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

— 25th International Conference on Pattern Recognition—

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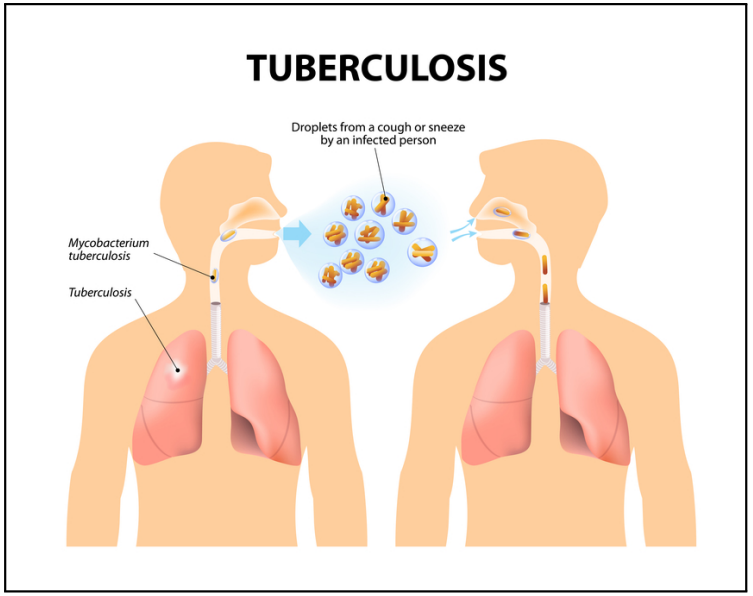
Jan. 10–15, 2021, Milan, Italy

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

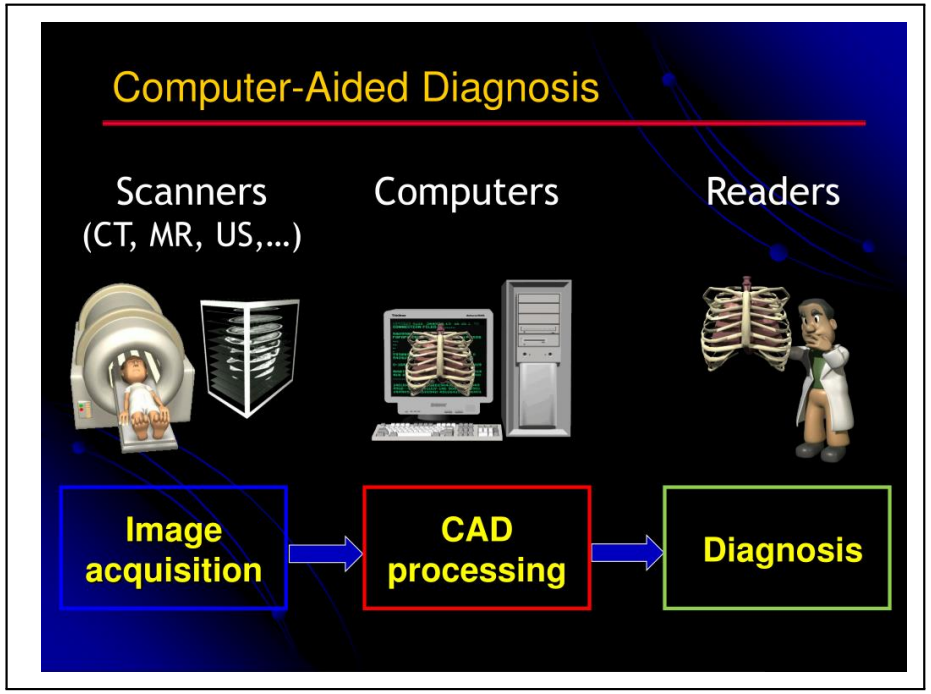
Digital Solutions to Detect Tuberculosis

Solutions:

- Image feature based classification
- Automatic feature based classification

Problems:

- Lack of large data collections
- Adaptability issues for out-of-scope data



Related Work

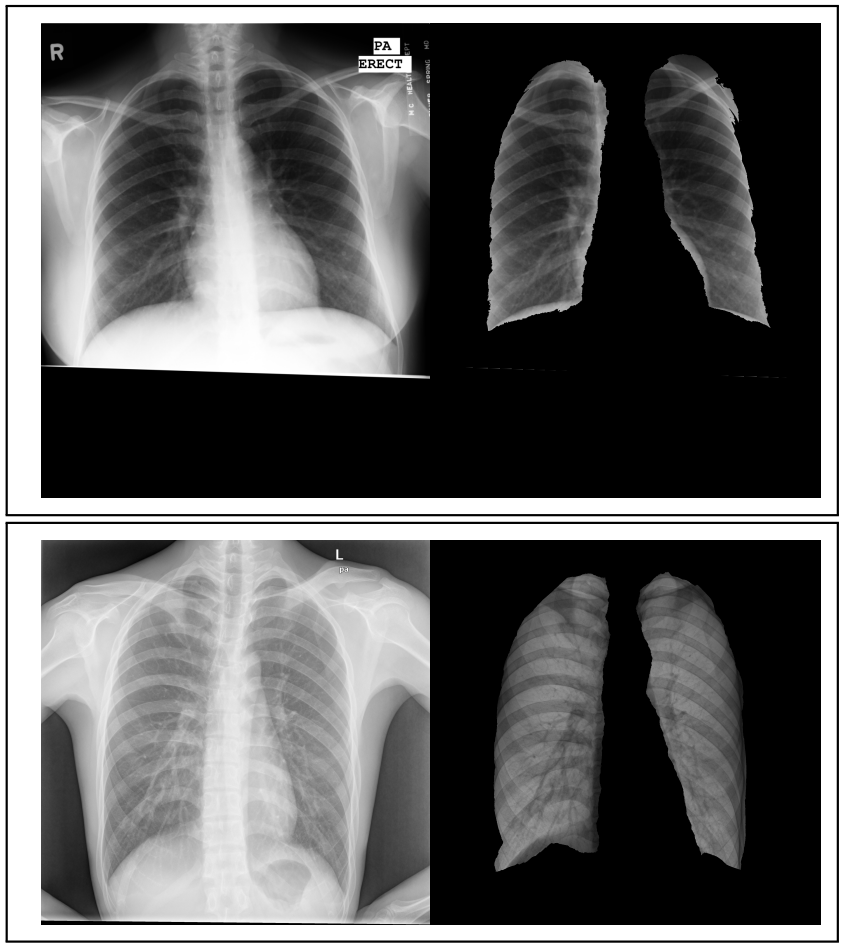
Data

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%)

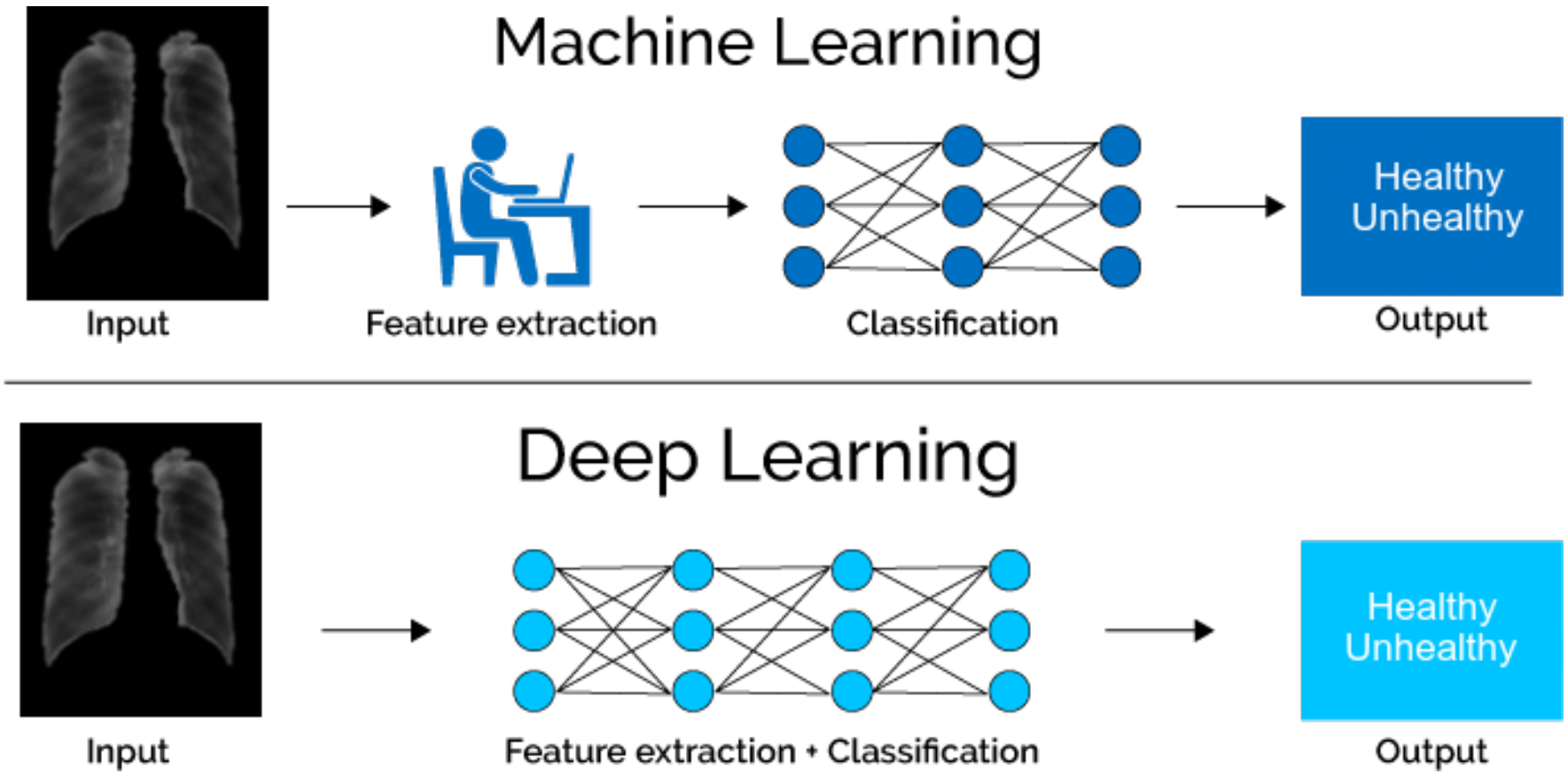
Vajda et al.[7]:

- 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



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

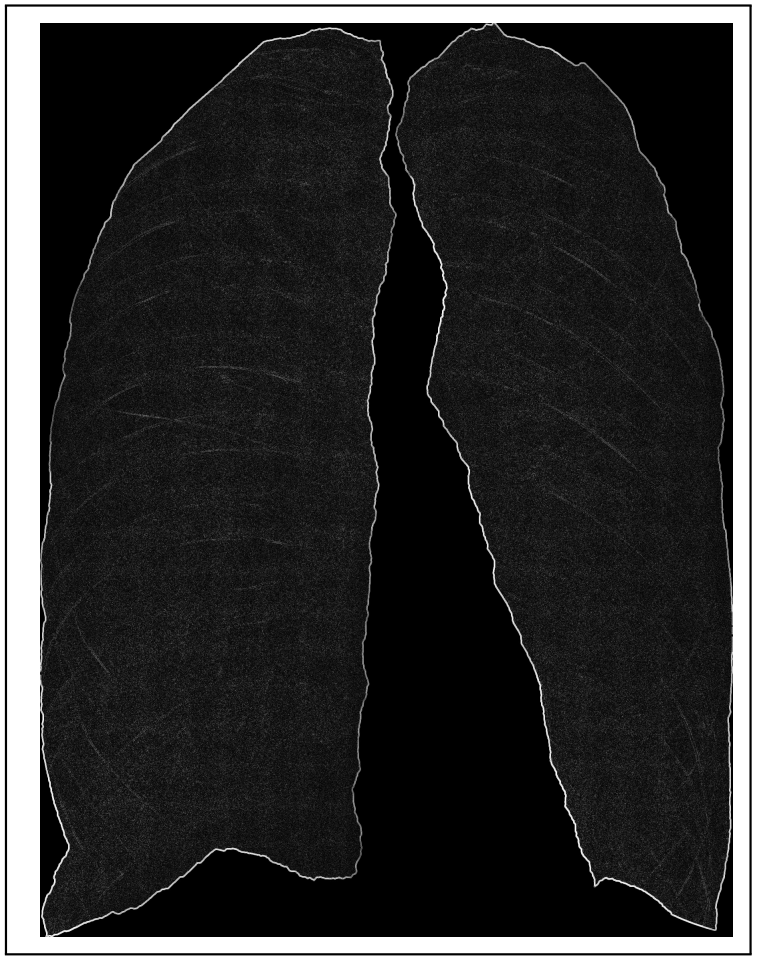
Motivation

Structural feature extraction (LoG):

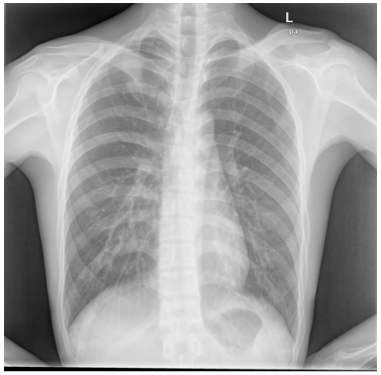
- Mathematically sound and interpretable
- Fast and easy to extract
- Invariant to image density changes

"Zoom in" capability:

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

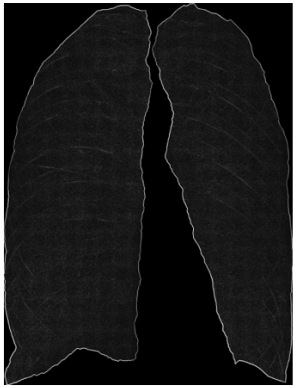


System Overview

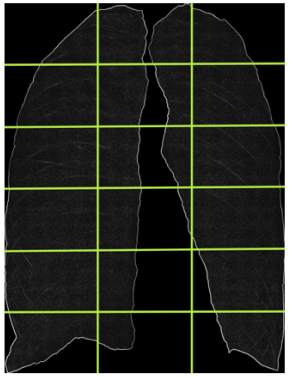


Original CXR image

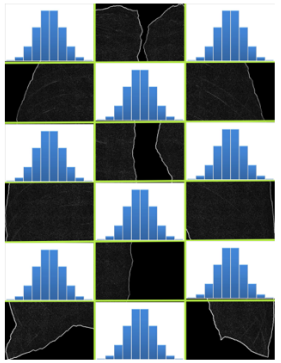
ROI extraction



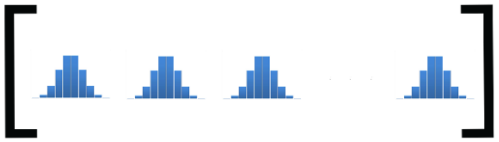
LoG image



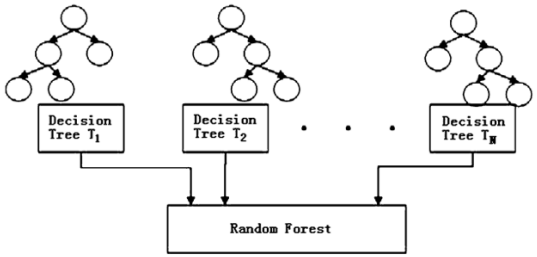
LoG image split



Histogram extraction



Local LoG histograms' consolidation into a feature vector



CXR Decision:
Healthy/Unhealthy

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

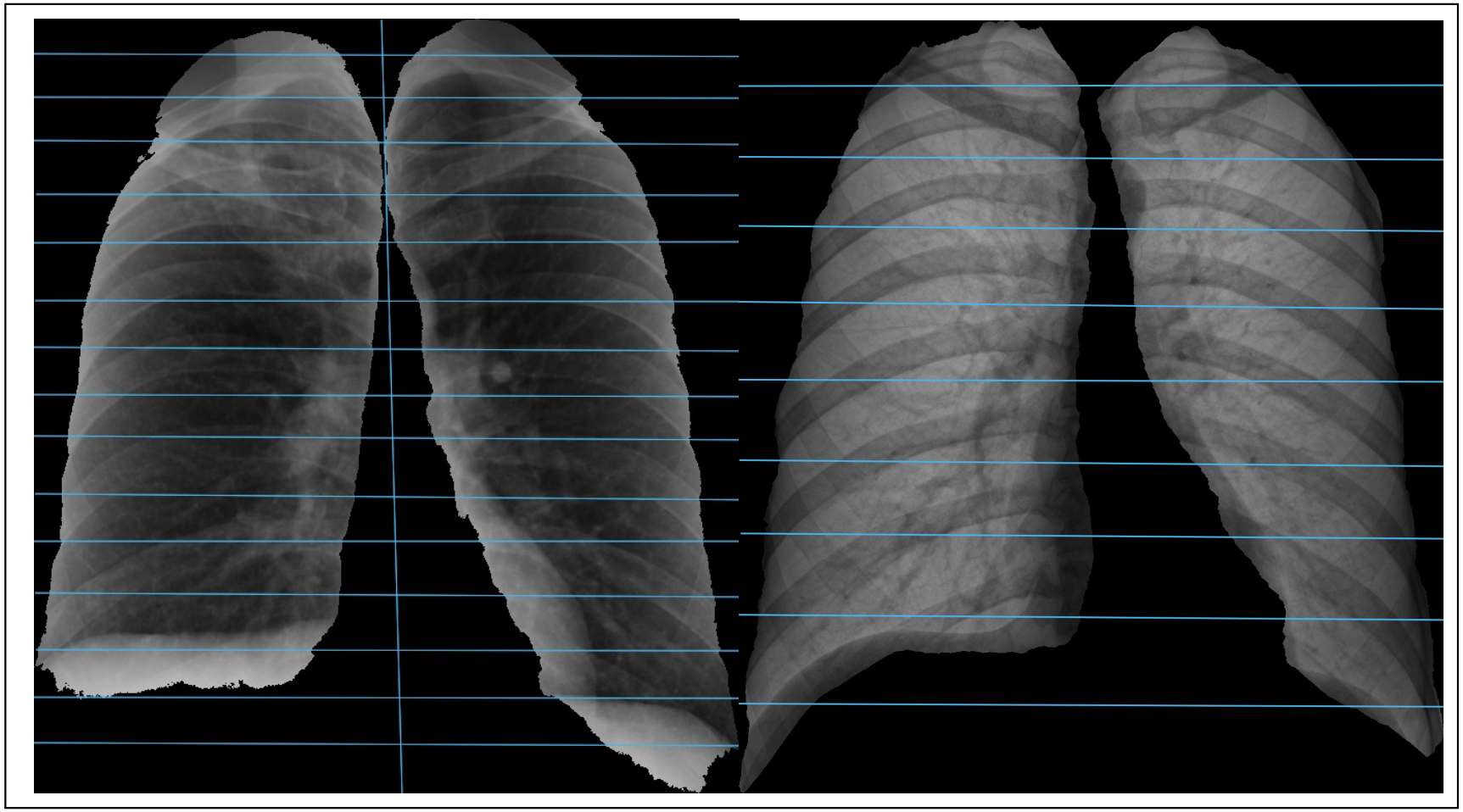
Timing for the different stages:

Database	Montgomery	Shenzhen
ROI extraction	1.98 (sec/img)	12.55 (sec/img)
Image resize	1.46 (sec/img)	8.35 (sec/img)
LoG extraction	25 (msec/img)	122 (msec/img)
RF classification	1.34 (msec/img)	0.31 (msec/img)

Deep Learning with Keras

Details about the Feature Extraction Phase

Dataset	# rows	# columns	# bins	values range
Montgomery	16	2	44	1 - 45
Shenzhen	10	1	40	5 - 45



Test Protocols

Evaluation Metrics:

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

K-fold cross validation:

- 10 folds

Results

ACC/AUC Using LoG Features and Topological Information

Classifier	Montgomery ACC (%)	Montgomery AUC	Shenzhen ACC (%)	Shenzhen AUC
KNN	69.05	0.681	**97.26**	**0.973**
MLP	71.43	0.707	91.32	0.914
SVM	54.76	0.500	74.89	0.749
RF	**83.33**	**0.815**	96.35	0.964

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

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

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

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