



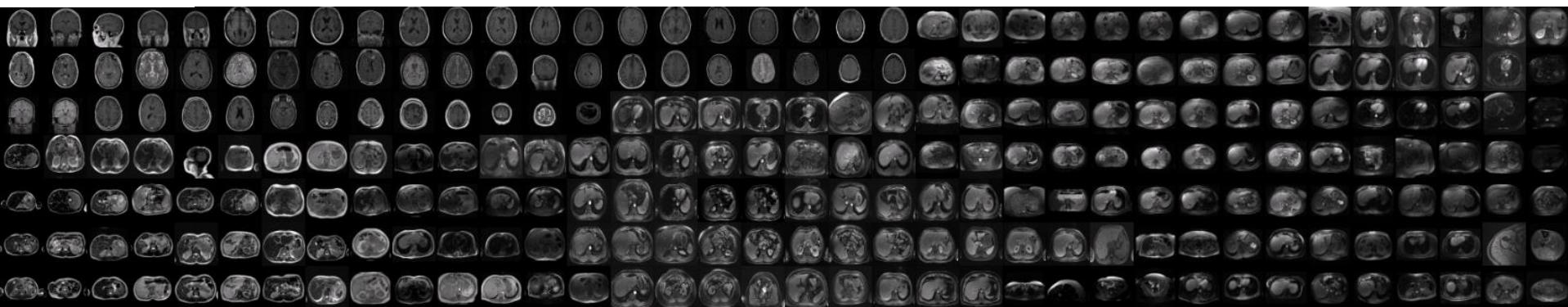
# Big Data, Weak Label and True Clinical Impacts for Radiology Imaging Diagnosis

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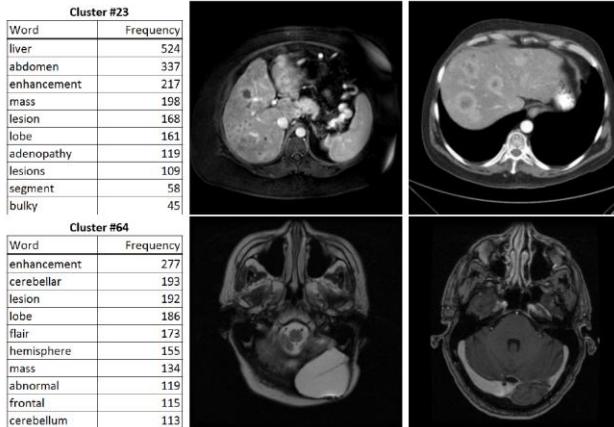


Medical Computer Vision and Health Informatics Workshop

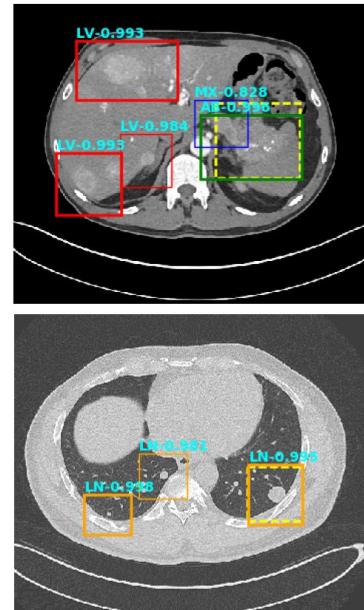


- The availability of well-labeled data is the key for large scale machine learning, e.g. deep learning
- Different levels of annotations are required for a variety of medical imaging problems.

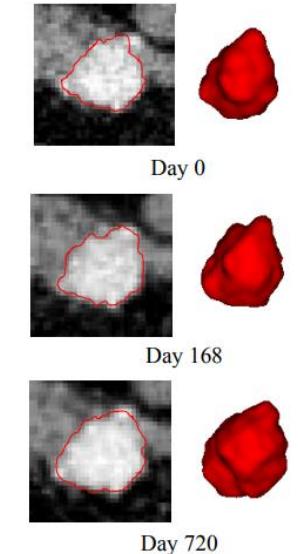
Classification (image label)



Localization(b-box)



Segmentation (mask) \*



Ground truth of tumor growth at different time points.

\* Image Credit: Ling Zhang et. al, "Personalized Pancreatic Tumor Growth Prediction via Group Learning", MICCAI 2017

- High quality labels for large medical imaging database are NOT available
- Annotation on medical images usually requires professionals with clinical training.
- Conventional ways for collecting image labels are NOT applicable, e.g.
  - Internet search followed by crowd-sourcing

*Large scale natural image datasets*



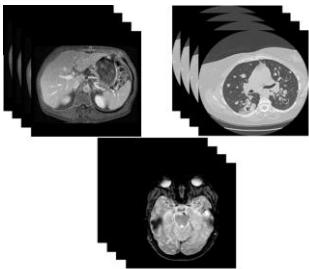
*Large scale  
Medical Image  
dataset*



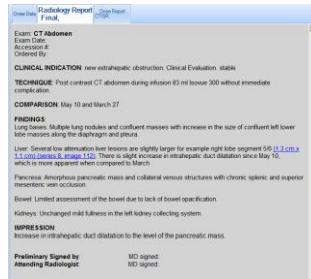
\* Dataset logos shown here are from respective public dataset websites.



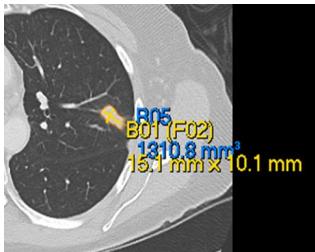
## Hospital PACS



Images (different patient across time)



Associated report  
(Findings, attributes)



Clinical Annotation  
(measure, location, lesion contour)



## GT Label for Learning

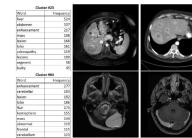
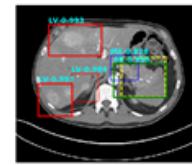
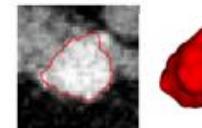


Image Label



Bounding box



Mask

Dig where doctors care!



## I. Unsupervised Joint Mining of Deep Features and Image Labels:

- Hypothesised “Convergence”: better labels lead to better trained Convolutional Neural Network (CNN) models which consequently feed more effective deep image features to facilitate more meaningful clustering/labels.
- Clinical Application: image categorization / classification

## II. Mining of Radiology Reports via NLP:

- A two-stage process: pathology detection plus negation and uncertainty elimination.
- Clinical Application: disease classification / localization

## III. Utilizing Clinical Annotation as Weak Supervision:

- Annotations suggest location information
- Clinical Application: disease detection



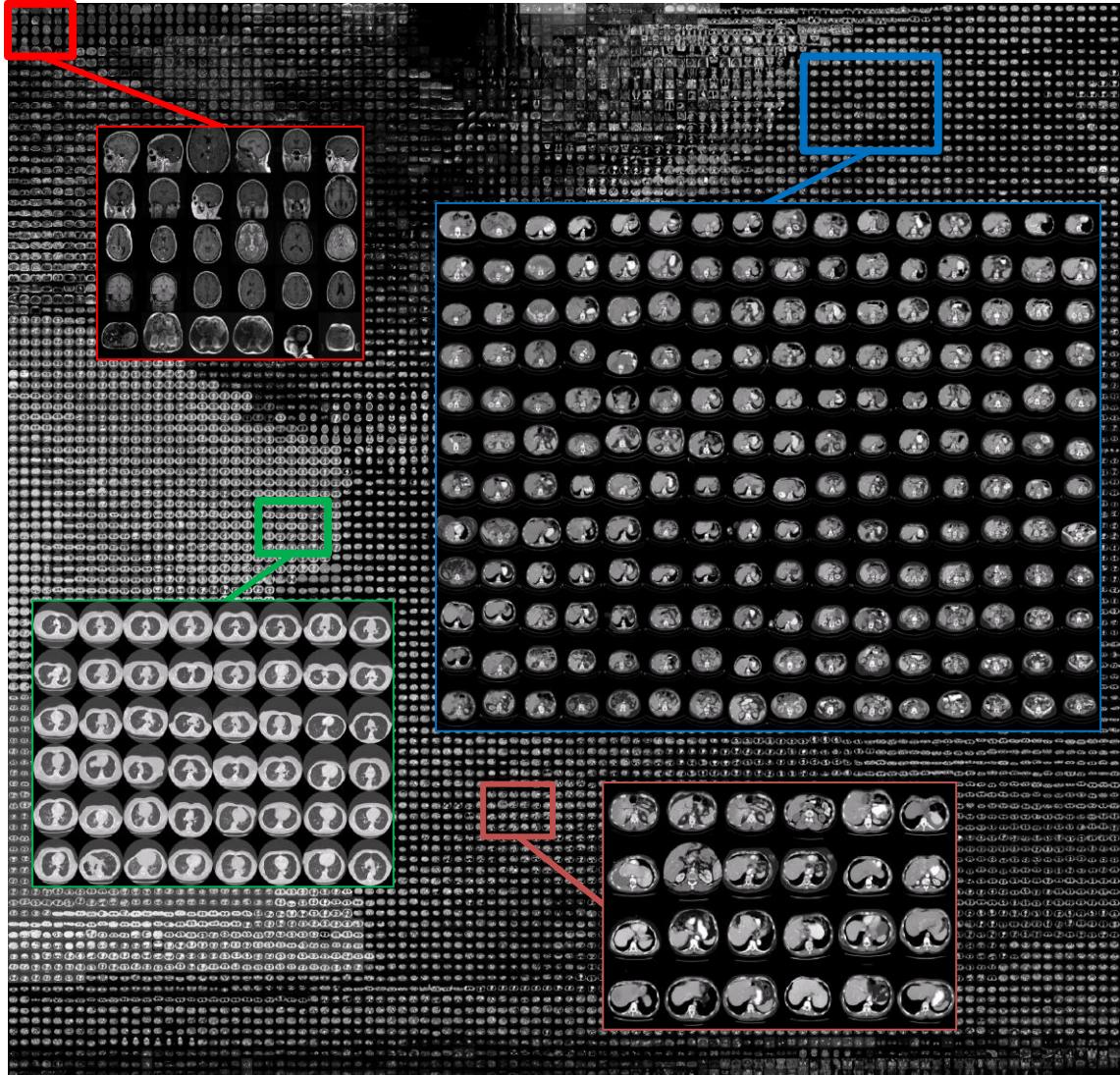
# Case Study 1

## Unsupervised Categorization of Images

X. Wang et al. Unsupervised Joint Mining of Deep Features and Image Labels for Large-scale Radiology Image Annotation and Scene Recognition. IEEE WACV, 2017

US Patent Application 62/302,096

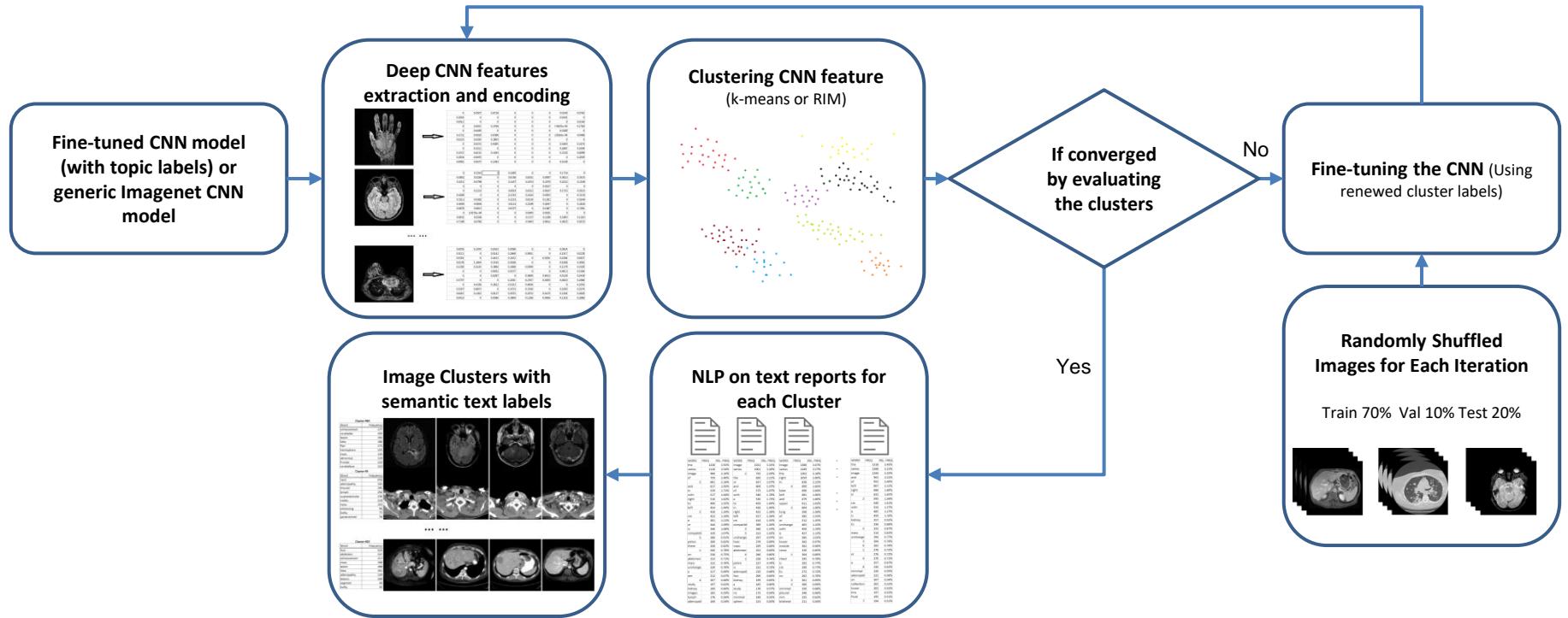
- “Keyimage” dataset: 215,786 key images from 17,845 unique patients.
- Key images are significant one or more images in a study referenced in the linked radiological report.
- Key images are directly extracted from the DICOM file and resized as 256\*256 bitmap images (.png).
- Their intensity ranges are rescaled using the default window settings stored in the DICOM header files



\* 10000 random images from the dataset, using CNN FC7 features of images embedded with t-SNE

# Unsupervised Categorization

The proposed framework is designed towards automatic medical image annotation

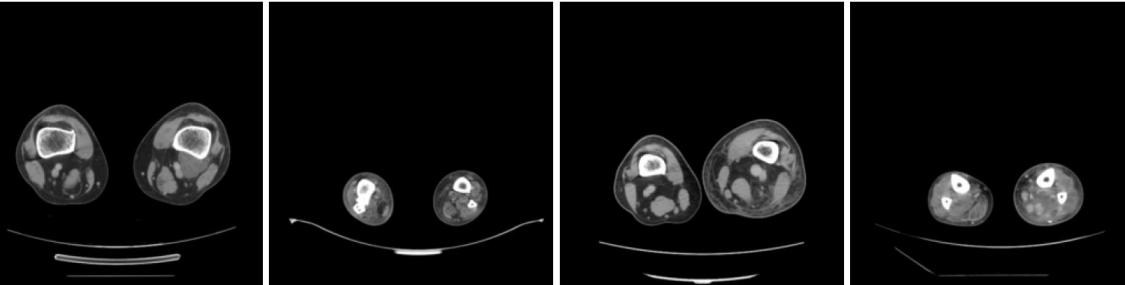


- Hypothesized “convergence”: better labels lead to better trained Convolutional Neural Network (CNN) models which consequently feed more effective deep image features to facilitate more meaningful clustering/labels.



# Sample Categories

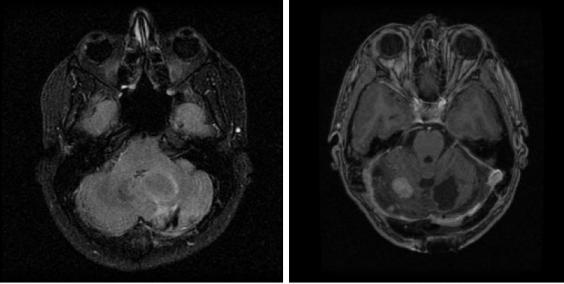
Cluster #14	
Word	Frequency
calf	369
mass	263
subcutaneous	205
thigh	204
lesion	127
lower	124
enhancing	111
bone	105
fossa	92
nerve	88



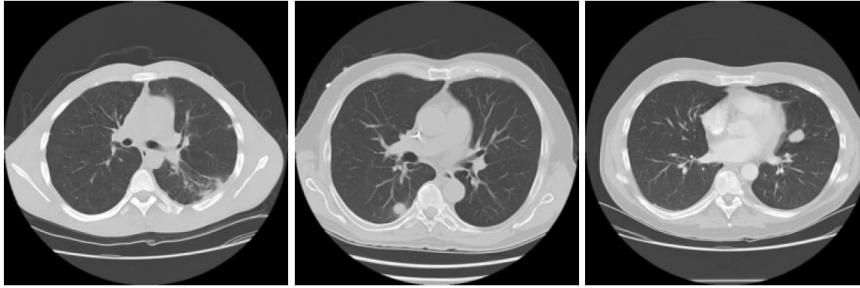
Cluster #23	
Word	Frequency
liver	524
abdomen	337
enhancement	217
mass	198
lesion	168
lobe	161
adenopathy	119
lesions	109
segment	58
bulky	45



Cluster #64	
Word	Frequency
enhancement	277
cerebellar	193
lesion	192
lobe	186
flair	173
hemisphere	155
mass	134
abnormal	119
frontal	115
cerebellum	113



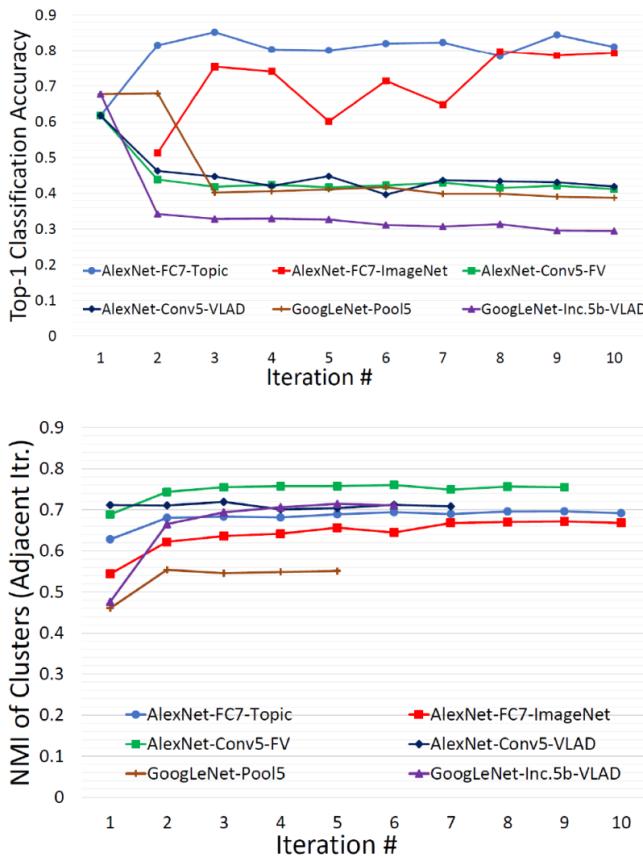
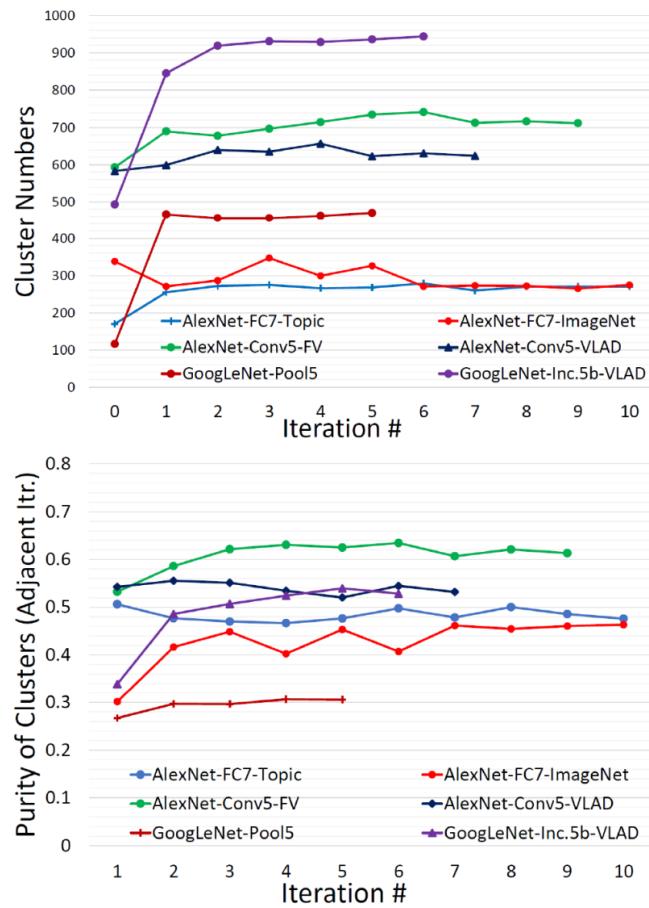
Cluster #224	
Word	Frequency
lung	637
lobe	450
chest	361
mass	215
nodule	160
pleural	158
adenopathy	128
granulomata	111
atelectasis	86
pericardial	81





- Clustering via K-means only or over-fragmented K-means followed by Regularized Information Maximization (as an effective model selection method), are extensively explored and empirically evaluated.
- Two convergence measurements have been adopted, i.e., Clustering Purity and Normalized Mutual Information (NMI).
- Newly generated clusters are better in terms of
  - Visually more coherent and discriminative from instances from other clusters
  - Balanced classes with approximately equivalent images per cluster
  - The number of clusters is self-adaptive according to the nature of data

# Quantitative Results



- The convergence of our categorization framework is measured and observed in the cluster-similarity measures, the CNN training classification accuracies and the self-adapted cluster number.
- AlexNet-FC7-Topic is preferred by two radiologists, which results in total 270 categories. The adopted FC7 feature is able to preserve the layout information of images.

- Images from the same scene category may share similar object patches but are different in overall setting, e.g. buildings all have windows but in different style.
- Integrate patch mining as a form of image encoding into our LDPO framework and perform the categorization and patch mining iteratively.

**MIT Indoor-67 (I-67)**

indoor scenes | 67 classes  
 15620 images



Airport

**Building-25 (B-25)**

Architecture Style | 25 classes  
 4794 images



American Craftsman

**Scene-15 (S-15)**

Indoor & outdoor | 15 classes  
 4485 images



Bedroom

- The purity and NMI measurements are computed between the final LDPO clusters and GT scene classes ( purity becomes the classification accuracy against GT).
- We compare the LDPO scene recognition performance to those of several popular clustering methods.
- The state-of-the-art fully-supervised scene Classification Accuracies (CA) for each dataset are also provided.

Dataset	KM [57]	LSC [4]	AC [22]	EP [10]	MDPM [34]	LDPO-A-FC	LDPO-A-PM	LDPO-V-PM	Supervised
Clustering Accuracy (%)								CA(%)	
<b>I-67 [44]</b>	35.6	30.3	34.6	37.2	53.0	37.9	63.2	<b>75.3</b>	<b>81.0[8]</b>
<b>B-25 [62]</b>	42.1	42.6	43.2	43.8	43.1	44.1	59.2	<b>59.5</b>	<b>59.1 [42]</b>
<b>S-15 [32]</b>	65.0	76.5	65.2	73.6	63.4	73.1	<b>90.1</b>	84.0	<b>91.6 [66]</b>
Normalized Mutual Information									
<b>I-67 [44]</b>	.386	.335	.359	-	.558	.389	.621	<b>.759</b>	-
<b>B-25 [62]</b>	.401	.403	.404	-	.424	.407	<b>.588</b>	.546	-
<b>S-15 [32]</b>	.659	.625	.653	-	.596	.705	<b>.861</b>	.831	-

\* KM: k-means; AC: agglomerative clustering ; LSC: large-scale spectral clustering ; EP: ensemble projection + k-means;  
 MDPM: mid-level discriminative patch mining + k-means



## Case Study 2

# Mining of Image Labels via NLP in Radiology Reports

X. Wang, Y. Peng, et al. ChestX-ray8: Hospital-scale Chest X-ray Database and Benchmarks on Weakly-Supervised Classification and Localization of Common Thorax Diseases. CVPR, 2017

US Patent Application 62/476,029



# NH Chest X-ray

# A Sample Radiology Report

## Chest X-ray Radiology Report

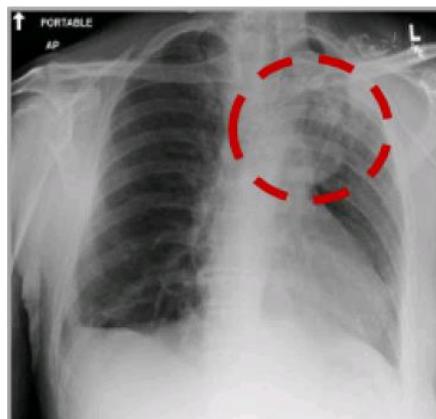
### ***Findings:***

unchanged left lower lung field **infiltrate**/air bronchograms.  
Unchanged right perihilar **infiltrate** with obscuration of the right heart border. no evidence of new infiltrate. no evidence of pneumothorax the cardiac and mediastinal contours are stable.

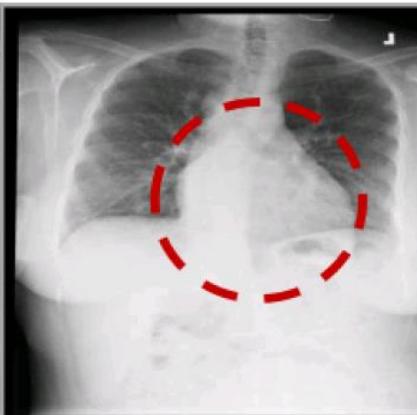
### ***Impression:***

1. no evidence pneumothorax.
2. unchanged left lower lobe and left lingular. consolidation / bronchiectasis.
3. unchanged right middle lobe infiltrate

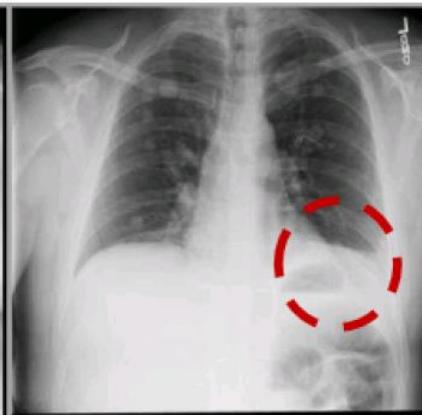
# 8 Common Thorax Diseases



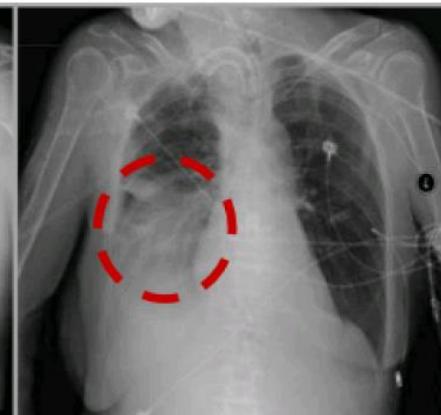
Atelectasis



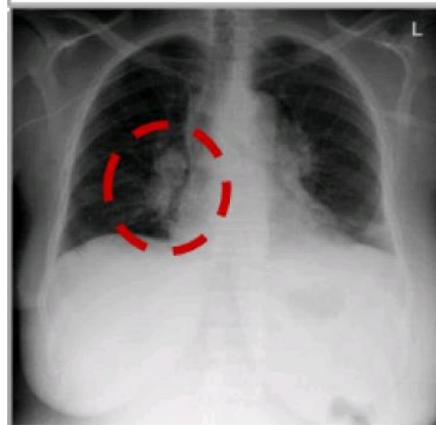
Cardiomegaly



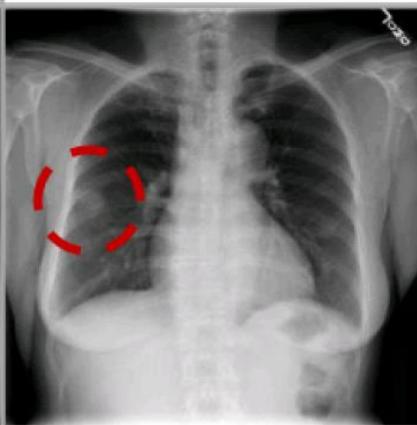
Effusion



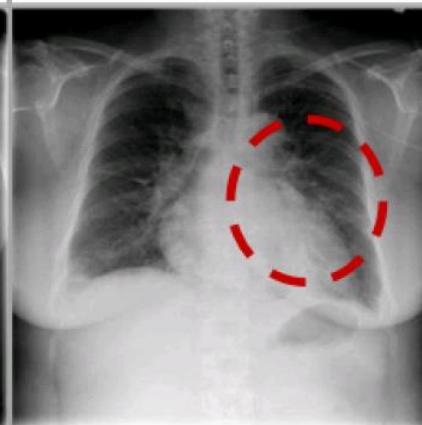
Infiltration



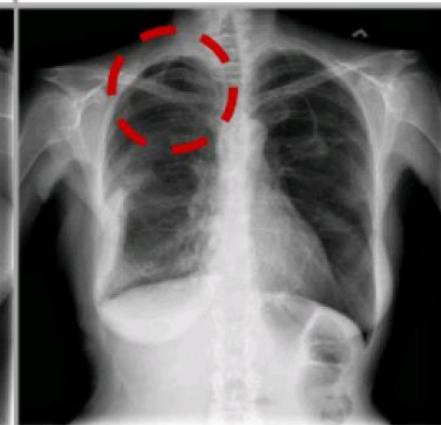
Mass



Nodule



Pneumonia



Pneumothorax



## Stage 1: Pathology Detection

- **DNorm** is used to map every mention of keywords in a report to a unique concept ID in the Systematized Nomenclature of Medicine Clinical Terms ( SNOMED-CT), a standardized vocabulary of clinical terminology for the electronic exchange of clinical health information.
- Another ontology-based approach, **MetaMap**, is adopted for the detection of Unified Medical Language System (UMLS) Metathesaurus.
- The results of DNorm and MetaMap are merged

Pneumonia	C0032285	pneumonia
	C0577702	basal pneumonia
	C0578576	left upper zone pneumonia
	C0578577	right middle zone pneumonia
	C0585104	left lower zone pneumonia
	C0585105	right lower zone pneumonia
	C0585106	right upper zone pneumonia
	C0747651	recurrent aspiration pneumonia
	C1960024	lingular pneumonia
Pneumothorax	C0032326	pneumothorax
	C0264557	chronic pneumothorax
	C0546333	right pneumothorax
	C0546334	left pneumothorax

Sample SNOMED-CT concepts

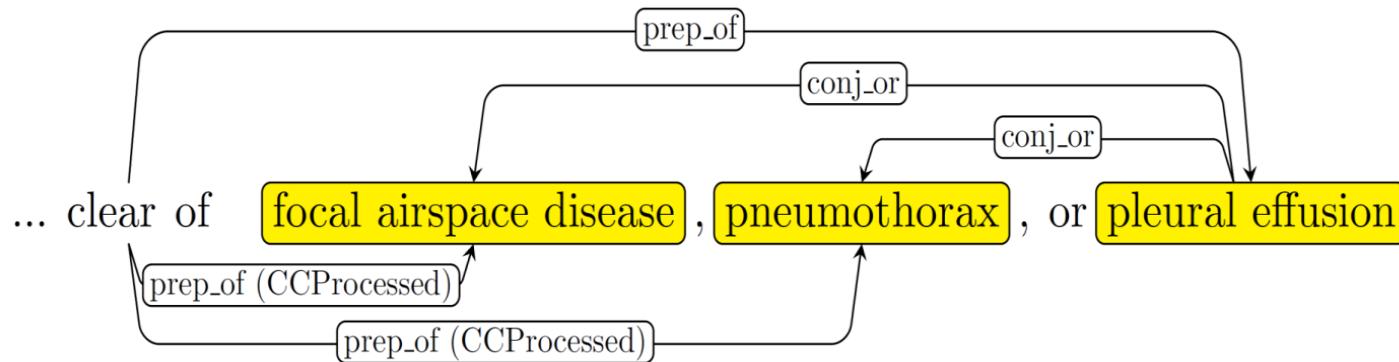
## Stage 2: Removal of negation and uncertainty

- Rule out those negated pathological statements and uncertain mentions of findings and diseases
- Defined the rules on the dependency graph, by utilizing the dependency label and direction information between words, e.g.

Rule	Example
<b>Negation</b>	
no $\leftarrow$ * $\leftarrow$ DISEASE * $\rightarrow$ prep_without $\rightarrow$ DISEASE clear/free/disappearance $\rightarrow$ prep_of $\rightarrow$ DISEASE * $\rightarrow$ prep_without $\rightarrow$ evidence $\rightarrow$ prep_of $\rightarrow$ DISEASE no $\leftarrow$ neg $\leftarrow$ evidence $\rightarrow$ prep_of $\rightarrow$ DISEASE	No acute pulmonary disease changes without focal airspace disease clear of focal airspace disease, pneumothorax, or pleural effusion Changes without evidence of acute infiltrate No evidence of active disease
<b>Uncertainty</b>	
cannot $\leftarrow$ md $\leftarrow$ exclude concern $\rightarrow$ prep_for $\rightarrow$ * could be/may be/... difficult $\rightarrow$ prep_to $\rightarrow$ exclude may $\leftarrow$ md $\leftarrow$ represent suggesting/suspect/... $\rightarrow$ dobj $\rightarrow$ DISEASE	The aorta is tortuous, and cannot exclude ascending aortic aneurysm There is raises concern for pneumonia which could be due to nodule/lymph node interstitial infiltrates difficult to exclude which may represent pleural reaction or small pulmonary nodules Bilateral pulmonary nodules suggesting pulmonary metastases

## Stage 2: Removal of negation and uncertainty

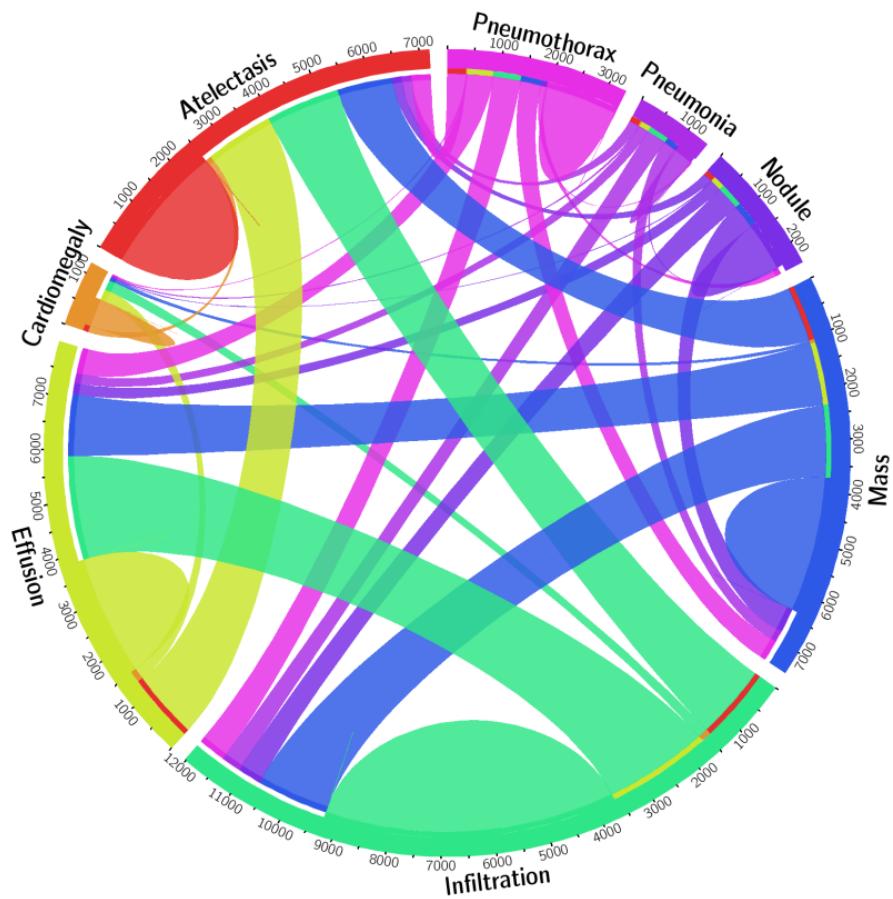
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# ChestX-ray Dataset Statistics

Item #	OpenI	Ov.	ChestX-ray8	Ov.
Report	2,435	-	108,948	-
Annotations	2,435	-	-	-
Atelectasis	315	122	5,789	3,286
Cardiomegaly	345	100	1,010	475
Effusion	153	94	6,331	4,017
Infiltration	60	45	10,317	4,698
Mass	15	4	6,046	3,432
Nodule	106	18	1,971	1,041
Pneumonia	40	15	1,062	703
Pneumothorax	22	11	2,793	1,403
Normal	1,379	0	84,312	0

- # of images in each disease category with Overlay (Ov.) compared with OpenI



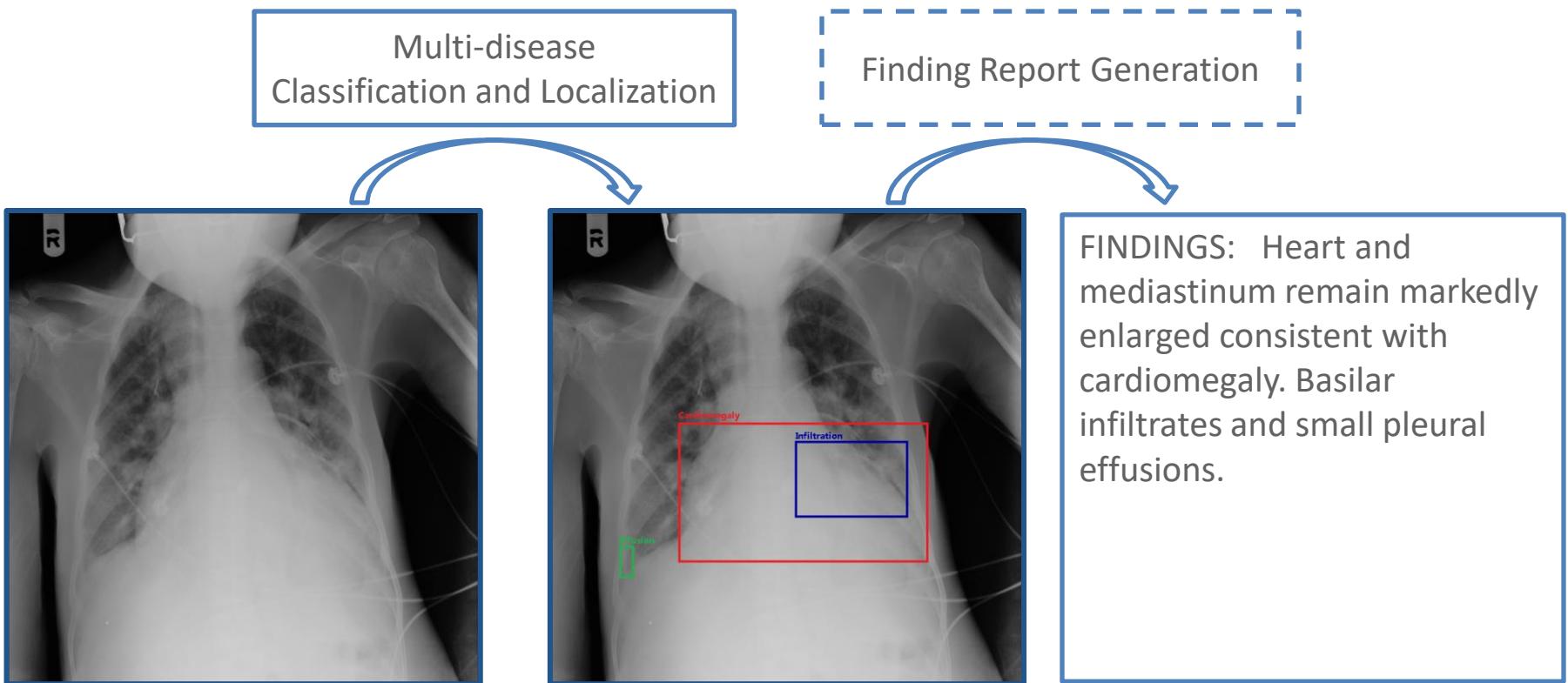
- Graphical illustration of correlations among diseases



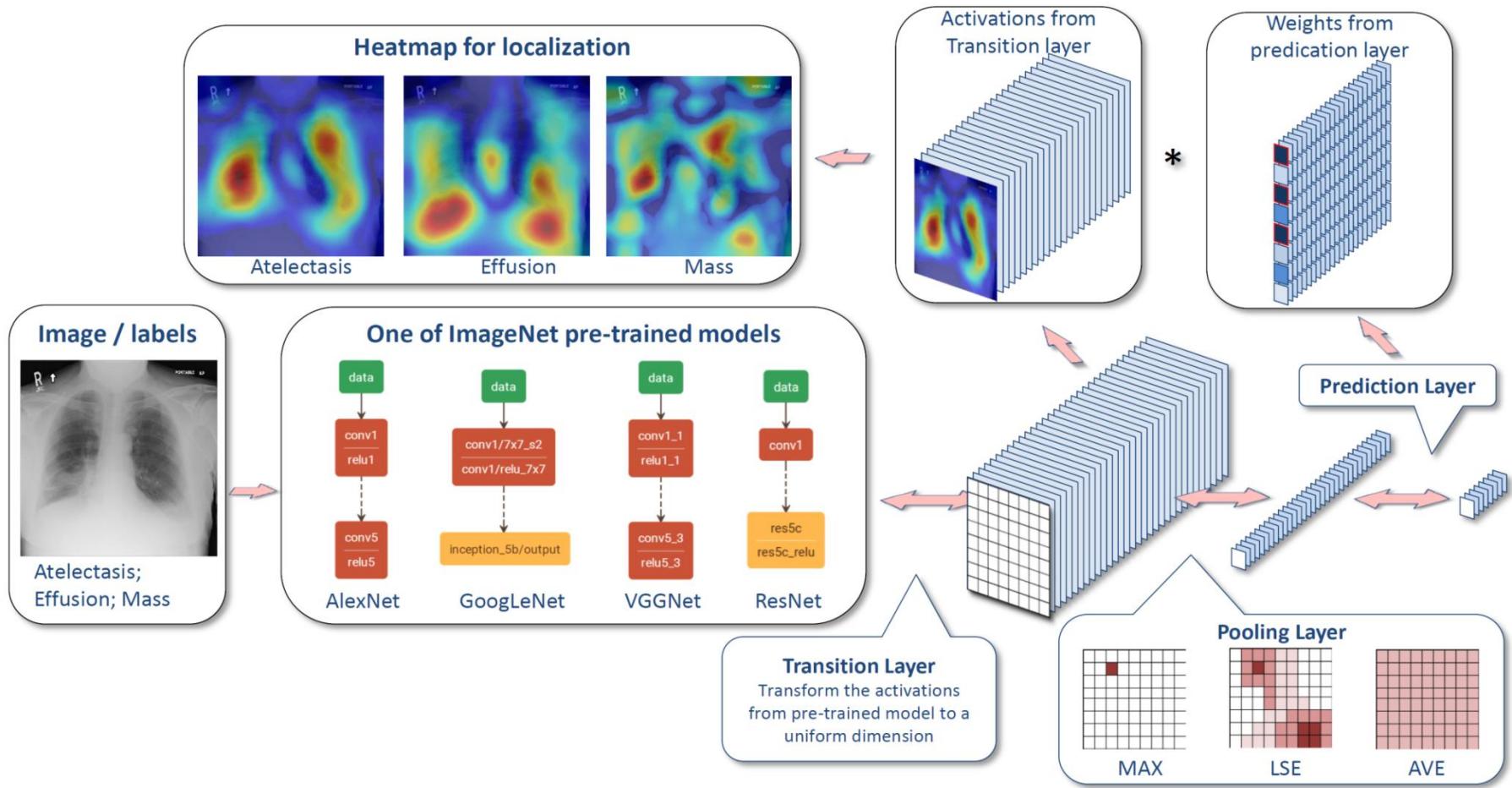
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Pneumothorax	22	11	2,793	1,403
Normal	1,379	0	84,312	0

Disease	MetaMap			Our Method		
	P /	R /	F	P /	R /	F
Atelectasis	0.95	/ 0.95	/ 0.95	0.99	/ 0.85	/ 0.91
Cardiomegaly	0.99	/ 0.83	/ 0.90	1.00	/ 0.79	/ 0.88
Effusion	0.74	/ 0.90	/ 0.81	0.93	/ 0.82	/ 0.87
Infiltration	0.25	/ 0.98	/ 0.39	0.74	/ 0.87	/ 0.80
Mass	0.59	/ 0.67	/ 0.62	0.75	/ 0.40	/ 0.52
Nodule	0.95	/ 0.65	/ 0.77	0.96	/ 0.62	/ 0.75
Normal	0.93	/ 0.90	/ 0.91	0.87	/ 0.99	/ 0.93
Pneumonia	0.58	/ 0.93	/ 0.71	0.66	/ 0.93	/ 0.77
Pneumothorax	0.32	/ 0.82	/ 0.46	0.90	/ 0.82	/ 0.86
<i>Total</i>	0.84	/ 0.88	/ 0.86	0.90	/ 0.91	/ 0.90

Table 2. Evaluation of image labeling results on OpenI dataset. Performance is reported using P, R, F1-score.



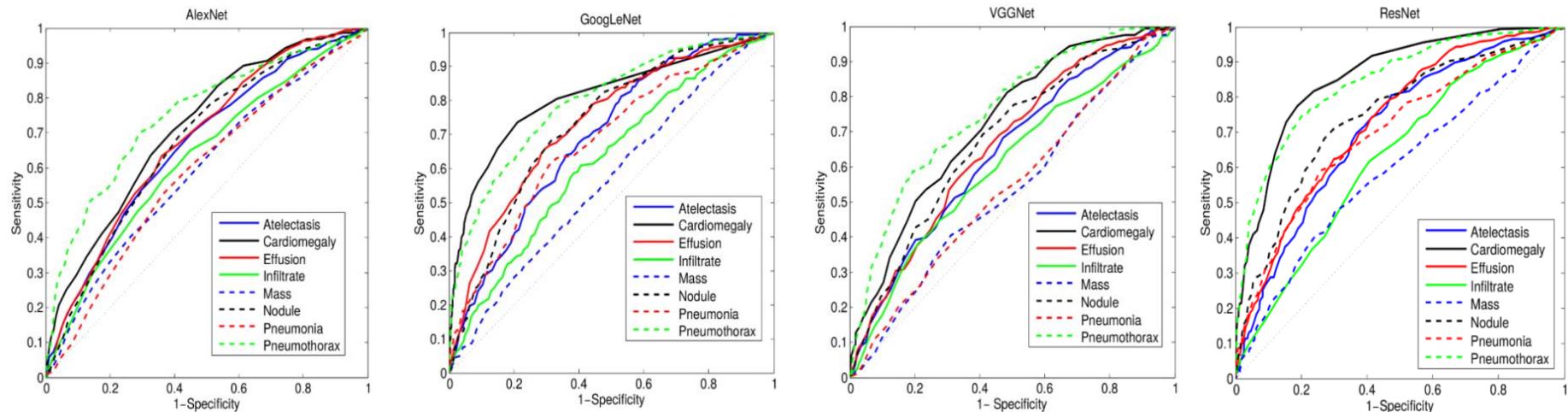
# Multi-label Classification and Localization Framework



# Experiment Setting

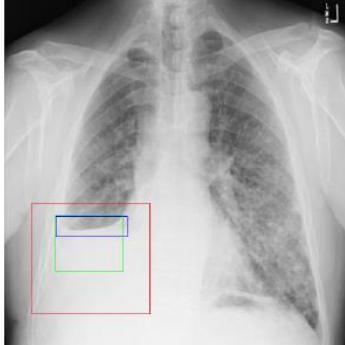
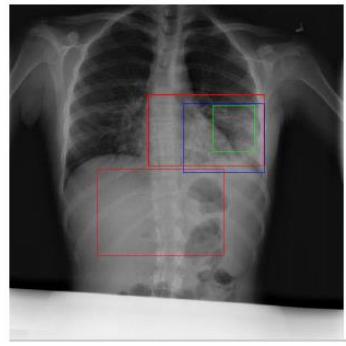
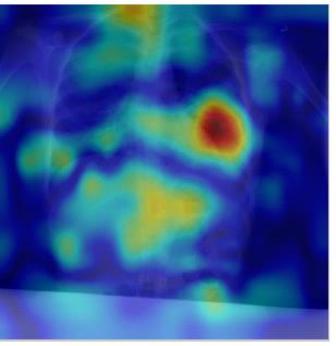
- Randomly shuffled the dataset into three subgroups: i.e. training (70%), validation (10%) and testing (20%)
- Multi-label CNN architecture is implemented using Caffe framework
- The ImageNet pre-trained models, i.e., AlexNet, GoogLeNet, VGGNet-16 and ResNet-50 are obtained from the Caffe model zoo
- Due to the large image size and the limit of GPU memory, reduce the image batch size while increasing the iter size to accumulate the gradients. We set batch size \* iter size = 80

## Multi-Disease Classification Results



Setting	Atelectasis	Cardiomegaly	Effusion	Infiltration	Mass	Nodule	Pneumonia	Pneumothorax
Initialization with different pre-trained models								
<b>AlexNet</b>	0.6458	0.6925	0.6642	0.6041	<b>0.5644</b>	0.6487	0.5493	0.7425
<b>GoogLeNet</b>	0.6307	0.7056	0.6876	0.6088	0.5363	0.5579	0.5990	0.7824
<b>VGGNet-16</b>	0.6281	0.7084	0.6502	0.5896	0.5103	0.6556	0.5100	0.7516
<b>ResNet-50</b>	<b>0.7069</b>	<b>0.8141</b>	<b>0.7362</b>	<b>0.6128</b>	0.5609	<b>0.7164</b>	<b>0.6333</b>	<b>0.7891</b>
Different multi-label loss functions								
<b>CEL</b>	0.7064	0.7262	0.7351	0.6084	0.5530	0.6545	0.5164	0.7665
<b>W-CEL</b>	0.7069	0.8141	0.7362	0.6128	0.5609	0.7164	0.6333	0.7891

Table 3. AUCs of ROC curves for multi-label classification in different DCNN model setting.

Radiology report	Keyword	Localization Result	
findings: no appreciable change since XX/XX/XX. small right pleural effusion. elevation right hemidiaphragm. diffuse small nodules throughout the lungs, most numerous in the left mid and lower lung. impression: no change with bilateral small lung metastases.	Effusion; Nodule		
findings: unchanged left lower lung field infiltrate/air bronchograms. unchanged right perihilar infiltrate with obscuration of the right heart border. no evidence of new infiltrate. no evidence of pneumothorax the cardiac and mediastinal contours are stable. impression: 1. no evidence pneumothorax. 2. unchanged left lower lobe and left lingular consolidation/bronchiectasis. 3. unchanged right middle lobe infiltrate	Pneumonia; Infiltration		

\*Correct bounding box (in green), false positives (in red) and the ground truth (in blue)



# Case Study 3

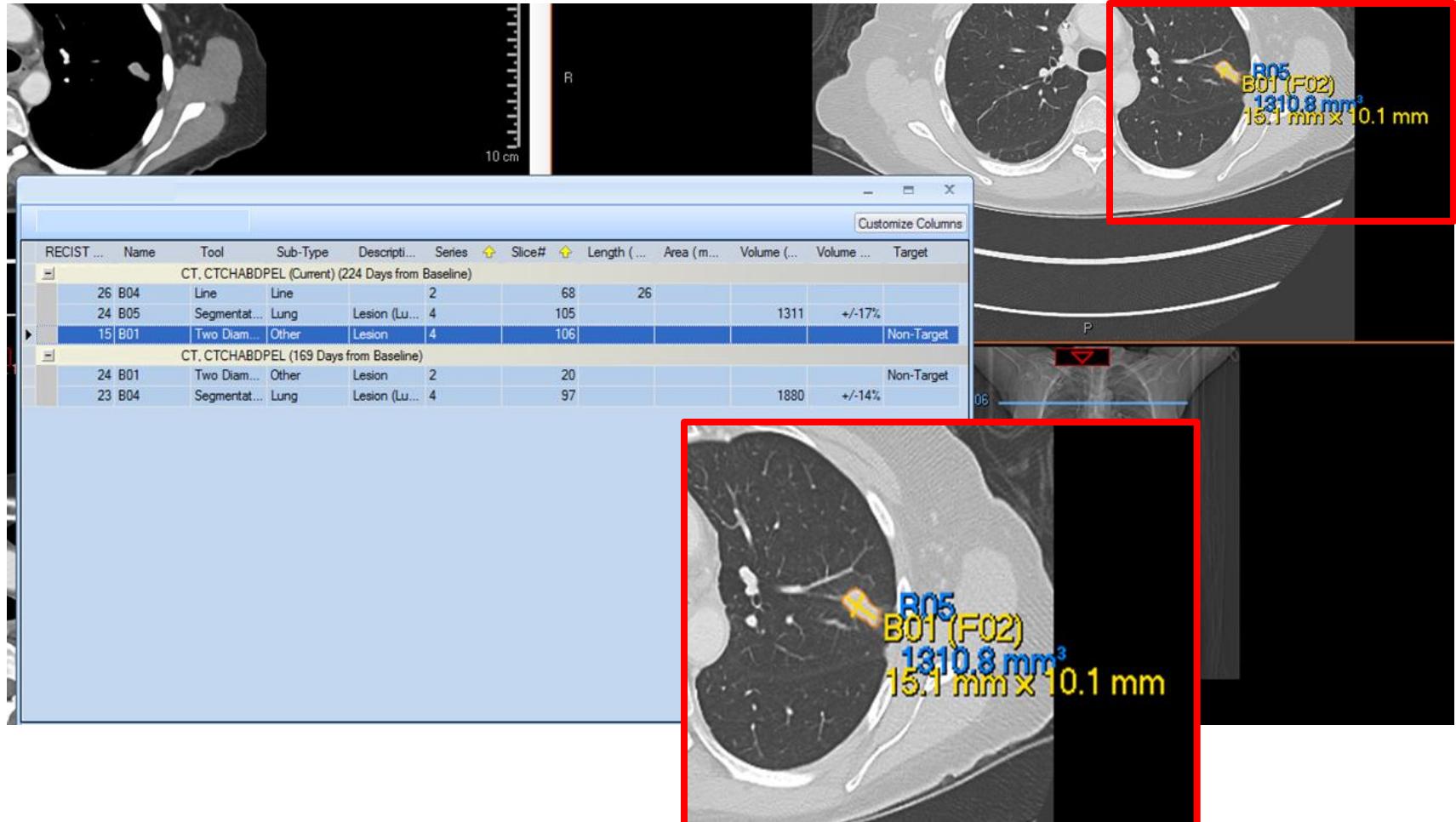
## Utilizing Clinical Annotation as Weak Supervision

X. Wang, K. Yan et al. DeepLesion: Automated Deep Mining, Categorization and Detection of Significant Radiology Image Findings using Large-Scale Clinical Lesion Annotations, RSNA 2017

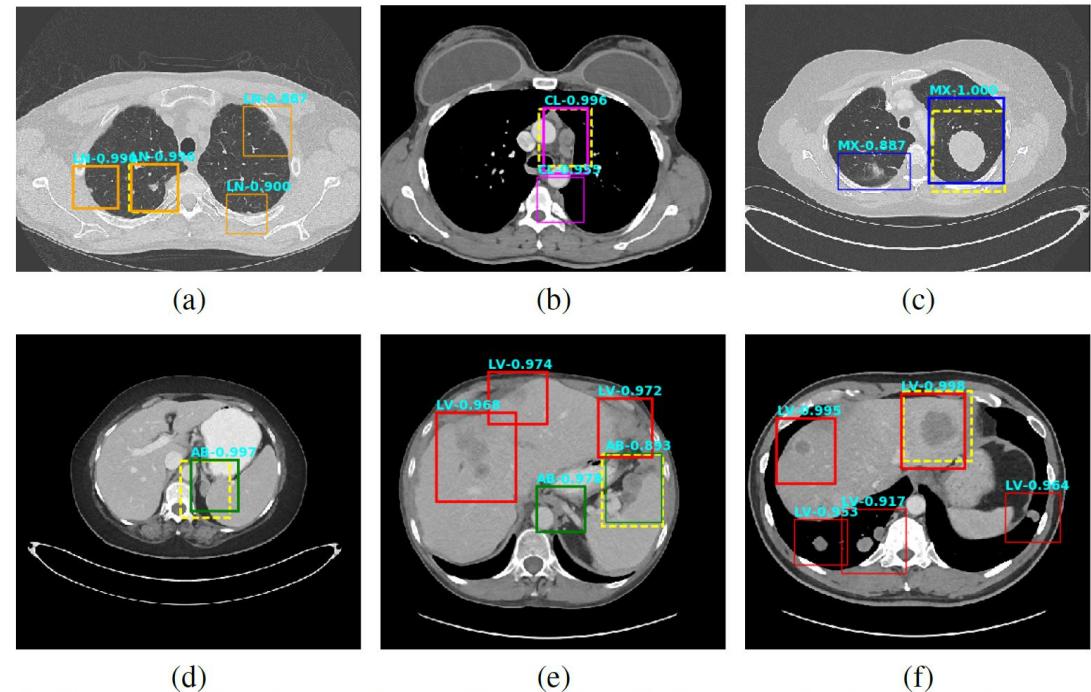
US Patent Application 62/514,223



# Clinical Annotation Data



- A new computer-aided detection paradigm with weak annotations mined from large scale retrospective clinical datasets.
- Different from traditional CADe system
- Multi-category multi-lesion detection in 3D volume
- Almost effortlessly from the workload perspective required for radiologists or human annotators.



**Fig. 4.** Six sample detection results are illustrated with the annotation lesion patches as yellow dashed boxes. The outputs from our proposed detection framework are shown in colored boxes with LiVer lesion (LV) in red, Lung Nodule (LN) in orange, ABdomen lesion (AB) in green, Chest Lymph node (CL) in magenta and other MiXed lesions (MX) in blue. (a) Four lung lesions are all correctly detected; (b) Two lymph nodes in mediastinum are presented; (c) A Ground Glass Opacity (GGO) and a mass are detected in the lung; (d) An adrenal nodule; (e) Correct detections on both the small abdomen lymph node near aorta but also other metastases in liver and spleen; (f) Two liver metastases are correctly detected. Three lung metastases are detected but erroneously classified as liver lesions.



# Conclusion

- It is time to dig into the enormous collection of clinical data sleeping in the PACS.
- Three attempts are demonstrated to utilize retrospective clinical data for building large scale quality-labeled datasets for data-hungry learning paradigms.
- Discussed methods could be applied on many hospital PACS system to mine various collections of data.
- By mining and sharing all these existing data, the medical image analysis and diagnosis could be improved significantly using cutting-edge machine learning techniques.

# **Special Issue at Machine Vision Applications (Springer)**

## **Learning and Understanding of Biomedical Big Data**

### **Scope:**

- Present state-of-the-art theories and novel applications in biomedical big data analysis;
- Survey the recent progress in this area;
- Build benchmark datasets.

### **Possible topics:**

- Biomedical Big Data Representation
- Biomedical Big Data Learning
- Biomedical Big Data Understanding and Applications

### **More details:**

<https://www.springer.com/computer/image+processing/journal/138>

Prepare according to the online submission  
requirements of “Machine Vision and  
Applications”

## Deadlines

- Submission Deadline: September 1, 2017
- First Review: November 3, 2017
- Revisions Due: December 22, 2017
- Final Decision: March 23, 2018
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## Questions?

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# THANK YOU!

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