

# Deeper Image Quality Transfer: Training Low-Memory Neural Networks for 3D Images

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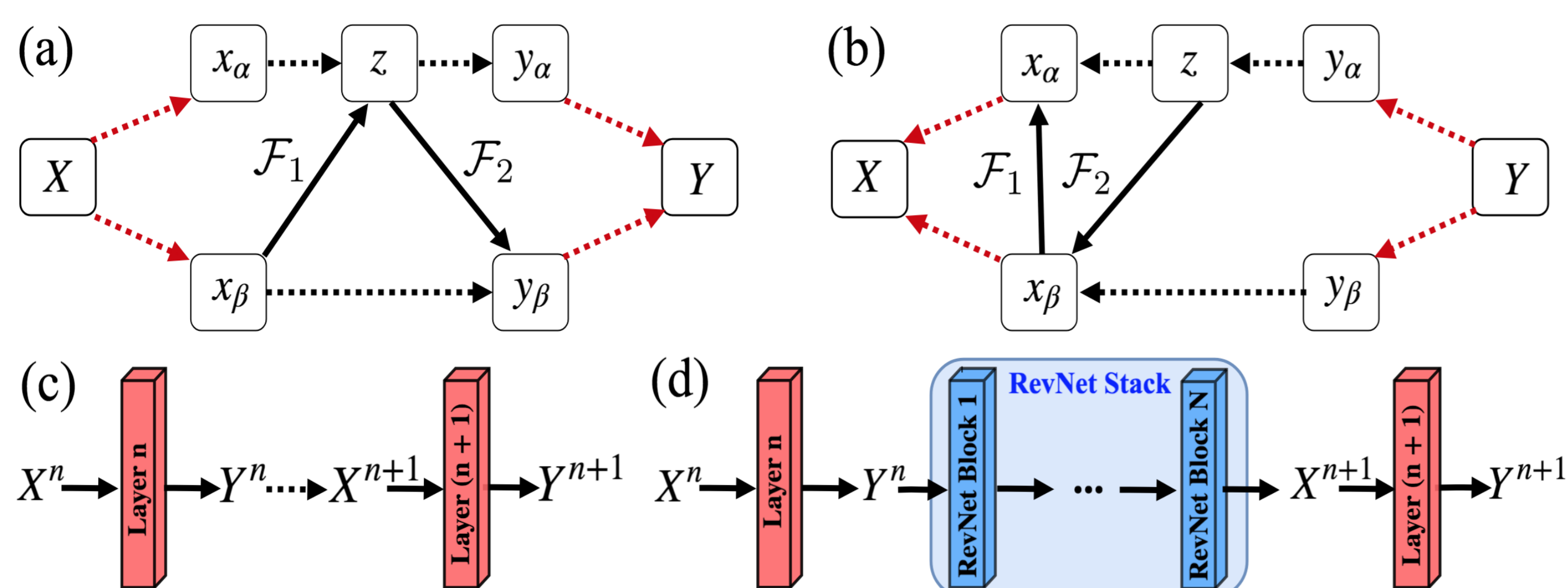
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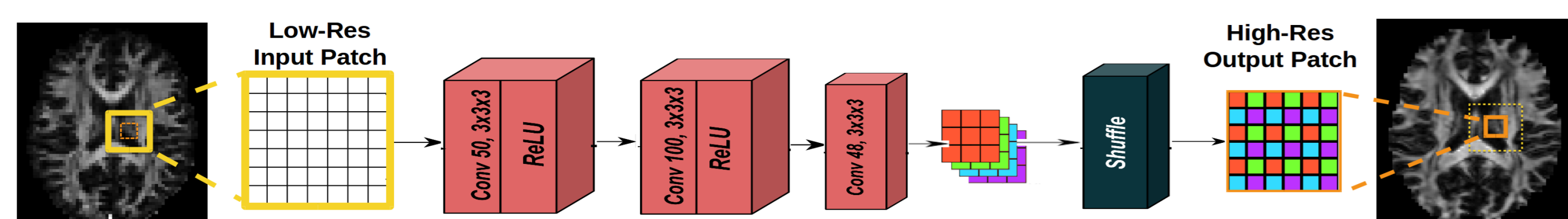
## Summary

1. We address the memory demands of 3D, high-resolution, multi-channelled medical images in deep learning.
2. We use memory-efficient backpropagation techniques, elongating deep architectures with negligible memory increase.
3. With a slight memory increase we obtain state-of-the-art results in Image Quality Transfer [1]: HCP super-resolution.
4. This methodology can be applied to most other tasks involving deep learning.
5. Our code is publicly available.

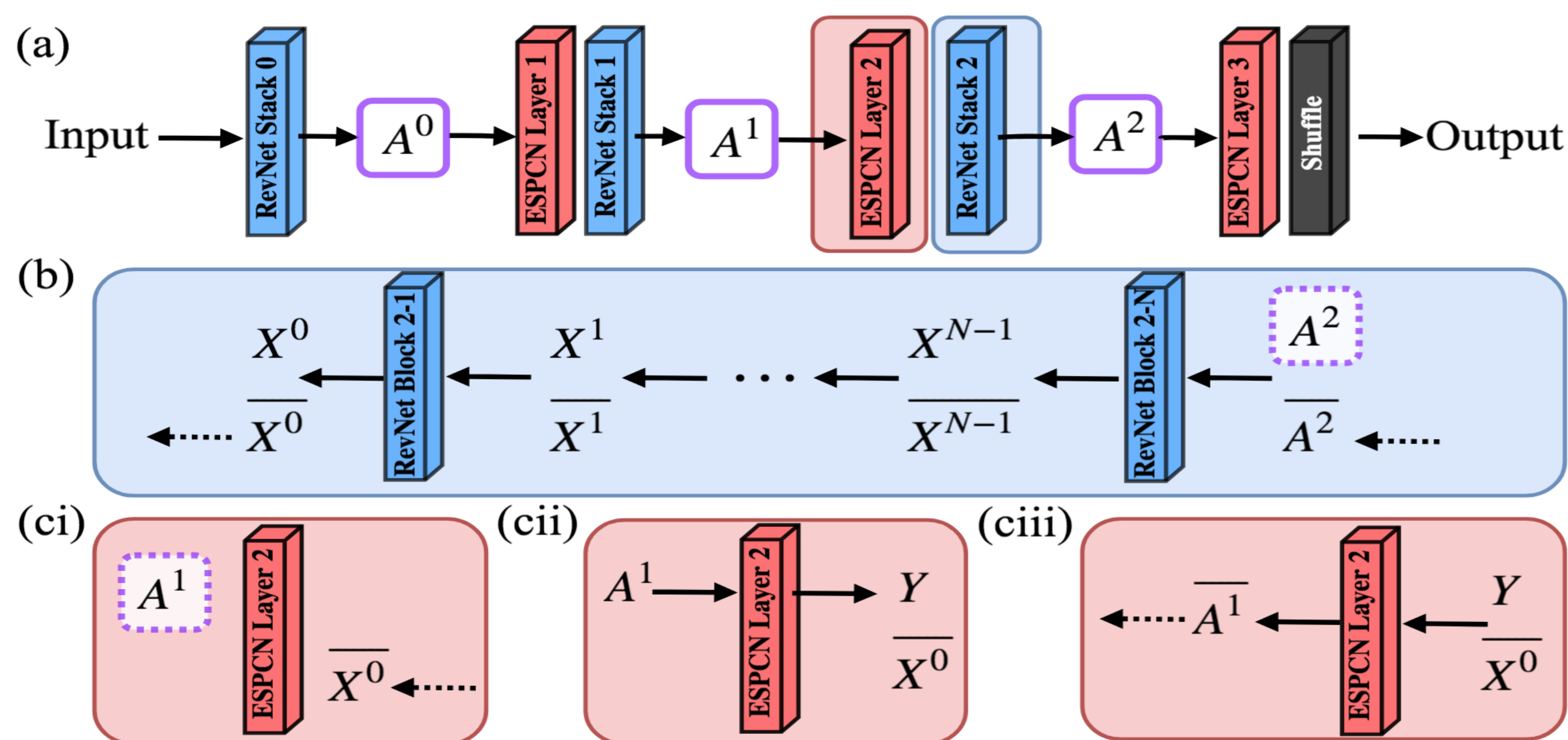
## Memory-Efficient Deep Learning



A Reversible Network [3] (top) and architecture elongation (bottom). We combine Reversible Networks [3] with Checkpointing [2] for our low-memory system.



2D illustration of the baseline network 3D ESPCN [4], which holds state-of-the-art for HCP super-resolution

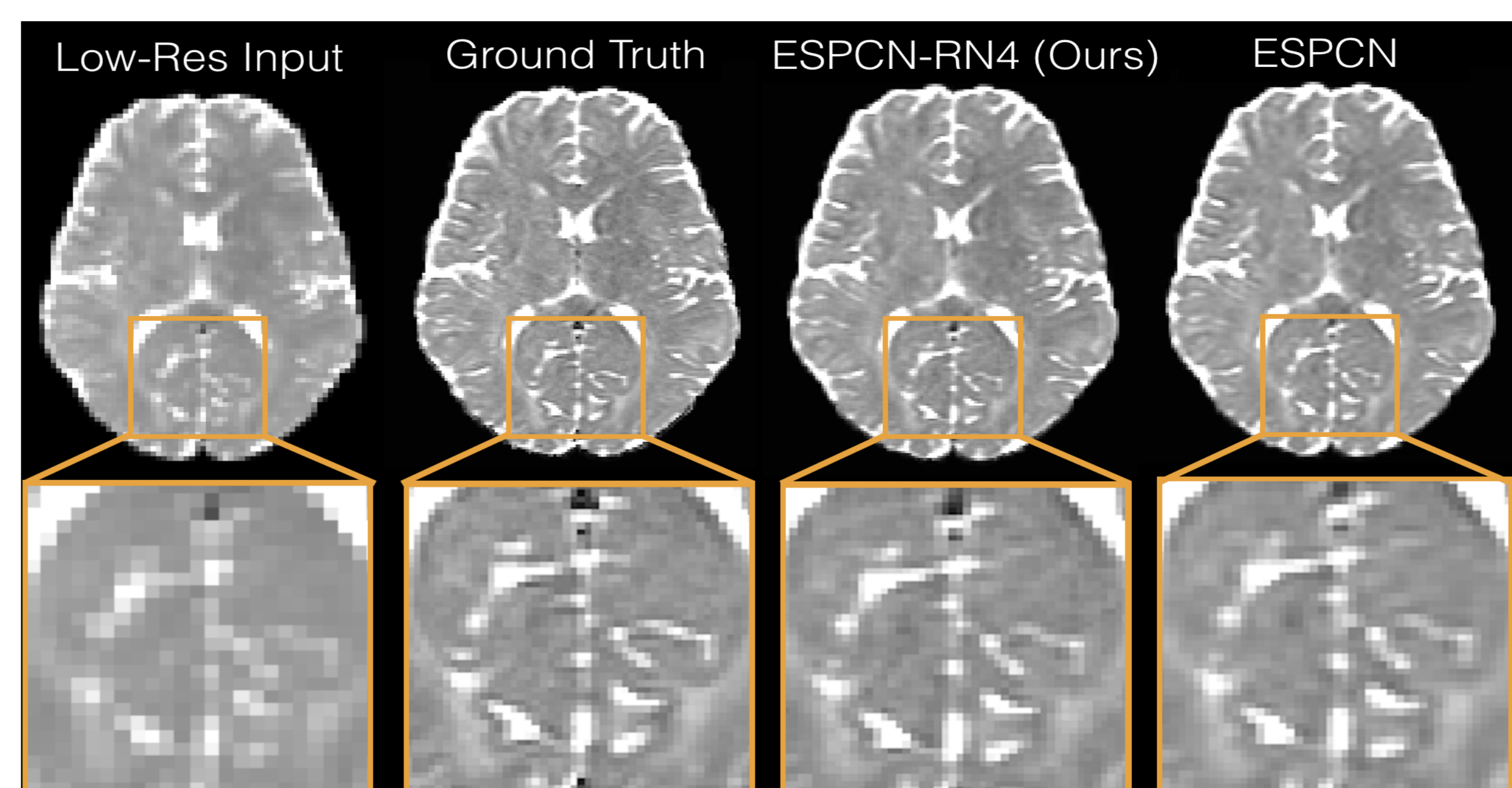


We augment the ESPCN (a) and illustrate the manual forward (a) and backward propagation (b,c), in our low memory system.

## Results

Model	Subjects	RMSE Brain Interior	RMSE Brain Edge	RMSE Total
ESPCN	8	6.33 ( $\pm 0.30$ )	14.01 ( $\pm 1.12$ )	9.72 ( $\pm 0.64$ )
ESPCN-best-[4]	8	6.29 ( $\pm 0.29$ )	13.82 ( $\pm 0.31$ )	9.76 ( $\pm 0.51$ )
ESPCN-RN2	8	5.78 ( $\pm 0.28$ )	13.17 ( $\pm 1.16$ )	9.06 ( $\pm 0.66$ )
ESPCN-RN4	8	5.71 ( $\pm 0.24$ )	12.84 ( $\pm 1.18$ )	8.86 ( $\pm 0.66$ )
ESPCN-RN6	8	7.33 ( $\pm 1.43$ )	13.03 ( $\pm 1.19$ )	9.76 ( $\pm 0.88$ )
ESPCN-RN8	8	9.54 ( $\pm 4.38$ )	12.78 ( $\pm 1.25$ )	11.08 ( $\pm 2.66$ )
ESPCN	16	6.12 ( $\pm 0.29$ )	13.42 ( $\pm 1.15$ )	9.33 ( $\pm 0.65$ )
ESPCN-RN4	16	5.51 ( $\pm 0.25$ )	12.40 ( $\pm 1.23$ )	8.56 ( $\pm 0.68$ )
ESPCN	32	6.12 ( $\pm 0.29$ )	13.42 ( $\pm 1.15$ )	9.33 ( $\pm 0.65$ )
ESPCN-RN4	32	5.58 ( $\pm 0.25$ )	12.13 ( $\pm 1.24$ )	8.46 ( $\pm 0.67$ )

Comparing mean and std error (RMSE) on 8 test HCP subjects, where we first vary number of RevNet blocks per stack, then training set. Network input size  $11^3$ , upsampling rate  $r = 2$ .



Mean diffusivity maps on an axial slice: low-resolution input, ground-truth, high-resolution reconstruction from best ESPCN-RN4, ESPCN [4].

Model	Memory Usage (MB)	Computational Time (s)
ESPCN	523	20
ESPCN-RN4	541	309
ESPCN-RN4 Naive	1091	231

Comparing the memory usage and computational time: baseline ESPCN, our low memory system (ESPCN-RN4), augmented ESPCN where we ignore the low-memory opportunity and use standard backpropagation (ESPCN-RN4 Naive).

## References

- [1] D. Alexander and et al. Image quality transfer and applications in diffusion mri. *In: NeuroImage 152*, (2017) 283-298.
- [2] T. Chen and et al. Training deep nets with sublinear memory cost. *arXiv preprint arXiv:1604.06174* (2016).
- [3] A. Gomez, M. Ren, and et al. The reversible residual network: Backpropagation without storing activation. *In: NIPS*, (2017).
- [4] R. Tanno and et al. Bayesian image quality transfer with cnns: exploring uncertainty in dmri super-resolution. *In: MICCAI* (2017).