DLCV HW3 Report

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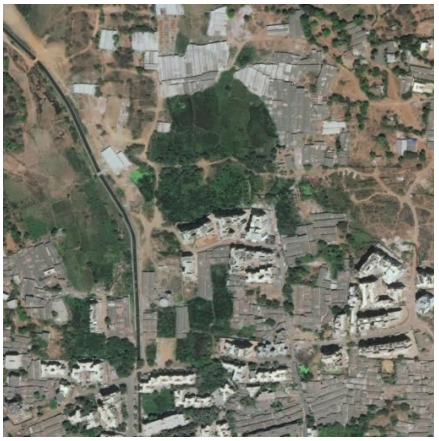
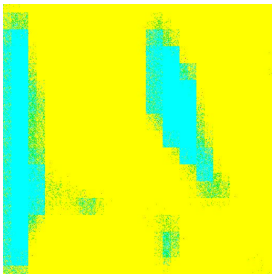
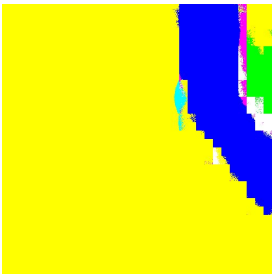
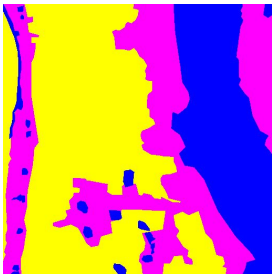
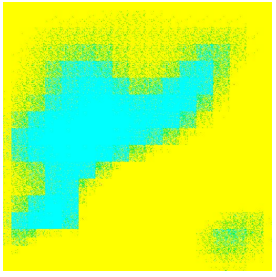
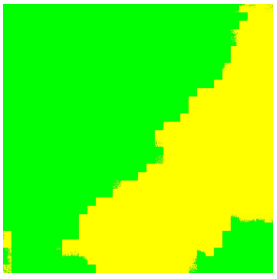
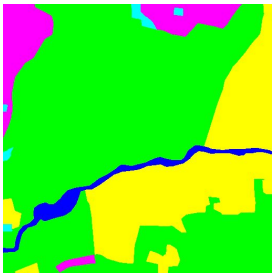
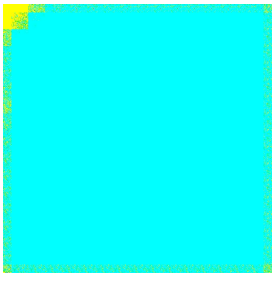
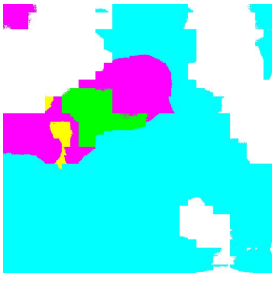
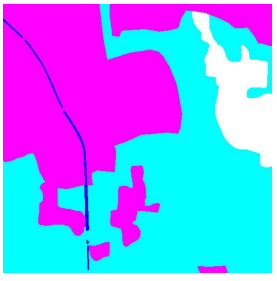
1. (5%) Print the network architecture of your VGG16-FCN32s model.

Layer (type)	Output Shape	Param #
input_1 (InputLayer)	(None, 512, 512, 3)	0
block1_conv1 (Conv2D)	(None, 512, 512, 64)	1792
block1_conv2 (Conv2D)	(None, 512, 512, 64)	36928
block1_pool (MaxPooling2D)	(None, 256, 256, 64)	0
block2_conv1 (Conv2D)	(None, 256, 256, 128)	73856
block2_conv2 (Conv2D)	(None, 256, 256, 128)	147584
block2_pool (MaxPooling2D)	(None, 128, 128, 128)	0
block3_conv1 (Conv2D)	(None, 128, 128, 256)	295168
block3_conv2 (Conv2D)	(None, 128, 128, 256)	590080
block3_conv3 (Conv2D)	(None, 128, 128, 256)	590080
block3_pool (MaxPooling2D)	(None, 64, 64, 256)	0
block4_conv1 (Conv2D)	(None, 64, 64, 512)	1180160
block4_conv2 (Conv2D)	(None, 64, 64, 512)	2359808
block4_conv3 (Conv2D)	(None, 64, 64, 512)	2359808
block4_pool (MaxPooling2D)	(None, 32, 32, 512)	0
block5_conv1 (Conv2D)	(None, 32, 32, 512)	2359808
block5_conv2 (Conv2D)	(None, 32, 32, 512)	2359808
block5_conv3 (Conv2D)	(None, 32, 32, 512)	2359808
block5_pool (MaxPooling2D)	(None, 16, 16, 512)	0
fc_conv1 (Conv2D)	(None, 16, 16, 4096)	18878464
fc_conv2 (Conv2D)	(None, 16, 16, 4096)	16781312
conv2d_1 (Conv2D)	(None, 16, 16, 7)	28679
conv2d_transpose_1 (Conv2DTr	(None, 512, 512, 7)	200704
activation_1 (Activation)	(None, 512, 512, 7)	0

Total params: 50,603,847
Trainable params: 50,603,847
Non-trainable params: 0

2. (10%) Show the predicted segmentation mask of validation/0008_sat.jpg, validation/0097_sat.jpg, validation/0107_sat.jpg during the early, middle, and the final stage during the training stage. (For example, results of 1st, 10th, 20th epoch)

0008_sat.jpg	0097_sat.jpg	0107_sat.jpg
		

	epoch 2	epoch10	final epoch	ground truth
0008_ mask.jpg				
0097_ mask.jpg				
0107_ mask.jpg				

(final epoch指的是training時earlystopping前的model，epoch 1的時候model還沒學到什麼東西，整張圖幾乎都同個顏色，因此這裡以epoch 2的output來做比較，Q4比較不同model的部分也同理)

3. (15%) Implement an improved model which performs better than your baseline model. Print the network architecture of this model.

(1)VGG16-FCN16s :

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 512, 512, 3)	0	
block1_conv1 (Conv2D)	(None, 512, 512, 64)	1792	input_1[0][0]
block1_conv2 (Conv2D)	(None, 512, 512, 64)	36928	block1_conv1[0][0]
block1_pool (MaxPooling2D)	(None, 256, 256, 64)	0	block1_conv2[0][0]
block2_conv1 (Conv2D)	(None, 256, 256, 128	73856	block1_pool[0][0]
block2_conv2 (Conv2D)	(None, 256, 256, 128	147584	block2_conv1[0][0]
block2_pool (MaxPooling2D)	(None, 128, 128, 128	0	block2_conv2[0][0]
block3_conv1 (Conv2D)	(None, 128, 128, 256	295168	block2_pool[0][0]
block3_conv2 (Conv2D)	(None, 128, 128, 256	590080	block3_conv1[0][0]
block3_conv3 (Conv2D)	(None, 128, 128, 256	590080	block3_conv2[0][0]
block3_pool (MaxPooling2D)	(None, 64, 64, 256)	0	block3_conv3[0][0]
block4_conv1 (Conv2D)	(None, 64, 64, 512)	1180160	block3_pool[0][0]
block4_conv2 (Conv2D)	(None, 64, 64, 512)	2359808	block4_conv1[0][0]
block4_conv3 (Conv2D)	(None, 64, 64, 512)	2359808	block4_conv2[0][0]
block4_pool (MaxPooling2D)	(None, 32, 32, 512)	0	block4_conv3[0][0]
block5_conv1 (Conv2D)	(None, 32, 32, 512)	2359808	block4_pool[0][0]
block5_conv2 (Conv2D)	(None, 32, 32, 512)	2359808	block5_conv1[0][0]
block5_conv3 (Conv2D)	(None, 32, 32, 512)	2359808	block5_conv2[0][0]
block5_pool (MaxPooling2D)	(None, 16, 16, 512)	0	block5_conv3[0][0]
fc_conv1 (Conv2D)	(None, 16, 16, 4096)	18878464	block5_pool[0][0]
fc_conv2 (Conv2D)	(None, 16, 16, 4096)	16781312	fc_conv1[0][0]
conv2d_1 (Conv2D)	(None, 16, 16, 7)	28679	fc_conv2[0][0]
conv2d_transpose_1 (Conv2DTrans	(None, 32, 32, 7)	784	conv2d_1[0][0]
conv2d_2 (Conv2D)	(None, 32, 32, 7)	3591	block4_pool[0][0]
add_1 (Add)	(None, 32, 32, 7)	0	conv2d_transpose_1[0][0] conv2d_2[0][0]
conv2d_transpose_2 (Conv2DTrans	(None, 512, 512, 7)	50176	add_1[0][0]
activation_1 (Activation)	(None, 512, 512, 7)	0	conv2d_transpose_2[0][0]

Total params: 50,457,694
Trainable params: 50,457,694
Non-trainable params: 0

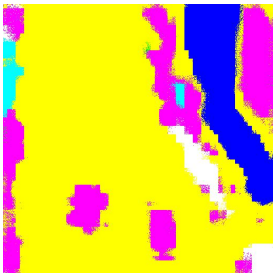
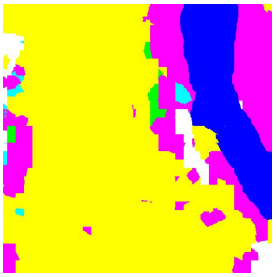
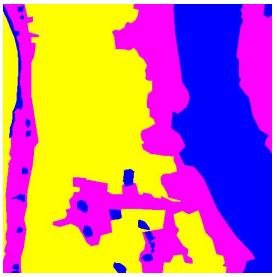
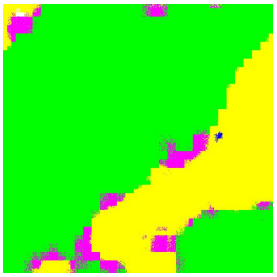
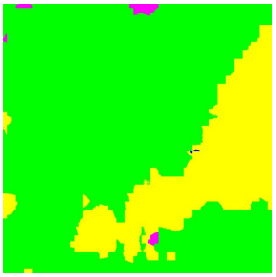
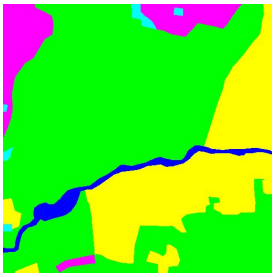
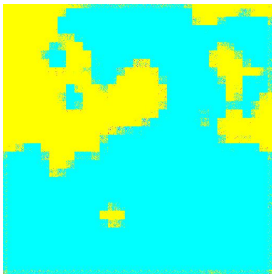
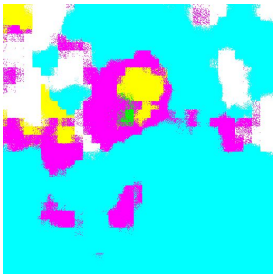
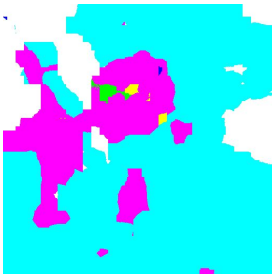
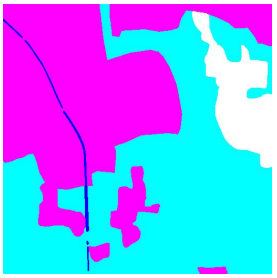
(2) VGG16-FCN8s :

Layer (type)	Output Shape	Param #	Connected to
input_1 (InputLayer)	(None, 512, 512, 3)	0	
block1_conv1 (Conv2D)	(None, 512, 512, 64)	1792	input_1[0][0]
block1_conv2 (Conv2D)	(None, 512, 512, 64)	36928	block1_conv1[0][0]
block1_pool (MaxPooling2D)	(None, 256, 256, 64)	0	block1_conv2[0][0]
block2_conv1 (Conv2D)	(None, 256, 256, 128	73856	block1_pool[0][0]
block2_conv2 (Conv2D)	(None, 256, 256, 128	147584	block2_conv1[0][0]
block2_pool (MaxPooling2D)	(None, 128, 128, 128	0	block2_conv2[0][0]
block3_conv1 (Conv2D)	(None, 128, 128, 256	295168	block2_pool[0][0]
block3_conv2 (Conv2D)	(None, 128, 128, 256	590080	block3_conv1[0][0]
block3_conv3 (Conv2D)	(None, 128, 128, 256	590080	block3_conv2[0][0]
block3_pool (MaxPooling2D)	(None, 64, 64, 256)	0	block3_conv3[0][0]
block4_conv1 (Conv2D)	(None, 64, 64, 512)	1180160	block3_pool[0][0]
block4_conv2 (Conv2D)	(None, 64, 64, 512)	2359808	block4_conv1[0][0]
block4_conv3 (Conv2D)	(None, 64, 64, 512)	2359808	block4_conv2[0][0]
block4_pool (MaxPooling2D)	(None, 32, 32, 512)	0	block4_conv3[0][0]
block5_conv1 (Conv2D)	(None, 32, 32, 512)	2359808	block4_pool[0][0]
block5_conv2 (Conv2D)	(None, 32, 32, 512)	2359808	block5_conv1[0][0]
block5_conv3 (Conv2D)	(None, 32, 32, 512)	2359808	block5_conv2[0][0]
block5_pool (MaxPooling2D)	(None, 16, 16, 512)	0	block5_conv3[0][0]
fc_conv1 (Conv2D)	(None, 16, 16, 4096)	18878464	block5_pool[0][0]
fc_conv2 (Conv2D)	(None, 16, 16, 4096)	16781312	fc_conv1[0][0]
conv2d_1 (Conv2D)	(None, 16, 16, 7)	28679	fc_conv2[0][0]
conv2d_transpose_1 (Conv2DTrans	(None, 32, 32, 7)	784	conv2d_1[0][0]
conv2d_2 (Conv2D)	(None, 32, 32, 7)	3591	block4_pool[0][0]
add_1 (Add)	(None, 32, 32, 7)	0	conv2d_transpose_1[0][0] conv2d_2[0][0]
conv2d_transpose_2 (Conv2DTrans	(None, 64, 64, 7)	784	add_1[0][0]
conv2d_3 (Conv2D)	(None, 64, 64, 7)	1799	block3_pool[0][0]
add_2 (Add)	(None, 64, 64, 7)	0	conv2d_transpose_2[0][0] conv2d_3[0][0]
conv2d_transpose_3 (Conv2DTrans	(None, 512, 512, 7)	12544	add_2[0][0]
activation_1 (Activation)	(None, 512, 512, 7)	0	conv2d_transpose_3[0][0]

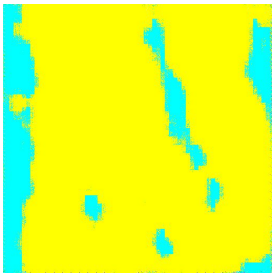
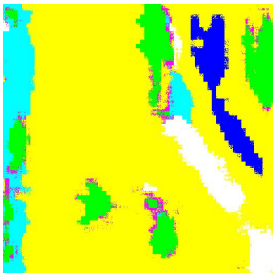
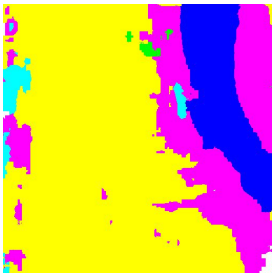
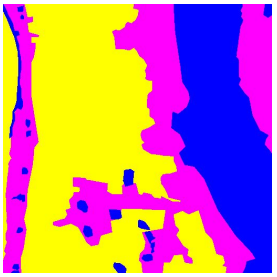
Total params: 50,422,645
Trainable params: 50,422,645
Non-trainable params: 0

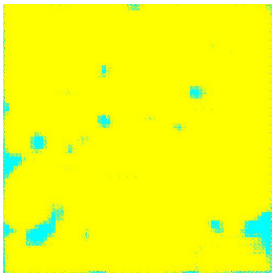
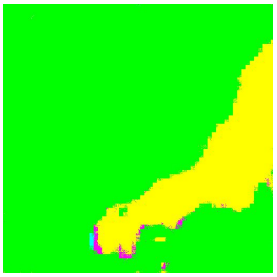
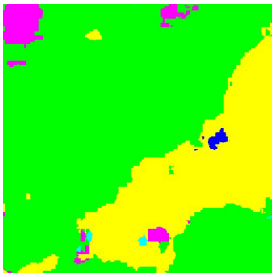
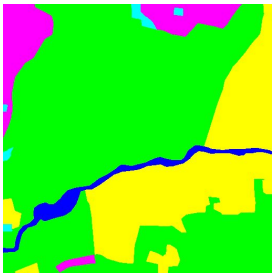
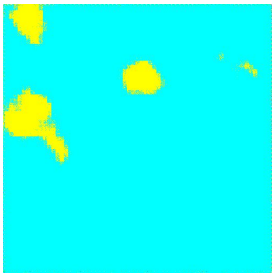
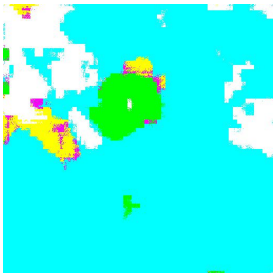
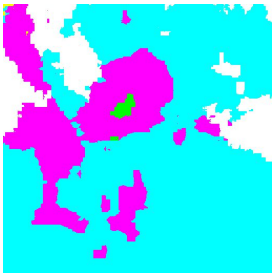
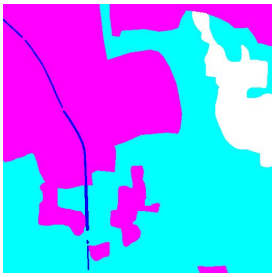
4. (10%) Show the predicted segmentation mask of validation/0008_sat.jpg, validation/0097_sat.jpg, validation/0107_sat.jpg during the early, middle, and the final stage during the training process of this improved model.

VGG16-FCN16s :

	epoch 2	epoch 10	final epoch	ground truth
0008_ mask.jpg				
0097_ mask.jpg				
0107_ mask.jpg				

VGG16-FCN8s :

	epoch 2	epoch 10	final epoch	ground truth
0008_ mask.jpg				

0097_ mask.jpg				
0107_ mask.jpg				

5. (15%) Report mIoU score of both models on the validation set. Discuss the reason why the improved model performs better than the baseline one. You may conduct some experiments and show some evidences to support your discussion.

	FCN_32s	FCN_16s	FCN_8s
class #0	0.71774	0.74861	0.75908
class #1	0.87164	0.86890	0.87564
class #2	0.25933	0.29304	0.34733
class #3	0.74692	0.76598	0.78900
class #4	0.70425	0.74807	0.73500
class #5	0.65134	0.64684	0.64123
mean_IoU	0.658988	0.678574	0.691213

由上面第四小題的output圖片比較可以看出，和baseline的32s model的結果相比，16s和8s的結果好上許多，而8s的又比16s稍好一些，從mean_IoU值來看也是相同結果，推測是因為16s和8s的model架構中都有將前面幾層還沒經過MaxPooling壓縮的layer接到後面來，因此可以保存更多圖片的細節，使得在做segmentaion時可以將細微的地方切得更好，從圖片也可觀察到，比起FCN_32s，這兩個 improved model 的結果多了更多的細節，像是一些零星的有色碎塊，而不是整大片都相同的顏色，這都會使得mean_IoU的值有所提升。

6. (5%) [bonus] Calculate the result of d/dw G(w):

objective function:

$$G(\boldsymbol{w}) = -\sum_n \left[t^{(n)} \log \mathrm{x}(\boldsymbol{z}^{(n)}; \boldsymbol{w}) + (1 - t^n) \log \left(1 - \mathrm{x}(\boldsymbol{z}^{(n)}; \boldsymbol{w})\right) \right] \geq 0$$

$$\boldsymbol{w}^* = \arg\min_{\boldsymbol{w}} G(\boldsymbol{w})$$ choose the weights that minimise the network's surprise about the training data

$$\frac{\mathrm{d}}{\mathrm{d}\boldsymbol{w}} G(\boldsymbol{w}) = \sum_n \frac{\mathrm{d}G(\boldsymbol{w})}{\mathrm{d}x^{(n)}} \frac{\mathrm{d}x^{(n)}}{\mathrm{d}\boldsymbol{w}} = -\sum_n (t^{(n)} - x^{(n)}) \boldsymbol{z}^{(n)}$$ = prediction error x feature

$$\boldsymbol{w} \leftarrow \boldsymbol{w} - \eta \frac{\mathrm{d}}{\mathrm{d}\boldsymbol{w}} G(\boldsymbol{w})$$ iteratively step down the objective (gradient points up hill) 39

Bonus:

$$\frac{d}{dw} G(w) = \sum_n \frac{dG(w)}{dx^{(n)}} \frac{dx^{(n)}}{dw}$$

$$x_i = \frac{1}{1+e^{-a}}, \qquad a = \sum_{j=1}^{n} z_j w_{ij}.$$

$$\frac{\partial G}{\partial w_{ij}} = -\left(\frac{t_i}{x_i} - \frac{1-t_i}{1-x_i}\right) \frac{dx_i}{dw_{ij}}$$

$$= -\frac{t_i - x_i}{x_i(1-x_i)} \cdot \frac{\partial x_i}{\partial a} \cdot \frac{\partial a}{\partial w_{ij}}.$$

$$= -\frac{t_i - x_i}{x_i(1-x_i)} \cdot (x_i(1-x_i)) \cdot z_j.$$

$$= -z_j (t_i - x_i)$$

$$\Rightarrow \frac{d}{dw} G(w) = -\sum_n \left(t^{(n)} - x^{(n)}\right) z^{(n)} \quad \#.$$