Research on digital health for designing scalable pervasive healthcare monitoring, rehabilitation, and home-based healthcare systems

**Improving Tuberculosis Diagnostics using
Deep Learning and Mobile Health Technologies
among Resource-poor Communities in Peru**

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Disclosure

I have no actual or potential conflict of interest in relation to this presentation.

Tuberculosis (TB)

- Infectious disease which remains a major cause of death globally.
- Affects the **most disadvantaged populations** and involves complex treatment regimes.
- **10.4 million** new cases every year.
- 60% of the cases occurred in six countries: India, Indonesia, China, Nigeria, Pakistan and South Africa.
- 95% of the deaths occurred in countries with low and middle income.

TB in Peru

- Highest incidence per capita in the Americas.
- High incidence of virulent multi-drug resistant infection.
- It is reducing 1.5% a year, slightly slower than globally (1.65%).
- The reduction needs to increase to 4-5% in order to ending epidemics of TB by 2030.
- The TB diagnosis delay is one of the main factors to the spreading.
- The mHealth Technologies and Deep Learning algorithms could reduce the delays.

Barriers

1. Lack of large-scale, real-world, well annotated and public x-ray image database dedicated to automated TB screening.
2. Lack of mobile devices-based computing system that can offer accurate diagnosis by analysing TB x-rays images.

mHealth

Challenge

Lack of large scale, well-annotated, real-world X-ray Image Dataset

Lack of mobile device-based computing system

Solution!

- * International research team
 - * Clinical and research collaborators
 - * Develop Annotation software

- * Develop a Mobile-cloud system
 - * Deep learning model Training in cloud server

System Overview

- **Mobile Application**

- Image Capturing and Data Transmission

- **Cloud Server**

- X-ray Image Annotation
 - Deep Learning (CNN)-based Data Analytics

Datasets

- ImageCLEF, JSRT Digital Image Database, ANODE Grand Challenge Database
 - Not dedicated for TB diagnostics.
 - Only one or two TB manifestations.
 - Contains manifestations that are not related with TB.
 - Less than 200 images per dataset
- Our dataset (developing)
 - Images provided by the **Peru – Partners in Health¹**.
 - So far, 4701 images (4248 with TB manifestations)
 - For each image is informed the occurrence of the TB manifestations.

¹ <http://www.pih.org/country/peru>

Sample of Manifestations

- (a) Air space consolidation which showing glass opacity with consolidation in the right middle lobe;
- (b) Miliary pattern with seed-like appearance;
- (c) Cavity located at the lower lobe (annotated by arrows);
- (d) Pleural effusion, which is excess fluid that accumulates in the pleural cavity;
- (e) Calcified granulomata: The red arrow indicates a large 5 cm diameter squamous cell carcinoma of the right lower lobe and there is 1.5 cm bright opacity in the middle of the mass (which is a calcified granuloma). Additional calcified granulomatous areas are medial to the mass, as indicated by blue arrow.

TB Manifestations in Our Dataset

1. Alveolar Infiltrates (47.90%)
 2. Interstitial Pattern (47.16%)
 3. Lymphadenopathy (41.82%)
 4. Cavitation (25.14%)
 5. Consolidation (9.63%)
 6. Pleural Effusion (9.29%)
 7. Ghon Focus (0.57%)
 8. Miliary Disease (0.53%)
- One x-ray may contain more than one manifestation at the same time.

Proposed Computational Model

- Extraction of region proposal
- Compute CNN features
- Region Classification
- TB manifestation recognition

ROI Annotations

- To train the classifier with the exactly position of the manifestations, we need a specialized annotation of a pulmonologist.

Annotation Software (1/2)

TB Project Annotation

About your collaboration:

You annotated 5 images. We need 145 more from you (3.33%)
We still have 1170 remaining annotations to get this cycle done.

Welcome,
[Sign Out](#)
[Change Password](#)

Polygons in this image (3)

[Hide all polygons](#)

Drag a tag on top of another one to create a part-of relationship.

- [Airspace Consolidations](#)
- [Airspace Consolidations](#)
- [Cavitation](#)

Get New
Image

Skip
Image

About this annotating cycle: Cavitation

Below you may check some information which you can use as support for your annotation.

Source: Peru collaborators dataset

Film Quality	: Suboptimal
Technique	: PA
Diagnosis	: Abnormal
Suspicious findings for TB	: Cavitation
Airspace Consolidations	: Bilateral
Interstitial Pattern	: Bilateral
Lymphadenopathy	: Yes
Pleural Effusion	: None
Suspicious for TB	: Yes

Annotation examples using curry manual images performed by Dr. Bernardo:

Annotation Software (2/2)

The annotation software uses parts of the Label Me Tool 3.0 open source code.
Available in: <http://labelme.csail.mit.edu/>

Proposed Approach: Deep Learning (CNN) Model Structure

- Input
- Convolutional Layer
- Sub-sampling/Pooling Layer
- Fully-connected Layer
- Output

Proposed Approach: Training Strategy

- Dataset
 - ImageNet (millions of images)
 - X-ray TB image datasets(~4700 images)
- Caffe + Cuda 6.5
 - Model Zoo(publicly released)
 - GPU accelerating, Nvidia K80
- Pretrain + finetune
 - GoogLeNet Model on ImageNet
 - Finetune on our TB datasets

Experimental Result (1/2)

- Dataset: 4701 images from Peru
- Two categories: Abnormal(4248 images) vs Normal (453 images)
- Convolutional Neural Network(CNN)
 - GoogLeNet Model
 - Pre-trained on ImageNet, fine-tuned on our X-ray dataset
 - Binary classification: 4/5 of the images for training, 1/5 of the images for testing

# of iteration	10,000	30,000	50,000	80,000	100,000
Average precision	82.8%	88.6%	89.0%	89.5%	89.6%

Table1: Average Precision for binary classification

Experimental Result (2/2)

- Dataset: 4701 images from Peru
- Four categories, Same training strategy

Category(TB Manifestation)	Total Image #	Image # Used for Training	Image # Used for Testing
Cavitation	1182	946	246
Lymphadenopathy	202	162	40
Infiltration	2252	1802	450
Pleural Effusion	560	448	112

Table2: Data distribution for different TB manifestation

# of iteration	10,000	30,000	50,000	80,000	100,000
Average precision	43.48%	61.68%	61.92%	62.05%	62.07%

Table3: Average Precision for multi-class classification

Future Steps (1/3)

- Continue to develop the large scale, real-world X-ray TB database.
- Improve the classification accuracy for the deep learning computational models.
- Implement a scalable solution by making the mobile device based system available as an open source platform.
- Conduct field-testing in tuberculosis clinics in Peru in a Pilot Study.

Future Steps (2/3)

■ Pilot Study

Future Steps (3/3)

- Classifier Accuracy
 - We will compare the manifestations found automatically with the manifestations found by the Physician.
- Usability of the Mobile Software
 - We will analyze the impact of a mHealth in the work of Nurses and Physicians.
- Speed of the Diagnosis
 - We will compare the speed to a patient receive TB diagnosis in comparison with the regular waiting time (using the physical x-ray).

Conclusion (1/2)

- Currently, TB remains as one of the world's deadliest diseases.
- The mHealth might assist the TB diagnosis mainly among resource-poor communities.
- The lack of lungs x-rays images affect the development of a good software to automatic or aided diagnosis.
- The annotation software is a good alternative to get a reliable position of the TB manifestations.

Conclusion (2/2)

- Mobile technologies have the potential to reduce the burden of TB for better diagnosis.
- Deep learning technology, especially CNN, can further improve the classification accuracy of X-ray images.
- Our integrated system can reduce the diagnosis time, within resource-poor and marginalized communities.

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Q&A

Thank you!