# Mammographic Image Conversion Using a Conditional Generative Adversarial Network, cGAN

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## Abstract

An image conversion algorithm was developed to adjust characteristics of mammographic images acquired with a given system as if they had been acquired with a different system (Figure 1). This technique is useful to generate a new dataset for training and performance assessment of a computer-aided detection (CAD) device for use with a new image acquisition system.

## Introduction

Our work aims at using the conditional Generative Adversarial Network (cGAN) framework to simulate image acquisition with different mammography devices and provide an image conversion methodology that incorporates commonly-used concepts in the medical physics field, such as image sharpness and noise properties.

What — **Adjust characteristics of mammographic images acquired with a given system as if they had been acquired with a different system.**

Why — **Collecting cancer cases with a new mammographic system is burdensome. These cases are required to train or test a computer-aided breast cancer detection system for a new device.**

How — **Use a conditional Generative Adversarial Network (cGAN), a relatively new machine learning technique that has found wide use in imaging applications.**

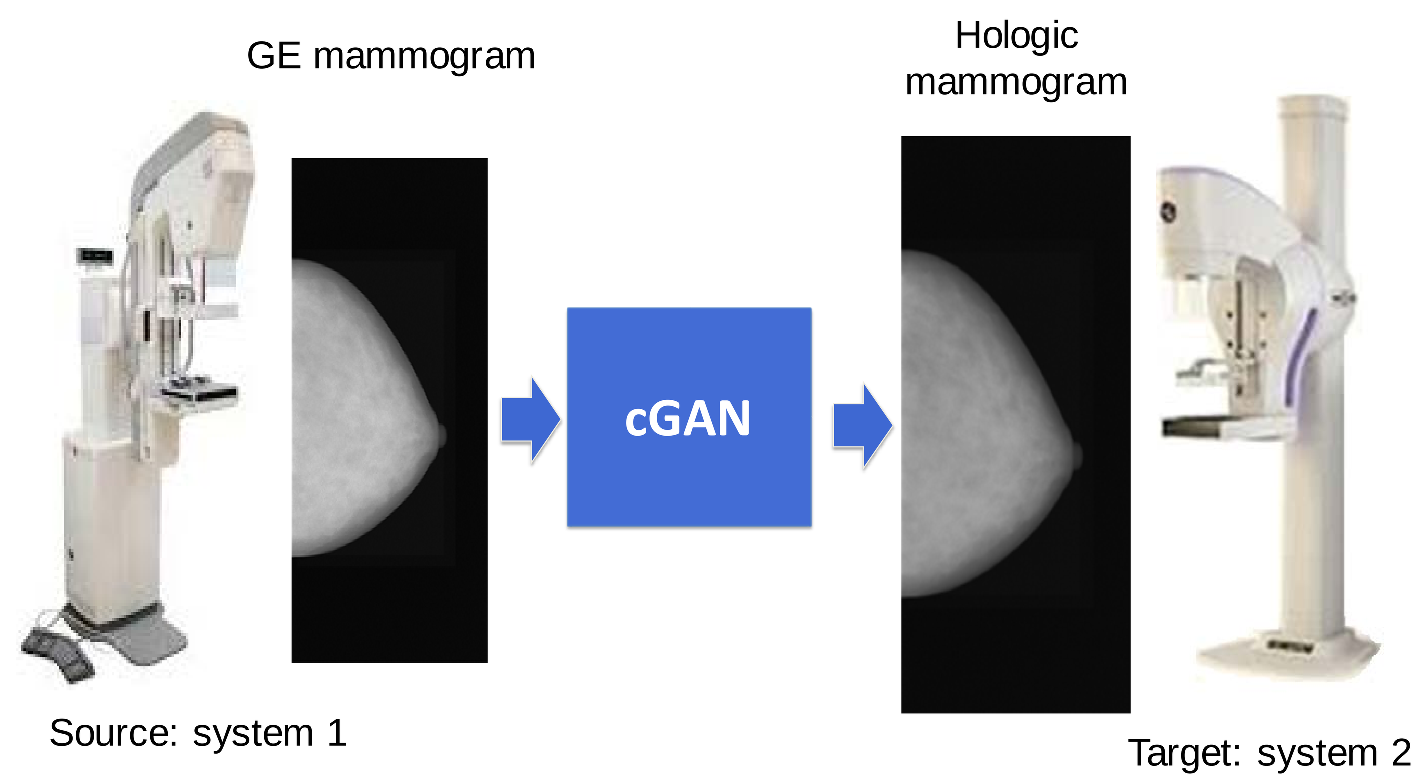


**Figure 1.** We aim to develop an AI-based image conversion algorithm to adjust characteristics of the radiographic images acquired with different image acquisition systems. When CAD developers are ready to apply their CAD device to a new mammographic acquisition system, they typically assess the device with images acquired using the new system. Collecting large repositories of clinical images containing verified lesion locations acquired by a new system is costly and time consuming. Converting mammographic images acquired by the source system into images that appear as if they were acquired by the new system will facilitate CAD device training and performance assessment without acquiring any images with the new system.

## Materials and Methods

- Our method was trained and tested on synthetic mammograms generated using 3D anthropomorphic breast phantoms and a Monte Carlo-based x-ray transport simulation technique to model commercially-available x-ray image acquisition systems.
- One independent slanted edge phantom image was coupled with each synthetically-generated anthropomorphic breast image and the pair was presented as a combined input into the network.
- Loss function was extended from a simple adversarial loss to a composite loss with new reconstruction loss terms:
  - a $L_2$ loss term, which is responsible for capturing the overall structure of the ground-truth image.
  - an edge-based loss ($L_e$ defined in Equation 1),
  - and a high-frequency error norm normalized ($HFENN$) loss ($L_h$ defined in Equation 2).

Last two terms emphasize the reconstruction of high frequency image contents, which were added to match the modulation transfer function (MTF) of the model with the MTF of the target system and adapt the network with the structural details of the breast images.

$$L_e(G) = \beta * E_{x,y}\left[\left\|S_y - S_{G(x)}\right\|_2\right] \quad , \quad \beta = 10 \tag{1}$$

where $S_{G(x)}$ is the generated edge image and $S_y$ is the edge image patch acquired with the target system.

$$L_h(G) = \alpha * E_{x,y}[HFENN] \; , \; \alpha = 10 \tag{2}$$

$$HFENN = \left\|LoG\big(y - G(x)\big)\right\|_2, \; y = \text{ground-truth} \tag{3}$$

$, LoG =$ Laplacian of Gaussian

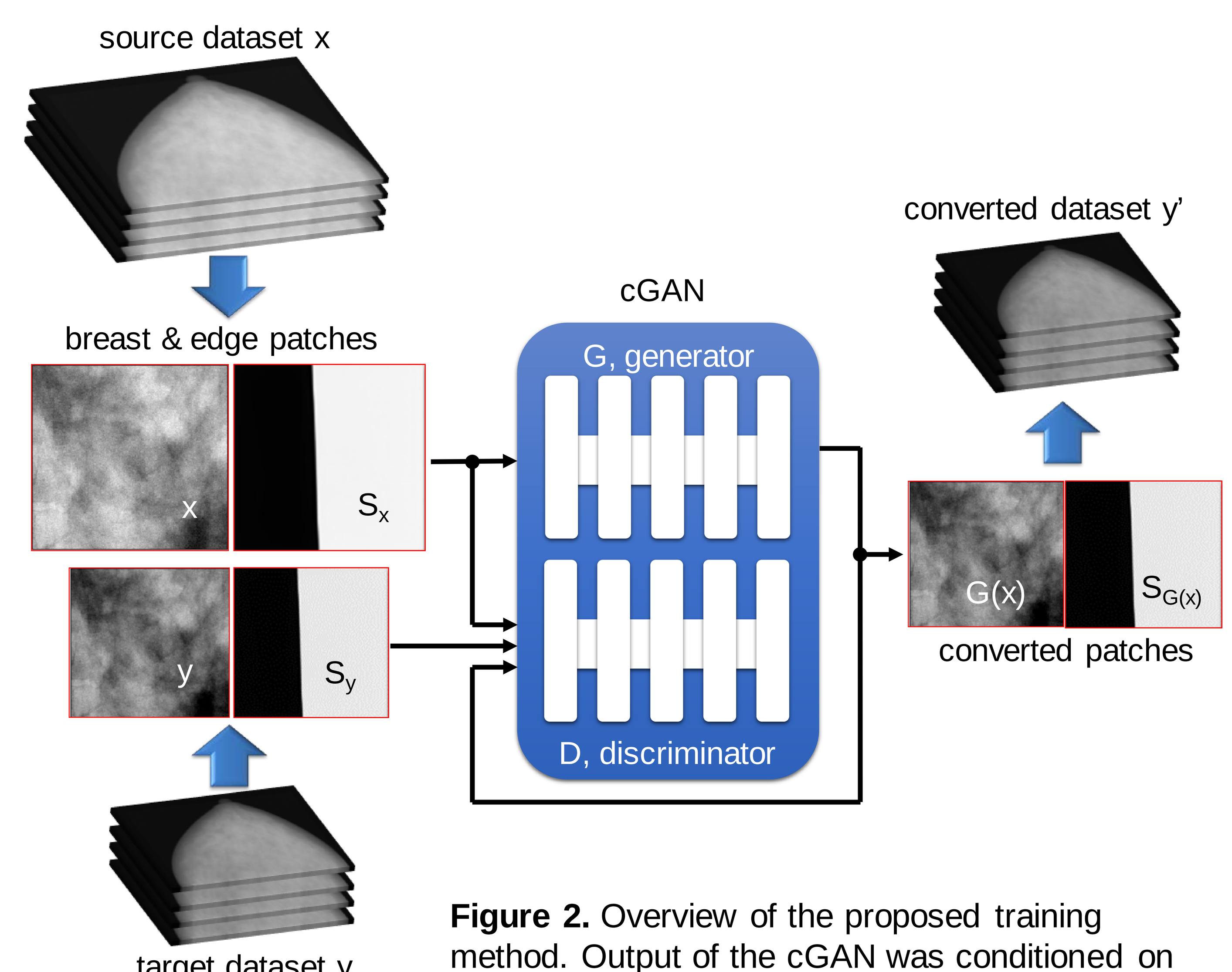


**Figure 2.** Overview of the proposed training method. Output of the cGAN was conditioned on the input image and hence cGAN forces the output image to be loyal to the input image in terms of the subtle anatomical details. Therefore, the diagnostic features of the breast image will be preserved. $S_x$ , $S_y$ , and $S_{G(x)}$ are slanted edge images generated by the source system, target system, and cGAN network, respectively.

## Results and Discussion

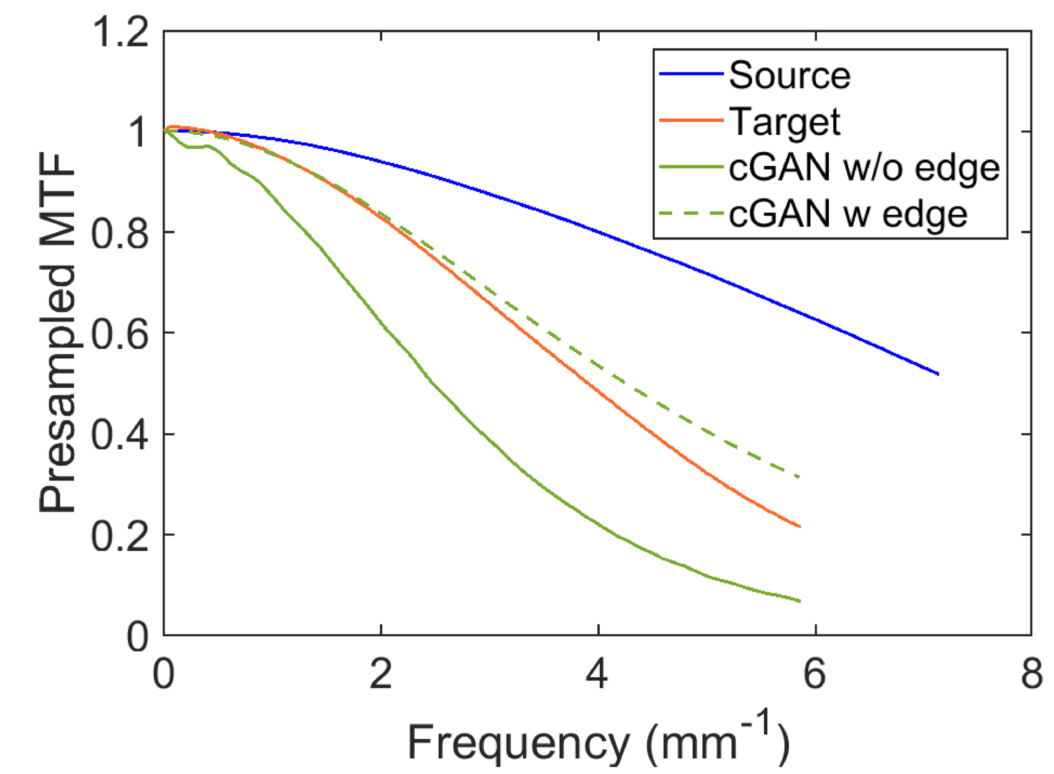


**Figure 3.** Our method was validated by comparing the presampled MTF of the cGAN model measured using the cGAN-generated edge image (green curves) with MTF of the source and target mammography acquisition systems, shown in blue and red curves, respectively.

- The solid green curve shows what happens when the slanted edge images are not included in training. The neural network has difficulty learning the edge profiles and hence the MTF measured from the cGAN-generated edge images is not close to the MTF of the target system.
- The dash green curve shows that including the slanted edge images in the training improves cGAN performance and brings the MTF of the cGAN model closer to that of the target system.

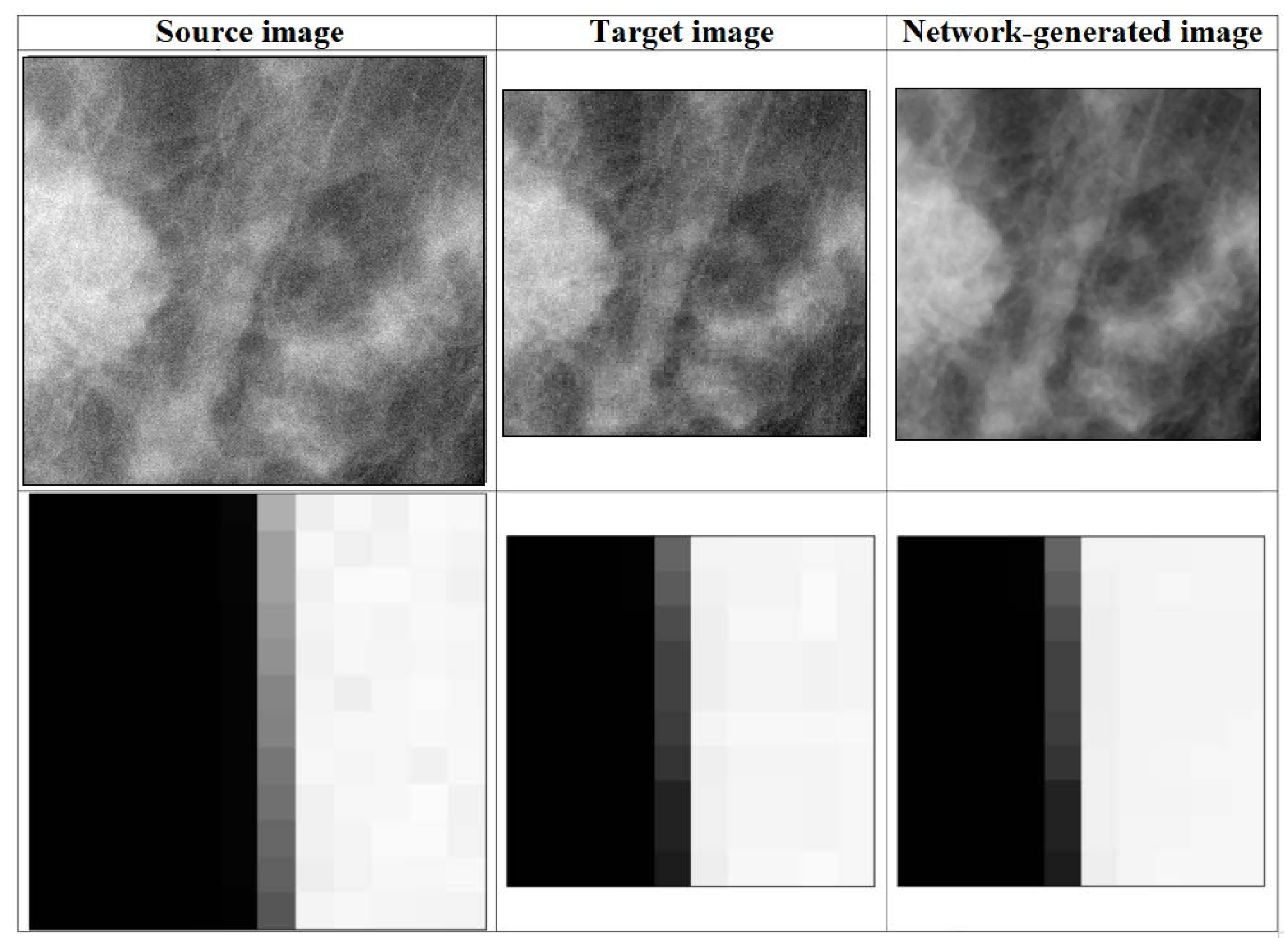


**Figure 4**: An example of the image conversion on a test image.

- Top panel shows the same patch of a synthetic breast images generated with the source system, target system, and cGAN, respectively. Comparing the cGAN-generated breast image with the target breast patch illustrates that the cGAN has learned the structures and details of the anthropomorphic breast. The Structural Similarity Index (SSIM) measured between the target and cGAN-generated breast image patches and averaged over all test patches was 0.89 ± 0.23. However, the high-frequency noise is smoothed, giving the generated image a slightly different appearance than the target image.
- bottom panel presents a small area of the corresponding edge images for each aforementioned category, confirming that network thrives in generating an edge similar to the target edge.

## Conclusion

- A GAN-based method was developed to adjust the sharpness of mammograms acquired with a source system to appear as if the they were acquired with a different target system.
- Our method was validated by matching the MTF of the network-generated edge image with the MTF of the target mammography acquisition system.
- Average SSIM of 0.89 between the cGAN-generated and the target breast patches illustrates that the cGAN has learned the structures and details of the anthropomorphic breast image. Adding edge patches to the training dataset led to a statistically significant improvement of 0.17 in SSIM.
- It may be possible to convert images of the same modality from one system to another using a GAN-based method.
- Our method may lead to increased number of images for development and validation of machine learning-based algorithms and may facilitate evaluation of devices that uses mammography images.

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