Super-Resolution of Degraded Low-Resolution X-Ray Images Using a Novel Patch-Based Generative Adversarial Network

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Abstract

In this work, we propose a patch-based generative adversarial network for super-resolution of degraded low-resolution X-ray images. The generated super-resolution X-ray images showed a structural similarity of 0.85 to the source X-ray images. Our model, XPGAN, outperforms interpolation techniques in reconstructing image detail and shows promise in recovering edges in degraded images. It also allows for memory efficient computation without sacrificing image fidelity. The network was trained and tested for X-ray images which were smoothed and downsampled by a factor of 4, corresponding to a 16x reduction in radiation dose. This method allows for the reconstruction of high-resolution X-rays from lower dose X-ray images. This could help reduce the cost of X-rays while minimizing radiation exposure.

Background

Left: High-resolution (HR) X-ray; Right: Low-resolution (LR) X-ray

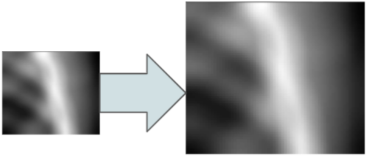
- Lower the resolution, lower the pathological detail
- Higher resolution requires higher radiation dose
- Need a way to increase resolution of low-dose X-rays

Another Problem - Converting CT data to X-Rays

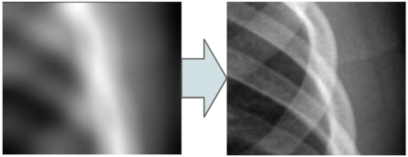
- CT resolution - $1 \times 1 \times 1$ mm
- X-ray resolution - 100×100 microns
- Conversion of CT data to X-ray projections gives lower resolution degraded X-ray images
- Conversion of LR X-ray projections to HR is required.

Goals

1 Increase resolution



2 Reconstruct lost detail

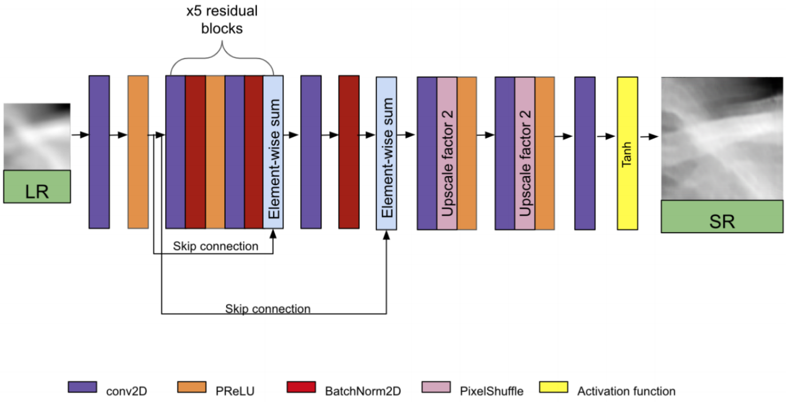


Motivation Behind XPGAN Design

The goals behind our generative adversarial network, XPGAN's design are:

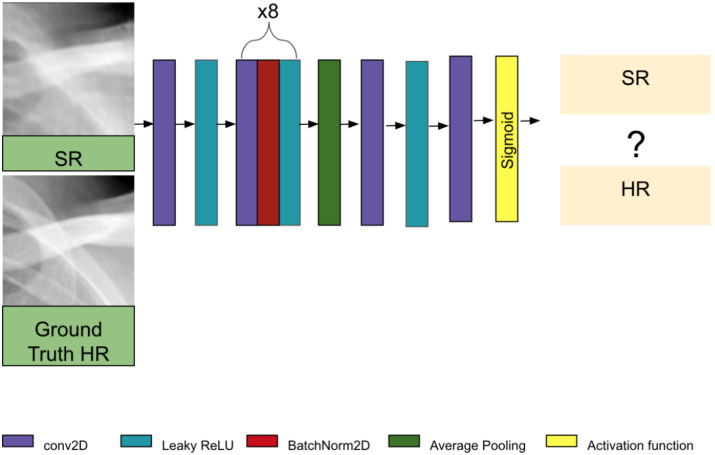
- Recovery of fine structural details
- High Penalty placed on artifacts
- Memory-efficient computation
- Robust model which works for X-rays of varied degradation levels.

Generator Architecture



[1] Ledig et al. Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network

Discriminator Architecture

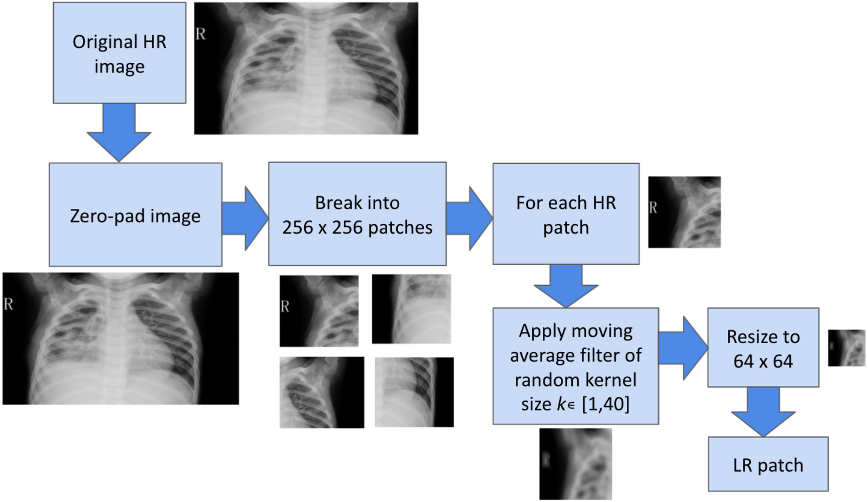


Losses

$$L_{gen} = \alpha(L_{adv}) + \beta(L_{mse}) + \gamma(L_{vgg/i,j}) + \delta(L_{gra})$$

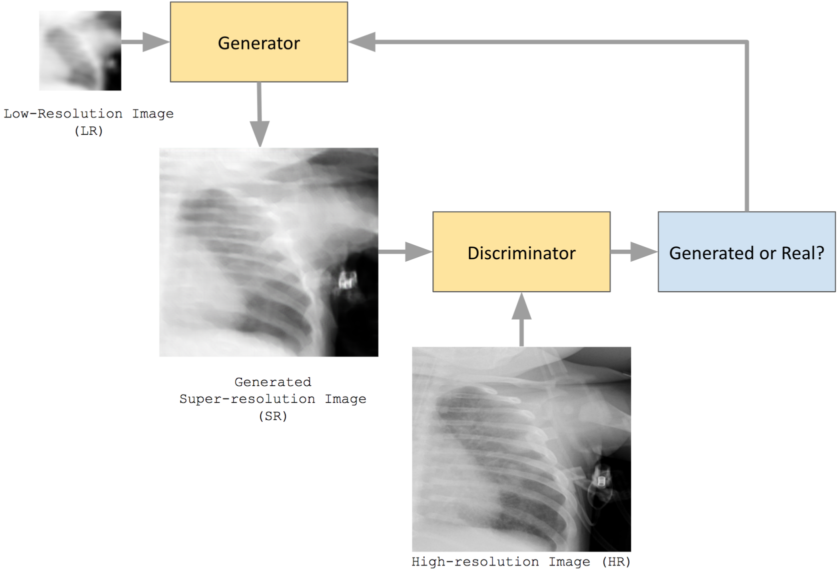
Adversarial Loss	Discriminator feedback
Mean Square Error Loss	Pixelwise error
Perceptual Loss	Preserves high-level features
Gradient Loss	Penalises blurring

Image Processing Pipeline During Training

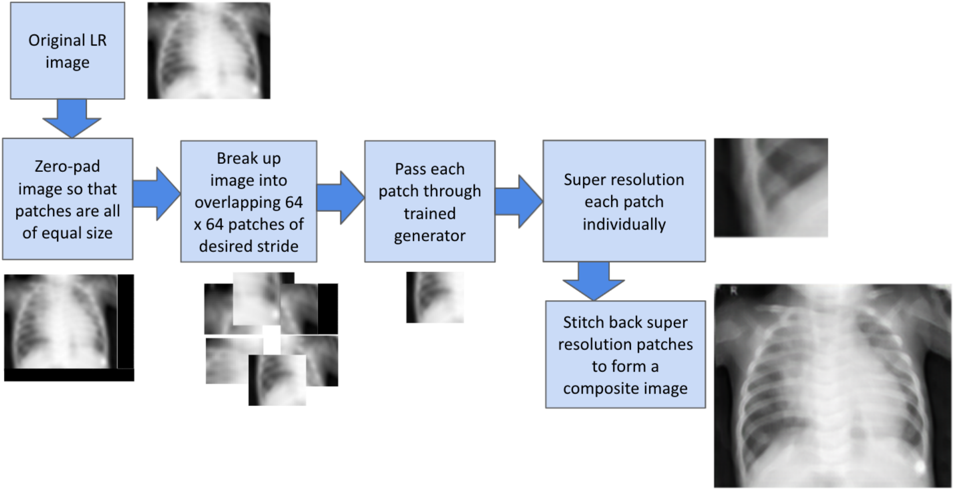


Training XPGAN

XPGAN is trained on LR-HR pairs of patches



Inference pipeline after training



Testing Methodology

- 5 test datasets; each with 3000 LR patches
- Dataset 1: simple moving average(SMA) filter of kernel size $k \in [1, 40]$ applied
- Datasets 2-5: 40×40 SMA, 30×30 SMA, 20×20 SMA, 10×10 SMA applied respectively
- Comparison of XPGAN's performance with bicubic interpolation

Results: Structural Similarity Index Measure (SSIM)

Dataset	XPGAN	Bicubic Interpolation
Randomly chosen $k \in [1, 40]$	0.85	0.81
$k = 40$	0.80	0.72
$k = 30$	0.83	0.74
$k = 20$	0.85	0.79
$k = 10$	0.89	0.86

SSIM comparison of XPGAN with bicubic interpolation on testing set

Results: Variance of the Laplacian

Dataset	XPGAN	Bicubic Interpolation
Randomly chosen $k \in [1, 40]$	30.58	1.72
$k = 40$	14.65	0.94
$k = 30$	23.85	0.99
$k = 20$	28.38	1.10
$k = 10$	31.08	1.69

Variance of the Laplacian comparison of XPGAN with bicubic interpolation on testing set

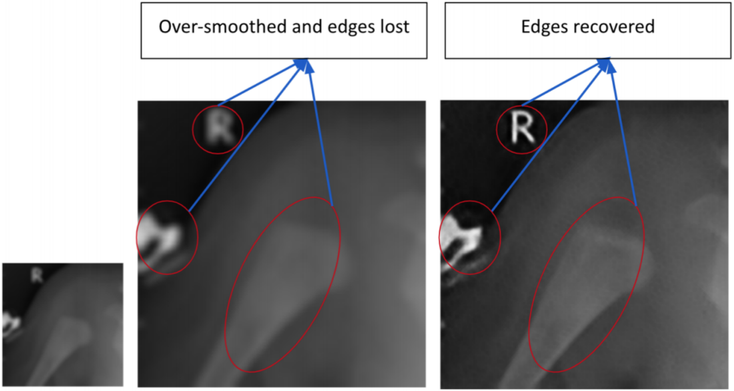
Discussion

- Laplacian measure shows that edges reconstructed and sharpness recovered
- SSIM shows that feature detail is recovered and there are fewer artifacts.
- Tested on datasets with varying filters; model is robust and can be used in practical settings

Example Test Image: Real HR Image

Real HR

Example Test Image: 10 x 10 filter

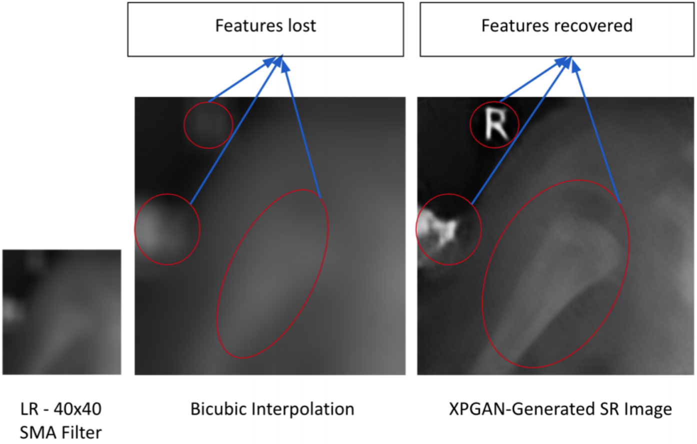


LR - 10x10 SMA Filter

Bicubic Interpolation

XPGAN-Generated SR Image

Example Test Image: 40 x 40 filter



Future Work

- Implement on CT based simulations of x-rays
- Perform radiologist reader study to check for acceptability of super-resolution X-ray images (ongoing)

Conclusion

- Smaller patches $\rightarrow$ preserve fidelity of original image as no resizing is required; memory-efficient
- Outperforms interpolation methods in
    - image sharpness
    - perceptual similarity to real HR images.
- Trained and tested for an upscaling factor of $4\times$ which corresponds to $16\times$ reduction in radiation dose.