StarDist: U-Net based CNNs on cell boundary detection of electron microscopy

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BROWN

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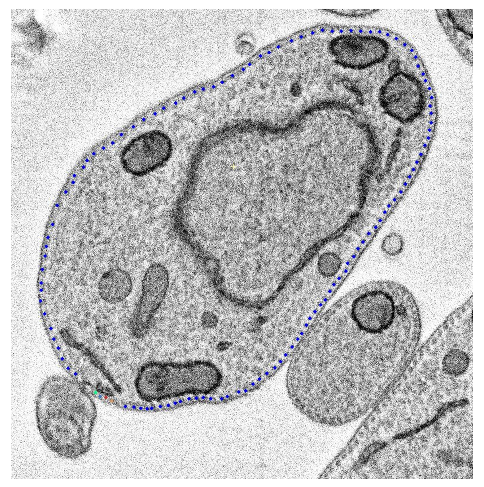
Motivation



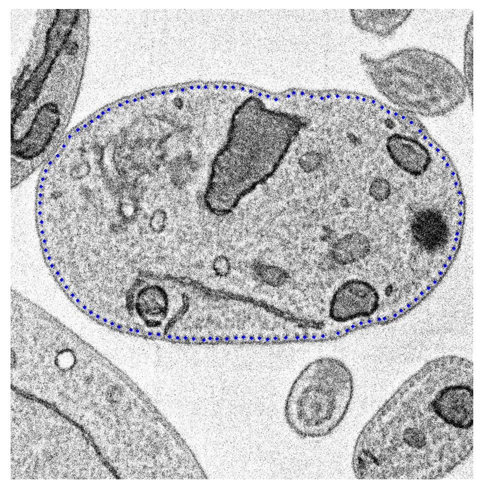


Figure 1 (left): A typical cell boundary labelling on an electron microscopy image (blue dots). Each dot represents a microtubule in the cell boundary.

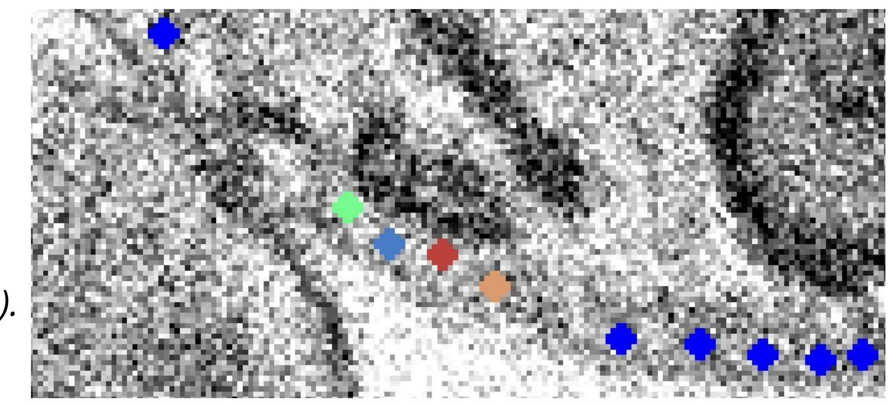


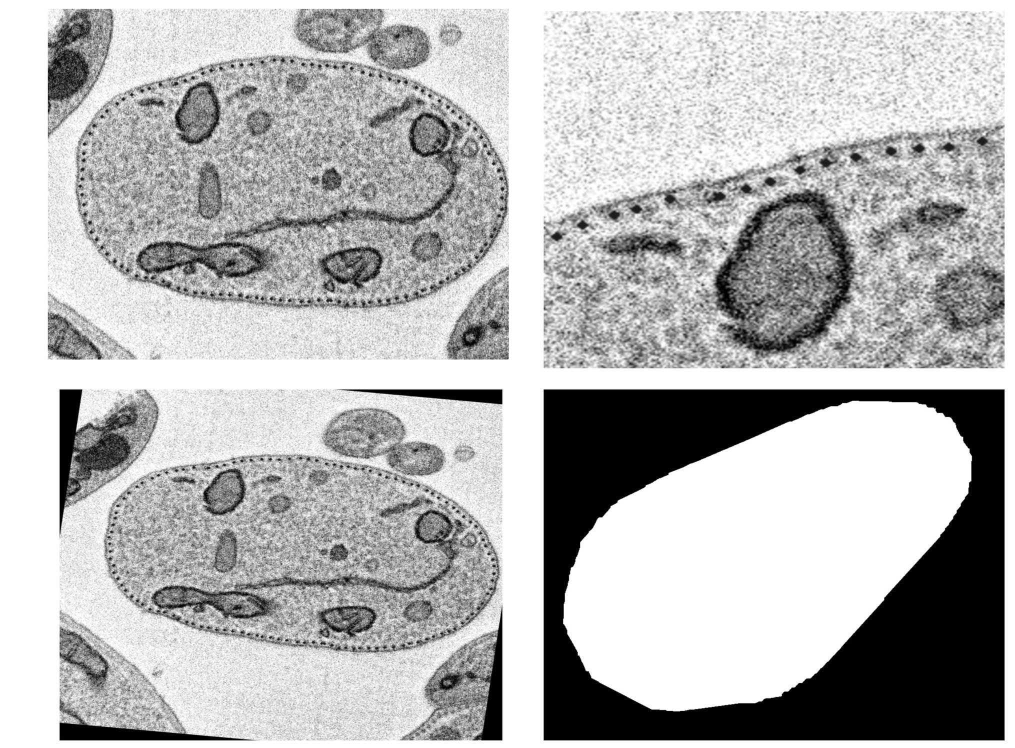
Figure 2 (above): Microtubules highlighted in Blue, MTQs highlighted in Green/GrayBlue/Red/Orange

Cell boundary labelling is one of the most common and fundamental steps in biomedical research. The labelled boundaries provide invaluable insight into structure and transformation of the cell. However, it is very time-consuming for researchers to hand-label them, and we have decided to help our fellow researchers out by utilizing Stardist, a U-Net based CNN that makes use of skip connections to learn cell boundaries.

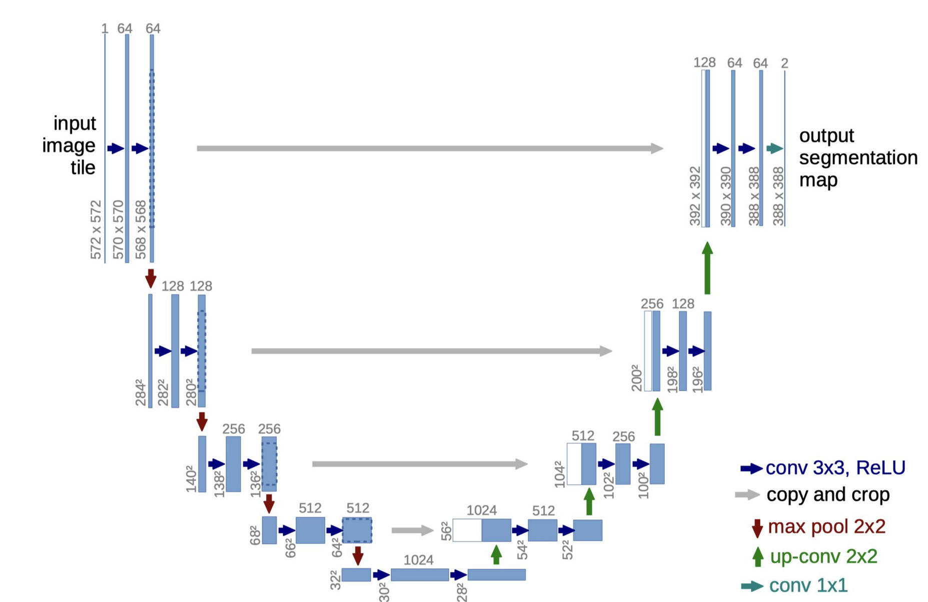
Goal

1. See if we can optimize the model by playing around with parameters such as learning rate, number of epochs, grid size, filter size, etc. Additionally work on adding image augmentation, changing around image sizes, etc.
2. See if there is image preprocessing that can be done to improve the performance, such as denoising or desaturating the image, cropping the image, etc.
3. Implement a simpler CNN that attempts to learn only the microtubule dots and compare it to StarDist.

Preprocessing



Model Architecture



$$w(\mathbf{x}) = w_c(\mathbf{x}) + w_0 \cdot \exp\left(-\frac{(d_1(\mathbf{x}) + d_2(\mathbf{x}))^2}{2\sigma^2}\right)$$

Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18. Springer International Publishing, 2015.

Labeling Examples

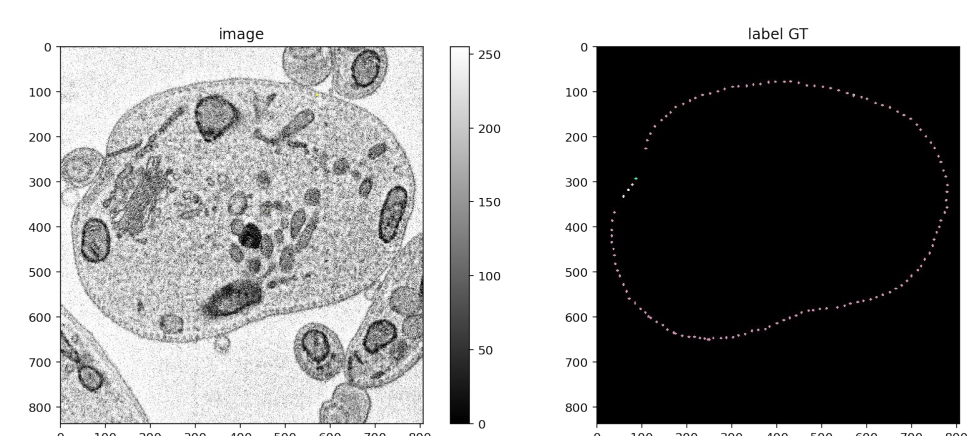


Figure 3 (top left): This is an image of a hand labeled cell used for training and testing.

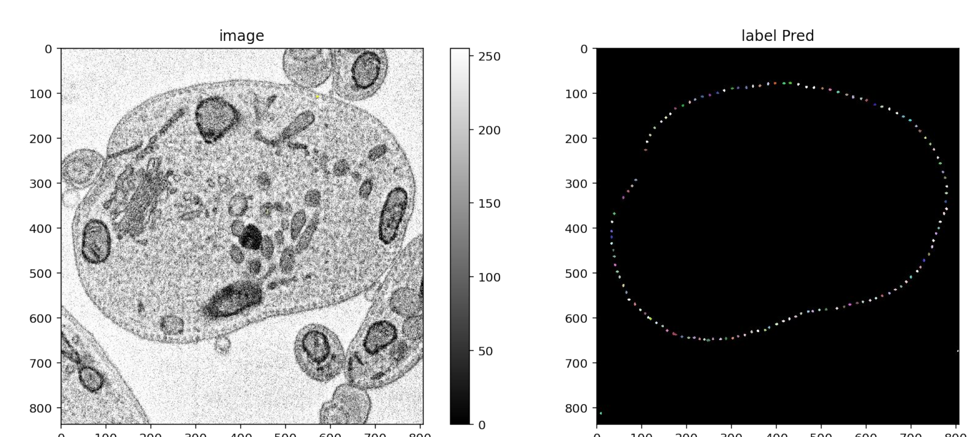
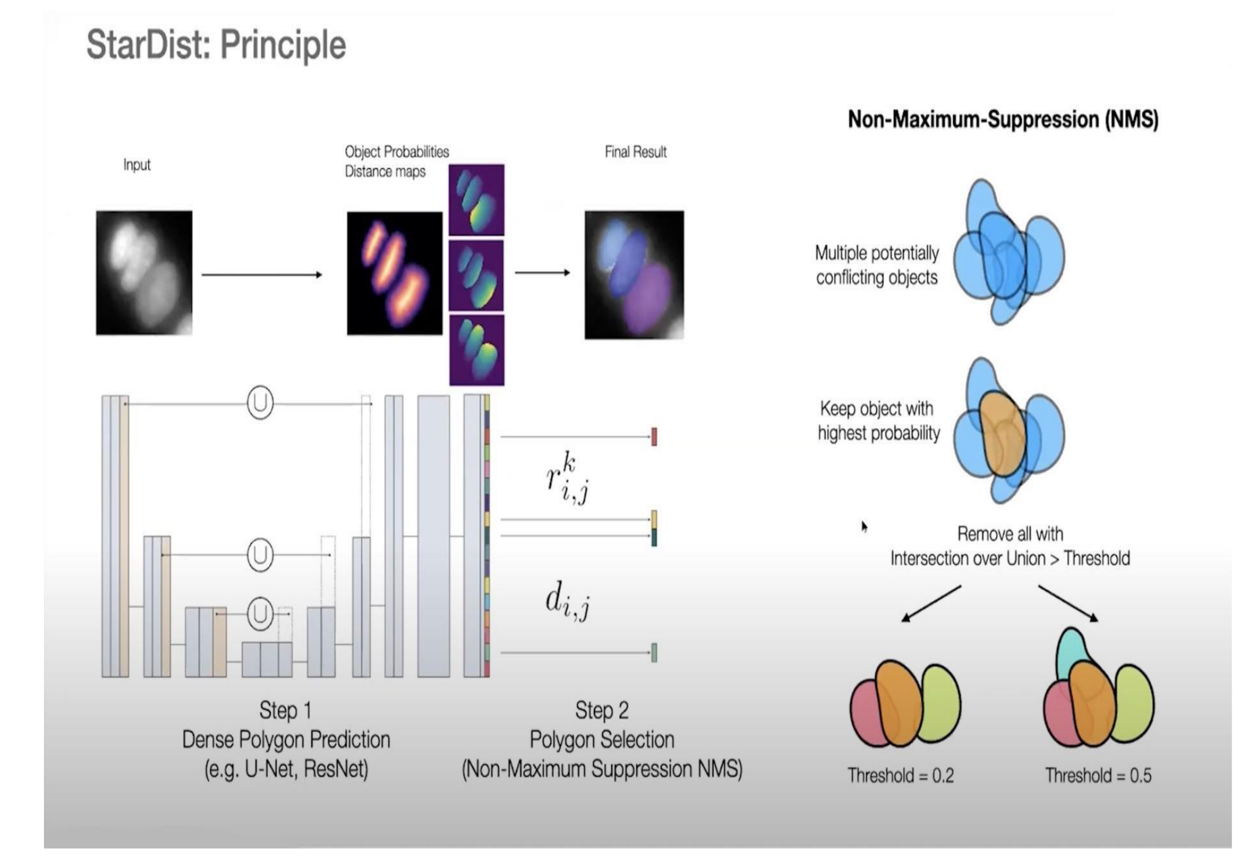


Figure 4 (bottom left): This is an image of the model's predicted labels for the Microtubules + MTQ combination

Utilizing U-Net CNNs and StarDist

U-Net is a type of CNN that captures the spatial information of an image by first downsampling it to generate a overview of the images pixels and then upsampling the picture to correlate the spatial information learned. The skip connections (grey lines) make sure that earlier downsampling information is joined to later upsampling information and improve accuracy.

StarDist is based on this U-Net model with a few extra steps to properly generate cell boundary output including data augmentation, normalization, non-maximal suppression and a generated segmentation pixel mask to predict object center probabilities.



Results (Based on Intersection-Over-Union Threshold from 0 - 1 Scale)

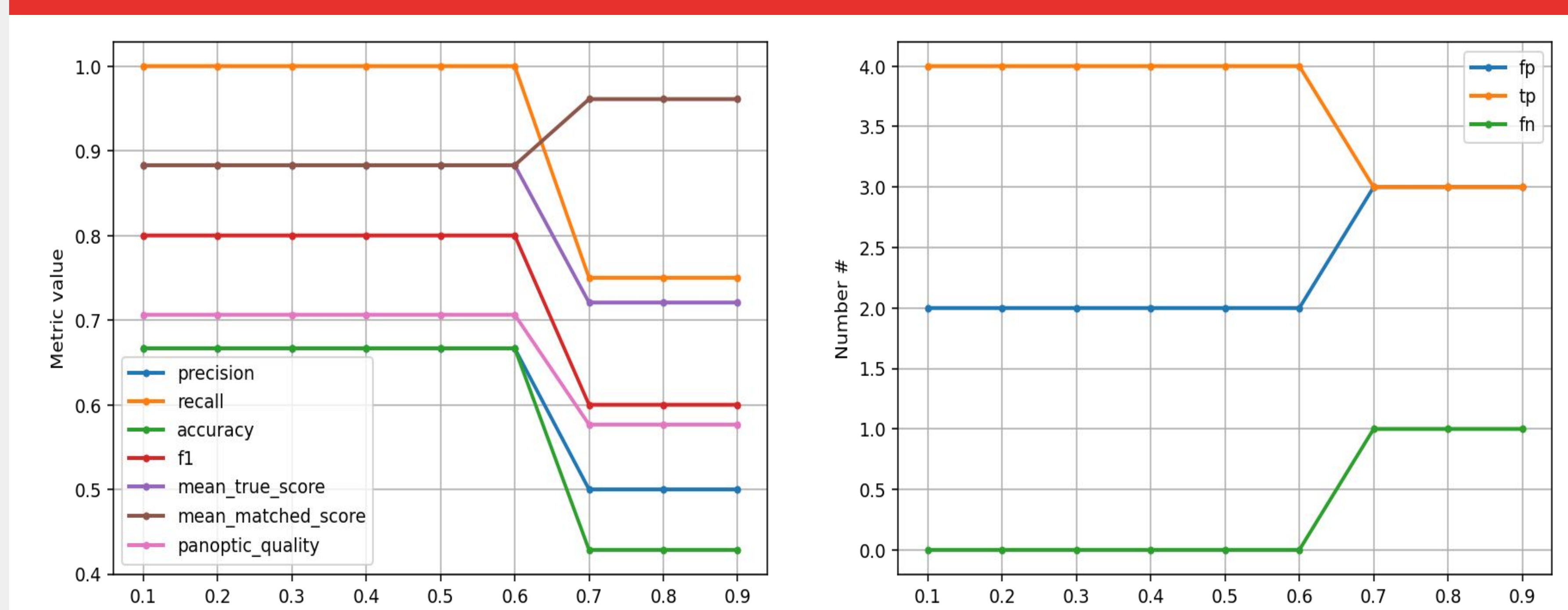


Figure 5: MTQ Results

IoU = intersection over union, 0 means any overlap is correct, 1 means completely overlapping

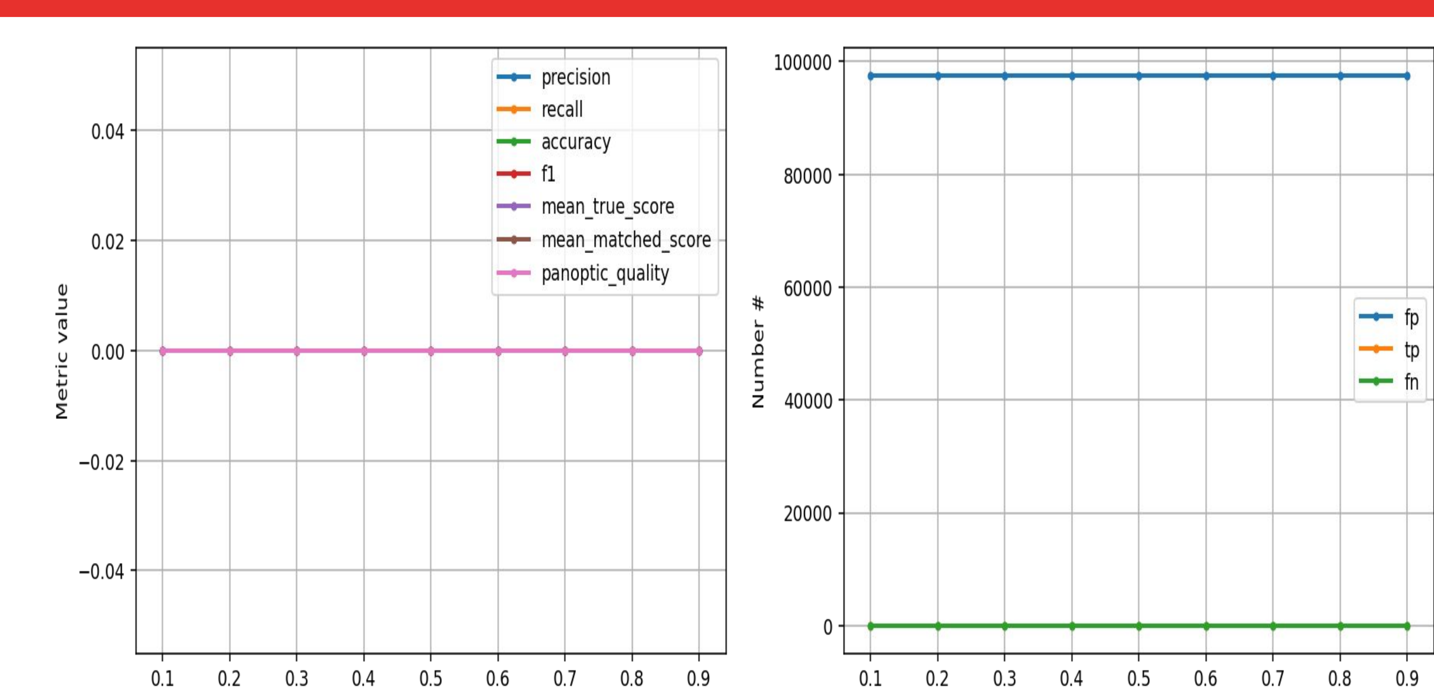


Figure 6: Microtubule Results

No difference in metric value across thresholds

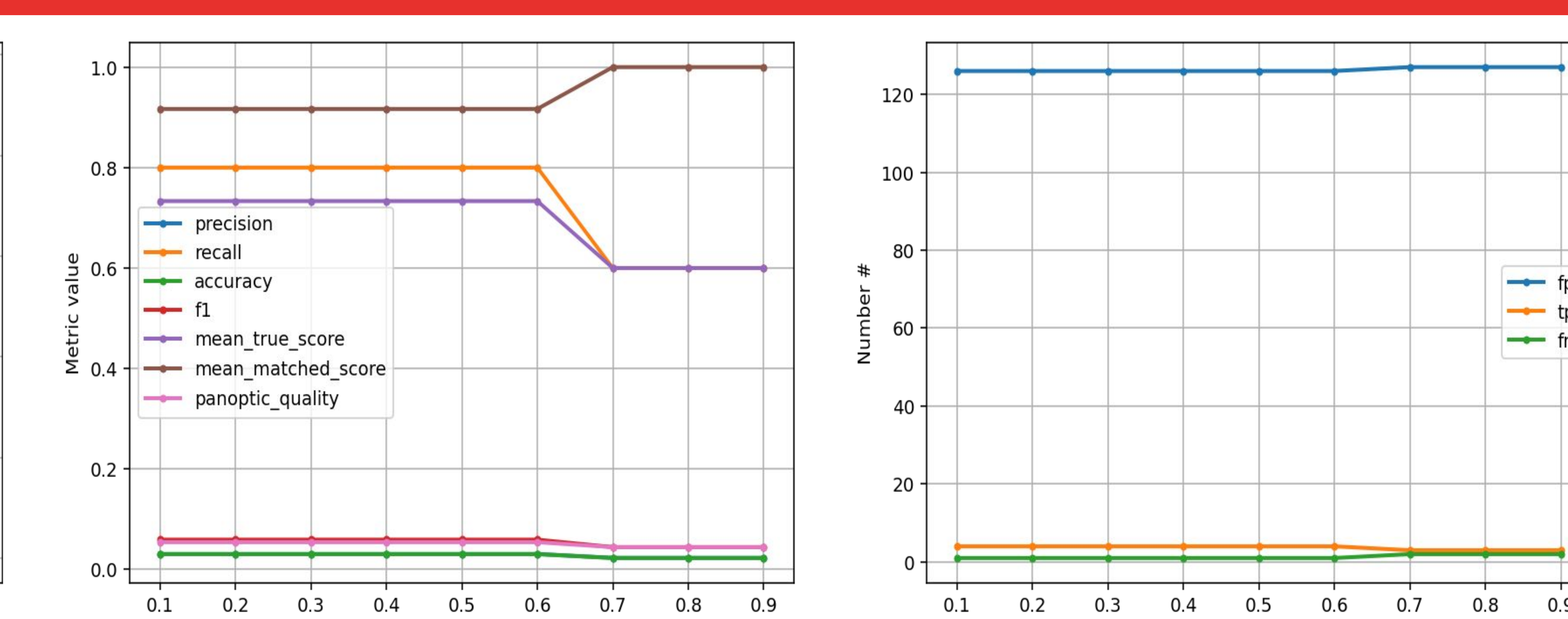


Figure 7: Microtubule + MTQ results (see Figure 4)

Captured labels but accuracy is low

References

[1] Huang, Huimin, et al. "Unet 3+: A full-scale connected unet for medical image segmentation." ICASSP 2020-2020 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). IEEE, 2020.
[2] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-net: Convolutional networks for biomedical image segmentation." Medical Image Computing and Computer-Assisted Intervention–MICCAI 2015: 18th International Conference, Munich, Germany, October 5-9, 2015, Proceedings, Part III 18. Springer International Publishing, 2015.
[3] Oktay, Ozan, et al. "Attention u-net: Learning where to look for the pancreas." arXiv preprint arXiv:1804.03999 (2018).

Acknowledgements

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