



SUBSTANTIATING DIAGNOSTIC CAPABILITIES WITH GENERATIVE ADVERSARIAL NETWORKS USING CHEST X-RAY IMAGES



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AGENDA

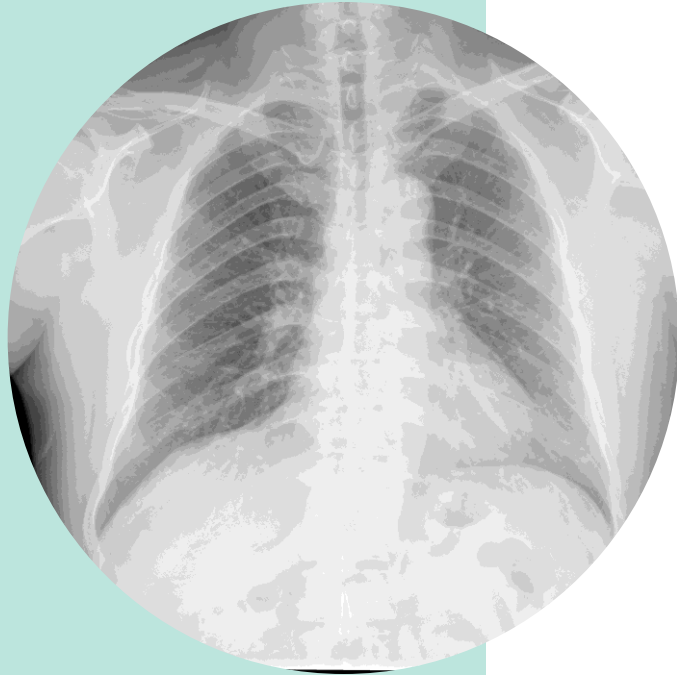
MOTIVATION

APPROACH

DATASET

CHALLENGES





NEARLY 3 MILLION TUBERCULOSIS CASES REMAIN UNDIAGNOSED EACH YEAR

Problem

Early and accurate diagnosis of Tuberculosis

Solution

Automated and real-time prediction of Tuberculosis with certain confidence

Why GAN?

It is more difficult to find examples of tuberculosis patients than healthy patients

Can be extended for diagnosis of other pulmonary diseases

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TRAINING AND TESTING ON MULTIPLE DATA SOURCES ADDS GENERALIZABILITY

- 336 cases with manifestation of tuberculosis
- 326 normal cases
- Resolution 3K X 3K

China Set - The Shenzhen set



- 58 cases with manifestation of tuberculosis
- 80 normal cases
- Resolution: 4020 X 4892 or 4892 X 4020

Montgomery County - Chest X ray



- 1,200 cases with manifestation of tuberculosis
- 5,000 healthy cases
- 5,000 sick & Non-Tb patients

TBX11K (512 X 512)



- Find Shenzhen set [Description from Openi library](#)
- Find Montgomery county set [Description from Openi library](#)
- Find TBX11K [Description from Kaggle](#)

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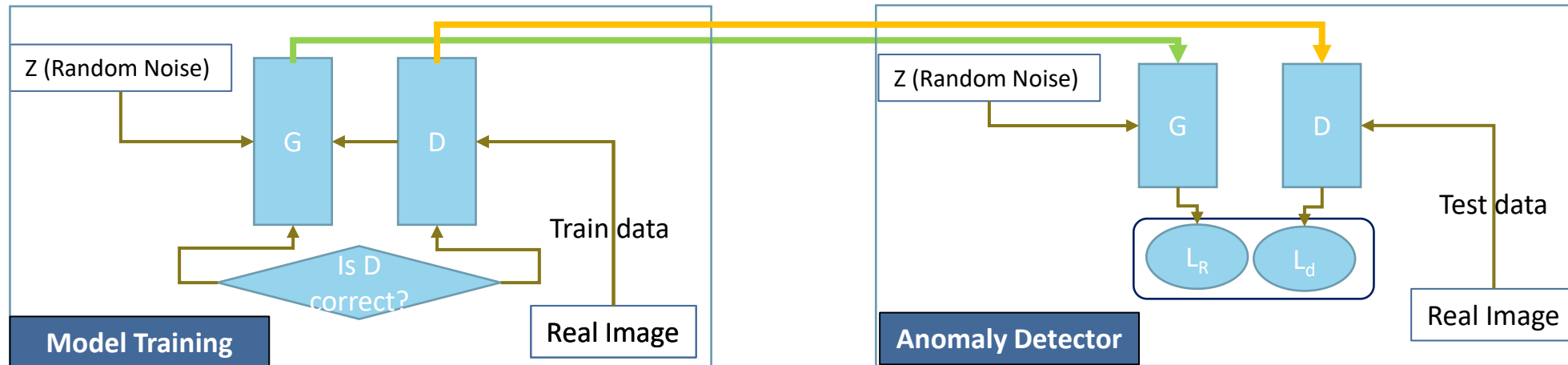
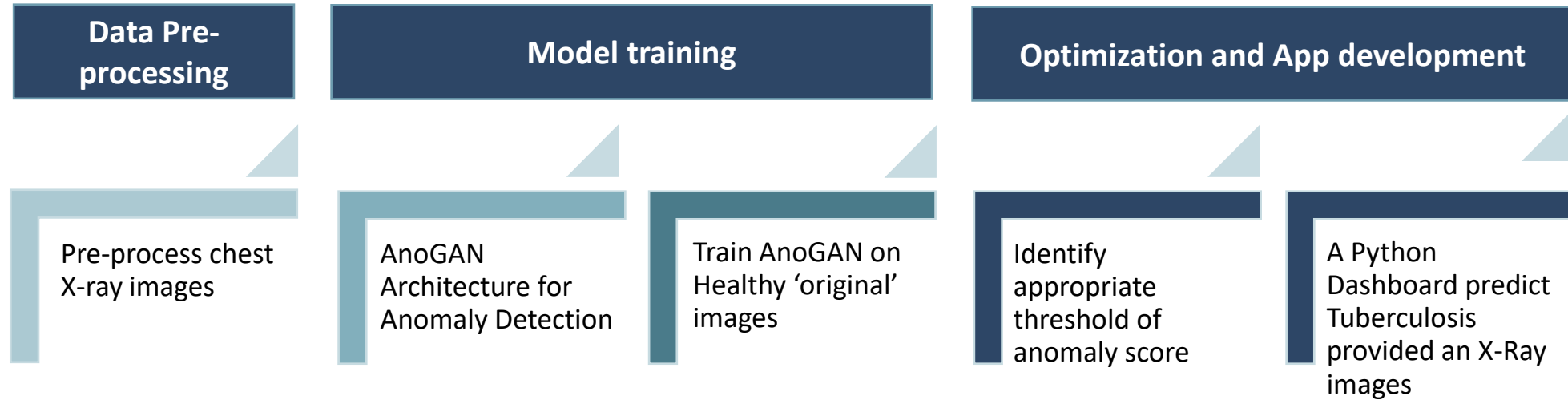
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GENERATE HEALTHY IMAGES USING GAN



CHOOSE THRESHOLD TO DETECT ANOMALOUS IMAGES

The GAN model attempts to generate real-like (non-anomalous or healthy) images, while generator and discriminant follows two-player minmax game with value function $V(G,D)$

$$\min_G \max_D V(D, G)$$

$$V(D, G) = \mathbb{E}_{x \sim p_{data}(x)} [\log D(x)] + \mathbb{E}_{z \sim p_z(z)} [\log(1 - D(G(z)))]$$

When GAN is supplied with a test anomalous image, total anomaly score is calculated which is a weighted sum of Residual Loss (L_R) and Discriminant loss (L_D)

$$\mathcal{L}_R(\mathbf{z}_\gamma) = \sum |\mathbf{x} - G(\mathbf{z}_\gamma)|.$$

$$\mathcal{L}_D(\mathbf{z}_\gamma) = \sum |\mathbf{f}(\mathbf{x}) - \mathbf{f}(G(\mathbf{z}_\gamma))|.$$

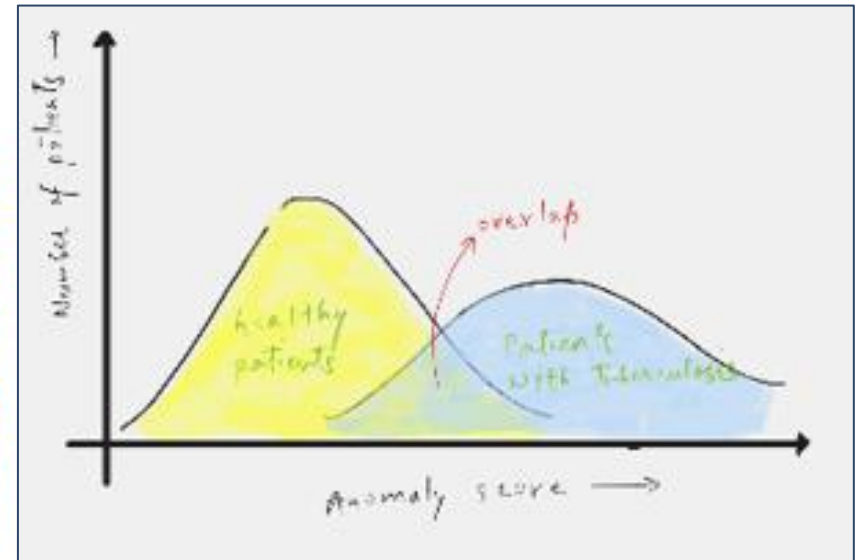
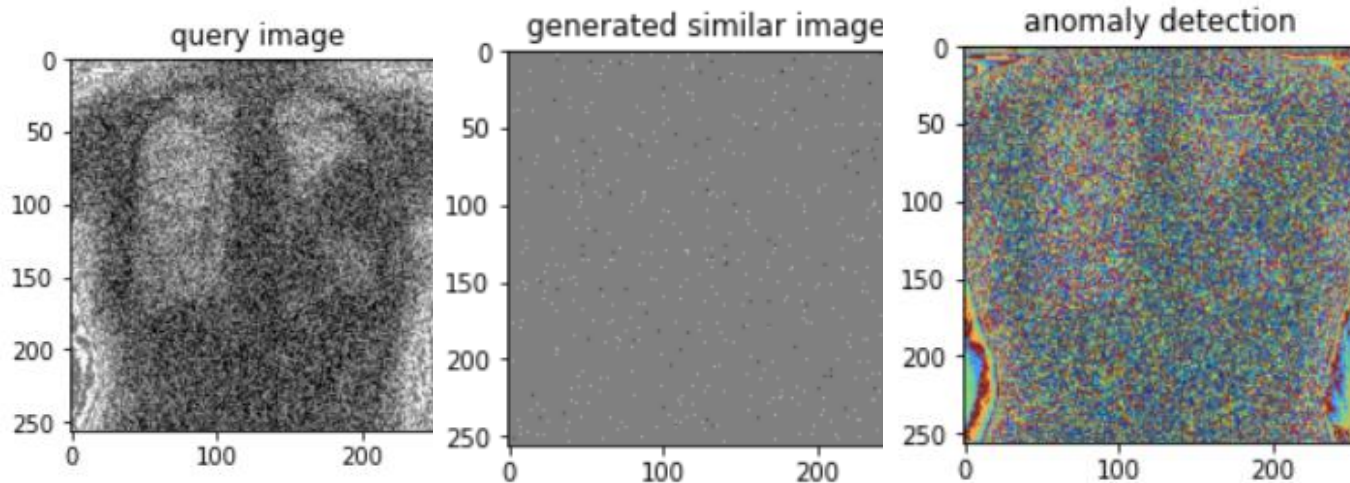
The distribution of anomaly scores from a well trained model should lie at a separable distance for healthy and un-healthy patients

MODEL PERFORMANCE DEPENDS ON INPUT IMAGES AND ANOMALY SCORE THRESHOLD

A trial AnoGAN model was trained using healthy patients of Shenzhen dataset, and for quicker training the resized input images were used, eventually affecting model performance

Absolute value of Anomaly score is meaningless, choosing right threshold is the key

Anomaly score - 10335713.0



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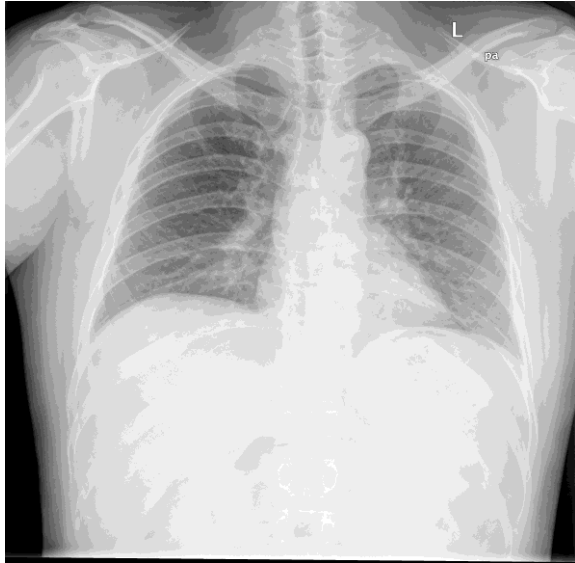
CHALLENGES



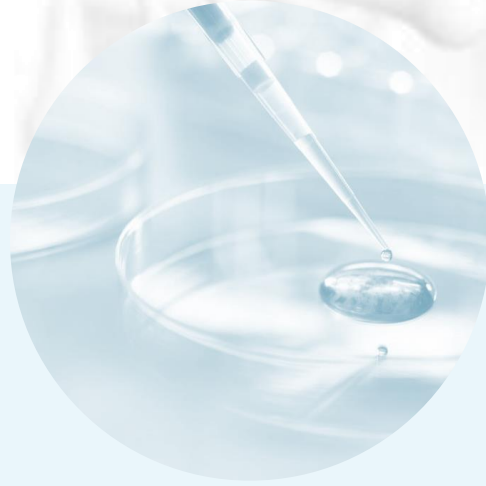
GANs ARE SLOWER TO TRAIN, F-ANOGAN MAY BE ADOPTED

- Current AnoGAN architecture takes > 1 hour to train on 320 images of shape 256X256 from Shenzhen set
 - Find detailed architecture and code on [my GitHub](#)
- Model deployment using Python Dash may make prediction mechanism slower and hence taking away the real-time prediction feature
- The current architecture deployment would not recommend predicting tuberculosis for test image with size less than 256 X 256

QUESTIONS?



Which one has Tuberculosis, Can you tell?



THANK YOU



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