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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
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
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 (1.33%)
We still have 1170 remaining annotations to get this cycle done.

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.
Future Steps (2/3)

- **Pilot Study**

  - TB Clinic
  - Patient
  - Physical x-ray
  - Nurse
  - X-ray picture
  - Hospital
  - Diagnostic / Treatment
  - Physician
  - Analysis
  - Analysis deidentified
  - Our Server
  - Processing
  - Feedback deidentified
  - Storage
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.
This project is supported in partial by

Q&A

Thank you!