Disclosures

• Patent royalties from iCAD, ScanMed, PingAn, Philips
• Research support from Ping An & NVIDIA
Fully-automated Small Bowel Segmentation

T Nguyen and RM Summers

http://www.youtube.com/watch?v=8rXxMAamhg8
Editorial

Ronald M. Summers, MD, PhD

Road Maps for Advancement of Radiologic Computer-aided Detection in the 21st Century
Quality Assurance
Correct Patient?
Study Done Correctly?
Old Comparisons Available?

Inspect Lungs and Pleura
Nodules?*
Infiltrates?*
Effusions? Pneumothorax?

Inspect Mediastinum and Hila
Masses?
Adenopathy?
Abnormal Vasculature (incl. P.E.)?*

Inspect Chest Wall
Axillary Adenopathy?
Bone Metastases?
Subcutaneous Nodules?

Global CAD Roadmap

Validation

Image Archive

Standards

Academic Societies and Industry

Product Development and PACS Integration

Researchers and Industry

Training

CME and Industry Seminars

Coordinated Funding

Foundations and Government

Summers RM, Radiology 2003
Opportunities

• Integration of lab results, omics, medical record
• Routine automated quantitation
• Triage and critical result monitoring
• Prognosis prediction
• Global health
• Opportunistic screening
Broad Scope of Applications

• Detection (Lung nodules, TB, Breast masses)
• Segmentation (organ & lesion volumetrics)
• Quantification and measurement (RECIST)
• Workflow optimization (CXR & ICH triage)
• Image reconstruction (Accelerated MRI)
• NLP of reports

Youbao Tang et al. MICCAI 2018
Radiation Oncology

- Organ & lesion segmentation for treatment planning
- Prognosis, response & staging
- Guidance for treating heterogeneous tumors
- Decision support for dose adaptation
- Dose distribution prediction
- Converting between modalities (MR ↔ CT)
Increases in Sensitivity with Deep Learning

6 – 17%  13%  34%

Colitis Detection

80 patients
80 controls

93.7% Sensitivity
95.0% Specificity
0.986 AUC
Pancreas Segmentation

H Roth et al., MICCAI 2016
Pancreas Segmentation

Bagheri et al., Academic Radiology 2019
Prostate Cancer Detection: Observer Study

Greer et al. Eur Radiol 2018

PI-RADS Score For Each Reader

<table>
<thead>
<tr>
<th>Reader</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>CAD</td>
<td>1</td>
<td>1</td>
<td>2</td>
<td>4</td>
<td>ND</td>
<td>2</td>
<td>4</td>
<td>ND</td>
<td>2</td>
</tr>
<tr>
<td>MRI</td>
<td>ND</td>
<td>ND</td>
<td>ND</td>
<td>3</td>
<td>3</td>
<td>ND</td>
<td>ND</td>
<td>ND</td>
<td>3</td>
</tr>
</tbody>
</table>

*ND = Not Detected

* *p<0.05
Reading Paradigms

- No reader (very time efficient)
- First reader (time efficient)
- Concurrent reader (balanced)
- Second reader (higher accuracy; time inefficient)
NIH Clinical Center provides one of the largest publicly available chest x-ray datasets to scientific community

The dataset of scans is from more than 30,000 patients, including many with advanced lung disease.
**ChestX-ray14**

### Image Sample cases

<table>
<thead>
<tr>
<th>A</th>
<th>B</th>
</tr>
</thead>
</table>

#### Original report

<table>
<thead>
<tr>
<th><strong>P</strong></th>
<th><strong>No finding</strong></th>
</tr>
</thead>
</table>

#### Findings:
- A single AP view of the chest demonstrates increasing bibasal interstitial opacities with decreased overall aeration. Increasing blunting of right costophrenic angle. Impression: increasing bibasal atelectasis with possible development of right pleural effusion.
- Normal no evidence of lung infiltrate.

#### Generated Report

<table>
<thead>
<tr>
<th><strong>findings:</strong></th>
<th><strong>pa and lateral views of the chest demonstrate lungs that are clear without focal mass, infiltrate or effusion</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>findings:</strong></td>
<td><strong>the cardiac and mediastinal contours are stable. Impression: no evidence of developing infiltrate.</strong></td>
</tr>
<tr>
<td><strong>findings:</strong></td>
<td><strong>the cardiomediastinal silhouette is normal size and contour. Pulmonary vascularity is normal in caliber and distribution. Impression: no evidence of acute pulmonary pathology</strong></td>
</tr>
</tbody>
</table>

---

**I + GR classification on ChestX-ray14**

- Atelectasis 0.732
- Cardiomegaly 0.844
- Effusion 0.793
- Infiltrate 0.666
- Mass 0.725
- Nodule 0.685
- Pneumonia 0.720
- Pneumothorax 0.847
- Consolidation 0.701
- Edema 0.829
- Emphysema 0.865
- Fibrosis 0.796
- Pleural_Thickening 0.735
- Hernia 0.876
- No finding 0.701

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X Wang et al. CVPR 2018
Domain Adaptation with Adversarial Networks

Yuxing Tang et al. MICCAI 2019
Deep Lesion Dataset

- 32,735 lesions
- 32,120 CT slices
- 10,594 studies
- 4,427 unique patients

Yan et al. JMI 2018; CVPR 2018; RSNA 2018
Automated Lesion Annotation

(i) Lesion #20994
TP: right kidney 0.9926
TP: cortex 0.9576
TP: hypodense 0.9405
TP: tiny 0.9375
FP: solid 0.9371
TP: kidney cyst 0.8896
TP: simple cyst 0.8326

(j) Lesion #12188
TP: external iliac lymph node 0.9929
FP: pelvic wall 0.9788
TP: lymphadenopathy 0.9018

Yan et al. CVPR 2019
(c) Expanded **right posterior rib** lesion

Posterior **left rib mass**

Right chest wall mass

Unchanged large **right 7th rib expansile mass**

(d) Complex **retroperitoneal mass** involving the region of the tail and body of the pancreas

Pancreatic tail mass

Centrally **hypoattenuating mass** within the pancreatic tail

Low attenuation pancreatic tail mass
Yan et al. MICCAI 2019

- "MULAN"
- lesion detection, tagging, and segmentation results on the test set of DeepLesion

Yan et al. MICCAI 2019
Comprehensive Spine Oncology Analysis

O’Connor et al. Radiology 2007; Yao et al. JMI 2017; Burns et al. JBMR 2020
Comprehensive Spine Fracture Analysis

Burns et al. Radiology 2017
Large-scale Body Composition Analysis

Challenges & Questions

- Interpretability / explainability
- Brittleness
- Domain shift
- Ethics / Trustworthy AI
Interpretability / Explainability

• Black-box algorithms
• Potential for bias
• Is it necessary?
• Saliency maps may not be accurate
• Many approaches including text explanations
Challenges & Questions

• Dataset annotation is expensive; how to do it much more cost-effectively?
• Multi-institutional data; how to get it?
• Radiologists can diagnose 1000’s of diseases; how to do this with ML?
• Radiologists can do “one-shot” learning, e.g., for rare diseases; how to do this with ML?
Conclusions

• Rapid developments in AI ➔ Exciting time for medical imaging research and patient care
• Practical clinical benefits in radiology expected
Deep learning in medical imaging and radiation therapy


Medical Physics 2019 [https://doi.org/10.1002/mp.13264]

Artificial Intelligence in Musculoskeletal Imaging: A Paradigm Shift

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A Road Map for Translational Research on Artificial Intelligence in Medical Imaging: From the 2018 National Institutes of Health/RSNA/ACR/The Academy Workshop

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JACR 2019 [https://doi.org/10.1016/j.jacr.2019.04.014]
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  - ISTP
  - IRTA
  - BESIP
  - CRTP
  - SIP

- Nvidia for GPU card donations
- CRADA with Ping An
To Learn More ...

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

github.com/rsummers11

X Wang et al. RSNA 2016