PROJECT SUMMARY

SEAi-MORE: A ShEllfish BehAvior MOnitoRing DEvice

Projet GitHub Repository: https://github.com/bssackmann/SEAi-MORE

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1.0 INTRODUCTION AND PROJECT OBJECTIVE

Over the past 5 months our team, *The Oly Shuckers*, has been working to develop a low cost, computer vision-based, Shellfish Behavior Monitoring Device – a project that our team lovingly refers to as the SEAi-MORE project.

Targeted end-users for this technology range from aquaculture producers who have an ongoing need to monitor and improve animal health and minimize losses in commercial production systems to academic research groups and laboratories who study these animals or use them as part of standard ecotoxicity tests.

The Oly Shuckers includes a group of talented data scientists and computer vision specialists from GSI as well as our teaming partners at the Pacific Shellfish Institute whose research and educational activities focus on publicly-funded research projects to evaluate the ecology, health, and diseases of shellfish. The Pacific Shellfish Institute also conducts social research to characterize the status of shellfish production and restoration along the West Coast, including socio-economic assessments of the benefits and costs of shellfish production, and barriers to entry for the shellfish industry.

The goals of the SEAi-MORE project were to build a system using the OAK-D camera to provide real-time measurements of *in situ* shellfish feeding behavior and determine how feeding behavior changes in response to environmental variability – for example, changes in light, temperature, food quantity or quality, and even pollutants in the water.

Using sensors (e.g., magnetic Hall Effect sensors) to measure valve position as a way of monitoring shellfish feeding behavior is a well-established approach. However, sensor-based approaches require physical manipulation and direct attachment of sensors to the shells of animals, making measurements challenging and greatly limiting the number of individuals that can be monitored. For the *OpenCV AI Competition 2021* we successfully developed an image-based approach that, in large part, streamlines and simplifies the effort required by end-users to collect this type of behavioral information.

While the initial focus of the SEAi-MORE project has been on oysters, locally grown and sourced in the Pacific Northwest, the general approach and framework that we have developed can easily be adapted to other types of bivalves – for example, mussels.

2.0 EXPERIMENTAL DESIGN

The setup for the project included 4 distinct phases:

- Phase 1 included setup of the OAK-D cameras for use in the field,
- Phase 2 involved creation of a 'Creature Containment' system to isolate individual animals so that they could be imaged under more consistent conditions,
- Phase 3 focused on animal selection and some of the distinguishing characteristics of the different types of oysters that were used for this project, and

- Phase 4 addressed setup of the aquarium that was used to hold the animals while time-lapse images were collected.

2.1 Camera Setup

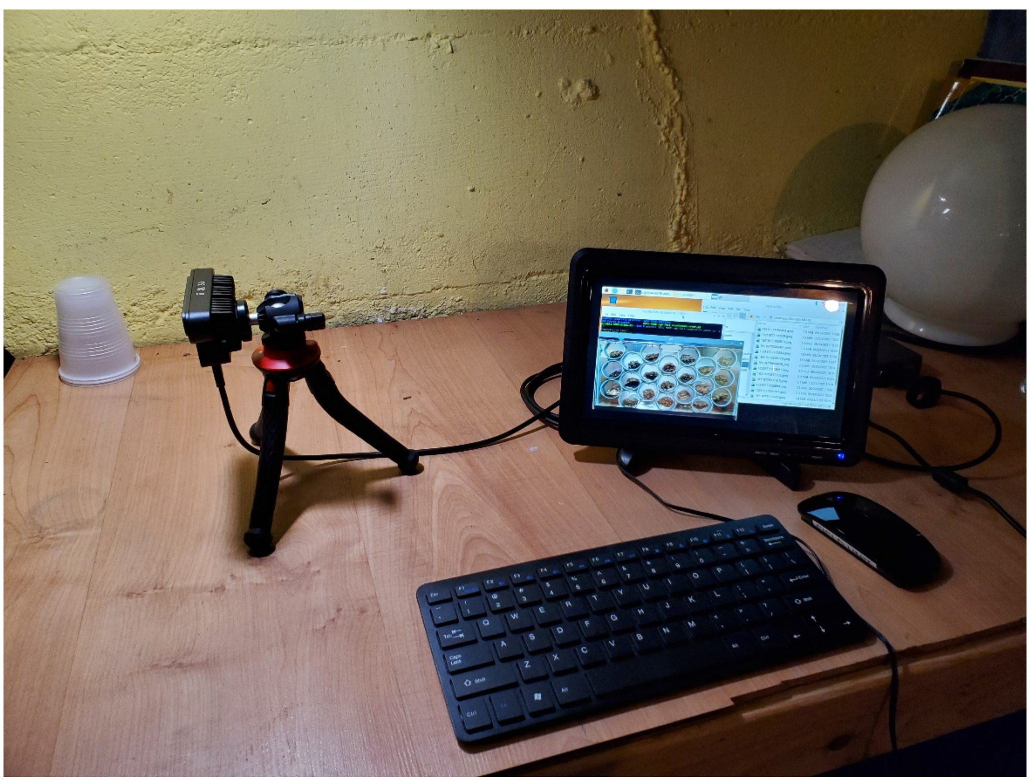
The camera setup for this project was straightforward.

The OAK-D cameras were situated on tripods facing the aquariums at fixed distances so they could capture all the animals in the scene. When collecting images in the field, the OAK-D cameras were connected to individual Raspberry Pi single board computers. We used Raspberry Pi 4, Model B devices, each with 8 GBs of RAM (Figure 1).

The example scripts provided with the OAKD-D cameras were adapted so that images could be collected at fixed intervals to generate time-lapse image sequences that showed the oysters opening and closing as they were feeding. All the images were collected at full 4K resolution so that we maintained as much detail as possible in the source imagery to support subsequent post-processing of the images.

The Python scripts developed and used to acquire the source imagery for this project are available on the SEAi-MORE GitHub repository.

Figure 1. OAK-D camera with Raspberry Pi used to collect time-lapse image sequences.



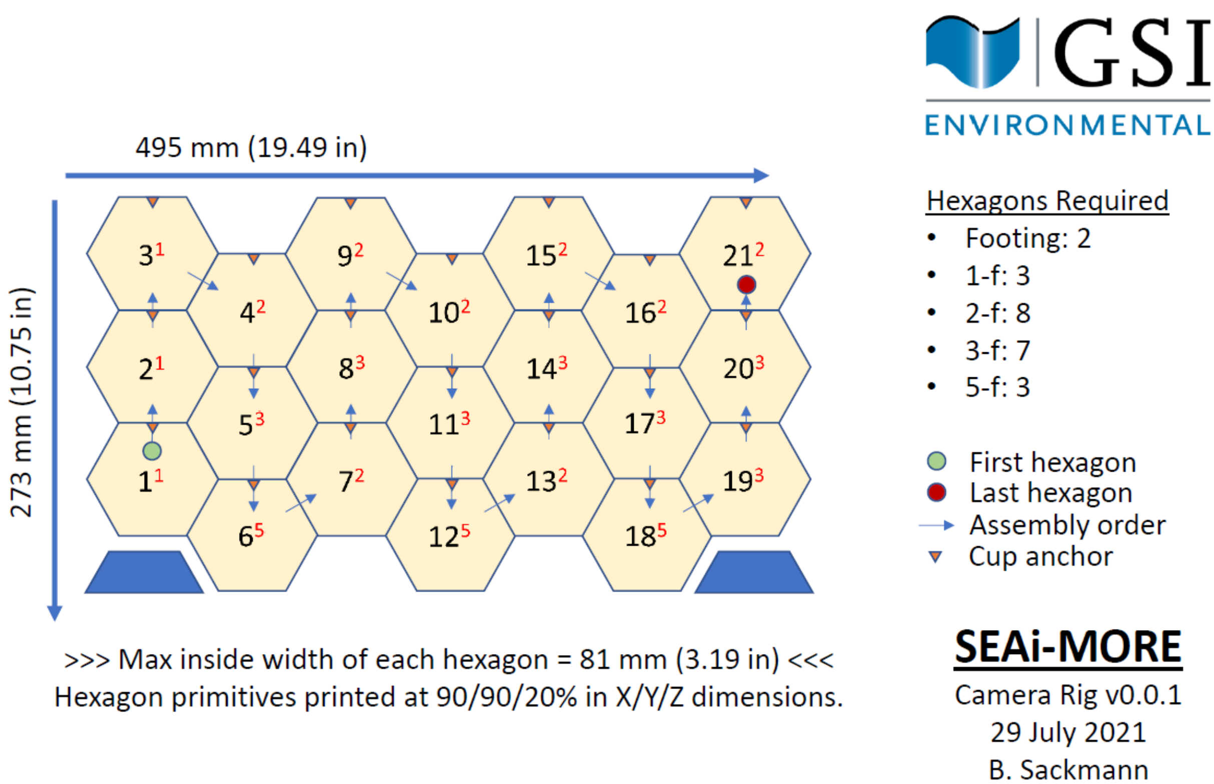
2.2 'Creature Containment' System

To make it easier to collect images of animals in a consistent way, and more easily differentiate between them, we designed a modular, 3d-printable, creature containment system (Figure 2). The system consists of a series of inter-locking hexagonal collars that hold white plastic cups to provide more consistent lighting and contrast between the animals being imaged and the background.

In our case we designed our hexagonal grid so that it fit into a standard 10-gallon aquarium. However, since the collars themselves are 3-d printable, it's possible to design custom grids to fit almost enclosure or experimental setup.

The hexagonal collars and support footings were all designed using Fusion 360 and all the 3d-print files and assembly instructions for the grid we used for the project are available on the SEAi-MORE GitHub repository.

Figure 2. Schematic and assembly instructions for the SEAi-MORE 'Creature Containment' system.



2.3 Animal Selection

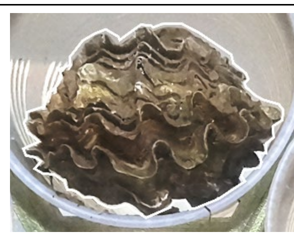
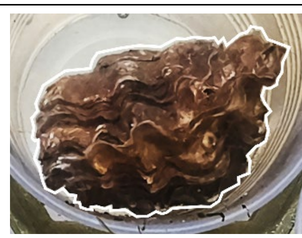
Both farm-raised oysters and wild marine oysters were utilized at different stages of the project. Three different species of oysters, of a variety of shapes and sizes, were collected and photographed (Figure 3):

- **Batch 1: Samish Bay Oysters -** previously flip bag (tumbled) oysters that were grown on the beach over the course of a few months. Flip bag tumbling the oysters produces smooth shells and sometimes a deeper cup.

- **Batch 2: Skookum Inlet Oysters -** from a natural setting where the larvae set on rocks and the oysters grew naturally on the beach. These oysters have the distinguishing frills/edges.

- **Batch 3: Totten Inlet Oysters** - from a previous experiment studying the survival and possible virus infection in an oyster population. This batch was grown in bags without any tumbling and were bred to have relatively deeper cups.

Figure 3. Examples of oysters used for the SEAi-MORE project.

Samish Bay Oysters (SEAi-MORE_v2)	**Skookum Inlet Oysters** (SEAi-MORE_v3)	**Totten Inlet Oysters** (SEAi-MORE_Trial1 and SEAi-MORE_Trial2)
		
		

The range of animal sizes, shapes, and distinguishing features helps ensure that our computer vision models are not unnecessarily biased to only one specific type of oyster, but instead can be used to study a wide-assortment of animals that one might encounter.

2.4 Aquarium Setup

Once the animals were harvested, and our creature containment system was constructed, we were ready to setup our aquarium and start taking pictures. Figure 4 illustrates the final aquarium configuration that was used throughout the project.

Figure 4. Image sequence of completed aquarium setup.

3.0 DATA COLLECTION

The next phase of the project involved taking a series of time-lapse images of animals in the aquarium that could be annotated and used to train our oyster detection models.

Both SuperAnnotate and Roboflow have strategic partnerships with OpenCV and provide web-based platforms that help streamline the image annotation and model training and deployment processes. We took the opportunity to evaluate both platforms as we annotated our images and developed our models for the *OpenCV AI Competition 2021* and found the range of services offered by each to be very robust and complimentary.

3.1 Image Acquisition

To develop and test our initial oyster detection models we collected four datasets. Images were collected on different days, with different camera settings, and included the variety of oysters described earlier (Table 1). In the first set of images collected on May 5th, we also chose to include mussels, in combination with oysters harvested from Samish Bay, to ensure that our modelling approach could be generalized to include other types of shellfish in the future.

The image sequence collected on May 25th included oysters harvested from Skookum Inlet and the animals' feeding behavior was apparent as they opened and closed their shells as they fed. Individual images for this dataset were collected every 60 seconds from a fixed camera position. We wanted to highlight this image sequence as it provided one of the 'lessons learned' on this project, in terms of how to properly configure and optimize the focus settings on the OAK-D cameras for this type of image acquisition.

For this sequence of images we let the camera autofocus as needed and the variation in the camera's focus resulted in some images that were blurry and others that were crisp, even though the camera was stationary and the animal movements were subtle. Having learned from our mistake, subsequent image sequences were collected using fixed-focus settings, which eliminated this particular issue and gave us much higher quality datasets to work with.

In total, we collected four datasets. Select images from the first two datasets were annotated and used to train our oyster detection models and the final two datasets were reserved for final testing and evaluation of those models.

Table 1. Summary of datasets developed for the SEAi-MORE project.

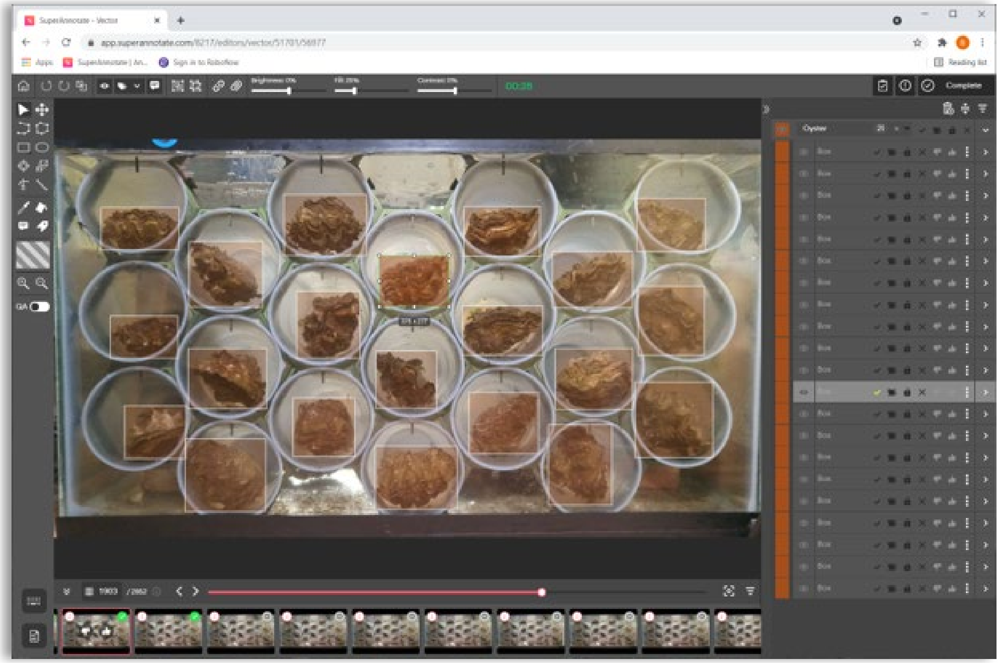
Dataset Use Summary									
Date	Dataset ID	Images Taken	Timelapse Interval	Resolution	Viewing Geometry	Autofocus	Images Annotated	Training/ Validation	Final Testing
5-May-21	SEAi-MORE_v2	1029	2 seconds	4K (3840 x 2160)	Variable	Variable	329 (32%)	X	
25-May-21	SEAi-MORE_v3	2852	60 seconds	4K (3840 x 2160)	Fixed	Variable	120 (4.2%)	X	
12-Jul-21	SEAi-MORE_Trial1	3198	10 seconds	4K (3840 x 2160)	Fixed	Fixed	0 (0%)		X
13-Jul-21	SEAi-MORE_Trial2	3024	10 seconds	4K (3840 x 2160)	Fixed	Fixed	0 (0%)		X

3.2 Image Annotation

SuperAnnotate made it easy to collaborate and distribute work across our team as we added bounding box annotations to all the images used to train our models. We found SuperAnnotate's interface to be very clean, intuitive, and fast (Figure 5). We also appreciated SuperAnnotate's Smart Prediction capabilities which let us iteratively train models that we used to speed up our annotation process and get a sense for how the models were performing as new images were annotated and added to the training datasets.

SuperAnnotate also provides several helpful dashboards and analytics reports and summaries that we used to manage the workload and to monitor our teams progress throughout the annotation phase of the project.

Figure 5. Example image that was annotated using SuperAnnotate.



3.3 Model Training and Deployment

After all our training images were annotated, the images and annotations were exported out of SuperAnnotate and imported into Roboflow for final model training and deployment.

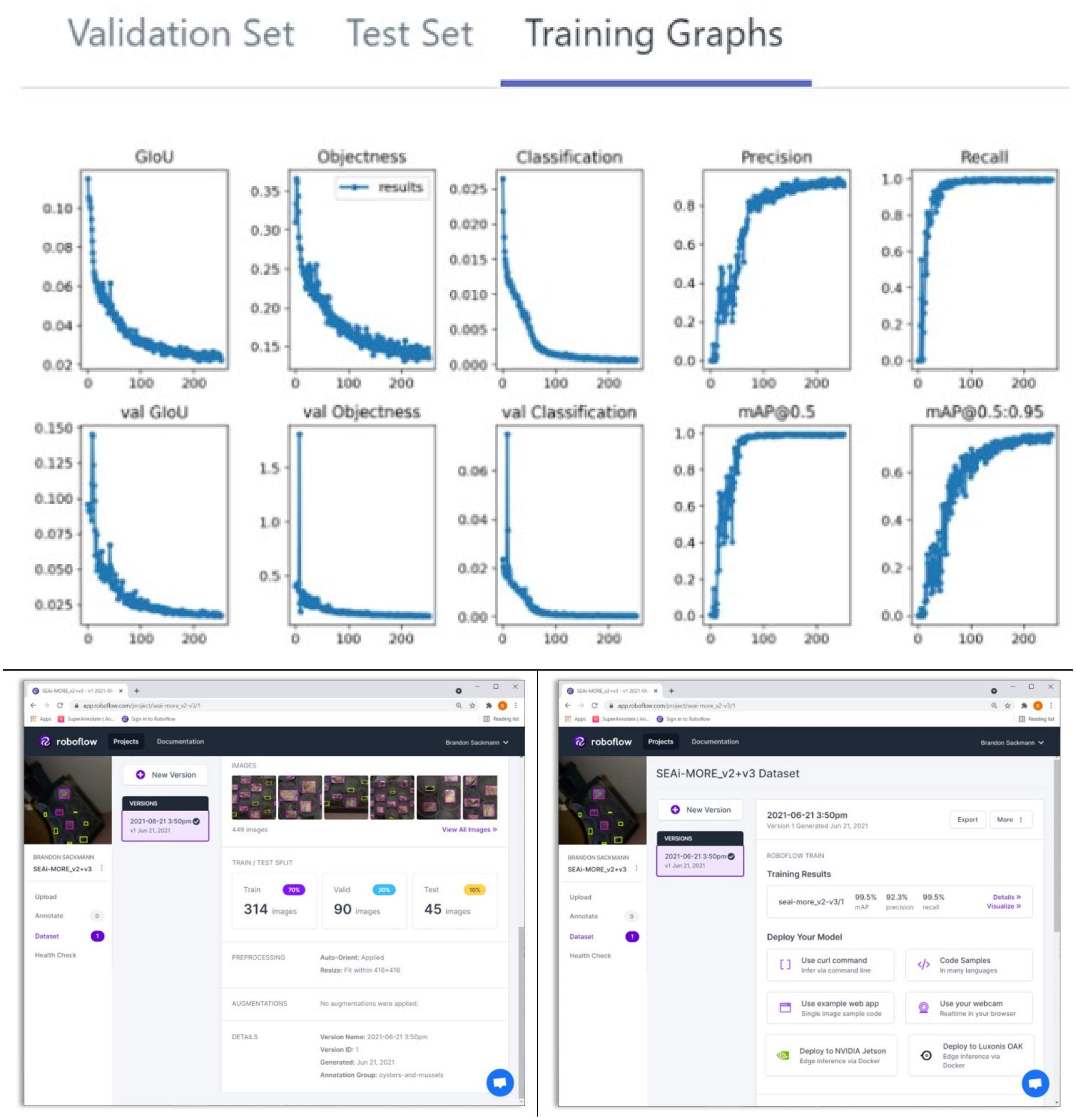
The complete set of 449 annotated images was divided into training, validation, and test datasets, using a typical 70/20/10 percent split and pre-processing steps were limited auto-orientation and resizing of images to 416 x 416 pixels, as recommended by Roboflow. Our final model was trained in a matter of minutes and immediately deployed and made available through a server hosted API (Table 2).

Roboflow also provides a number of helpful dashboards, data summaries, and analytics that helped us evaluate both the quality of our training dataset as well as the performance of the final model that was produced (Figure 6).

Table 2. Summary of settings used to train and deploy the final oyster detection model using Roboflow.

Roboflow Train Setup	
Source Images:	Images and annotations imported from SuperAnnotate (n = 449; COCO format)
Train/Valid/Test Split:	70% / 20% / 10% (n = 314 / 90 / 45)
Preprocessing:	[1] Auto-Orient, [2] Resize (Stretch to 416 x 416)
Augmentation:	None
Model Endpoint:	Hosted API (Remote Server)

Figure 6. Roboflow metrics for final oyster detection model.



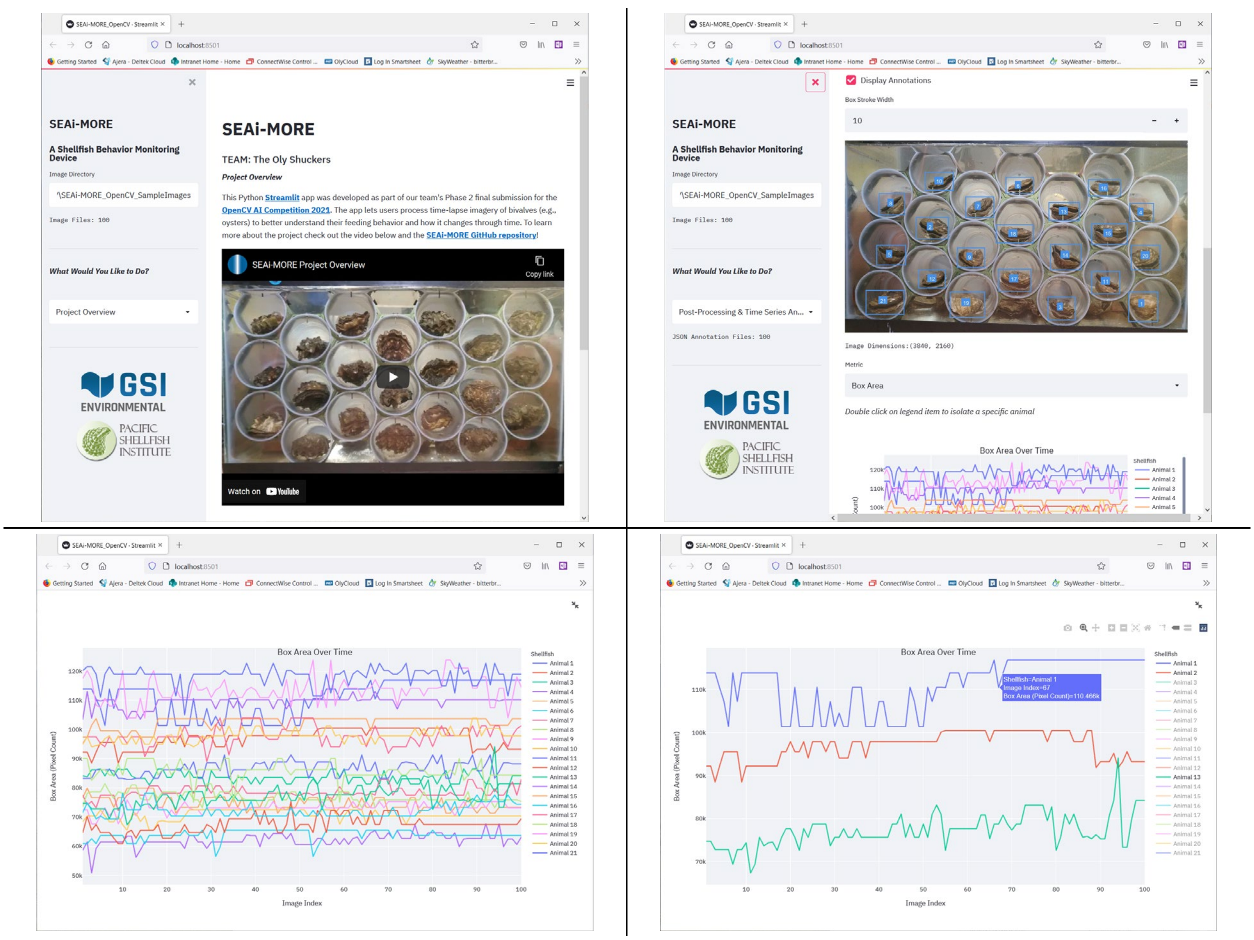
4.0 DATA PROCESSING

The final phase of the project culminated in the development of the SEAi-MORE web app. This app is an interactive Streamlit app that can be used to analyze new time-lapse sequences of oysters and develop animal-specific timeseries of different metrics that can help end-users understand the feeding behavior of their animals and how it changes through time (Figure 7).

Currently, the SEAi-MORE web app produces a select subset of derived metrics – for example, the area of the bounding box predictions for each animal can be viewed as interactive timeseries plots and the variability that one sees in these plots relates, in part, to the animals opening and closing their shells at different times. As the SEAi-MORE project matures we will be introducing additional functionality to the app and expanding the suite of derived metrics that we calculate.

The SEAi-MORE web app, as well instructions for how to use the app and where to download a sample set of images, can be found on the SEAi-MORE GitHub repository.

Figure 7. Screenshots of the SEAi-MORE web app.



5.0 FUTURE APPLICATIONS

In a laboratory setting it is possible to manipulate animals to generate measurable responses to specific environmental perturbations, one at a time, to minimize confounding responses (e.g., change light levels, sound levels, food quality/quantity, salinity). In future studies these types of deliberate manipulations will be conducted to simultaneously understand how different environmental stressors affect the animals and to generate a more robust image dataset that includes a range of animal behaviors to further refine our computer vision models. In addition to image-based data related to whether the animals' shells are open or closed, coincident water quality data will also be collected.

Examples of important ancillary measurements include:

- Temperature and salinity
- Total irradiance
- Sound pressure level
- Chlorophyll *a* fluorescence (as an indicator of food quantity)
- Turbidity
- Flow/current

After success in a laboratory setting has been achieved, we will attempt to deploy the OAK-D in an underwater housing to capture images of shellfish being cultivated at commercial aquaculture facilities. The goals of these follow-on studies will be to:

1. Demonstrate that the computer vision models trained with images collected in the lab can be generalized and used to analyze outdoor/underwater populations.

2. Characterize challenges associated with deploying an OAK-D device underwater for an extended period (i.e., days to weeks).

We anticipate that follow-on studies will result in a prototype monitoring device capable of monitoring shellfish feeding behavior both in controlled laboratory and outdoor/underwater settings. The device will later be extended to simultaneously measure key water quality parameters (e.g., temperature and light intensity). Eventually, all components will be integrated into a small, cost effective, solar-powered platform with fully integrated telemetry for real-time reporting.