

## A Appendix

Table 1 shows the architectural details of the proposed DermoNet.

**Table 1.** Architectural details of the proposed DermoNet. Here,  $/2$  and  $*2$  denote downsampling operator using strided convolution and upsampling using a factor of 2, respectively.

Input image: $384 \times 512 \times 3$					
Encoder			Decoder		
Input	Filter	Output	Input	Filter	Output
i-1	$7 \times 7, /2$	$192 \times 256 \times 64$	d-4-1	$1 \times 1$	$6 \times 8 \times 128$
i-2	$3 \times 3, /2$	$96 \times 128 \times 64$	d-4-2	$3 \times 3, *2$	$12 \times 16 \times 128$
e-1-1	$3 \times 3, /2$	$48 \times 64 \times 64$	d-4-3	$1 \times 1$	$12 \times 16 \times 256$
e-1-2	$3 \times 3$	$48 \times 64 \times 64$	d-3-1	$1 \times 1$	$12 \times 16 \times 64$
e-1-3	$3 \times 3$	$48 \times 64 \times 64$	d-3-2	$3 \times 3, *2$	$24 \times 32 \times 64$
e-1-4	$3 \times 3$	$48 \times 64 \times 64$	d-3-3	$1 \times 1$	$24 \times 32 \times 128$
e-2-1	$3 \times 3, /2$	$24 \times 32 \times 128$	d-2-1	$1 \times 1$	$24 \times 32 \times 32$
e-2-2	$3 \times 3$	$24 \times 32 \times 128$	d-2-2	$3 \times 3, *2$	$48 \times 64 \times 32$
e-2-3	$3 \times 3$	$24 \times 32 \times 128$	d-2-3	$1 \times 1$	$48 \times 64 \times 64$
e-2-4	$3 \times 3$	$24 \times 32 \times 128$	d-1-1	$1 \times 1$	$48 \times 64 \times 16$
e-3-1	$3 \times 3, /2$	$12 \times 16 \times 256$	d-1-2	$3 \times 3, *2$	$96 \times 128 \times 16$
e-3-2	$3 \times 3$	$12 \times 16 \times 256$	d-1-3	$1 \times 1$	$96 \times 128 \times 64$
e-3-3	$3 \times 3$	$12 \times 16 \times 256$	o-1	$3 \times 3, *2$	$192 \times 256 \times 32$
e-3-4	$3 \times 3$	$12 \times 16 \times 256$	o-2	$3 \times 3$	$192 \times 256 \times 32$
e-4-1	$3 \times 3, /2$	$6 \times 8 \times 512$	o-3	$2 \times 2, *2$	$384 \times 512 \times 1$
e-4-2	$3 \times 3$	$6 \times 8 \times 512$			
e-4-3	$3 \times 3$	$6 \times 8 \times 512$			
e-4-4	$3 \times 3$	$6 \times 8 \times 512$			
Output image: $384 \times 512 \times 1$					

Tables 2 and 3 show the performance of the proposed segmentation in terms of different metrics including AC, SE and SP, respectively. In addition, we also evaluate the sensitivity of the results with respect to the threshold, which is used to convert the output to a binary mask (see Table 4). Fig. 1 shows some cases from ISBI 2017 challenge dataset, where the Jaccard Coefficients (JC) were low.

**Table 2.** Performance comparison for different network architectures on ISBI 2016 challenge test set

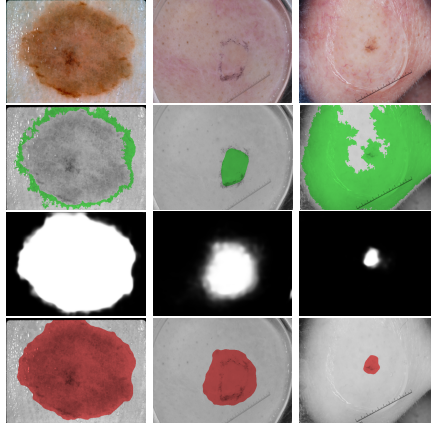
	Method	JC	AC	SE	SP
<b>Average</b>	<i>FCN</i>	72.6%	90.89%	87.07%	91.17%
	<i>U-Net</i>	80.36%	94.23%	87.83%	95.04%
	<b><i>DermoNet</i></b>	<b>82.5%</b>	<b>94.95%</b>	<b>90.28%</b>	<b>95.94%</b>

**Table 3.** Performance comparison for different network architectures on PH2 dataset. Here, JC denotes jaccard coefficient loss and CE denotes cross-entropy loss, respectively.

	Method	JC	AC	SE	SP
<b>Average</b>	<i>FCN</i>	75.8%	90.31%	88.26%	94.33%
	<i>U-Net</i>	84.8%	93.69%	91.55%	<b>96.86%</b>
	<b><i>DermoNet</i></b>	<b>85.3%</b>	<b>94.08%</b>	<b>92.92%</b>	96.59%

**Table 4.** Jaccard distance comparison of the proposed segmentation methods for different threshold on ISBI 2016 challenge test set

Method	FCN	U-Net	<b>DermoNet</b>
<i>th=0.2</i>	54.46%	79.24%	79.12%
<i>th=0.3</i>	57.94%	78.78%	81.0%
<i>th=0.4</i>	69.08%	80.35%	82.15%
<i>th=0.5</i>	72.62%	80.36%	82.58%
<i>th=0.6</i>	72.54%	79.74%	82.18%
<i>th=0.7</i>	64.83%	78.01%	81.08%
<i>th=0.8</i>	62.15%	77.49%	79.43%
<i>th=0.9</i>	66.12%	74.92%	77.08%



**Fig. 1.** Cases where our proposed segmentation failed (mis-segmentation). (a) shows the original images from ISBI 2017. (b) is the ground truths provided in ISBI 2017. (c) and (d) are the outputs of DermoNet without and with thresholding, respectively.