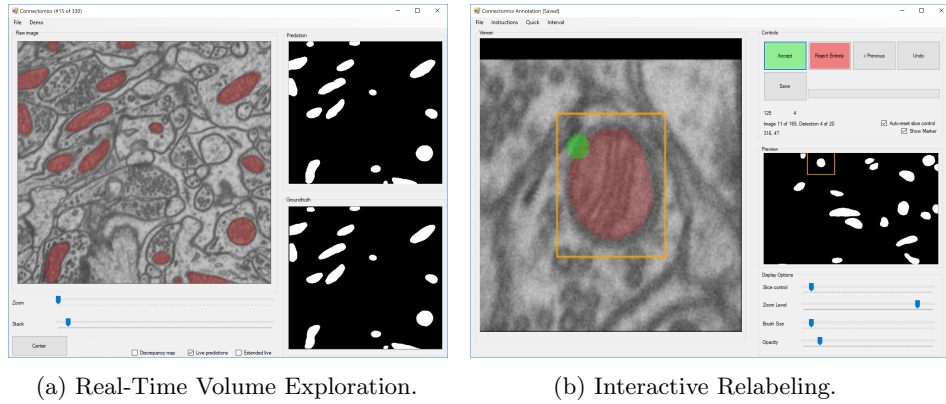


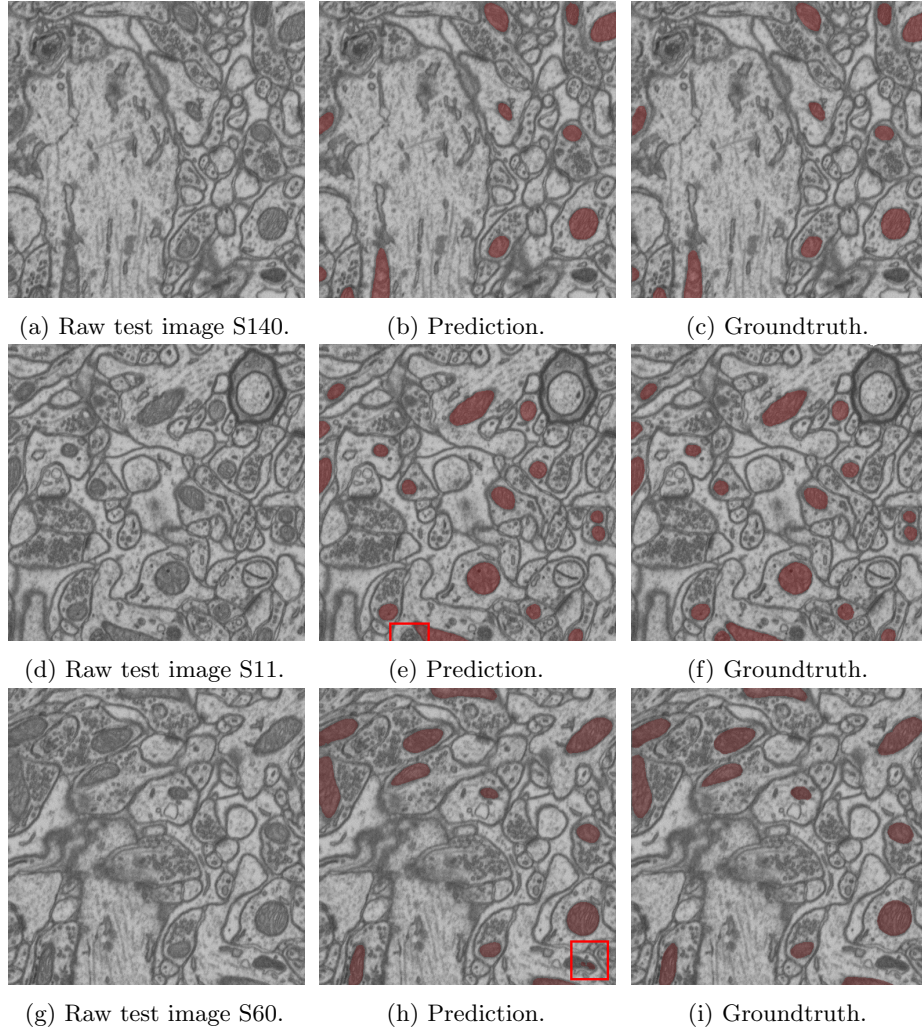
# Supplemental Material: Fast Mitochondria Segmentation for Connectomics

Author name(s) withheld

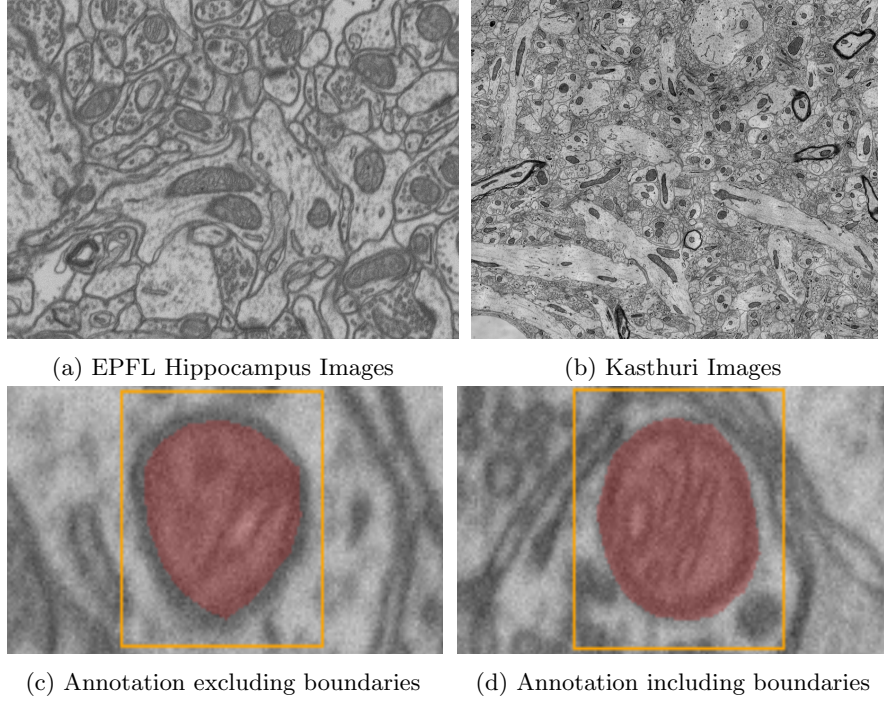
Address withheld



**Fig. 1: Developed Software.** (a) An application to perform real-time mitochondria detection using a client/server framework. (b) Our annotation framework that lets users proofread individual mitochondria labels. All developments are available as open source software [Link omitted for review].



**Fig. 2: Additional Results on the EPFL Hippocampus Dataset.** Notice mistakes on the bottom in (e), where parts of mitochondria are missing (FN), and in the bottom right in (h), where the detector shows minor spurious detections (FP). We show raw output here, both mistakes are at least partially corrected with simple post-processing (Z-filtering).



**Fig. 3: Image Variability and Membrane Inconsistencies.** Edges in the EPFL Hippocampus benchmark dataset (a) are less clear and crisp than in the higher resolution Kasthuri dataset (b). The original ground truth presented by Lucchi et al. [1] includes both annotations excluding boundaries (c) and including boundaries fully (d). The inconsistency causes metrics to be less reliable, and was addressed during our re-annotation process.

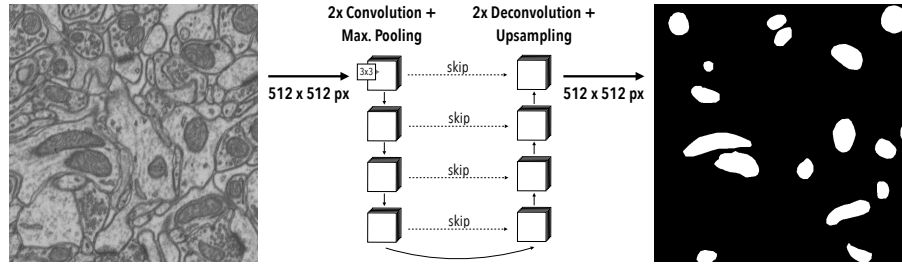


Fig. 4: **Our Mitochondria Detector.** We extend a 2D U-Net architecture [2] to output predictions at full resolution ( $512 \times 512$  pixels), reduce the number of learnable parameters, and employ extensive data augmentation.

Table 1: **Network Architecture.** A detailed description of our proposed network architecture inspired by Ronneberger et al. [2]. We show the different layers/types, their respective output shapes, number of parameters, and layers that are connected to them.  $B$  stands for the respective batch size used, as reported in the main paper.

Layer (type)	Output Shape	Parameters	Connected to
input-1	$B, 512, 512, 1$	0	
conv2d-1	$B, 512, 512, 16$	160	input-1
conv2d-2	$B, 512, 512, 16$	2320	conv2d-1
max-pooling2d-1	$B, 256, 256, 16$	0	conv2d-2
conv2d-3	$B, 256, 256, 32$	4640	max-pooling2d-1
conv2d-4	$B, 256, 256, 32$	9248	conv2d-3
max-pooling2d-2	$B, 128, 128, 32$	0	conv2d-4
conv2d-5	$B, 128, 128, 64$	18496	max-pooling2d-2
conv2d-6	$B, 128, 128, 64$	36928	conv2d-5
max-pooling2d-3	$B, 64, 64, 64$	0	conv2d-6
conv2d-7	$B, 64, 64, 128$	73856	max-pooling2d-3
conv2d-8	$B, 64, 64, 128$	147584	conv2d-7
dropout-1	$B, 64, 64, 128$	0	conv2d-8
max-pooling2d-4	$B, 32, 32, 128$	0	dropout-1
conv2d-9	$B, 32, 32, 256$	295168	max-pooling2d-4
conv2d-10	$B, 32, 32, 256$	590080	conv2d-9
dropout-2	$B, 32, 32, 256$	0	conv2d-10
up-sampling2d-1	$B, 64, 64, 256$	0	dropout-2
conv2d-11	$B, 64, 64, 128$	131200	up-sampling2d-1
merge-1	$B, 64, 64, 256$	0	dropout-1, conv2d-11
conv2d-12	$B, 64, 64, 128$	295040	merge-1
conv2d-13	$B, 64, 64, 128$	147584	conv2d-12
up-sampling2d-2	$B, 128, 128, 128$	0	conv2d-13
conv2d-14	$B, 128, 128, 64$	32832	up-sampling2d-2
merge-2	$B, 128, 128, 128$	0	conv2d-6, conv2d-14
conv2d-15	$B, 128, 128, 64$	73792	merge-2
conv2d-16	$B, 128, 128, 64$	36928	conv2d-15
up-sampling2d-3	$B, 256, 256, 64$	0	conv2d-16
conv2d-17	$B, 256, 256, 64$	16448	up-sampling2d-3
merge-3	$B, 256, 256, 96$	0	conv2d-4, conv2d-17
conv2d-18	$B, 256, 256, 32$	27680	merge-3
conv2d-19	$B, 256, 256, 32$	9248	conv2d-18
up-sampling2d-4	$B, 512, 512, 32$	0	conv2d-19
conv2d-20	$B, 512, 512, 16$	2064	up-sampling2d-4
merge-4	$B, 512, 512, 32$	0	conv2d-2, conv2d-20
conv2d-21	$B, 512, 512, 16$	4624	merge-4
conv2d-22	$B, 512, 512, 16$	2320	conv2d-21
conv2d-23	$B, 512, 512, 2$	290	conv2d-22
conv2d-24	$B, 512, 512, 1$	3	conv2d-23
<b>Total</b>		<b>1,958,533</b>	

## References

- [1] Aurélien Lucchi et al. “Supervoxel-Based Segmentation of Mitochondria in EM Image Stacks with Learned Shape Features”. In: *IEEE Transactions on Medical Imaging* 31.2 (2012), pp. 474–486.
- [2] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. “U-Net: Convolutional Networks for Biomedical Image Segmentation”. In: *International Conference on Medical image computing and computer-assisted intervention*. Springer. 2015, pp. 234–241.