Automatic Tuberculosis Detection Using Chest X-ray Analysis With Position Enhanced Structural Information

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Facts, Medical solutions
Data, Digital solutions
System description, Motivation, Details
Feature extraction, Test protocols, Results
Introduction
Facts about Tuberculosis

▶ One of the major life threats (WHO, 2019)
▶ Caused by the Mycobacterium Tuberculosis
▶ Affects lungs, brain, kidneys and spine
▶ Africa and southeast Asia are the most affected
▶ Mortality rate of 1.5 million/year
▶ 9.6 million people developing the disease/year
Medical Solutions to Detect Tuberculosis

Detection:
- Sputum smear microscopy
- Culture methods
- Chest x-ray (CXR) interpretation by radiologists

Problems:
- Elevated medical costs
- Lack of trained personnel
- Unreliable human readings (fatigue, visual impairment)
- Mass screening is difficult
Digital Solutions to Detect Tuberculosis

Solutions:
- Image feature based classification
- Automatic feature based classification

Problems:
- Lack of large data collections
- Adaptability issues for out-of-scope data
Related Work
Data

Montgomery collection:
- Montgomery county DHHS
- Size: 1000x1200 pixels (in average)
- 138 lung images (80 healthy, 58 unhealthy)
- Manually annotated (by radiologists)

Shenzhen collection:
- Shenzhen Hospital in China
- Size: 4020x4892 pixels (in average)
- 676 lung images (342 healthy, 334 unhealthy)
- Manually annotated (by radiologists)
Related Work

Jaeger et al.[4]:
- Lung segmentation (graph cut approach)
- Features extraction (HOG, LBP, CH, IH, GM, SH, etc.)
- SVM classification
- Accuracy: Montgomery (78.3%) and Shenzhen (84.10%)

Vajda et al.[7]:
- Lung segmentation (Atlas method)
- Features extraction (HOG, LBP, CH, IH, GM, SH, etc.)
- Features selection
- MLP classification
- Accuracy: Montgomery (78.3%) and Shenzhen (95.57%)

Pasa et al.[5]:
- ROI extraction
- Black bands or borders cropped from the edges of the images
- CNN classification
- Accuracy: Montgomery (79.0%) and Shenzhen (84.4%)
Related Work Summary

Machine Learning:
- Pros:
  - Explicit image features extraction
  - Large variety of classifiers
  - Limited number of training samples
  - Promising results
- Cons:
  - Dependent on image pre-processing/feature extraction
  - Feature extraction can be time consuming

Deep Learning:
- Pros:
  - Automatic feature extraction
  - Slow
  - Promising results
- Cons:
  - No control over the feature extraction
  - Requires large number of training samples
System Overview
Motivation

Structural feature extraction (LoG):

- Mathematically sound and interpretable
- Fast and easy to extract
- Invariant to image density changes

“Zoom in” capability:

- Analyze local image regions
- Different pathologies appear in specific lung regions
- Structural information encoding by local histograms accumulation
System Overview

Original CXR image → ROI extraction → LoG image → LoG image split

CXR Decision: Healthy/Unhealthy

Local LoG histograms’ consolidation into a feature vector → Histogram extraction

H. Yepdjio & S. Vajda
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System Details

System requirements:
- 8 core Intel CPU 2.8 GHz
- 24 GB RAM
- Ubuntu 18.04 LTS
- Python, OpenCV, Pickle
- Tensorflow, Scikit-learn, Keras

Timing for the different stages:

<table>
<thead>
<tr>
<th>Database</th>
<th>Montgomery</th>
<th>Shenzhen</th>
</tr>
</thead>
<tbody>
<tr>
<td>ROI extraction</td>
<td>1.98 (sec/img)</td>
<td>12.55 (sec/img)</td>
</tr>
<tr>
<td>Image resize</td>
<td>1.46 (sec/img)</td>
<td>8.35 (sec/img)</td>
</tr>
<tr>
<td>LoG extraction</td>
<td>25 (msec/img)</td>
<td>122 (msec/img)</td>
</tr>
<tr>
<td>RF classification</td>
<td>1.34 (msec/img)</td>
<td>0.31 (msec/img)</td>
</tr>
</tbody>
</table>
# Details about the Feature Extraction Phase

<table>
<thead>
<tr>
<th>Dataset</th>
<th># rows</th>
<th># columns</th>
<th># bins</th>
<th>values range</th>
</tr>
</thead>
<tbody>
<tr>
<td>Montgomery</td>
<td>16</td>
<td>2</td>
<td>44</td>
<td>1 - 45</td>
</tr>
<tr>
<td>Shenzhen</td>
<td>10</td>
<td>1</td>
<td>40</td>
<td>5 - 45</td>
</tr>
</tbody>
</table>
Test Protocols

Evaluation Metrics:

- AUC: computing the area under the receiver operational characteristic (ROC) curve
- Accuracy (ACC) = \( \frac{\text{# of correctly recognized images}}{\text{# of total images}} \times 100 \)

K-fold cross validation:

- 10 folds
Results
### ACC/AUC Using LoG Features and Topological Information

<table>
<thead>
<tr>
<th>Classifier</th>
<th>Montgomery ACC (%)</th>
<th>Montgomery AUC</th>
<th>Shenzhen ACC (%)</th>
<th>Shenzhen AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>KNN</td>
<td>69.05</td>
<td>0.681</td>
<td>97.26</td>
<td>0.973</td>
</tr>
<tr>
<td>MLP</td>
<td>71.43</td>
<td>0.707</td>
<td>91.32</td>
<td>0.914</td>
</tr>
<tr>
<td>SVM</td>
<td>54.76</td>
<td>0.500</td>
<td>74.89</td>
<td>0.749</td>
</tr>
<tr>
<td>RF</td>
<td><strong>83.33</strong></td>
<td><strong>0.815</strong></td>
<td>96.35</td>
<td>0.964</td>
</tr>
</tbody>
</table>

**Classifiers:**
- KNN: KDTree, Euclidean distance, $k = 3$ neighbors
- MLP: sequential model, ReLU, three hidden layers (750, 400, 400 neurons), Adam optimizer
- SVM: linear kernel
- RF: 900 estimators, Gini impurity criterion

**Conclusion:**
- Best results for Shenzhen obtained by KNN ($k = 3$)
- Best results for Montgomery obtained by RF (900 estimators)
Comparison with Other Systems

<table>
<thead>
<tr>
<th>Method</th>
<th>Montgom. ACC (%)</th>
<th>Montgom. AUC</th>
<th>Shenzhen ACC (%)</th>
<th>Shenzhen AUC</th>
<th>Classifier Used</th>
</tr>
</thead>
<tbody>
<tr>
<td>Our method</td>
<td>83.33</td>
<td>0.815</td>
<td>96.35</td>
<td>.964</td>
<td>RF</td>
</tr>
<tr>
<td>Vajda et al. [7]</td>
<td>78.3</td>
<td>0.87</td>
<td>95.57</td>
<td>0.99</td>
<td>MLP</td>
</tr>
<tr>
<td>Jaeger et al. [4]</td>
<td>78.3</td>
<td>0.86</td>
<td>84.10</td>
<td>0.88</td>
<td>SVM</td>
</tr>
<tr>
<td>Hwang et al. [1]</td>
<td>–</td>
<td>0.991</td>
<td>–</td>
<td>0.977</td>
<td>CNN</td>
</tr>
<tr>
<td>Hwang et al. [2]</td>
<td>67.4</td>
<td>0.884</td>
<td>83.7</td>
<td>0.926</td>
<td>CNN</td>
</tr>
<tr>
<td>Islam et al. [3]</td>
<td>–</td>
<td>–</td>
<td>88.0</td>
<td>0.91</td>
<td>CNN</td>
</tr>
<tr>
<td>Rajaraman et al. [6]</td>
<td>–</td>
<td>–</td>
<td>89.9</td>
<td>0.948</td>
<td>CNN</td>
</tr>
<tr>
<td>Pasa et al. [5]</td>
<td>79.0</td>
<td>0.811</td>
<td>84.4</td>
<td>0.90</td>
<td>CNN</td>
</tr>
</tbody>
</table>

Conclusions:

- Best accuracy values: 83.33% (Montgomery) and 96.36% (Shenzhen)
- Area under the curve: 5th best (Montgomery), 3rd best (Shenzhen)
- Our system uses a single feature (LoG).
- Our classifier is trained with a limited number of images.
Conclusion
Conclusion

- TB is one of the major life threats costing millions of lives each year.
- Existing solutions to diagnose TB are:
  - Costly
  - Sometimes unreliable
  - Resource demanding
- Our CXR analysis system is:
  - Automatic/affordable/fast image processing solution
  - Uses LoG image feature (intensity changes)
  - “Zoom in” functionality for local image analysis
  - Comparable/better results than current state-of-the-art systems
Bibliography


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*Scientific Reports* 9 (12 2019).

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