

# Removing the Foreground and Background of Chest X-rays using a Generative Adversarial Network (GAN)

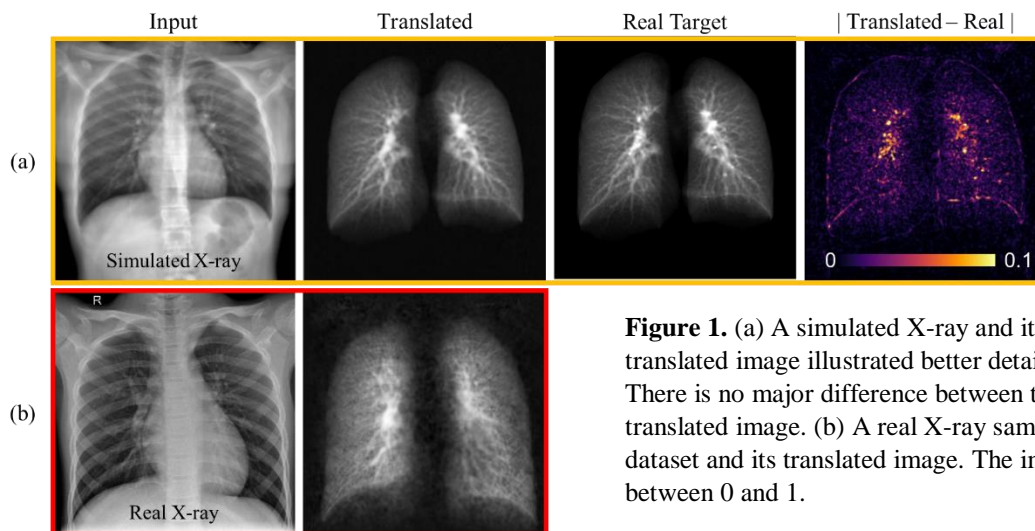
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**Introduction:** Chest X-rays are commonly used to train deep learning models which can detect COVID-19 pneumonia. However, the foreground and background (e.g. ribs, heart, and spine) can be noisy to the models and shade some parts of the lung structure. As a result, the models may learn the wrong features (i.e. regions outside the lung) for decision making. The Pix2Pix GAN has shown its success in image-to-image translation (1). In this study, we proposed a generative model which was inspired by the Pix2Pix GAN to translate the Chest X-rays to lung images without the foreground and background noises.

**Materials and Methods:** 508 lung computed tomography (CT) scans were collected from patients who joined the post-COVID-19 clinic at the University of Iowa Hospitals & Clinics for follow-up. The CT slices in coronal view were averaged to generate the simulated X-rays for the input images. In addition, we applied the lung masks to the CT scans to remove the regions outside the lungs. After removing those regions, the slices in coronal view were also averaged to make the targets for the image-to-image translation. The proposed GAN model was trained with the Wasserstein Loss to deal with the vanishing gradient problem of the traditional binary cross-entropy loss (2) which is used in the original Pix2Pix GAN. Finally, the model was evaluated by feeding with real X-rays sampled from the CheXpert dataset.

**Results and Discussion:** As shown in **Figure 1(a)**, the proposed GAN model performed well on the training images. There is no obvious difference ( $<10\%$ ) between the real target and the synthetic target. As for real chest X-rays, the model was able to delineate the shape of the lung and the large vessels (**Figure 1(b)**). Although there are no target images for chest X-rays, the translated images could be further compared with annotations in radiology reports of these images to inspect any observations of lung diseases/conditions.



**Figure 1.** (a) A simulated X-ray and its translated image. The translated image illustrated better details of the lung structure. There is no major difference between the real target and the translated image. (b) A real X-ray sampled from the CheXpert dataset and its translated image. The images are normalized between 0 and 1.

**Conclusions:** This study demonstrated the feasibility of translating X-rays to lung images without foregrounds and backgrounds which can be used to provide a clear lung image for diagnosis and an augmented image for deep learning models of lung diseases.

## References:

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2. Arjovsky M, Chintala S, Bottou L. Wasserstein generative adversarial networks. In International conference on machine learning 2017 Jul 17 (pp. 214-223). PMLR.