

Cell Segmentation and Classification - Unet

CS 736 Medical Image Computing Course Project

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1 Introduction

- We implement the U-Net CNN from the original [paper](#) in PyTorch.
- We use cross-entropy loss like in the paper for the first dataset([Fluo-N2DH-GOWT1](#)) and the second dataset([EM Stacks](#)) since it is giving a sharper segmentation. We weight the loss according to the relative weights of the foreground and background. This is critical since the background is around 96% of the image.
- Since we didn't have a val set for the second dataset, we did a 23-7 split on our train set.
- We use Adam optimization.
- The same network architecture and tiling/mirroring strategies are used as described in the paper.
- Idea for segmentation: We can change the number of output channels in the Unet architecture to the number of classes. A categorical cross entropy loss (which we have implemented) is used for training. Argmax over the output channels gives the predicted class. Segmentation is also achieved since there is a background class also.

Hyperparameters used are as follows:

RandomAffine ranges	(-0.1,0.1), [-0.01,0.01]
Batch size	3
Learning rate	0.001
Momentum	0.9
Number of epochs	30 (Fluo) , 60 (EM)
Threshold	1.2 , (argmax)

Hyperparameters

2 Results

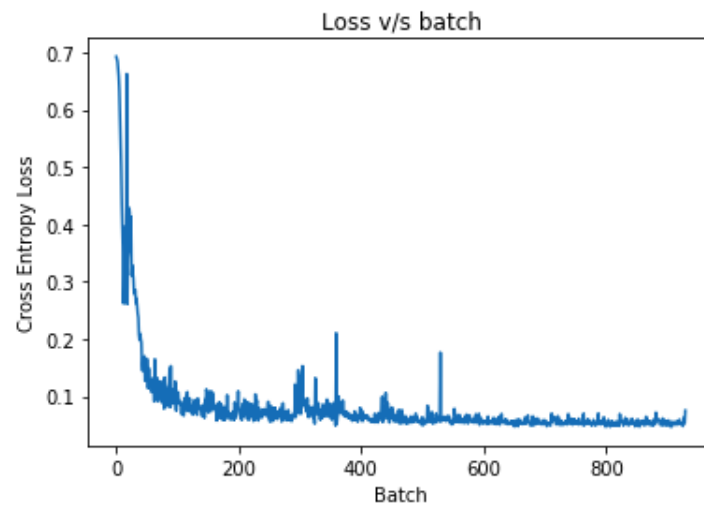
- The models were evaluated using the Intersection-Over-Union metric on the validation sets, weighted by the class frequencies.
- The threshold given in the above table maximized the IOU metric on the validation set.

Fluo-N2DH-GOWT1	0.67766
EM Stacks	0.75085

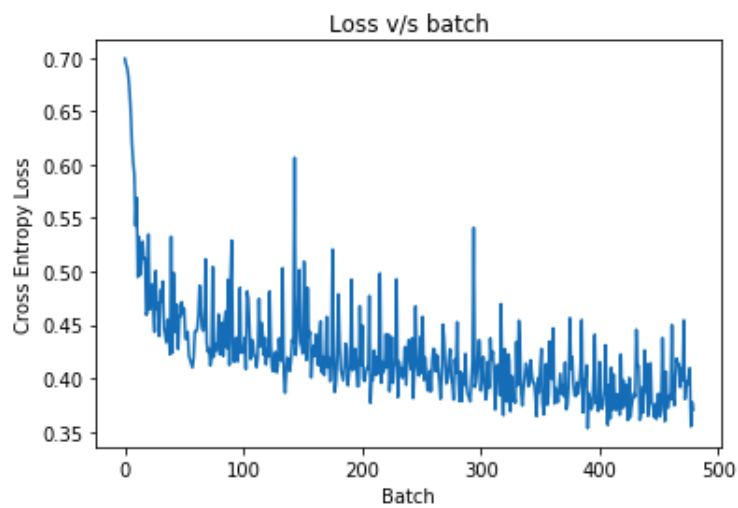
IOU metric over validation set

3 Loss function graphs

3.1 Fluo-N2DH-GOWT1

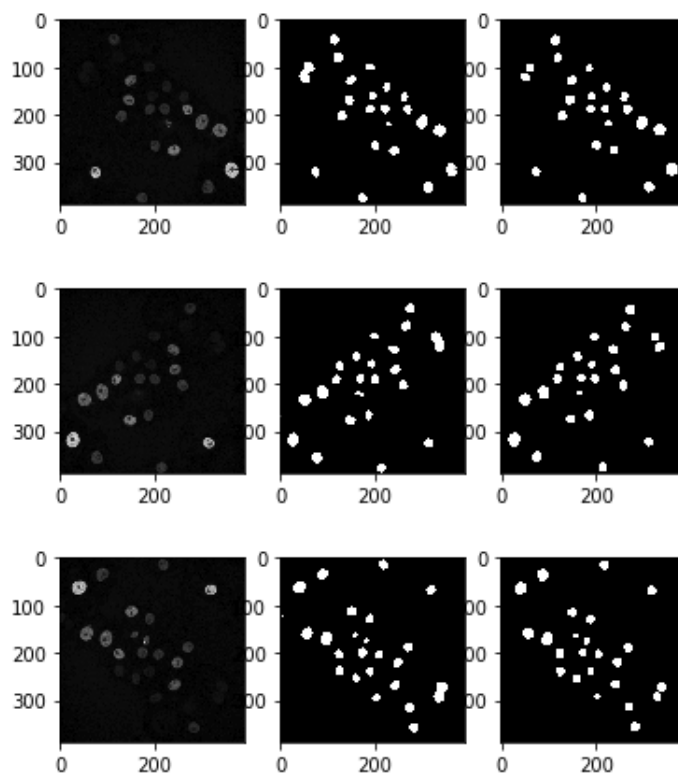


3.2 EM Stacks

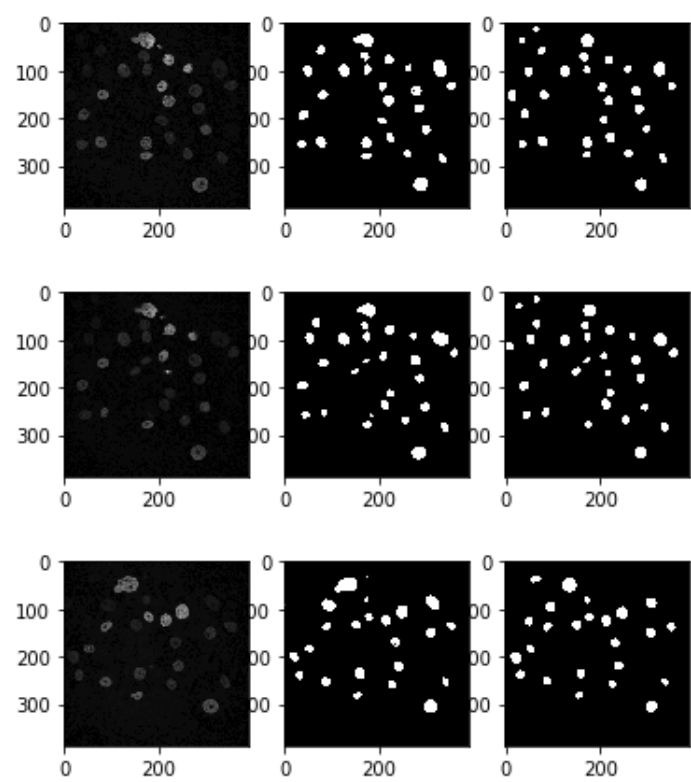


3.3 Fluo-N2DH-GOWT1

3.3.1 Training set

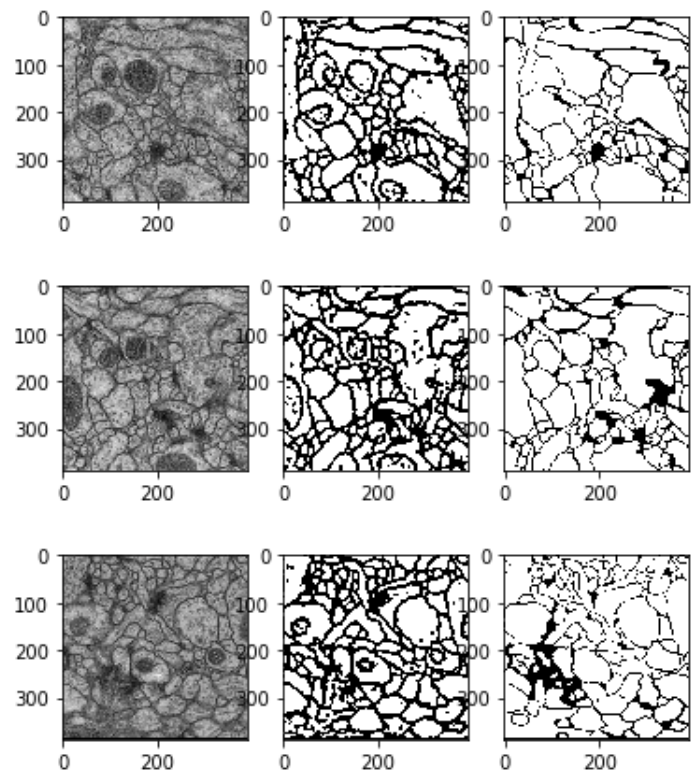


3.3.2 Validation set

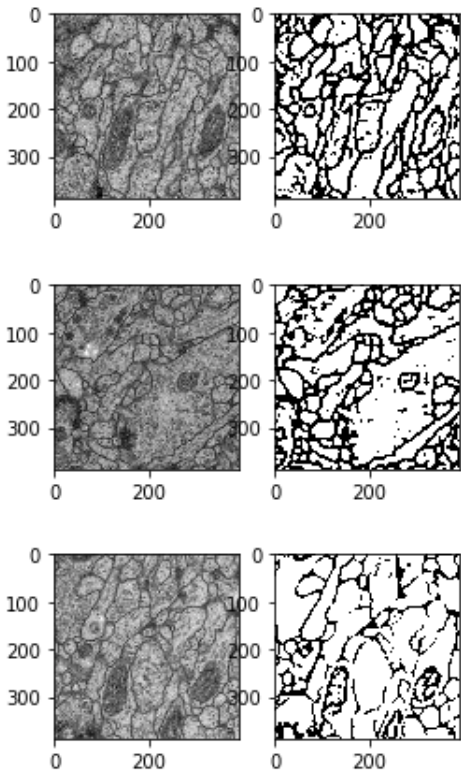


3.4 EM Stacks

3.4.1 Training set

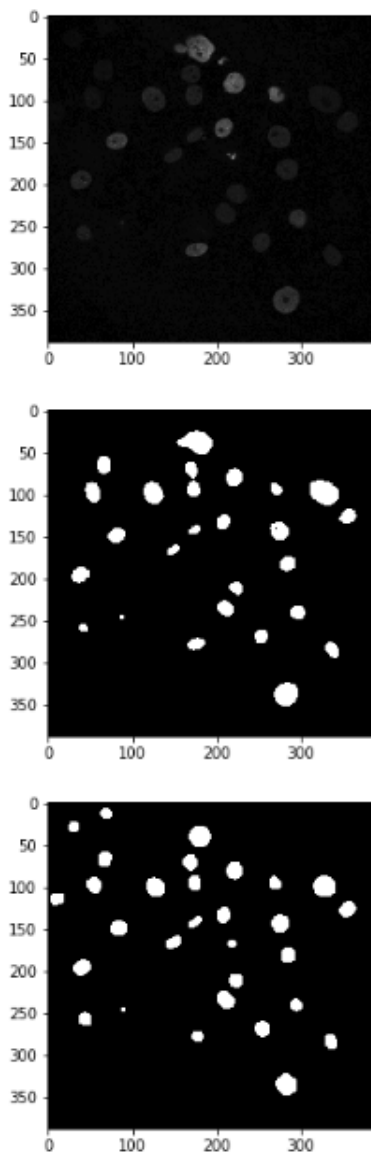


3.4.2 Test set



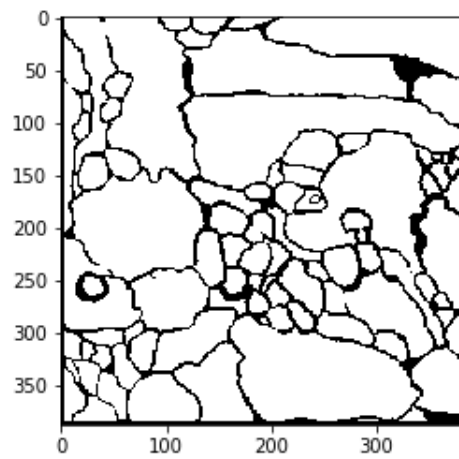
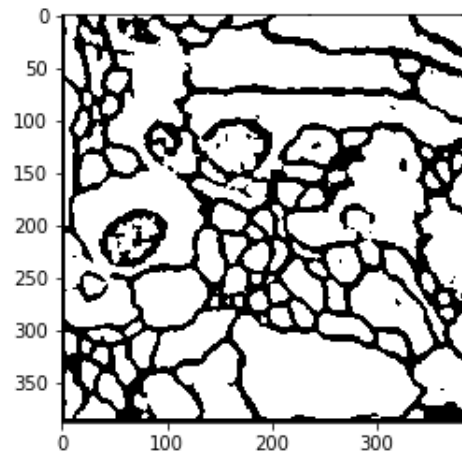
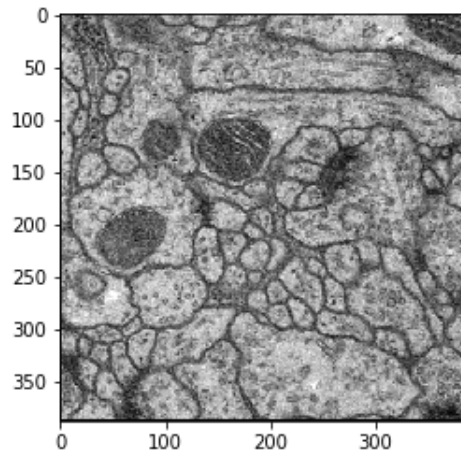
4 Analysis

4.1 Fluo-N2DH-GOWT1



- We observe that the model is able to get the segmentation correctly for almost of the cells
- It is not able to segment the cells which are very close to the boundary and of low intensity. This is since the Unet architecture has Crop-and-Copy connections due to which the information about these cells not retained with high confidence
- The model also observe that the model merges cells that are very close to each other. This is since in the downward part of the network finer details are lost. Although the crop-and-copy connections provide some information about these details, it might not be sufficient for the such close cell boundaries.

4.2 EM Stacks



- We can observe that it gets the general segmentation of the cell boundaries correct.
- It incorrectly produces boundaries around some cell's nuclei.

- It is unable to properly segment cells in the corners of the image, probably because of the Crop-and-Copy architecture of UNet due to which the confidence in this area is low.
- A positive thing about this model is that it seems to find the thinnest of (correct) boundaries, while mostly ignoring the spurious boundaries. This is perhaps due to our weighting of the classes.
- Slightly better segmentation were obtained when we evaluated on zoomed-in regions of the images, but we didn't keep it.