The Impact of Deep Learning on Radiology

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

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

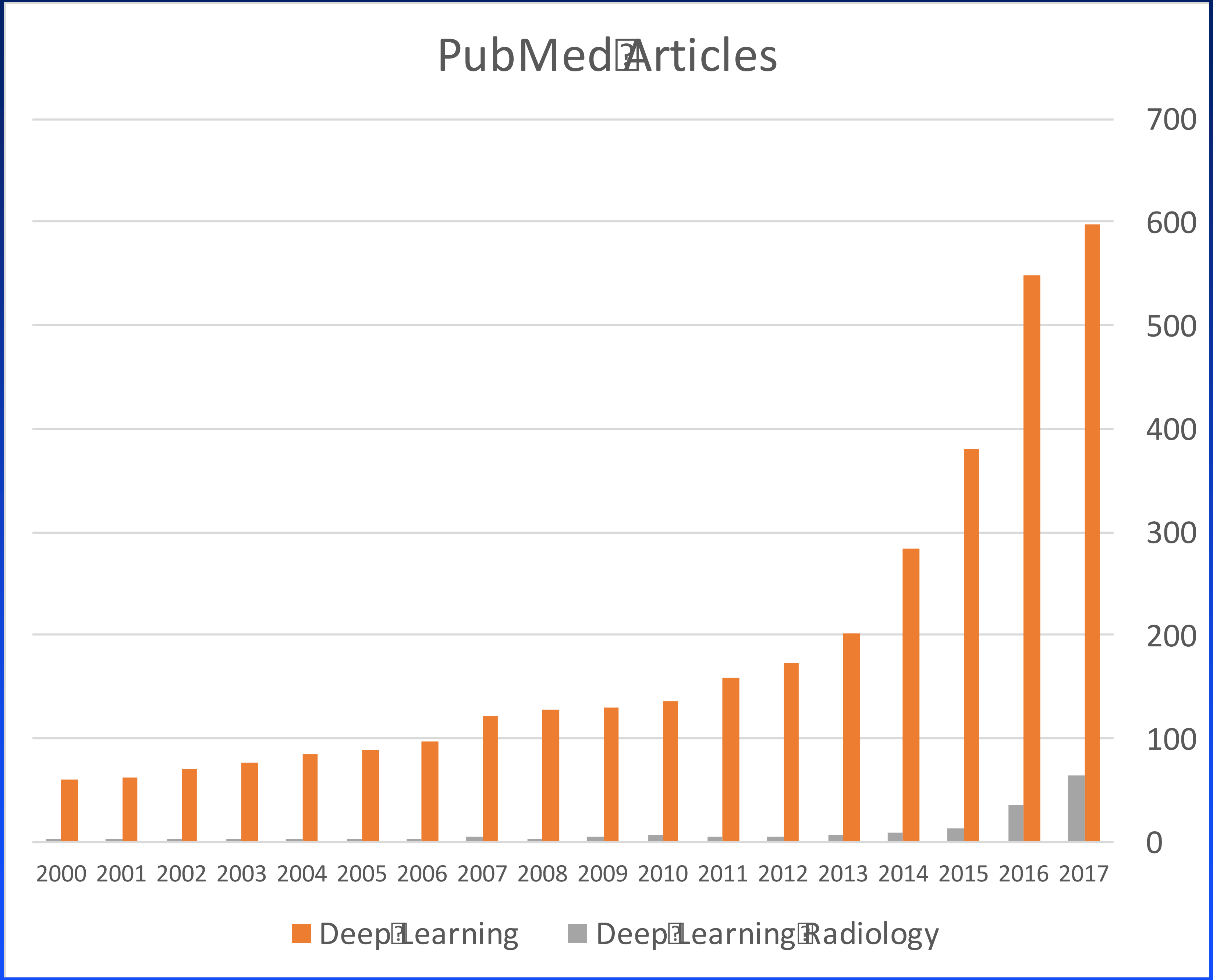
- Background
- Radiology imaging applications
- Data mining radiology reports and images
- Challenges and pitfalls

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 the 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


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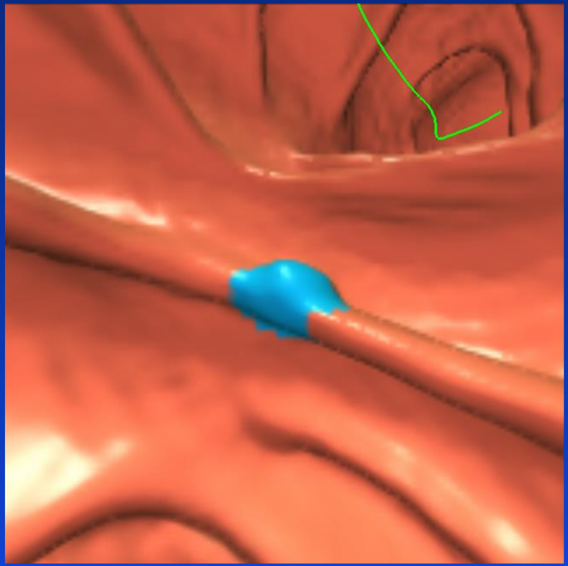
2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017
Deep Learning
Deep Learning Radiology

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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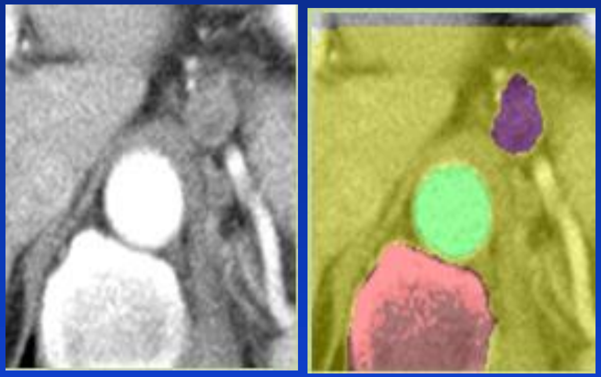

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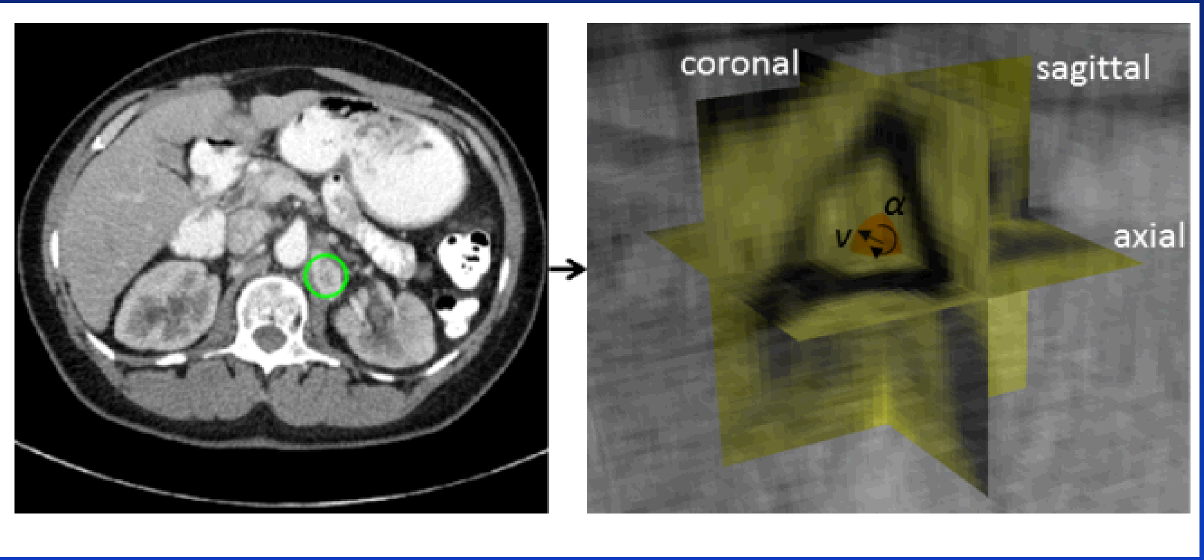
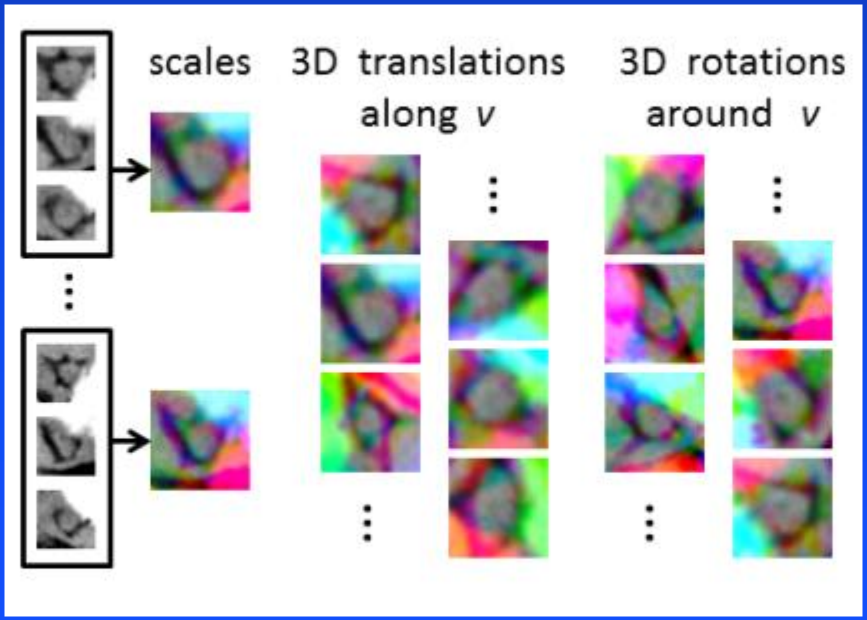
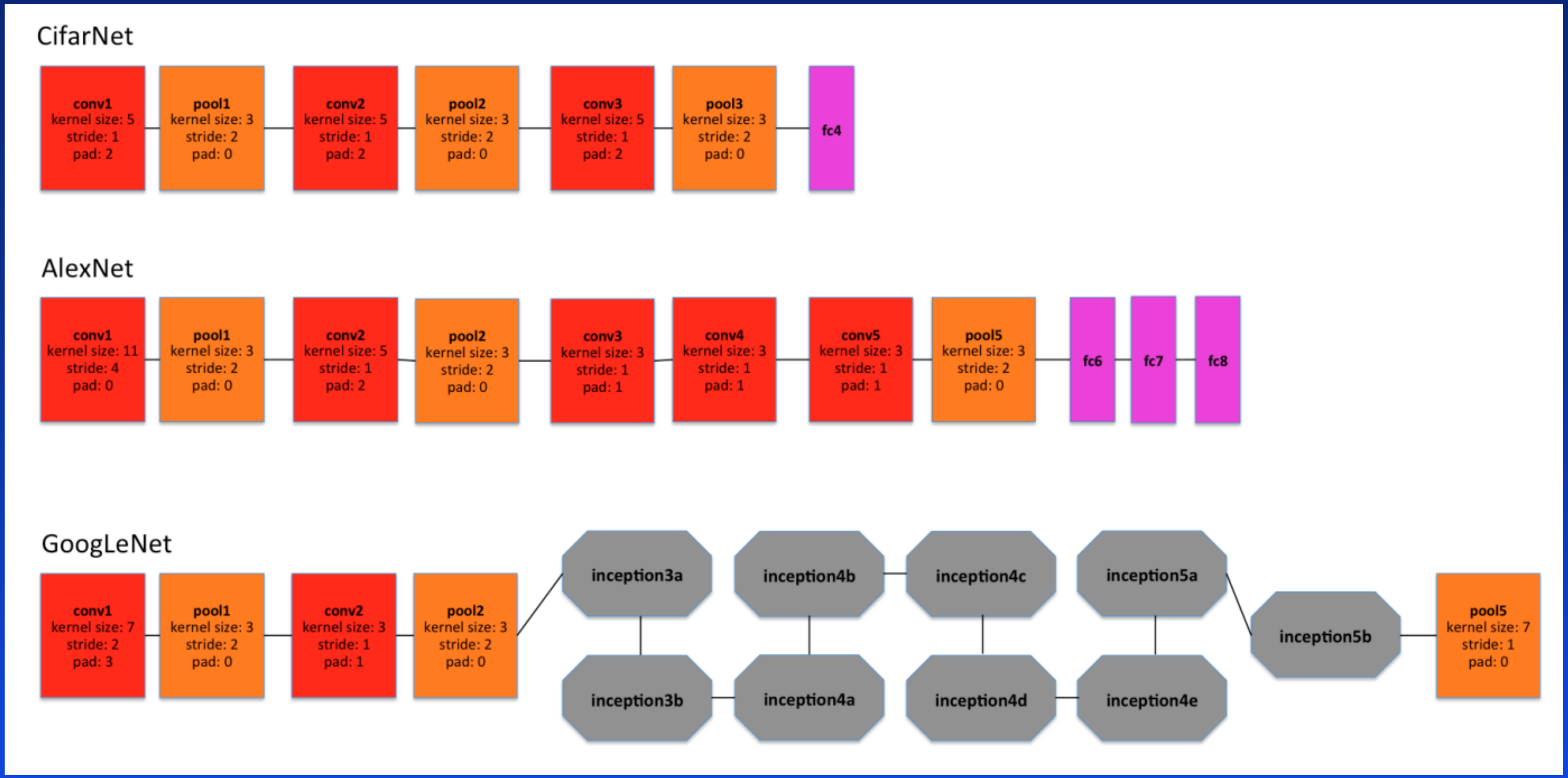
Hua, Liu, Summers et al. ARRS 2012; Roth et al. IEEE TMI 2015





- 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

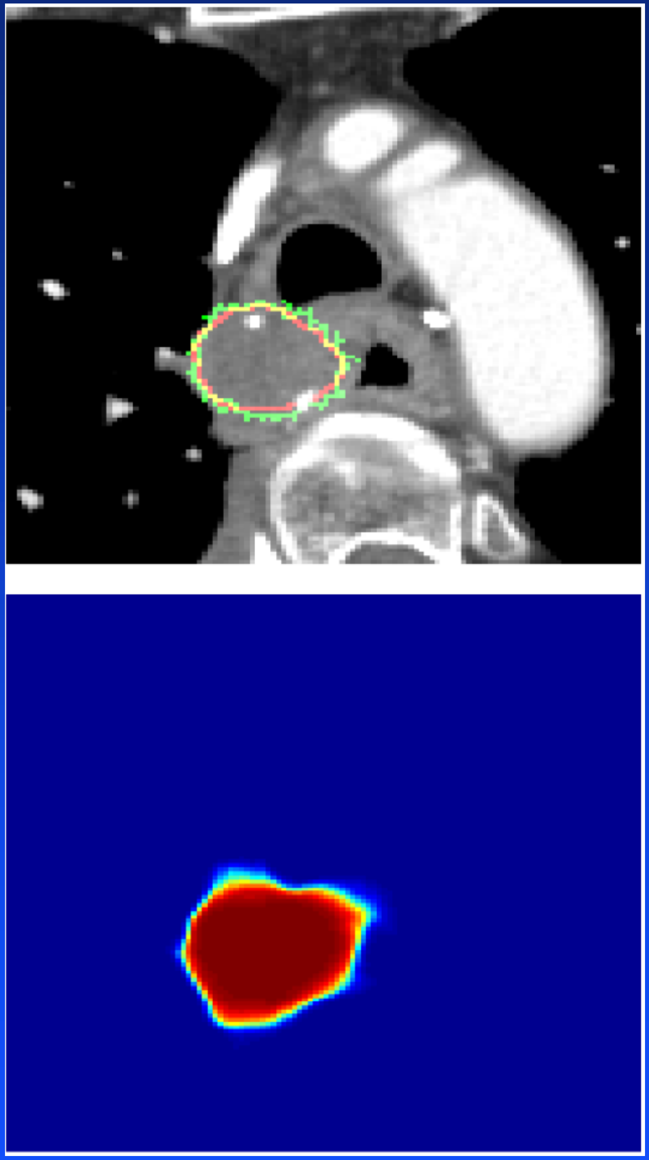
H Roth et al., MICCAI 2014

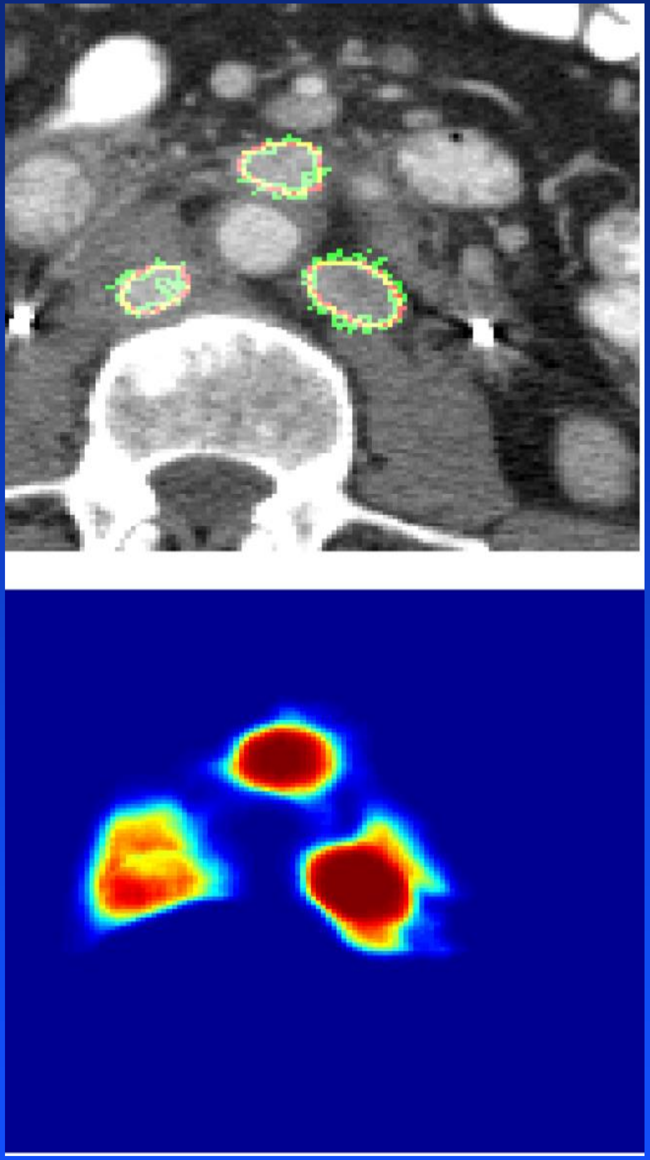


- Deeper CNN model performed best
- GoogLeNet for mediastinal LNs
- Sensitivity 85% at 3 FP/vol.

HC Shin et al., IEEE TMI 2016

Lymph Node Segmentation

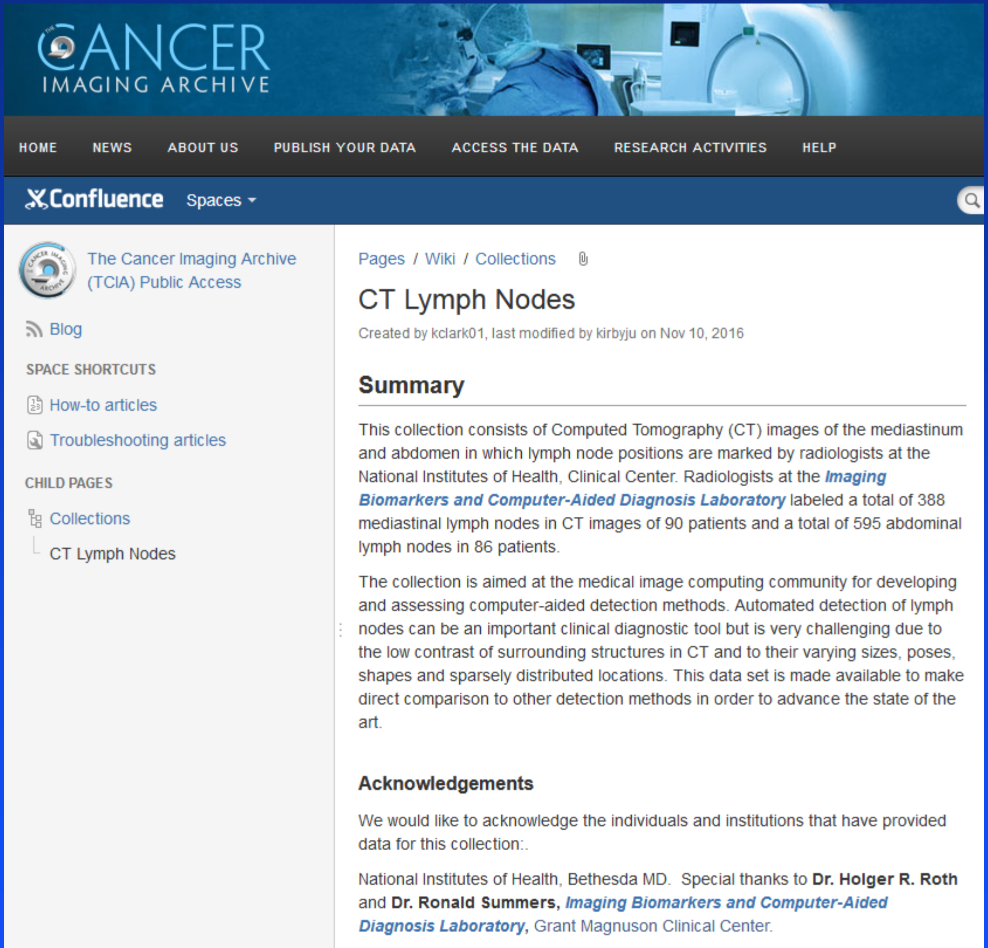




I Nogues et al. RSNA 2016

Lymph Node CT Dataset

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



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CHILD PAGES

Collections

CT Lymph Nodes

Pages / Wiki / Collections

CT Lymph Nodes

Created by kclark01, last modified by kirbyju on Nov 10, 2016

Summary

This collection consists of Computed Tomography (CT) images of the mediastinum and abdomen in which lymph node positions are marked by radiologists at the National Institutes of Health, Clinical Center. Radiologists at the ***Imaging Biomarkers and Computer-Aided Diagnosis Laboratory*** labeled a total of 388 mediastinal lymph nodes in CT images of 90 patients and a total of 595 abdominal lymph nodes in 86 patients.

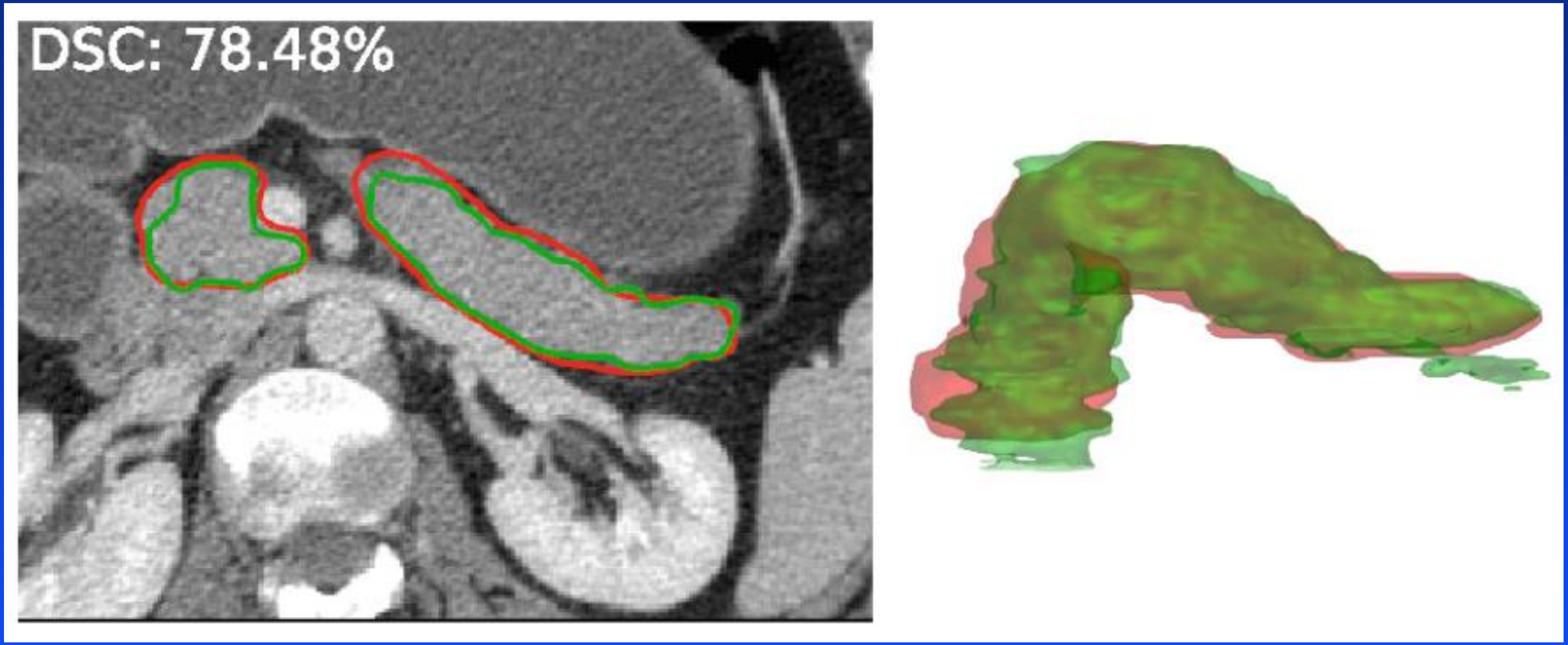
The collection is aimed at the medical image computing community for developing and assessing computer-aided detection methods. Automated detection of lymph nodes can be an important clinical diagnostic tool but is very challenging due to the low contrast of surrounding structures in CT and to their varying sizes, poses, shapes and sparsely distributed locations. This data set is made available to make direct comparison to other detection methods in order to advance the state of the art.

Acknowledgements

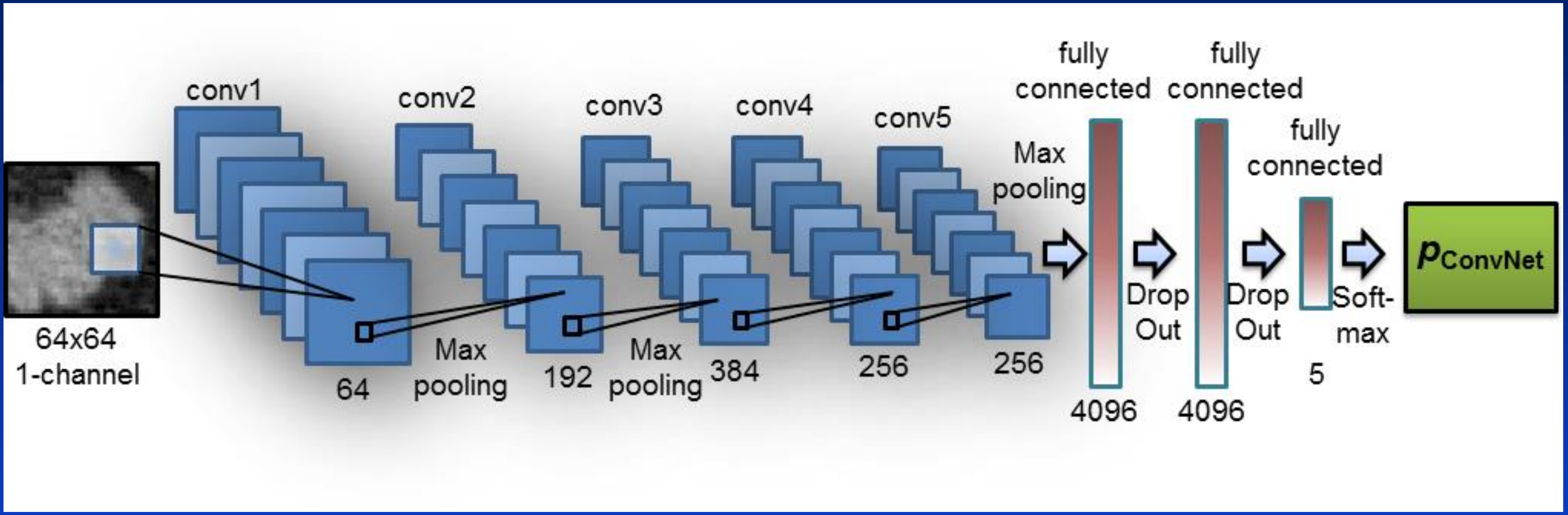
We would like to acknowledge the individuals and institutions that have provided data for this collection:.

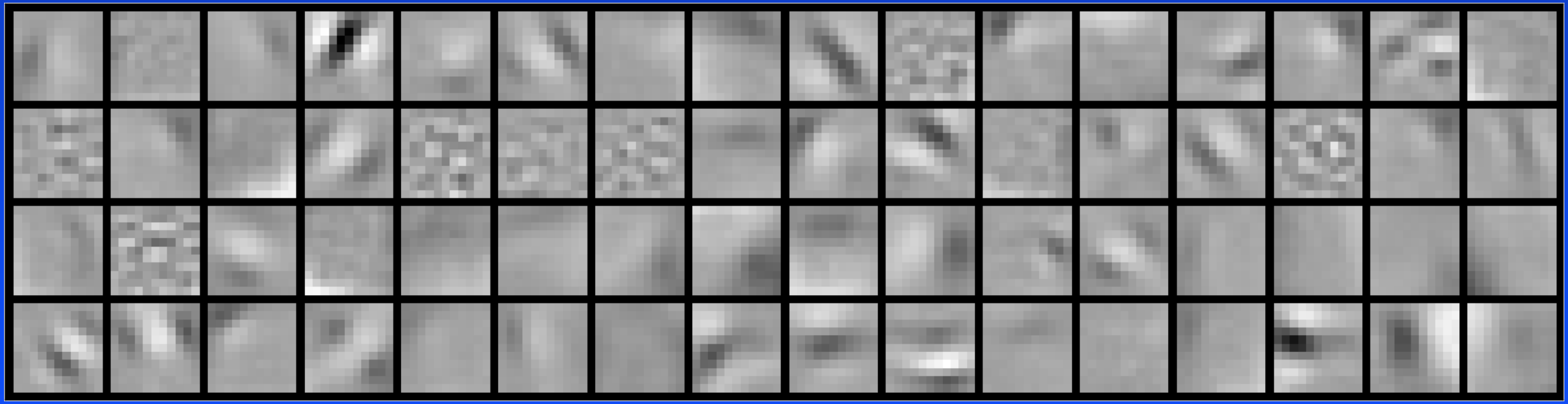
National Institutes of Health, Bethesda MD. Special thanks to **Dr. Holger R. Roth** and **Dr. Ronald Summers,** ***Imaging Biomarkers and Computer-Aided Diagnosis Laboratory,*** Grant Magnuson Clinical Center.

Pancreas CAD using CNN



H Roth et al., MICCAI 2016





H Roth et al., SPIE MI 2015

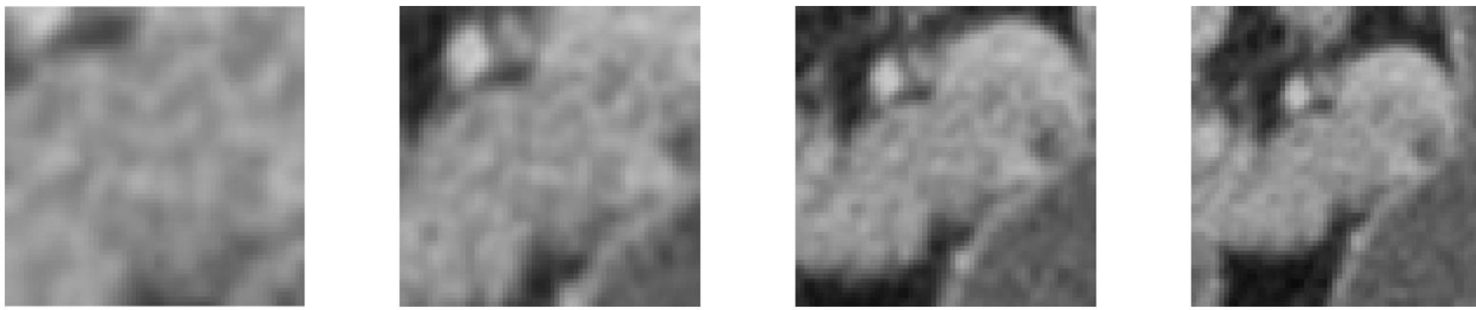
Data Augmentation

- During training, input images are sampled at different scales and random non-rigid deformations
- Degree of deformation is chosen such that the resulting warped images resemble plausible physical variations of the medical images
- Can help avoid overfitting

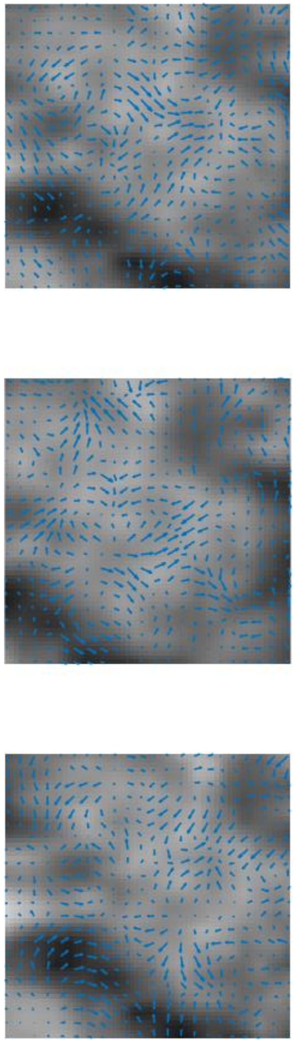
ConvNet training with scales and non-rigid deformations

Data augmentation at each superpixel bounding box:

- N_s scales (zoom-out)



- N_d deformations



TPS deformation fields

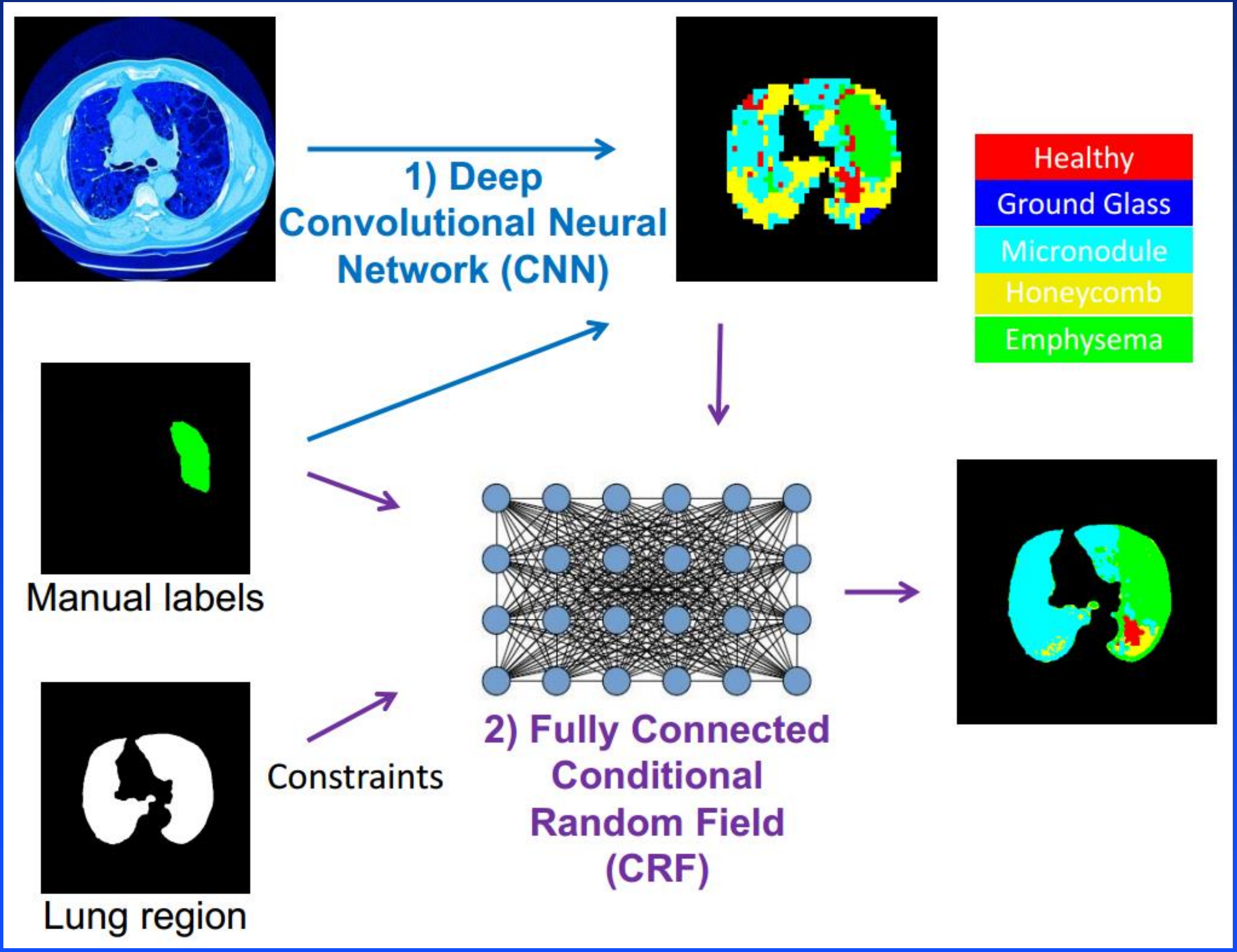
~800k training images from 60 patients

Roth et al. RSNA 2015

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

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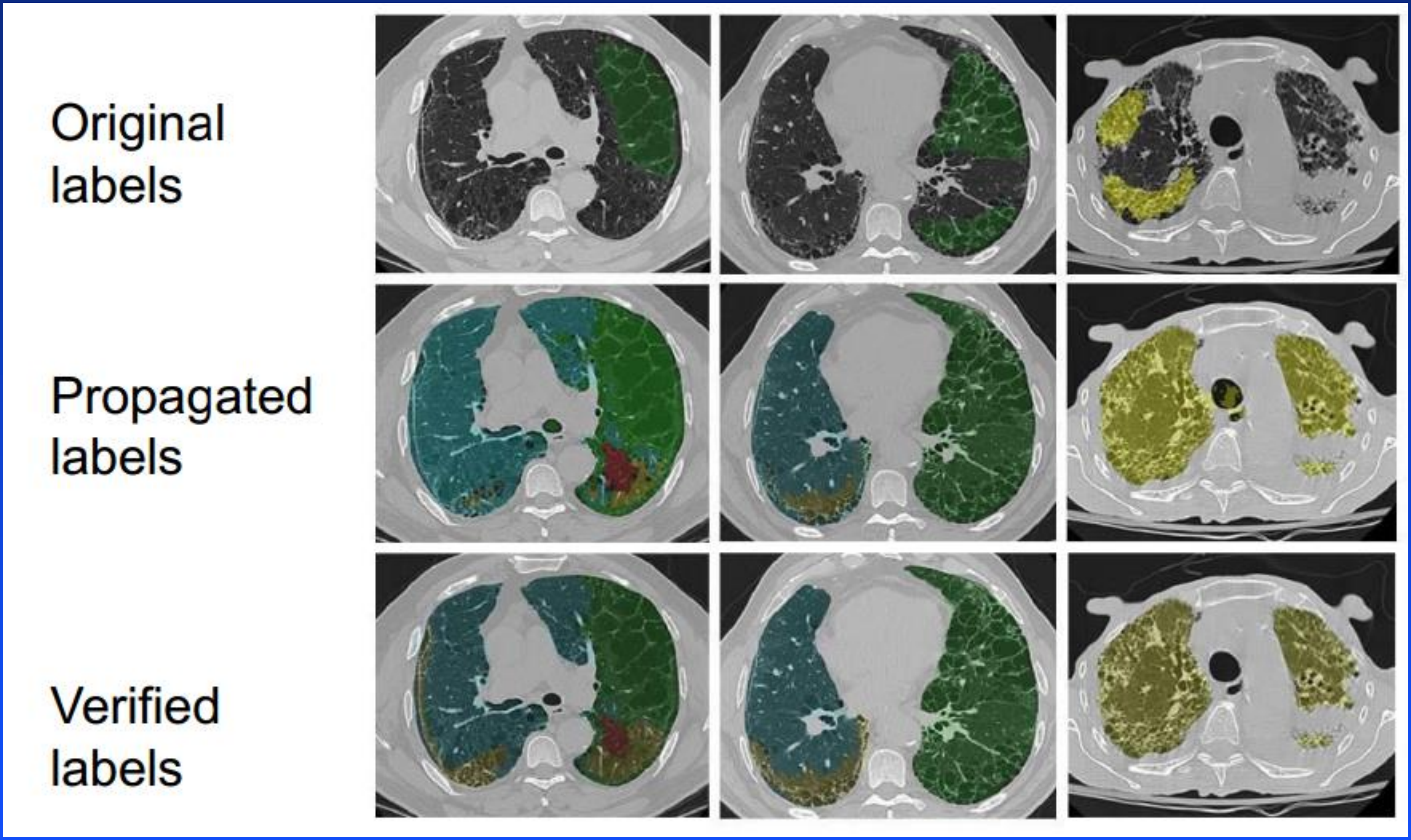
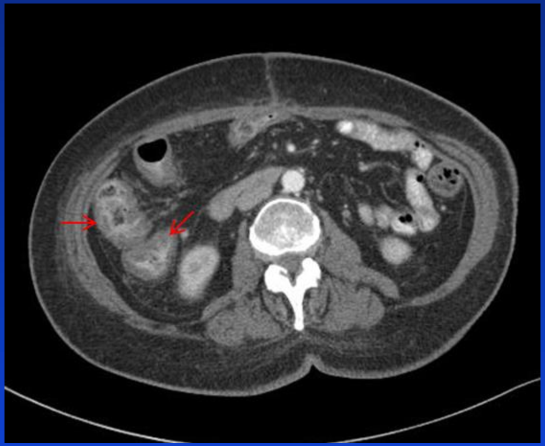
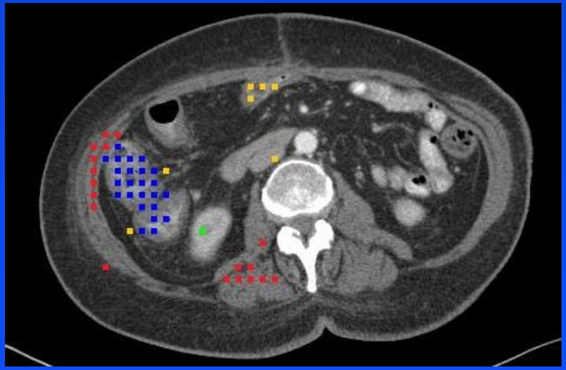
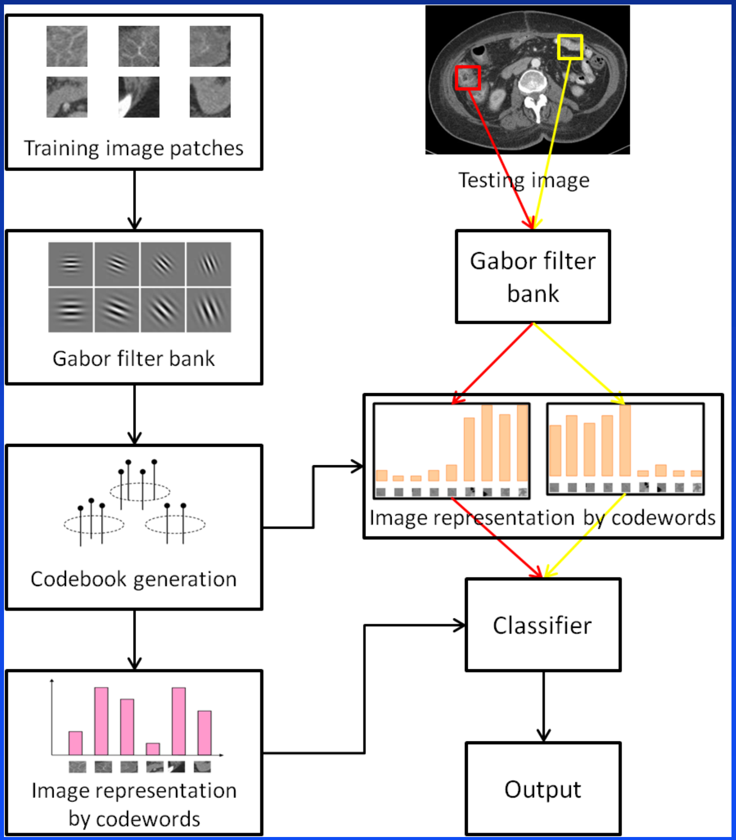


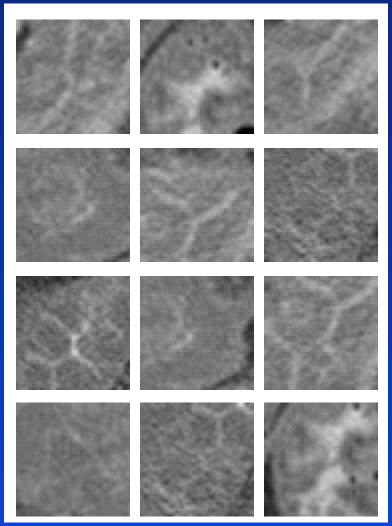
Gao et al. IEEE ISBI 2016

Colitis CAD



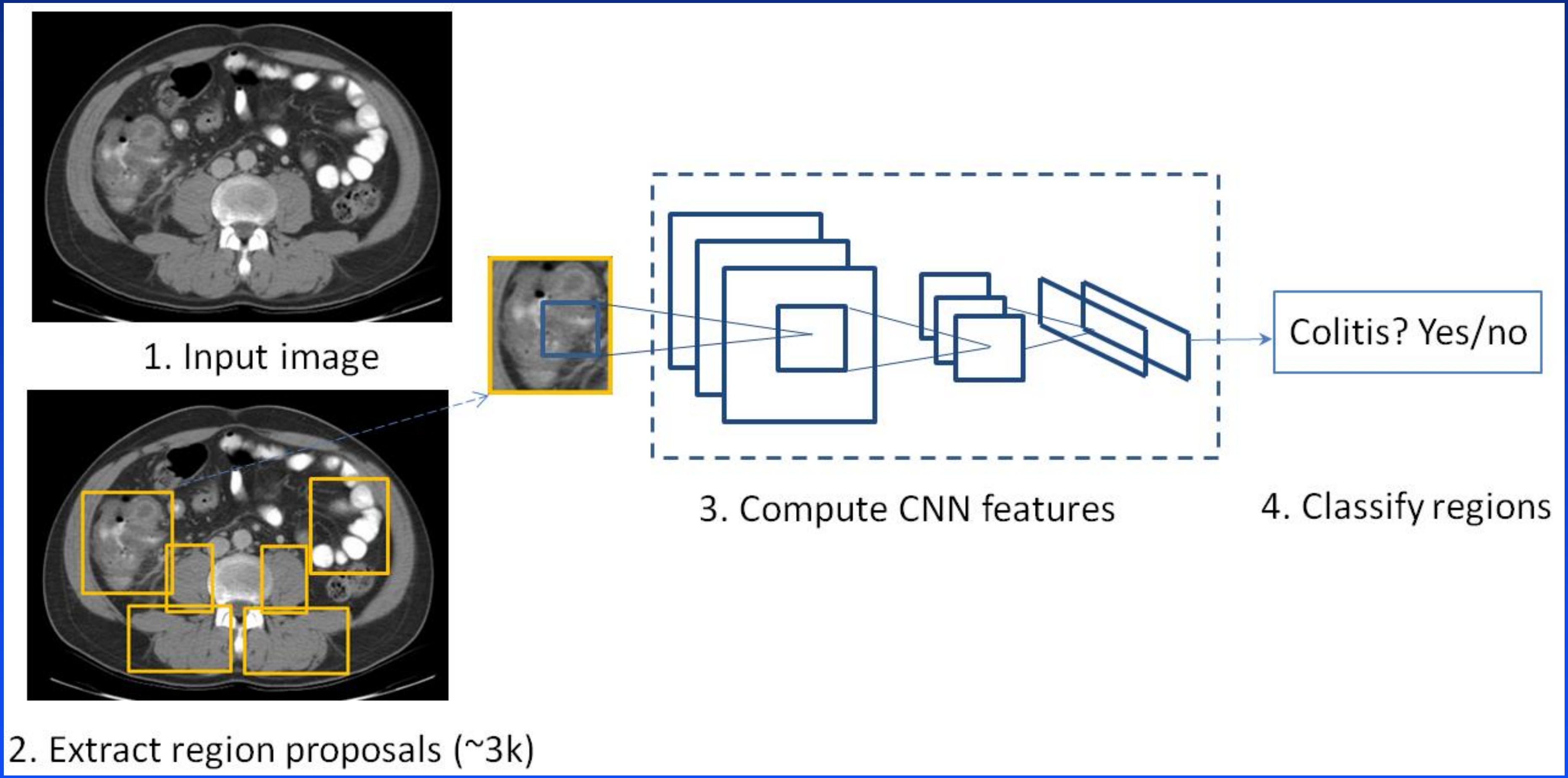






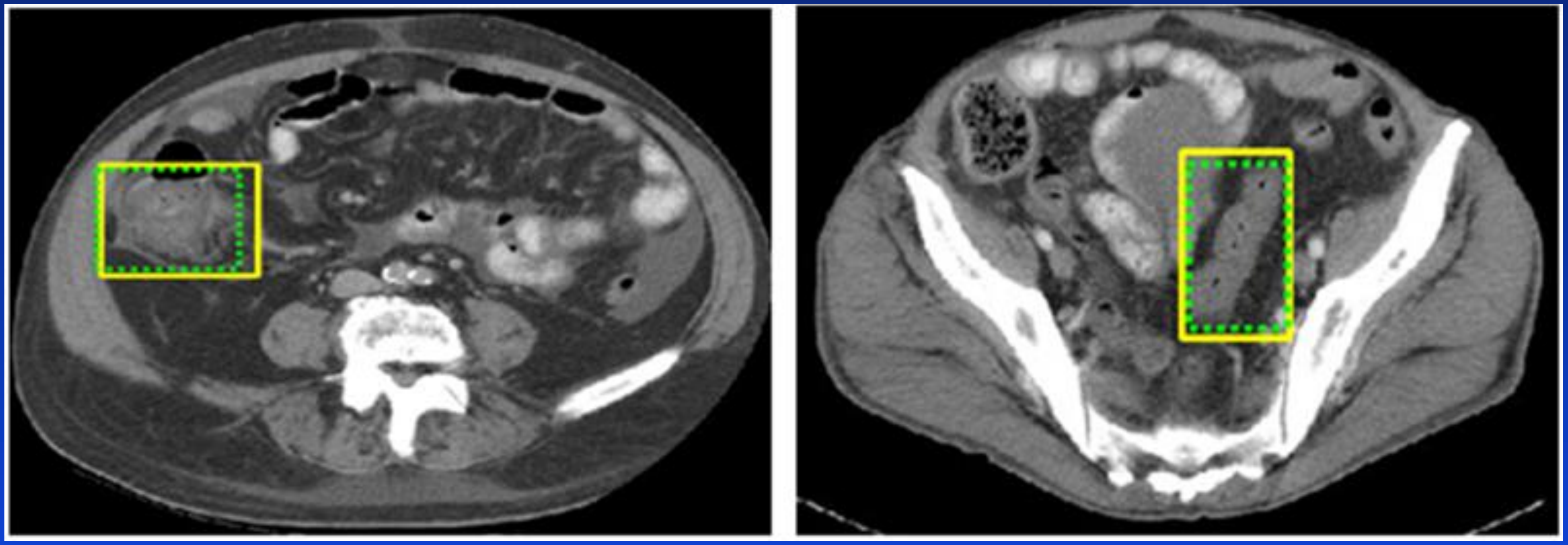
Wei et al. SPIE, ISBI 2013

Colitis CAD



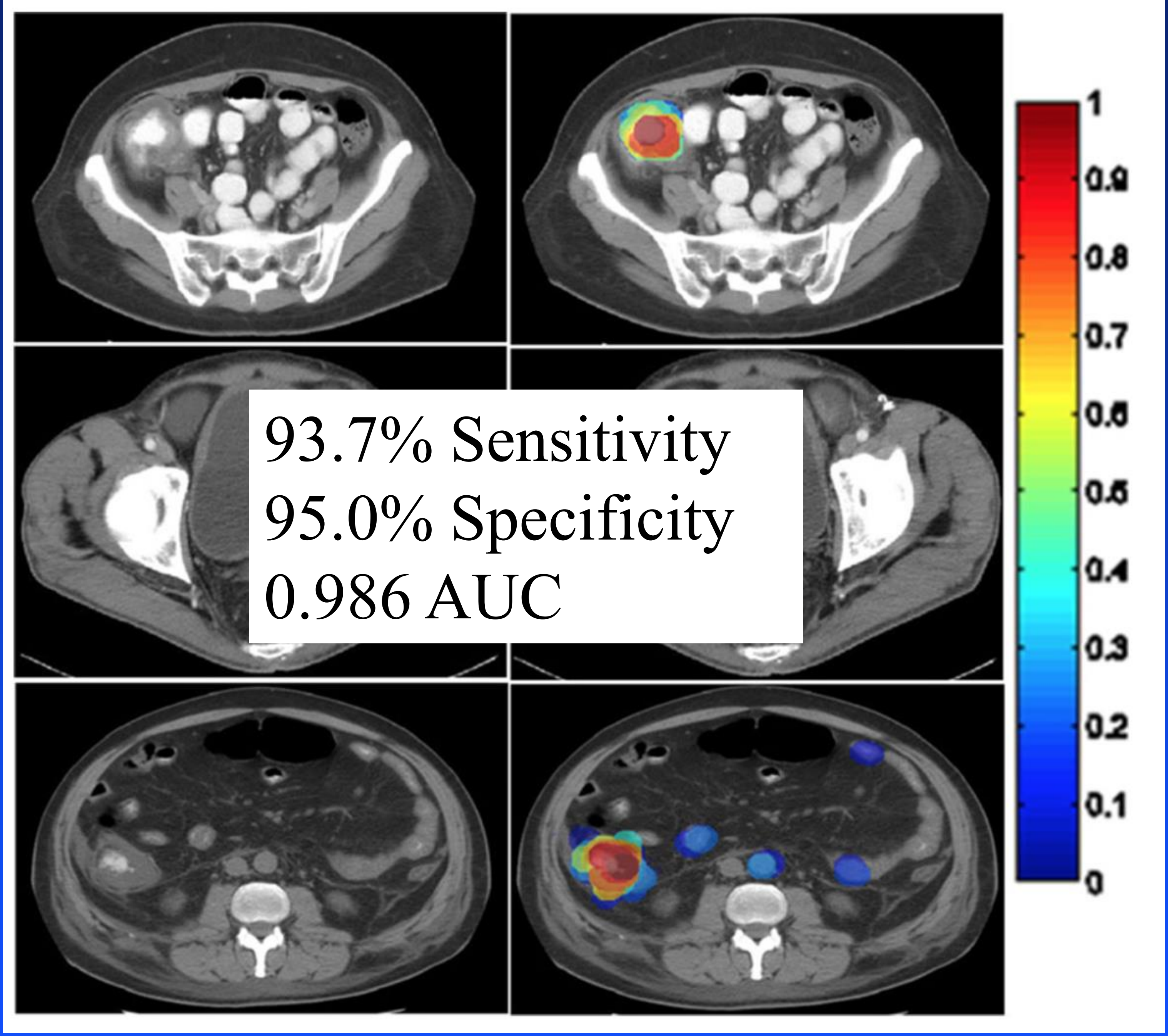
J Liu et al. SPIE Med Imaging 2016

Colitis CAD



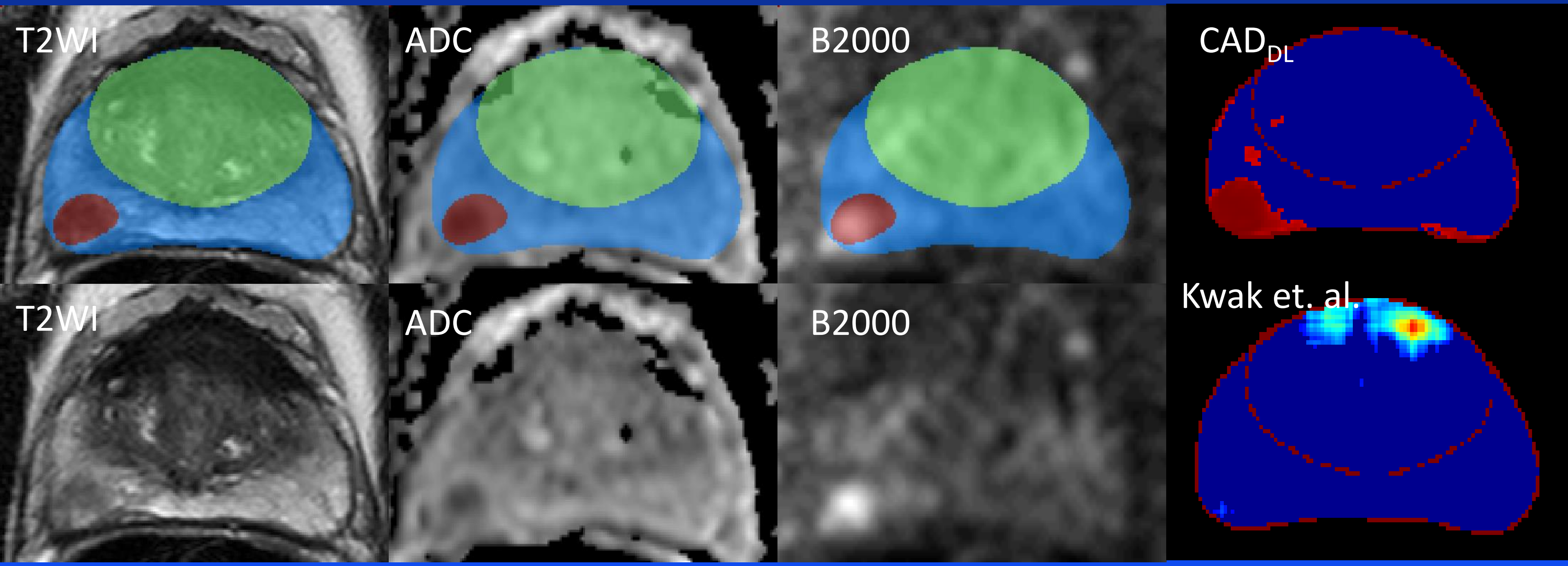
- 26 CT scans of patients with colitis
- 260 images
- 85% sensitivity at 1 FP/image

J Liu et al. SPIE Med Imaging and ISBI 2016



J Liu et al. Med Phys 2017

Prostate



Tsehay et al. SPIE MI 2017

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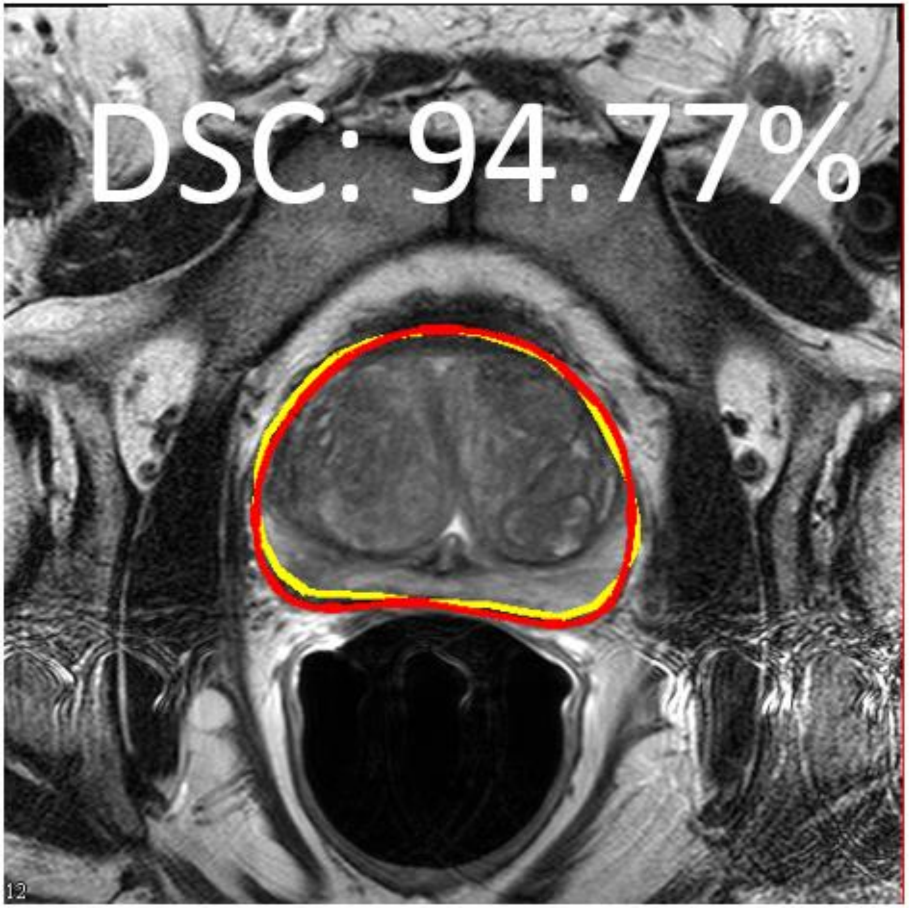
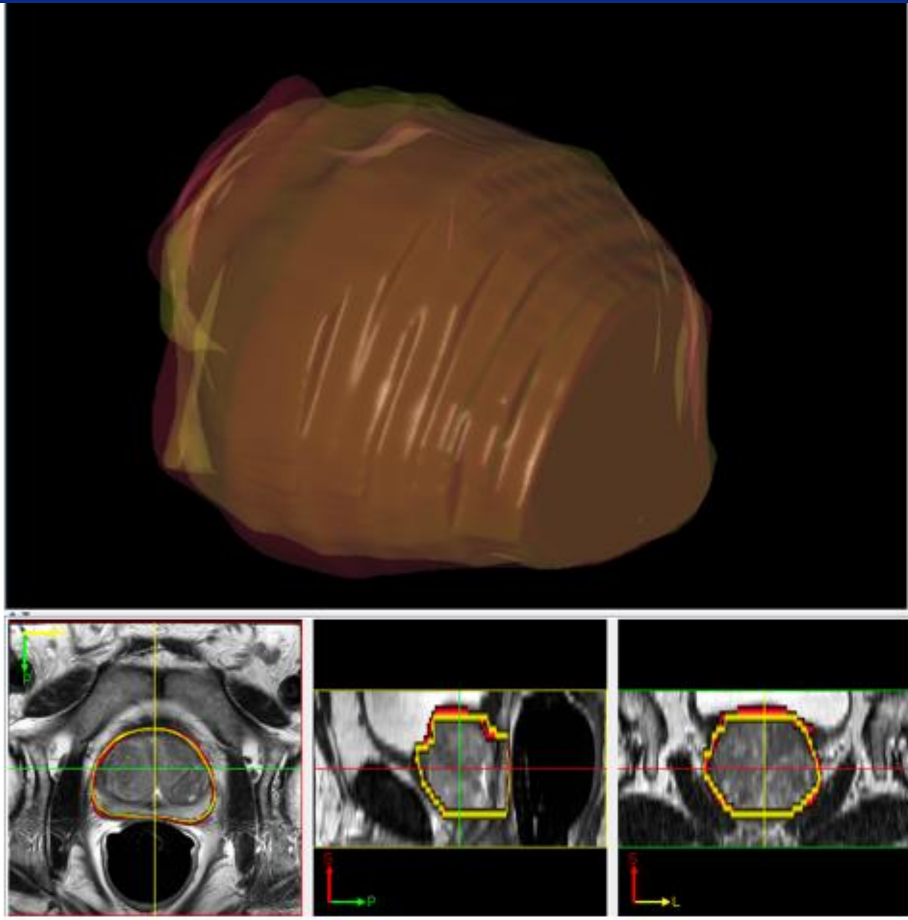
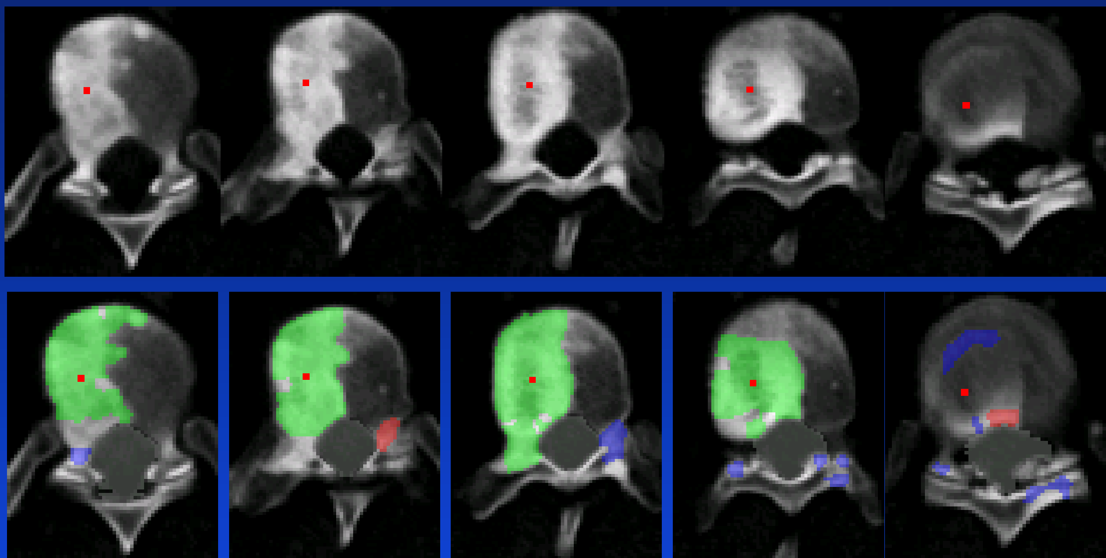
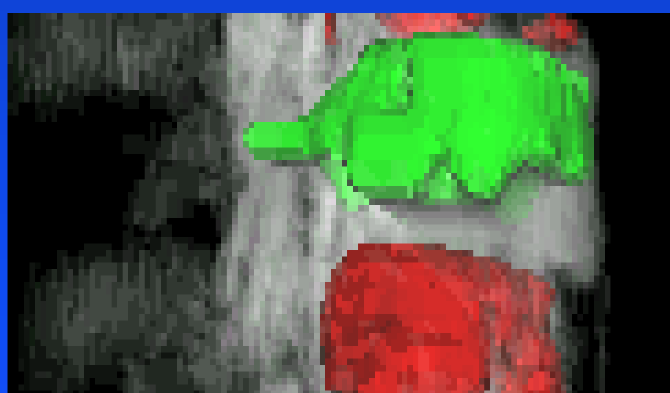




Cheng et al. SPIE MI 2017

Spine Metastasis CAD





J Burns, J Yao et al. RSNA 2011; Radiology 2013

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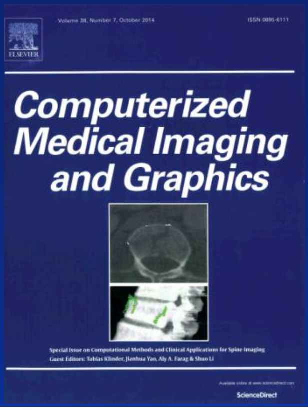
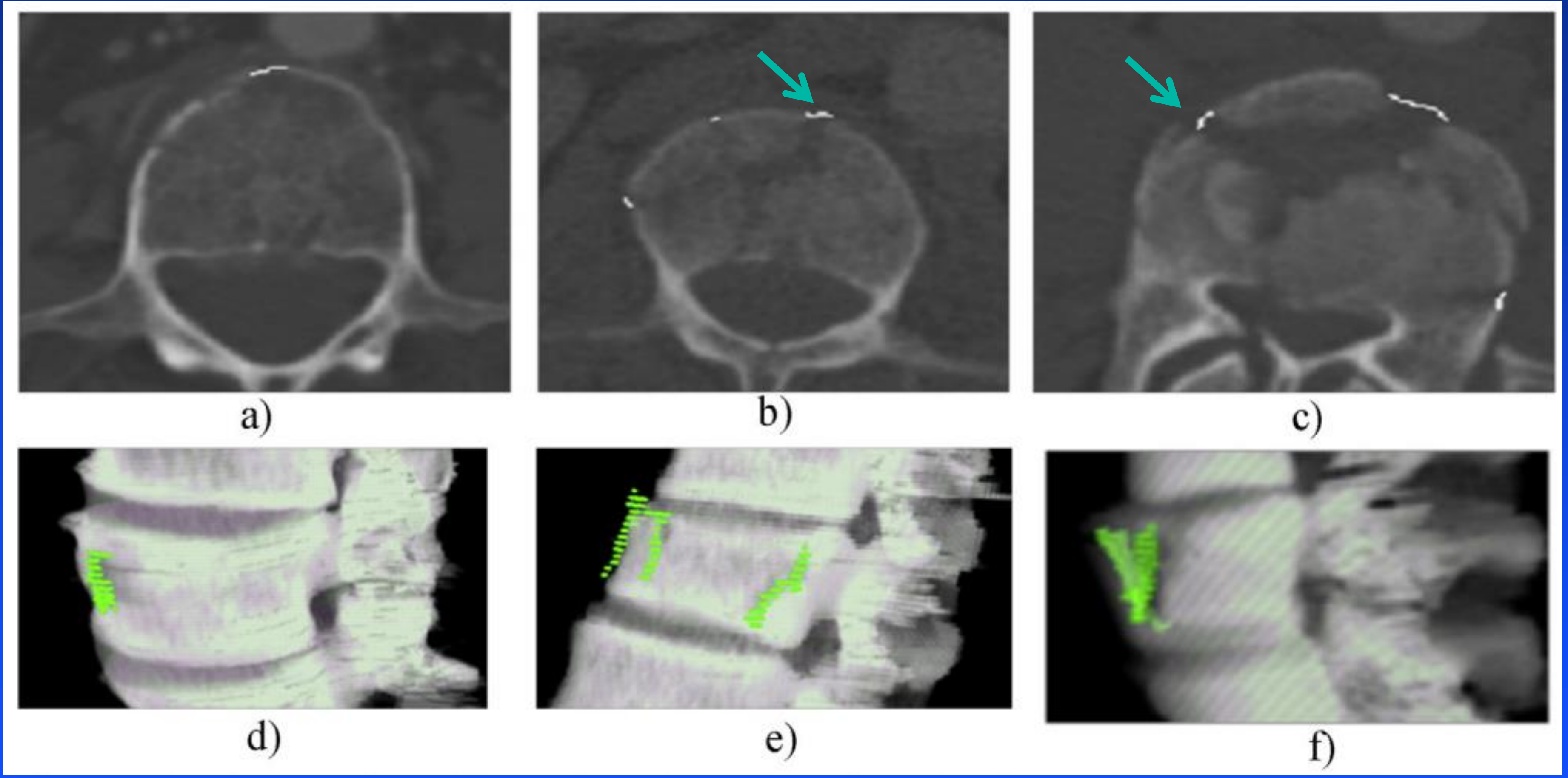
Roth et al. IEEE TMI 2015

Vertebral Fracture CAD





Yao et al. CMIG 2014

Vertebral Fracture CAD

ORIGINAL RESEARCH ■ COMPUTER APPLICATIONS

Radiology

Automated Detection, Localization, and Classification of Traumatic Vertebral Body Fractures in the Thoracic and Lumbar Spine at CT[1]

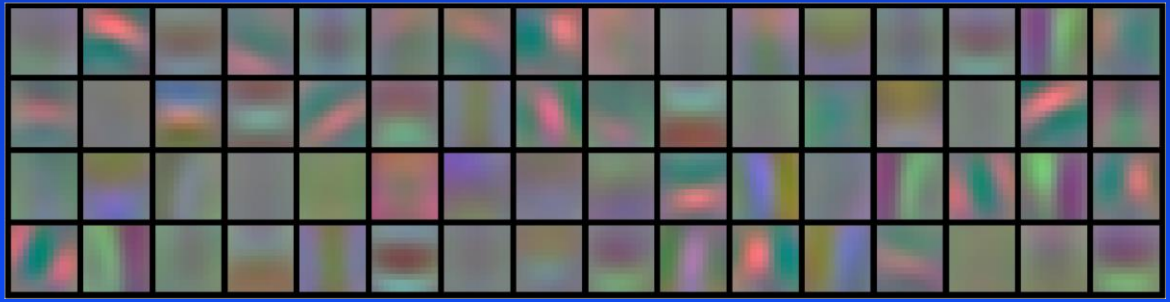
Joseph E. Burns, MD, PhD
Jianhua Yao, PhD
Hector Muñoz, BS
Ronald M. Summers, MD, PhD

Purpose: To design and validate a fully automated computer system for the detection and anatomic localization of traumatic thoracic and lumbar vertebral body fractures at computed tomography (CT).

- 92% sensitivity for fracture localization
- 1.6 FPs per patient
- Most common FP: nutrient foramina (39% of all FPs)

Burns et al. Radiology 2016

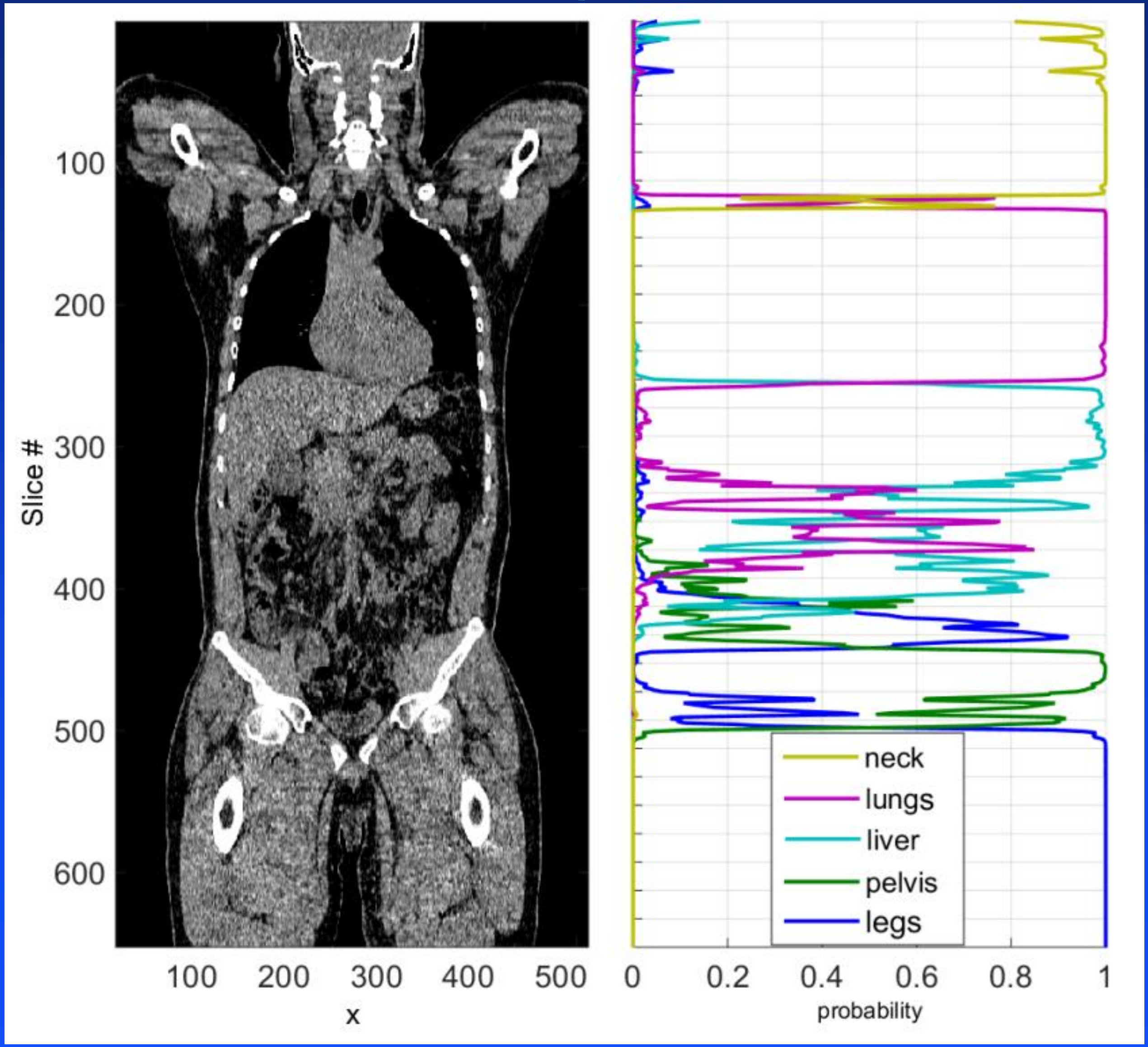
Posterior Elements Fracture CAD



- 18 trauma patients
- 55 fractures
- Test set AUC 0.857
- 71% / 81% sensitivities at 5 / 10 FP/ patient

Roth et al. SPIE Med Imaging 2016

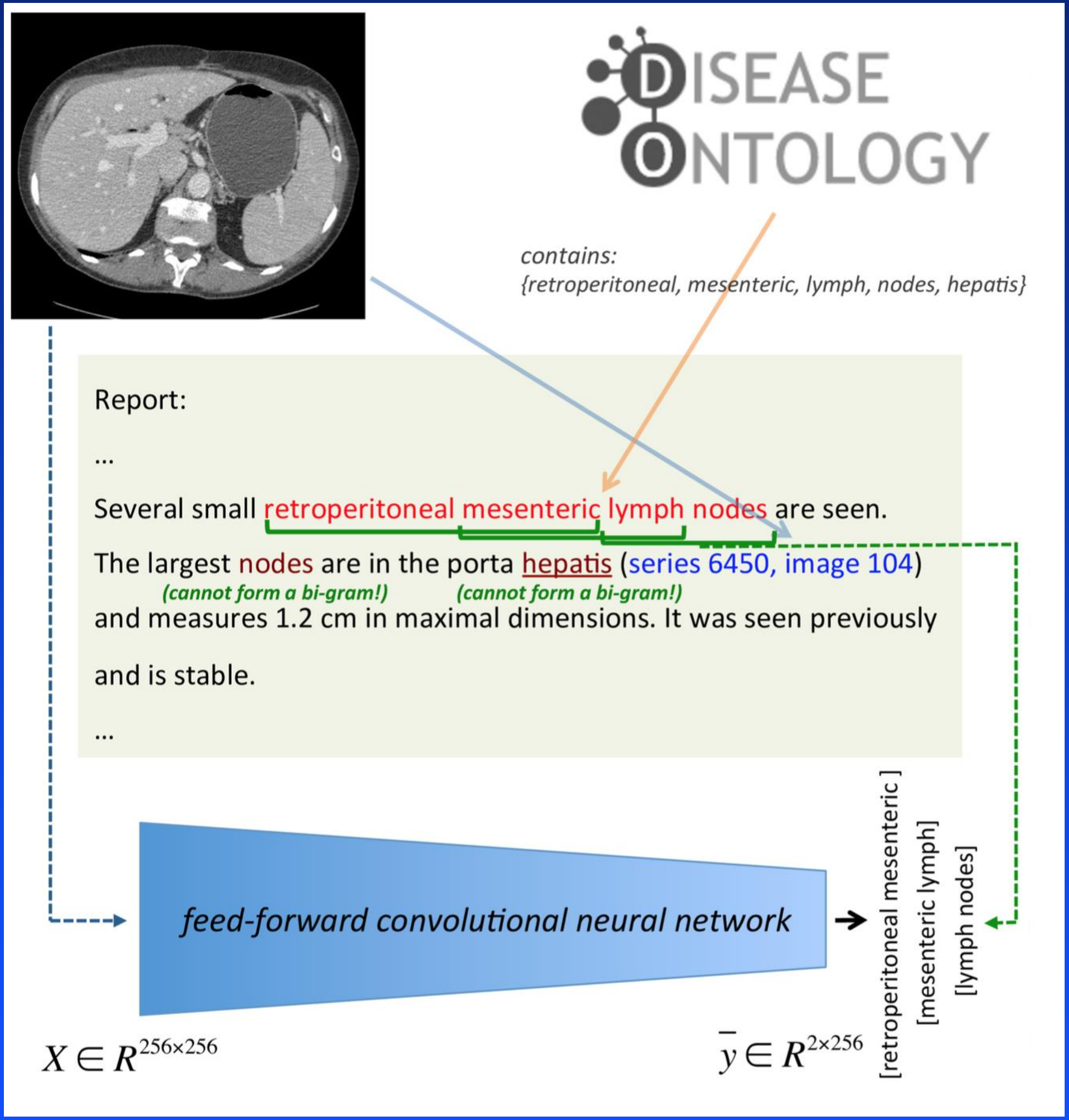
Anatomy Classification Using Deep Convolutional Nets



- 1,675 patients
- 4,298 images
- Test set AUC 0.998
- 5.9% classification error

H Roth et al., IEEE ISBI 2015

Data Mining Reports & Images



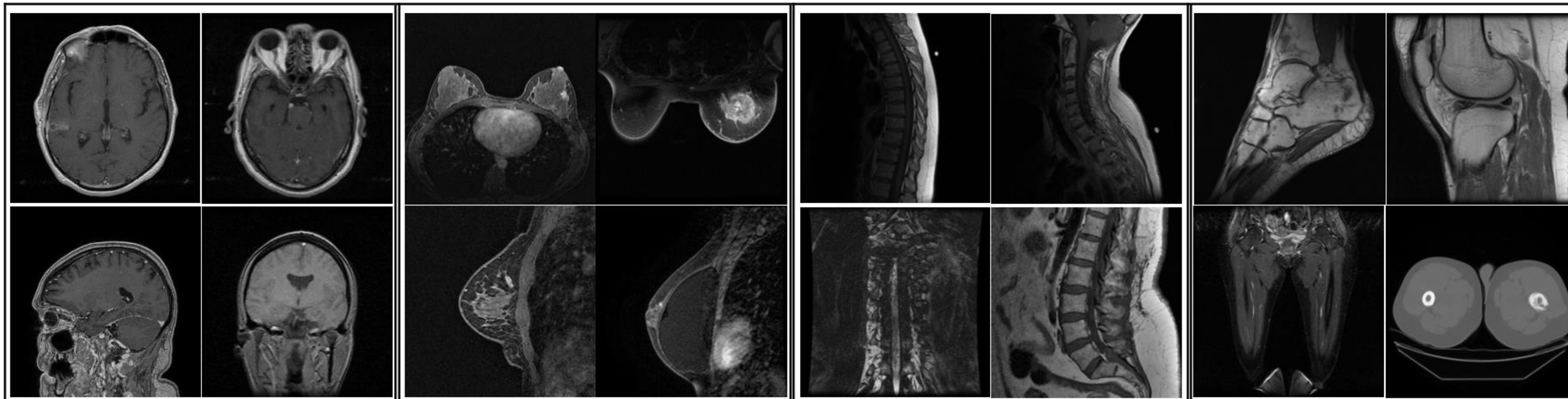
HC Shin et al. CVPR 2015

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

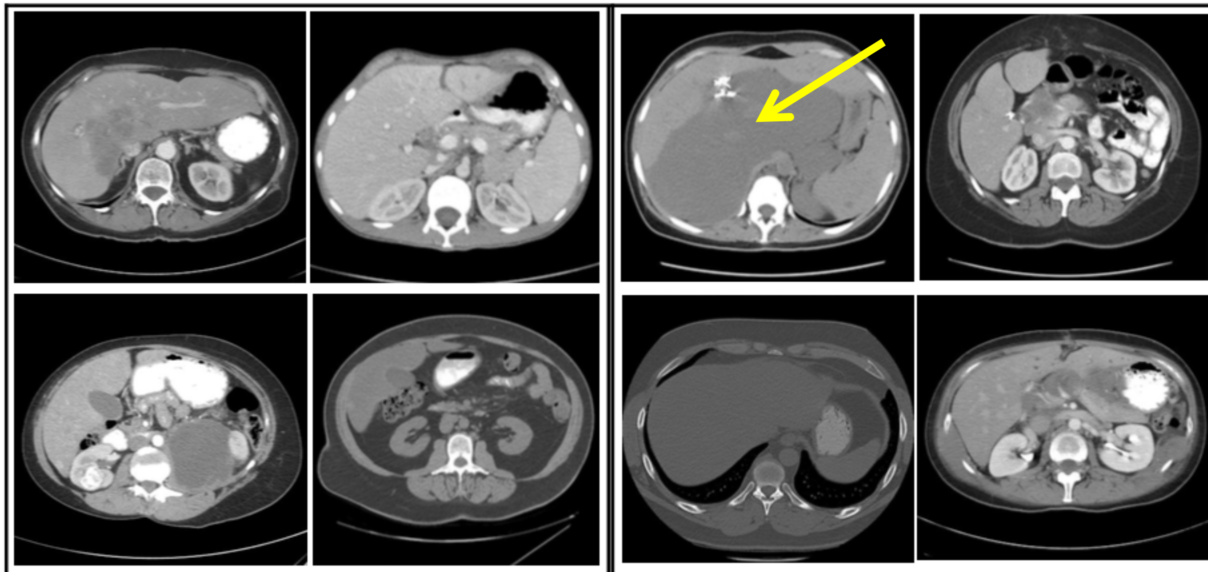
Data Mining Reports & Images



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

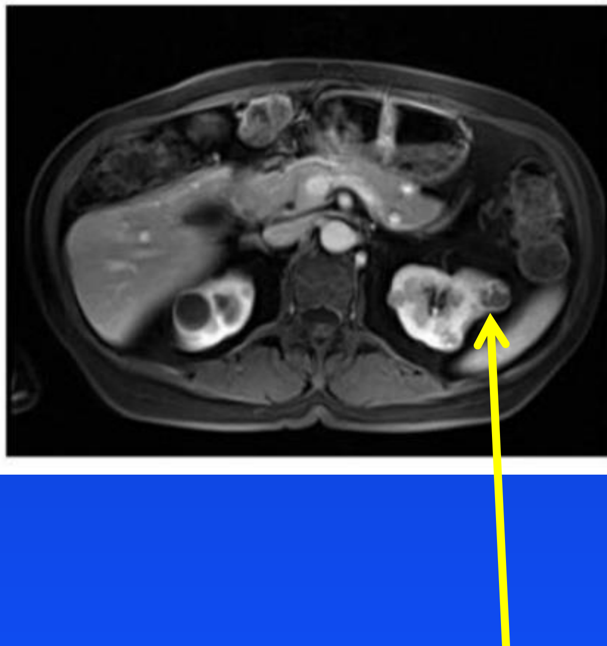


Topic 77-0:
kidney,images,abdomen,e.g,prior,mass,pancreas,following,cysts,adrenal,liver,foci,renal,contrast,approximate,including,focus,cyst,bilateral,masses,size,enhancing,for,also,given,possibly,mid,2.5,vascular,without,due,nephrectomy,please,1.5,from,few,multiphase,subcentimeter,least,comparison,patient,dual-phase,length,apparent,complication,obtained,upper,s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



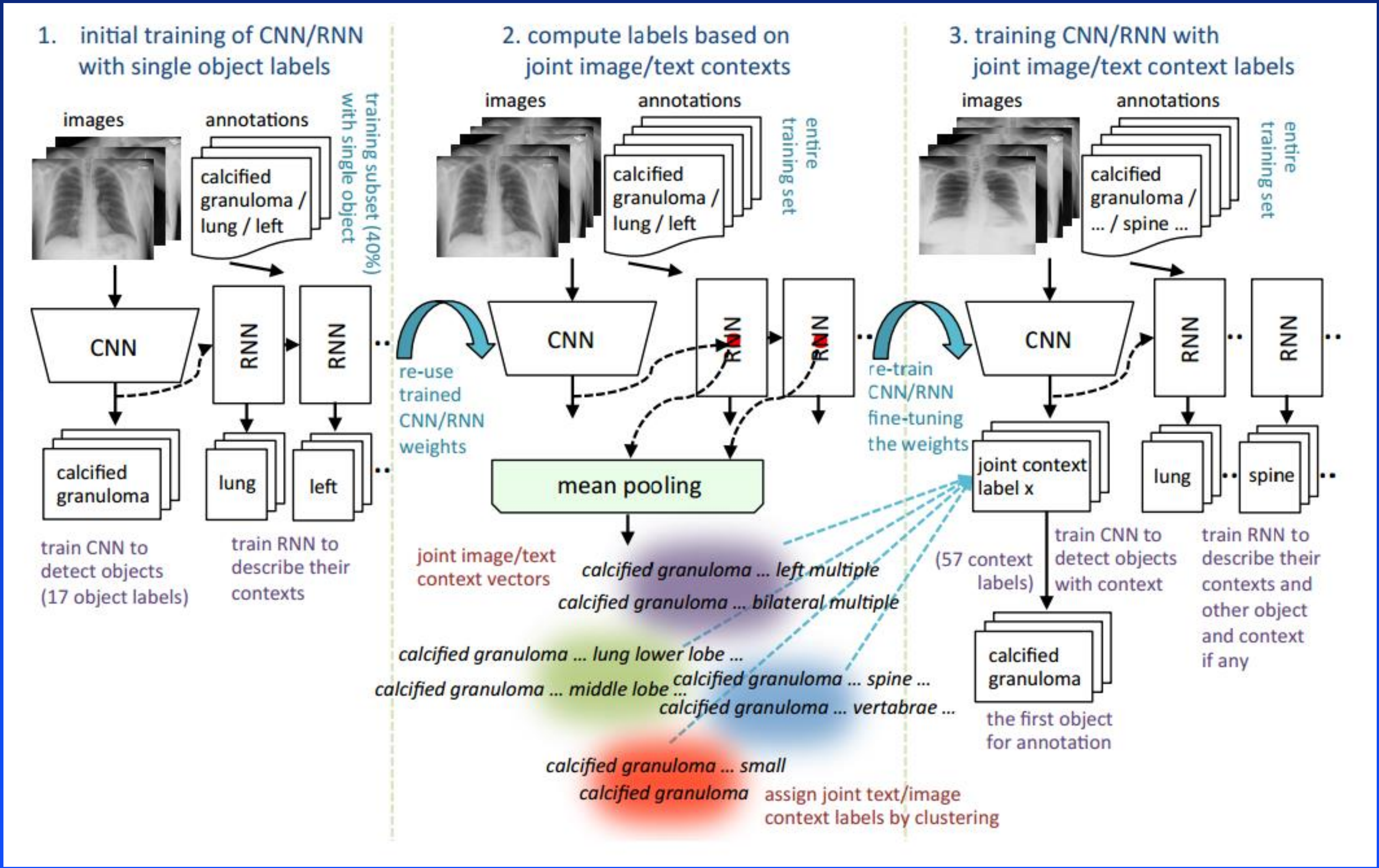
diameter
mass
kidney

avg distance: 0.33

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

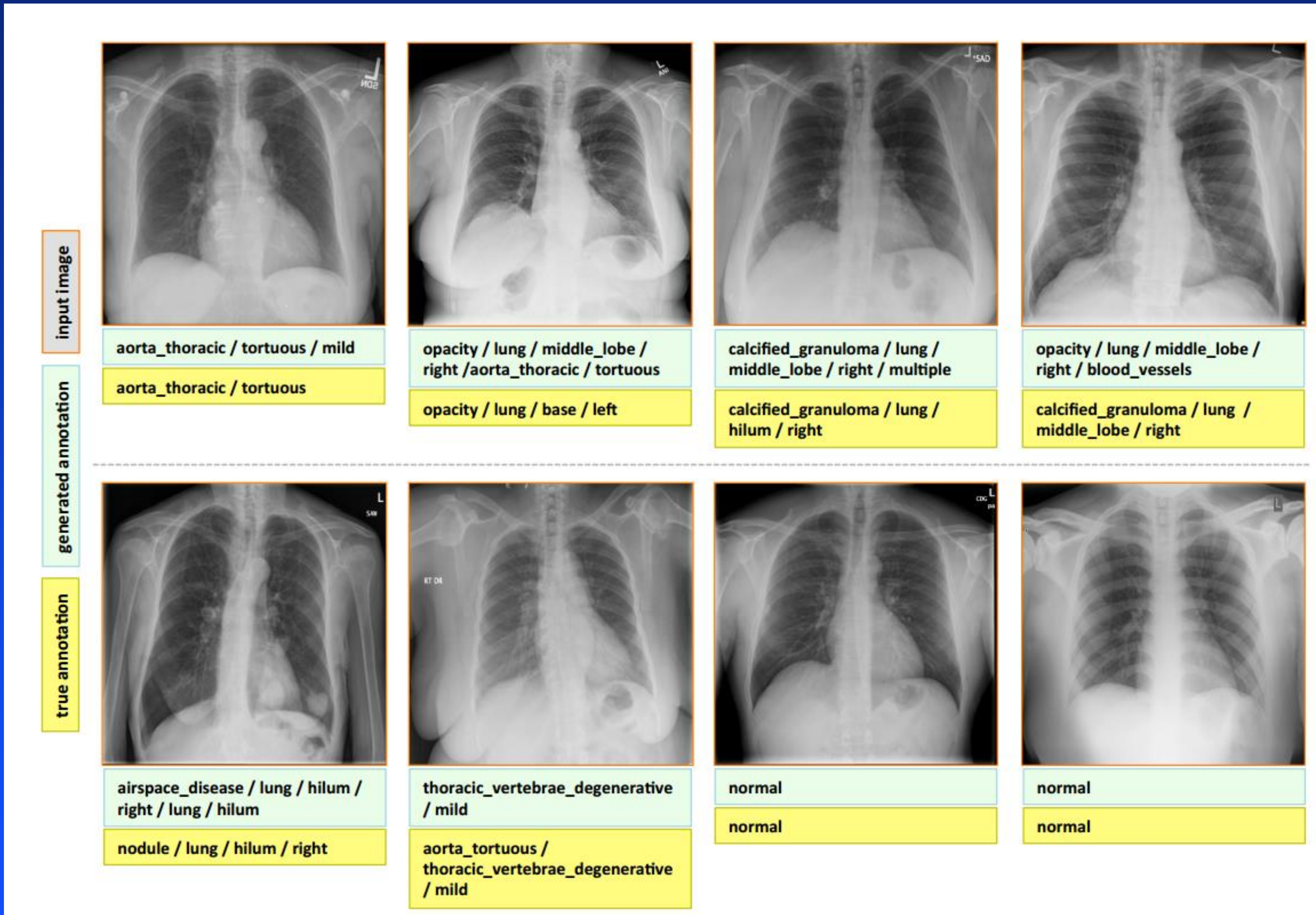
HC Shin et al. CVPR 2015 & JMLR 2016

Data Mining Reports & Images



HC Shin et al. CVPR 2016

Data Mining Reports & Images



HC Shin et al. CVPR 2016

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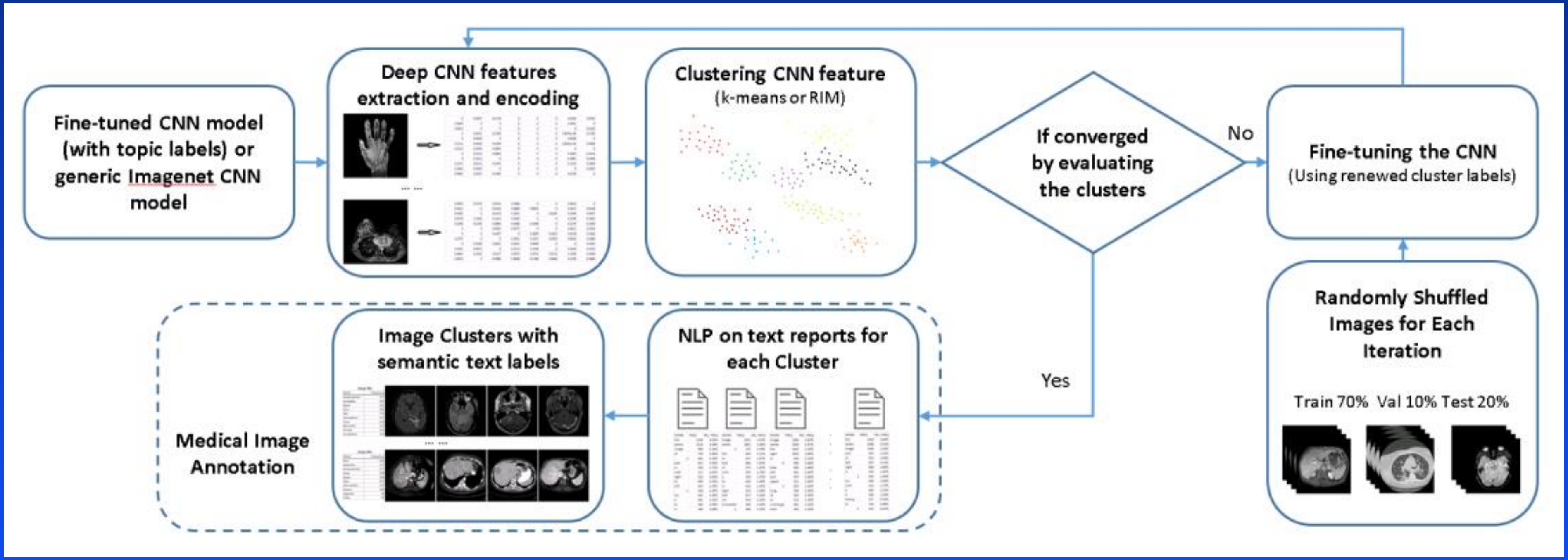
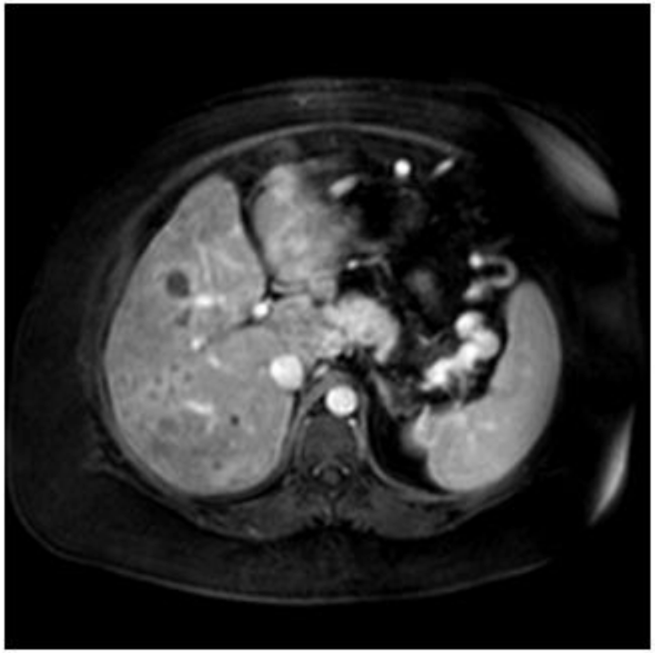


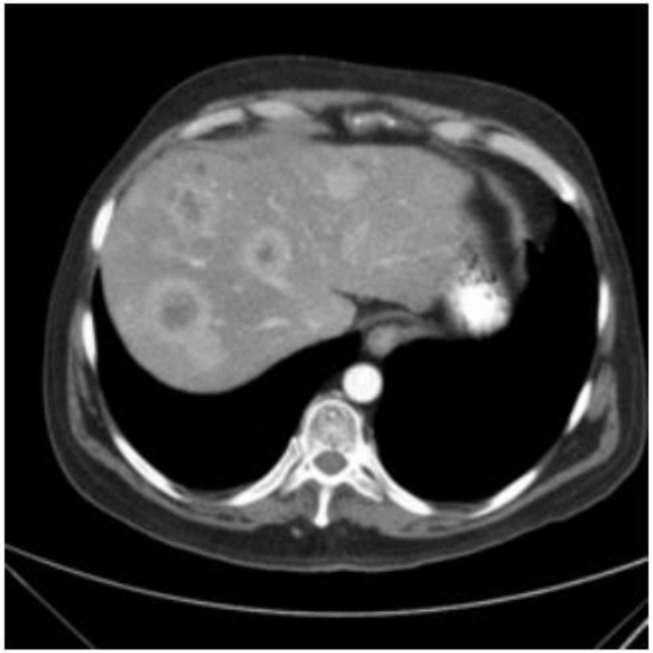
X Wang et al. WACV 2017

Data Mining Reports & Images

Cluster #23

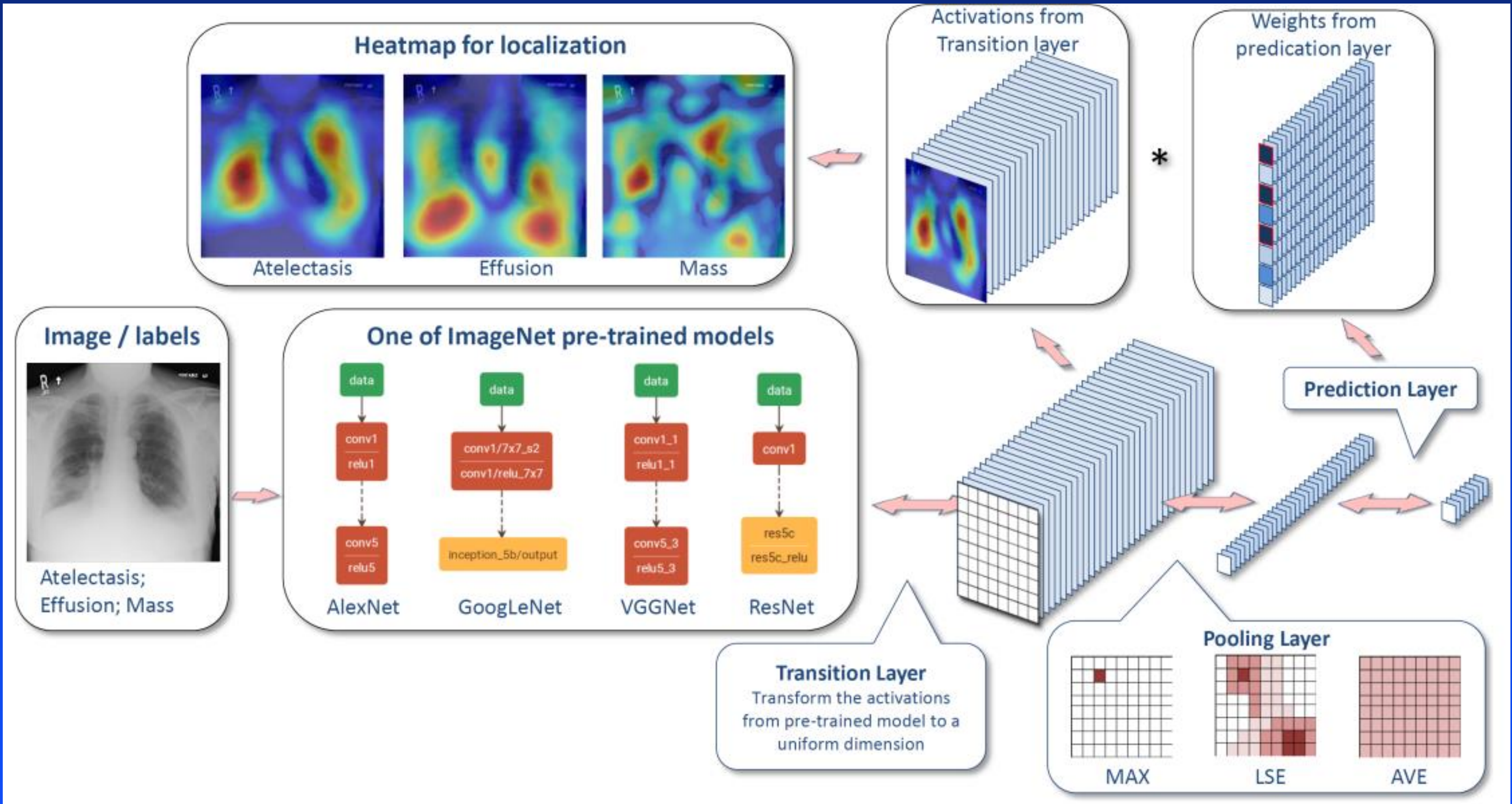
Word	Frequency
liver	524
abdomen	337
enhancement	217
mass	198
lesion	168
lobe	161
adenopathy	119
lesions	109
segment	58
bulky	45





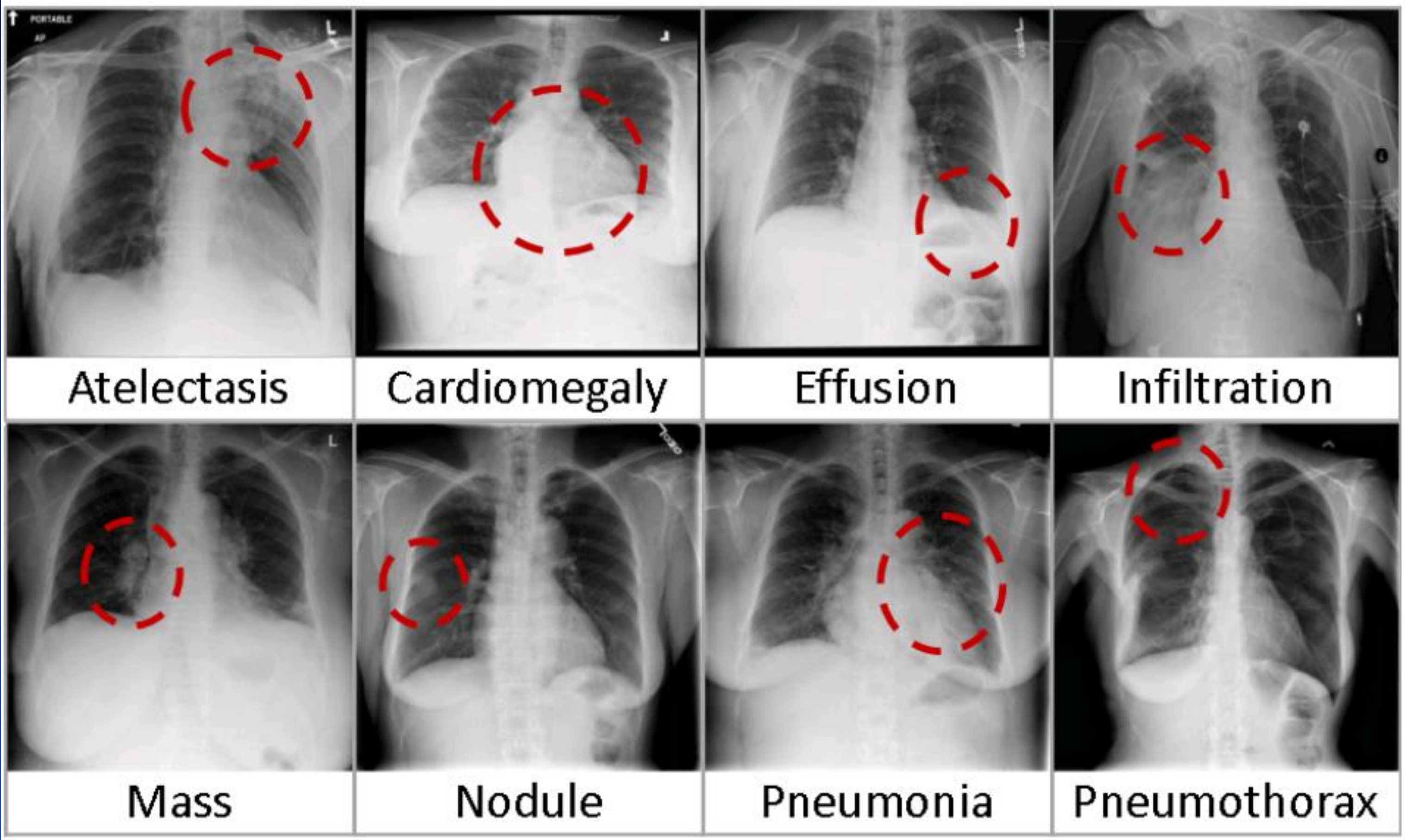
X Wang et al. WACV 2017

Data Mining Reports & Images



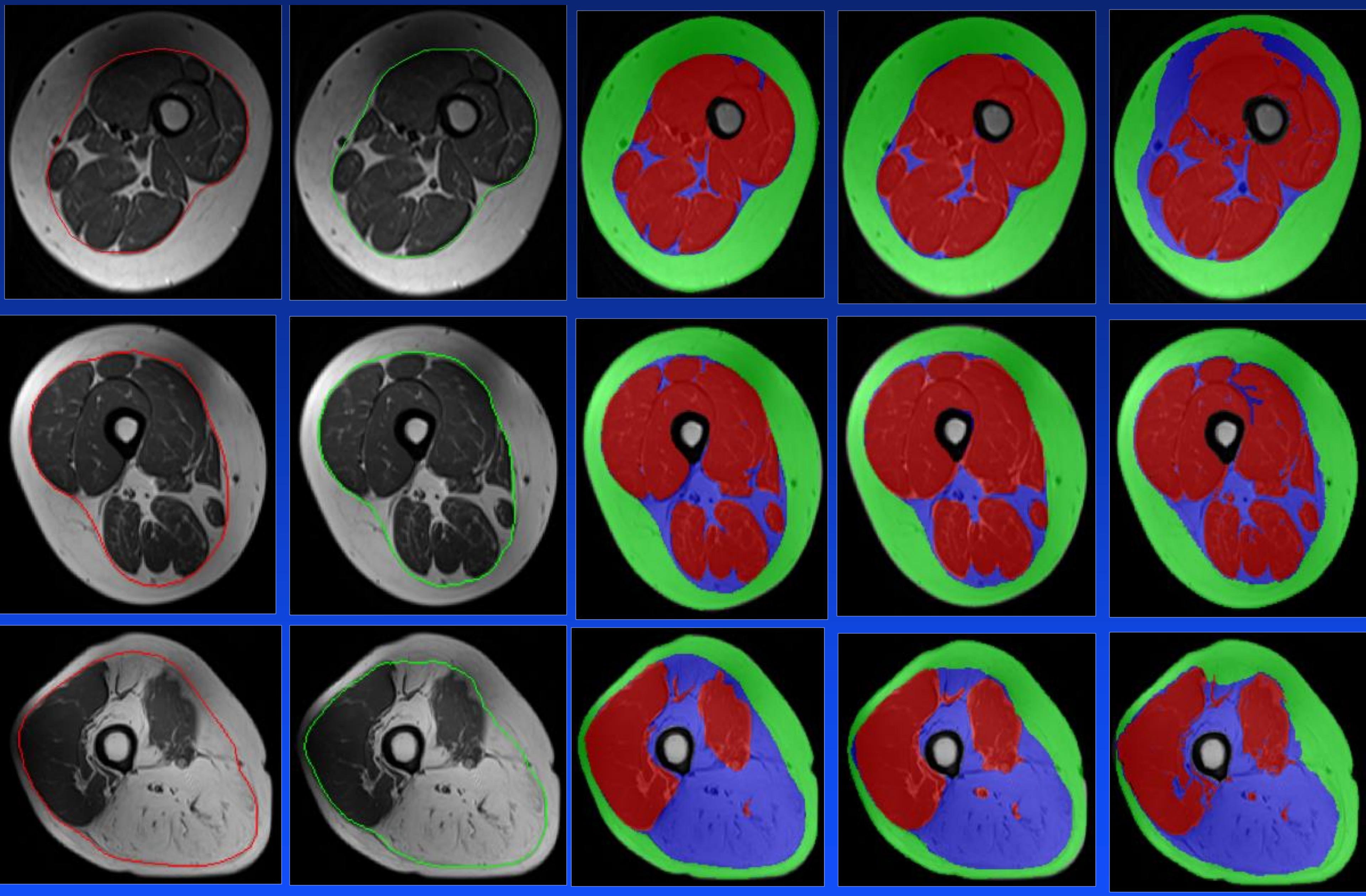
X Wang et al. CVPR 2017

ChestX-ray8



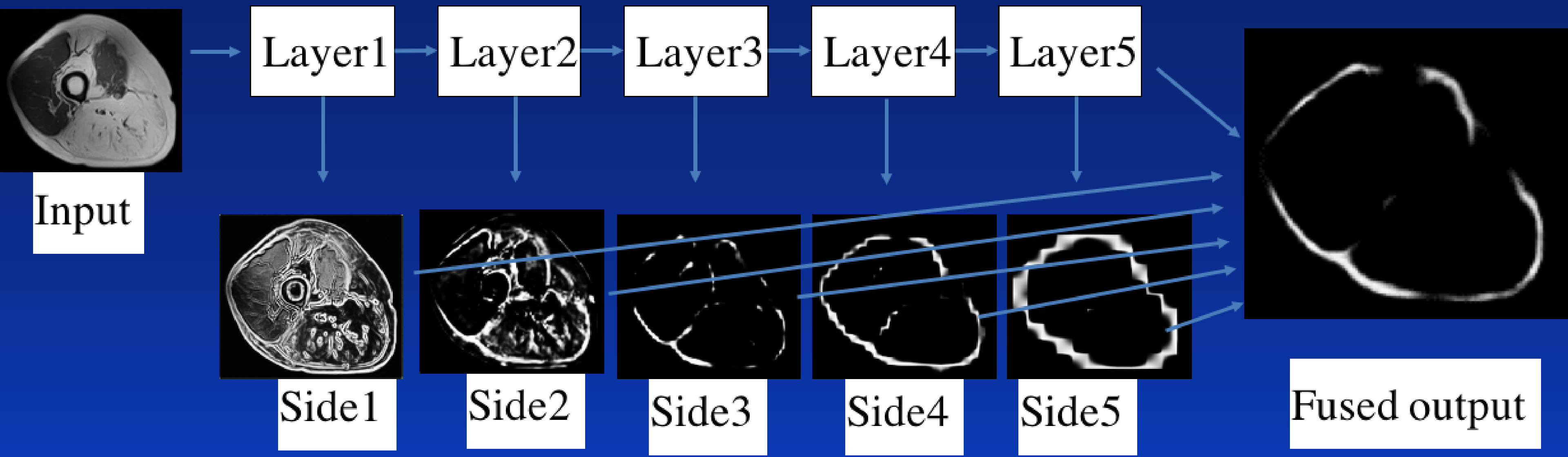
T(IoBB)	Atelectasis	Cardiomegaly	Effusion	Infiltration	Mass	Nodule	Pneumonia	Pneumothorax
T(IoBB) = 0.1								
Acc.	0.7277	0.9931	0.7124	0.7886	0.4352	0.1645	0.7500	0.4591
AFP	0.0823	0.0487	0.0589	0.0426	0.0691	0.0630	0.0691	0.0264

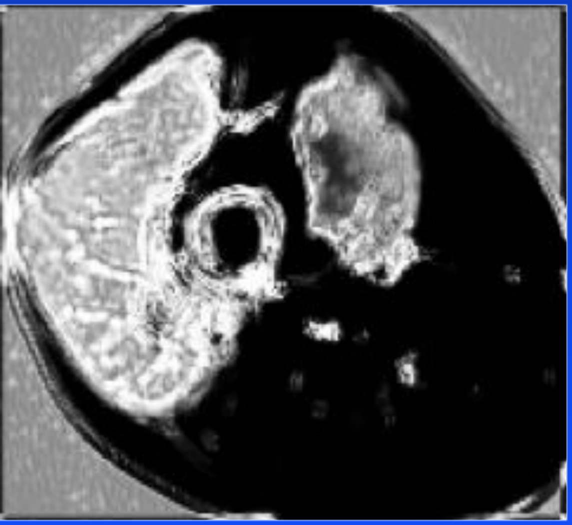
X Wang et al. CVPR 2017

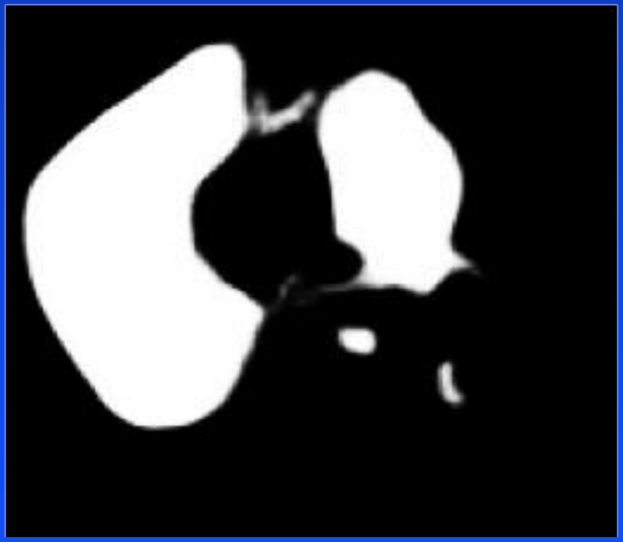


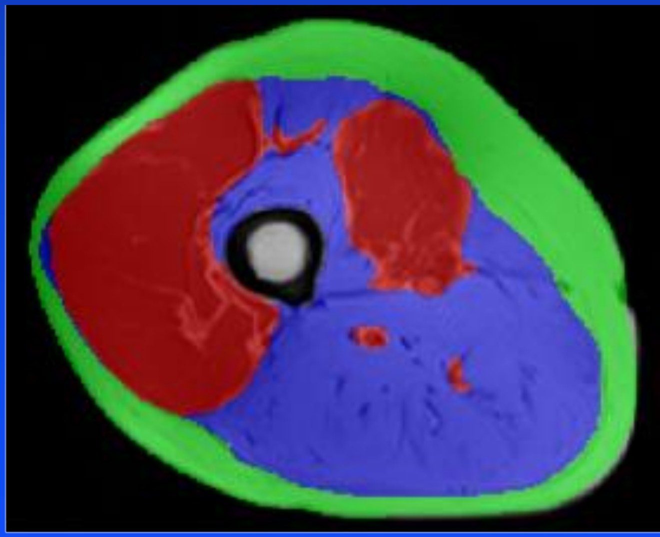
a) b) c) d) e)

J Yao et al. MICCAI 2017









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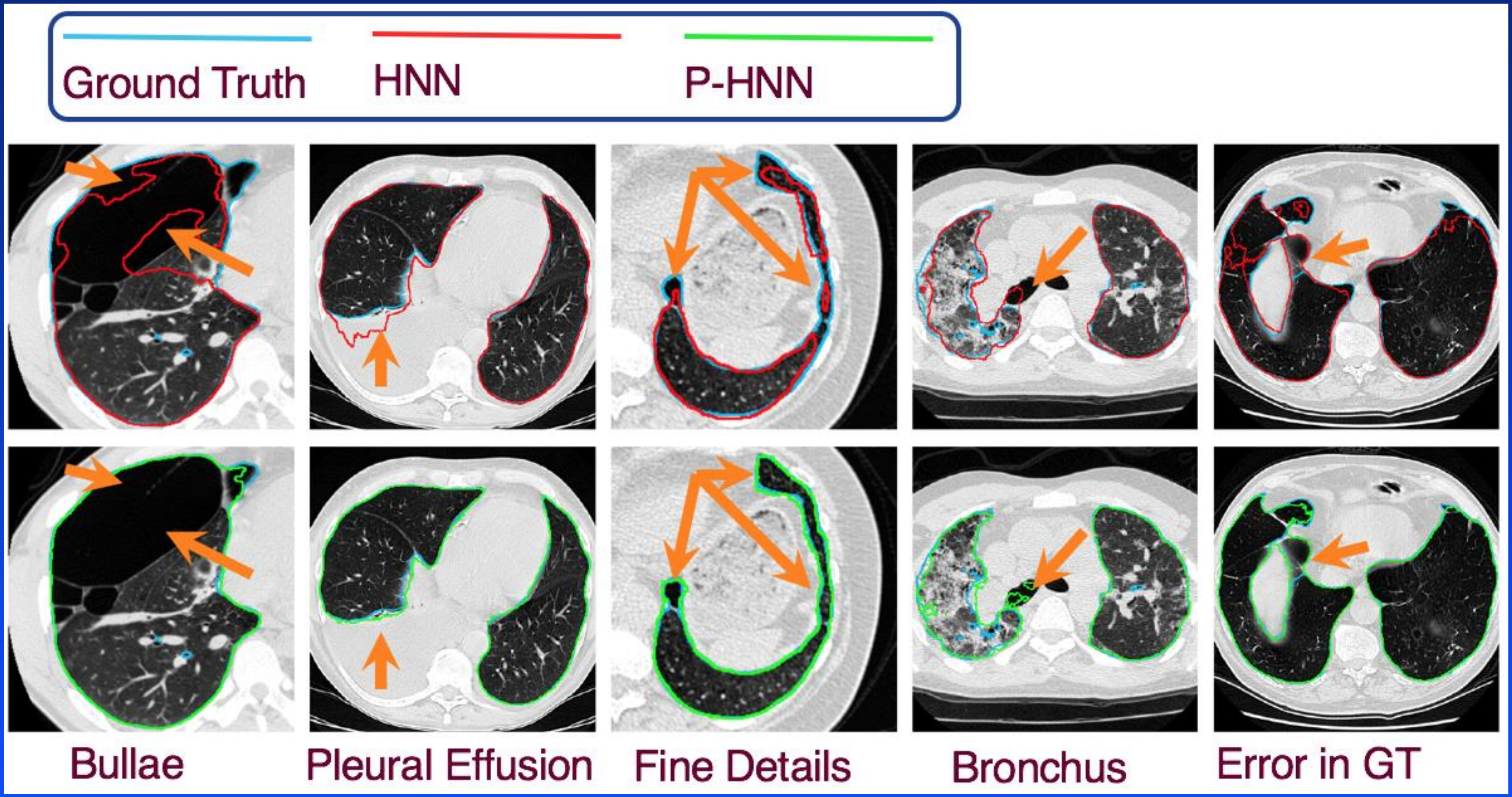

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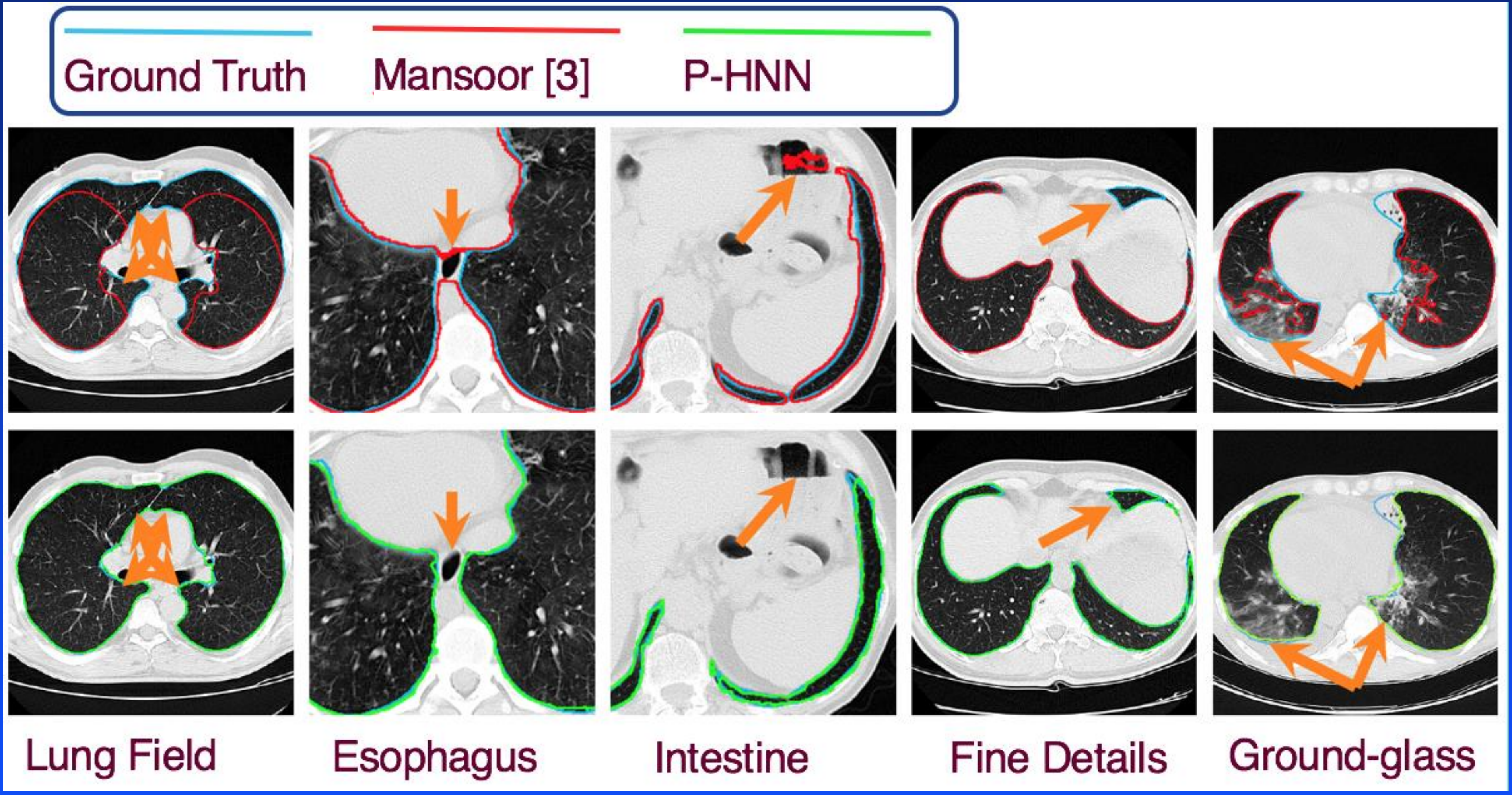

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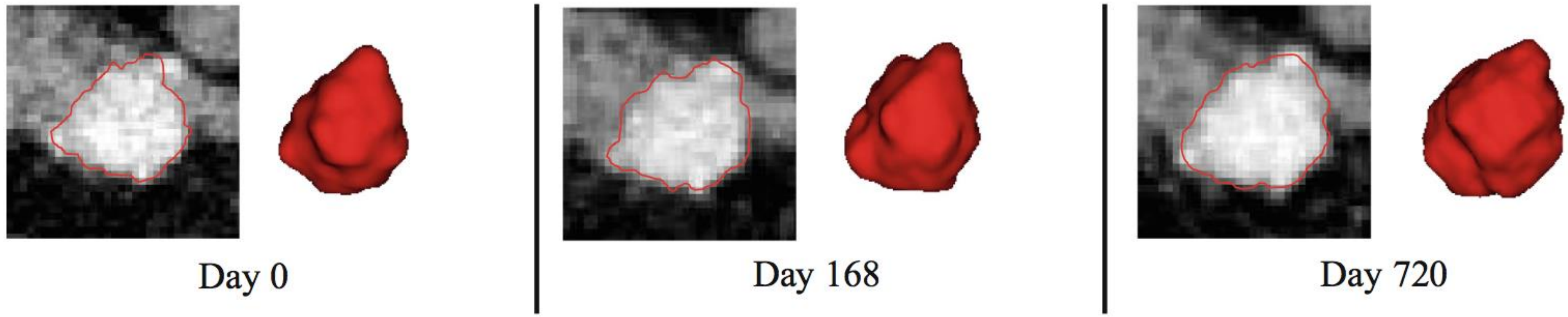
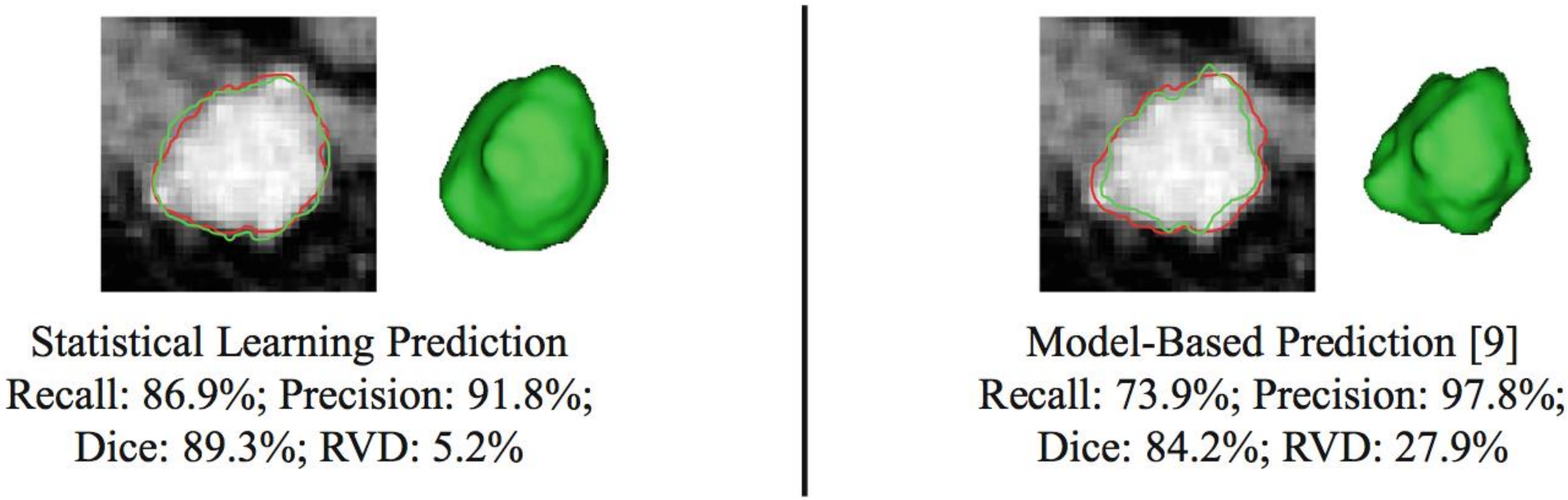


(a) Ground truth of tumor growth at different time points.



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

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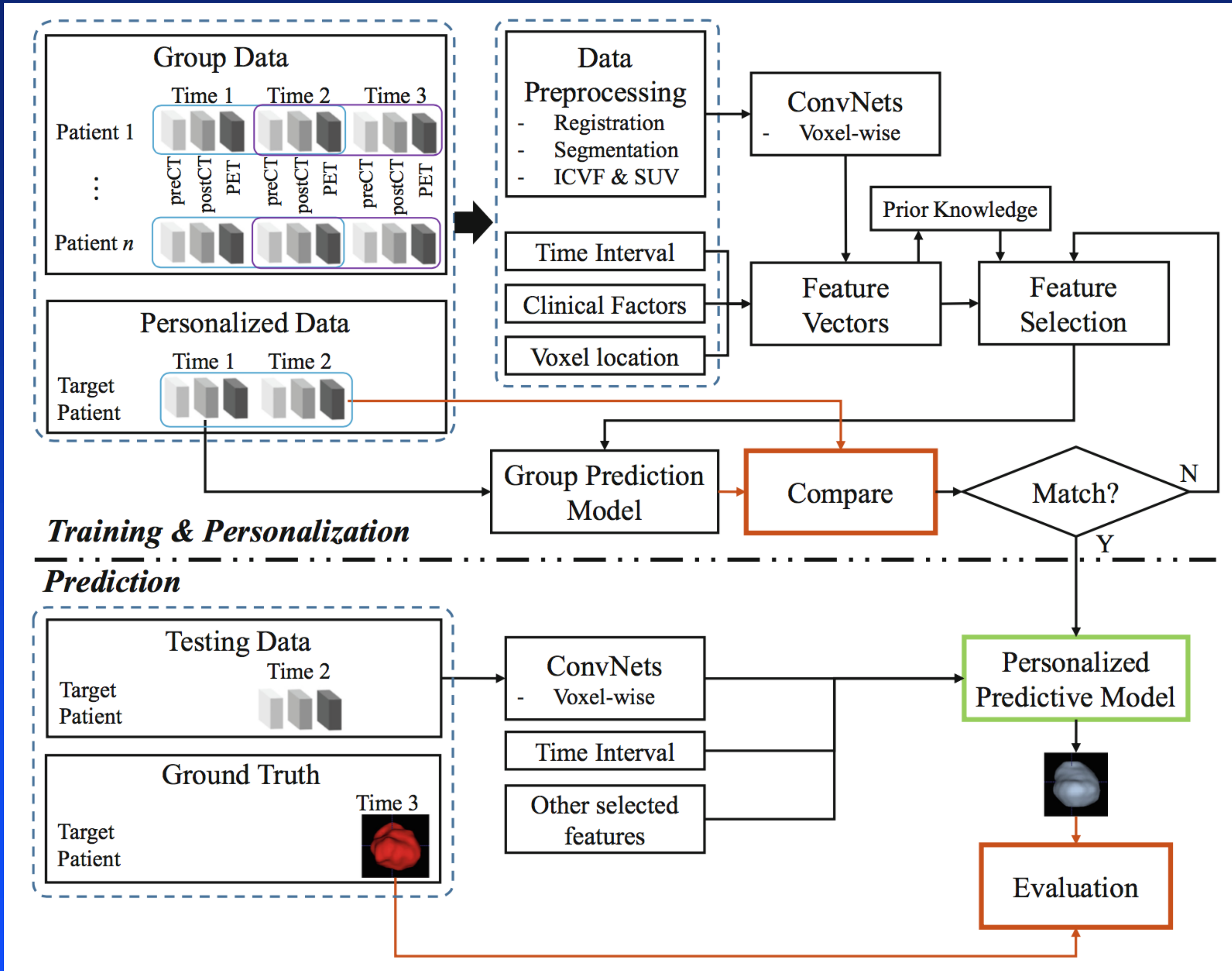

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Challenges and Pitfalls

- 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

Imaging 3.0

- We can add value by making our reports more quantitative; AI & DL can help do this
- Doing so is a sure-fire way to add new useful information to improve patient care and maintain our clinical relevance
- It is important to be aware of the benefits of AI & DL, not just the risks

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

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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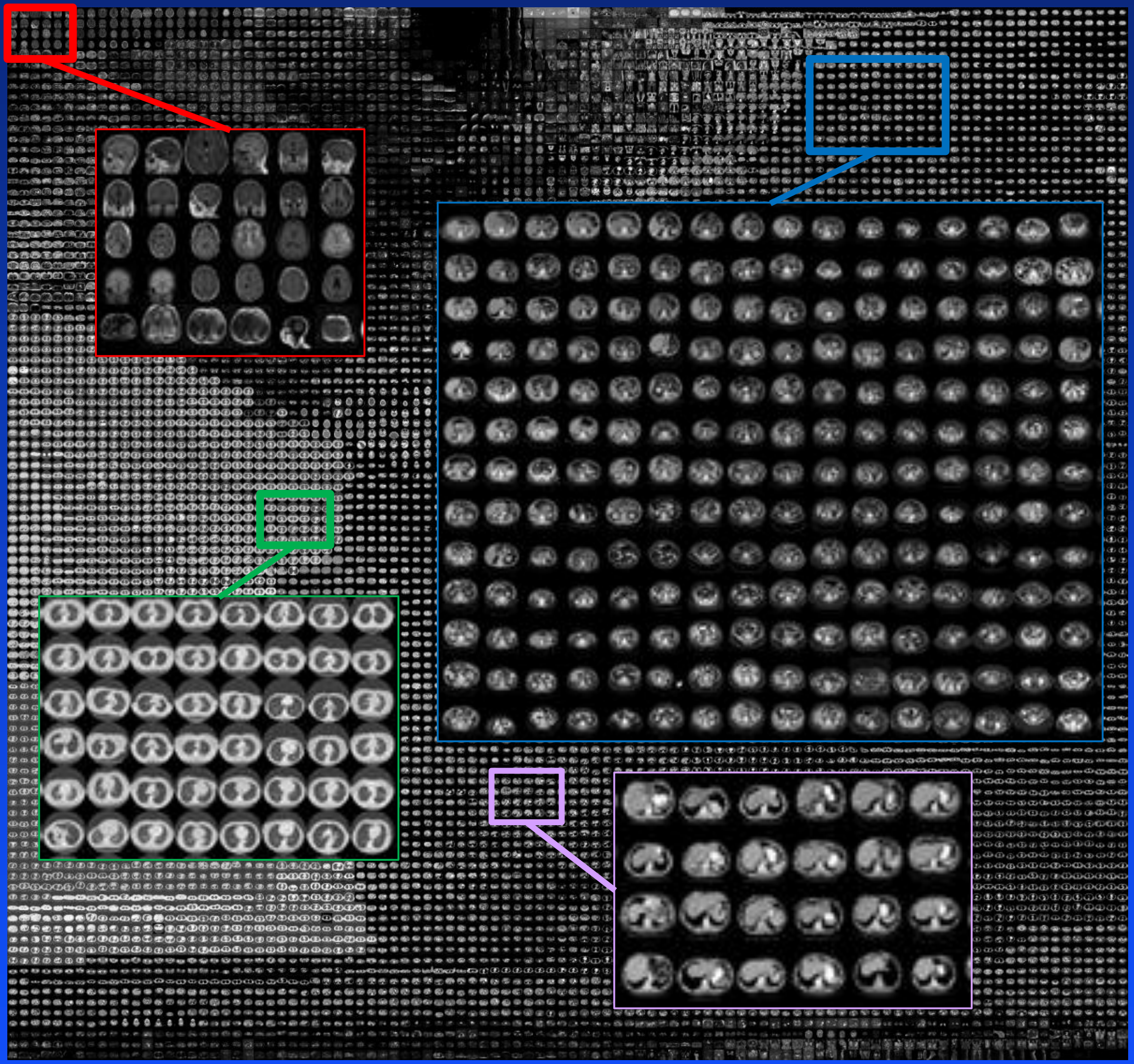
  - ISTP
  - IRTA
  - BESIP
  - CRTP

To Learn More …



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

X Wang et al. RSNA 2016