



Browser-Based Video Monitoring of Oyster Count, Identity, and Open/Closed State



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ABSTRACT

Aquaculture is crucial for our ecosystems, economy, and sustenance yet many farmers still inspect shellfish manually, which is very inefficient. This project investigates whether adding cross-frame tracking and temporal-state smoothing can improve oyster monitoring performance compared with traditional frame-only detection methods. We trained a YOLOv8s model and implemented IOU-based tracking with confidence-weighted temporal smoothing in a browser-based detection app. Across 18 test videos, smoothed state labels were correctly classified in up to 87.7% of detected oysters, consistently outperforming raw per-frame labels, while confirmed oyster counts more closely matched ground-truth totals than raw per-frame counts in two-thirds of test videos. These results provide preliminary evidence that video context measurably stabilizes oyster state monitoring over frame-only detection.

METHODOLOGY

The first portion of our project involved curating a dataset of oyster images and short videos gathered from previous projects, Roboflow, YouTube, and other sources. After examining existing work and deploying the 2025 baseline model, all data was annotated in Roboflow as "Oyster-Open," or "Oyster-Closed," with the "Oyster-Indeterminate" class being removed to increase accuracy. The second portion of our work consisted of training our own YOLOv8s model, chosen for its balance between speed and accuracy and its suitability for devices with weaker GPUs. Lightweight cross-frame tracking and counting was integrated to keep oyster IDs consistent with temporal smoothing. The third portion of our work involved comparing frame-only detection against temporal smoothing methods, adding browser features such as a detection log to track oyster data frame by frame, a permanent video player with video settings, and a desktop alert system for oyster state changes. And, finally, assembling a final product that includes a working prototype, dataset, and a documented GitHub repository, with a final report, presentation, and poster.

DATASET

The test set consists of 18 short video clips. Overall, the dataset contains 9615 images, with 75% in training, 5% in validation, and 20% in testing. Oysters are annotated with bounding boxes and a state, "Oyster-Open" or "Oyster-Closed".

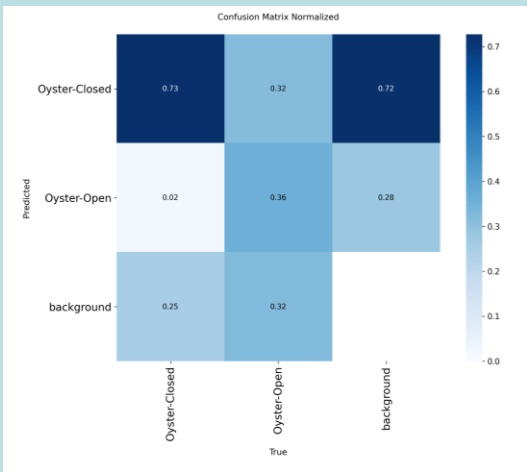


Figure 1. Confusion matrix for best performing YOLOv8s model

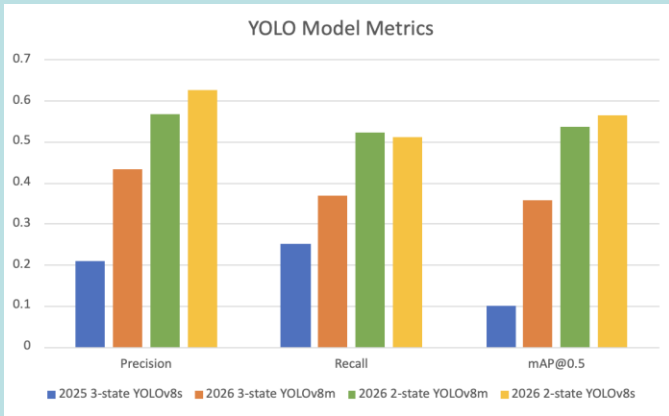


Figure 2. Bar chart comparing the performance of multiple models on the test set

MODEL PERFORMANCE

Removing the "Oyster-Indeterminate" class improved model performance. Our best performing model had precision/recall of 0.625/0.512 and mAP@0.5 of 0.565. By viewing the confusion matrix, it appears the main issues with the model are a significant number of false positives and misclassification of open oysters. These problems may be a result of class imbalance in the dataset, with 61251 closed oysters but only 24588 open oysters.

COUNTING AND TRACKING

When a video is played in the browser application, the two counts, total confirmed oysters and current detections, are displayed in the upper left corner. Oysters must be detected for 5 consecutive frames to count towards the confirmed total, making the count more stable than frame by frame detection. The unique tracking IDs are displayed alongside the class labels. The tracking works well for videos with no camera movement, or where the movement is slow and steady. In these cases, most of the oyster IDs remain consistent throughout the video, and even oysters that are missed by the detection for a few frames can be reidentified correctly. Tracking uses both intersection over union (IOU) and standard distance to determine if oysters are the same across frame. Bounding boxes with IOU over 0.5 are counted as the same oyster, and if the IOU threshold is not met, distance is checked. When comparing distance, IOU must still be over 0, so quick, unsteady camera movement can lead to oysters being assigned new IDs.

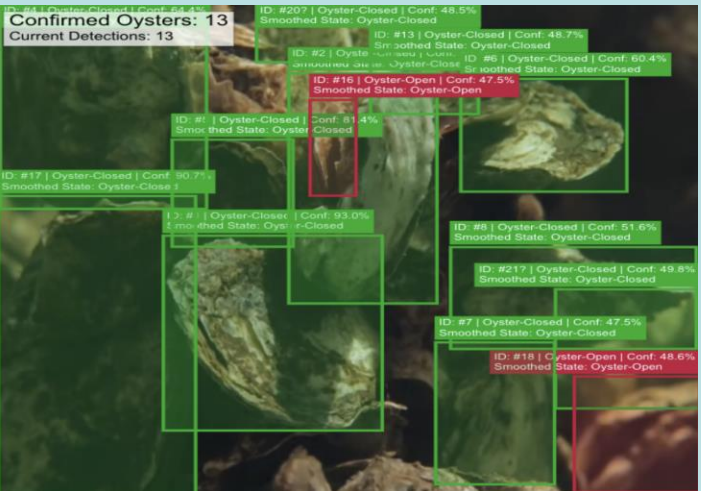


Figure 3. Screenshot of a video being played in the browser app

STATE SMOOTHING

The system uses confidence weighted temporal smoothing to stabilize oyster classification. For each oyster ID, the seven most recent predictions and confidence scores are stored. The confidence for each class is summed and the one with greater weight is selected. After at least three observations, the displayed smoothed state changes only when the opposing state receives at least 65% of the total confidence weight. Missed detections do not add votes, allowing isolated errors or brief visibility loss to be ignored. We ran all test set videos through the system and counted the detected oysters, as well as how often the smoothed labels and raw, per frame labels were correct. The smoothed state labels matched the ground truth state more often than the raw labels.

BROWSER APP FEATURES

To produce more quantitative data, a frame logging module was added to the system along with a download button for a .CSV file containing the data in the browser app allowing the detections to be persistently stored and used for research. The frame-logging module keeps track of oyster counts, IDs, states, confidences, and bounding box coordinates alongside timestamps, which allows us to more clearly see when oysters change state and check the consistency of counts and IDs. Additionally, to increase the functionality of the browser-based detection app, a desktop alert system was implemented to notify the user of oyster state changes, along with a permanent video player with buttons to play, pause, rewind, and control the speed of videos.

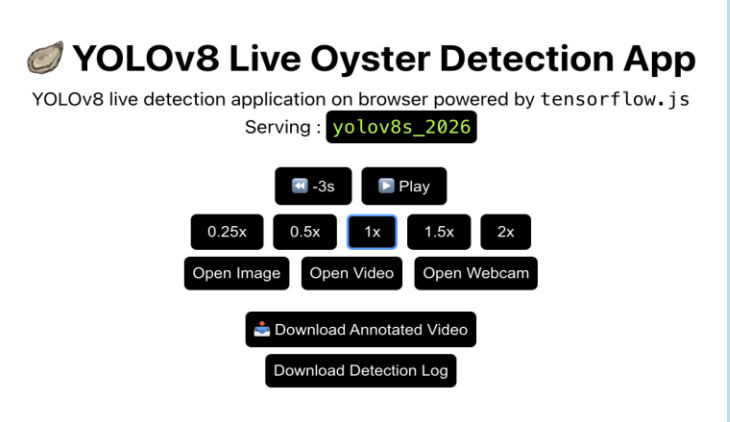


Figure 4. Screenshot of the browser app run on a local host

CONCLUSION

With the importance of monitoring shellfish's health in aquaculture and the development of detection technology, there's a call for improving this fairly new technology to urgently help our shellfish farmers. We addressed the issue with a newly trained YOLOv8s model to introduce more consistent, accurate oyster counts, IDs, and temporal state tracking into the existing using an enhanced dataset and temporal state smoothing. We have expanded and refined the dataset using new and existing content and implemented new features to increase the browser app functionality for users.

Our research contributed the tracking and data-logging infrastructure needed to test whether adding video context improves oyster monitoring over frame-only detection—turning our project's hypothesis into something measurable and useful for future research. The main focus for future iterations of this project is around developing a per oyster adaptive state smoothing method that will allow the smoothing system to work effectively across oysters with different levels of visual clarity and prediction reliability.

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