Artificial Intelligence Super-Resolution Image Reconstruction Is a Promising Solution to Reduce Cost of Digital Pathology Image Storage

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Background

- Artificial intelligence (AI) and deep convolutional neural networks (CNNs) can learn fine-grain features from digital pathology images, allowing them to make highly-accurate predictions to support a variety of diagnostic and disease classification use cases.
- The cost associated with the storage of large numbers of full-resolution whole-slide images represents a significant barrier to the full adoption of digital pathology.
- Herein we propose a deep learning approach to use super resolution to reconstruct downsized images as an initial step for reducing storage costs. We demonstrate its performance and potential with a comparative analysis on 4X-resolved images.

Design

- Dataset for this investigation consists of 11,620 (700 x 700 pixel) scenes from an internal database of peripheral blood images, partitioned into training (9000), validation (1000), and test (1620) sets. Figure 2 contains examples of these scenes.
- Original and 4X bicubic down-sampled scenes are referred to as HR and LR, respectively. LR scenes were 4X area-interpolated back up to the full-resolution dimensions and are referred to as i-HR (interpolated HR) and serve as the interpolation baseline for comparison purposes. Training and validation scenes were used to train Generator/Discriminator CNNs that super-resolve LR scenes to produce high-resolution scenes referred to as SR.
- Training proceeds in two stages, starting with 20,000 steps of coarse training of Generator model, based on an EDSR-type architecture (32 blocks, 64 filters), with ADAM optimizer and pixel-wise mean-squared error loss. In second stage, Generator is paired with a Discriminator CNN, trained to distinguish between HR and SR scenes, using alternating updates in a GAN-style fine-tuning for an additional 30,000 steps. Results on three quality metrics, PSNR, SSIM and LPIPS, on three models (M1, M2, M3) that performed best on validation set were used to compute metrics on holdout test set.

Design (Cont.)

- The key innovation and what accounts for the quality of the resulting super-resolved scenes is the way the GAN's Generator is fine-tuned with a perceptual loss, that is the weighted sum of the Generator's cross-entropy loss and a content loss from a pre-trained VGG-19 CNN that uses the MSE of the feature space projections of the SR and HR scenes to produce a loss that encourages perceptually-superior reconstructions from the manifold of natural-looking images.

Figure 1

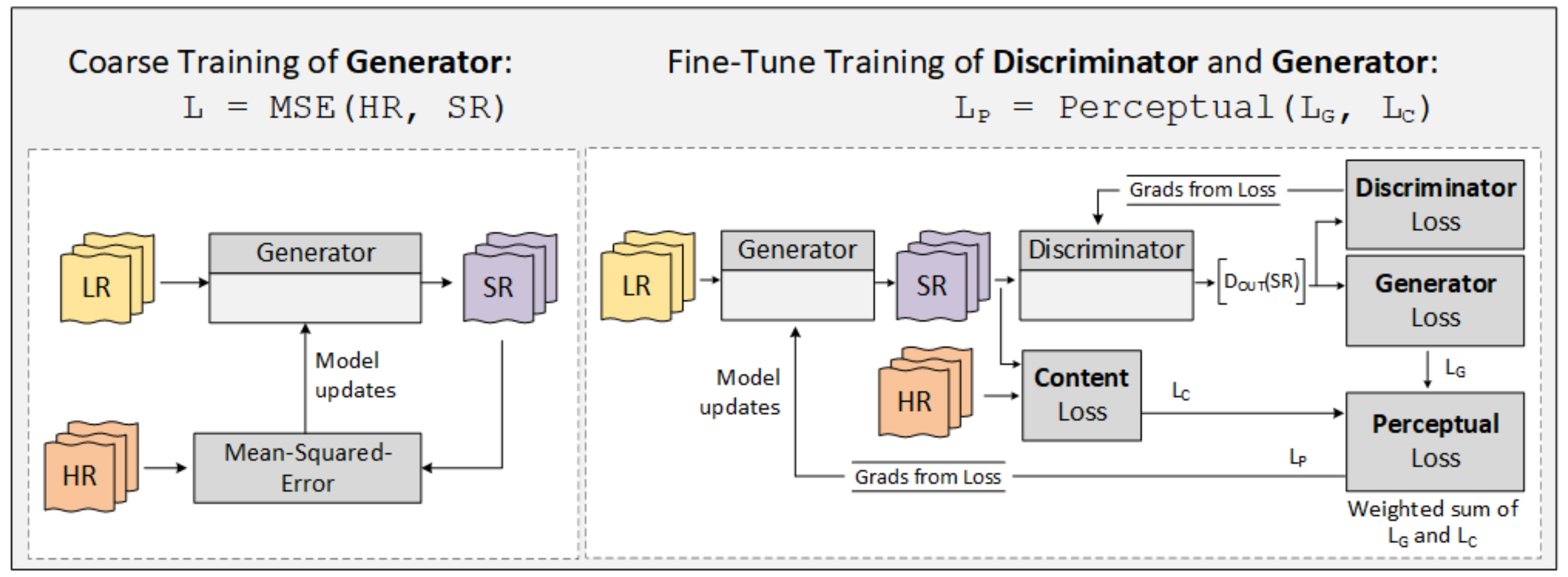
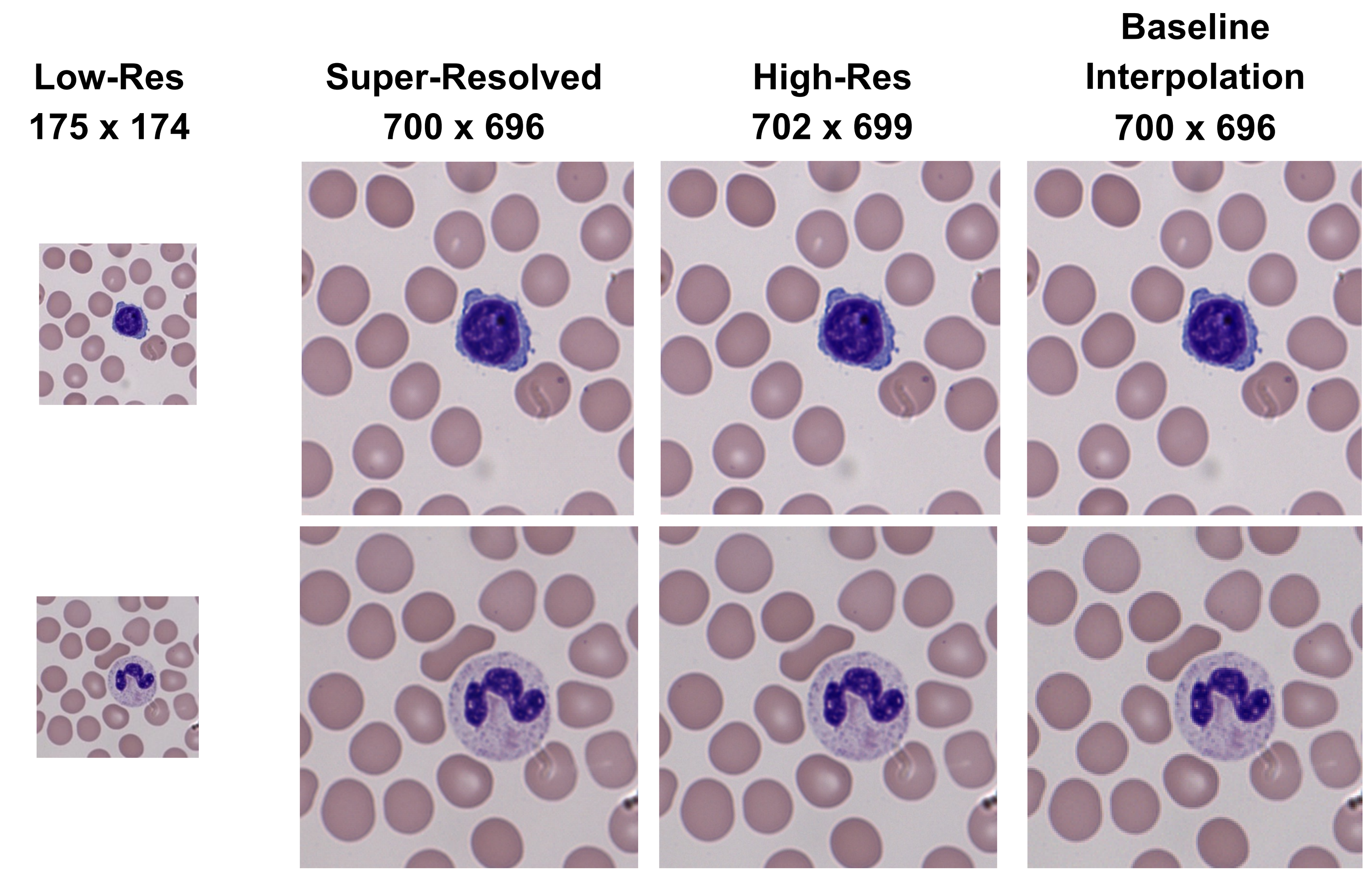


Figure2



Results

- The proposed approach in all three models produces SR images with a high degree of similarity with the HR reference image (Figure 2)
- ALL three computed metrics (PSNR, SSIM, and LPIPS) are significantly better for the SR scenes than the interpolation baseline scenes. The metrics for these three models are shown in Table.

Set	Num Scenes	Model ID	Model Alias	Metrics on SR Images			Metrics on I-HR Interpolated		
				PSNR Higher is Better	SSIM Higher is Better	LPIPS Lower is Better	Ref PSNR Bicubic + Area Interpolation	Ref SSIM Bicubic + Area Interpolation	Ref LPIPS Bicubic + Area Interpolation
Test	1620	M1	Small	**31.265**	**0.878**	**0.123**	29.162	0.822	0.407
		M2	Med	30.441	0.859	0.139			
		M3	High	29.634	0.859	0.141			

Conclusion

- CNNs provide a promising tool to generate high-quality super-resolved images from downsized digital pathology slides, which will significantly reduce slide storage costs.
- We have achieved promising results for 4X scale factors for *SR* that might be extended to higher scale factors, translating directly to reduced storage costs.

References

- Enhanced Deep Residual Networks for Single Image Super-Resolution, Bee Lim, Sanghyun Son, Heewon Kim, Seungjun Nah, Kyoung Mu Lee, CVPR-2017.
- Photo-Realistic Single Image Super-Resolution Using a Generative Adversarial Network, Christian Ledig, Lucas Theis, Ferenc Husz´ar, Jose Caballero, Andrew Cunningham, Alejandro Acosta, Andrew Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang, Wenzhe Shi, CVPR-2017