Bridging the Gap: Effective training on synthetic images for classification of *Xenopus laevis* embryo

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Problem Statement

The primary objective of this project is to develop a model that accurately identifies and counts the number of fertilized and unfertilized *Xenopus laevis* embryos using images of embryos in a petri dish.

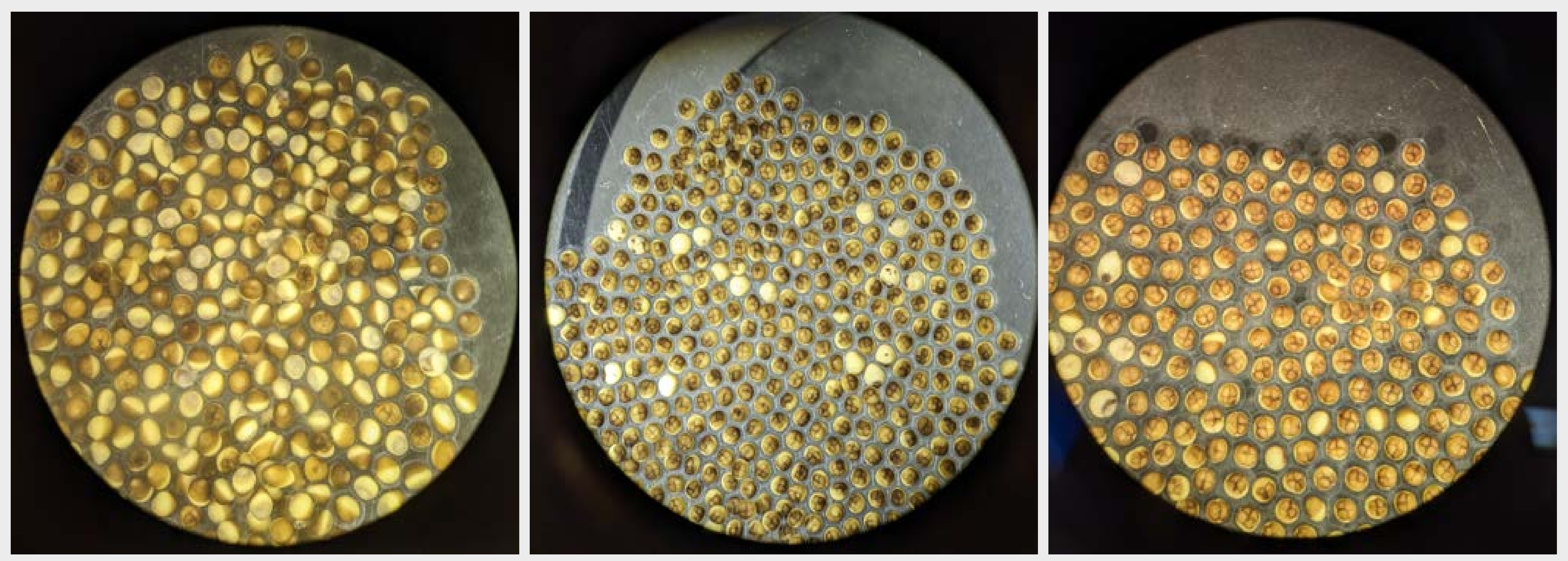


Figure 1. Embryos in petri dish

By automating the annotation process, the model aims to eliminate the need for manual counting, annotation and improve the efficiency of tracking the development of *X. laevis* embryos for AGGRC and MBL. Our study presents a solution using a YOLO10b based Convolutional Neural Network (CNN) that uses synthetically generated images for training and does remarkably well on images taken under microscope.

Data Generation

To create the synthetic images for the training and validation, 200 images of fertilized embryos, 200 images of unfertilized embryos, and 100 background images were cropped.

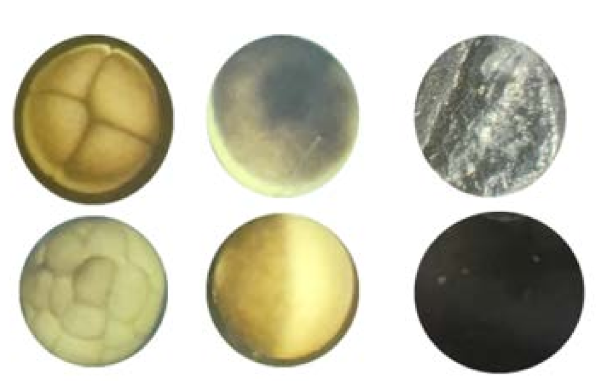


Figure 2. Cropped fertilized embryo, unfertilized embryo and background (left to right)

The scatter-yolo CLI tool was used to generate synthetic images along with their YOLO annotations for training. Embryos were spawned iteratively based on the location of the previously placed egg at an angle of $\frac{i\pi}{4}$ where $i \in [1, 8]$ to ensure a realistic distribution.

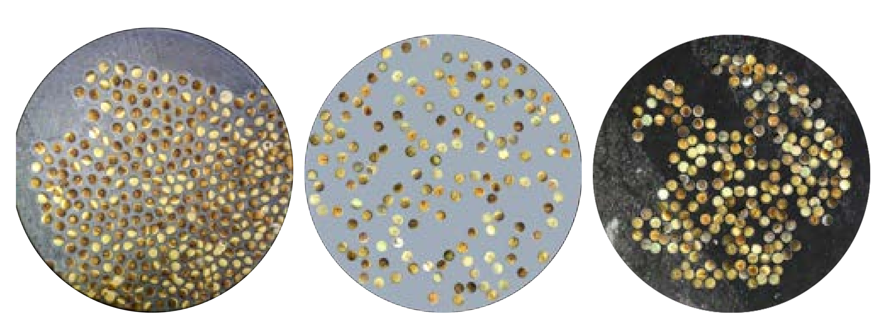


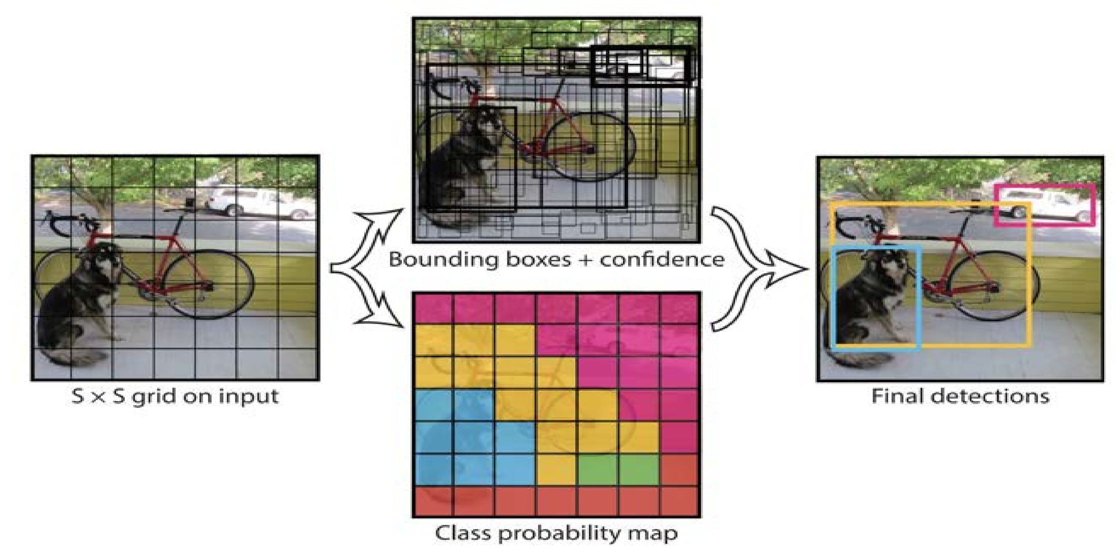
Figure 3. Original Image, Intermediate synthetic image, and Final image synthetic image (left to right)

Results of Data generation process

- Using scatter-yolo CLI tool we have created dataset of 1194 synthetic images.
- We have kept fertilization embryo percentages of 20, 40, 60, and 80.
- It took around 30 minutes to generate this dataset.

Working of YOLO10b

You Only Look Once (YOLO) is a Convolutional Neural Network. The 'b' stands for balanced accuracy. YOLO is designed for object detection and classification tasks.



Training & Experiment

- 95% of the dataset was used for training, and 5% for validation.
- During training, each egg in the image was matched to its bounding box using the YOLO annotation.
- Trained for 50, 100, and 150 epochs with IOU from 0.1 to 0.8.
- Set dropout to 50% and minimum detection confidence to 0.45 or higher.
- Tested with optimizers: SGD, AdamW, Adam, RAAdam, and NAdam on CUDA machine.

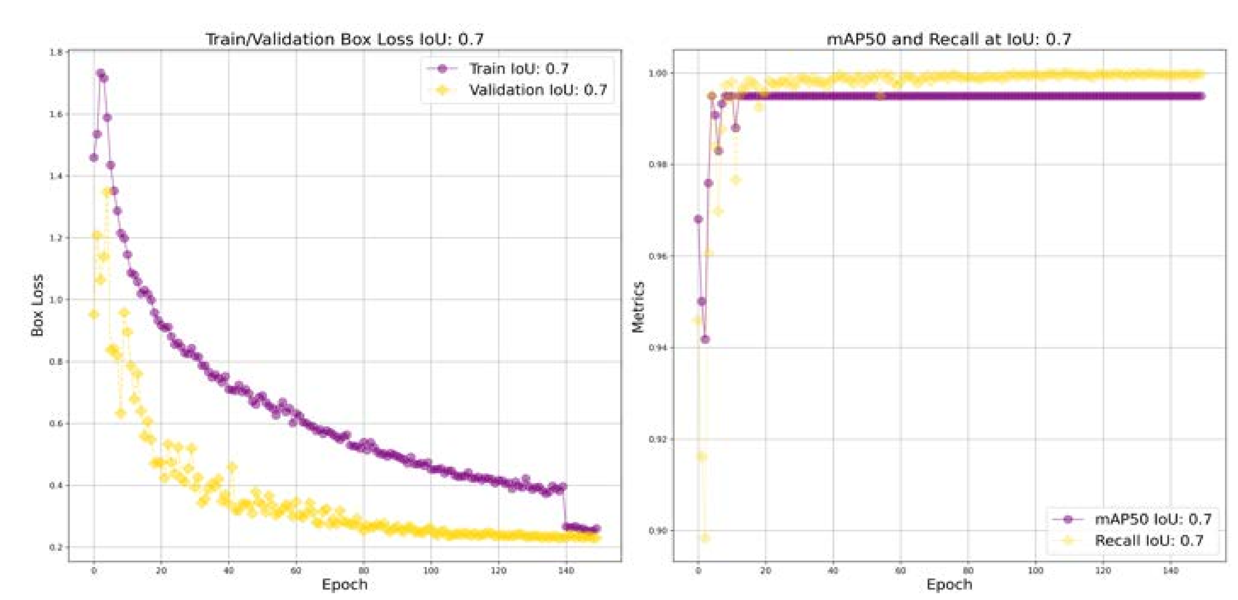


Figure 4. Loss plot for SGD optimizer

Testing on 120 synthetic images

Synthetic testing data was generated from cropped embryos that were not included in the training or validation datasets.

Testing results on synthetic dataset

Model	Accuracy	Precision	Recall	MCC	F1
Adam	87.29	0.9972	0.7459	0.7699	0.8535
AdamW	89.36	0.9856	0.7970	0.8014	0.8814
SGD	**89.97**	0.9939	0.8027	0.8140	0.8881

Testing on Original images from lab

Model performances were evaluated in terms of mean of percentage accuracy per image (API), closeness of prediction (CP) and ratio of predicted fertilized over actual fertilized ($PFoAF$).

$$API = \frac{N_p - N_m}{N_t} \times 100; \quad CP = \frac{PF - AF}{AF}; \quad PFoAF = \frac{PF}{AF} \times 100$$

where, N_p: number of total predictions; N_m: number of miss-classifications; N_t: total number of embryos in an image; PF: number of predicted fertilized embryos; AF: number of actaul fertilized embryos.

Testing results on 24 Original Images from lab

Model	API ±Std	CP	PFoAF
Adam	**95.28 ±5.95**	0.046	0.975
AdamW	92.69 ±8.42	0.137	1.060
SGD	**95.67 ±5.69**	0.050	0.964

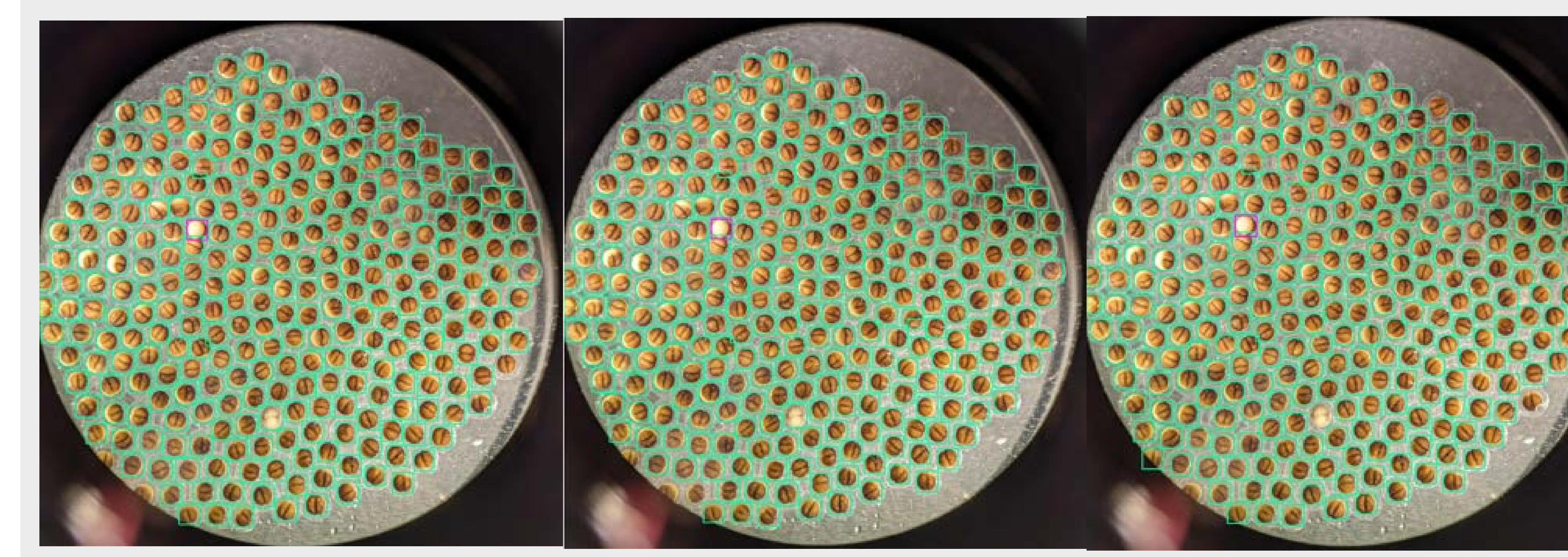


Figure 5. Prediction using three models Adam, AdamW and SGD with prediction accuracy 100, 99.29 and 98.57 respectively (left to right).

Future Work

- Testing new methods for same problem
- Predicting different stages of embryo development.

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- Cole Brumfield for helping with initial data curation.

References

[1] Joseph Redmon, Santosh Divvala, Ross Girshick, and Ali Farhadi. You only look once: Unified, real-time object detection, 2016.