Automatic Identification and Classification of Tuberculosis Findings on Chest Radiographs for Global Surveillance Programs

TB or not TB....

L R Folio, DO, MPH (presenter)
National Institutes of Health (NIH), Clinical Center
Jenifer Siegelman, MD, MPH
Brigham and Women's Hospital, Boston, MA
Yi Xiang Wang MD
The Chinese University of Hong Kong, Hong Kong
P. X. Lu MD
Shenzhen No. 3 Hospital, China
Sameer Antani, PhD
National Library of Medicine, NIH
Stefan Jaeger, PhD
National Library of Medicine, NIH

Presenter Disclosures/ Disclaimer

- Potentially related
  - Issued patent on CT processing/ viewing method
  - Patent Pending on portable imaging inclinometer
  - Books published
    - Chest Imaging: An Algorithmic Approach to Learning
    - Combat Radiology
- Unrelated
  - Research agreement with Carestream Health
  - Patent Pending on CT compression to mp4

The content is solely the responsibility of the presenter and does not necessarily represent the official views of the National Institutes of Health

Background

- One third of world population infected with TB*
  - Countries with high TB incidence screen with CXR **
    - Many with disproportionally reduced number of radiologists

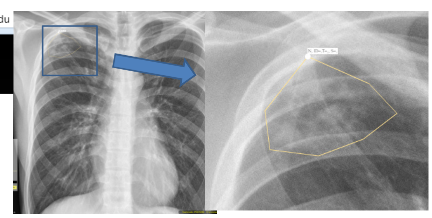
Purpose

- Develop automated TB classification algorithm
  - In addition to abnormality detection on chest x-ray
- Evaluate ability to detect and classify (future)
- Help curtail spread of tuberculosis internationally
  - With improved TB mass-screening and surveillance

* CDC Global Tuberculosis Elimination: http://www.cdc.gov/globalhealth/programs/tb.htm
** van Cleeff MR. The role and performance of chest X-ray for the diagnosis of tuberculosis: a cost-effectiveness analysis in Nairobi, Kenya. BMC Infect Dis. 2005 Dec

Methods

- Two radiologists identified abnormal findings
  - In 342 CXRs of patients with confirmed TB
    - From The Shenzhen No. 3 People's Hospital in China
  - Compared to normal CXR
  - Annotated each CXR on Firefly annotation tool*

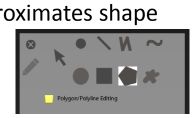


* firefly.cs.missouri.edu
University of Missouri

CXR Annotating Process

1. Identify and classify each abnormal finding
2. Choose drawing tool that approximates shape

   Polygon, circle, dot, etc.



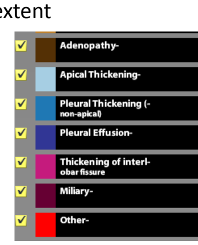
3. Outline each abnormality on the CXR

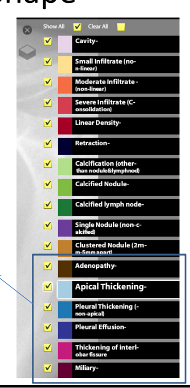
Radiologists applied intentional over-reading
– Advocated by the WHO Lime book*

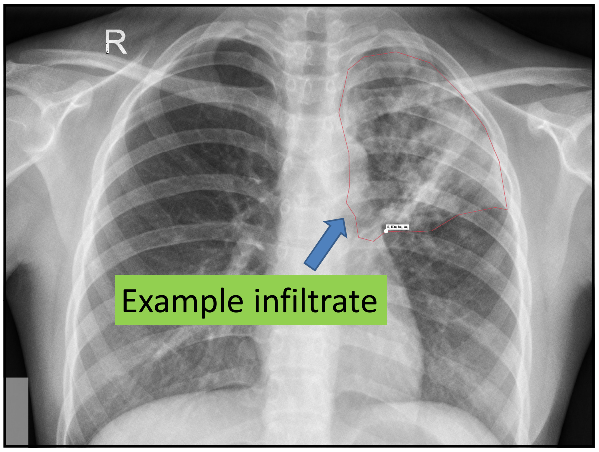
* **World Health Organization: Tuberculosis prevalence surveys: a handbook**
http://www.who.int/tb/advisory_bodies/impact_measurement_taskforce/resources_documents/thelimebook/en/

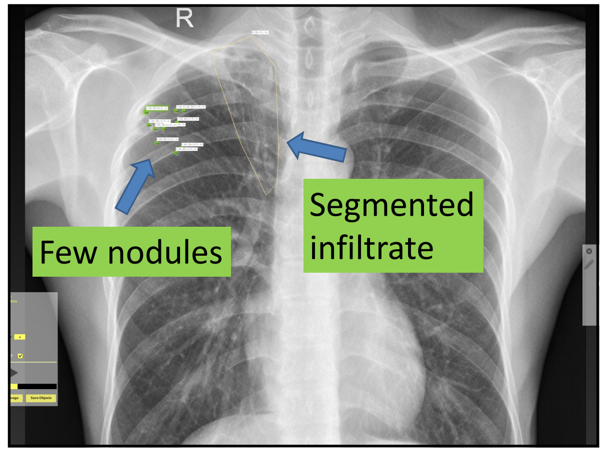
Finding Classification, Shape

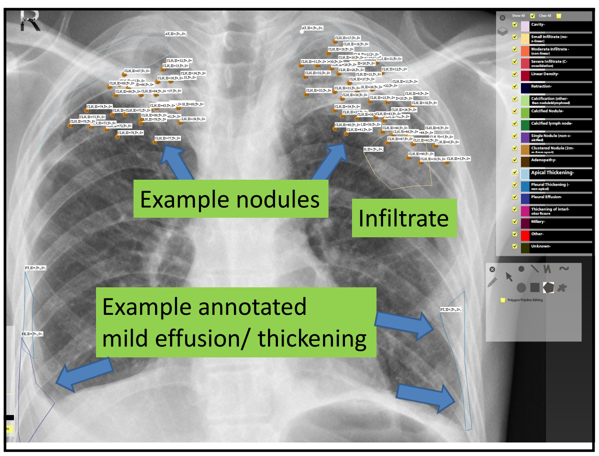
- Select one of 17 classifications
  - Nodule, infiltrate, cavity, etc.
  - Severities/ extent





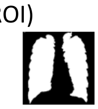






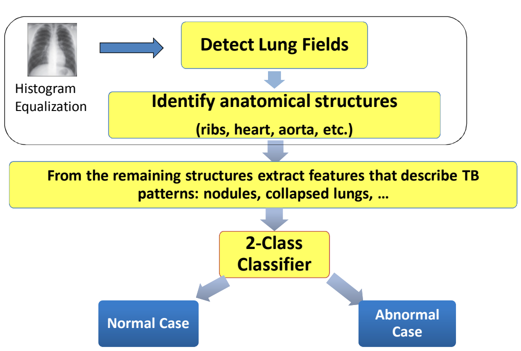
Automated Classification

1. Lung fields are segmented (identifies ROI)
   (image of lung outlined)



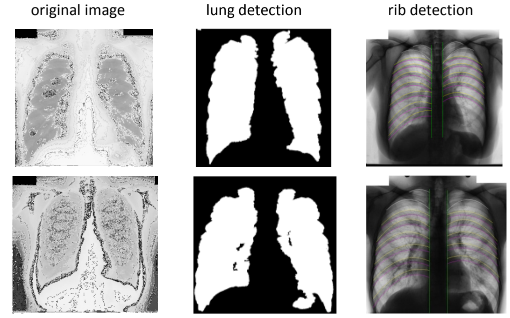
2. Features are computed within ROI
   Histogram analysis (i.e. nodules have peaks)
3. Feature vectors are classified (normal or not)
   TB or not TB is work in progress..

System Architecture



1. Lung Segmentation

original image lung detection rib detection



Candemir S, Lung segmentation in chest radiographs using anatomical atlases with nonrigid registration. IEEE Trans Med Imaging. 2014 Feb.

Methods: 2. Feature Computation

- Compute histogram-based texture features
  - Including histogram of gradients (HOG),
  - Local binary patterns (LBP) and other features
- Features concatenated into a single feature vector
  - i.e. String of numbers for each chest x-ray image
- Resulting strings are used to train and test linear support vector machine (neural network best)
- Classifier assessed by AUC through cross validation
  - Compared with same number of normal CXR's

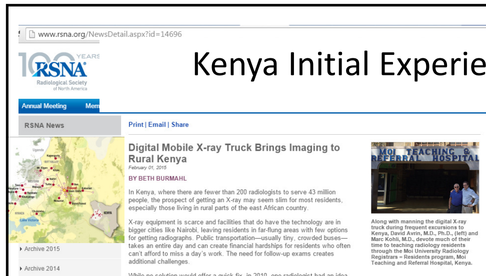
Results

- Radiologists labeled 1671 abnormal findings in 342 CXRs
- Our system classified CXRs as either normal or abnormal
  - With **95%** AUC (area under ROC curve)
  - Sensitivity and specificity is 99.76%
- Abnormalities are classified with variable accuracy;
  - Infiltrates were correctly classified in 90% of cases
  - Severity were correctly graded in 87% of cases
    - Consistently for both radiologists.
- Degree of similarity (Using feature-specific distance function)
  - between previously annotated regions and suspicious regions
    - in newly presented CXRs for interactive computer-aided diagnostics

Global Deployment Aims

- Prevents losing patients from rural clinics
  - Immediacy, minimizes disease spread, etc.
- Triage: severe patients get images read first
- Reduce radiologist footprint
  - from days to hours (since radiologists are scarce)
- Commonly two scenarios
  1. Patients without prior drug treatment
  2. Avoid drug incompatibilities in HIV infected

Kenya Initial Experience



- Automated system now in place in Africa
  - Associated with mobile/ portable x-ray in Kenya*

*X-ray Truck Visits Rural Kenya. RSNA News. Feb 2015.

Initial Field Results

- CXR on 40 patients per week
- Initial pilot suggests no false negatives
  - Similar rate of published over-reading**

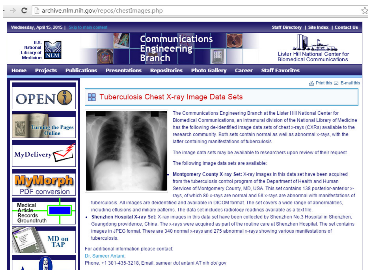


* Jaeger S. et al. Automatic tuberculosis screening using chest radiographs. IEEE Trans Med Imaging. 2014 Feb

Significance of Conclusions

- Potential for automated TB identification/ classification
  - Based on our pilot radiologist /automation comparison
- Current prototype discerns abnormalities in 95%
- Our resultant statistics provide clues
  - To frequency/ common locations of TB manifestations
- Help establish TB / HIV screening in developing regions
  - Per WHO recommendations

- Images now available on line*
- Segmented dataset will soon be available
- Labeling: looking for volunteer radiologists



* http://www.ncbi.nlm.nih.gov/pmc/articles/PMC4256233/
https://ceb.nlm.nih.gov/repos/chestImages.php

Thank you….

Les.Folio@nih.gov

Acknowledgements

- This research was supported in part by the Intramural Research Program of the National Institutes of Health (NIH), National Library of Medicine (NLM), and Lister Hill National Center for Biomedical Communications (LHNCBC).
- Thanks to Sema Candemir, PhD
  - for lung segmentations

References

- Candemir S, Jaeger S, Palaniappan K, Musco J, Singh RK, Xue Z, Karargyris A, Antani SK, Thoma GR, McDonald CJ. Lung segmentation in chest radiographs using anatomical atlases with nonrigid registration. IEEE Trans Med Imaging. 2014 Feb;33(2):577-90. doi: 10.1109/TMI.2013.2290491. Epub 2013 Nov 13.

- TB Screening:
- Jaeger S, Karargyris A, Candemir S, Folio L, Siegelman J, Callaghan FM, Xue Z, Palaniappan K, Singh RK, Antani SK, Thoma GR, Wang Y, Lu P, McDonald CJ. Automatic tuberculosis screening using chest radiographs. IEEE Trans Med Imaging. 2014 Feb;33(2):233-45. doi: 10.1109/TMI.2013.2284099. Epub 2013 Oct 1.

Jaeger S, Karargyris A, Candemir S, Siegelman J, Folio L, Antani S, Thoma G, McDonald CJ.
Automatic screening for tuberculosis in chest radiographs: a survey. Quant Imaging Med Surg 2013;3(2):89-99.

 www.amepc.org/qims Quant Imaging Med Surg 2013;3(2):89-99

Table 1 Comparison table of TB detection methods

	Preprocessing methods	Texture features	Geometry features	Classification	Dataset (# images)	Accuracy	TB manifestation
Noor (57)		Daubechies Wavelet Coefficients		Clustering			All
Xu (58)		LBP, HOG, GICOV & KLD	Template matching & Circularity	SVM	35	82.8%	Cavities
Song (59)	Rib detection with curve fitting and rules		Curve fitting		200	85%	Focal TB
Maduskar (26)	Bone suppression	Intensity moments of Gaussian derivatives	Relative position within lung	kNN	1,765		All
Rijal (60)		Phase Congruency & statistical measures		Euclidean distance	100	100%	All
Leibstein (61)	High-pass FFT filter & rib suppression	LBP & LoG					Nodules
Koeslag (62)			Template matching on Fourier domain	Hard threshold	120	94%	Miliary
Sarkar (63)	Detection of anatomical structures using intensity profile & local contrast enhancemen		Size	Adaptive threshold			Infiltration & Cavitation
Le (64)	A rule-based Watershed segmentation to detect lung fields	Average and maximal grey levels of pixels in a moving window		Local threshold			Nodules
Hariharan (65)	Clustering to perform lung segmentation & Fuzzy-based contrast enhancement						
Noor (3)		12 texture measures on the Daubechies Wavelet coefficients		PCA, probability ellipsoids & discriminant functions	100	94%	All
Shen (18)	Predefined mask to segment lungs	GICOV	Circularity	Bayesian	131	82.35%	Cavities
Tan (66)	Semi-automatic lung segmentation	Mean, Variance, Entropy & Third moment		Decision tree	95	94.9%	All
Arzhaeva (67)		Central moments		LDC& voting		42-95%	All
Lieberman (68)		Central moments			1,200		All
Jaeger (48)	Histogram equalization & statistical lung shape model	Intensity, LBP	Hessian shape features	SVM	138	83% (AUC)	All

LBP, Local Binary Pattern; HOG, Histogram of Oriented Gradients; GICOV, Gradient Inverse Coefficient Of Variation; KLD, Kullback–Leibler divergence; SVM, Support Vector Machine; kNN, k-nearest neighbor; LoG, Laplacian of Gaussian; PCA, Principal Component Analysis; LDA, Linear Discriminant Classifier; AUC, Area under ROC curve

Quantitative Imaging in Medicine and Surgery, Vol 3, No 2 April 2013 95