Supplementary for
ShapeMamba-EM: Fine-Tuning Foundation Model with Local Shape Descriptors and Mamba Blocks for 3D EM Image Segmentation

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Dataset	Species	Tissue	Annotations	Image Modality	Resolution
ISBI 2012	Drosophila	Brain-VNC	Cell	SEM	$50 \times 4 \times 4nm$
SNEMI3D	Mouse	Brain-cortex	Cell	SEM	$30 \times 4 \times 4nm$
MitoEM-H	Human	Cortex	Mitochondria	mbSEM	$30 \times 8 \times 8nm$
MitoEM-R	Rat	Cortex	Mitochondria	mbSEM	$30 \times 8 \times 8nm$
Lucchi++	Mouse	Hippocampus	Mitochondria	FIB-SEM	$5 \times 5 \times 5nm$
Kasthuri++	Mouse	Cortex	Mitochondria	ssEM	$30 \times 3 \times 3nm$
CREMI	Drosophila	Brain	Cell, Synapse	TEM	$40 \times 4 \times 4nm$
EMR-50	Rat	Cortex	Synapse	mbSEM	$30 \times 8 \times 8nm$
Gauy	human	Platelet	Axon, Mitochondria	SBF-SEM	$50 \times 10 \times 10nm$
NucMM-Z	Zebrafish	Brain	Nuclei	SEM	$30 \times 4 \times 4nm$

Table 1. Details of the datasets.

Dataset	Training Set	Testing Set	Patch Size	σ
ISBI 2012	24×512×512	6×512×512	100×256×256	50
SNEMI3D	80×1024×1024	20×1024×1024	100×256×256	50
MitoEM-H	400 × 4096 × 4096	100 × 4096 × 4096	100×256×256	5
MitoEM-R	400 × 4096 × 4096	100 × 4096 × 4096	100×256×256	5
Lucchi++	165 × 1024 × 768	165 × 1024 × 768	100×256×256	5
Kasthuri++	85 × 1643 × 1613	75 × 1334 × 1553	100×256×256	5
CREMI	3×125×1000×1000	3×125×1000×1000	100×256×256	50(cell)/5(syn)
EMR-50	100×700×700	99×1000×1000	100×256×256	5
Gauy	74×800×800	121×609×400	100×256×256	15(axon)/5(mito)
NucMM-Z	18×64×64×64	9×64×64×64	64×64×64	2

Table 2. Parameters of the experiments.

Dataset	Method	Dice		mAP	
		SOTA	Ours	SOTA	Ours
ISBI2012	PS-Net [6]	0.94	0.958	-	0.951
SNEMI3D	DMT [2]	0.971	0.964	-	0.961
CREMI(Synapse)	CleftNet [4]	0.831	0.834	-	0.865
Kasthuri++	HIVE-Net [7]	0.962	0.968	-	0.936
Lucchi++	DualRel [5]	0.934	0.94	-	0.954
MitoEM-H	ATFormer [1]	-	0.847	0.782	0.877
MitoEM-R	ATFormer [1]	-	0.852	0.682	0.93
NucMM-Z	U3D-BCD [3]	0.879	0.915	0.894	0.907

Table 3. Comparison with SOTA results. For each of the eight datasets, we choose the SOTA method with the best Dice or mAP performance for comparison. The performance in the original paper of the methods is reported. Since the EM-R50 and Gauy datasets lack corresponding SOTA methods reporting performance with these metrics, no SOTA methods are chosen for these two datasets.

References

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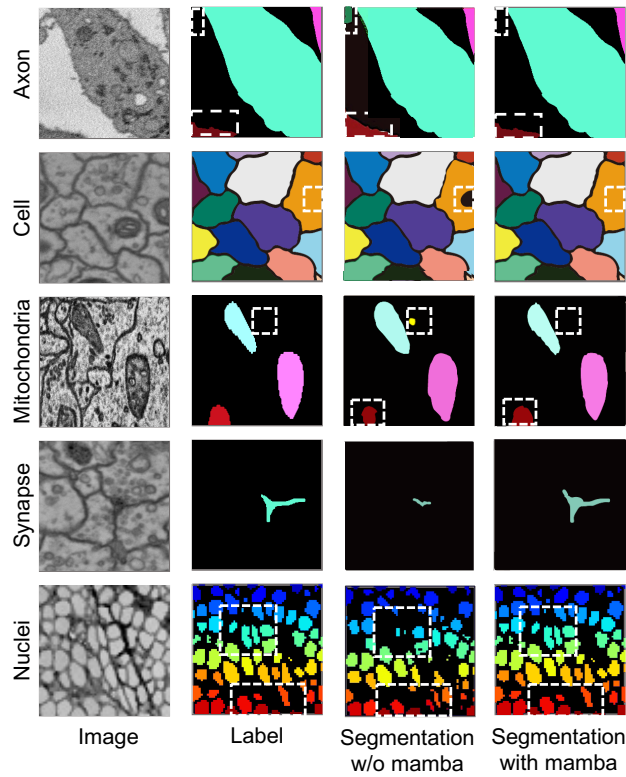
Fig. 1. The segmentation results of the models with and without the 3D Mamba Adapter.

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