Supplementary Material for Deep 3D Dual Path Nets for Automated Pulmonary Nodule Detection and Classification

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1. Detailed network structure for 3D Faster R-CNN with Deep 3D Dual Path Net in Nodule Detection

The encoder network is adapted from DPN92 directly by changing 7×7 filters into 3×3 [1]. The numbers of blocks are changed from 3, 4, 20, 3 to 2, 2, 2, 2. The decoder network is to make the network symmetric. The stride 2 of 3D convolution is added in the first $3\times3\times3$ convolution in each block.

Stage	Output	Weights
Pre-dual	96×96×96, 24	3×3×3, 24
path		
Dual path	48×48×48, 48	$[1\times1\times1,24]$
block 1		$3\times3\times3$, 24, (stride 2) $\times2$
		$\lfloor 1 \times 1 \times 1, 32 \rfloor$
Dual path	24×24×24, 72	$(1\times1\times1,48)$
block 2		$3\times3\times3$, 48, (stride 2) $\times2$
		[1×1×1, 56]
Dual path	12×12×12, 96	$[1\times1\times1,72]$
block 3		$3\times3\times3$, 72, (stride 2) $\times2$
		L _{1×1×1} , 80
Dual path	6×6×6, 120	(1×1×1, 96
block 4		$\langle 3 \times 3 \times 3, 96, (\text{stride } 2) \rangle \times 2$
		[\(1 \times 1 \times 1, 104\)
Deconv. 1	12×12×12, 216	2×2×2, 216
Dual path	12×12×12, 152	[1×1×1, 128]
block 5		√3×3×3, 128
		[1×1×1, 136]
Deconv. 2	24×24×24, 224	2×2×2, 152
Dual path	24×24×24, 248	(1×1×1, 224
block 6		$3\times3\times3,224$ $\times2$
		$\lfloor 1 \times 1 \times 1, 232 \rfloor$
Output	24×24×24, 3×5	Dropout, p=0.5
		$1 \times 1 \times 1, 64$
		1×1×1, 15

2. Detailed network structure for 3D Faster R-CNN with Deep 3D Residual Network in Nodule Detection

The encoder network is adapted from Res18 directly by changing 7×7 filters into 3×3 [2]. We find the latest reference for 3D Res18 network in [3], and will add it into the reference.

the reference.		1
Stage	Output	Weights
Pre-	96×96×96, 24	3×3×3, 24
Residual		3×3×3, 24
Residual	48×48×48, 32	$3\times3\times3,32$
block 1		$(3\times3\times3, 32, (stride 2))\times2$
Residual	24×24×24, 64	$\int 3\times 3\times 3$, 64
block 2		$(3\times3\times3, 64, (stride 2))\times2$
Residual	12×12×12, 64	∫3×3×3, 64
block 3		$3\times3\times3$, 64, (stride 2) 5×3
Residual	6×6×6, 64	$\int 3\times 3\times 3$, 64
block 4		$\lfloor 3 \times 3 \times 3, 64, \text{ (stride 2)} \rfloor \times 3$
Deconv. 1	12×12×12, 128	2×2×2, 64
Residual	12×12×12, 64	3×3×3, 64
block 5		3×3×3, 64√×3
Deconv. 2	24×24×24, 128	2×2×2, 64
Residual	24×24×24, 64	∫3×3×3, 64↑
block 6		\\\3\times3\times3, 64\\\\5\times3
Output	24×24×24, 3×5	Dropout, p=0.5
		$1\times1\times1$, 64
		$1 \times 1 \times 1, 15$
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3. Detailed network structure for Deep 3D Dual Path Net in Nodule Classification

We design 3D dual path network with 92 layers for nodule classification.

Stage	Output	Weights	
Pre-dual	32×32×32, 64	3×3×3, 64	
path			
Dual path	32×32×32, 320	[1×1×1, 96)
		{	}
			J

block 1		$3\times3\times3$, 96, (stride 2) $\times3$
		1×1×1, 272
Dual path	16×16×16, 672	(1×1×1, 192
block 2		$3\times3\times3$, 192, (stride 2) $\times4$
		[1×1×1, 544]
Dual path	8×8×8, 1528	$[1\times1\times1,384]$
block 3		$3\times3\times3$, 72, (stride 2) $\times20$
		\(\lambda \times 1 \times 1, 1048 \)
Dual path	4×4×4, 2560	(1×1×1, 768
block 4		$\langle 3 \times 3 \times 3, 768, (\text{stride } 2) \times 3 \rangle$
		\(\lambda \times 1 \times 1, 2176 \)
Output	2560	3D average pool
	2	2560×2

References

- [1] Y. Chen, J. Li, H. Xiao, X. Jin, S. Yan, and J. Feng. "Dual path networks." In Advances in Neural Information Processing Systems, pp. 4468-4476. 2017.
- [2] K. He, X. Zhang, S. Ren, and J. Sun. "Deep residual learning for image recognition." In Proceedings of the IEEE conference on computer vision and pattern recognition, pp. 770-778. 2016.
- [3] F. Liao, M. Li, Z. Li, X. Hu, and S. Song. "Evaluate the Malignancy of Pulmonary Nodules Using the 3D Deep Leaky Noisy-or Network." arXiv preprint arXiv:1711.08324 (2017).