DeScarGAN: Disease-Specific Anomaly Detection with Weak Supervision

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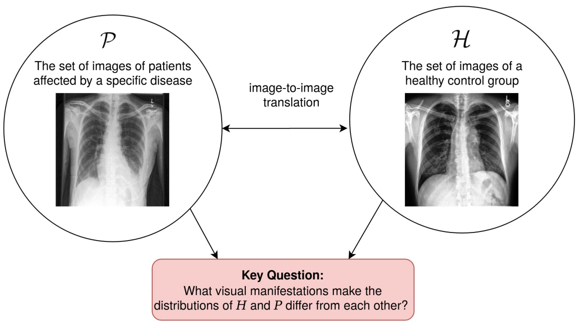
Background

Anomaly detection and localization in medical images is a task that can be tackled with deep neural networks. We present DeScarGAN, a method that is able to detect structural changes of existing anatomical structures, e.g. changes in the pleural space due to pleural effusions.



We train in a weakly supervised manner: We use only the information whether the image belongs to the set $\mathcal{H}$ or $\mathcal{P}$.

Method

We train a Generative Adversarial Network (GAN) [1] inspired by StarGAN [2] for image-to-image translation. A diagram showing the workflow of our method is given in Figure 1.

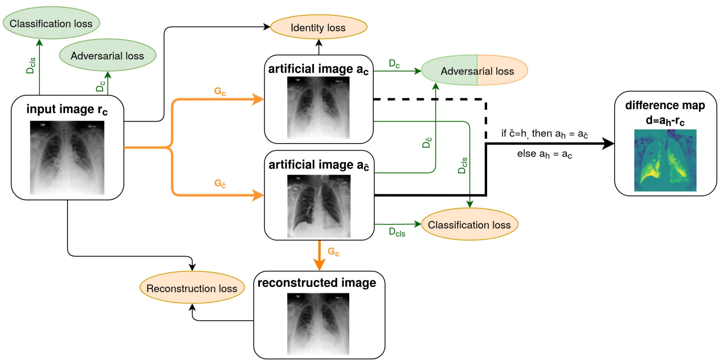


Fig. 1: Workflow of our method. The components of the loss functions for the discriminator are shown in green, the ones for the generator in orange. An input image is translated to images of both an artificial healthy and an artificial diseased subject. The output is the difference between the input image and the generated artificial image of the set $\mathcal{H}$.

- c : Class label for the image, can either be $c = p$ if the image belongs to $\mathcal{P}$, or $c = h$ if the image belongs to $\mathcal{H}$.
- $\bar{c}$: Contrary class to c.
- r_c : Real input image of class c.
- a_c : Generated artificial image of class c.
- G_c : Generator network generating an image of class c.
- D_c : Discriminator network for an image of class c.
- D_{cls} : Classification network sharing parameters with the discriminator D_c.

Evaluation

We designed a synthetic data set for the evaluation of our method. The sets $\mathcal{H}$ and $\mathcal{P}$ are defined as follows:

- $\mathcal{H}$: Two ellipses are present in the image, the background is structured in concentric waves with two origins.
- $\mathcal{P}$: An image of $\mathcal{H}$ is deformed such that the smaller ellipse shrinks to an even smaller ellipse.

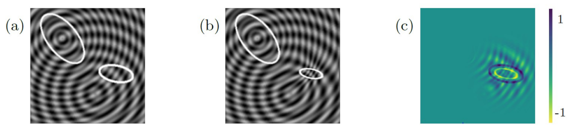


Fig. 2: Images (a) and (b) show exemplary images of the sets $\mathcal{H}$ and $\mathcal{P}$ respectively. Image (c) corresponds to the ground truth given by the difference (a) - (b).

Results

Our method outperforms state-of-the-art anomaly detection networks on the synthetic dataset with respect to the pixel-wise ground truth.

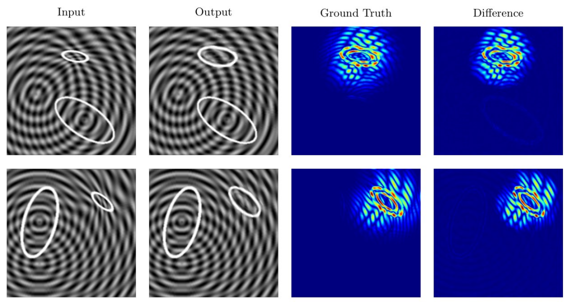


Fig. 3: Results of our method on the synthetic dataset. The difference map is very close to the ground truth.

We apply our method on the Chexpert dataset [3] on images showing pleural effusions. Our classification scores are better than the results of state-of-the-art classification networks.

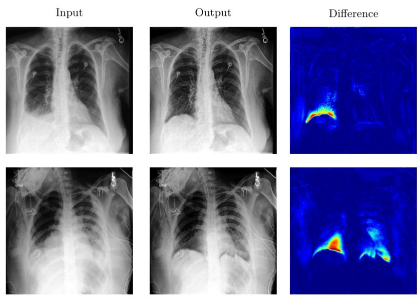


Fig. 4: Results of our method on the Chexpert dataset. The generated maps detect anomalies in a detailed manner and lead the attention to the relevant parts of the anatomy.

References

[1] Goodfellow et al., "Generative Adversarial Nets." *Advances in Neural Information Processing Systems*, 2014.

[2] Yunjey et al., " StarGAN: Unified Generative Adversarial Networks for Multi-Domain Image-to-Image Translation." *CVPR*, 2018.

[3] Irvin et al., "Chexpert: A large chest radiograph dataset with uncertainty labels and expert comparison." *Proceedings of the AAAI Conference on Artificial Intelligence*, 2019.