BIOELECTRIC FIELD MEASUREMENTS: AUGMENTING IMAGE RECOGNITION FOR FISHERIES MANAGEMENT

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QUESTION/HYPOTHESIS

Automated image recognition algorithms have the potential to significantly streamline the process of optical data analysis for fisheries management. However, the prevalence of naturally camouflaged species will likely limit the accuracy of these purely optical methods. This study investigates the question of whether bioelectric field measurements can feasibly be incorporated into object detection algorithms to improve the accuracy of automated stock assessment.

BACKGROUND

Accurate and efficient stock assessment methods of commercially relevant fish species are extremely important toward sustainable fisheries management. Optical data, such as benthic images generated by the Habitat Mapping Camera System (HabCam), have been successfully used for this purpose in the past by NOAA Fisheries, Northeast Fisheries Science Center and others. However, data analysis—involving manual annotations of thousands of sampled images—is time- and labor-intensive [1]. Therefore, the automation of this process using image recognition algorithms has the potential to significantly improve stock assessment efficiency.

Current state-of-the-art methods for automated image recognition implement machine learning to train convolutional neural networks (CNNs) [2]. In the simplest terms, CNNs for object detection consist of multiple layers of interconnected artificial neurons that detect different features in an input image, producing an output indicating the presence and location of particular objects of interest. The many parameters that dictate the behavior of these various neurons is generally optimized through the process of machine learning: A large training set of manually annotated images is input into the network, and parameters are iteratively changed to minimize error. By training on relevant datasets—such as HabCam images—this method should allow for the automated detection of species of interest.

However, the natural ability of camouflage in many commercially relevant species, such as the summer flounder (*Paralichthys dentatus*), will likely limit the accuracy of methods that rely on purely optical data. To compensate, it may be necessary to incorporate non-optical data. One option for this secondary modality is the detection of bioelectric fields: Numerous previous studies have demonstrated the production of measurable electric fields by various marine species, including several types of flatfish and skates [3,4]—both of which are likely to present optical detection challenges in benthic images.

INTRODUCTION

This research was completed at the Massachusetts Institute of Technology, Sea Grant College Program (MIT Seagrant). I selected this project because it combined my interest in machine learning and image recognition with an application in marine sustainability. Many sources of relevant background information were provided by mentors, Robert Vincent, Thomas Consi, and Paris Perdikaris. These initial resources pointed to additional options for further literature review of related articles.

PREDICTION

We hypothesize that the augmentation of trained image recognition algorithms with bioelectric field data will significantly improve the accuracy of automated detection, thereby identifying electric field measurements in combination with CNN-based object detection as a feasible method of automated image analysis to inform fisheries management. More specifically, we propose using these measurements to guide detection algorithms, allowing thorough computational analysis of regions of high electrical activity. We predict that preprocessing images in this way will decrease instances of false positives and false negatives by limiting the field of view to only regions that are likely to contain live species.

MATERIALS

Hardware	Software	Electronics
- 1x: Intel Xeon CPU E5-2623 v4 @ 2.60GHz - 4x: NVIDIA Titan X GPU - 1x: Toshiba 1 TB Canvio Slim II Hard Drive	- 1x: YOLOv2 Real-Time Object Detection - 1x: LabelImg Graphical Image Annotation Tool - 1x: Fedora 25 Linux Operating System	- 2x: Ag/AgCl Metal Electrodes - 1x: WPI DAM50 Differential Amplifier - 1x: Tektronix TDS Two Channel Digital Storage Oscilloscope

Table 1. Specific hardware and software components utilized for the development and testing of image recognition algorithms trained for automated stock assessment, in addition to specific electronic components used for preliminary electric field probe design. Other general materials were also used, such as monitors and keyboards, basic command line terminals, and various resistors and DC batteries.

PROCEDURE

The feasibility of this approach was investigated from both a hardware and software perspective:

Software: Design and Testing of Image Recognition Algorithm

1. Benthic images containing classes of interest—scallops, roundfish, flatfish, and skates—were extracted from 2013 and 2015 HabCam datasets. More than 5000 images were compiled for training, and 300 images (100 containing scallops, 100 containing roundfish, 50 containing skates, and 50 containing flatfish) were set aside for testing.
2. Using these 300 test images, two test sets were created to check for changes in accuracy due to the incorporation of electric field data. To simulate the result of field measurement-assisted preprocessing, one test set was cropped around areas expected to exhibit higher electrical activity, while the other test set was left untouched. The aspect ratio was held constant between test sets, while the size of the cropped images was set by the expected input size of the CNN.
3. All images were annotated by drawing and labeling bounding boxes around each instance of a species of interest. LabelImg was used to convert these annotations into formats compatible with recognition algorithms (VOC XML).
4. YOLOv2 (real-time object detection algorithm) was built from source and configured to interact with the compiled image sets.
5. The algorithm was trained using the annotated training set for over 80,000 iterations, saving parameters at various times throughout. Training was completed on a GPU-powered machine for speed.
6. Both test sets were input into the fully-trained algorithm to calculate accuracy across classes and assess the effect of electric field-assisted preprocessing. The predictions made by the algorithm were compared against the manually annotated, “true” bounding boxes to calculate the following metrics:

- Precision – Measure of the relevance of the algorithm’s decisions, defined as the percentage of total detections that are true positives
- Recall – Measure of the algorithm’s sensitivity, defined as the percentage of all available positives detected by the system
- Intersection over Union (IOU) – Measure of how accurately the algorithm positions its predicted bounding boxes (**Figure 1**)

$$\text{IOU} = \frac{\text{Area of Overlap}}{\text{Area of Union}}$$

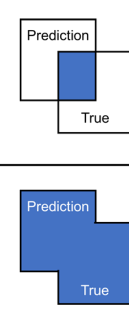

Figure 1. Definition of IOU. One of the metrics used to quantify accuracy of object detection algorithms, it reflects how much of the bounding box predicted by the algorithm overlaps with the true bounding box.

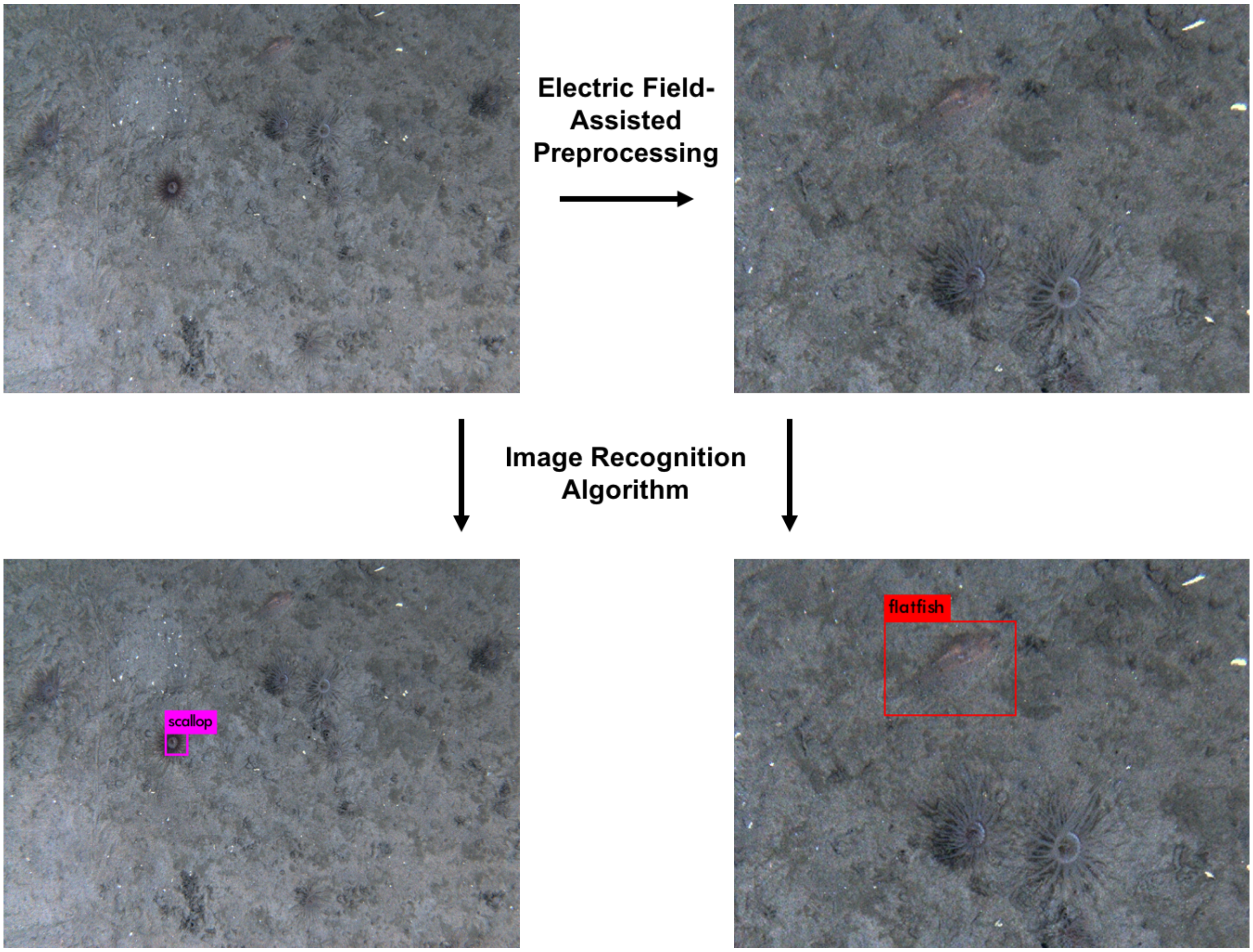

Figure 2. Predictions generated by the fully-trained algorithm when the input was both unprocessed (left) and preprocessed (right). The single flatfish of interest was correctly identified only in the preprocessed prediction, and a sea urchin was incorrectly labeled as a scallop in the unprocessed prediction, qualitatively demonstrating the ability of electric field-assisted preprocessing to limit false positives and false negatives.

Hardware: Preliminary Electric Field Probe Design

1. Preliminary sensor design was completed using two Ag/AgCl electrodes held at a fixed distance apart. Using the electrodes as inputs into a differential amplifier, voltage gradient was measured as the difference in voltage between two points at a known distance apart. The output of the differential amplifier was connected to an oscilloscope to visualize the resulting signal.
2. Signals from artificial electric fields induced by a 1.5 V DC battery were measured in fresh and saltwater to assess probe sensitivity.
3. A thorough literature review was conducted to determine expected characteristics of bioelectric fields generated by various marine animals, in addition to the expected electrical environment in which the measurements would be taken. Synthesizing this information and comparing to our observed traces, the feasibility of field measurements was assessed.

RESULTS

Effect of Electric Field-Assisted Preprocessing

Following training, the accuracy of the fully-trained algorithm—trained for more than 80,000 iterations—was assessed with both an unprocessed test set containing raw HabCam images and a preprocessed test set containing images cropped about areas of expected high electrical activity. Qualitatively, limiting the field of view with this type of preprocessing appears to yield the predicted improvement in performance. Both test sets were input into the fully-trained algorithm to generate two sets of predictions (**Figure 2**): The preprocessed predictions showed accurate detections that did not appear in the unprocessed predictions, while the unprocessed predictions contained false negatives not seen in the preprocessed predictions.

The difference in accuracy between test sets was also assessed quantitatively through the generation of precision-recall (PR) curves for each class of interest (**Figure 3)**, as well as average IOU values across all four classes (**Figure 4)**. PR curves reveal how precision and recall change as the threshold for a positive detection is varied, thus quantifying the ability of an algorithm to limit false positives and negatives. The resulting curves, which show that the processed test set more effectively maintains precision as recall increases, confirm the qualitative observations above. Furthermore, the most pronounced effect on PR appears in flatfish, as expected—natural camouflage makes them significantly more difficult to detect, allowing for the greatest improvement following preprocessing.

Average IOU across all classes was also calculated for both the unprocessed and preprocessed test sets as a measure of how accurately the algorithms predict the location and size of each bounding box. A similar trend was observed here, with the preprocessed test set yielding an IOU increase of more than 5%. Statistical analysis (two-tailed t test) confirms that this difference in accuracy is statistically significant (**Figure 4**).

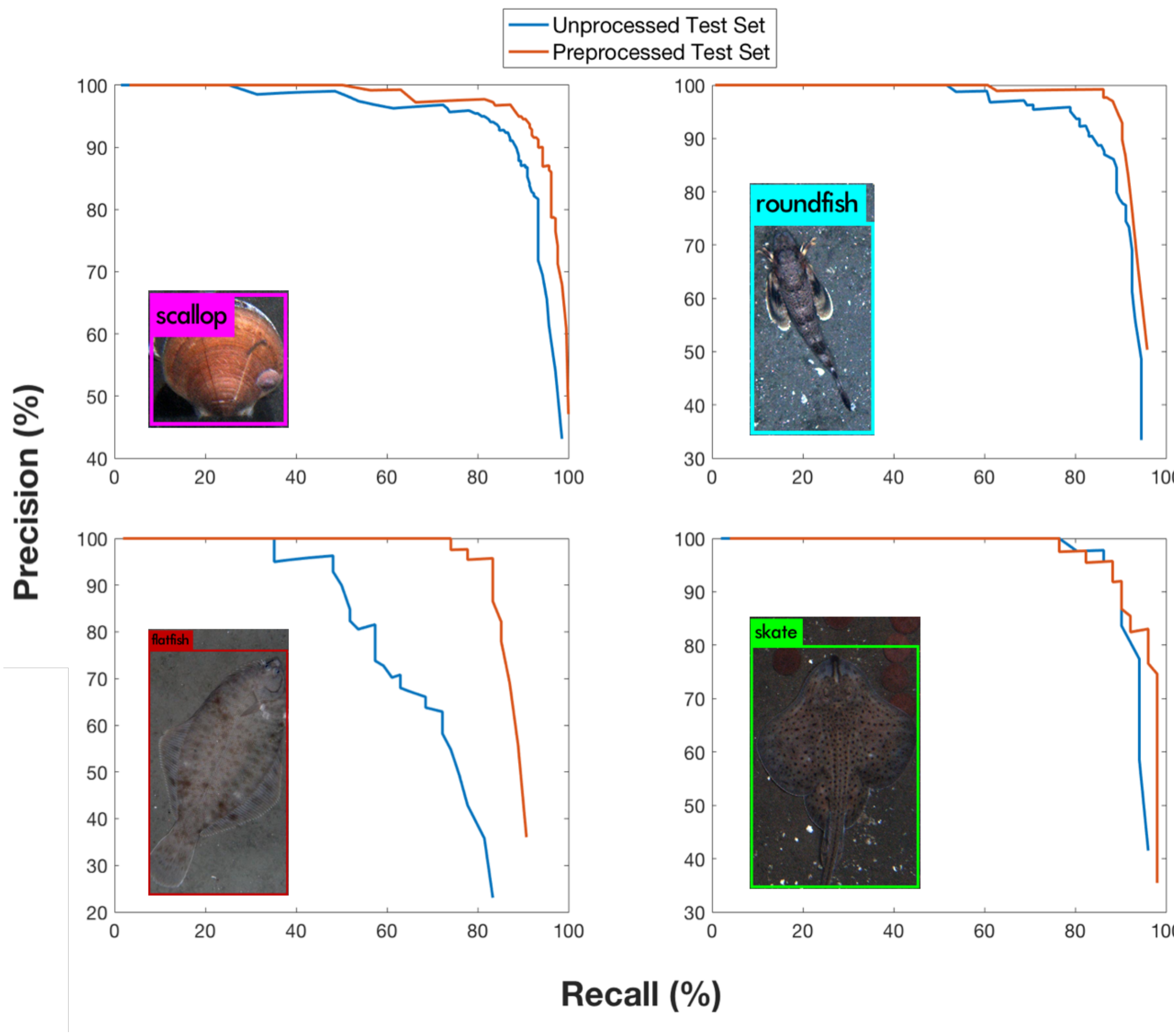

Figure 3. Precision-recall (PR) curves generated for the preprocessed and unprocessed test sets across each of the four classes of interest: scallops, roundfish, flatfish, and skates. Curves shifted up and to the right indicate that an algorithm more effectively maintains precision—limiting false positives—as recall increases—limiting false negatives. The preprocessed test set—in particular for flatfish, which are the most difficult to detect—shows improved PR as compared to the unprocessed test set.

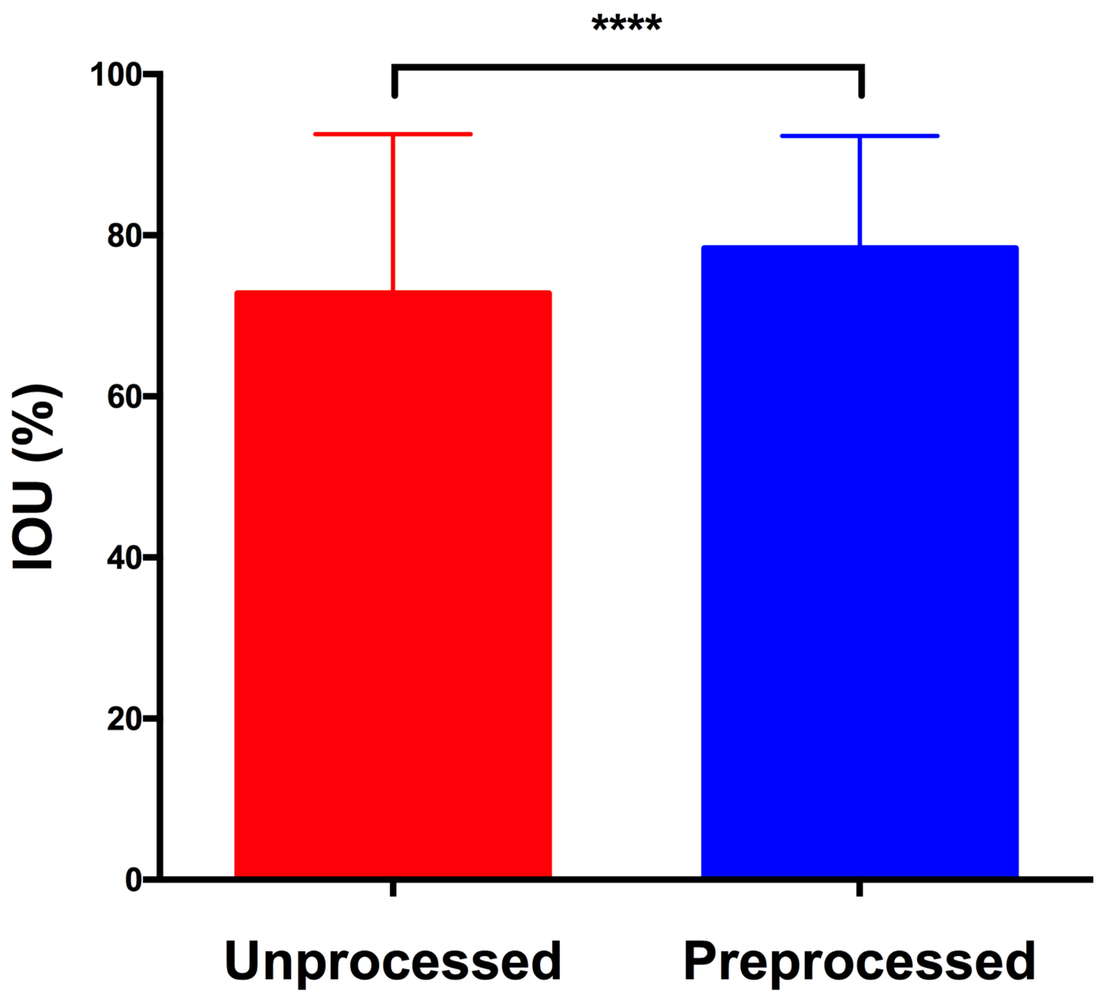

Figure 4. IOU values averaged across all objects (N = 489) in both the unprocessed and preprocessed data sets. Electric field-assisted preprocessing increases the average overlap between the predicted and true bounding boxes by approximately 7%. (****, $p < 0.0001$).

Feasibility of Electric Field Probe

Although datasets that simulate the results of electric field measurement-assisted preprocessing show promise, it remains to be seen whether these measurements can feasibly be made in the field. Literature searches reveal that the expected magnitude of the signals may be exceedingly low, particularly when measured from large distances: For example, it has been shown that small flounder produce an electric field of only 0.2 μV/cm at a distance of 10 cm [3,5]. Although the magnitude of this signal can be expected to increase with larger animals, such as the larger flatfish and skates of commercial interest, the measurement distance is also likely to be significantly greater when incorporated into the HabCam system—the typical distance at which the cameras and sensors are towed was cited as between 1-2 m by researchers from the Northeast Fisheries Science Center (see **Acknowledgments**). Furthermore, there are many sources of electrical noise in the system, considering the metal frame of the HabCam vehicle and its onboard power sources.

Therefore, it is important to assess whether these types of measurements are possible when incorporated into this electrical environment. This literature search reveals two important design constraints: The probe must be sensitive enough to pick up minute signals from a distance, as well as robust to significant electrical noise. With this in mind, we designed a preliminary sensor system based on previously reported designs [3,6]: Two Ag/AgCl electrodes would serve as inputs to a differential amplifier, and the difference in voltage can then be recorded digitally via a data acquisition

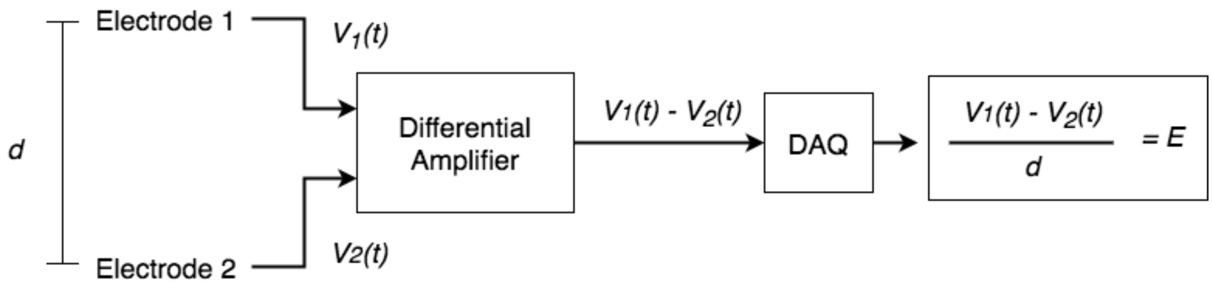

Figure 5. Block diagram of proposed electrical field probe. Two Ag/AgCl electrodes, held at a fixed distance, *d*, provide input signals, $V_1(t)$ and $V_2(t)$, to a differential amplifier. The difference between voltages is then input into a data acquisition (DAQ) device, allowing the calculation of the electric field, *E*, based on these measured values.

(DAQ) device. Based on the known distance, the electrical field can then be calculated (**Figure 5**).

A prototype of this system was fabricated using two Ag/AgCl electrodes and a WPI DAM50 differential amplifier, the output of which was visualized on an oscilloscope. An attempt was made to measure the electric field generated by a 1.5 V DC battery in both freshwater and saltwater, however, it proved impossible to effectively attenuate 60-Hz electrical noise, even in the controlled environment of a Faraday cage.

CONCLUSION

Taken together, the results from these studies identify the proposed approach to incorporate non-optical data into object detection algorithms for the automation of stock assessment as a promising one: The accuracy of a cutting-edge CNN-based object detection algorithm—as measured by IOU, precision, and recall—was significantly improved by cropping the test set of images about areas expected to contain species of interest based on non-optical data. The difference between PR curves, in addition to qualitative observation of the predicted bounding boxes for each set, suggest that this difference is likely due to a decrease in instances of false positives and false negatives, as predicted. However, the choice of bioelectric fields as the source of this data appears inherently flawed due to the exceedingly small magnitude of the signal, combined with the noisy electrical environment in which the signal would be measured. Therefore, other potential sources of non-visual data that can be incorporated into this type of object detection algorithm should be investigated. One possible alternative is the incorporation of three-dimensional data: The HabCam vehicle takes two stereo images, and the overlap between images can be used to determine the depth of objects in the image—future studies could focus on whether this type of data may allow similar preprocessing, by focusing detection on areas of increased height relative to background. If a feasible source of non-visual data can be determined, the improved accuracy of automated detection demonstrated here could significantly improve the efficiency of stock assessment.

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