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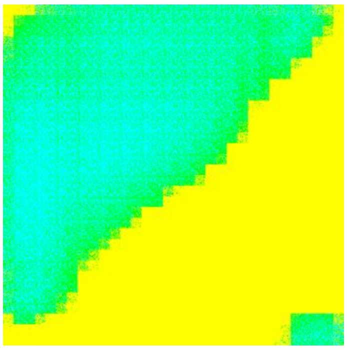
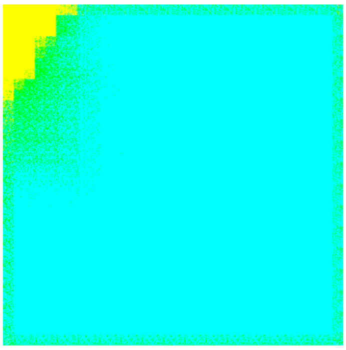
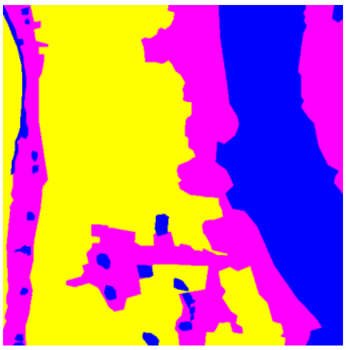
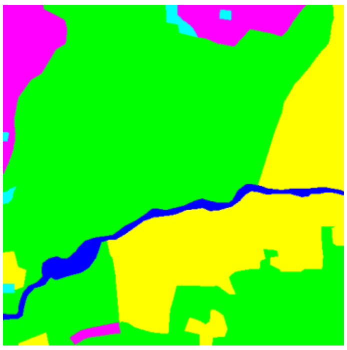
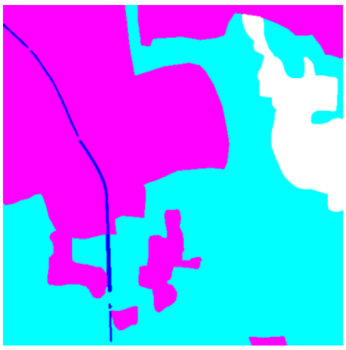
1. (5%) Print the network architecture of your VGG16-FCN32s model.

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
block6_conv1 (Conv2D)	(None, 16, 16, 512)	12845568
dropout_1 (Dropout)	(None, 16, 16, 512)	0
block7_conv1 (Conv2D)	(None, 16, 16, 512)	262656
dropout_2 (Dropout)	(None, 16, 16, 512)	0
block8_conv1 (Conv2D)	(None, 16, 16, 7)	3591
block9_transpose (Conv2DTran	(None, 544, 544, 7)	200704
cropping2d_1 (Cropping2D)	(None, 512, 512, 7)	0
activation_1 (Activation)	(None, 512, 512, 7)	0

Total params: 28,027,207
Trainable params: 28,027,207
Non-trainable params: 0

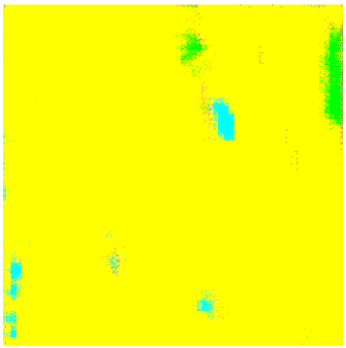
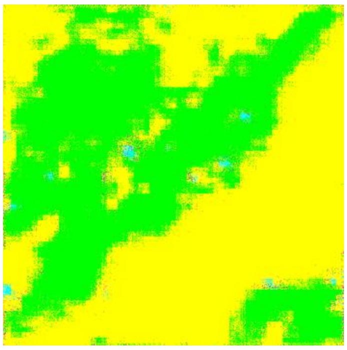
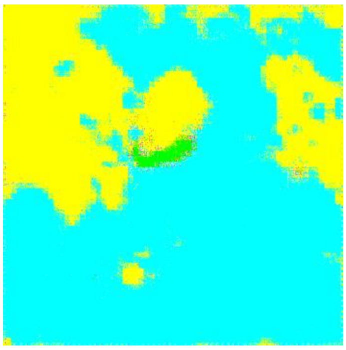
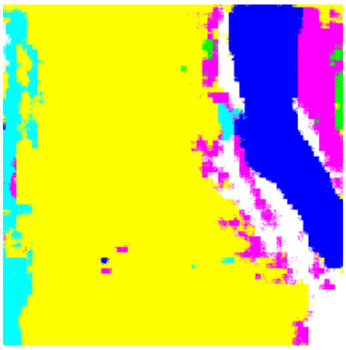
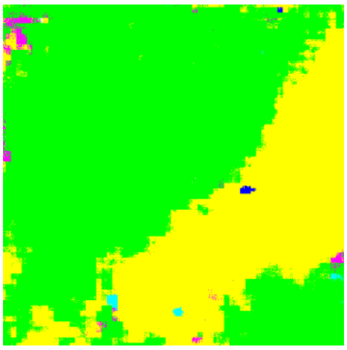
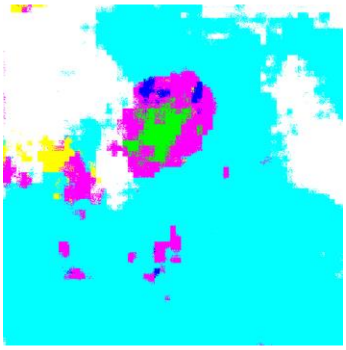
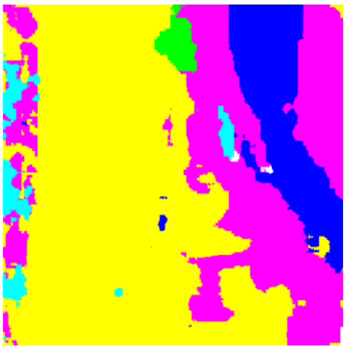
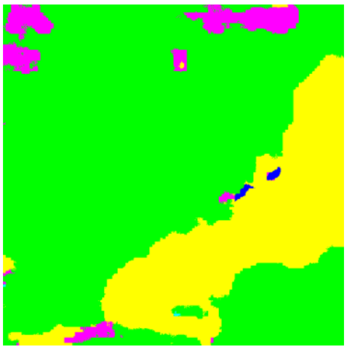
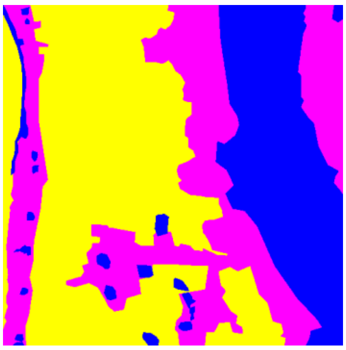
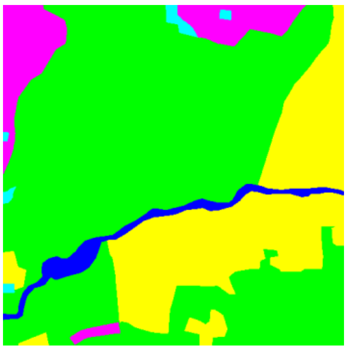
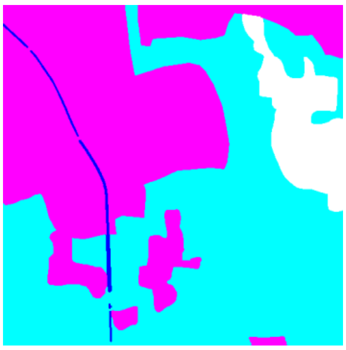
2. (10%) Show the predicted segmentation mask of validation/0008_sat.jpg, validation/0097_sat.jpg, validation/0107_sat.jpg during the early, middle, and the final stage during the training stage. (For example, results of 1st, 10th, 20th epoch)

	0008_mask.png	0097_mask.png	0107_mask.png
Early			
Middle			
Final			
Ground Truth			

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

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]
block6_conv1 (Conv2D)	(None, 16, 16, 512)	12845568	block5_pool[0][0]
dropout_1 (Dropout)	(None, 16, 16, 512)	0	block6_conv1[0][0]
block7_conv1 (Conv2D)	(None, 16, 16, 512)	262656	dropout_1[0][0]
dropout_2 (Dropout)	(None, 16, 16, 512)	0	block7_conv1[0][0]
score (Conv2D)	(None, 16, 16, 7)	3591	dropout_2[0][0]
upscore_1 (Conv2DTranspose)	(None, 34, 34, 7)	784	score[0][0]
fcn4_score (Conv2D)	(None, 32, 32, 7)	3591	block4_pool[0][0]
cropping2d_1 (Cropping2D)	(None, 32, 32, 7)	0	upscore_1[0][0]
add_1 (Add)	(None, 32, 32, 7)	0	fcn4_score[0][0] cropping2d_1[0][0]
upscore_2 (Conv2DTranspose)	(None, 66, 66, 7)	784	add_1[0][0]
fcn3_score (Conv2D)	(None, 64, 64, 7)	1799	block3_pool[0][0]
cropping2d_2 (Cropping2D)	(None, 64, 64, 7)	0	upscore_2[0][0]
add_2 (Add)	(None, 64, 64, 7)	0	fcn3_score[0][0] cropping2d_2[0][0]
upscore_3 (Conv2DTranspose)	(None, 520, 520, 7)	12544	add_2[0][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.

	0008_mask.png	0097_mask.png	0107_mask.png
Early			
Middle			
Final			
Ground Truth			

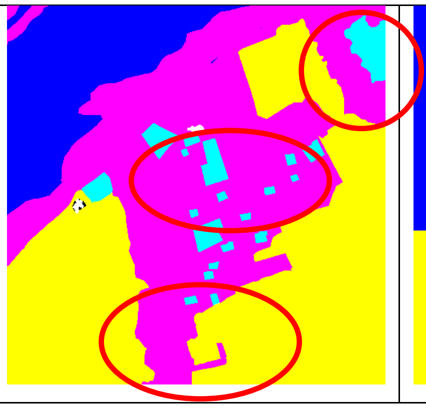
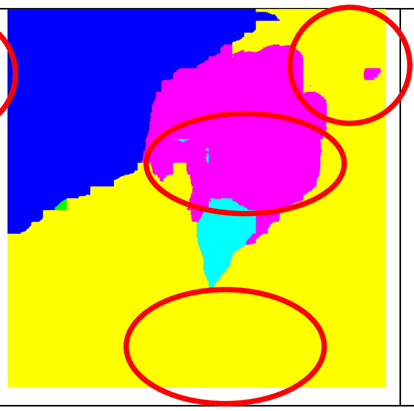
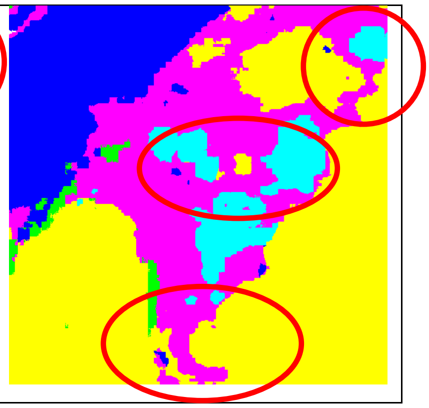
5. (15%) Report mIoU score of both models on the validation set. Discuss the reason why the improved model performs better than the baseline one. You may conduct some experiments and show some evidences to support your discussion.

	VGG16-FCN32s model	Improved model (VGG16-FCN8s model)
Class #0 Urban	0.74924	0.75377
Class #1 Agriculture	0.86632	0.88633
Class #2 Rangeland	0.26339	0.34878
Class #3 Forest	0.78939	0.81362
Class #4 Water	0.66142	0.76085
Class #5 Barren	0.66780	0.69878
Mean_iou	0.666260	0.710355

Reason:

在 FCN8s model 中，它並不是直接將最後一層的 score 直接放大 32 倍當成輸出，而是先放大兩倍，對第四層 maxpooling 輸出的 score 做 pixel wise 的相加，再放大兩倍，對第三層 maxpooling 輸出的 score 做 pixel wise 的加成，最後才放大回原圖的大小。藉由跟前面幾層的 score 做 pixel wise 加成，它能從中取得一些影像中較為細小的部分(小物件)，使得它的 image segmentation 在較為細小的部分有比較好的結果。(在有運用 Maxpooling 的卷積網路中，越後面的層數，特徵較為不明顯的部分會逐漸消失)

	Ground Truth	FCN32s model	FCN8s model
#1			

#2			

上面以兩個圖當作範例，紅色圓圈為我拿來比較的部分，在該區塊較為小的部分(顏色)，在 FCN32s model 中預測出來的結果裡，基本上這些相關的資訊(顏色)都消失不見，而在 FCN8s model 中還能看到部分的區塊，且有不錯的表現。這些因素，也導致最後 FCN8s 的 mean_iou 表現得比 FCN32s 還要好。

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