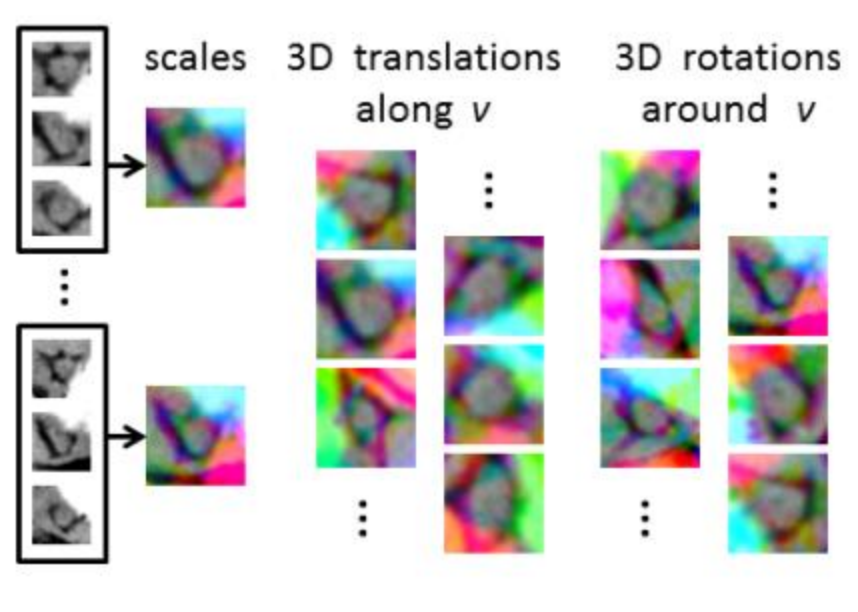
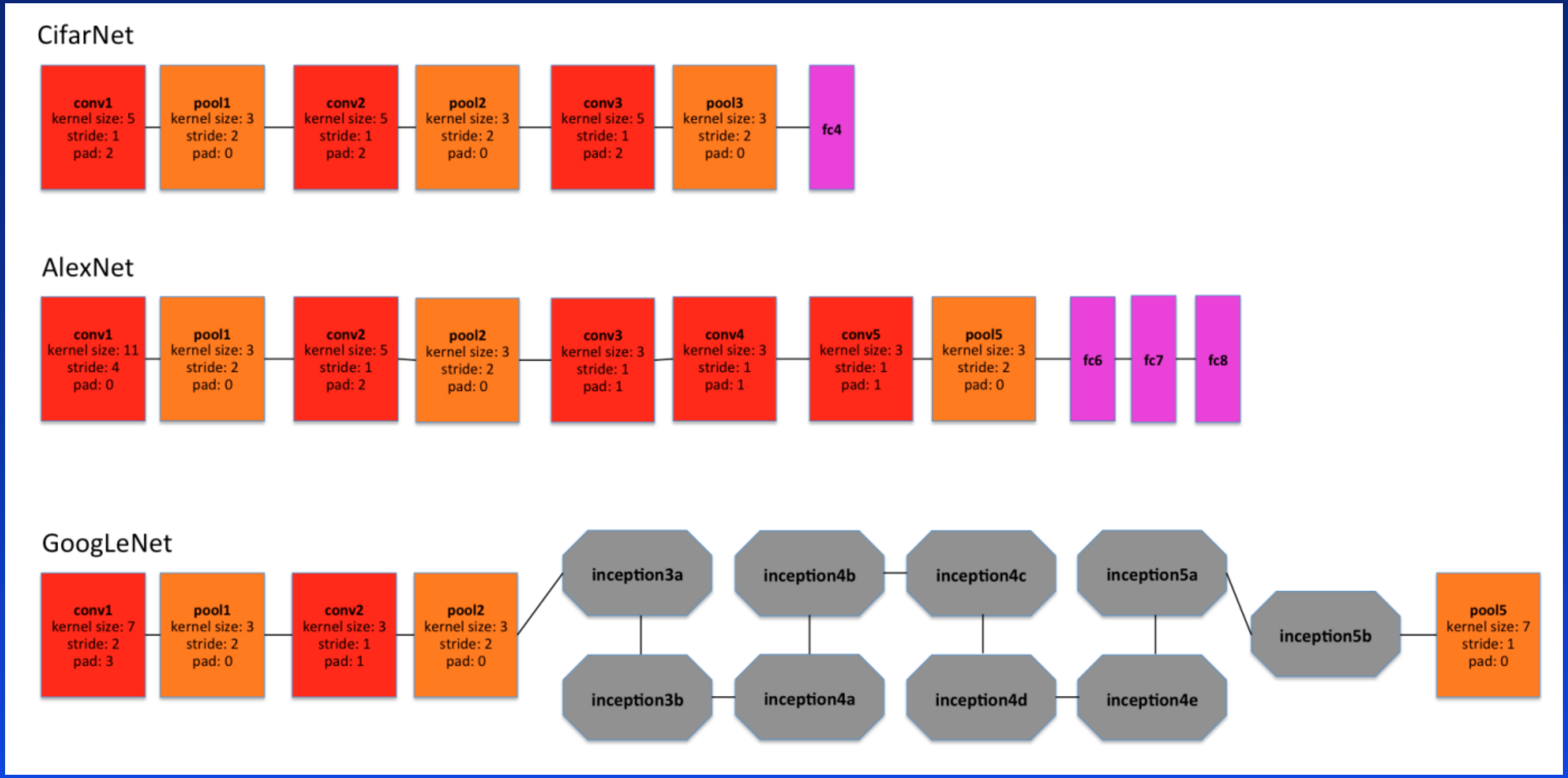
Hua, Liu, Summers et al. ARRS 2012; Roth et al. IEEE TMI 2015





- 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

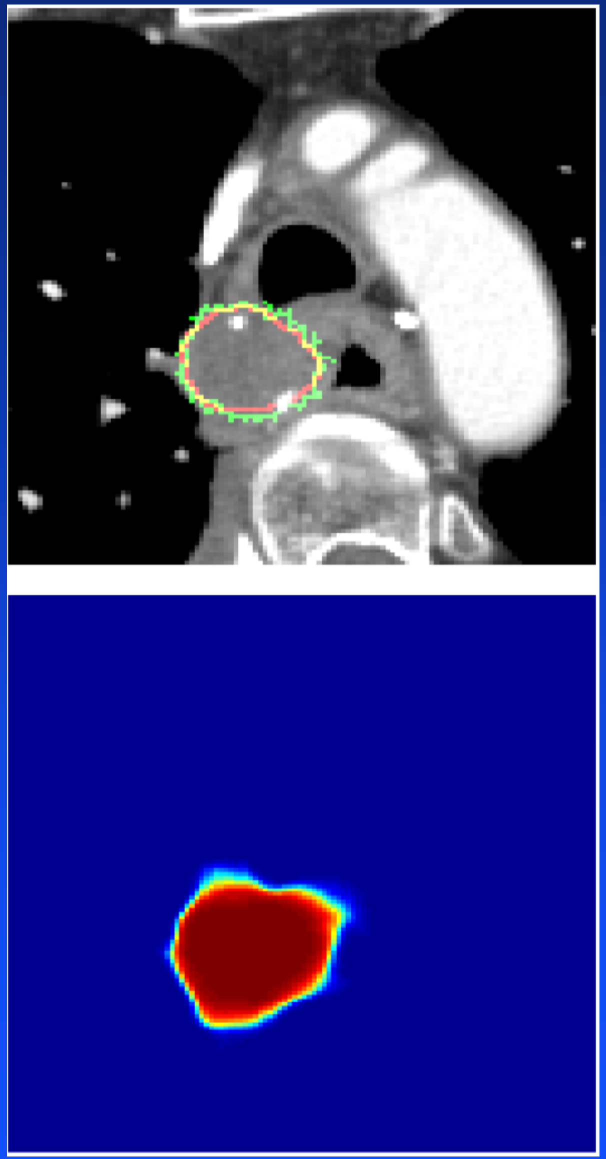
H Roth et al., MICCAI 2014

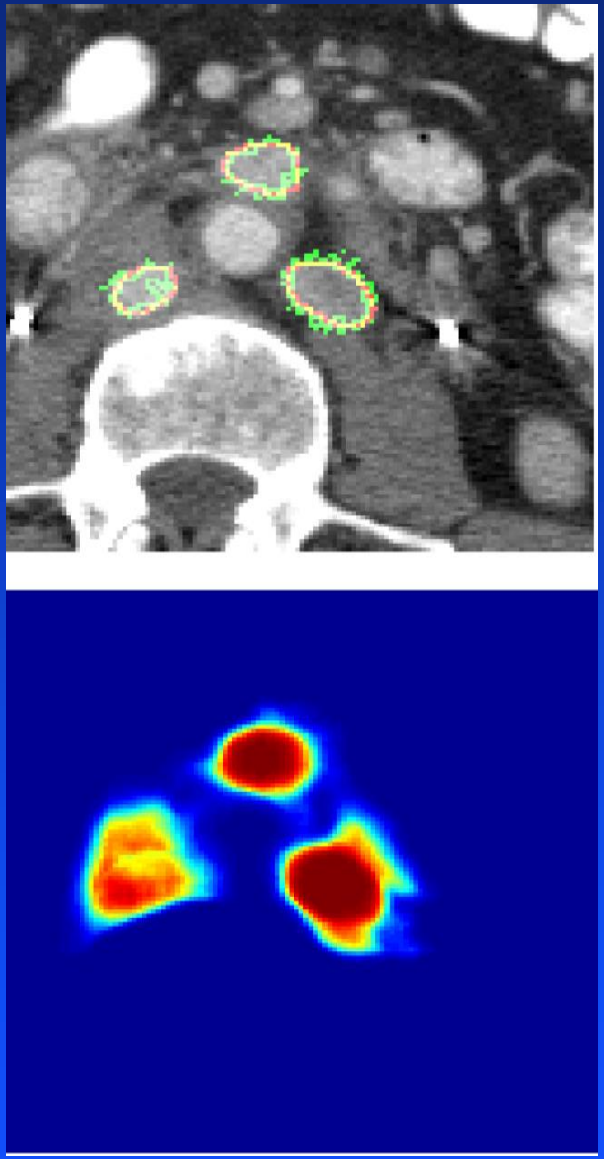


- Deeper CNN model performed best
- GoogLeNet for mediastinal LNs
- Sensitivity 85% at 3 FP/vol.

HC Shin et al., IEEE TMI 2016

Lymph Node Segmentation



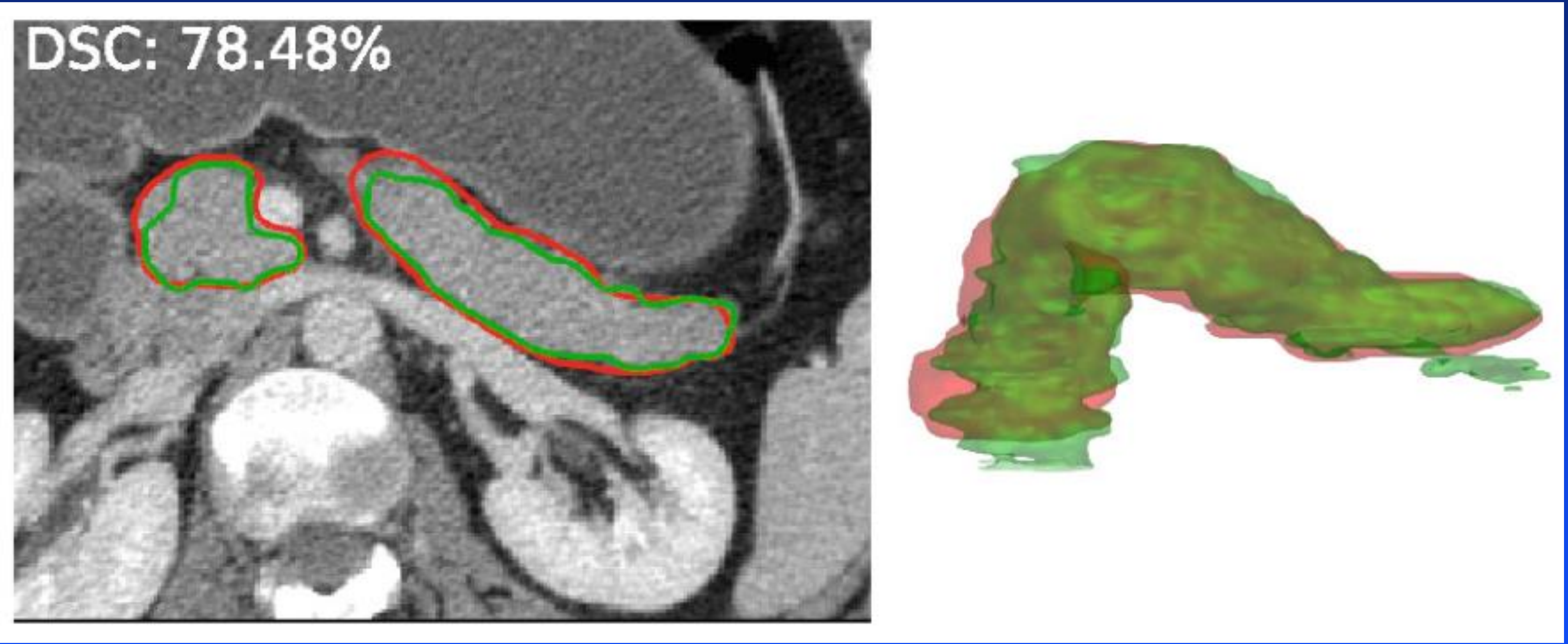


I Nogues et al. RSNA 2016

Lymph Node CT Dataset

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

Pancreas CAD using CNN

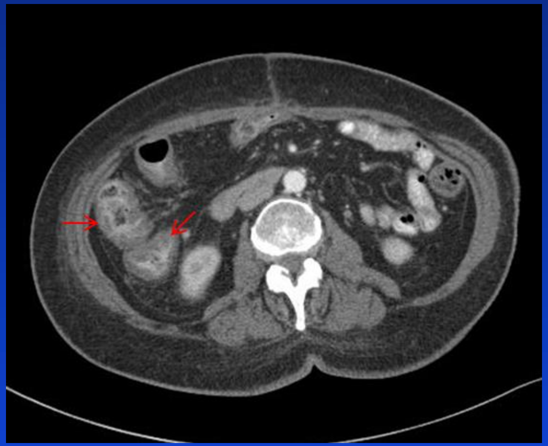


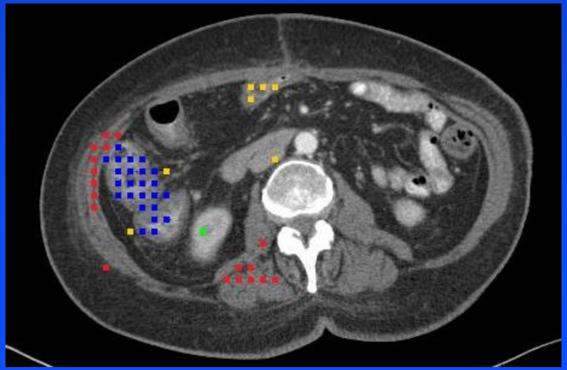
H Roth et al., MICCAI 2016

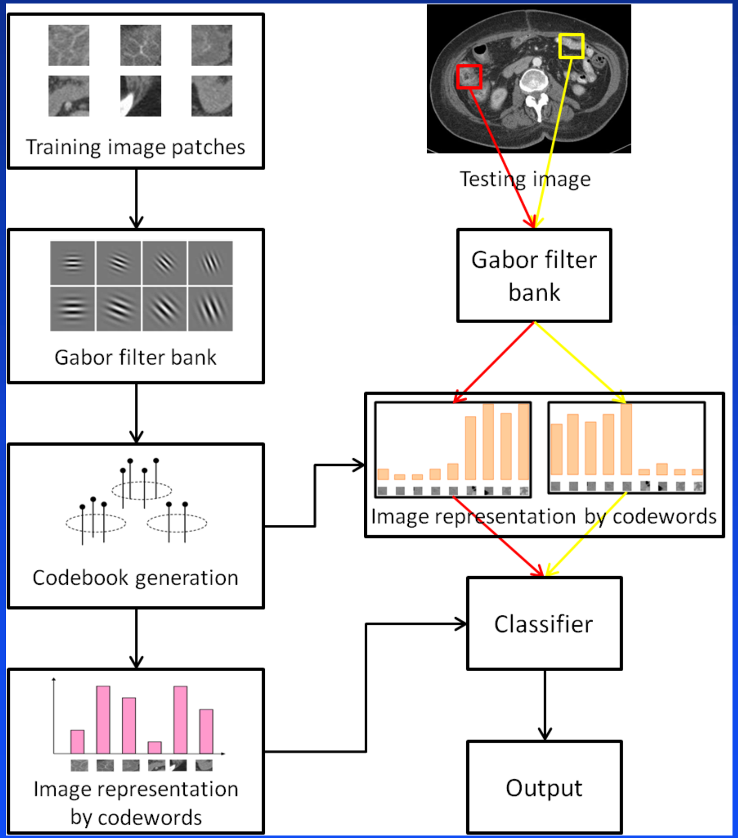
Pancreas CT Dataset

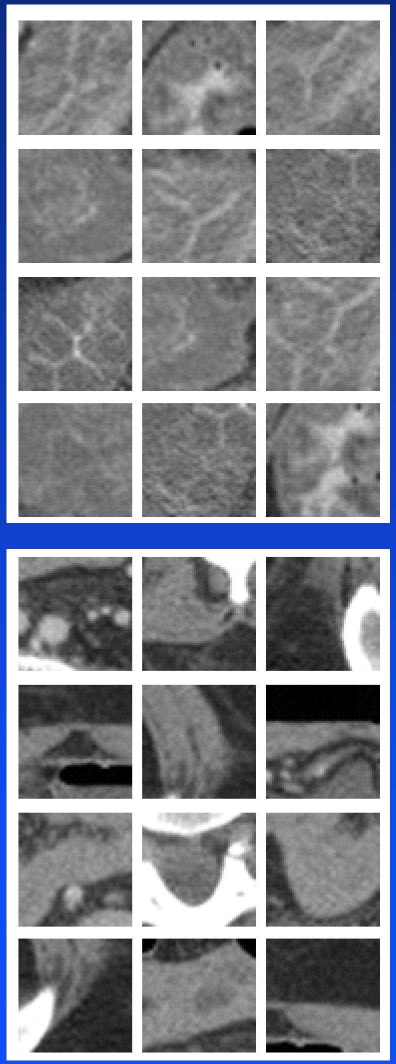
- doi.org/10.7937/K9/TCIA.2016.tNB1kqBU
- TCIA CT Pancreas
- 82 scans, 10 GB

Colitis CAD



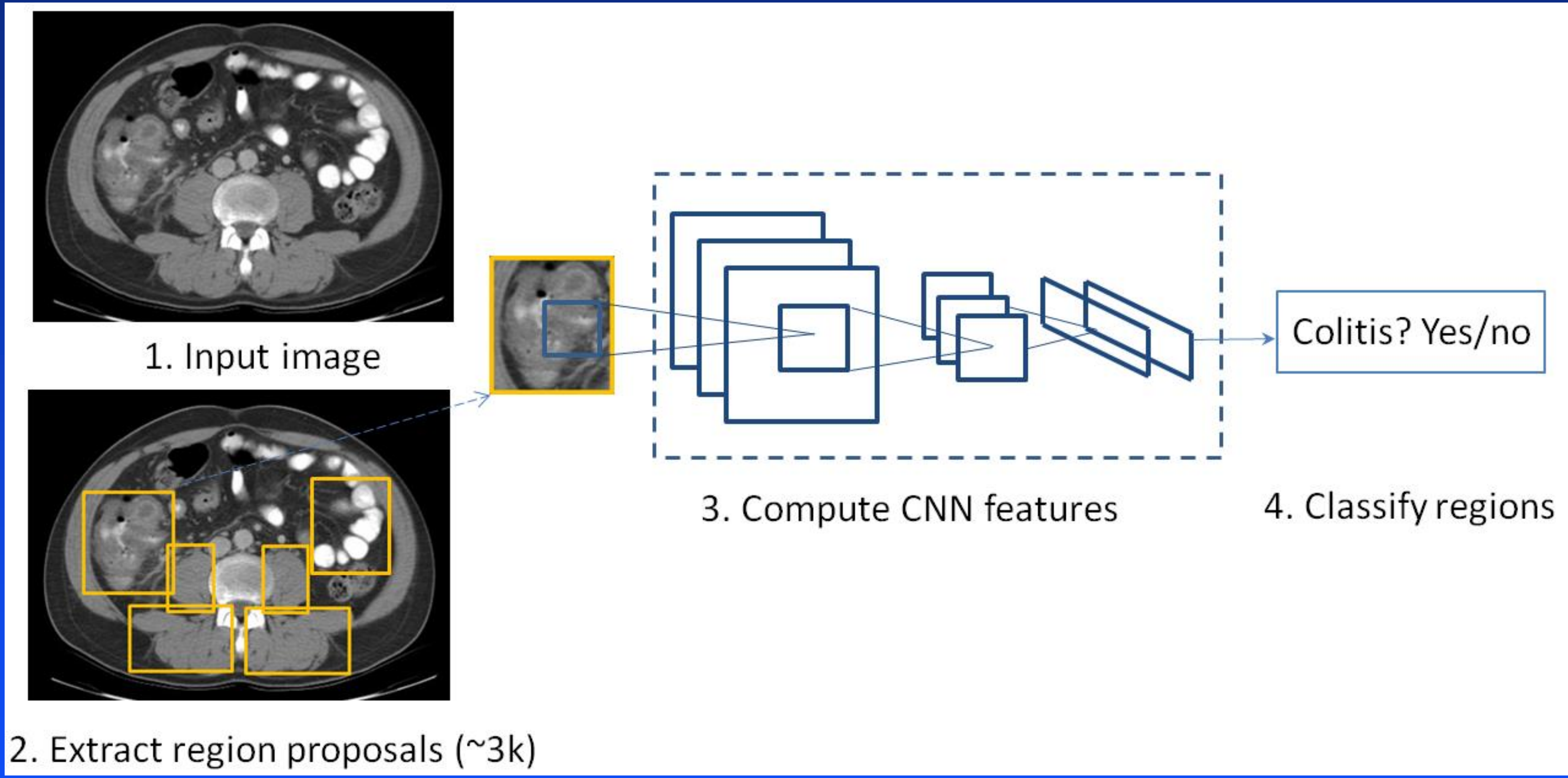






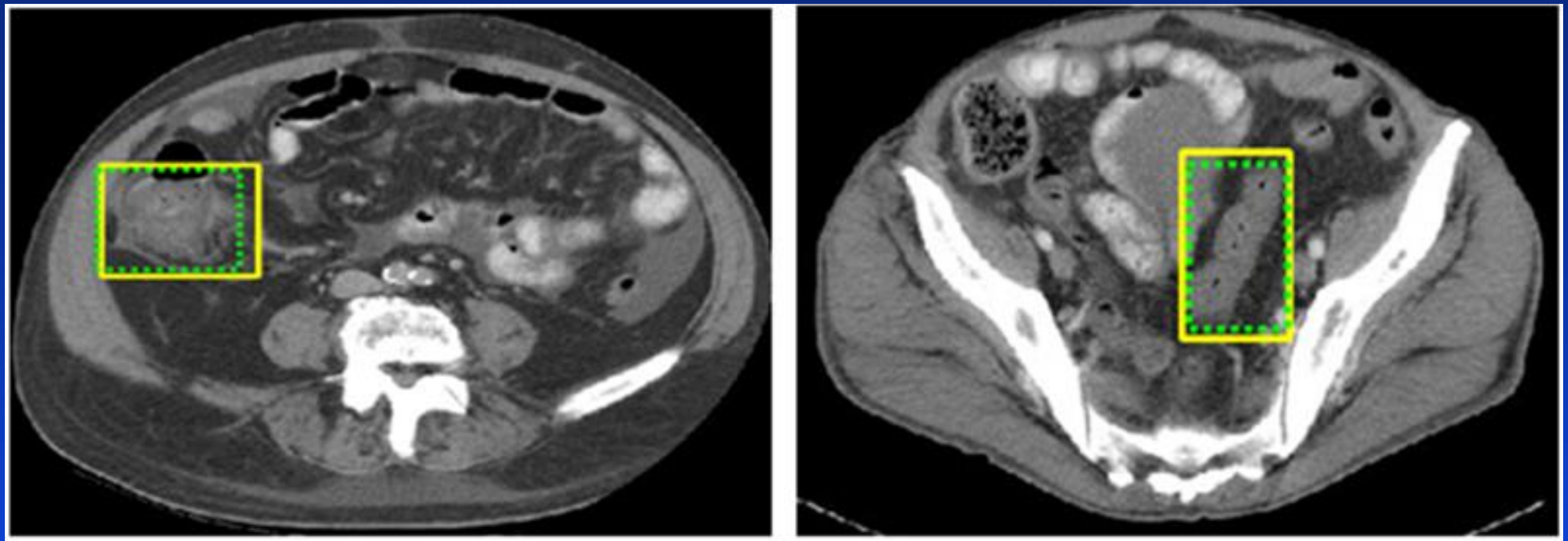
Wei et al. SPIE, ISBI 2013

Colitis CAD



J Liu et al. SPIE Med Imaging 2016

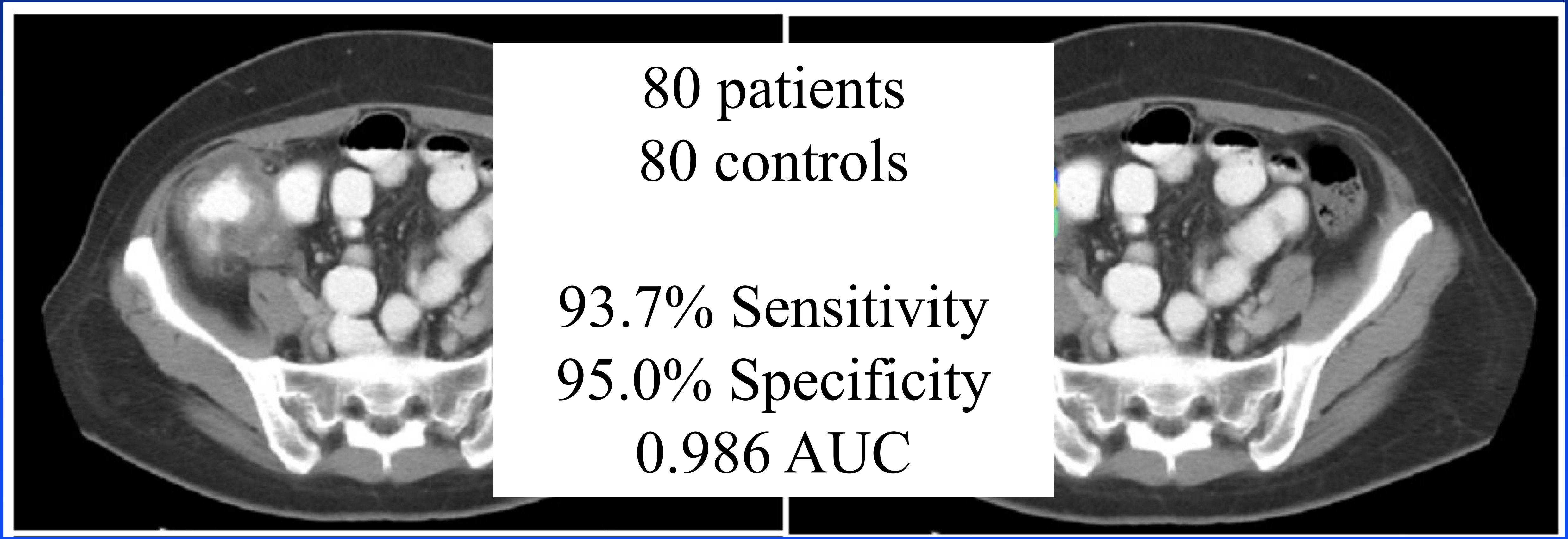
Colitis CAD



- 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

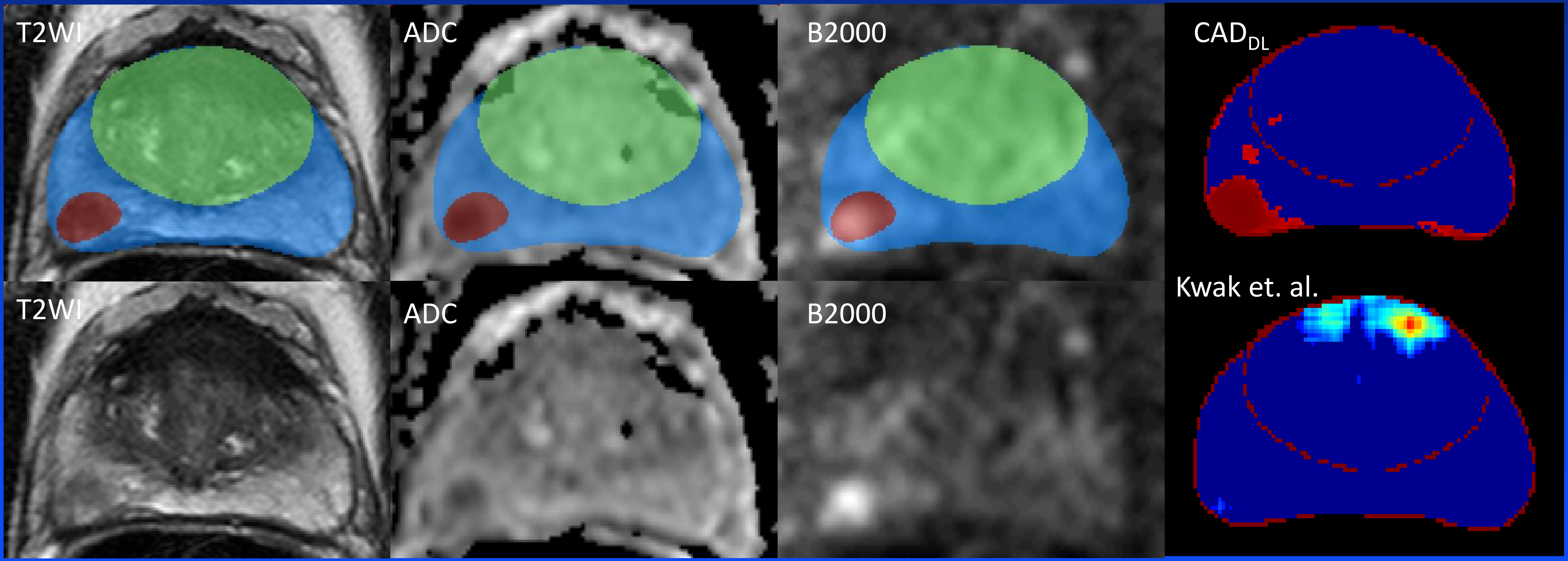


80 patients
80 controls

93.7% Sensitivity
95.0% Specificity
0.986 AUC

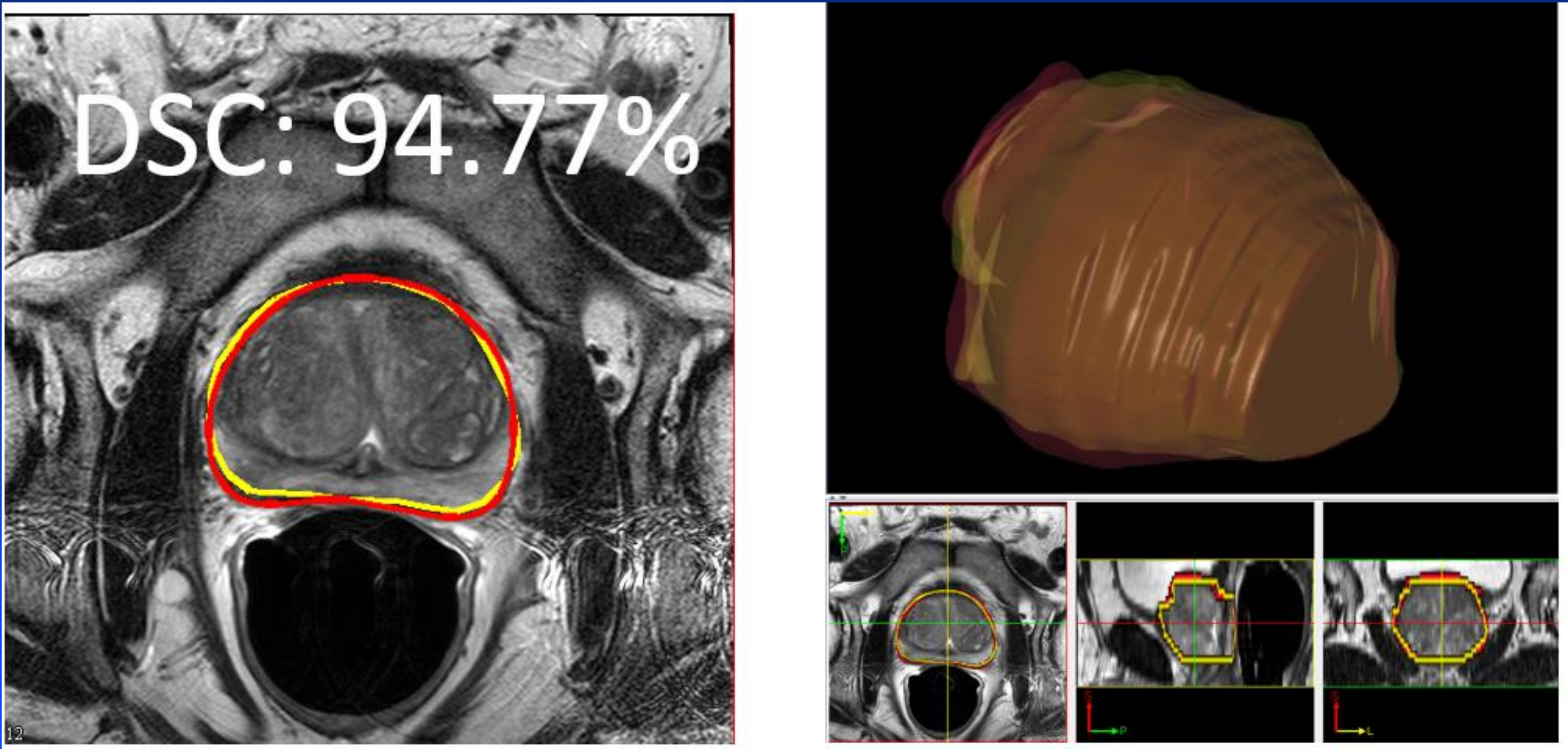
J Liu et al. Medical Physics 2017

Prostate



Tsehay et al. SPIE MI 2017

Prostate



Cheng et al. SPIE MI 2017

Prostate

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

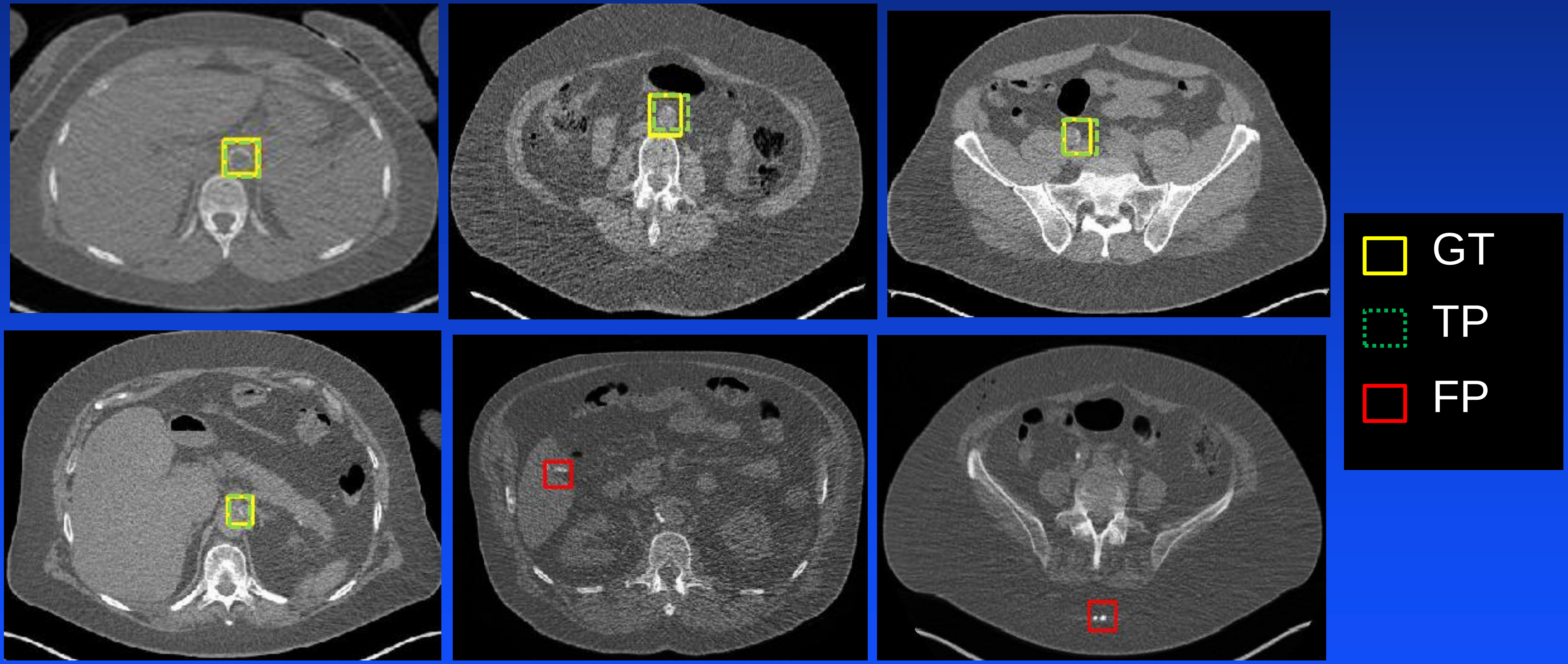
Methods	DSC + Std. dev (%)	HDRFDIST (mm)	AVGDIST (mm)	Images	Evaluation	Trim (α:0.95)
Klein et al.[1]	84.40 ± 3.10	10.20 ± 2.60	2.50 ± 1.40	50	Leave-one-out	Yes
Toth and Madabhushi[4]	87.66 ± 4.97		1.51 ± 0.78	108	Fivefold validation	Yes
Liao et al.[7]	86.70 ± 2.20	8.20 ± 2.50	1.90 ± 1.60	30	Leave-one-out	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	$\mathbf{89.77 \pm 3.29}$		$\mathbf{0.16 \pm 0.08}$	250	Fivefold validation	No

Cheng et al. JMI 2017

ProstateX Challenge

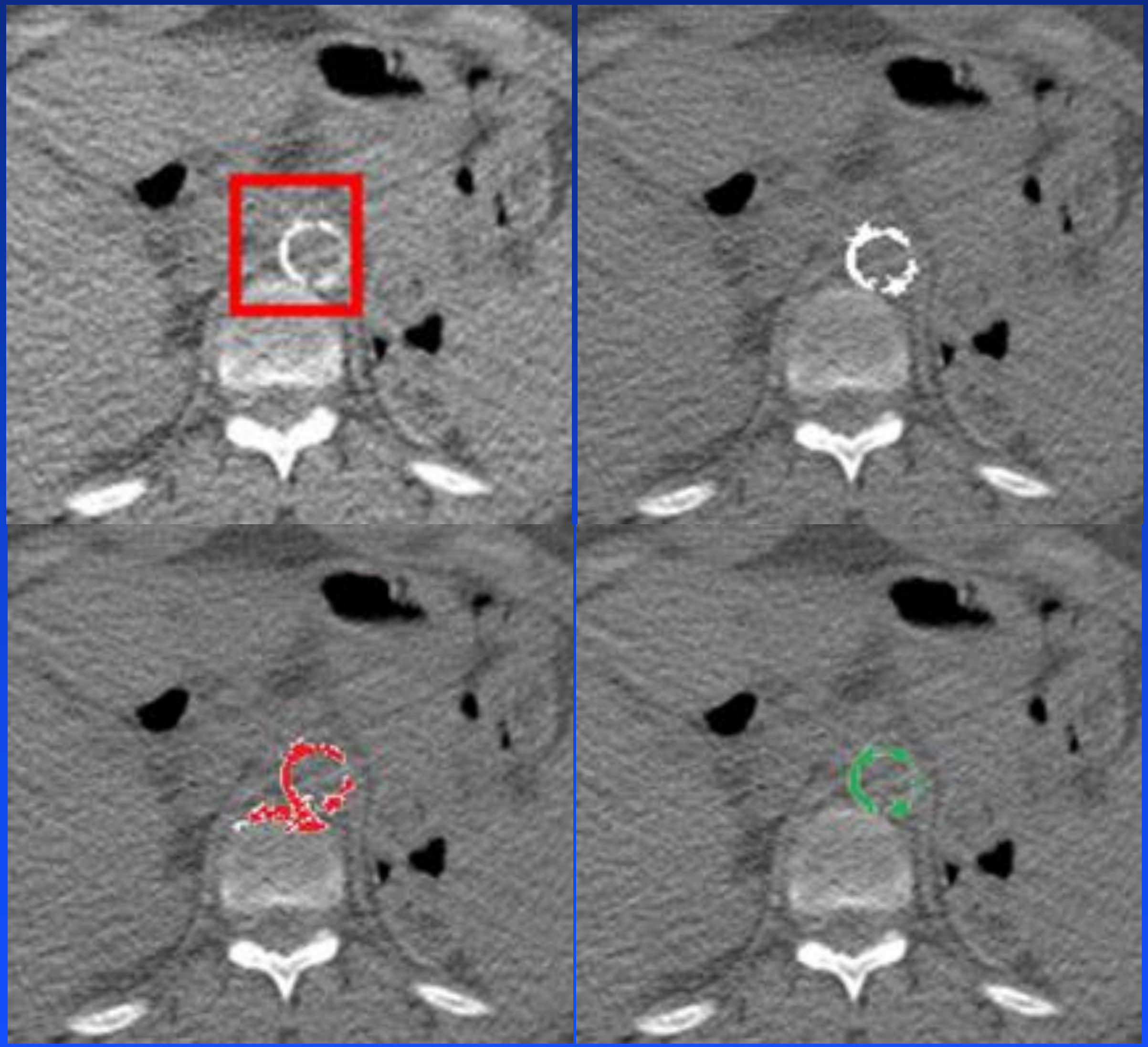
- SPIE/AAPM collaboration
- Prostate MRI CADx challenge
- 2 parts: malignancy and Gleason group prediction
- Dozens of competitors
- Winners used deep learning

Whole Body Calcium Scoring



K Chellamuthu, J Liu et al., ISBI 2017

Whole Body Calcium Scoring



GT

>=130HU

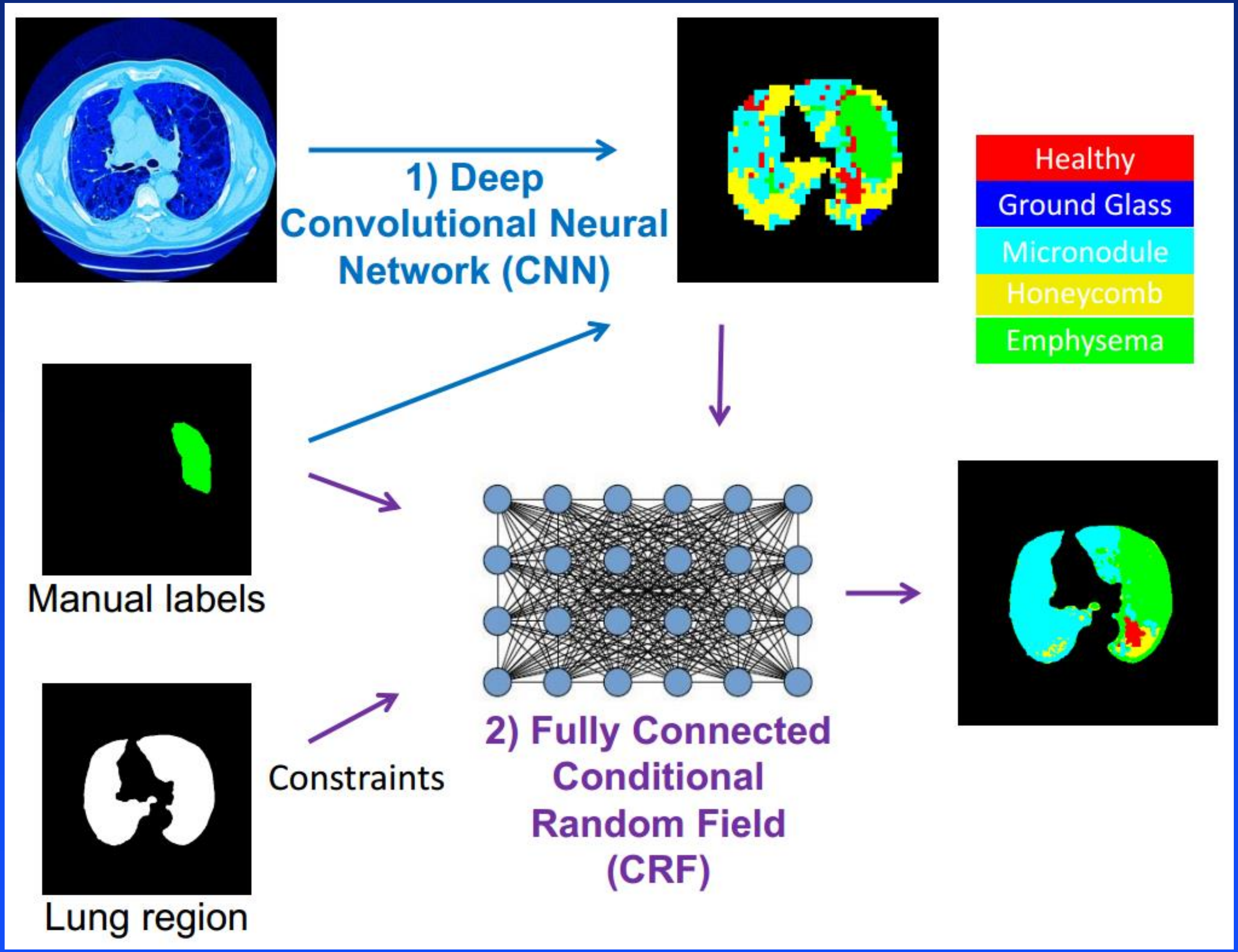
DICE=0.41

HED

DICE=0.82

K Chellamuthu, J Liu et al., ISBI 2017

Segmentation Label Propagation



Gao et al. IEEE ISBI 2016

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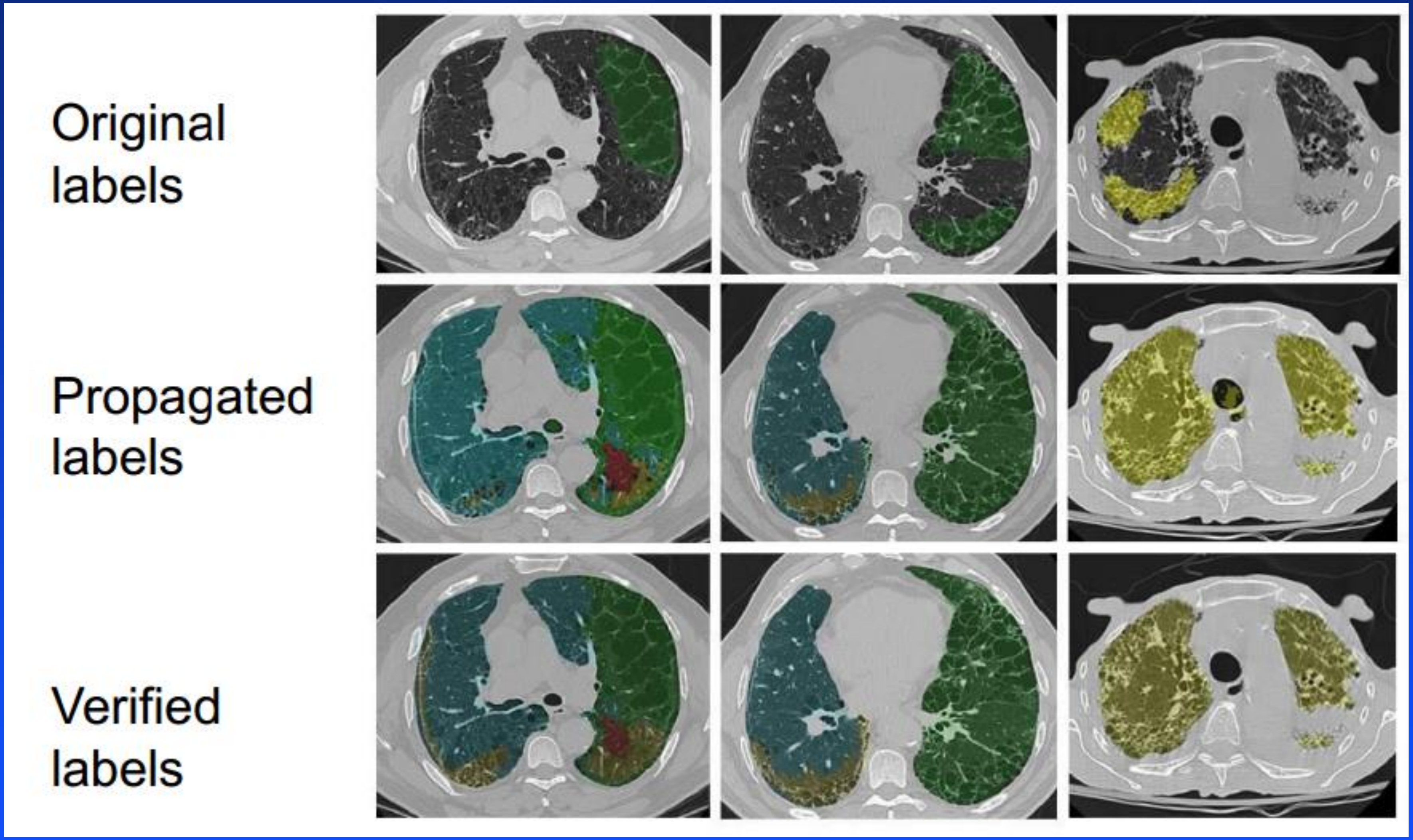
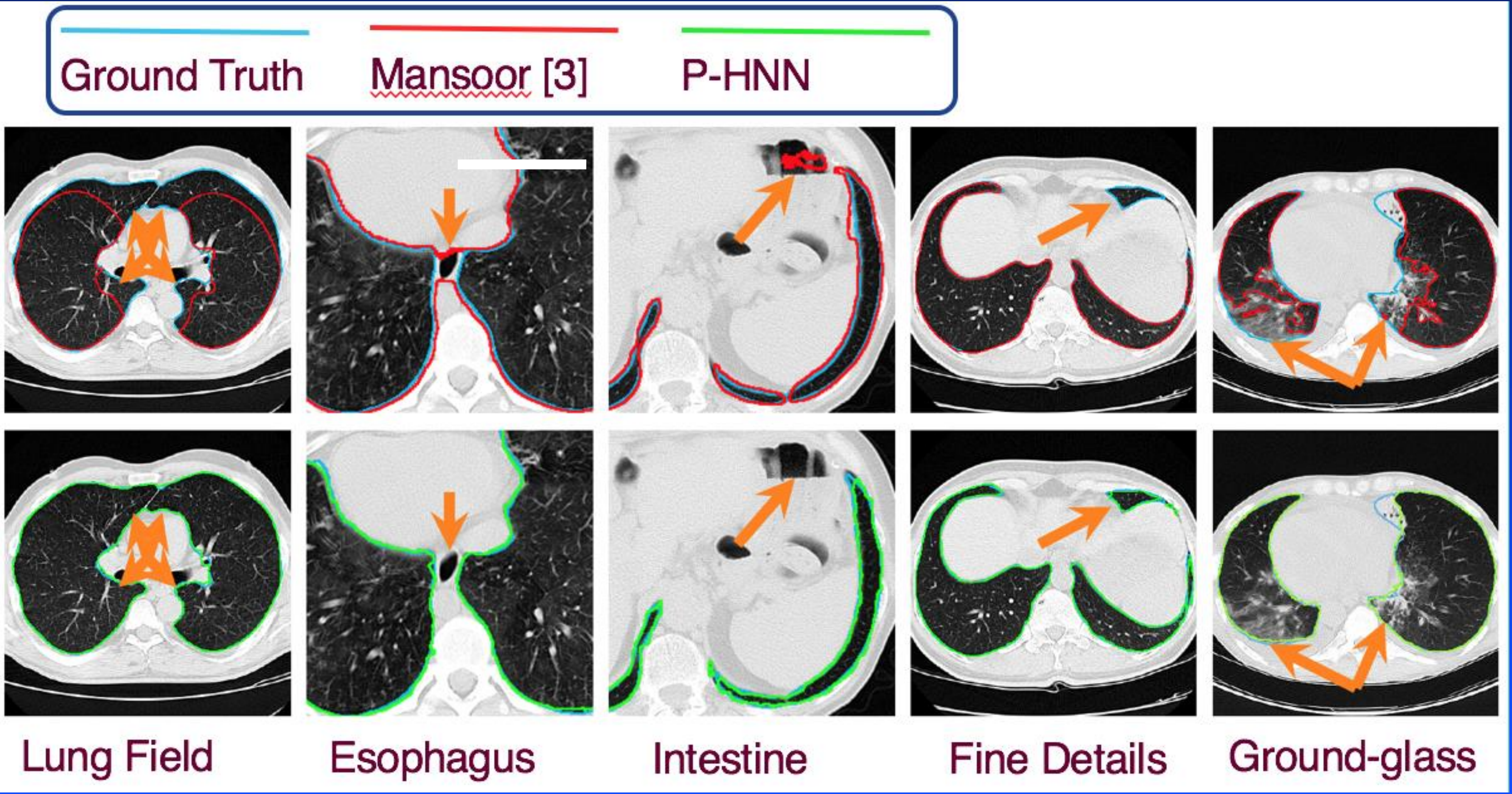
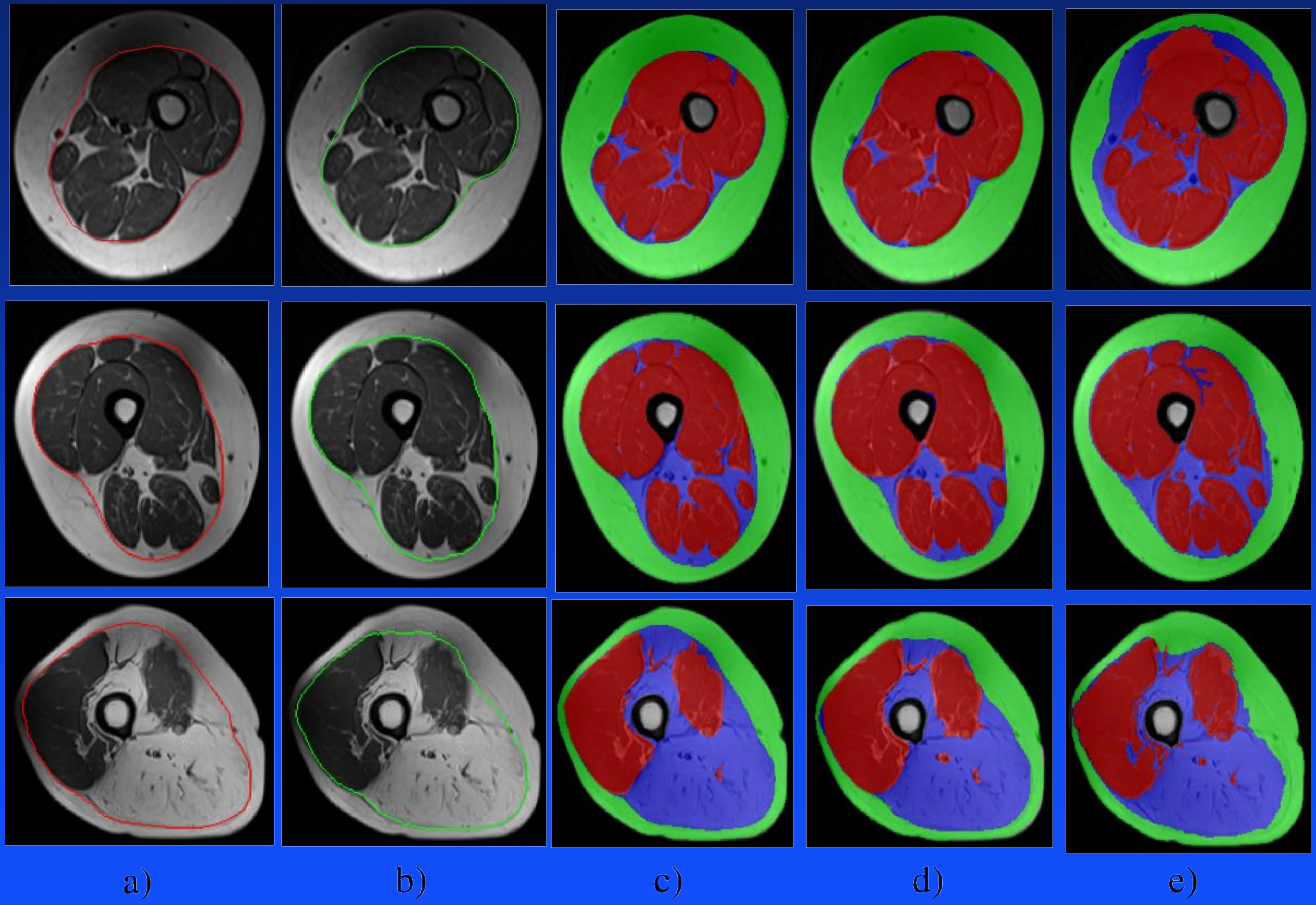


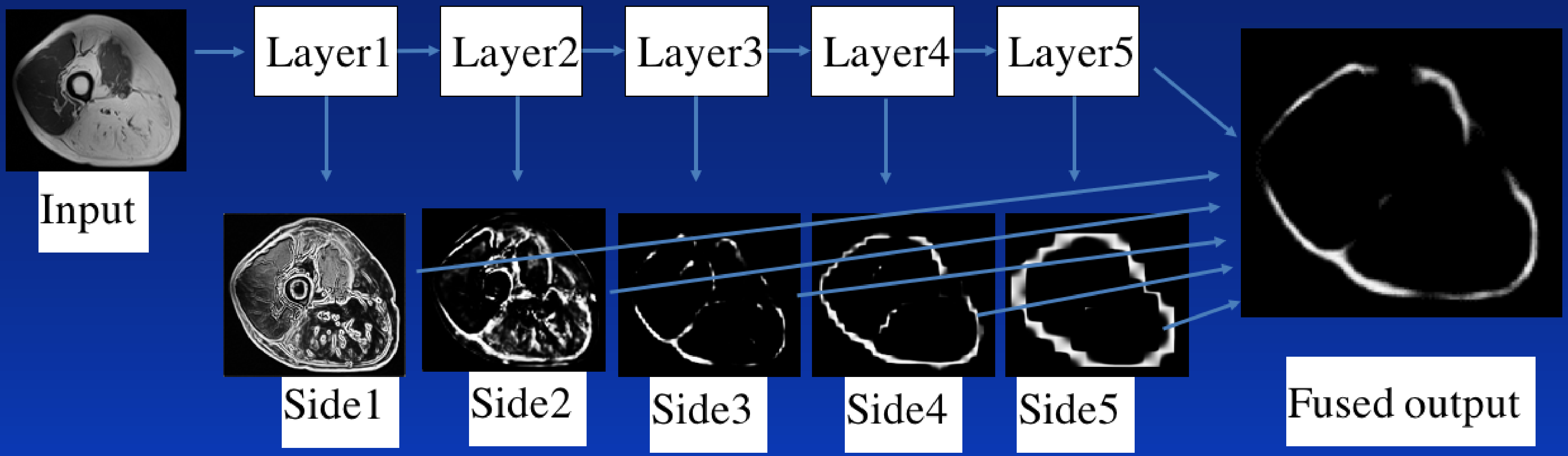
Gao et al. IEEE ISBI 2016

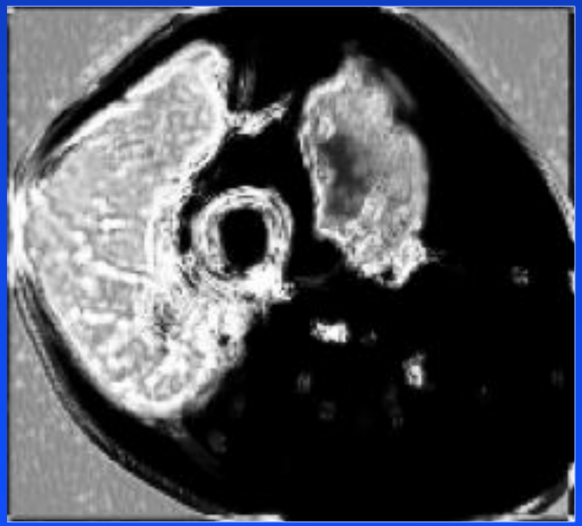


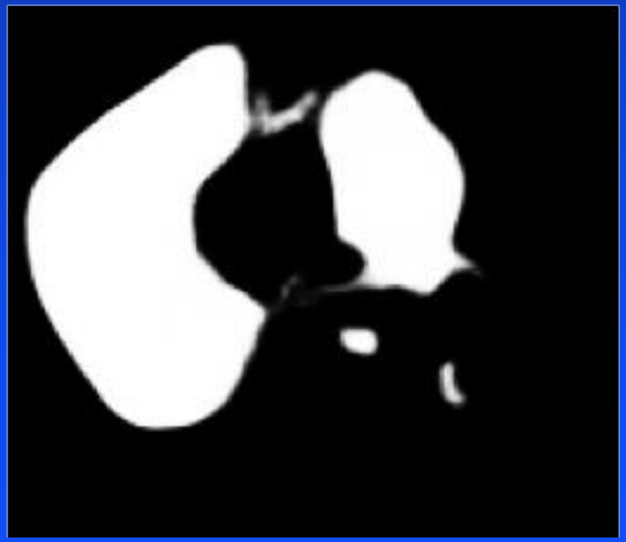
A Harrison et al. MICCAI 2017

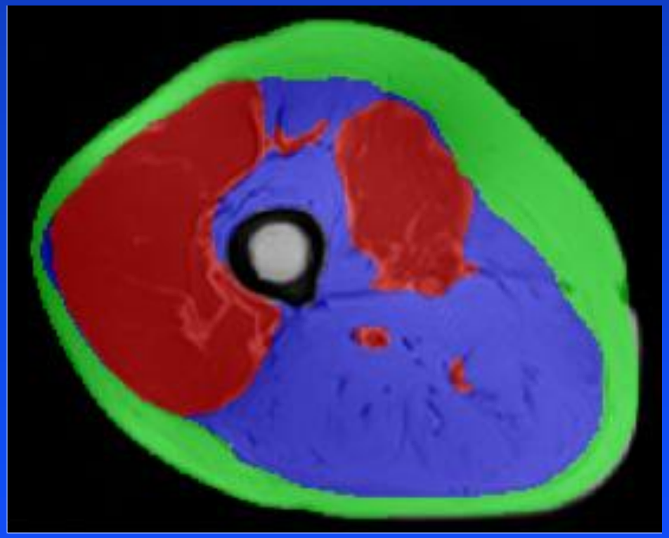


J Yao et al. MICCAI 2017

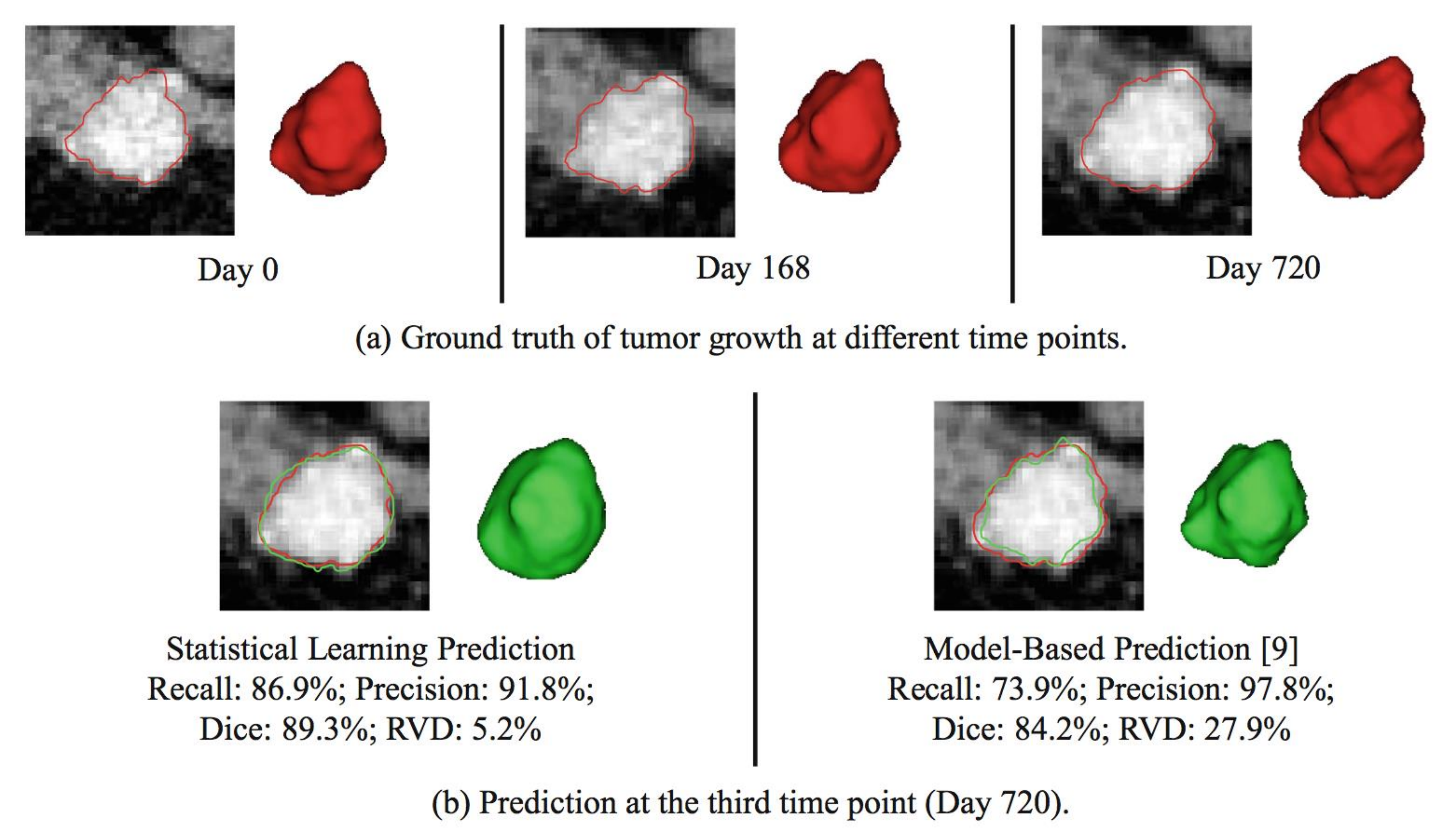








J Yao et al. MICCAI 2017

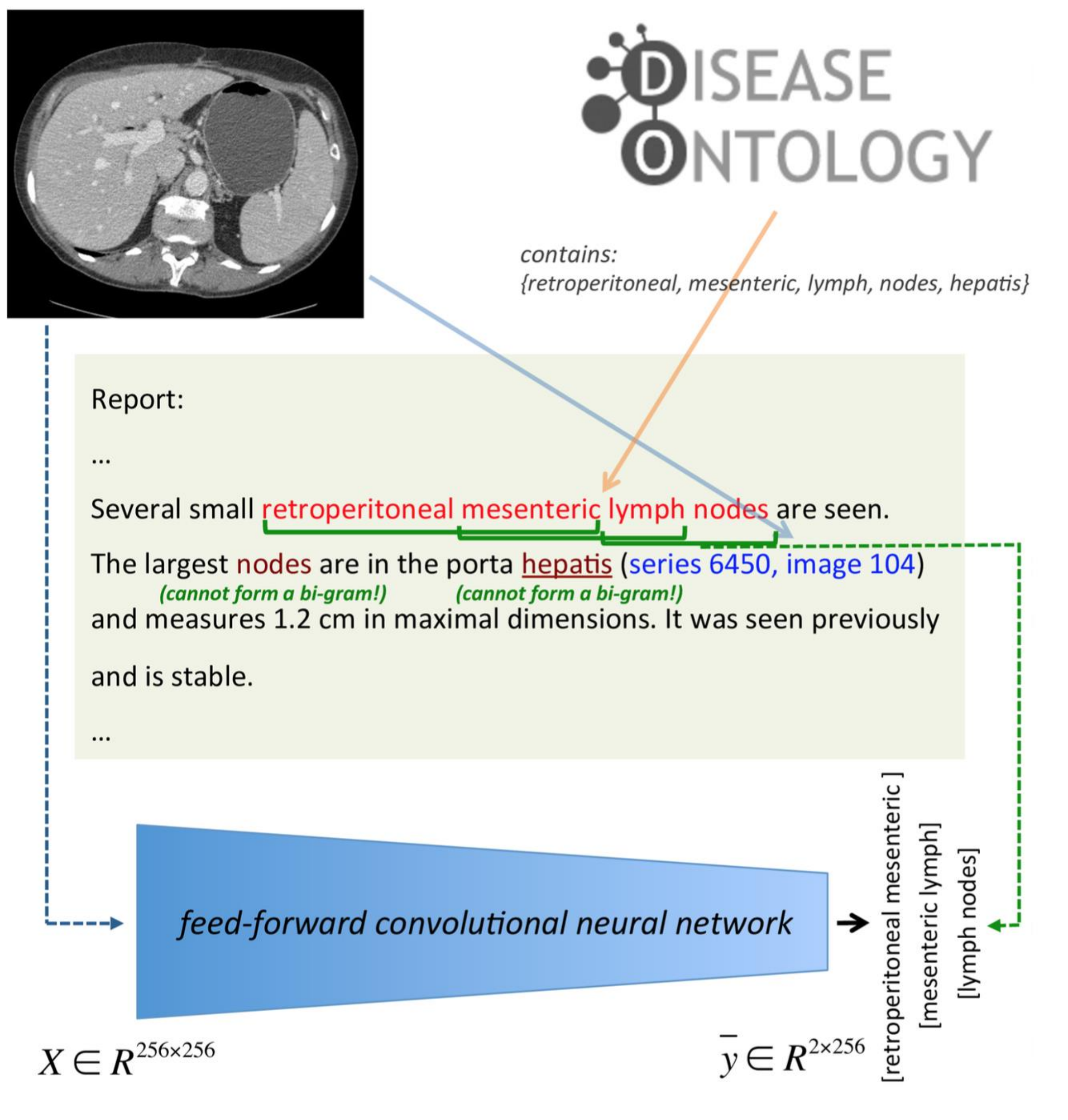


(a) Ground truth of tumor growth at different time points.

(b) Prediction at the third time point (Day 720).

L Zhang et al. MICCAI 2017

Data Mining Reports & Images



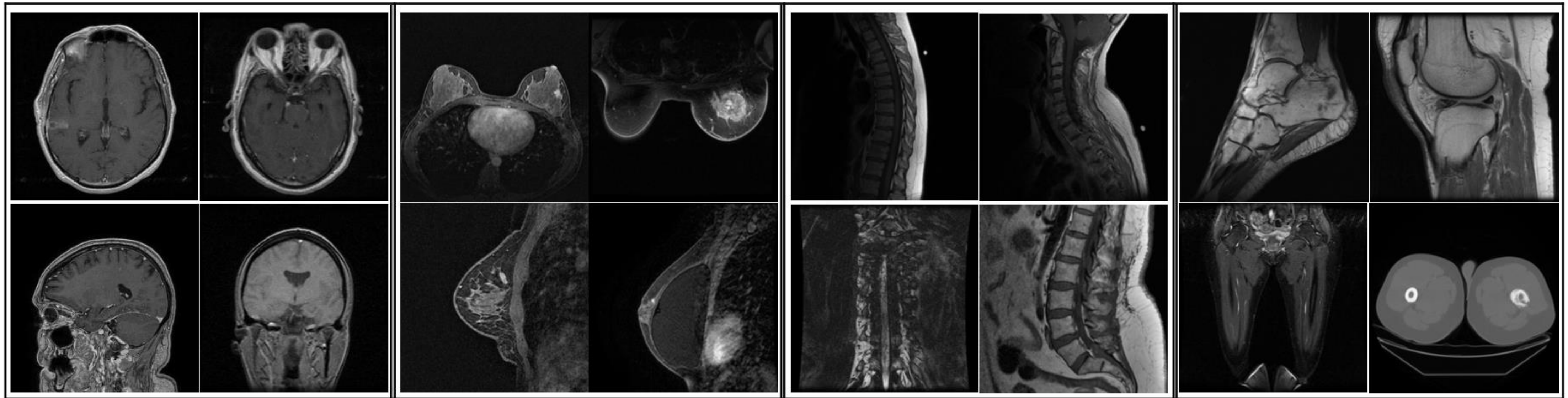
HC Shin et al. CVPR 2015

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

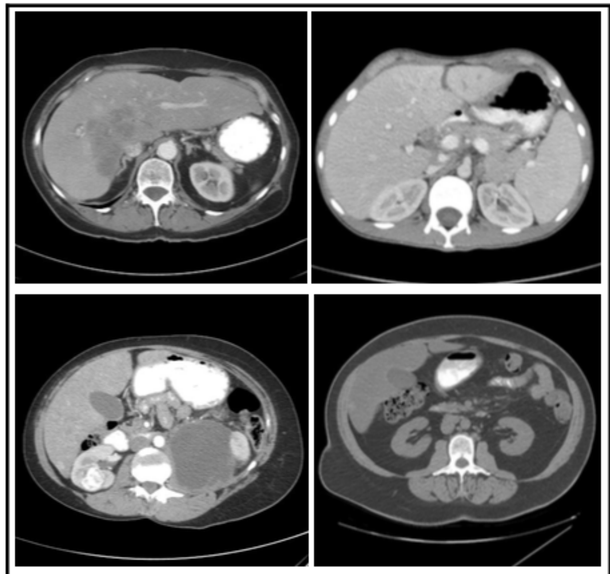
Data Mining Reports & Images



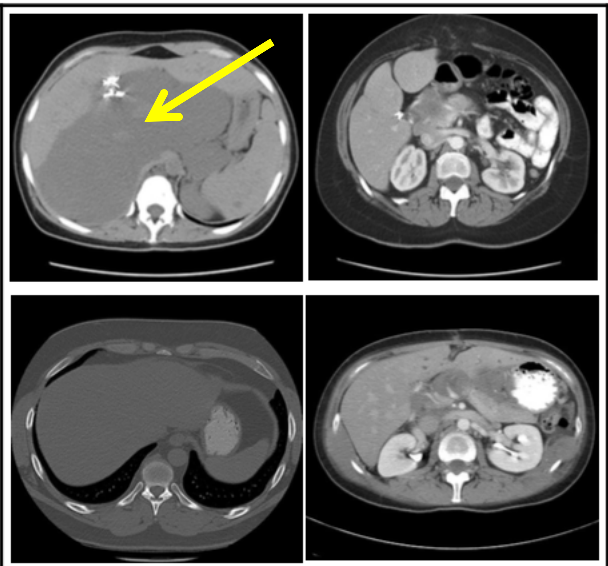
Topic 04:	**Topic 17:**	**Topic 31:**	**Topic 78:**
axial,contrast,mri,sagittal,post,flair,enhancement,blood,dynamic,brain,relative,volume,this,precontrast,from,tesla,fse,diffusion,gradient,resection,comparisons,maps,philips,progression,some,susceptibility,perfusion,stable,achieva,technique,echo,weighted,1.5,evidence,mass,findings,hemorrhage,enhanced,impression,frontal,signal,coronal,dti,tumor,t1-ffe,hydrocephalus,magnevist,reformations,bolus,lesion	breast,performed,suspicious,breasts,seen,impression,mass,screening,mammogram,dated,annual,cancer,mri,benign,bilateral,was,bi-rads,mammograms,Negative,dense,history,calcifications,images,views,studies,quadrant,mammography,volume,organ,aspect,suggested,category,mastectomy,before,tissue,enhancement,microcalcifications,heterogeneously,prior,family,examination,recommend,malignancy,high,suggest,outer,masses,developing,clip,patient	spine,cord,cervical,thoracic,spinal,level,canal,lumbar,sagittal,vertebral,neural,disc,signal,mri,body,technique,levels,findings,foramina,mild,disk,nerve,within,small,marrow,central,bodies,normal,impression,enhancing,conus,syrinx,this,narrowing,lesions,roots,contrast,throughout,bone,degenerative,foramen,protrusion,multiple,l5-s1,also,abnormal,c5-c6,posterior,changes,heights	bone,lesion,hip,knee,femoral,lytic,femur,proximal,head,sclerotic,joint,shoulder,hips,evidence,pelvis,distal,lesions,findings,humeral,lateral,fracture,medial,humerus,focal,impression,bony,prosthesis,history,iliac,pain,bilateral,blastic,avn,acetabulum,seen,marrow,sclerosis,view,both,osteolytic,cortical,heads,area,cortex,effusion,replacement,tibial,involving,consistent,views

HC Shin et al. CVPR 2015 & JMLR 2016

Topic: Metastases



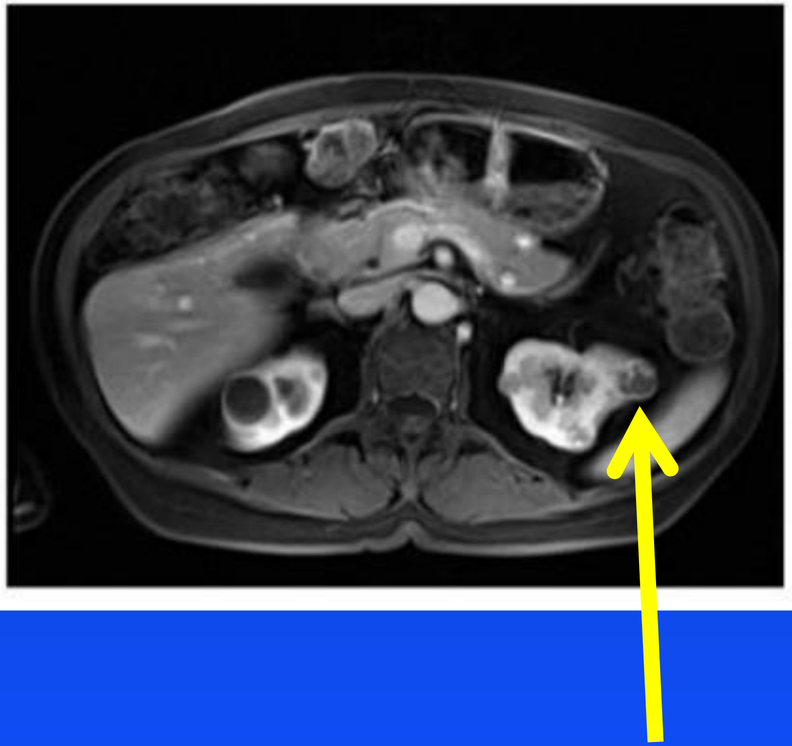
Topic 77-0:
kidney,images,abdomen,e.g,prior,mass,pancreas,following,cysts,adrenal,liver,foci,renal,contrast,approximate,including,focus,cyst,bilateral,masses,size,enhancing,for,also,given,possibly,mid,2.5,vascular,without,due,nephrectomy,please,1.5,from,few,multiphase,subcentimeter,least,comparison,patient,dual-phase,length,apparent,complication,obtained,upper,study,lower,vhl



Topic 77-2:
bulky,pelvis,bone,gross,since,liver,abdomen,calcification,vascular,study,lung,mass,isovue,dfov,without,contrast,administration,impression,metastasis,chest,for,images,mesenteric,axilla,following,hilum,cc/s,helical,multidetector,ascites,enteric,reason,apparent,complication,pleural,splenomegaly,pericardial,hydronephrosis,delay,effusion,mediastinum,obtained,300,spine,gallbladder,report,130,retroperitoneal,spleen,e.g

HC Shin et al. CVPR 2015 & JMLR 2016

Data Mining Reports & Images



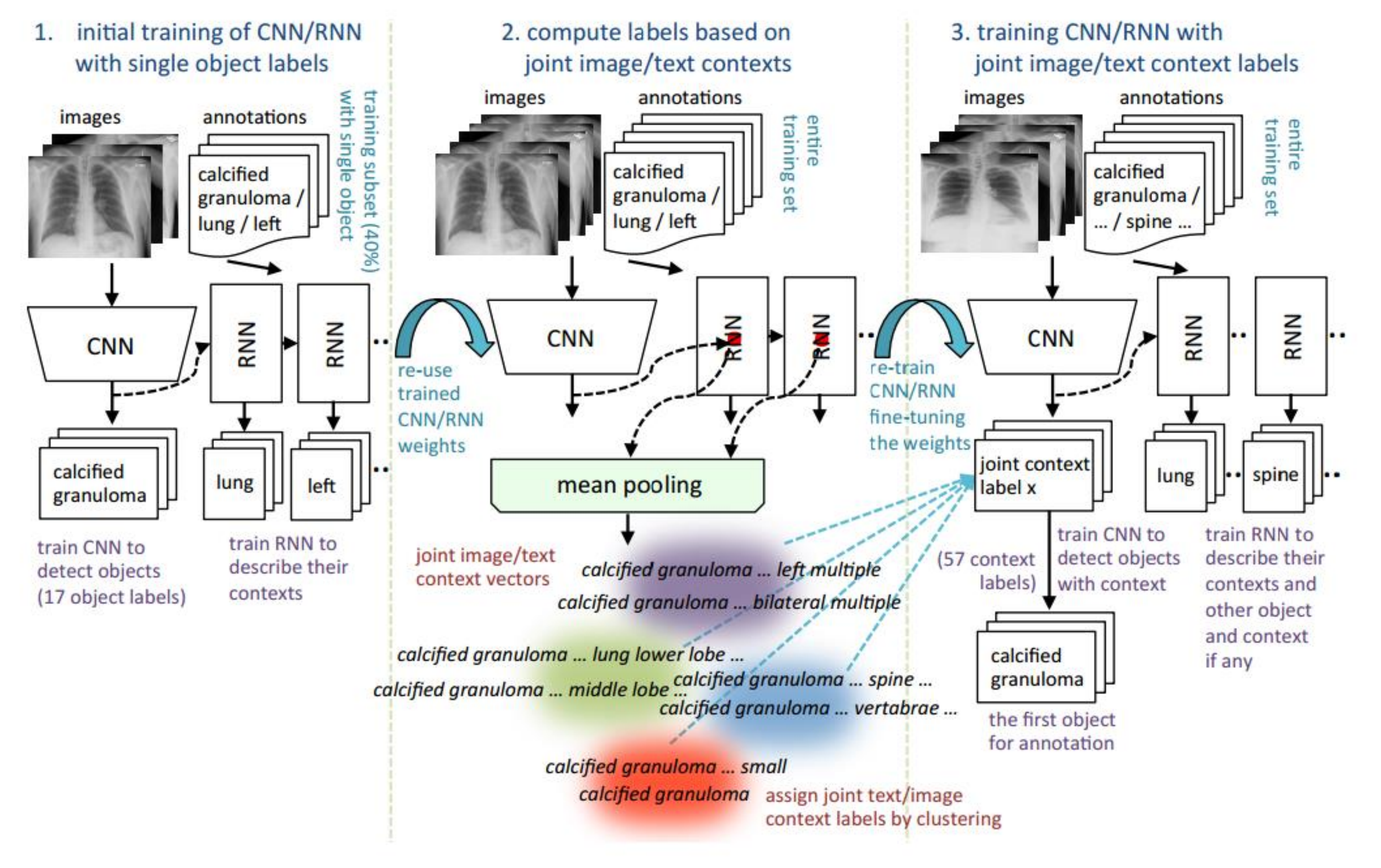
diameter
mass
kidney

avg distance: 0.33

"… and solid lobulated **mass** arises from the anterior lower pole of right **kidney** and measures 1.6 cm in **diameter** …"

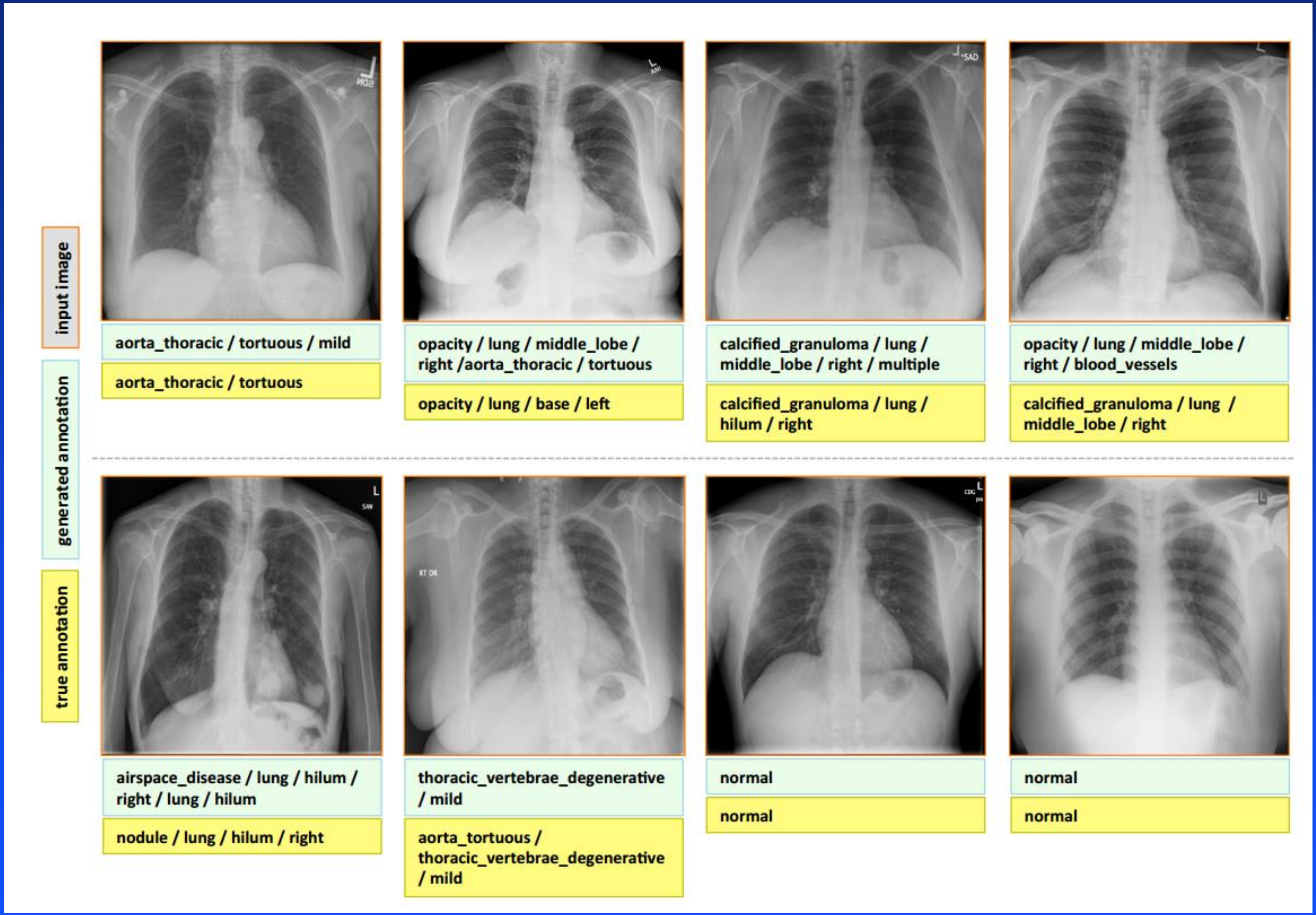
HC Shin et al. CVPR 2015 & JMLR 2016

Data Mining Reports & Images



HC Shin et al. CVPR 2016

Data Mining Reports & Images

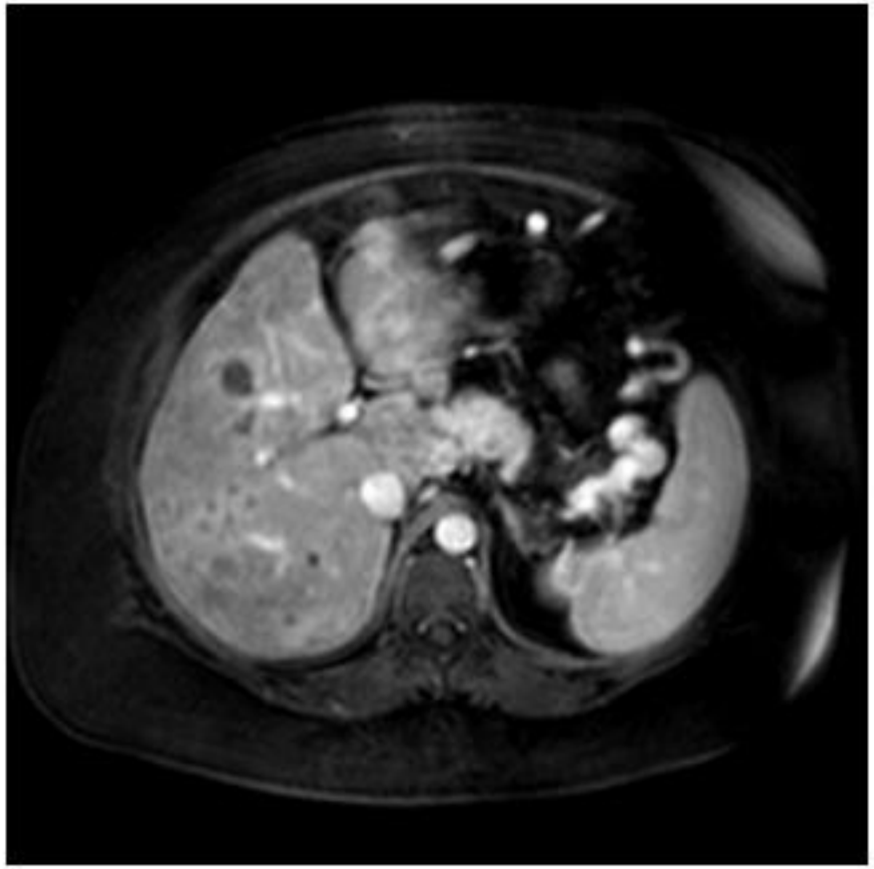


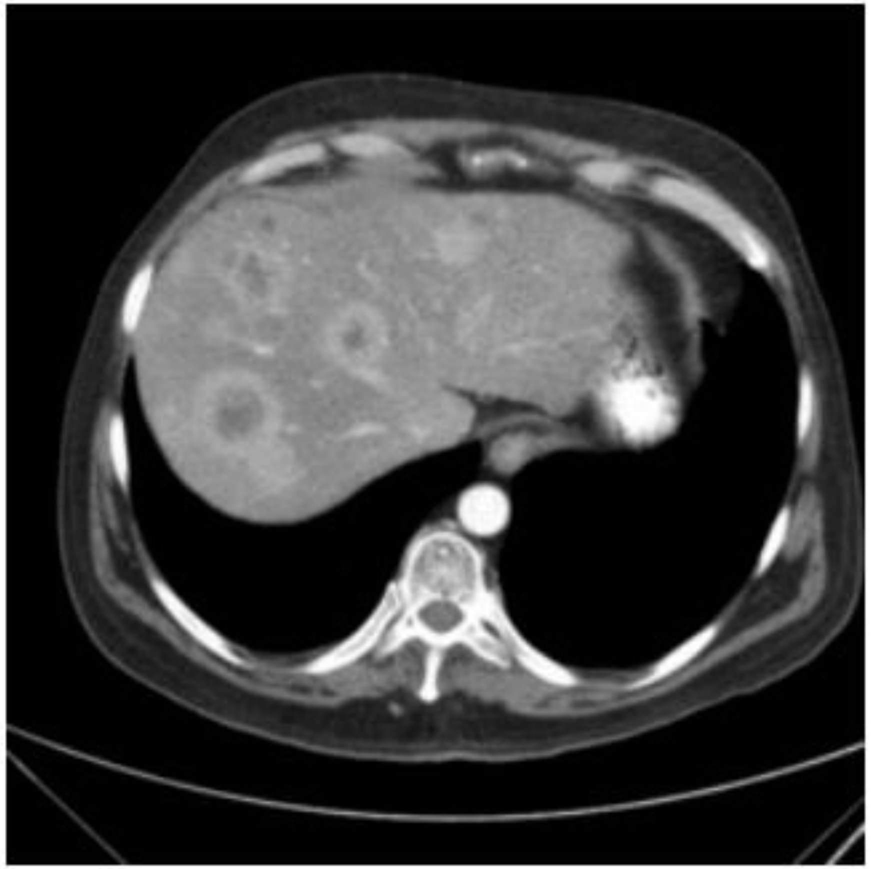
HC Shin et al. CVPR 2016

Data Mining Reports & Images

Cluster #23

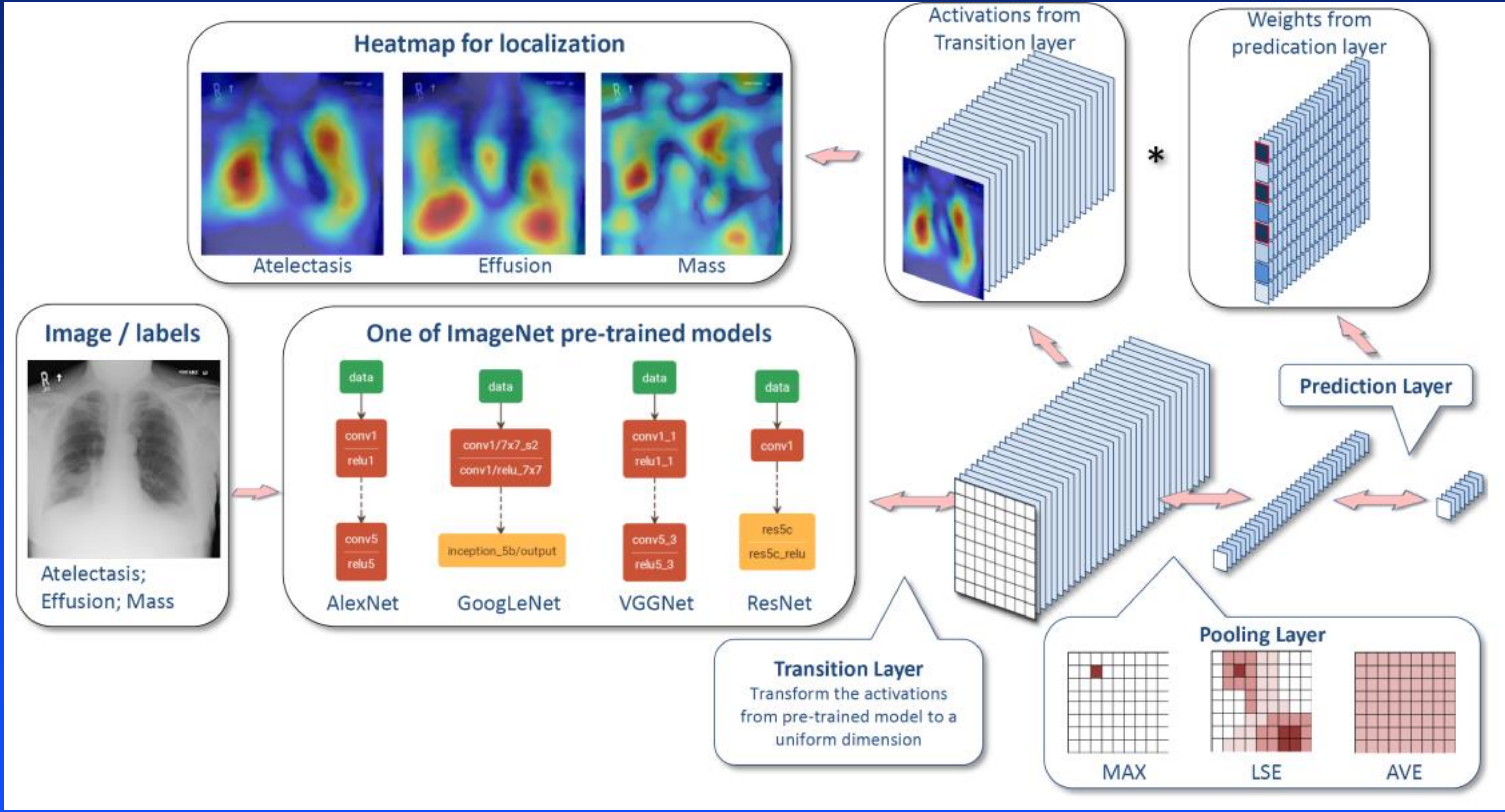
Word	Frequency
liver	524
abdomen	337
enhancement	217
mass	198
lesion	168
lobe	161
adenopathy	119
lesions	109
segment	58
bulky	45





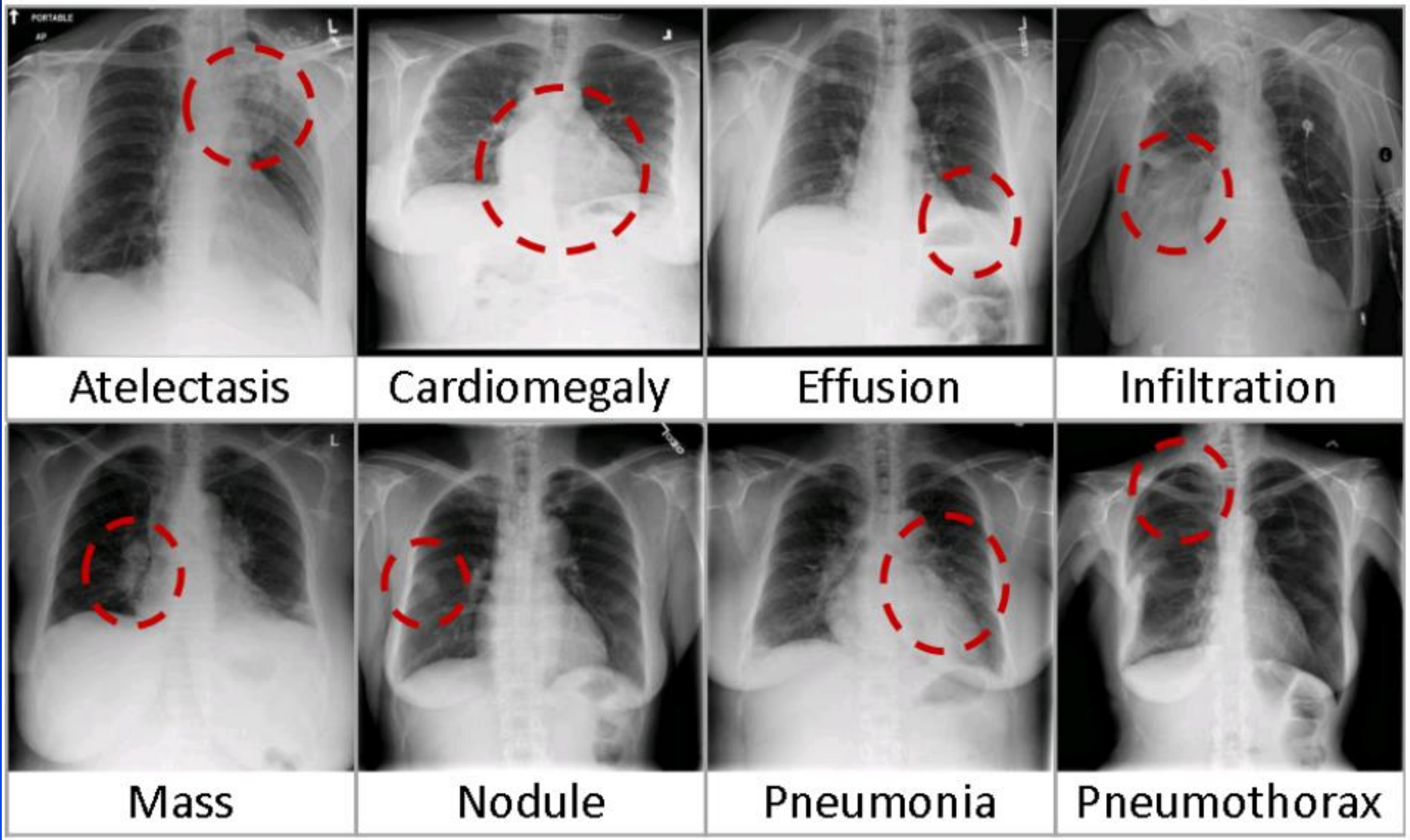
X Wang et al. WACV 2017

Data Mining Reports & Images



X Wang et al. CVPR 2017

ChestX-ray8

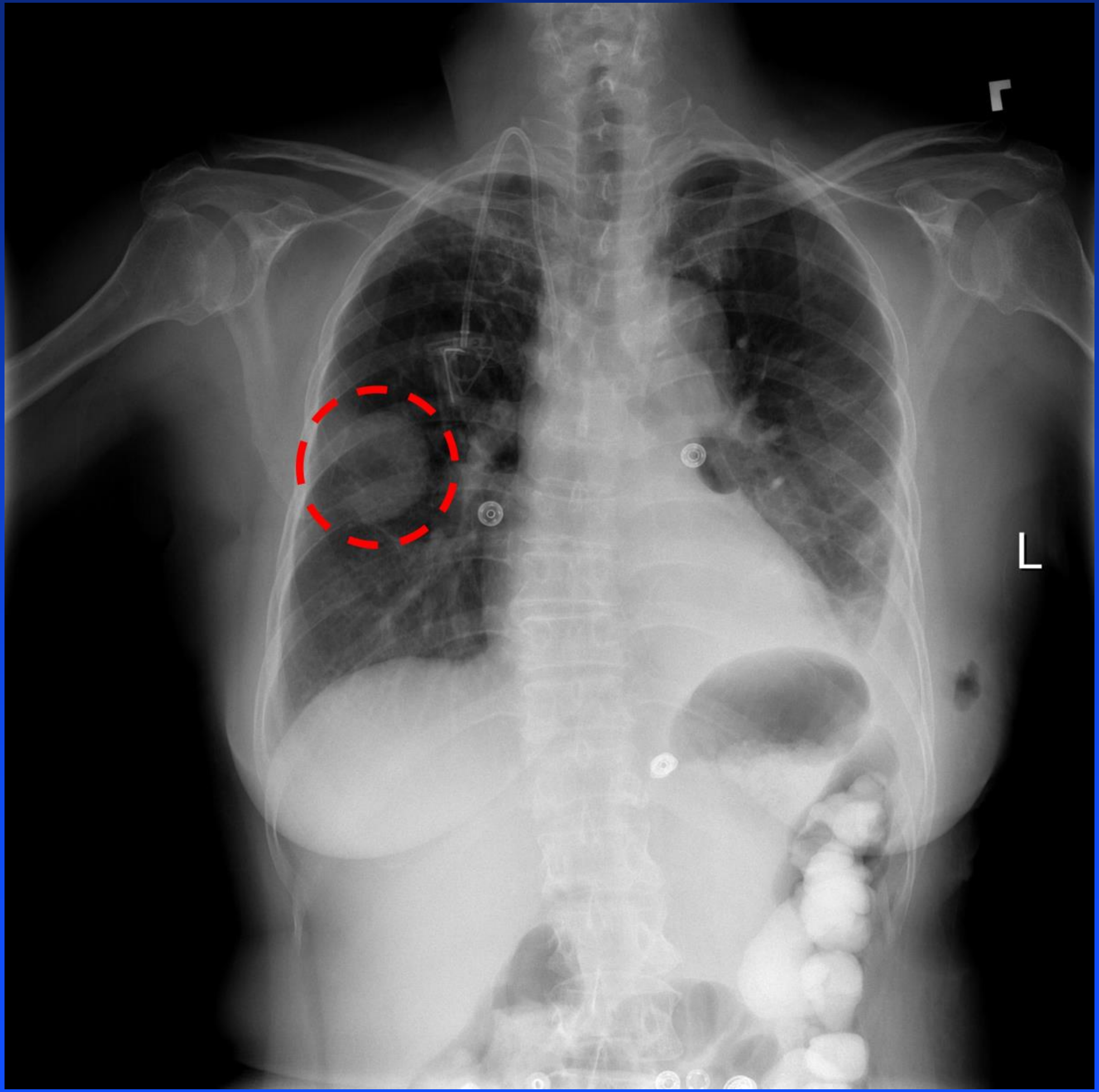


T(IoBB)	Atelectasis	Cardiomegaly	Effusion	Infiltration	Mass	Nodule	Pneumonia	Pneumothorax
T(IoBB) = 0.1								
Acc.	0.7277	0.9931	0.7124	0.7886	0.4352	0.1645	0.7500	0.4591
AFP	0.0823	0.0487	0.0589	0.0426	0.0691	0.0630	0.0691	0.0264

X Wang et al. CVPR 2017

ChestX-ray8 Dataset

- https://nihcc.app.box.com/v/ChestXray-NIHCC
- “ChestX-ray8 Dataset”
- 112,120 frontal-view chest radiographs, 30,805 unique patients
- 42 GB
- Metadata for all images
- Bounding boxes for 1000 images



AJR FOCUS ON:

Gastrointestinal Imaging • Review

Progress in Fully Automated Abdominal CT Interpretation

Ronald M. Summers[1]

AJR 2016; 207:67–79

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.

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

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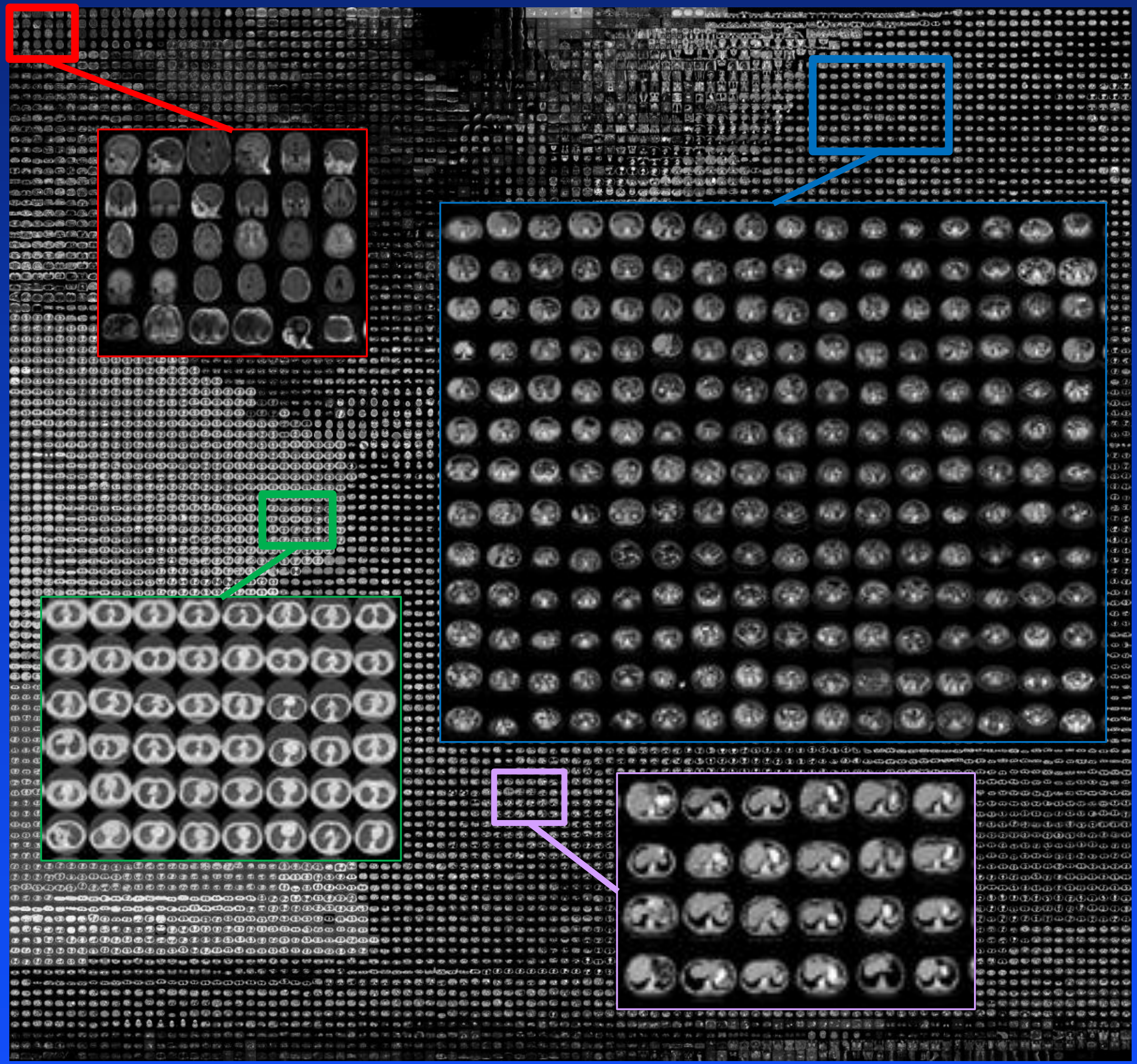

www.cc.nih.gov/drd/summers.html

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