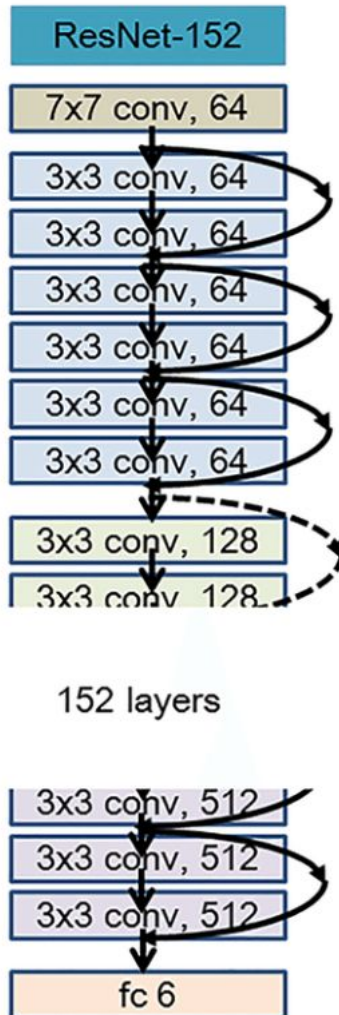


DLCV HW1 Report

Problem 1

1. Model of method B

Resnet-152



2. Accuracy on validation set

Model A	Model B
56.44%	90.72%

3. Implementation details of model A

optimizer: **Adam** with $\text{lr} = 2\text{e-}3$

lr_decay: Exponential decay

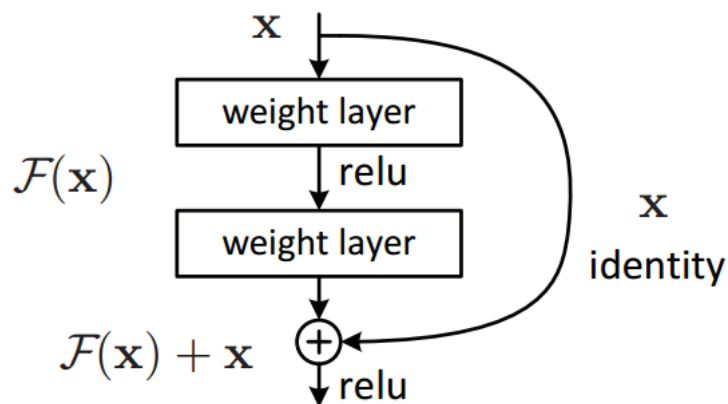
loss function: **CrossEntropyLoss()**

cross validation: **1-fold**

batch normalization: Add **BatchNorm2d** in CNN block

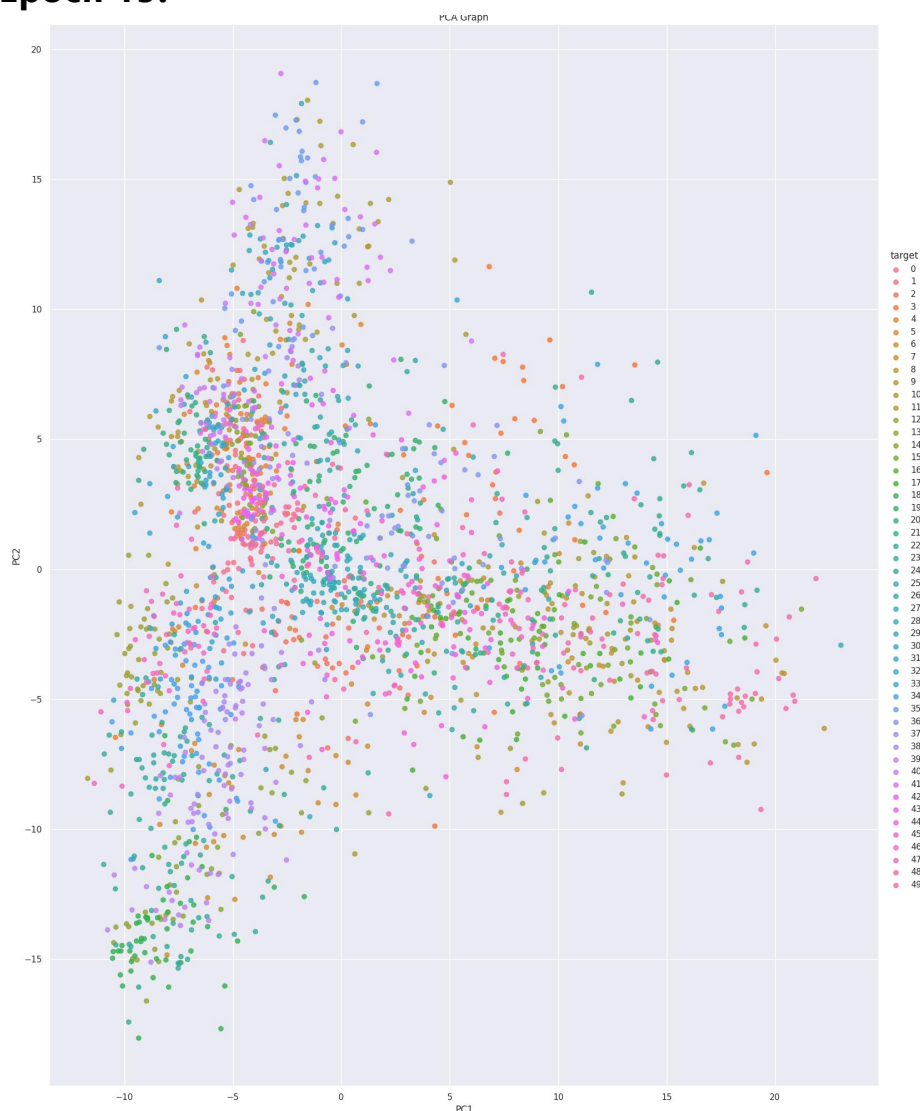
4. Method in B: Resnet152

Resnet 引進了 **Residual Block**(x 跳過layer直接輸入到下一層的activation function)的機制使得原本在深層CNN容易發生的gradient vanishment/gradient explosion的問題得到緩解



5. PCA result

Epoch 15:



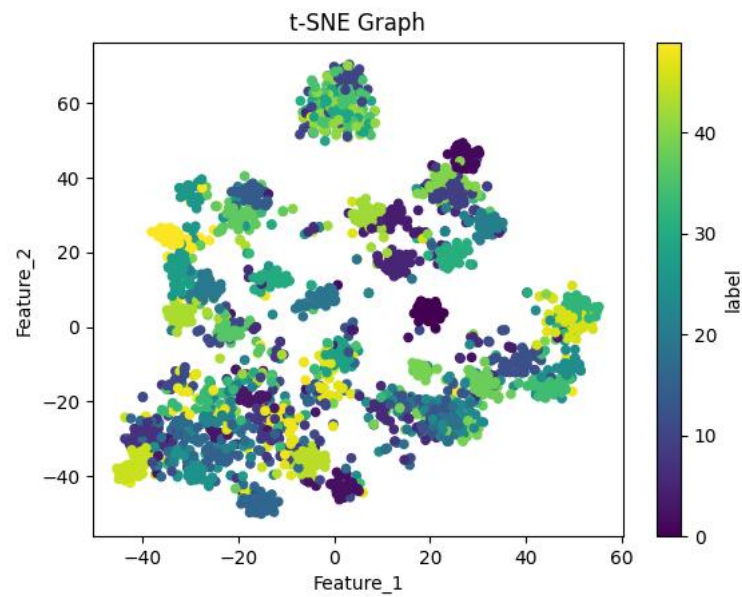
Epoch 50(last epoch):



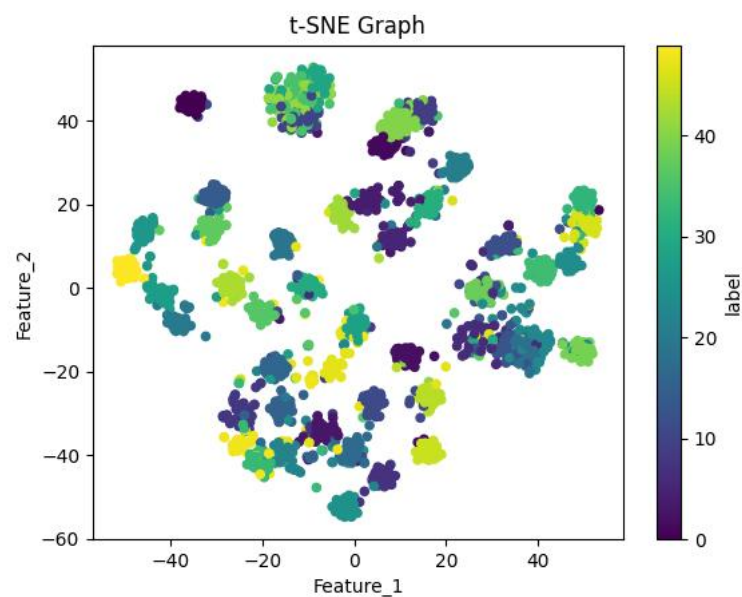
PCA主要是要做到降維的目的同時希望留下最重要的特徵，可以看到在2-dim的圖中，模型在Epoch 15時還不能很好的分類不同class的feature但到epoch 50時已經可以把同class的feature拉近並把不同class的feature推遠

6. t-SNE result

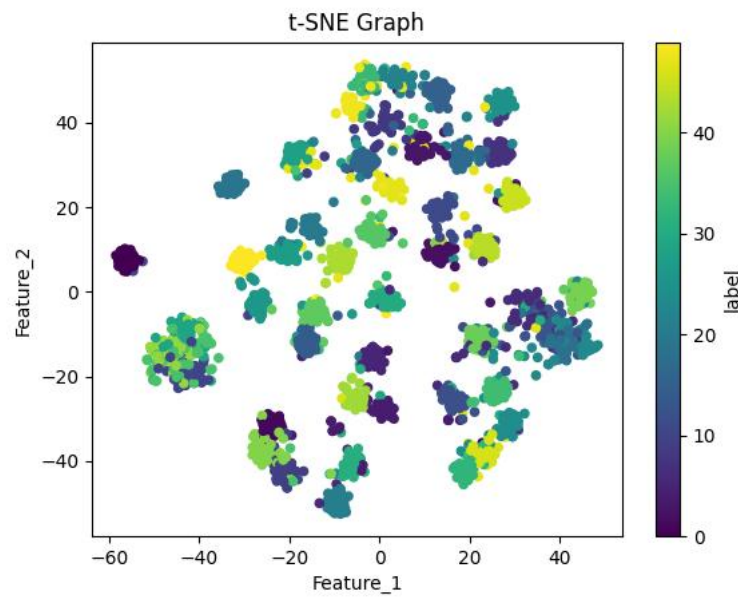
Epoch 1:



Epoch 15:



Epoch 50(last epoch):

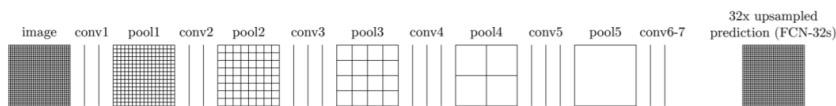


t-SNE是一種非線性的降維法，常用於模型的視覺化觀察，

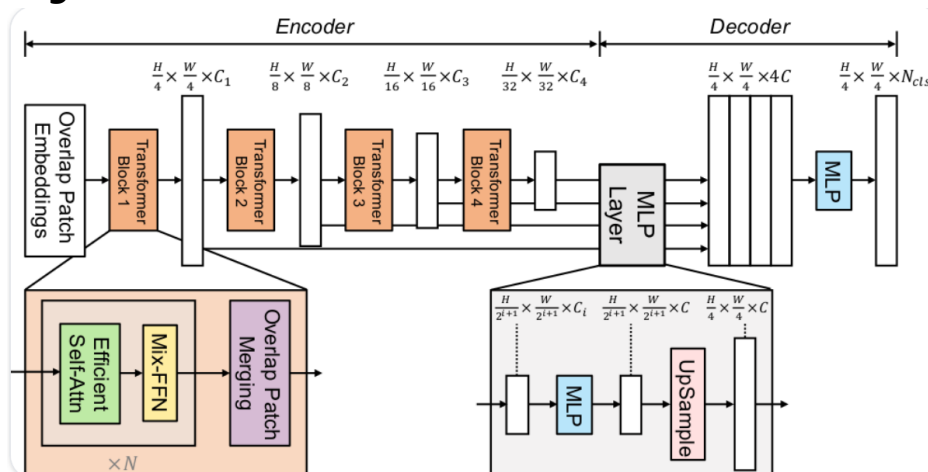
可以看到Epoch數越大相同class的點分布越集中不同class的點分布則會散開

Problem 2

1. VGG16-FCN32



2. Segformer



Differs from VGG16-FCN32:

Segformer在encoder的部分是使用transformer encoder(self-attention)並且decoder方面使用輕量的MLP layer與VGG使用CNN當backbone十分不同

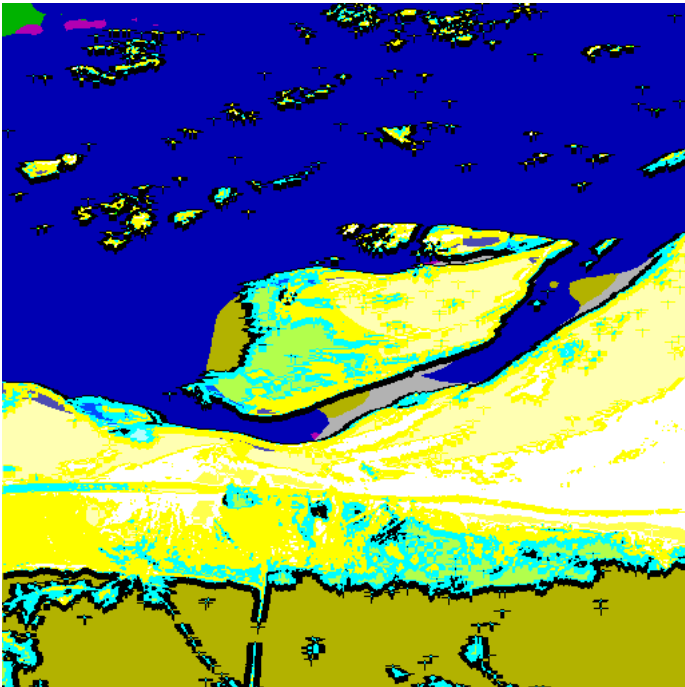
3. mIoU of two models on the validation set

Model A	Model B
70.20%	75.68%

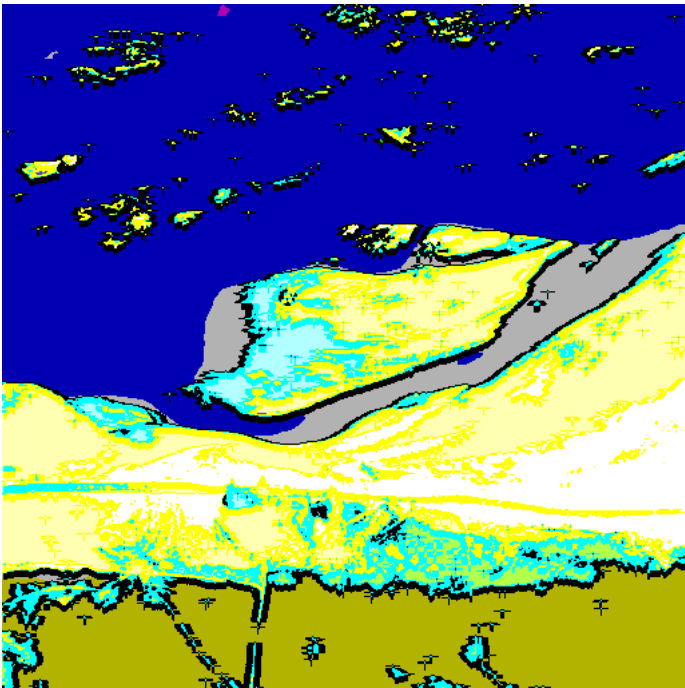
4. segmentation masks

0013_sat.jpg

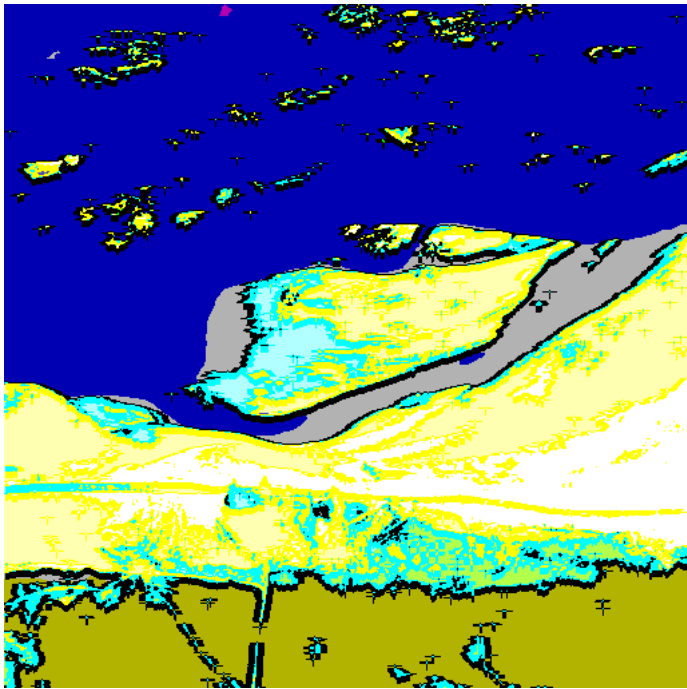
Epoch 1:



Epoch 10:

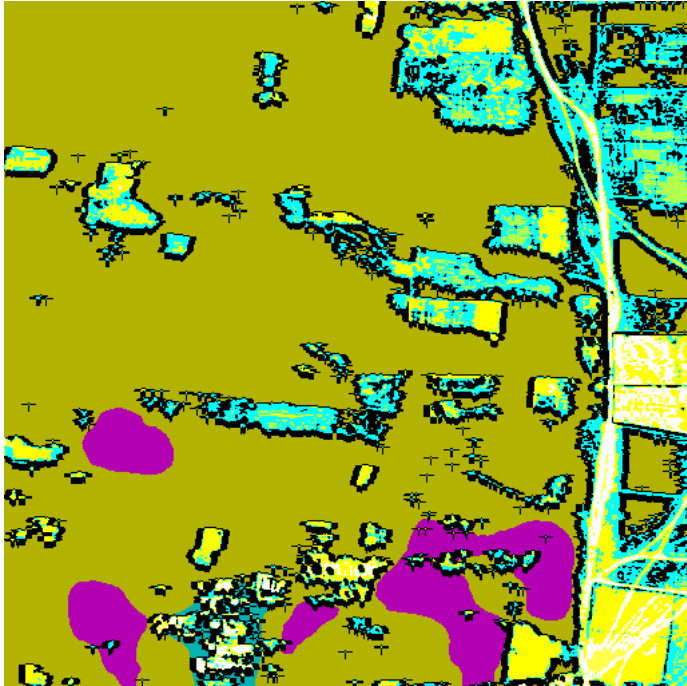


Epoch 20:

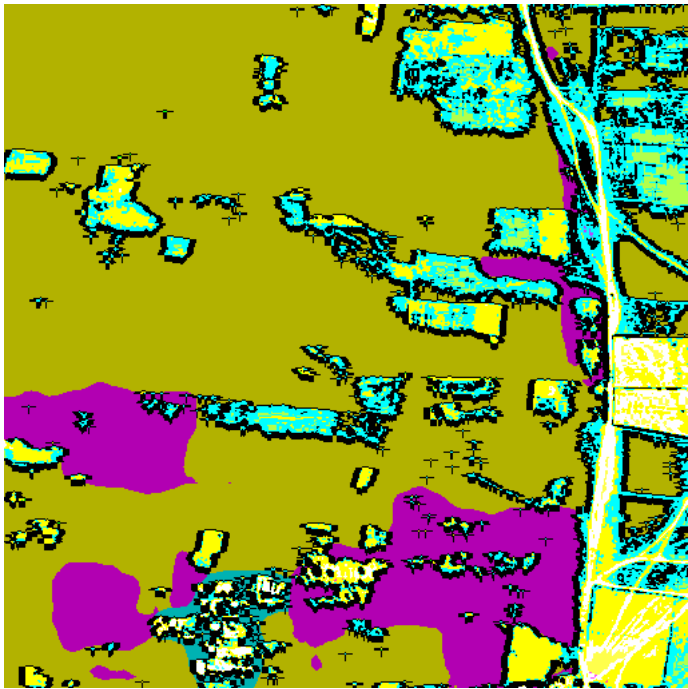


0062_sat.jpg

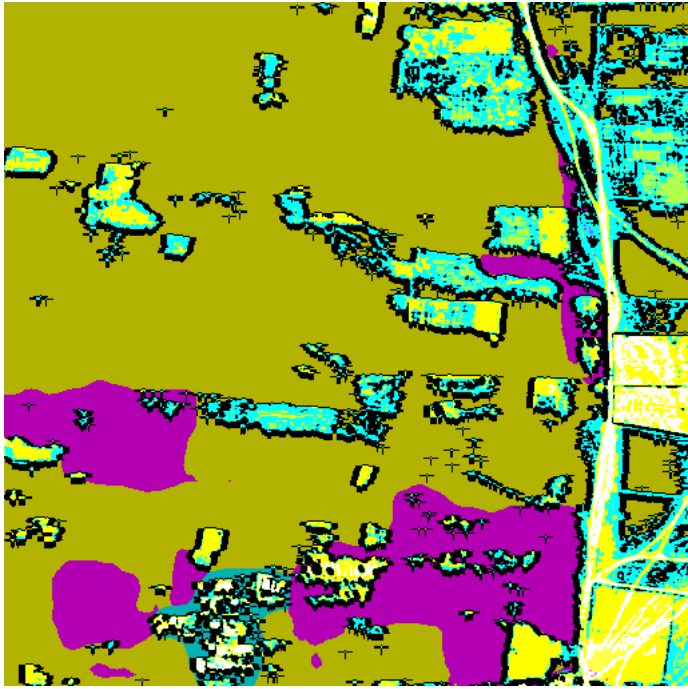
Epoch 1:



Epoch 10:

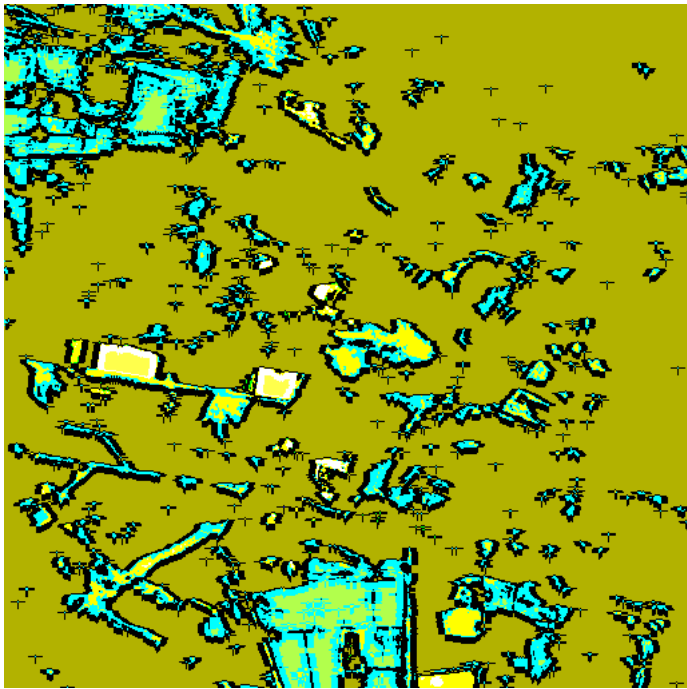


Epoch 20:

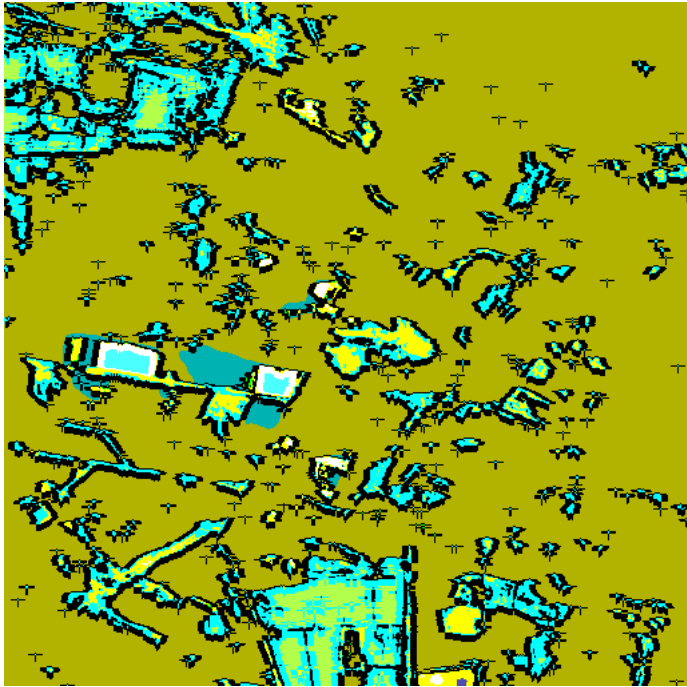


0104_sat.jpg

Epoch 1:



Epoch 10:



Epoch 20:

