

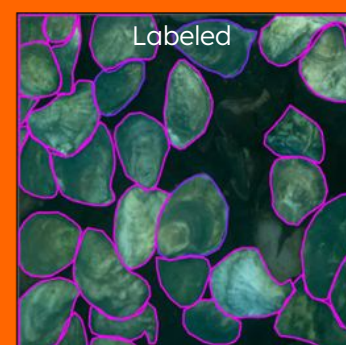
Abstract

The United Nations projects that the global human population will grow to eleven billion by 2100. As the populace increases, the demand for food will likewise grow. The global farming sector will need to help meet the increasing demand by boosting its efficiency and production volume. These industries must increase their output by improving their current practices by implementing innovative technologies that improve growth. One area that needs improvement is the oyster farming industry, which still uses practices from the 19th century. If oyster farming modernizes, it has the potential to provide a large high, protein food source. This research sought to create an automated monitoring system that will allow oyster farmers to remotely track the health and activity of their oyster crops. To create such a system, we use high-performance computing and deep learning to adapt an object detection model, YOLOv5_OBB, to recognize oysters under three different states of activity. By periodically using the object detector, farmers can use the activity to help infer the health of their oyster crops, reducing the amount of work required and thus increasing efficiency. In addition to its applications in aquaculture, the systems developed in this project can be used in oyster restoration efforts, helping monitor the health of the restored populations, such as those in the Chesapeake Bay.

Methods

Data Collection

- Build a large dataset containing oysters under various states of activity



Training

- Train the object detection model on the oyster dataset

Orientation Detection

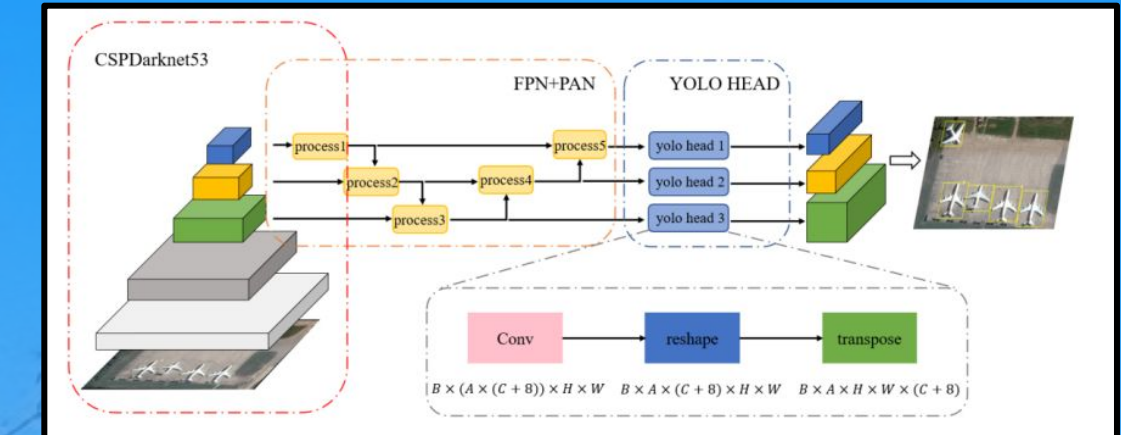
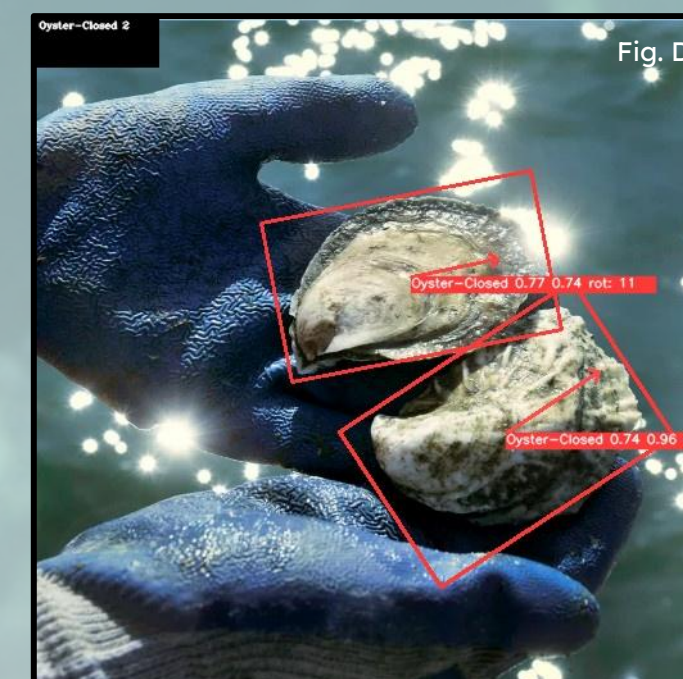
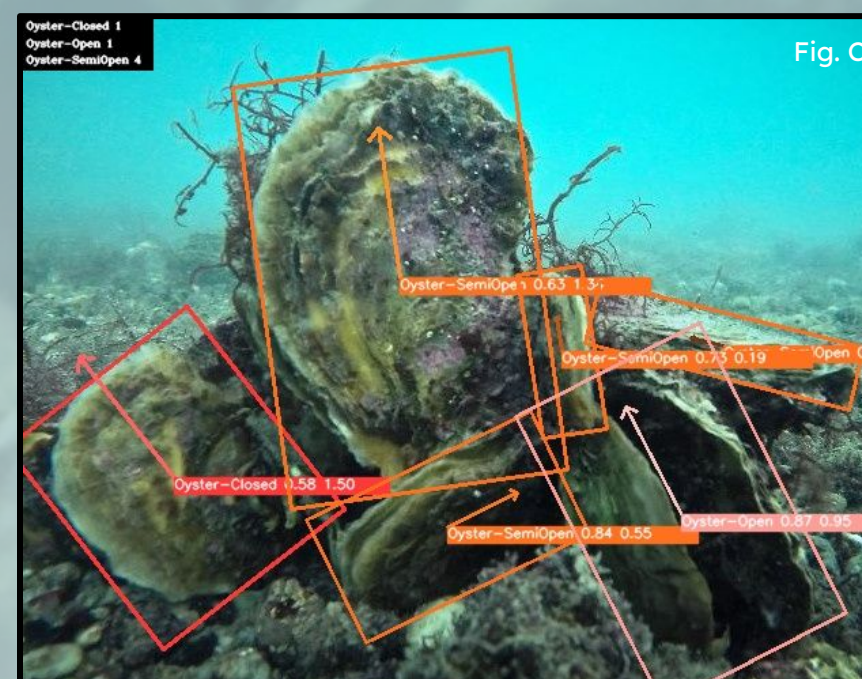
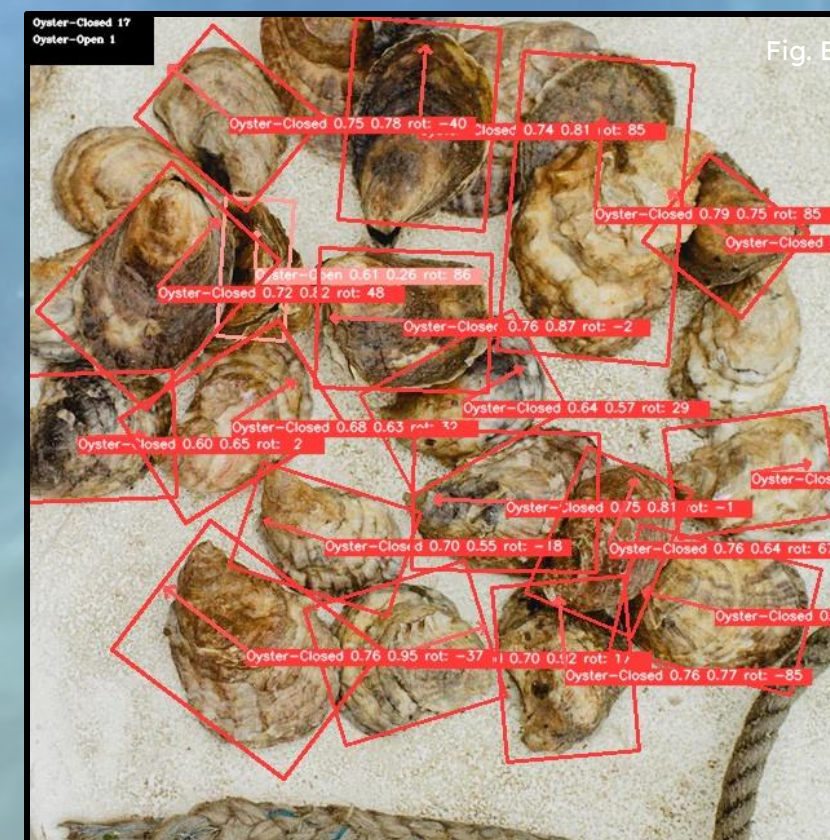
- Modify the model to allow for more detailed orientation inference.

	Precision	Recall	mAP 0.5	mAP 0.05:0.95
ylo5n	0.48	0.47	0.45	0.18
ylo5x	0.53	0.62	0.53	0.28

The two models trained for 325 epochs on the same dataset. The time needed to train yolov5n was much shorter than the time required for yolov5x. Higher numbers indicate better performance.

Results

- Trained models were run on various images containing oysters to measure their performance visually. Every detected oyster is labeled with its predicted class, followed by the confidence score, inferred orientation factor, and the degrees of rotation for the bounding box.
- The confidence score measures how confident the model is that there is an oyster inside the bounding box. The orientation factor measures how much the oyster's opening is facing the camera; the smaller the number, the more the opening is facing the camera.
- The Yolov5x model can detect more of the smaller oysters within a given scene and has better fitting bounding boxes than yolov5n.
- Furthermore, the model is capable of classifying oysters in environments that were not present in the training dataset. An example of such is present in Figure D.
- However, the detector does have some limitations. Firstly, the model has trouble distinguishing between empty oyster shells and living oysters.
- Second, the model may not find all the oysters within a given scene, meaning that the model's recall has room for improvement.
- Finally, the orientation inference is entirely subjective to the camera's perspective from which a photo or video was taken. The orientation of oysters directly facing the camera cannot be accurately inferred by the model due to the lack of 3-dimensional information.



Previous Work



Our Work



Conclusions & Future Work

By taking advantage of preexisting object detection models, this project used a custom compiled dataset to train an object detector to classify oysters into three different states of activity. The use of this system will help farmers increase the efficiency of their food production.

In addition, this project attempted to improve previous work by using the oysters' orientation to assist in activity recognition.

Increasing the dataset size is one possible step to improving the model's performance.

Feeding the output of this model into another network may improve activity classification.

The use of 3-dimensional information may allow for more accurate activity classification.

References

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