


SmartPass: 2024 Progress Updates

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MARCH 2024

This addendum serves as an update to the 2021 publication SmartPass: An Innovative Approach to Measure Fishing Effort Using Smart Cameras and Machine Learning. Herein we offer an update on progress regarding the Oregon case study, an overview of a pilot study conducted by technology provider Ai.Fish that tested edge-deployment of a SmartPass system and current status of application in the blue swimming crab fishery in Lampung Province, Indonesia.

CASE STUDY

OREGON SMARTPASS

Since the SmartPass white paper was published in February 2021, the partnership between Oregon Department of Fish and Wildlife (ODFW), CVision AI and Environmental Defense Fund (EDF) has grown from a short-term pilot of the SmartPass system into a successful rollout of customized camera systems that serve as a reliable component of ODFW's Ocean Recreational Boat Survey. These customized camera systems are now deployed in three out of the eleven major coastal 'passes' in the state, with plans to expand to all eleven major passes by the summer of 2024.

Design Improvements

Over the past two years, CVision AI has implemented wireless transfer of video data, a digitized entry & data export system, AI vessel traffic alerts and internet connectivity alerts.

Wireless data transmission

Wireless transmission of video footage greatly increases ODFW staff efficiency compared to manually transferring data by hard drive. By eliminating the need to travel to camera sites, staff can allocate time to other activities. This feature also provides business continuity benefits as staff can conduct video counts anywhere with an internet connection.

"During periods of low activity or short staffing we can quickly review effort levels and use this information to determine the best allocation of catch sampling resources."

Justine Kenyon-Benson
Ocean Sampling Project, Assistant Project Leader, ODFW

Digitized Entry & Data Export

CVision AI has helped ODFW to transition from a paper-based data entry system to a digitized entry system which has improved the speed of data entry for the majority of staff using the new system. Instant and easy access to the data simplifies tasks such as pulling statistics on fishing effort trends by month under this digitized approach. Additionally, a streamlined report-generating feature enables expedient exporting of vessel traffic data while sorting by time and location (**Figure 1**).

Port	Date	Range	Entering Vessel	Cumm. Total Enter	Exiting Vessel	Cumm. Total Exit	Comments
Newport	9/12/23	08:15:00-08:45:00	4	7	11	113	heavy fog
Newport	9/12/23	08:45:00-09:15:00	5	13	2	115	heavy fog
Newport	9/12/23	09:15:00-09:45:00	2	15	3	118	heavy fog
Newport	9/12/23	09:45:00-10:15:00	9	24	1	119	heavy fog
Newport	9/12/23	10:15:00-10:45:00	8	32	2	121	heavy fog
Newport	9/12/23	10:45:00-11:15:00	7	39	3	124	
Newport	9/12/23	11:15:00-11:45:00	8	47	1	125	
Newport	9/12/23	11:45:00-12:15:00	13	60	4	129	
TOTAL			139	141	140	140	

Figure 1. Digital entry faux report

Figure 2. AI vessel traffic alert feature

AI Vessel Alert Feature

The system provides an AI-powered vessel traffic alert feature that informs the human reviewer to incoming vessel activity (**Figure 2**). This feature is designed to increase the attentiveness of the human reviewer to reduce the number of unrecorded boats traveling through a pass.

Internet Connectivity Alerts

As the SmartPass system relies on wireless data transfers, good internet connectivity is crucial for creating a steady supply of management data. While two out of three camera sites currently operate without any connectivity issues, the camera system in Charleston operates on a shared internet connection and occasionally has outages which, in rare instances, can create video backlogs. However, the camera system has been set up such that it can keep recording during these outages and sends backlogged video footage once connectivity is restored. Furthermore, the system has been customized to send alerts to staff when these outages occur so that the issue can be remedied. In instances where Wi-Fi connectivity is not possible, the SmartPass system is also capable of operating over cellular networks.

Fine-tuning AI Performance in Oregon

The SmartPass algorithm pipeline consists of three major components: vessel detection, vessel tracking and vessel classification. The detector identifies a vessel when it appears in a frame. The tracker then connects tracks of individual vessels from one frame to the next and ultimately determines whether a count is made for a vessel entering or exiting the area. The classifier makes a preliminary determination of the type of vessel that is detected.

In 2020, during the SmartPass pilot phase, algorithm-generated recreational boat counts were compared to human review counts to assess performance of AI. While the computer algorithm results showed promise, vessel detection in foggy weather proved challenging. To tackle this issue two algorithms were developed to perform better under different visibility conditions: one fine-tuned for foggy weather and one for clear weather. The performance of these two algorithms was compared to the original "generalized" algorithm that was not fine-tuned to any specific weather condition. **Figure 3** displays the relative performance of each algorithm using mean average precision[1] as a scoring metric. Intuitively, the algorithm fine-tuned for clear weather was best able to detect vessels in clear weather conditions, the algorithm fine-tuned for foggy weather performed best in foggy weather and the generalized algorithm performed best on a data set that contained all weather conditions (a mix of clear and foggy weather). While the generalized algorithm may perform better on a data set consisting of all weather conditions, the combined performance of the two weather-specific algorithms is superior. The next step for integrating the weather-specific algorithm improvements into the SmartPass system involves installing a weather predictor to automatically activate the appropriate algorithm for the current weather conditions.

Weather Condition Present in Vessel Image	Clear Weather Algorithm	Foggy Weather Algorithm	Generalized Algorithm
Clear Conditions	0.9	0.6	0.8
Foggy Conditions	0.5	0.8	0.6
All Weather Conditions (clear and foggy)	0.7	0.4	0.8

Figure 3. Mean average precision score of detection algorithms in their domain and in the opposing domain. (Scores range from 1 to 0 with higher scores indicating better performance).

[1] Mean average precision (mAP) evaluates the robustness of object detection models.

PILOT PROJECT

AI.FISH EDGE COMPUTING

To date, SmartPass systems have required either hard drive retrieval or wireless transmission of video data before AI vessel counts are produced. This process can be time-consuming and costly for some users. With this in mind, technology provider Ai.Fish and EDF collaborated to develop a camera with a machine learning algorithm designed to detect boats with the capability of computing on the edge, meaning the ability for video data to be collected, processed and analyzed by computer algorithms on site and with no input from the user. Cost-effective autonomous SmartPass systems may also allow for scaling in new geographies where affordability is crucial, such as small-scale fisheries in the developing tropics.

Project Overview

Ai.Fish designed and implemented a working system prototype featuring low-powered computing equipment integrated with a camera installed in weatherproof housing (**Figure 4**). The camera system was installed in Newport, Oregon and operated from May 25 to July 17, 2023, capturing 1106 hours of footage.

Figure 4. Ai.Fish SmartPass camera – Newport, Oregon

Performance Evaluation

This study compared AI-generated counts to the counts made by two human reviewers. Prior to this study, any AI-generated count that differed from a human reviewer's count was considered incorrect, but the assumption that human reviewers produce 100% accurate counts turned out to be problematic. In fact, in this study boat counts by two human reviewers agreed only 84% of the time. Since human counts were conducted by multiple reviewers, counts confirmed by both reviewers were considered 'correct' and were compared to the AI counts to assess AI accuracy. Where reviewers disagreed, the AI count was considered correct if it matched at least one reviewer's count. Where reviewers disagreed and there was no AI match, the higher count by the human reviewer was considered the correct count.

The algorithm demonstrated promising results, returning a 91.6% accuracy rate overall when compared to human vessel counts (**Figure 5**). The system performed well in various conditions, where performance only slightly decreased under light fog and rainy conditions. The AI counts were slightly more likely to register false positives (instances where the system falsely detected a vessel) in adverse weather compared to clear weather.

Figure 5. Vessel counts across human and AI review

	Vessels Entering Port	Vessels Exiting Port	Total Vessel Count
Human count	2,040	2,294	4,334
Algorithm count	1,840	2,130	3,970
Absolute percent error*	9.8%	7.1%	8.4%
F1 score	0.945	0.958	0.952

**Absolute percent error* quantifies the accuracy of AI counts compared to human counts; *F1 score* considers both precision [fraction of boat counts that are actually boats] and recall [probability that a boat was counted given it was present], with a score of 1 indicating perfect recall and precision.

Key Takeaways

Overall, the results indicated SmartPass' viability for monitoring fishing activity with impressive accuracy. The ability for this system to operate on the edge is an important step in reducing the cost of the technology and increasing the range of potential applications. Cloud storage costs are eliminated when the algorithm operates on the edge. Further investigation into root causes of AI and human errors in this study might reveal additional adjustments that could be made to further improve performance.

CASE STUDY

INDONESIA SMARTPASS

Small-scale fisheries globally lack data on fishing effort and catch. In Indonesia, small-scale fishing boats comprise 90% of the country's fishing activity, yet their docking at non-official ports (i.e., river mouths within villages) creates a challenge for collecting accurate data. Surveys help to measure a vessel's average catch on a given day, but obtaining census level data on how many vessels are fishing and when and where they are fishing remains a significant challenge. To address this, EDF and CVision AI have been operationalizing SmartPass systems in Lampung province, Indonesia in partnership with the provincial government to illuminate fishery participation and effort. During the 2020 pilot, CVision AI trained a machine learning algorithm to detect and track vessels using approximately 1200 video files from Indonesia. Initial algorithm performance was very encouraging, demonstrating the promise that this system has.

Since the pilot, two camera systems have been deployed in the fishing villages Muara Gading Mas and Kuala Teladas, which represent key ports in the blue swimming crab fishery. A new vessel detection algorithm was trained on 73,000 images across Oregon, Indonesia and other locations to further improve system performance. The camera placements in ports, as opposed to coastal passes, introduces greater vessel activity in frame which creates challenges for the algorithm. In the case of Kuala Teladas, towed items behind boats occasionally caused double counts and floating objects were sometimes miscounted as vessels (**Figure 6**). In Muara Gading Mas, there were a significant number of structures and small vessels in the background that created challenges for the vessel detection and tracking algorithm (**Figure 7**). These challenges will require further algorithm refinement but each new SmartPass system deployment expands the library of video footage, providing much needed data for continued improvement.

Figure 6. Vessel image - Kuala Teladas, Indonesia

The basic requirements—that a natural or man-made 'pass' can be monitored from a location with a power supply and a modest amount of security to protect the system itself—are somewhat common in small-scale fisheries contexts. ***These efforts demonstrate the significant potential that SmartPass systems have for application to small-scale fisheries, not just in Indonesia, but globally.***

Figure 7. Vessel image - Muara Gading Mas, Indonesia

OPPORTUNITIES FOR FURTHER IMPROVEMENT

While the machine learning component of SmartPass is continually being improved, future development includes improving vessel classification functions and improving the way human validation of data is deployed. The vessel detection and tracking algorithms have shown impressive accuracy, and vessel classification algorithms have shown promise. Cataloging fishing effort by vessel class can potentially aid fishery managers in estimating catch. In Oregon, for example, recreational fishing vessels are likely to have very different catch compositions compared to commercial fishing vessels. In many small-scale fisheries, vessel class indicates which type of gear is used and thus which species of fish are targeted, allowing more precise management insights. Fishing vessel shapes and sizes can vary significantly depending on location, and every new deployment provides additional opportunities for algorithm improvement and refinement. Eventually it may even be possible to track individual fishing vessel activity, which has great potential in the context of identifying and tracking illegal fishing activity. In addition, thermal image cameras could be explored to improve vessel visibility at night.

As this technology improves and progresses towards greater incorporation into everyday use by fisheries managers, the AI component can be accompanied by metrics to streamline human validation. For example, future iterations of the SmartPass system could produce a confidence-level index for AI-generated counts. On days where the level of confidence in AI counts is high (e.g., clear weather) the AI counts can be relied upon, but on days with lower confidence (e.g., heavy fog) human review or human validation of AI counts could occur. This has the potential to reduce staff time spent reviewing camera footage while maintaining a review process that ensures accurate counts.

The significant improvements already achieved and the opportunities for growth outlined in this addendum demonstrate that SmartPass is ready to be deployed to new geographies and applications. At this stage, SmartPass has established itself as a viable tool for estimating fishing effort with a variety of features that can be customized to suit the needs of fisheries managers around the world.

ACKNOWLEDGEMENTS

We wish to thank Harlisa and Dennis Kurniawan (EDF Indonesia) for their invaluable efforts on the Indonesia SmartPass project. We would also like to thank the EDF interns Adam Ansari, Varun Hande and Karthik Ayyalasomayajula for their contributions to improving SmartPass detection algorithms.