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## **Supplementary Materials**

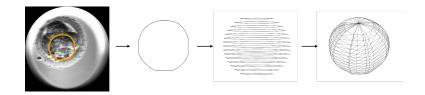


Fig. 1. Illustration of the mesh generation process. From left to right: (1) a cell is segmented at its most in-focus plane; (2) the cell outline is converted into a polygon; (3) copies of the polygon are generated above and below the equatorial polygon, getting smaller the further away they are; (4) a mesh is produced by generating triangles between the polygon vertices.

GINConv Linear Unput → Hidden) BatchNorm1D B1LU Linear (Hidden → Hidden) BatchNorm1D
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Fig. 2. A GNN architecture. Input and output dimensions for linear layers are provided in parentheses. Specific layer sizes used in our experiments can be found in Table 2.



**Fig. 3.** Comparison of perspective (left) and orthographic (right) camera projections when used to view 3D reconstructions.

**Table 1.** Breakdown of datasets used in each experiment. All data was collected between 2018 and 2021. The American and Belgian clinics provided 11 focal planes whereas the French clinic only provided 7. The segmentation model was trained on a mixture of the three clinic datasets, stratified by cell count. The GNN experiment used t8 focal stacks from 80 euploid embryo transfers conducted at the American clinic (the only clinic which provided ploidy data) which led to 44 live births. All clinics used Embryoscope time-lapse incubators.

Experiment	Phase	Clinic	Ν
Segmentation Mode	Training and Cross-Validation	American Belgian French	309 102 87
	NMS Hyperparameter Tuning	American Belgian French	$38 \\ 4 \\ 50$
	Testing	American Belgian French	8 32 2
User Study	Reconstruction Rating	American	15
GNN	Training and Cross-Validation	American	80

**Table 2.** Hyperparameter values and search strategies for each experiment. GS = GridSearch; MC = Memory Considerations; BO = Bayesian Optimisation; DK = Domain Knowledge. Bayesian optimisation was performed over 100 trials using the Optuna framework (v3.4.0).

Experiment	Hyperparameter	Value	Selection Method	Search Range (if applicable)
	SGD Learning Rate	0.005	$\mathbf{GS}$	$\{0.01, 0.005, 0.001\}$
	SGD Momentum	0.9	$\mathbf{GS}$	$\{0, 0.9, 0.99\}$
	SGD Weight Decay	0.0005	$\mathbf{GS}$	$\{0, 0.0005, 0.005\}$
	SGD Batch Size	8	MC	-
NMS Thresholds	Classic NMS IoU	0.6	GS	$\{0.6, 0.7, 0.8, 0.9\}$
	Classic NMS Confidence	0.8	$\mathbf{GS}$	$\{0.6, 0.7, 0.8, 0.9\}$
	Crowd NMS IoU	0.6	$\mathbf{GS}$	$\{0.6, 0.7, 0.8, 0.9\}$
	Stack NMS IoU	0.6	$\mathbf{GS}$	$\{0.6, 0.7, 0.8, 0.9\}$
	Stack NMS Confidence	0.8	$\mathbf{GS}$	$\{0.6, 0.7, 0.8, 0.9\}$
	Stack NMS Window Size	1	DK	-
	MLP Hidden Layer Size	32	BO	$2^{[0, 11]}$
	Number of Graph Convs	3	BO	$\{1, 2, 3\}$
Neural	Graph Conv Operator	GINConv	r GS	$\{\operatorname{GCNConv},\operatorname{GINConv}\}$
	Adam Learning Rate	8.9e-3	BO	$10^{-5}, 0]$
	Adam Weight Decay	1.5e-2	BO	$10^{-5}, 0]$