Deep Learning Meets Aquaculture: Advanced Oyster Seeds (0-2 mm) Quantification with Stardist Neural network

Oyster Team

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Sea Grant

Louisiana Sea Grant is an organization that helps with marine and coastal life conservation, protection, and study.

We are collaborating with Sarah Bodenstein, a postdoctoral researcher in the oyster research lab, to accomplish our project's objective.

Introduction

Problem

- **Project Goal:** The project aims to count oyster seeds size 0-2mm from an image of a Petri dish.
- **Task:** We tailored a Stardist Neural network that uses image segmentation to determine how many oysters are in a certain image.

Introduction-Seed Collection

Collection

- After gathering the oyster seeds in a bottle, they are taken out and placed through size-based filters.
- Three size categories are used to segregate the seeds: 0–2 mm, 2-4 mm, and >4 mm.

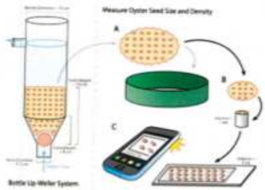

Figure: Bottle and filtering process

Annotation

Fiji and LabKit

- Our goal is to mark each seed in images with known seed counts. We do this to train our code to become capable of identifying each seed within an image.
- To accomplish this, we used the LabKit software integrated within Fiji.

Figure: Original Oyster Image(left), Partially Annotated Image (right)

Stardist

Basics

- Uses a neural network, based on U-net, to identify star-convex polygons.
- Probabilities are obtained for each pixel saying how likely a pixel is to be in a polygon.
  - Probabilities found using the neural network.
- 32 radial directions measured from a pixel to the boundary of the polygon.
- Better at predicting cell shape than other image analysis methods.

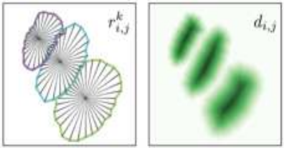

Figure: Star-Convex Polygons

Architecture

- U-net
  - Convolutional neural network
- Post-processing
  - Non-maximal suppression

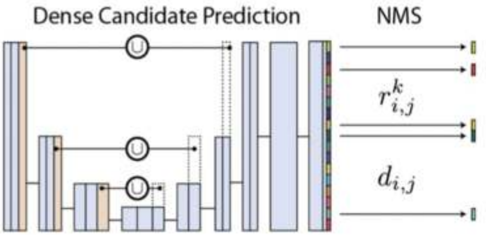

Figure: U-net architechture

Stardist

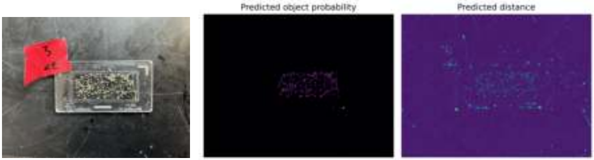

Figure: Star Dist- Object probabilities and radial distance

- The machine learning model is based on Stardist. Given this technology, we hope to reduce the amount of time spent on hand counting oysters for growth and distribution.
- Stardist has U-net as the backbone and considers object probabilities and radial distances.
- Below Figure (5) shows the object probabilities and radial distance of an input image.

Augmentation

- **Augmentation:** In the context of machine learning and data science, augmentation refers to the process of artificially expanding a dataset by applying various transformations to the existing data. These transformations may include rotations, flips, brightness adjustments, scaling, cropping, and noise addition, among others.
- **Purpose:** The purpose of augmentation is to introduce variability in the dataset, helping models learn to generalize better and become less prone to overfitting, especially when the amount of original data is limited.

Augmentation

To mitigate issues like data scarcity and model overfitting, augmentation techniques can be classified into four categories:

- **Absent Augmentation**: No changes applied, providing a baseline comparison.
- **Basic Augmentation**: Simple transformations, including adjustments in brightness and contrast, to account for minor visual variations.
- **Intermediate Augmentation**: Adds techniques like rotation, flipping, and shifting to increase dataset diversity.
- **Advanced Augmentation**: Builds on prior methods, incorporating zoom and shear transformations to introduce further variability.

Augmentation

- **Intermediate Augmentation**: (Rotation, Flipping, and Shifting)
  - ▷ Offers a greater variety of images by introducing spatial transformations.
  - ▷ increases the model's resilience to positional changes and orientations,
  - ▷ enhancing its ability to generalize.
- **Advanced Augmentation**: (Incorporating zoom and shear transformations)
  - ▷ Creates even more diverse transformations, introducing scale variations and shape distortions.
  - ▷ Maximizes the diversity of the dataset, making the model more robust and adaptable to a wide range of real-world imaging variations.
  - ▷ Each augmentation level is designed to progressively increase data diversity, allowing models to learn from a broader range of possible image variations.

Evaluation metrics

Training- Loss Functions

The loss function, a metric of the model's accuracy, being minimized:

- $L(p, p', r, r') = L_{prob}(p, p') + p' L_{dist}(p, p', r, r')$ where (p,r) are the predictions and (p',r') is the ground truth.
- $L_{prob}(p, p') = -p' ln(p) - (1 - p') log(1 - p)$
- $L_{dist}(r, r') = \frac{1}{n} \sum_k |r_k - r'_k|$

Evaluation metrics

Training- Distance Loss

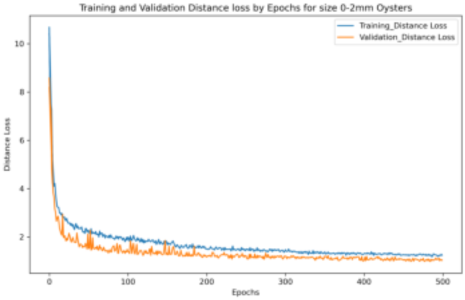

Figure: Distance Loss

- The data was split into an 75-25 training-to-testing ratio.
- The training and validation plots are similar, which is an indicator of a good model. The loss quickly falls and begins to flatten out at 50 epochs but still steadily improves.

Evaluation metrics

Training-Probability Loss

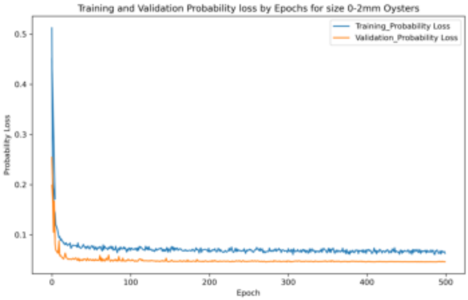

Figure: Probability Loss

- Probability loss decreases from 0.5 to 0.2 with in the first 50 epochs.
- The difference between the training loss and validation loss is almost 0.05, indicates that the model is performing consistently on both the training and validation datasets.

Evaluation Metrics-Tests & Results

- Precision = TP / (TP + FP)
- Recall = TP / (TP + FN)
- F1 = (2 × Precision × Recall) / (Precision + Recall)
- Accuracy = (TP + TF) / (TP + TF + FP + FN)

Evaluation metrics

Results-Prediction

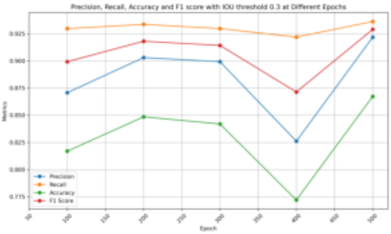

Figure: Metrics- Precision, F1 score, Recall, Accuracy

- The evaluation metrics gradually increase over the course of more epochs.
- The dataset was split into 75 percent training and 25 percent testing and model was evaluated using an Intersection over Union (IoU) threshold equal to 0.3.
- Testing the epochs of this model, a noticeable jump in accuracy occurs at 500, indicating the importance of prolonged training iterations in order to enhance the model's accuracy further.

Results

Figure: Predictions Oysters: Count-134(left), Count-96(right)

- The best model gave 75 percent accuracy when predicting images with darker backgrounds.
- Accuracy drops when images with lighter backgrounds are introduced

GUI

Figure: GUI Prediction of Oyster Image

In the Future

- we would like to study oysters of sizes 4mm-6mm and continue our research in developing a robust machine-learning model.
- Additionally, we aim to develop a GUI based on the best model to count oysters of different sizes.
- We also would like to train our models on images of oysters taken on lighter backgrounds, as when the model predicted on those types of images, accuracy would drop.

Figure: 4mm-6mm Oysters

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- https://www.laseagrant.org/outreach/aquaculture/oyster-research-lab/lab-staff/
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Thank you for listening!