Project Goal:

- Electron microscopy (EM) provides scientists at The Schroeder Laboratory with a variety of biological insights into neural networks and synapses.
- However, due to the substantial data generated from the biological specimens being analyzed, the process of manual cell segmentation is labor-intensive and timeconsuming.
- This project assesses and optimizes three different open-source machine learning models. Our objective is to determine which model delivers the highest efficiency, precision, and ease of use for our laboratory needs.



Cell Segmentation:

AI Models for Neuron Segmentation: A Comparative Study Stella Wilcox¹, Ellie Conklin², and Nathan Schroeder^{2, 3}

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Current Segmentation Models:





3D-UNet Metrics: Training Accuracy = Value: 0.9904 at step 500 Training Loss = Value: 0.4809 at step 1000 Validation Accuracy = Value: 0.8838 at step 1000 Validation Loss = Value: 0.4709 at step 1000 Final Accuracy score = 88.38%

Cellpose Metrics:

us with metrics.

Cellpose did not provide

Detectron2 Metrics: (Metrics for validation set, 10 *images*)

Average Accuracy = 90.30%**Average Precision =** 26.35% **Average Recall** = 28.20% **False Negatives** = 8.14% **False Positives** = 12.18%



Conclusions:

- **3D-UNet**: Achieved 88.38% accuracy but had high validation loss, suggesting overfitting.
- **Cellpose**: User-friendly but lacks direct performance metrics.
- **Detectron2**: High accuracy (90.30%) but low precision (26.35%) and recall (28.20%), indicating many false positives and negatives. While 3D-UNet and Detectron2 are promising, improvements in precision and recall are needed.

Future Work:

- <u>Cellpose:</u> The 3d version of Cellpose should be used if it displays metrics.
- <u>3DUnet:</u> More time should be spent on a watershed algorithm.
- <u>Detectron2</u>: Augmentation should be added, and more time should be spent exploring and adjusting the hyperparameters.

References:

Jyothi, P., & Dhanasekaran, S. (2023b). An attention 3DUNET and visual geometry group-19 based deep neural network for brain tumor segmentation and classification from MRI. Journal of Biomolecular Structure and Dynamics/Journal of Biomolecular Structure & Dynamics, 1–12. https://doi.org/10.1080/07391102.2023.2283164 Merz, G., Liu, Y., Burke, C. J., Aleo, P. D., Liu, X., Kind, M. C., Kindratenko, V., & Liu, Y. (2023). Detection, instance segmentation, and classification for astronomical surveys with deep learning (deepdisc): detectron2 implementation and demonstration with Hyper Suprime-Cam data. Monthly Notices of the Royal Astronomical Society, 526(1), 1122–1137. https://doi.org/10.1093/mnras/stad2785

Abdusalomov, A. B., Islam, B. M. S., Nasimov, R., Mukhiddinov, M., & Whangbo, T. K. (2023). An improved forest fire detection method based on the DetectRon2 model and a deep learning approach. Sensors, 23(3), 1512. https://doi.org/10.3390/s23031512

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