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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, sighly 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

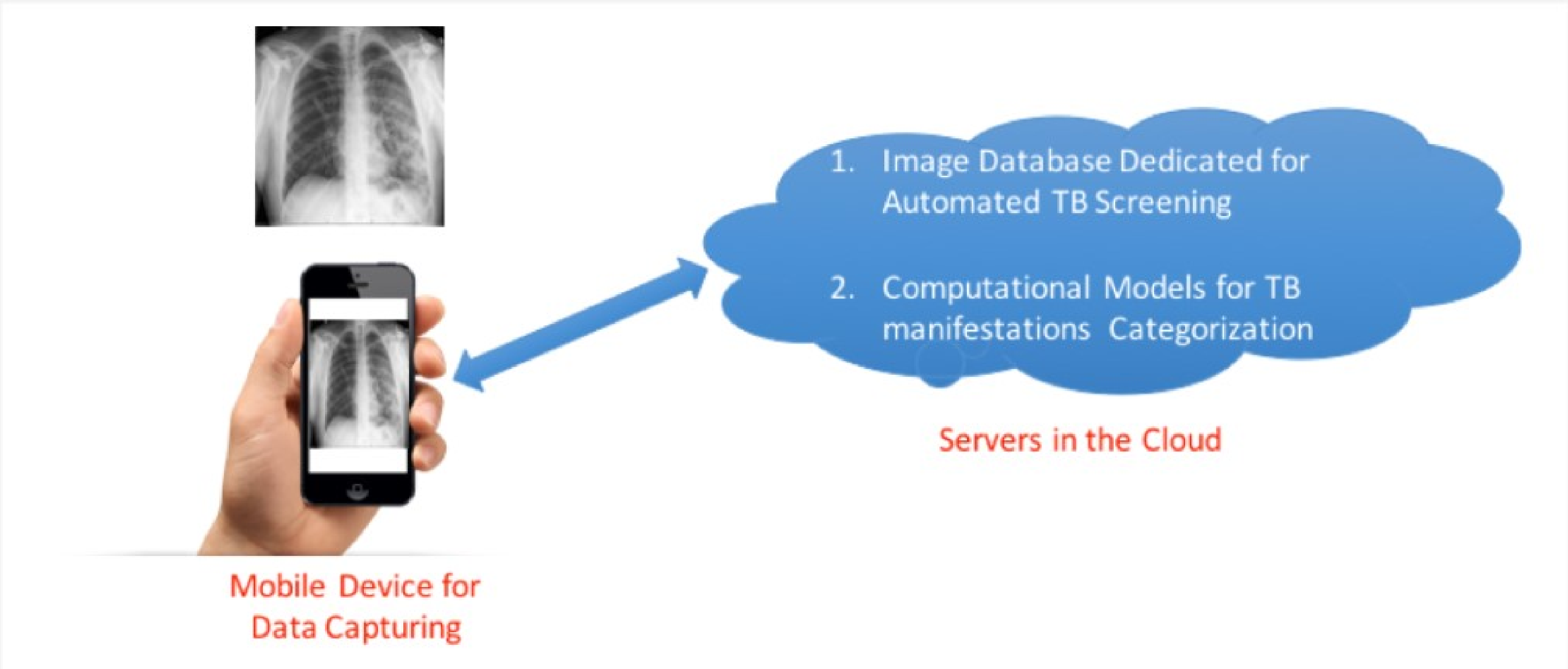
Lack of mobile device-based computing system

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

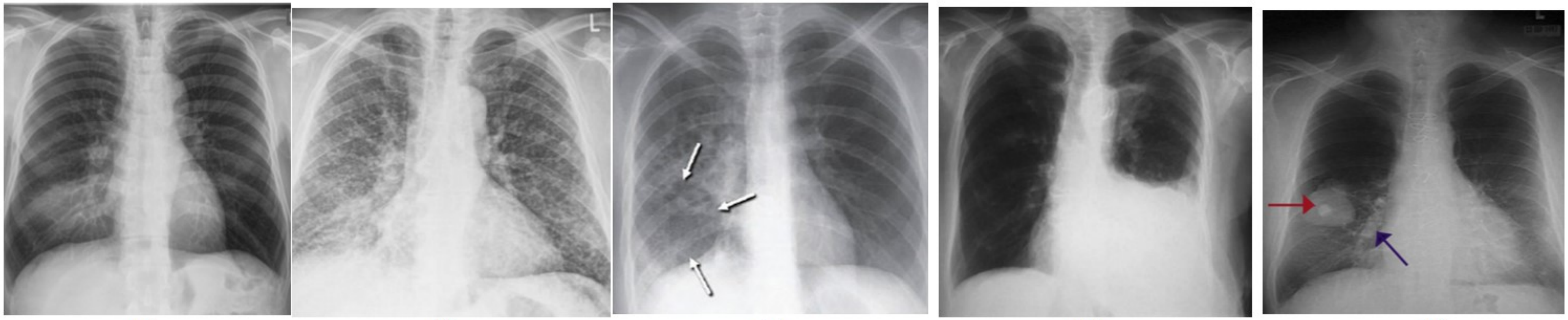
Datasets

- 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 Health[1].**
  - So far, 4701 images (4248 with TB manifestations)
  - For each image is informed the ocurrence of the TB manifestations.

[1] http://www.pih.org/country/peru

Sample of Manifestations



(a) (b) (c) (d) (e)

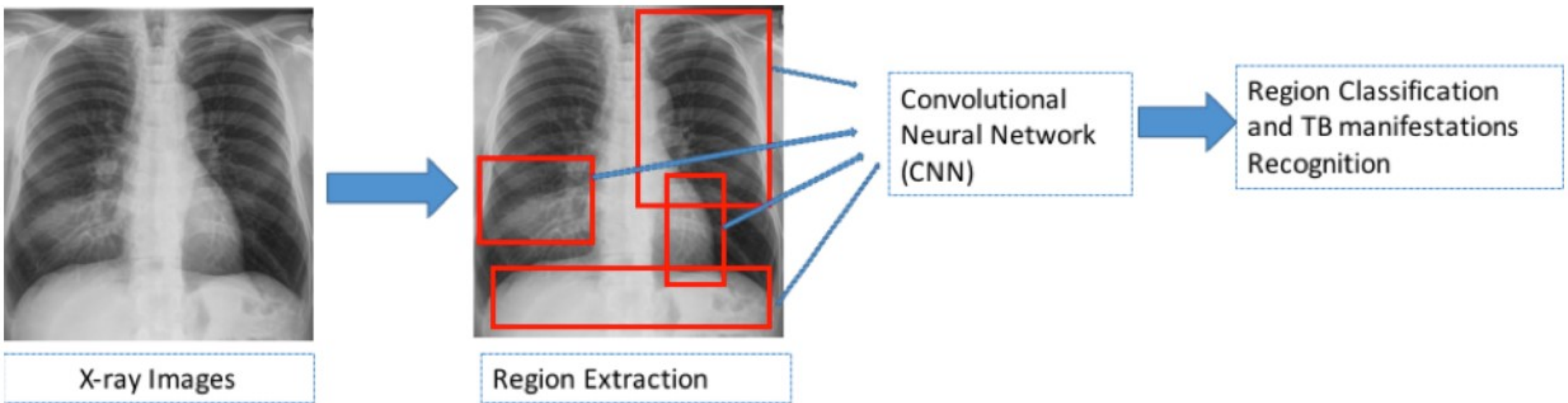
- (a) Air space consolidation which showing glass opacity with consolidation in the right middle lobe;
- (b) Miliary pattern with seed-like appearance;
- (c) Cavity located at the lower lobe (annotated by arrows);
- (d) Pleural effusion, which is excess fluid that accumulates in the pleural cavity;
- (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.

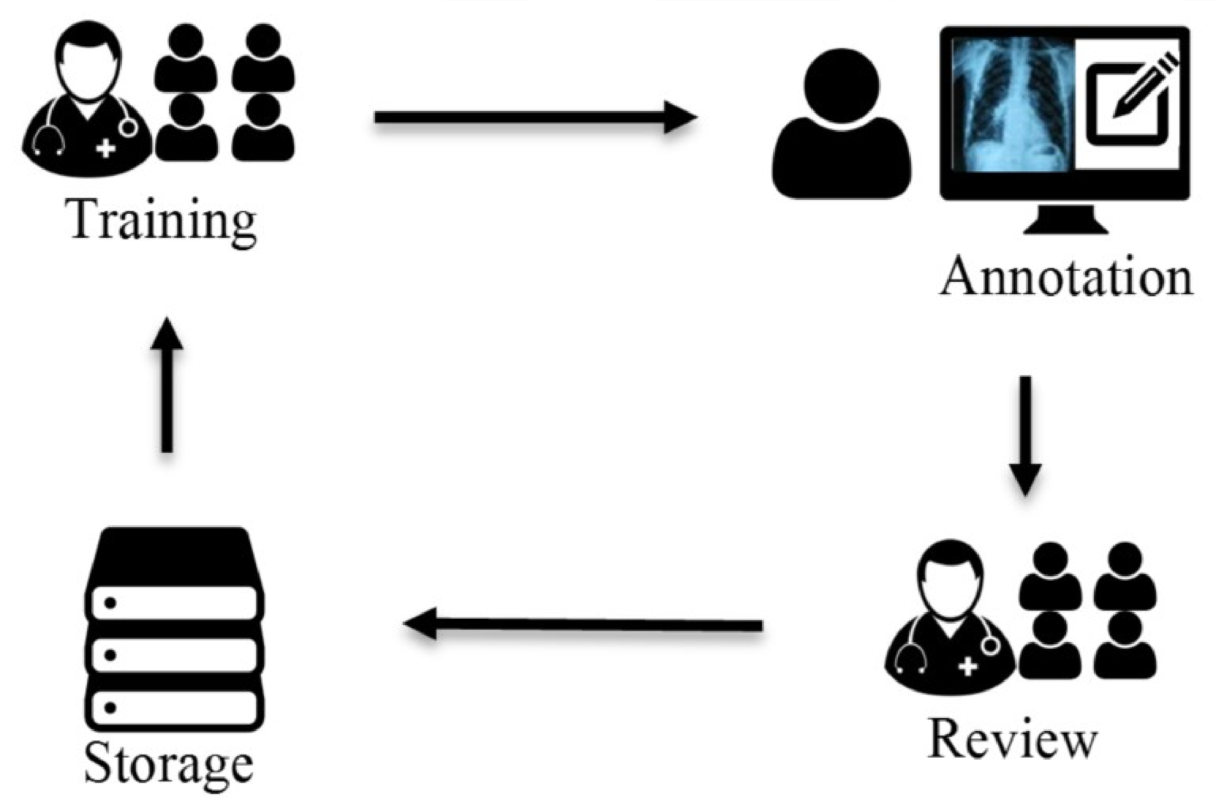
Proposed Computational Model



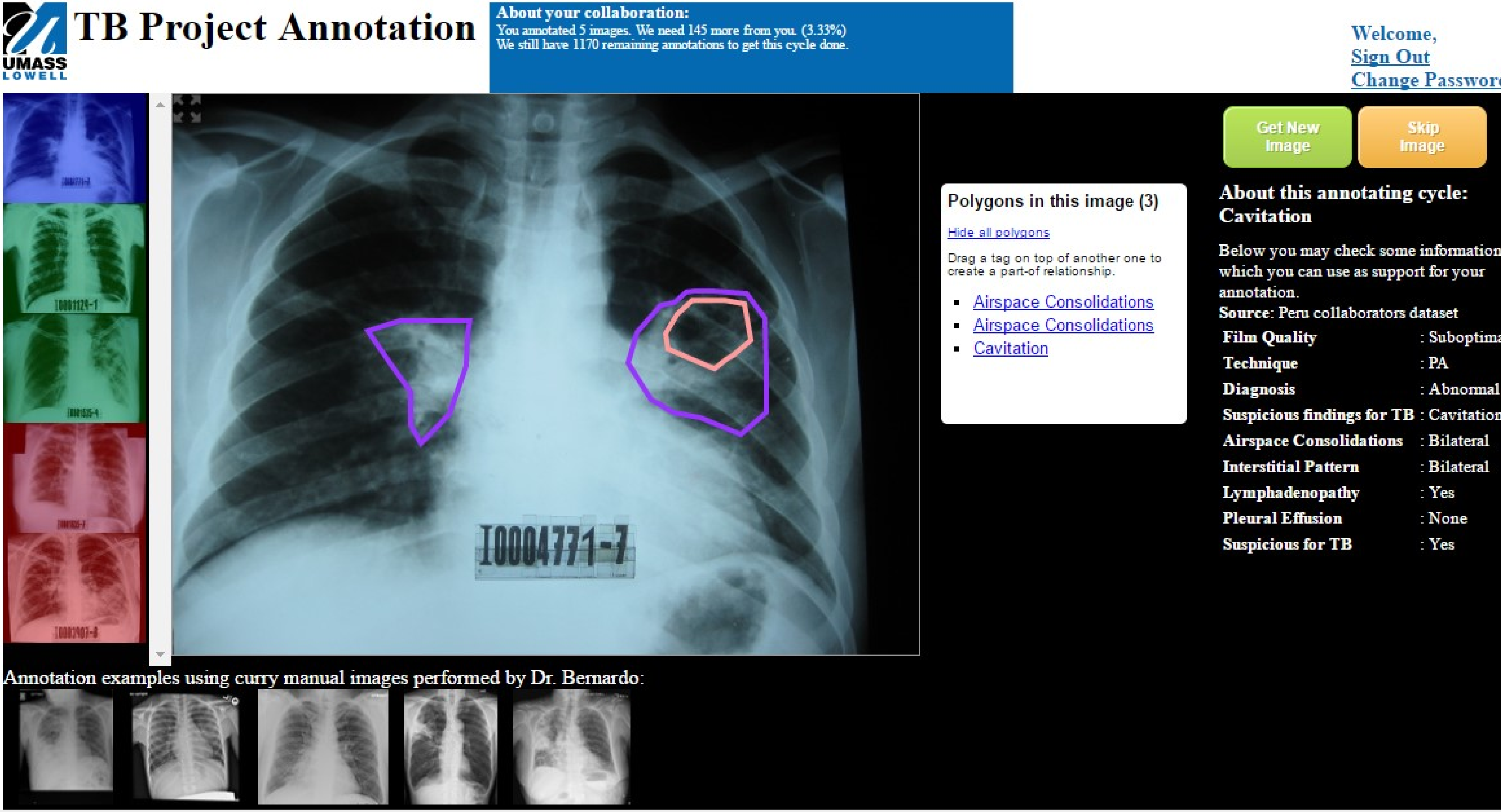
- Extraction of region proposal
- Compute CNN features
- Region Classification
- TB manifestation recognition

ROI Annotations

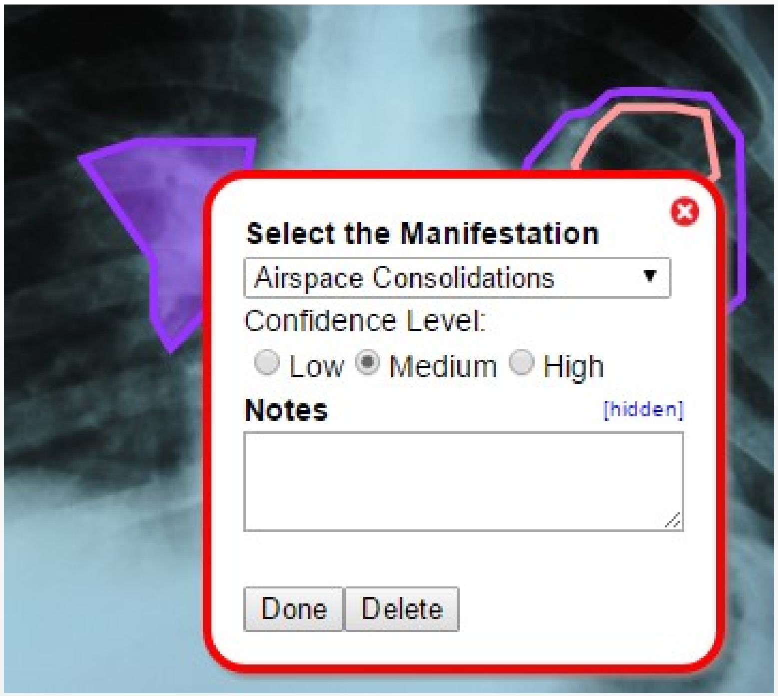
- To train the classifier with the exaclty position of the manifestations, we need a specialized annotation of a pulmonologist.

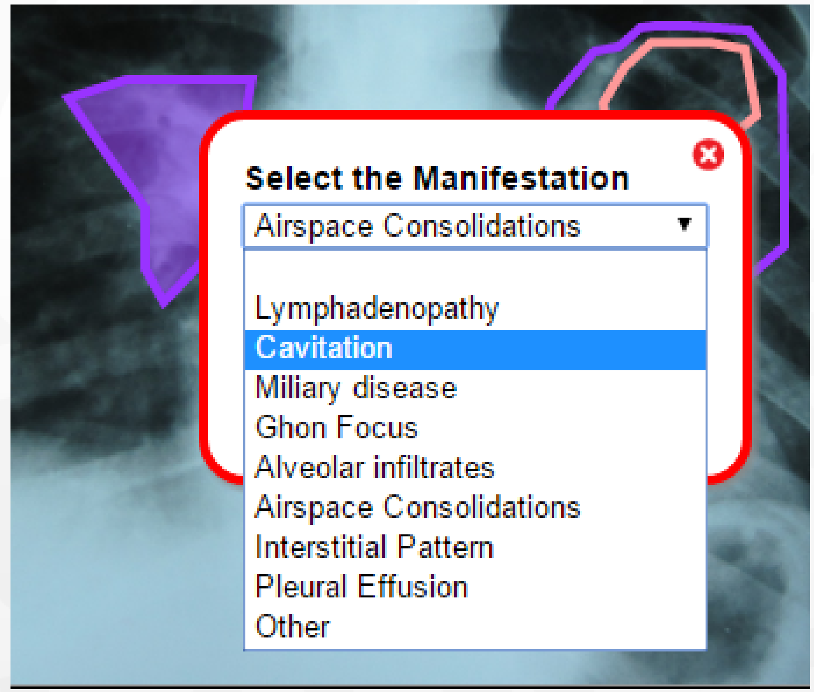


Annotation Software (1/2)



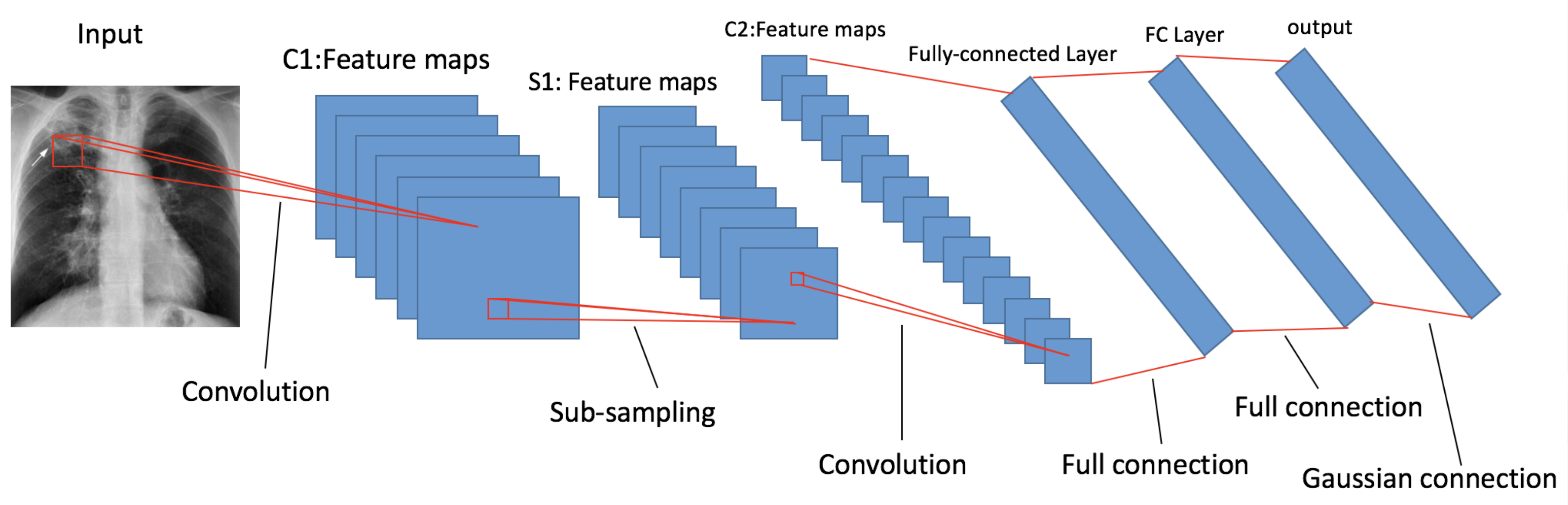
Annotation Software (2/2)





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%

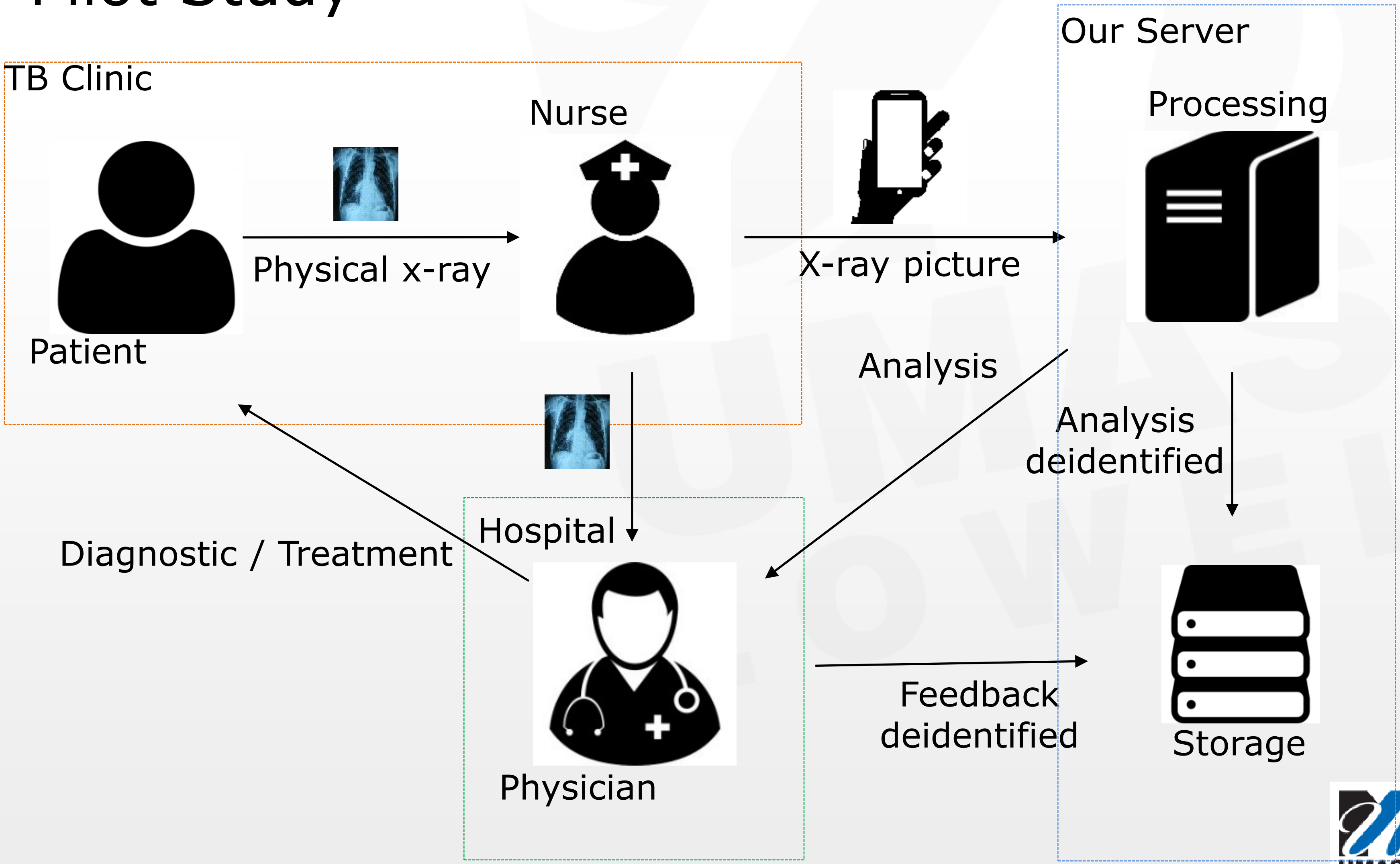
Table3: Average Precision for multi-class classification

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.

Acknowledgement

- *This project is supported in partial by*
  - *NSF/NIH Smart and Connected Health Program:* SCH:INT:A Sociotechnical Systems approach for Improving Tuberculosis Diagnostics Using Mobile Health Technologies, $1.29M, 2015-2019, PIs: Prof. Yu Cao, Benyuan Liu, and Maria Brunette

Q&A

Thank you!