



Inception-based Deep Learning Architecture for Tuberculosis Screening using Chest X-rays

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Motivation

- ❑ Primary need of **screening TB** (Tuberculosis) in **resource constrained regions** of the world.
- ❑ **Chest X-rays** are considered as promising **indicators** for the onset of TB, and there is an **existent infrastructure** of **low-cost chest radiography** around the world.
- ❑ **Lack of skilled radiologists** hinders the screening process.
- ❑ **Computer vision** based **automated diagnosis** systems offers a powerful alternative.
- ❑ **Deep learning** based **Convolutional Neural Networks (CNNs)** are adept at learning custom features from a given spatial data distribution.

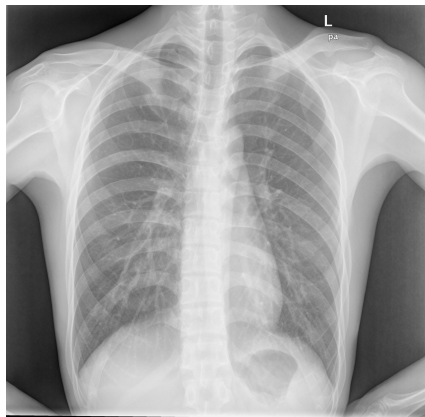
Contribution

- ❑ We propose an **end-to-end CNN architecture** that automates the screening process of TB using chest X-rays.
- ❑ The proposed model is derived from the **Inception Net V3** architecture, which makes use of **multiscale feature** extracting modules (**Inception modules**).
- ❑ The model **learns TB related visual features** from the chest X-ray data and performs **better than the state-of-the-art** deep learning methodology on the used datasets.
- ❑ We study the **computational efficiency** of the model from a **resource perspective** (availability of **GPU** and **model size**).
- ❑ The effect of input chest X-ray **image size** on model performance is also studied.

Dataset Description

Table I: Dataset composition

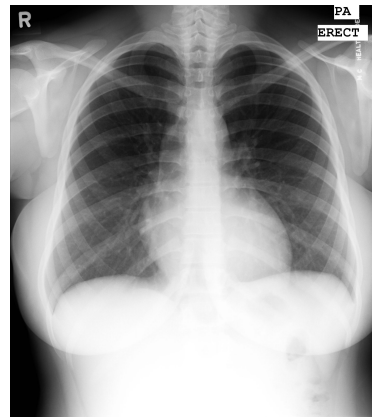
Dataset	Tuberculosis +ve	Normal
Shenzhen, China	342	340
Montgomery County, USA	58	80



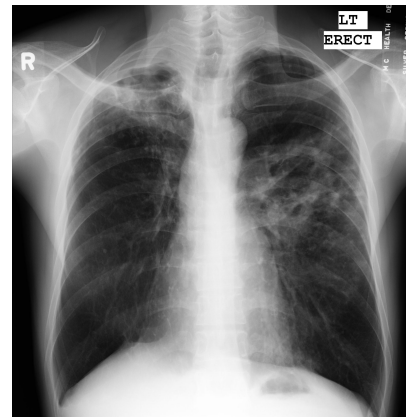
Normal, China



Abnormal, China



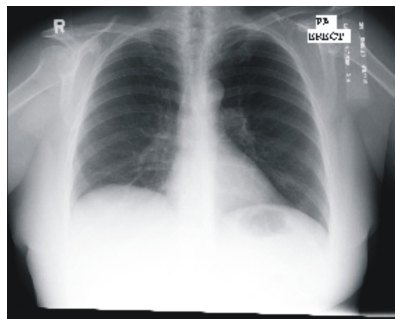
Normal, USA



Abnormal, USA

Fig. I: Randomly sampled chest X-rays from the used datasets. Anatomical and recording instrument variability between the datasets can be well observed.

Preprocessing



1. Raw Chest X-ray



2. Mask generated using
pre-trained CNN



3. Applying mask & ROI
cropping

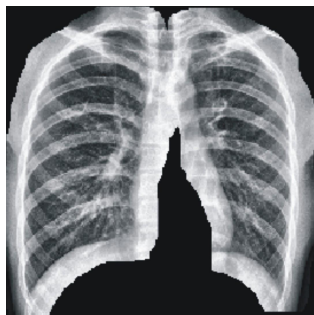


4. CLAHE
(Contrast Equalization)

Fig. II: Preprocessing pipeline



Shenzhen, China chest X-rays



Montgomery County, USA chest X-rays



Fig. III: Sample preprocessed images

Proposed Methodology

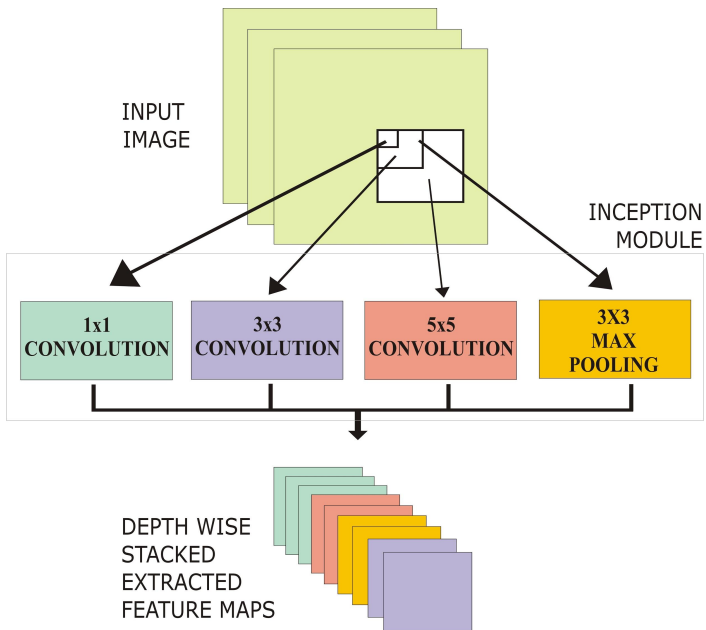
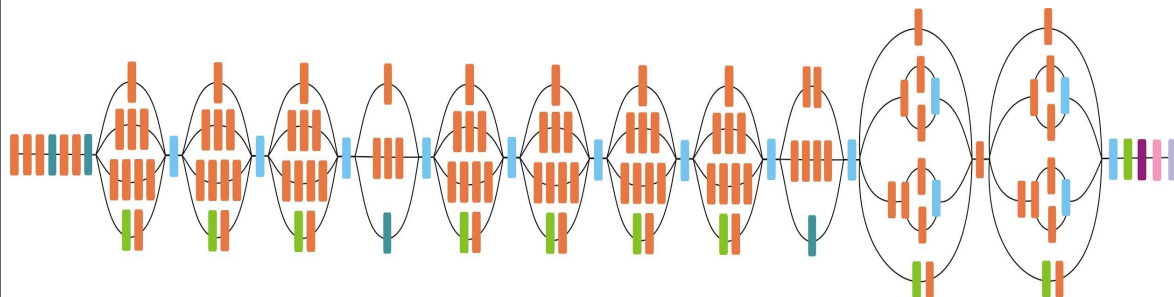
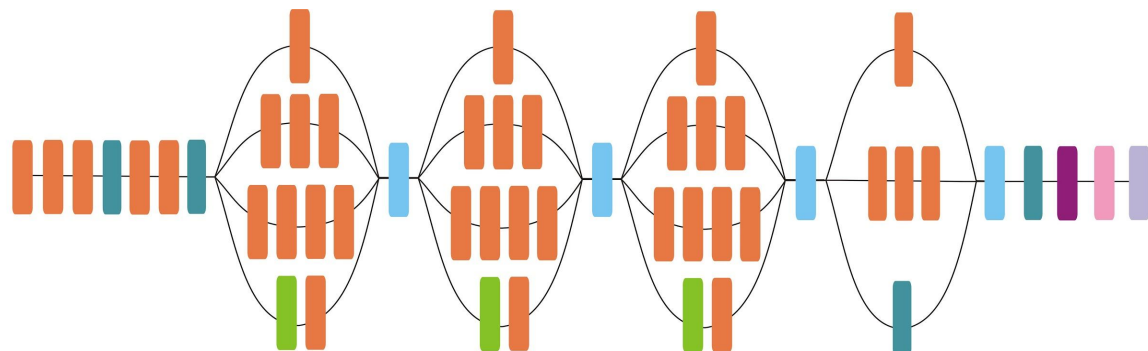


Fig. IV: The Inception Module



Results and Analysis

Fold	ACC	AUC	SEN	SPEC	PREC
1	93.93	0.96	0.91	0.96	0.96
2	93.93	0.94	0.93	0.93	0.93
3	93.93	0.99	0.94	0.93	0.94
4	88.05	0.94	0.85	0.90	0.90
5	95.45	0.95	0.94	0.96	0.96
6	81.81	0.94	0.75	0.87	0.86
7	89.55	0.95	0.88	0.90	0.90
8	90.90	0.94	0.87	0.93	0.93
9	96.96	0.97	0.97	0.96	0.97
10	92.42	0.98	0.87	0.96	0.96
μ	91.70	0.96	0.89	0.93	0.93
σ	± 4.16	± 0.02	± 0.05	± 0.02	± 0.03

Table II: Shenzhen, China

Fold	ACC	AUC	SEN	SPEC	PREC
1	83.89	0.90	0.75	0.93	0.93
2	89.97	0.92	0.80	0.96	0.94
3	79.16	0.89	0.75	0.89	0.91
4	96.89	0.95	0.84	0.98	0.96
5	86.85	0.90	0.79	0.95	0.94
6	88.73	0.91	0.80	0.96	0.94
7	82.37	0.89	0.75	0.93	0.92
8	90.97	0.92	0.82	0.96	0.95
9	91.11	0.94	0.84	0.97	0.95
10	84.17	0.90	0.79	0.94	0.94
μ	87.47	0.92	0.76	0.95	0.95
σ	± 4.3	± 0.04	± 0.05	± 0.03	± 0.03

Table III: Montgomery County, USA

Results and Analysis

Dataset	Metric	[1]	[2]	[3]	[4]	[5]	Our Method
China	ACC	83.00	84.00	84.40	86.74	90.00	91.70
	AUC	0.92	0.92	0.90	0.92	0.94	0.96
USA	ACC	67.00	76.00	79.00	77.14	--	87.47
	AUC	0.88	0.83	0.81	0.90	--	0.92

Table IV: Comparative Study

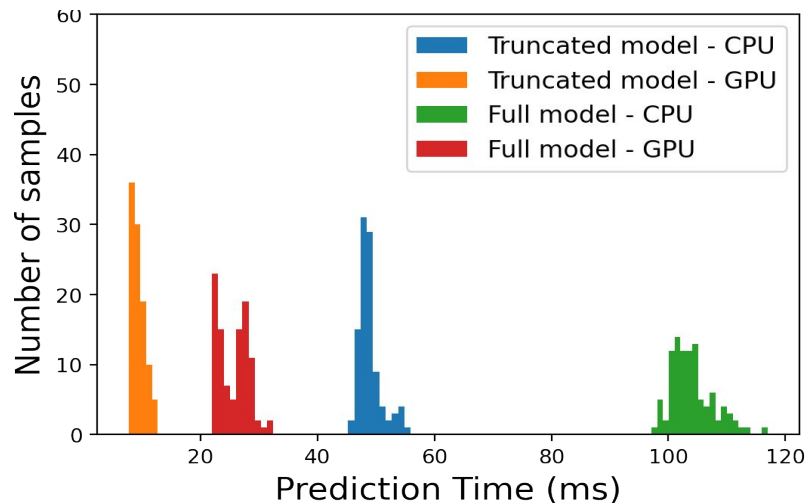


Fig. VII: Distribution of prediction time for 100 randomly sampled CXRs.

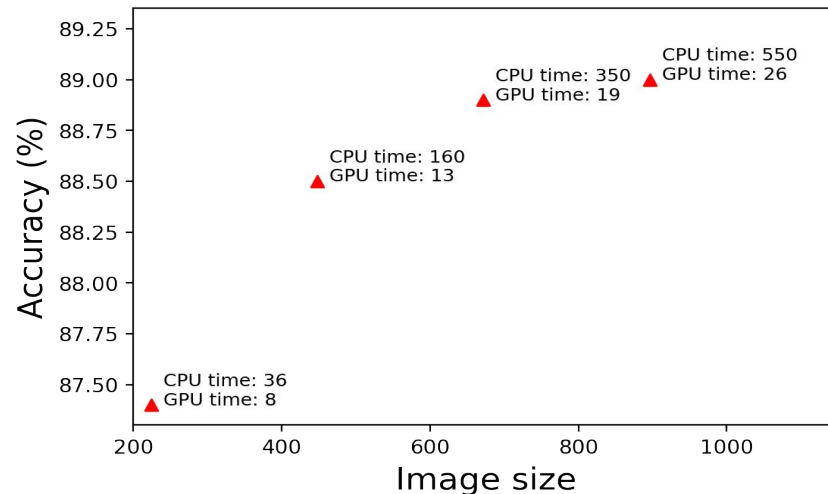
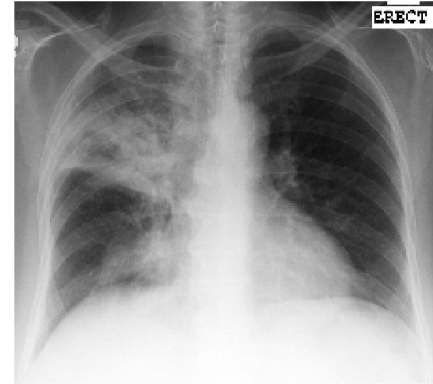
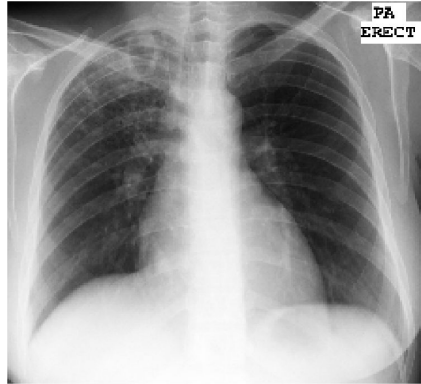
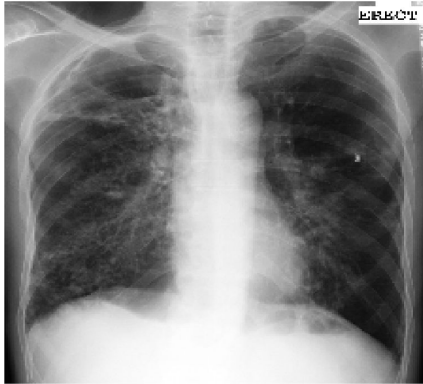


Fig. VIII: Speed-accuracy trade-off using images of larger sizes.

Results and Analysis

Input chest
X-ray images



Grad-CAM
activation map
overlayed on
input images.



Fig. IX: Grad-CAM visualization of learnt feature maps.

Conclusion

- ❑ An end-to-end CNN model is proposed to screen TB using chest X-ray images.
- ❑ The model learns TB specific visual/texture features using convolutional kernels of varying sizes within Inception modules. This enables a multiscale analysis of the chest X-rays.
- ❑ Contrary to ensemble methods, the proposed model is computationally lighter while maintaining superior performance.
- ❑ The model is also robust to dataset variability like anatomical and chest X-ray recording instrument parameters.
- ❑ The proposed methodology provides a fast yet accurate procedure to undertake mass screening of TB in resource constrained regions of the world

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Thank you!