AI for Algal Enumeration, Classification, and Monitoring.

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Project Overview:

Stage 1: Model Testing
- Classification model testing
- Data augmentation testing
- Object detection model testing

Stage 2: Project specific model design and testing
- Application of object detection model testing and transfer learning
- Model pipeline design and testing
- Integration of eDNA data to ground truth training data classifications

Stage 3: Data collection and large-scale application
- Applying pipeline to collect data records for seasonal cycles
- Organizing a spatial and temporal data structure to promote data accessibility

Stage 4: Predictive community modelling
- Use community data collected to test different methods of predictive modelling

Impacts:

- **Dataset generation** – allows for predictive modelling to be applied mitigations and effective resource planning.
- **Faster classification and count** – will aid in classification and count time, providing a streamlined process.
- **More precise classification** – eDNA data to ground truth training data means the model pipeline will be trained more accurately.

Stage 1.1: Classification model and data augmentation testing

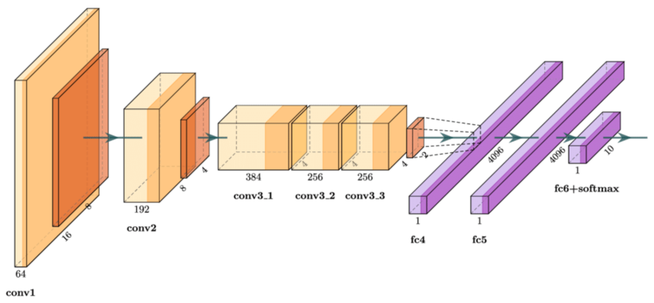


Figure 1: AlexNet architecture for classification (2).

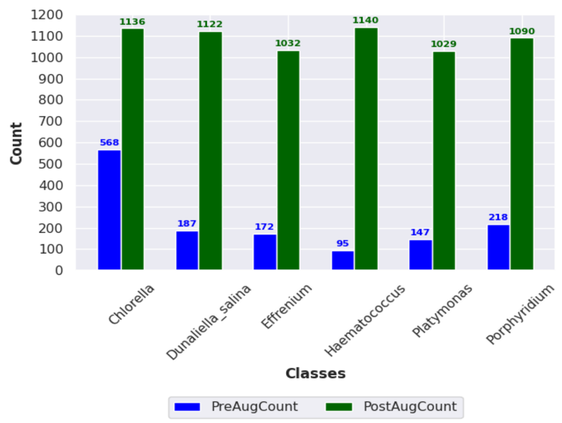


Figure 3: Number of images per genera before and after data augmentation.

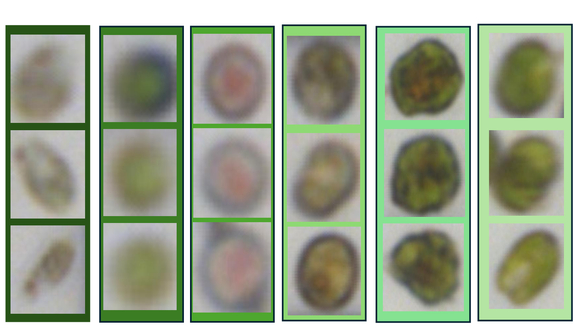


Figure 2: All genera (*Dunaliella salina*, *Chlorella*, *Porphyridium*, *Effrenium*, *Haematococcus*, *Platymonas* – listed left to right) from dataset (1) before augmentation.

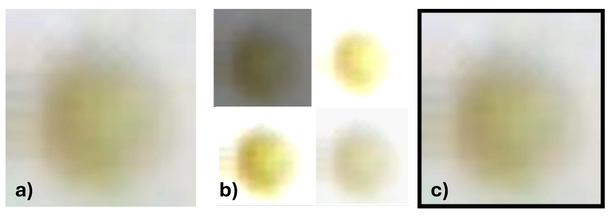


Figure 4: examples of augmentation applied to Chlorella: original image (a), colour jitter (b), padding (c).

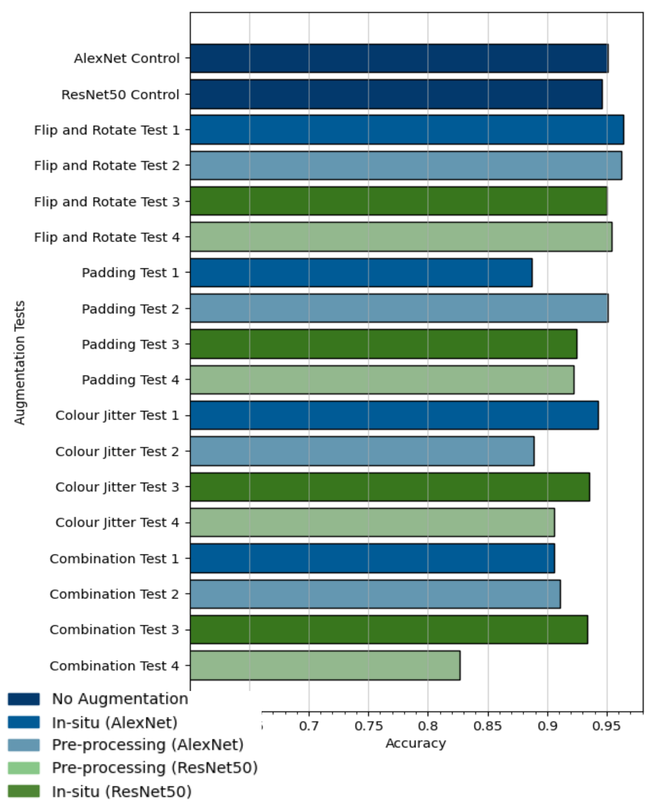


Figure 5: Augmentation accuracies for AlexNet and ResNet50, dataset described in Figure 2.

Stage 1.2: Object detection model testing

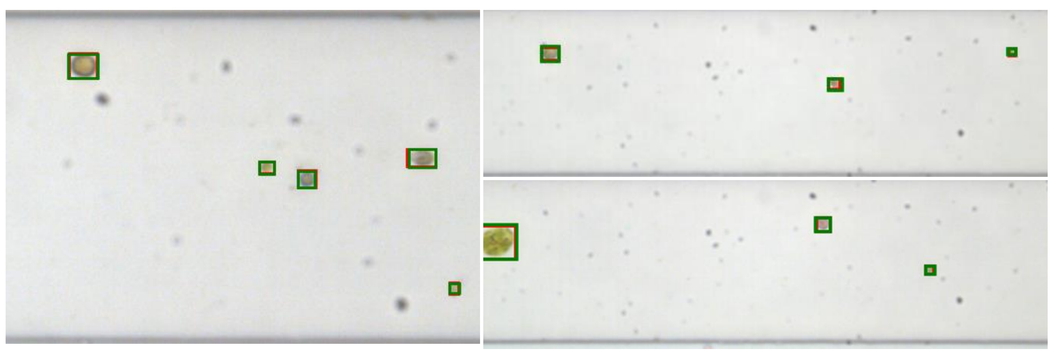


Figure 6 (Above): Output images from Faster R-CNN, trained for 500 epochs with no data augmentation, showing training labels/ ground truthing data (green) and model predictions (red).

Figure 7 (Left): Outputs from YOLOv8n.pt run for 1000 epochs undertaking object detection and classification (probabilities shown on each cell label).

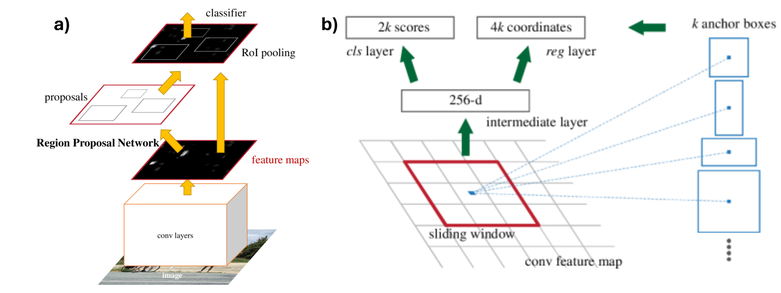


Figure 7 a) Faster R-CNN architecture and **b)** region proposal diagram (3).

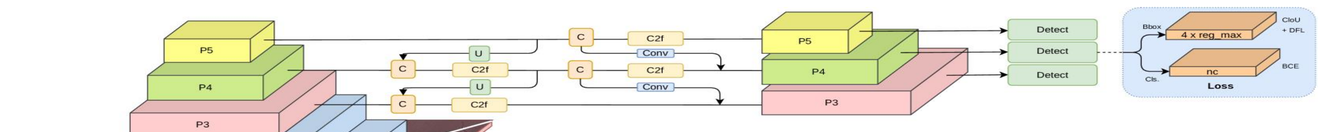


Figure 8 (Left): Diagram of Yolov8 architecture where C represents a concatenate function and U is unsampling (4).

Stage 2.1: Object detection with project developed data & transfer learning

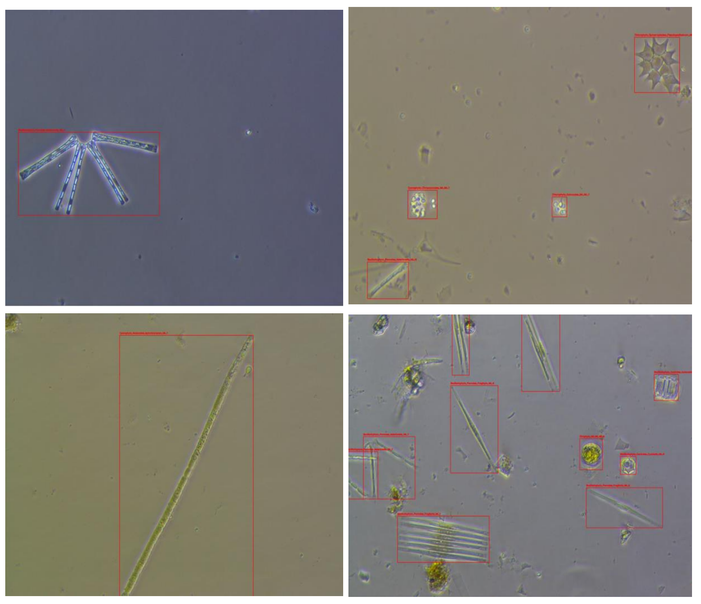


Figure 9: Project developed training data with annotated bounding boxes.

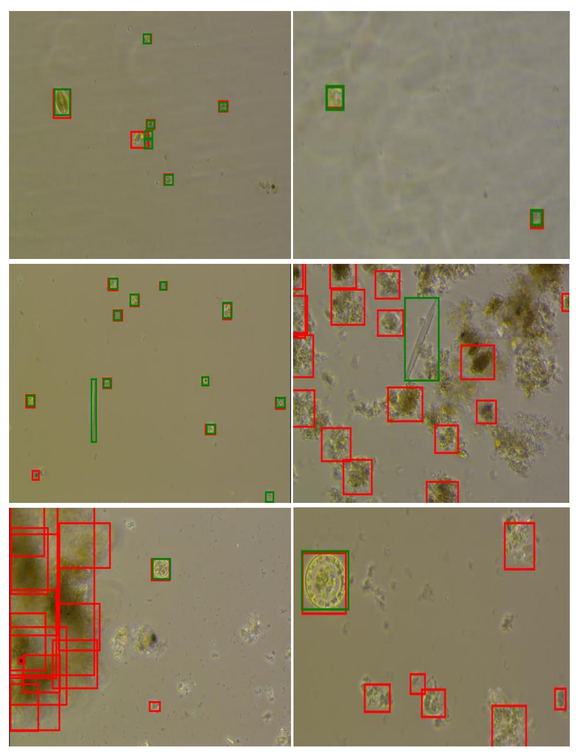
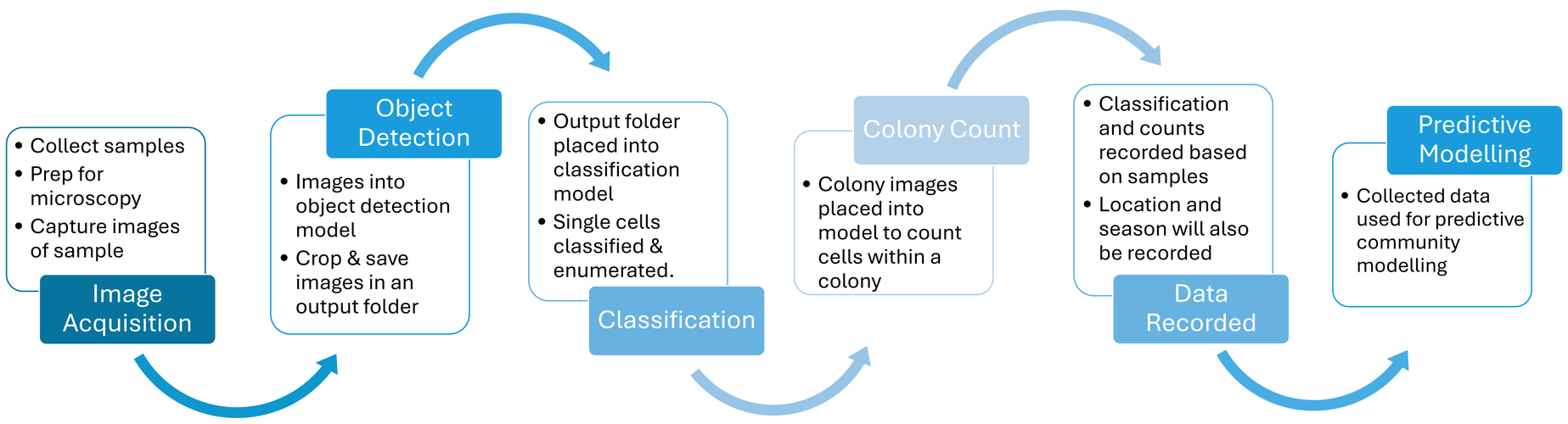


Figure 10: Output images from Faster R-CNN tested on a small batch of project data, trained for 100 epochs with no data augmentation, showing training labels/ ground truthing data (green) and model predictions (red).

Stage 2.2: Pipeline Design



References:

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