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

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

UMCCTS 7th Annual Research Retreat

Marlon F. Alcantara
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.
Learning with Purpose

**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 Health**¹.
  - 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](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. (23.3%)
We still have 1,170 remaining annotations to get this cycle done.

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

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:
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

<table>
<thead>
<tr>
<th># of iteration</th>
<th>10,000</th>
<th>30,000</th>
<th>50,000</th>
<th>80,000</th>
<th>100,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average precision</td>
<td>82.8%</td>
<td>88.6%</td>
<td>89.0%</td>
<td>89.5%</td>
<td>89.6%</td>
</tr>
</tbody>
</table>

Table 1: Average Precision for binary classification
**Experimental Result (2/2)**

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

<table>
<thead>
<tr>
<th>Category (TB Manifestation)</th>
<th>Total Image #</th>
<th>Image # Used for Training</th>
<th>Image # Used for Testing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cavitation</td>
<td>1182</td>
<td>946</td>
<td>246</td>
</tr>
<tr>
<td>Lymphadenopathy</td>
<td>202</td>
<td>162</td>
<td>40</td>
</tr>
<tr>
<td>Infiltration</td>
<td>2252</td>
<td>1802</td>
<td>450</td>
</tr>
<tr>
<td>Pleural Effusion</td>
<td>560</td>
<td>448</td>
<td>112</td>
</tr>
</tbody>
</table>

Table 2: Data distribution for different TB manifestation

<table>
<thead>
<tr>
<th># of iteration</th>
<th>10,000</th>
<th>30,000</th>
<th>50,000</th>
<th>80,000</th>
<th>100,000</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average precision</td>
<td>43.48%</td>
<td>61.68%</td>
<td>61.92%</td>
<td>62.05%</td>
<td>62.07%</td>
</tr>
</tbody>
</table>

Table 3: 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.
- Pilot Study

**Future Steps (2/3)**

- **Processing**: Nurse takes X-ray picture.
- **Analysis**: Analysis of X-ray picture.
- **Analysis deidentified**: Feedback deidentified.
- **Storage**: Feedback stored.

**TB Clinic**: Patient gets physical x-ray.

**Hospital**: Physician receives diagnostic/treatment.

**Our Server**: Processed data.

**Diagnose / Treatment**: Nurse, Hospital, Physician, Our Server.
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).
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.
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.
Acknowledgement

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Thank you!