HOW CAN WE MAKE GAN PERFORM BETTER IN SINGLE MEDICAL IMAGE SUPER-RESOLUTION? A LESION FOCUSED MULTI-SCALE APPROACH

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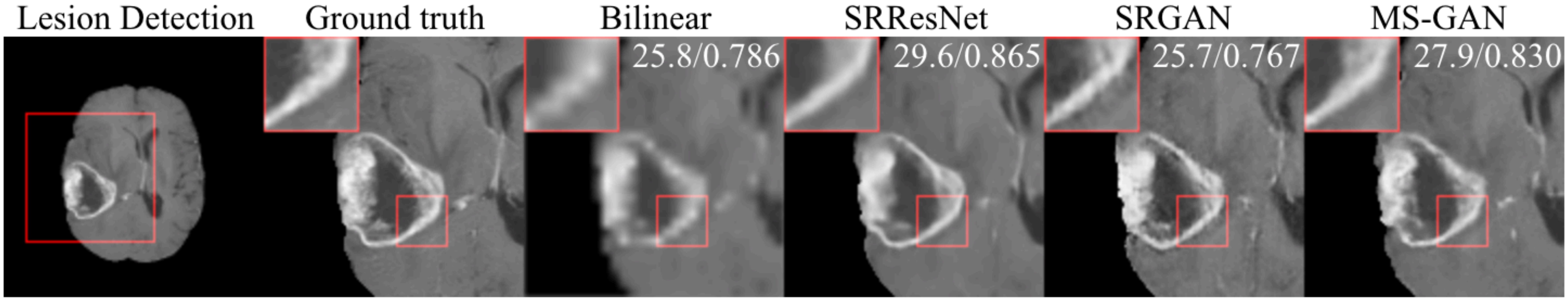

Introduction

Generative Adversarial Network (GAN) based methods have achieved high performance on single image super-resolution (SISR) tasks. However, it is still challenging for medical images due to low image quality, unrealistic patterns introduced by GANs, unstable training and collapse mode. In this paper, we propose a novel multi-scale lesion focused SR method (MS-GAN) and carry out a comparison study of GAN variations, to achieve a more stabilised and efficient training and improved perceptual quality of SR results.

Methods

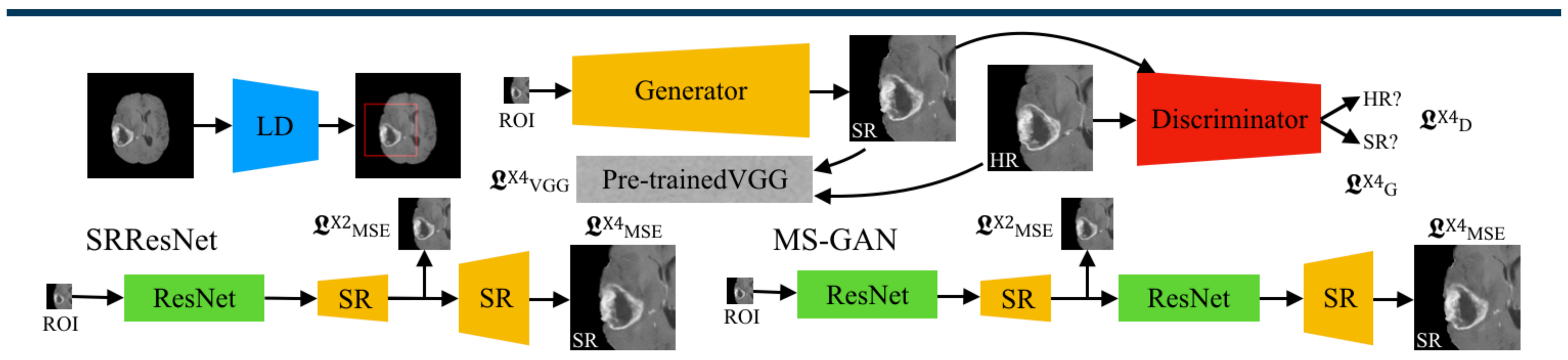

Fig 2. Our proposed lesion focused multi-scale super-resolution neural networks. LD is a pre-trained lesion detection neural network. Two architectures of generators (SRResNet and MS-GAN) are tested. Adversarial loss, MSE loss and perceptual loss are also displayed.

LD: our method is lesion focused[1].

MS-GAN: SR is performed gradually with SRResNet[2].

GAN Variations: the vanilla GAN, Wasserstein GAN, and WGAN with Gradient Penalty[3] are compared.

Losses of Generator: including pixel-wise mean-square-error of both X2 and X4 SR results, perceptual loss[2], and the adversarial loss:

$$\mathfrak{L}_{\mathrm{SR}} = \mathfrak{L}_{MSE}^{X2} + \mathfrak{L}_{MSE}^{X4} + \mathfrak{L}_{VGG}^{X4} + \mathfrak{L}_{G}^{X4}$$

Data

All experiments have been done with brain tumour T1CE MRI images of 163 patients from BraTS 2018 dataset. The slices within tumour were randomly divided for training (9559 slices) and validation (2368 slices). All the images were normalised to zero-mean-unit-variance, and the LR images were simulated by downsampling the HR ground truth images.

Results

PSNR/SSIM and proposed mean-opinion-score (**MOS**) are used for both quantitative and perceptual evaluations.

MOS: An MR physicist performed blinded scoring for shuffled images (100 HR ground truths with their corresponding SR results). Scale—0 (non-diagnostic), 1 (poor), 2 (fair), 3 (good) and 4 (great); image qualities: over-smooth (S); motion and other kind of artefacts (A); unrealistic textures (U); and too noisy or low SNR (N).

Table 1: Quantification comparison using PSNR, SSIM and MOS (the best *performance* in bold)

	MOS	Poor	Fair	Good	Great	S	A	U	N	PSNR	SSIM
GAN+Pre_train	1.80±0.529	25	71	3	1	2	5	92	91	25.2±1.88	0.715±0.0670
WGAN+Pre_train	3.15±0.669	1	13	56	30	19	0	4	3	27.0±1.94	0.804±0.0498
WGAN	3.09±0.694	1	17	54	28	18	3	7	3	**27.2±1.96**	**0.806±0.0499**
WGAN-GP	3.10±0.686	2	13	58	27	3	0	14	14	26.7±1.96	0.788±0.0558
WGAN-GP+$\mathfrak{L}_{MSE}^{X2}$	3.15±0.698	1	15	52	32	3	0	17	17	26.2±2.00	0.786±0.0577
MS-GAN	**3.26±0.626**	1	7	57	35	5	1	11	8	26.7±1.97	0.789±0.0554
Ground Truth	3.28±0.838	3	16	31	50	1	20	14	9		

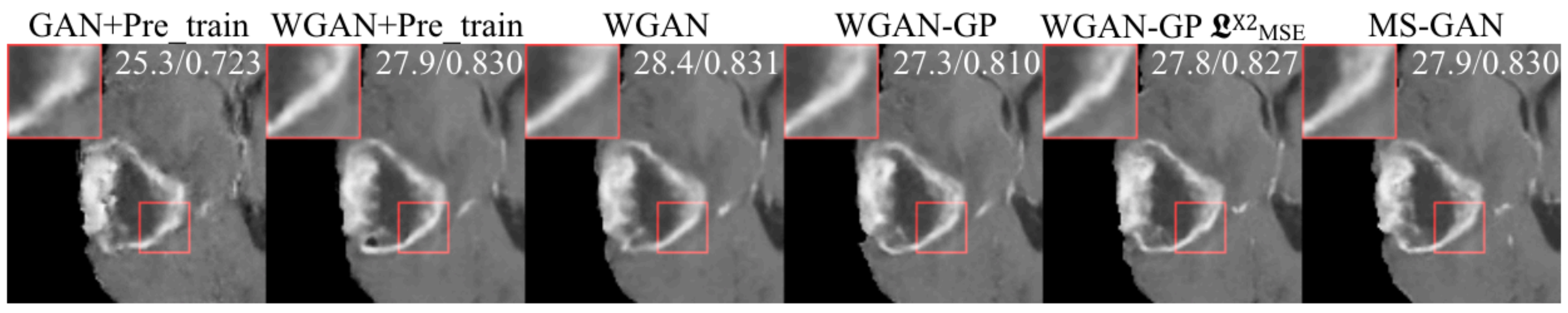

Fig 3. The generated SR images of LFSR with GAN variations and MS-GAN. PSNR and SSIM are also displayed.

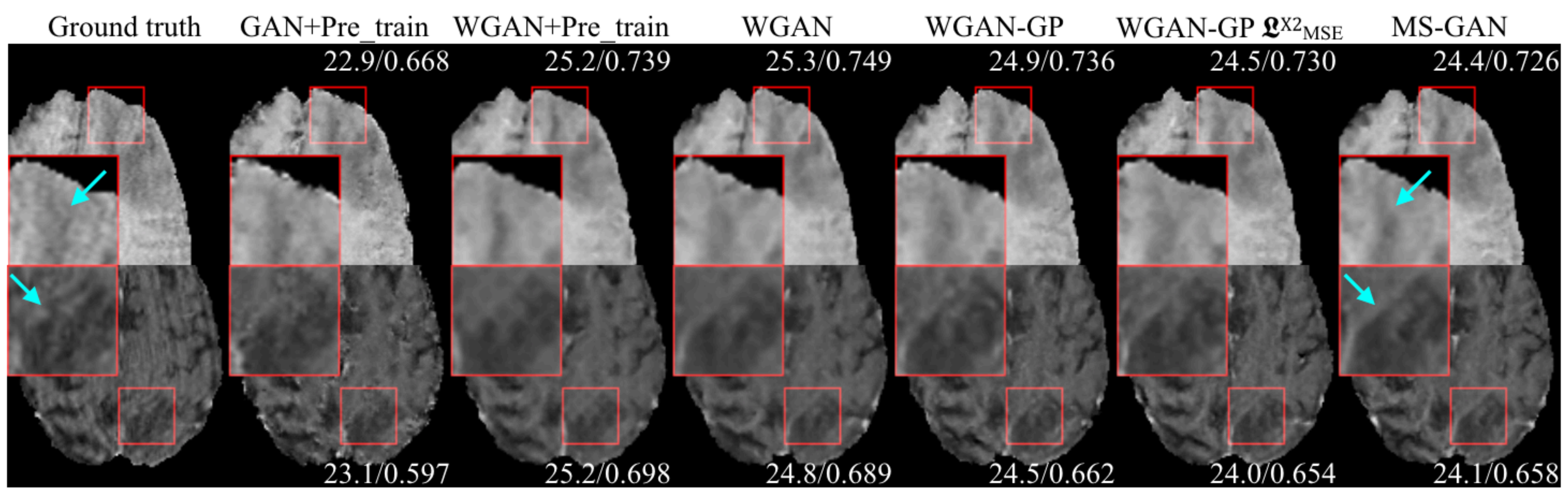

Fig 4. GAN based methods can remove the artefacts in poor image quality ground truth images. Furthermore, our MS-GAN can enhance the edges and textures of tumour regions (cyan arrows).

Conclusion

Our proposed LFSR with MS-GAN with WGAN-GP can avoid introducing unrealistic textures and over-smoothing, and achieve perceptually more realistic SR images (high PSNR/SSIM, and equal MOS with HR ground truths) with less training cost.

References

[1] Zhu, Jin, Guang Yang, and Pietro Lio. "Lesion focused super-resolution." Medical Imaging 2019: Image Processing. Vol. 10949. International Society for Optics and Photonics, 2019.

[2] Ledig, Christian, et al. "Photo-realistic single image super-resolution using a generative adversarial network." Proceedings of the IEEE conference on computer vision and pattern recognition. 2017.

[3] Gulrajani, Ishaan, et al. "Improved training of wasserstein gans." Advances in Neural Information Processing Systems. 2017.

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Full Paper: https://arxiv.org/abs/1901.03419 Code: https://github.com/GinZhu/MSGAN