FISHERIES REPORT

ON THE EDGE

Understanding the value of using on vessel assessment to determine priorities of fishing activity review in near real-time.

2024

The Nature Conservancy

productops

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General Statement

productOps is an independent consulting firm working at the request of The Nature Conservancy (TNC) on advancing the capabilities of electronic monitoring (EM) in global fisheries management.

productOps wrote this report to assist others in developing advanced EM programs that may make use of edge technologies to assess activity at sea. This work represents the efforts and results of the Costa Rica Edge Project, which was led by TNC, relying on its years of experience, innovation, and leadership in global fisheries and EM programs, and executed by productOps and other contracted technology partners with participation by Incopesca and by local vessel owners and fishers.

Disclaimer

This report is only for the purpose of information sharing. It is not intended to be a peer-reviewed scientific paper and should be used as a reference only. Additional information can be requested through TNC.

In some cases information has been intentionally omitted to protect the privacy of participants and the intellectual property of partners.

Please contact The Nature Conservancy with any questions or comments.

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FOREWORD

Over 3 billion people rely on fish and seafood as a major source of protein in their diet.* Managing our oceans to be sustainable is no easy task. Overfishing is a common issue, but so are human rights, national security, and geopolitical tensions.

Managing our common resources can be a challenge, especially when industrial scale commercial fishing can quickly tip the scales and greatly reduce numbers of endangered, threatened, and protected species.

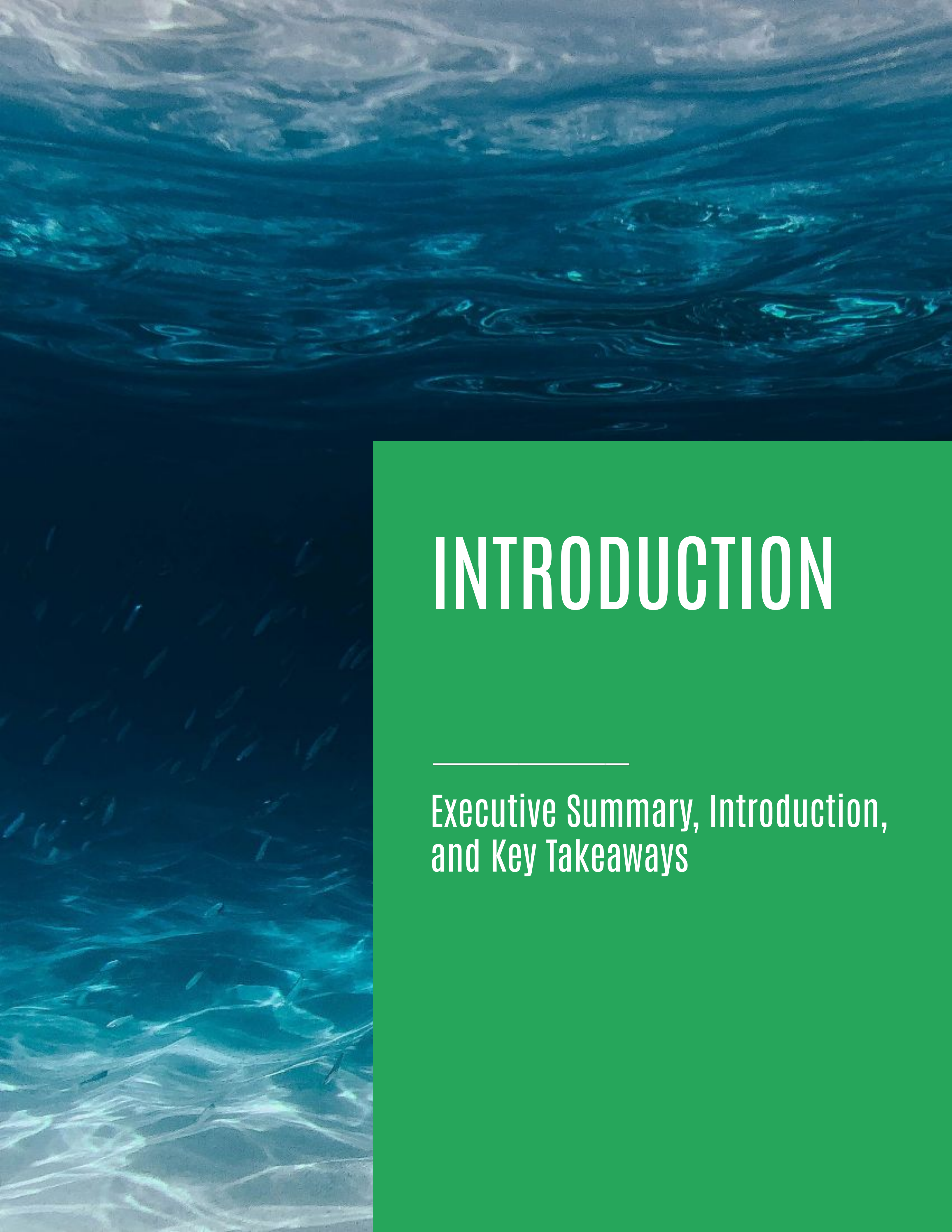
Making important assessments and decisions is critical to fisheries management, and to do that managers need data. Today, however, the data is insufficient to properly manage fisheries. Many fisheries operate with bad data, slow data, or no data, especially when it comes to first-mile data (data during fishing operations).

We need to stay vigilant and innovative to develop new tools that will help us better manage our resources and respect all life (including the lives—and incomes—of people).

We are excited to share this project with you and hope you will join us in innovating and creating better futures for sustainability at sea.

* https://www.fao.org/state-of-fisheries-aquaculture/2020/en/

The greatest danger to our planet is the belief that someone else will save it.
– Robert Swan OBE



INTRODUCTION

Executive Summary, Introduction, and Key Takeaways

Introduction

How can we best influence positive change in fisheries management?

The primary reason for this project was to find new ways of accelerating change in fisheries management, specifically in fisheries that are operating with little to no monitoring and areas that have significant conservation and regulation issues.

To do this, the project explored the use of edge computing and Artificial Intelligence (AI) to gain insights quickly and answer the question "how can fishery managers get quick access to high-impact monitoring data from EM systems and eLogs?"

Many of the tools used in this project, such as electronic monitoring (EM) and eLogs, are commonplace in monitoring programs. What is new here is the innovation in AI and edge systems to get near real time results.

This project tackled many logistical and AI challenges to determine where future efforts can best be applied to advance the state of fisheries monitoring.

Logbooks are often used as the source of truth for traceability efforts, but often these are unverified and offer only a narrow and biased view into fishing activities. Can edge computing, AI, and other sensor data be used to validate the trustworthiness of logbooks?

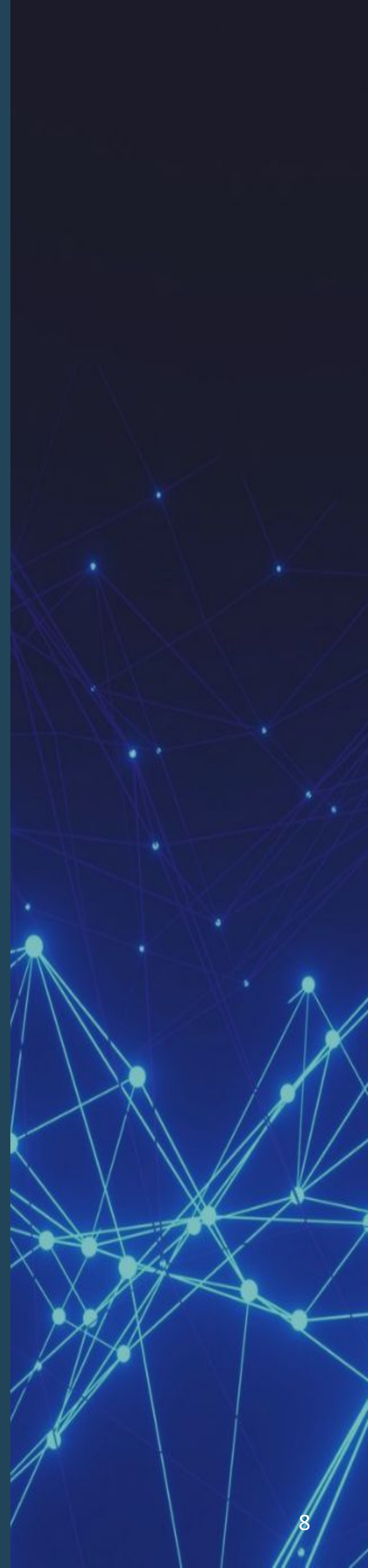
— Edge, AI, and Computer Vision are new tools that EM providers and fisheries managers are using to help automate the review of fishing activities. How precise does AI need to be to rank eLogs and prioritize oversight activities?

— eLogs can help monitor fishing activity, but they are not always used and are often filled with errors. Can a prioritization program improve the quality of these logs and make them more ubiquitous?

DEEP DIVE:
WHAT IS EDGE COMPUTING?

Edge computing is a form of distributed computing that moves data processing and storage closer to the end user. Properly used, edge computing techniques make data processing faster and require less bandwidth. This technology is essential for real-time processing and operations applications. For example, edge computing in autonomous cars instantly evaluates vital sensor data to enable decision-making. In healthcare systems, edge computing enables fast, local data analysis and real-time patient monitoring, which reduces response times and improves patient outcomes.

Edge computing reduces dependence on centralized cloud services for long-distance communication, which lowers costs and bandwidth requirements. It also improves data security and privacy, which is crucial for compliance in industries like healthcare and finance. Edge computing facilitates a wide range of contemporary applications by guaranteeing effective, safe, and rapid data processing—a crucial function in a world growing more connected and more dependent on data.



DEEP DIVE: WHAT IS ELECTRONIC MONITORING?

Electronic monitoring in industrial fishing refers to the use of electronic systems and human analysts to capture and analyze data on fishing activities, including catch composition, fishing effort, compliance with regulations, and bycatch. EM systems typically consist of video cameras, sensors, GPS, and other electronic devices installed on fishing vessels to monitor and record activities.

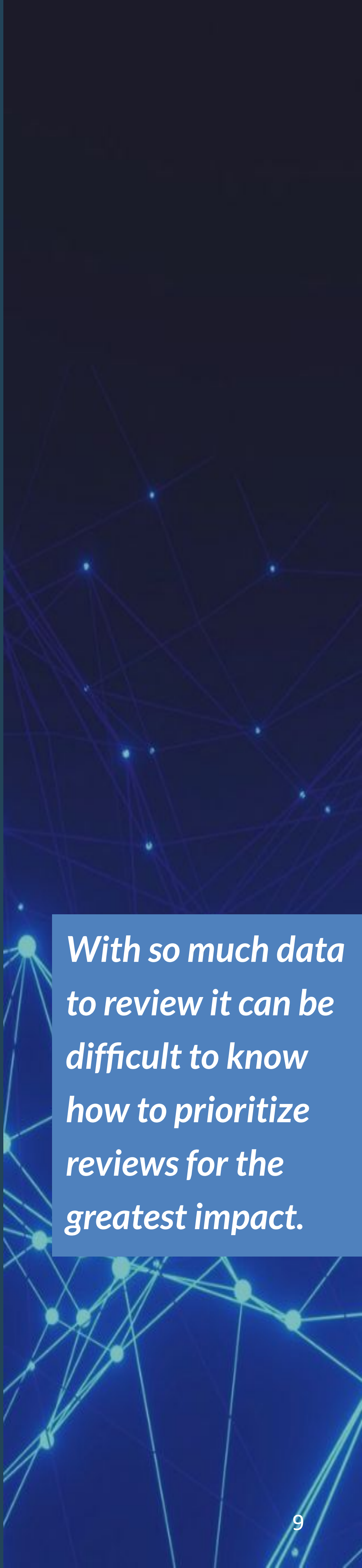
EM does not replace human observations on board a vessel. It augments management programs, especially programs facing high costs and space constraints aboard vessels.

Benefits of EM include reduced costs, continuous monitoring, data integrity, and enhanced transparency. EM is often implemented in the following use cases:

- **Compliance and Enforcement** – Recording the handling of species to ensure that regulations are followed.
- **Bycatch Reduction –** Enhancing the ability to implement and enforce bycatch reduction strategies.
- **Data Collection** – Providing accurate and timely data for better stock assessments and management decisions.
- **Scientific Research –** Improving understanding of marine ecosystems and the impacts of fishing.

EM programs face several challenges:

- **Timeliness –** Current EM systems still struggle to get data to analysts and decision makers in time to make key decisions. With so much data to review, it can be difficult to know how to prioritize reviews for the greatest impact.
- **Data Management –** The large volume of data generated by EM systems requires effective storage, processing, and analysis.
- **Privacy Concerns –** Fishermen may object to the use of recorded data, especially if it includes personally identifiable data.



With so much data to review it can be difficult to know how to prioritize reviews for the greatest impact.

EXECUTIVE SUMMARY

The Nature Conservancy's Large-Scale Fisheries team seeks to improve the effectiveness and efficiency of electronic monitoring. This project tested the feasibility, hurdles, and opportunities of conducting EM data review prioritization of fishing activities at sea in near real time using AI and edge computing.

Objectives:

This project sought to assess the value of edge computing on vessels, identify significant technological and operational gaps in the use of edge computing on vessels, and determine what must be done to fill those gaps. Project activities included:

- Building, testing, deploying, and evaluating a system that assesses the fishing activities on board the vessel and prioritizes monitoring data for human review.
- Discovering and documenting how fishery management tools such as EM, AI, eLogs, and edge computing can be combined to determine review priorities.

Deliverables

The project produced two primary deliverables:

- This report on research methodologies and findings on the feasibility of deploying a prioritization assessment at sea.
- Recommendations and a roadmap toward implementing an edge-based solution in a real-world EM program at scale.

Project Approach:

This project was carefully designed to use existing technology and policies wherever possible and to include all project stakeholders, including vessel captains and owners. This project focused on semi-industrial longline vessels, which impacted many of the choices involved: numbers and types of cameras, camera placement, data collection choices, power use, recording times, communication equipment, and AI models.

Key project elements include:

- Voluntary participation by stakeholders – all data were used for learning, not to enforce existing policy.
- Initial trials on longline vessels out of Central America (Eastern Tropical Pacific).
- Partnerships with providers for eLogs, AI, and EM
- A focus on proof of concept and research that paves the way for innovation.

How is this project unique?

This is not an EM project

Although this project relies on EM systems and analysis, this is not an EM project. Rather, this project used EM to explore how these systems can be extended and augmented to improve fisheries management.

This is not an implementation project

This is not an operational implementation for fisheries management or a pilot program expected to immediately expand in region and scale. Instead, this project explored new ways of gathering, analyzing, and transmitting data to decision makers. Some things worked, and some things needed improvement. The project goal was to determine what those things are and how to make the best use of funding and resources to improve monitoring and management of fisheries.

This project is a series of tests and experiments and will not be used for fisheries compliance

Using on-board cameras and systems to monitor activity can make stakeholders, especially captains and crew, nervous. This project was not about compliance or regulation. Neither will the data be used for stock assessment or to set policy and fishing limits.

This is not an AI project

Although AI was crucial to this project, the accuracy of the AI models and counting algorithms were not the project focus. EM and AI companies are doing great work to improve the accuracy and usefulness of AI in EM, and this project made no attempt to duplicate that effort. Rather, this was about how AI detection and counting can be used with other technologies, including EM, eLogs, and other sensor data.

The AI models will always have room for improvement, and some of those improvements are included in the recommendations; however, the success of this project was not tied to the accuracy of the models used.

THE PROBLEM

Data Driven Decision Making

Today, many oceanic and coastal fisheries lack the data required to manage their operations effectively. This is especially true of first-mile data and data about crew interactions with ETP species.

Management practices and capabilities vary widely among regions and fisheries but every fishery can improve, especially in three critical areas:

- Methods, sources, types, and volume of data gathering
- Timely data analysis
- Analysis cost reduction

In some fisheries, the current monitoring solutions—specifically, human onboard observers and/or EM systems with onshore human analysts—are not feasible or affordable at scale. These fisheries face many challenges to implementing an effective monitoring program.

Understanding the three primary challenges to better fisheries management through data.

Gathering Data
Data is primarily gathered from three sources: logbooks, onboard observers, and onshore analysts using video and sensors. eLogs can be unreliable and monitoring has its own issues. No data source will capture all events accurately.

Timely data analysis
Data can take weeks, months, or even years to go through analysis and become available to drive management decisions. This time reduces possible impact on fisheries management outcomes.

Analysis cost reduction
Monitoring programs are expensive, especially for fisheries where margins and operating budgets may already be constrained. With targeted intervention and thoughtful evolution, the monitoring industry could realize appropriate growth, reduced costs, and increase impacts.

THE PROBLEM

Background on Fisheries Management

Management programs can be expensive and difficult to implement. Many fisheries face unique challenges and have competing objectives. This makes a unified approach extremely difficult.

Science vs. Regulation

Some fisheries focus on gathering data they can use to determine fishery health and set policies, while others focus on regulations that often include punitive measures for fishermen.

Exclusive Economic Zones (EEZs)

Monitoring activity in EEZs is vital for economic and environmental sustainability for many countries. This can have a large impact on scientific data gathering as well as regulatory and economic impacts.

Human Onboard Observers

Human onboard observers have been used for decades to record both scientific and regulatory data on fishing activity and species health. While this can be effective in some fisheries, it is not feasible in others. Additionally human onboard observations have well-documented limitations and safety concerns, and these programs can be very expensive and difficult to scale. These programs are especially problematic on smaller vessels, which have no room for additional crew, and for operators who have no funds to pay for an observer on every smaller vessel. Many longline vessels fall into this category—even some of the larger ones.

Current EM Programs and Systems

EM systems, specifically cameras and recording equipment on boats, have been around for over 20 years. Widespread use in global fisheries management is a more recent development and the EM solution is evolving into a more mature market, with several companies offering sophisticated solutions including AI and transmission of data at sea. Yet many of these new solutions still come with challenges such as high costs and long delays in getting analyzed data—some users may face delays of a year or more to receive analyzed data from a fishing event.

Measuring Prioritization and Changing Behavior

How fishing sets are prioritized today

EM's greatest strength is also its greatest weakness: it captures a lot of data, but a human still needs to review and analyze that data . Because of this, many programs review only a small data sample—usually 10%–20% of a given trip. Getting the data to the analyst can take time, and because the data is randomized the analyst may not be reviewing the data most relevant to the management program.

Longline fishing trips are typically reviewed by set. A set refers to the process of setting the baited longline in the water, then hauling the longline in to retrieve the catch. Often, analysts will review a percentage of sets for the total trip. Some agencies have opted for lower review rates of 5%–25% sampling (depending on many factors) to assess the state of the fishery.

THE PROBLEM

This selection is usually randomized , sometimes in a black box known only to the analyst, which has implications for trust—an analyst could skip a dataset that shows issues with EM equipment in order to protect the EM provider, or may look specifically for issues or problematic datasets provided by a competitor.

While random sets work well enough, many of the biggest issues may still be hiding in the 80% or more of unreviewed activity. Additionally, if captains know that most data will not be reviewed, they may feel more willing to participate in activities such as illegal handling or misreporting.

Even in longline fisheries that have 100% coverage (meaning that all vessels record all activity), analyzing all the available data and video footage is usually too expensive and too time consuming.

Why EM on the Edge

Electronic monitoring (EM) is a means to capture and later analyze information about fishing operations. This currently requires human analysts to review the data and create a log of fishing operation events. Based on this analysis, measures can be taken to correct IUU fishing practices, reward good practices, and improve fishery management. EM data can also be used to increase operational efficiency and product pricing (by encouraging optimal handling practices) while increasing traceability and reducing risk in the supply chain.

For EM to be successful and gain wider adoption, at least two things need to happen: overall net costs must shrink and analysis times must be reduced. Current limitations of at-sea data transmission make both things harder to do. In an ideal world, data would be sent to the cloud for processing in near real time, but that is not currently plausible.

Analyzing data on the vessel while at sea (using edge computing) offers a solution to some of the issues facing EM today. Near real-time processing of fishing operations is ideal for reducing risk. Rapid analysis using AI will allow managers to prioritize vessels for review based on evidence of higher-risk behaviors. Additionally, edge processing ensures first-mile traceability, associating important catch and operational metrics with individual fish that are later sold to market. With enough trusted data, fish could even be sold in near real time and increase profits to vessel operators that use these systems, thereby driving even greater adoption of this technology that supports science and compliance in fisheries.

PROJECT CHALLENGES

This project focused on edge-based calculations, which pose a unique set of challenges. Many of the advances in EM and AI have been in cloud or on-site computer processing. Some gains have been made in edge computing for EM, but these gains tend to be focused on specific tasks, whereas this project focused on creating a broad array of data and AI evaluations.

Creating a seamless, automated system with multiple partners can be difficult. A good portion of this project involved working continuously with partners to refine the process to calculate a prioritization score.

While a major challenge in this project is to build viable AI models to accurately count fish, logistical challenges such as system outages, null data, incorrectly entered data, and other data anomalies are also prevalent.

Refining this system and targeting these improvement areas holds real promise edge-based computing for use in prioritization and creating more sophisticated workflows.

Primary Challenges:

- **Creating an assessment module.** This is the component of the project that calls for the most development and some creative engineering
- **Innovation trial and error.** When the project began, no viable out-of-the-box edge solutions or AI models were found that could accurately count fish on edge-based devices. Instead, custom AI models were created to use as the foundation of this project.

What about eLogs? Aren't they good enough?

Many programs use some form of self-reporting such as eLogs. The captain uses eLogs to record trip details, including catch. The obvious issue is that self-reporting as a primary method of data collection can be unreliable—particularly as a way of monitoring good fishing practices.

Some programs use a trust-but-verify system for eLlogs. This can work well, since self-reporting is more accurate if the people reporting events know that the logs will be verified.

EXAMPLE USE CASES

This project is exploring novel use cases for EM systems, eLogs, AI, edge computing, and other sensors . The learnings from this project can be used to advance several fisheries use cases.

1 Targeted EM review

Being able to quickly prioritize and get to the data that matters most.

2 Expedited response time

Decreased time between a significant event (e.g. , interactions with ETP species), data review, and remediation steps.

3 Increased efficiency

Increased efficacy and efficiency of regulatory and compliance inspections, including Port State Measures.

4 Traceability

Increased confidence in supply chain data with first-mile data validation.

5 Scientific research

Additional sensors can support scientific research into conservation and management issues such as water temperature and oxygenation.

6 Increased confidence

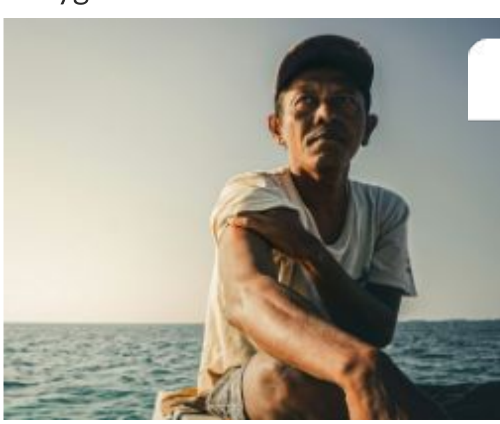
Lower risks of non-compliant suppliers and increased confidence for purchasers—more trusted, analyzed data means more power for supply chain partners.

7 Better planning

Increased visibility and data for fisheries management and future planning

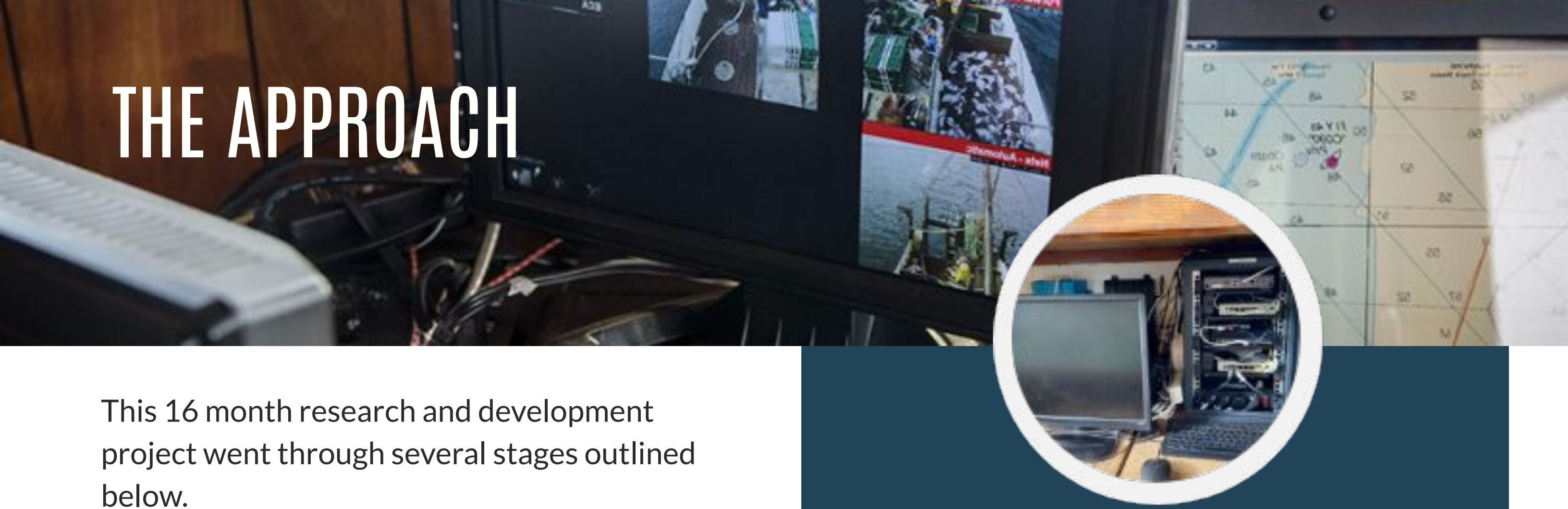
8 Product Quality

Increased market price if data can be used in near real time to ensure handling procedures that increase product quality.



9 Labor Conditions

Transparency in labor conditions and in health and welfare for fishermen and increased confidence in safety reports if data is extended to include labor practices.



THE APPROACH

This 16 month research and development project went through several stages outlined below.

Phase 1: Defining the project

The process began with solidifying project goals and discussing how the project would be managed and who would need to participate.

Phase 2: Development and Training

This phase included customization, configuration, and development of the various components, including EM systems, AI training, hardware selection and configuration, eLog workflow customizations, eLog capabilities development, and the edge assessment module.

Phase 3: Trials, Results, and Learnings

The trial phase consisted of running the fully developed and configured system on a series of trips. This phase included the EM analysis of trips by Bureau Veritas to use as a comparison to the AI models, eLogs, and edge vectors.

Phase 4: Issues, Opportunities, and Recommendations

The final phase of this project is this report and the final recommendations based on the learnings and results of the trials.

Phase 1

January 2023
Project start and requirements

March 2023
Partner selection and system architecture

Phase 2

June – September 2023
System installation on vessels and pre-trial trips

September 2023
AI labeling and training begins with partners

November 2023
AI training complete

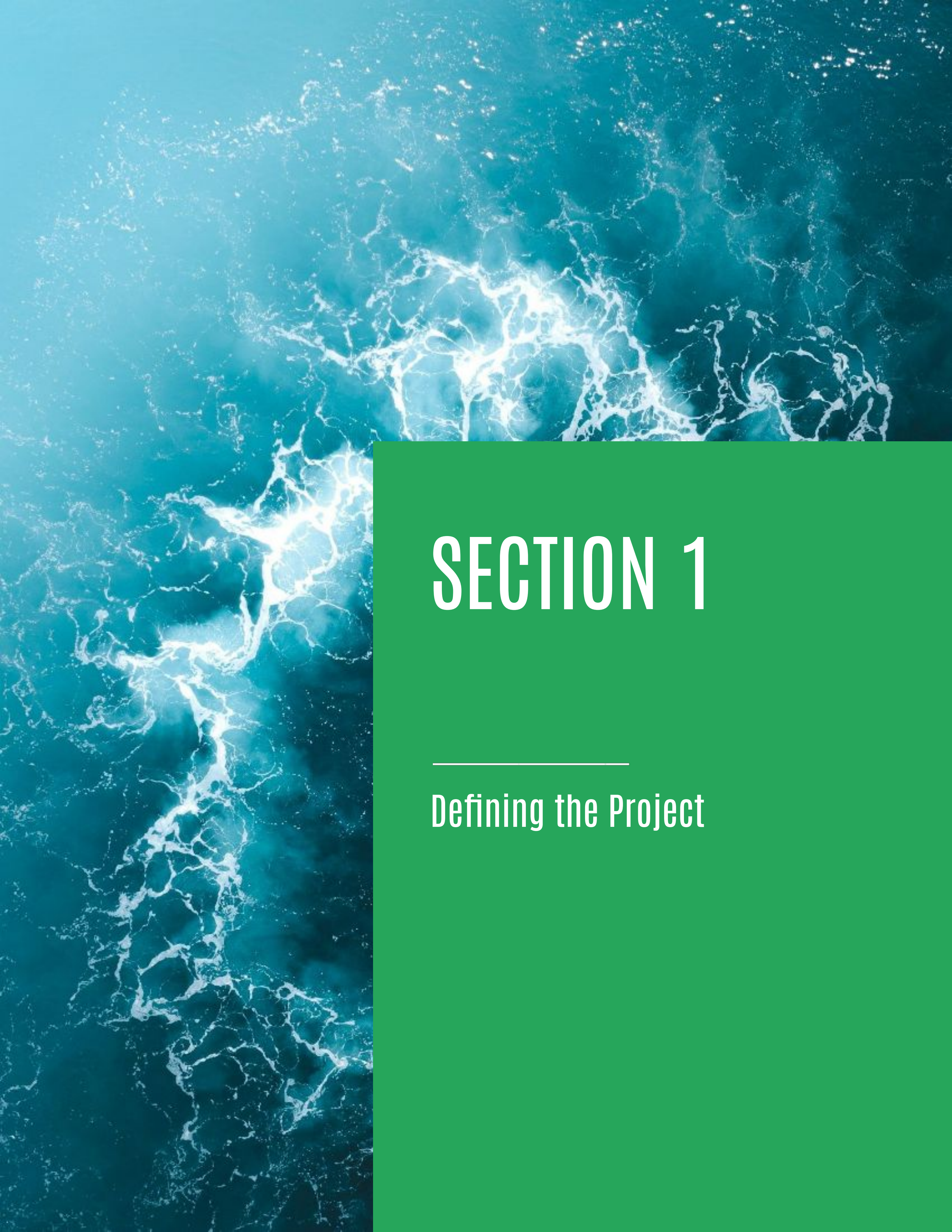
December 2023
Vessels updated with new AI models and software

Phase 3

January – April 2024
Vessel trips running proof-of-concept trials; EM analysis

Phase 4

May – June 2024
Project results and recommendations



SECTION 1

Defining the Project

DEFINING THE PROJECT

The first phase of this project was to define what the project would do, from its goals to its system and technical requirements. The team also selected partners to assist with major technical and logistical components of the project.

Ultimately four partners were selected:

- Two AI companies that could develop separate AI models to be used to detect catch counts during fishing activity based on the EM footage.
- An established EM provider who could supply equipment, installation, and review of the footage.
- An eLog provider to supply a system where captains could enter fishing data during fishing operations, which would be compared to AI model counts.

TNC in Costa Rica served as liaison with the fishing sector to ensure the technology was applied on the water and to facilitate day-to-day communication with participating vessels and supply-chain actors. productOps was contracted to perform the edge engineering and assessment development and to manage the project, including vendor selection.

KEY COMPONENTS

productOps partnered with industry providers for key components:

- EM hardware for video and EM operations
- Edge hardware
- eLog application
- EM trip analysis
- AI model training, including labeling and image procurement
- AI model implementation on the edge

COMPONENT SUCCESS

Project success did not require success of any component of technology. The final project analysis includes recommendations for improvement for any elements that proved inadequate. Where the technology and operations showed that priority assessment at sea is viable, the final recommendations provide a roadmap to scaling the project to more vessels.

PROJECT GOALS

The primary question that launched this project was whether fishing activity could be prioritized for review in a meaningful way while the vessel was still at sea. Although the question appears straightforward, it becomes tricky when considering the definition of "meaningful" prioritization. Given that difficulty, the project team hypothesized that **AI and other data sources can be used to determine a priority of data to review.**

The team then set out to test that hypothesis by determining whether an edge-based system, using currently available systems and data, could prioritize datasets for human review.

If this were possible, analysts could act more quickly, guided by the AI's prioritization. For certain high-priority events, video could be sent wirelessly to an analyst for immediate review. Because video transfer can be expensive, this would be reserved for the highest-priority events. If the review identified a serious violation, immediate actions could be taken to address it, such as contacting the captain to change behavior, meeting the vessel at port, or recalling the vessel to port.

In contrast, vessels with a proven record and a low enough priority might be able to dock and leave without transferring the trip's data—completely bypassing a review.

These are only examples and both prioritization and appropriate actions would be determined by the fishery managing the program.

PRIMARY PROJECT GOALS

1. Determine whether current data can be analyzed at sea to create a prioritization score for fishing sets.
2. Determine whether systems can be reliably integrated to process data through an assessment workflow.
3. Identify gaps in current technology to reach a meaningful pre-EM analyzed assessment of fishing activity.
4. Identify the barriers to scaling a viable solution.
5. Generate recommendations based on learnings.
6. Document the project so that others may learn from the process and results.

PROJECT GOALS

SECONDARY PROJECT GOALS

7 Determine whether an edge system can reliably work with little use of ship-to-shore data communications.

8 Learn what type of hardware is recommended for edge processing.

9 Determine whether AI models can be effectively compared to other data sources generated at sea.

10 Remote support: Demonstrate the ability to support operation of onboard systems from land-based locations.

11 Investigate possible incentives for vessel participants. Can captains be encouraged to change behavior?

12 Reduce data transfer logistics: Demonstrate the ability to send EM data to analysts without shipping hard drives.

13 Determine cost analysis for creating edge-based review prioritization at scale. Does edge analysis reduce costs?

14 Determine whether edge analysis and results can reduce time between EM and review of high-priority events.

15 Consider how future Edge projects might improve traceability programs.

EDGE SYSTEM TECHNICAL GOALS

In addition to the research and development project goals, the project team established technical goals for the edge system.

Note: It is possible for the project to meet its goals without achieving the system technical goals because the edge system was not intended to be a product prototype; rather, it was a way to research how edge systems might improve fisheries monitoring and management.

PRIMARY TECHNICAL GOALS

1. Integrate all systems together using the edge system.
2. Build an AI model (system) that can count fish during a set.
3. Compare AI fish counts and eLogs in order to prioritize sets for analyst review.
4. Execute a set of vectors to determine a prioritization score.
5. Send assessment results to the cloud for further action and data storage.
6. Automate the system so it operates with little to no human support.
7. Identify key fishing activity events on the vessel.

SECONDARY TECHNICAL GOALS

8. Resolve discrepancies between EM fields and eLog fields and establish equivalencies.
9. Execute or assign specific actions tied to corresponding "Prioritization Level".
10. Apply thresholds for target and non-target species.
11. Develop an AI model that can successfully distinguish interactions at a species level.
12. Evaluate capabilities of edge hardware for object detection and counting in fisheries.

PROJECT SUCCESS CRITERIA

The primary measure of success was whether it was possible to perform a series of trials that would inform the industry on ways of improving current EM programs. These trials included evaluating whether it was possible to determine a significant difference in set priorities, enabling near real-time review so analysts could follow up as close to the time of the event as possible.

The success criteria and metrics come from the project goals defined above. Some criteria support multiple goals. The success criteria and metrics form the basis of the project research, development, and evaluations.

PRIMARY SUCCESS CRITERIA

1 Systems are installed and operational as intended while vessels are at sea.

Metric: Systems check and supporting data. Possible values: **success**, **fail**, **intermittent.**

2 The edge system can access the raw data from EM cameras and eLogs.

Metric: Data validation. Possible values: **success**, **fail**, **intermittent.**

3 eLogs systems can be modified to allow captains to annotate events with images.

Metric: QA test on eLog systems to match requirements. Possible values: **success**, **fail**, **partial.**

4 Process fish detection by using AI on EM videos.

Metric: AI models run and produce results. Result output of fish counts can be used as an input for other systems.

5 Edge computing can compare AI outputs, eLog data, and other data at the level of catch count per set.

Metric: Verify that the edge project created a result based on these two value sets. Possible values: **success**, **fail**, **intermittent.**

6 Data is sent to the cloud and processed in a data lake for data analysis.

Metric: Verify that the data is in S3. Possible values: **success**, **fail**, **intermittent.**

7 Trials run successfully with no direct intervention from support team.

Metric: Record of trips that require support. Possible values: **success**, **fail**, **intermittent.**

8 Key events are detected using only on-vessel technology and data (fishing activity, missing eLogs).

Metric: Comparison of data from edge system and EM analysts list of events. Possible values: **success**, **fail**, **partial.**

PROJECT SUCCESS CRITERIA

SECONDARY SUCCESS CRITERIA

9 eLog behavior can be used to help determine prioritization (i.e., captains are using the system).

Metric: Systems check and supporting data. Possible values: **success**, **fail**, **intermittent.**

10 Actions can be taken based on a predetermined set of thresholds or triggers.

Metric: Results show consistency and data in cloud is distinct enough to create a trigger. Possible values: **success**, **fail**, **undetermined**.

11 System issues can be resolved while the vessel is at sea.

Metric: Review support activity for resolutions that did not require action at port. Value: **number of trips** that did not require in port resolutions (not including standard EM data).

12 Data is sent from the local network to a server accessible by the EM provider (in less time than it would take to mail the drives).

Metric: Compare number of days to upload to EM analysts to average number of days to mail and customs. Value: **number of days difference**. Positive number is success.

13 Captains follow project guidelines and incentives motivate compliance.

Metric: Review logs, support issues, and EM results for instances where captains were not following instructed practices. Interview with captains and owners may provide more insight.

14 Edge devices can be compared on performance and potential recommendations on usage

Metric: Review the performance of two different edge devices on their capabilities and performance. Determine recommendation of future projects.

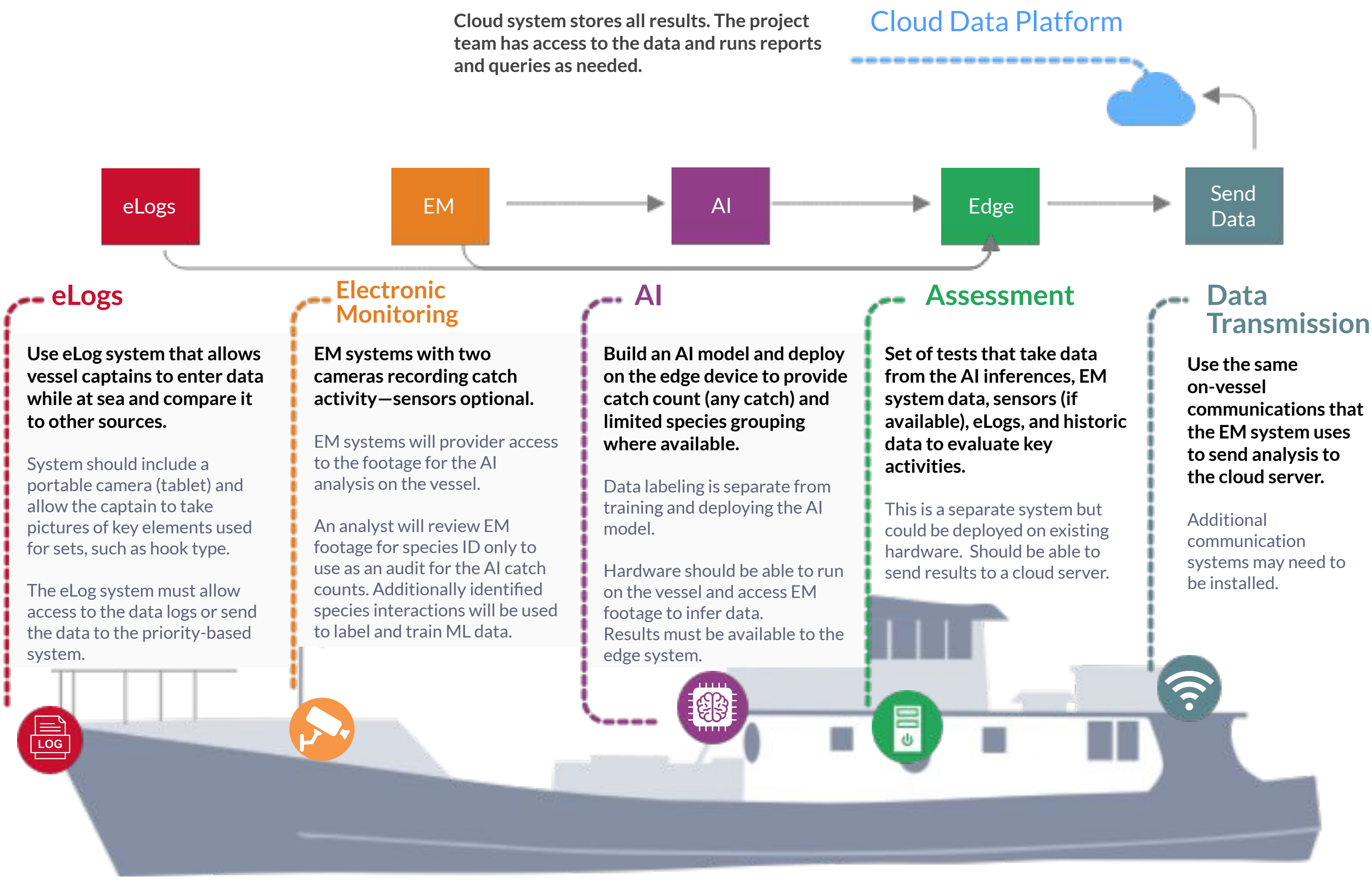
TECHNICAL REQUIREMENTS

PARTNER SELECTION & CONTRACTS

The project team recognized five main areas of technical expertise that were needed on the project:

- AI engineering
- eLog services
- EM services
- EM analysis
- Edge engineering and assessment development

EDGE ASSESSMENT ACTIVITIES & SYSTEM ARCHITECTURE



TECHNICAL REQUIREMENTS

Project scoping activities established the following technical and system requirements for the project overall, the EM system, the eLog system, and the edge computing system.

The edge-based system will process eLog data, process EM video data using AI, and then compare the results. These results will be used to determine a prioritization score for a given fishing set.

Additional systems may also be used to help assess a prioritization score but not as part of the AI validation. These systems may include:

- VMS or AIS systems for GPS locations of events
- EM system status data for operational considerations (the less reliable the EM data, the higher the priority for review)

The EM System

The EM system is responsible for providing analysts the information they need to determine what happened on the vessel. The analysis and supporting data are different depending on program goals. This also means that equipment and operational requirements will vary per program and EM vendor.

One of the core elements in all EM systems is the video from one or more cameras. This pilot used the video from the EM system, which was processed with an AI model to identify catch events.

The EM system must accommodate:

- Edge system access to the video files
- Timestamp and camera information in each file name
- A standardized format that the edge system can use to parse the time and camera

The eLog System

At a minimum, the eLog system will:

- Allow the vessel operator to easily enter catch events as they happen or within a few minutes of a set completion
- Require the vessel operator to confirm a set
- Identify each individual event by set

Despite the Phase 1 focus validating total catch numbers, more detailed information should be available, including:

    - Species—target catch, bycatch (including non-fish and endangered species)
    - Fate
    - Weight / size
    - Time of Event
    - Location
    - ETP flag

TECHNICAL REQUIREMENTS

The Edge System

The edge system will have five main functions:

- Integrate all data sources
- Process the EM video with AI
- Validate AI data with eLog information for the same set
- Assess a prioritization score
- Send notifications

Integrating Data

The edge system will receive or access the raw records from all installed systems. All data will be saved locally; large files and personally identifiable data (video) will be deleted after a certain amount of time. This requirement enables broad and creative cross-referencing calculations on the edge.

Running AI

The edge computer needs:

- Run CV AI models at real-time speed on HD video, >10fps
- Draw only modest power, <100W
- Process the raw AI model output

Software Requirements

Software will run on the edge to support the five main functions. High level requirements include:

- Power resiliency - the software must gracefully handle unexpected shutdowns
- Error resiliency - the software must gracefully resume after an internal error
- Data resiliency - the software must perform as much work as possible if portions of data are unavailable

Validating Fishing Activity Data

Based on a query of the AI results and the eLog results, compare the data and come up with a validation score.

Example: The eLog indicates there were 23 catch events for set 123; the AI determined that there were 25 individual catch events with a confidence of over 80%. There is an 8% difference in the two systems.

Assessing a Prioritization Score

Based on a set of values including the data validation score, determine an overall prioritization score. Although the focus for the initial pilot will be on the eLog to EM logbook comparison, the assessment could include additional information:

- EM equipment status (cameras not working or occluded)
- eLog catch information on ETP
- GPS information (fishing in illegal zones)
- Previous scores, considering long track records of accuracy or non-compliance
- Other vessel systems such as TMT's IUU Vessel List, including risk trends (improving or declining)

Send Data

The edge system will send the assessment and vector results from the edge system to a cloud-based system. The edge must also upload supporting data, adjusting the upload size to available bandwidth as needed .

THE LAB

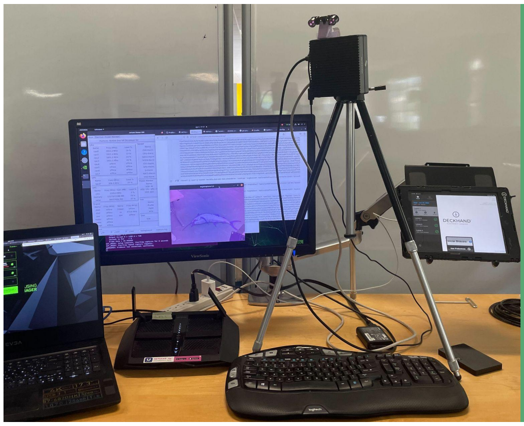
DEVELOPMENT AND SUPPORT

productOps set up a development lab in its Santa Cruz, California, headquarters with equipment and code from each partner. This allowed productOps to run a simulation of deployed systems in a lab environment. productOps was also able to rapidly test and deploy other hardware and systems configurations, including cameras.

Actual EM systems were not included in the main lab; however, THALOS provided a virtual system in its offices in France that productOps was able to access and test.

Before hardware was installed on the vessels, productOps conducted initial systems testing using test video files provided by THALOS. After hardware was installed on the boats, video files and other edge data were copied into the development lab for use as development data.

Throughout the project, productOps used the lab to confirm results, prototype updates, and provide operational support.



The Importance of a Lab

In R&D projects, a good test lab can make the difference between success and failure. A lab should be able to recreate issues that are happening in other environments, such as on a vessel. Ideally, lab systems will be identical copies of deployed systems, and projects will be fully tested in a lab before being deployed in the field.

THE VESSELS

Vessel Characteristics

The project included three artisanal long line fishing vessels, each measuring 12 meters in length from bow to stern. These vessels have a capacity of 10,000 kilograms in the hold and operate on a 12 volt electrical system.

The vessels run a single long line with their primary winch. The line supports 300-700 hooks.

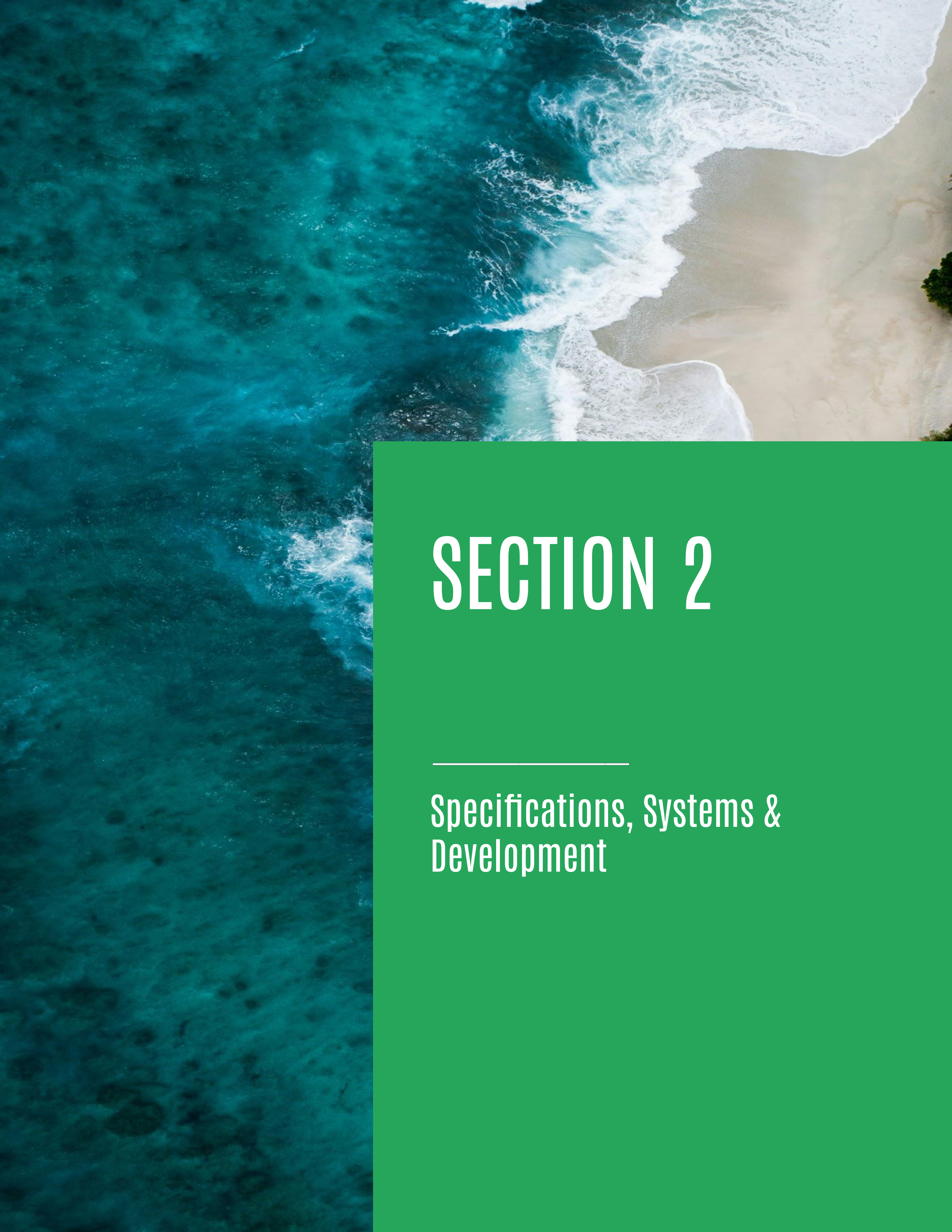
The crew size for each vessel ranges from 3 to 4 members. Vessel owners in the area typically own a few boats and hire out to captains and crew.

Fishing Activity

The vessels conduct monthly fishing trips, typically departing on the 1st of each month. Each trip usually lasts around 25 days at sea. However, in the case of poor fishing conditions or insufficient catch, the duration of the trip can be extended by a few weeks to ensure an adequate haul of fish.

EM in Small-Scale Fisheries

Artisanal and small-scale fisheries represent about half of the world's fishing effort and play a crucial socio-economic role in many coastal communities. The adoption of EM supports effective fisheries management and provides better market access and higher prices through certification. However, the costs associated with EM systems are often prohibitive for vessel owners operating on tight margins. Efforts being made to address these challenges include developing low-cost and scalable EM solutions tailored to small-scale fisheries.



SECTION 2

Specifications, Systems & Development

DEVELOPMENT

Development Overview

Technical development and configuration began in April 2023. The initial goal was to create a centralized hardware system (edge device) that could exchange data with the other systems on the vessel.

Each partner made customizations or developed solutions to meet their specifications for the project. This process was particularly lengthy for the AI companies due to the difficulty of procuring fishing video that was relevant to the Costa Rican fishery.

Development Process

The systems and applications for this project were developed by productOps and the technical partners over the course of eight months.

Once the required EM systems were installed and functional, the fishers took several trips to record data. After these trips were completed, the video was labeled and then used to improve the AI models before final installation.

All systems were available, at least in part, for the initial installation and deployment trips used to compile AI model training data. These initial data gathering trips were also used to test system connectivity and primary configurations.

Each system required different levels of customization and development, including specific processes and timelines. The goal was to have a unified edge system as the core component accessing the various systems.

EM System and Communications
- Component selection
- Network configuration
- Hardware installations
- Pre-trial testing and issue resolution
- Video gathering for AI training

AI Labeling and Training
- AI model development
- Data acquisition and labeling
- Update AI model update

eLog Development
- Workflow and UX design
- Feature development
- Train and test with Captains

Edge Development
- Hardware selection
- Scoring algorithm (vectors) creation
- API creation
- Installation and testing

SYSTEMS DEVELOPMENT & CONFIGURATION

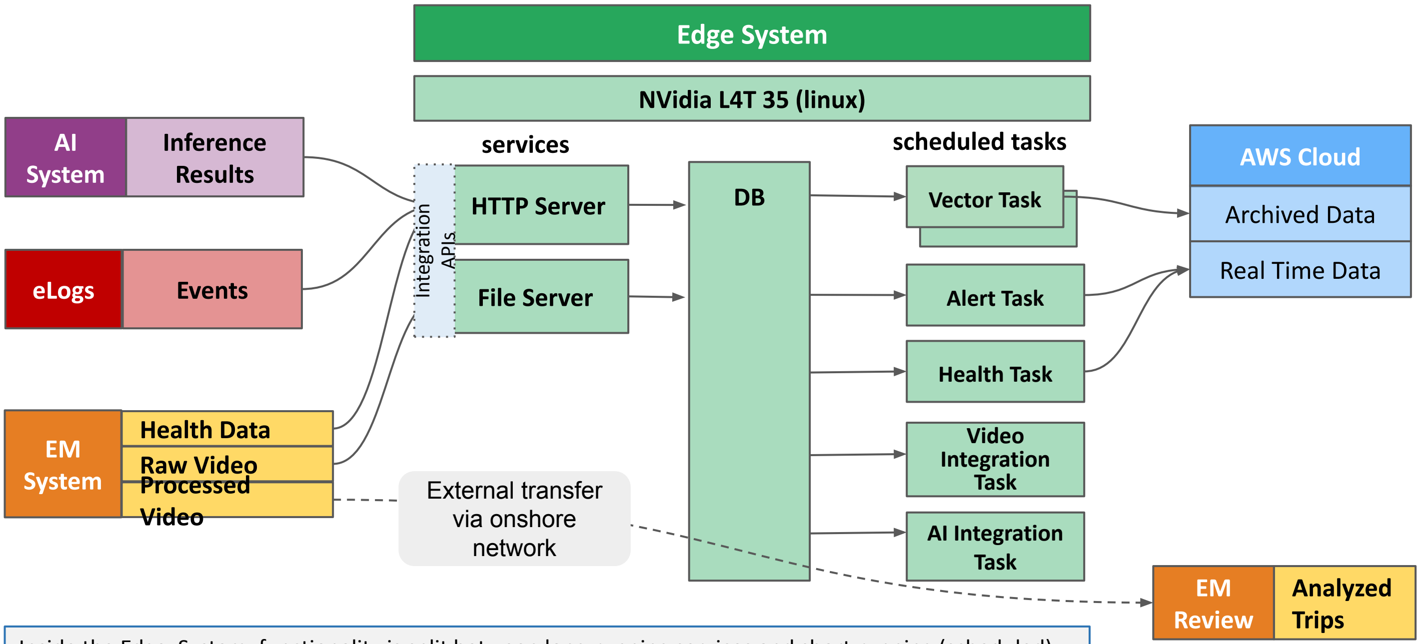
System Overview

The overall system includes 5 main components:

1. **EM System** – The cameras and supporting equipment used to record fishing activity for later review. This also includes satellite connectivity used for communications and remote access.
   Technical Partner: THALOS
2. **eLogs –** Allows captains to enter data about their fishing activity while at sea and integrates with the edge system for comparison with other data sources.
   Technical Partner: Deckhand
3. **AI Models –** Models that use video from the EM system to detect fish and provide a catch count.
   Technical Partners: Ai.Fish and OnDeck
4. **Edge System –** Integrates all components and processes data directly on the vessel in near-real-time for risk assessment and prioritization.
   Developed by: productOps
5. **EM Analysis –** Post trip examination of electronic monitoring footage to record fishing activity.
   Technical Partner: Bureau Veritas

Architecture Overview

The edge computer sits in the middle of the system architecture and does the work of integrating other services. This minimized the amount of bespoke work needed for partners to integrate their products.



Inside the Edge System, functionality is split between long-running services and short-running (scheduled) tasks. A large set of modular APIs allows a wide set of acceptable Integration strategies.

EM SYSTEM: Components

EM System Components

The core components of the THALOS OceanLive EM system are cameras, a gps module, hard drives, and servers supporting local network and satellite connectivity. The selection of devices was entrusted to THALOS, which chose components already proven in their existing systems.

Cameras

The EM system in this project uses rugged IP cameras (Mobotix M26). It was decided that two cameras would be optimal for vessels of this size. Power and data are transmitted over Ethernet cables.

The cameras record continuously and output at 1080p in MJPEG format at 7,500 Kbps, which referred to here as "uncompressed." The AI on the edge system runs inference on this uncompressed video source. The videos are re-encoded and compressed to H.264 format for storage and transfer, after which the uncompressed source is deleted.

GPS

A dedicated GPS module is installed on one camera. The data collected from GPS are:

- Date and time
- Latitude and longitude
- Speed
- Course

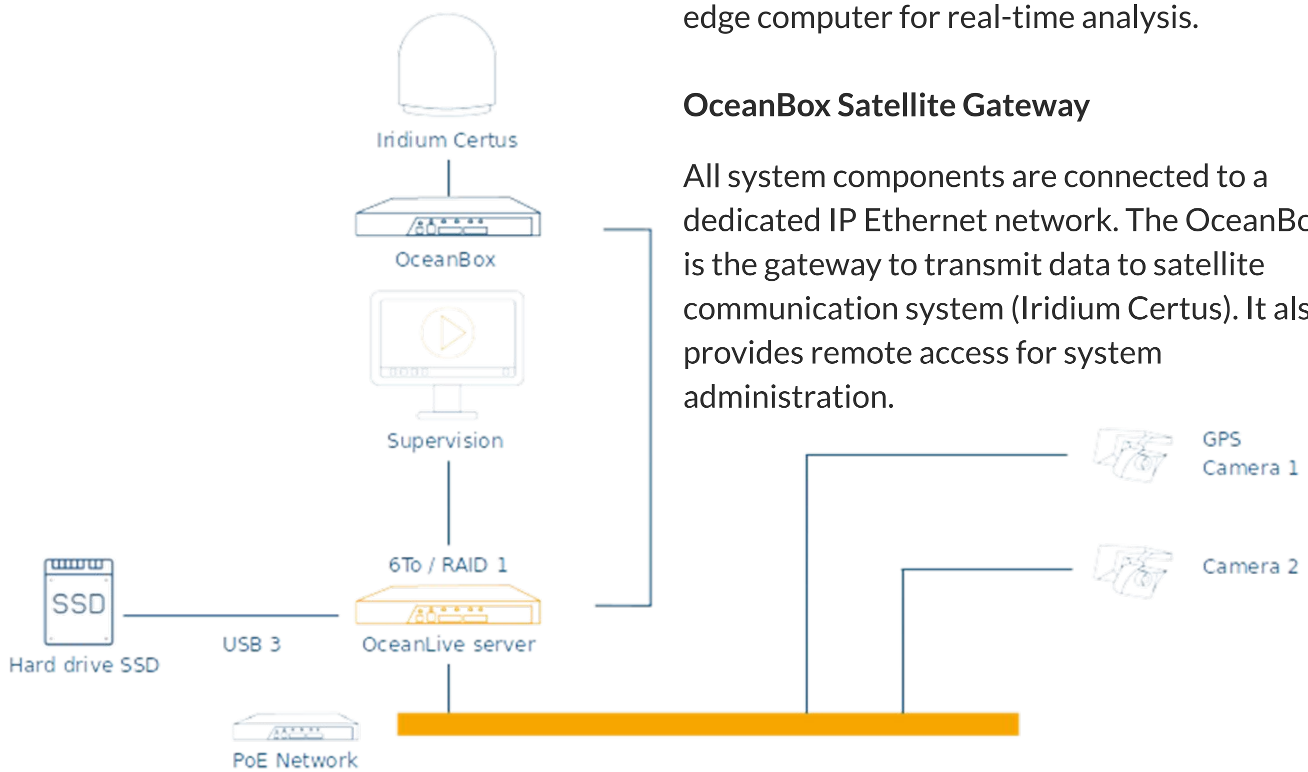
These data are received every second. A subsampling of one position every minute is applied to stored data.

OceanLive Server

The OceanLive server collects and stores the data. Videos and positions are shared with the edge computer for real-time analysis.

OceanBox Satellite Gateway

All system components are connected to a dedicated IP Ethernet network. The OceanBox is the gateway to transmit data to satellite communication system (Iridium Certus). It also provides remote access for system administration.



EM SYSTEM: Communications & Network

Network Configuration

The participating vessels did not have network communications installed. Outside of radio communications and very near shore cellular networks, the vessels and fishers were largely isolated from communications.

During scoping, it was determined that satellite connectivity was essential for the project's operational needs. While the edge device can operate without a satellite connection, satellite connectivity enabled debugging and remote support.

The satellite service for this project was provided by THALOS and uses the Iridium Certus satellite connectivity connected directly to THALOS's custom network routing hardware.

THALOS has two remote support systems built into each vessel's network:

1. Remote desktop access
2. A VPN to the local network

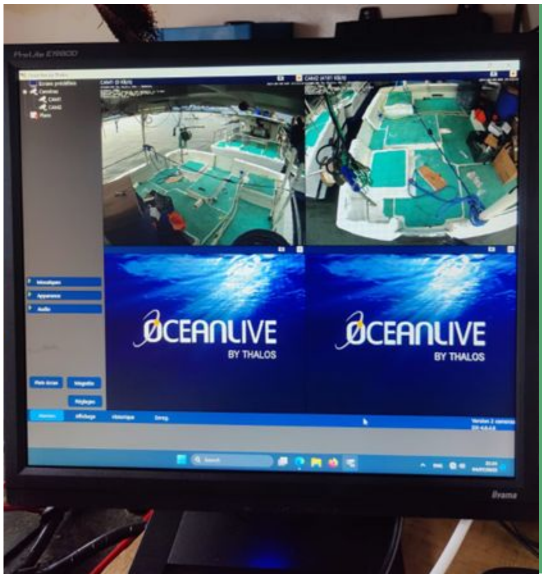
Both systems are designed for internal use only. For this project, THALOS granted VPN access to integration partners.

Communications Service Costs

This project required higher data usage to move select video files and data outputs to the cloud for further analysis while the vessels were still at sea. productOps selected the 1 GB/month data plan to accommodate this project, which cost about $1,300 USD per month per vessel.*

To avoid expensive overage charges, productOps requested a daily update of on-vessel data usage for each vessel. In months where only a portion of the data plan was used, productOps used the additional capacity to transfer extra sampling data, such as videos.

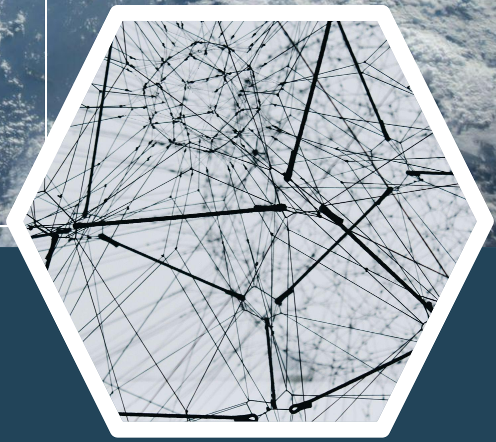
*Due to an EM configuration issue early in the project, the vessels were using an unusually high amount of data. THALOS resolved this issue; however, to cover this contingency and to ensure the ability to run further evaluations, one vessel's data plan was extended to 5 GB/month for three months (~$1,750 USD / month).



Other Benefits

Satellite data service offers quality of life and safety improvements for fishers. Fishers have found it very valuable to be able to connect with family and others using text applications. As an incentive for this project, network rules were set up to allow fishers to connect their personal devices to the vessel's network for specific apps. Because of the expense of the data plans, app access was limited. All vessels had access to WhatsApp, and a fishery application was trialed to improve the captain's ability to find good fishing locations.

ON THE HORIZON: Low Earth Orbit Satellites



Since 2023, EM systems have begun using low earth orbit (LEO) satellites from companies such as Starlink.

These satellites work in large constellations that are increasingly accessible even from remote locations on the high seas, and provide connectivity for a fraction of the cost of traditional satellite networks. Perhaps more importantly, the transfer rates and limits are much higher than for traditional data plans.

Higher speeds, higher data limits, and reduced service costs raise possibilities not only for better operations of today's EM systems and fisheries management but also for new capabilities. Some examples include cloud-based, near-real-time AI, hybrid analysis by AI and human analysts, and improved time to action.

New broadband capabilities could also improve the lives and safety of fishers and permit greater automation of vessels and fishing operations. Ultimately, LEO satellites may help to identify fishing zones and reduce interactions with ETP species.

Many EM companies are trialing LEO systems now, and interest is rapidly growing. This technology will introduce new data streams, and EM companies and fishery managers need to be prepared for dealing with new, large, near-real-time data management.

EM SYSTEM: Installations & Pre-Trial Trips

Hardware Installations

Originally planned for early spring 2023, the installations commenced in June 2023. This delay was due to the procurement of EM equipment, the selection of vessels, and the coordination with vessel operators. productOps traveled to Costa Rica to oversee the installation of the EM equipment and edge hardware, ensuring all systems were correctly deployed and operational.

During installation it was discovered that the best camera angle required a mounting that extended outside of the boat and pointed inwards. To mitigate the risk of damage from other vessels in a tightly packed port, custom mounts were designed on the fly to allow the cameras to swivel and lock in place for protection when not in use.

THALOS procured and installed the satellite systems and processed the service agreements.

The installation of the edge device was relatively straightforward and involved plugging in the device, connecting it to power and ethernet, and running tests to ensure it was on the network and functioning properly. Specific instructions were provided to verify the device's operation.

Pre-Trial Trip Challenges

From early July to December, 11 pre-trial trips occurred. During this time, the project team focused on resolving various issues, continuing the development of edge and eLog software, gathering data for AI training, and training the AI models.

Power Supply

One significant challenge encountered during the pre-trial trips was the limited power supply on the vessels, which was strained by the additional equipment. Power is limited and critical on these vessels, relying on a 12V system for the engine, navigation systems, and basic radio communications; without it, the vessel would be stranded. Due to their concerns, the vessel crew would intermittently turn off certain parts of the system, causing confusion for those monitoring the equipment as it appeared that components were malfunctioning.

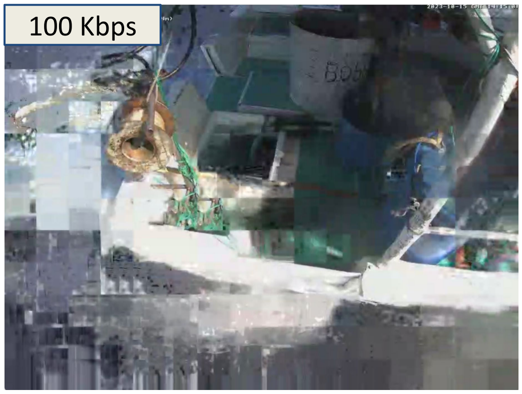
The initial attempt to mitigate the power issue involved installing solar panels, but these proved insufficient. Ultimately, diesel generators were installed, which effectively resolved the problem. Additionally, the crew was instructed to turn off the entire system if necessary, rather than just individual components.

EM SYSTEM: Pre-Trial Trips

Video Quality

A specific technical issue arose with the video frame rate during the video collection process. THALOS's standard configuration re-encodes the video to 2 fps at a 100 Kbps bit rate. To achieve the project's goal of tracking fish, the team requested a change to 16 fps.

Unfortunately, the frame rate change was initially deployed while keeping the bit rate the same, resulting in re-encoding at 16 fps at 100 Kbps for one trip and very low-quality images. Due to the project's tight timeline and the long turnaround time for receiving video, this project was forced to use the low quality video for AI model training. This re-encoding configuration error was fixed for the remainder of the project, with subsequent trips successfully re-encoding data in 1080p at 16 fps with a 750 Kbps constant bit rate.



Pre-Trial Timeline

June 2023
System installation on vessels

July 2023
Pre-trial trips begin

August 2023
Solar panels installed

September 2023
AI labeling and training begins with partners
Discovery of low frame rate issue

October 2023
Higher frame rate deployed on all vessels

November 2023
AI training complete

December 2023
Diesel generators installed

Vessels updated with new AI models and software

January 2024
Trial trips begin

ELOGS

The Deckhand platform from Real Time Data North America, LLC served as the eLog solution for the project. Deckhand is a workflow-driven electronic logbook platform that pairs core software with custom workflows designed for the unique requirements of regional or local fisheries. Real Time Data's staff scoped and built a workflow for participating captains. The workflow's UX closely matched how fishers work on the water with their specific gear type.

System Summary

- Deckhand Wheelhouse Units (iOS on iPad) on each vessel with mounting hardware and power supply
- Deckhand Pro v. 3
- Edge workflow v. 0.0.1 – 0.0.9

Workflow Design

Using Deckhand, captains could start their trip, record vessel and other identifying information, set/retrieve gear, add target and incidental catch data and ETP interactions, and terminate the trip. This design, combined with aspects of the interface itself, helped ensure more data was entered as soon as possible after an event occurred on deck.

Unique to the workflow in this project was an auto submission feature that occurred in the background when the user triggered certain types of events. Deckhand automatically submitted events to the edge server via an on-board local area network. Automatic submission of logged events with timestamps and validation was required to ensure better auditing of eLog events against camera recordings at the time of analysis. The workflow for the edge project accomplished this to a higher degree than any other Deckhand workflow currently available in the market.

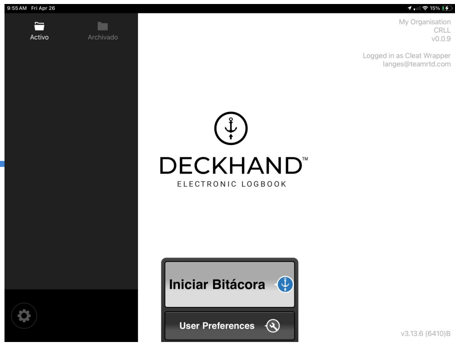
Gear Identification

A key element of the edge project workflow was the built-in ability to take photos. Captains were required to identify the gear they intended to deploy by taking a picture of the gear before the workflow would allow them to advance to the next view. Photos were automatically sent to the edge server in base64 format. Later in the project, photos were added as a generic feature for any instance in which captains wanted to take photos of ETP events or other occurrences on deck.

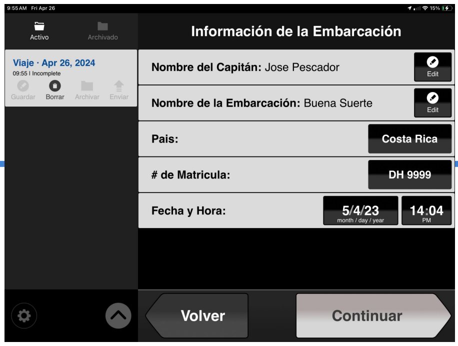
Updates

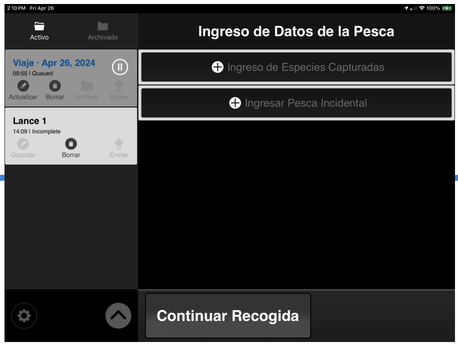
Workflow updates were deployed, sometimes within hours of receiving feedback, to participating vessels. Updates loaded when a user initiated a force quit/restart for a device in the field while on a Wi-Fi connection. A benefit of using Deckhand is having a responsive development team and a low-touch way to instantaneously provide updates once they're published.

ELOGS: Workflow Walkthrough

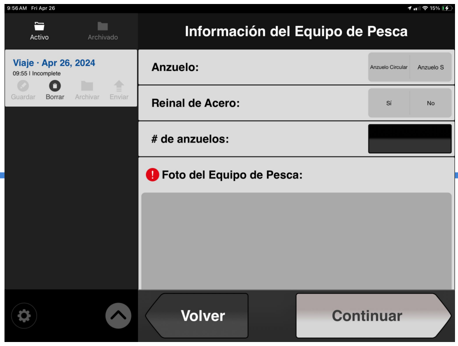


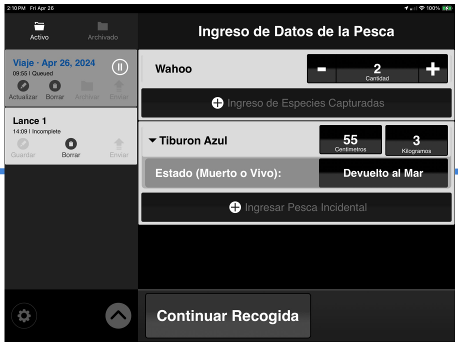
A captain initiates a trip from the Deckhand home screen and records their name, the name of the vessel, country, trip identifier, and date/time of departure.
Many fields auto-recall for greater efficiency on later trips.



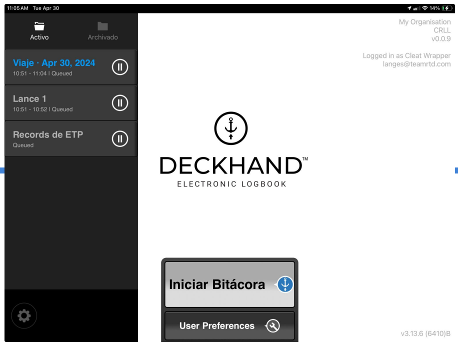


The captain enters details about the type of fishing gear, then uses the campera to verify the gear details with a photo. This photo is automatically transmitted to the edge server.

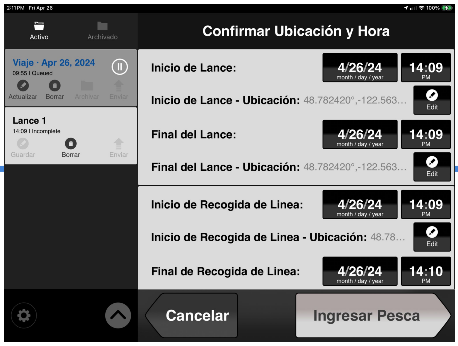




The captain can record sets and catch, including target and incidental catch. The captain can also record ETP interactions at any time.



After hauling any set, fishermen can verify GPS coordinates and timestamps for the beginning and end of each set. These coordinates are sent to the edge server automatically and verified using camera data. After the trip ends, Deckhand returns to the home screen, where the captain can review the trip, edit it, or archive it.



AI MODELS

AI Models Overview

Real-time analysis of EM data requires the ability to process video footage while at sea, as many longline fishing trips last for weeks and can produce hundreds of gigabytes of video files. Computer vision (CV), a form of AI involving the algorithmic understanding of visual content, enables real-time data analysis.

Development of this technology for commercial fisheries has been underway for several years, but until recently it required computing power only available in shore-based systems. Recent developments in edge technology have made it feasible to conduct CV analysis on low-powered computing devices.

AI approaches are still bespoke in the EM industry. This project used the efforts of two teams with different backgrounds. The AI teams aimed to support the demonstration of real-time automated analysis of EM data.

The Application of AI in Commercial Fishing

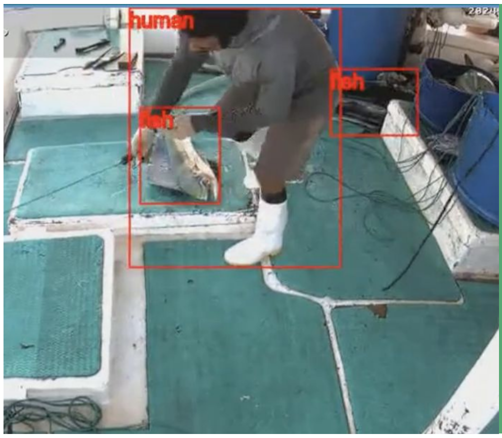
Three commercial fishing tasks are suited for AI assistance:

- Object detection
- Object tracking
- Object classification

Object detection involves analyzing image data to detect objects of interest—in this context, humans, fish, and non-fish animals.

Object tracking involves understanding detections across video frames, giving a sense of temporality of the object. An object detected in adjacent video frames is predicted to be the same object, which establishes a track. Subsequent frame analysis involves continued algorithmic prediction of whether detected objects are new or belong to an existing track.

Object classification involves determining the type of object that has been detected. In this project, classification involved species groupings rather than specific species.



Challenges of Counting

Counting objects in video is challenging even with clear, high-quality video. Counting objects in fishing video is challenged by many factors, including unclear imagery from dirty or wet cameras; occlusion of objects, because fishing vessels may be in close quarters and fish may be handled together; and challenges to reidentification caused by changes in the appearance of fish on the deck.

AI MODELS: Ai.Fish

Collection and Annotation of Training Data

Ai.Fish supported the development of a small training dataset specific to the Costa Rican environment. The in-house annotation team at Ai.Fish received one trip's worth of data collected from each participating vessel. Annotation involved manual review of every video frame to create highly accurate bounding boxes and preliminary labels (fish, non-fish, human).

In-house fisheries analysts then reviewed preliminary labels and updated these with species groupings (tuna, shark, ray, other, bird, turtle). Both AI companies then used JSON annotations for AI model training. Annotation was performed using CVAT (Computer Vision Annotation Tool) open-source software.

Challenges encountered in preparing the training dataset included the low frame rates of initial footage, obscured footage where camera views were blocked by unexpected objects, and difficulties that arose due to fishing during an El Niño season and near the end of the season. A lack of lighting during night fishing contributed to very low quality footage for training purposes.

Ai.Fish AI Model Development

Following the development of the training dataset, Ai.Fish conducted AI model training to acquaint an existing algorithm suited to tuna longline fishing with the potential environment, conditions, boat configuration, lighting, camera image quality, and fishing behaviors found on the participating vessels. This training employed the training dataset specific to this project and other supporting annotations of tuna longline fishing in the Pacific from Ai.Fish's extensive proprietary training library.

Training involves presenting the algorithm with a wide variety of accurately labeled imagery, which helps the algorithm recognize objects of interest in other videos. Ai.Fish also customized the existing algorithm to support detection by species grouping, compared to specific species detection.

During training, Ai.Fish also experimented with the optimal size for AI models to run successfully and in real-time on the edge system. The best performance came from a YOLOv8 model–a state-of-the-art open-source AI framework.

The model was trained using 35,447 frames from the project dataset . The model was then tested on a representative testing dataset which featured 8,215 fish detections and 7,119 human detections. There were no non-fish species available in the training dataset.

The algorithm tested at 98% precision when detecting humans and 90% precision when detecting fish—meaning it detected these object classes correctly 98% and 90% of the time.

The AI model also achieved 96% recall for humans and 83% recall for fish—a measure of the fraction of true positives out of all positives within the dataset. Fishing practices on the participating vessels contributed to some challenges in detecting fish; specifically, footage often included multiple fish left very close together on the deck for several frames.

AI MODELS: Ai.Fish

These detections significantly impacted recall performance. A segmented training with these overlapping annotations removed improved overall recall performance.

DEPLOYMENT

Running the AI model on the Xavier edge device required installing additional software applications and services to support video processing and store results. Current edge research at Ai.Fish uses Nvidia Orin equipment. For this project, Ai.Fish developed and adapted the edge operational software to suit the Xavier environment.

To facilitate video intake and processing, video files were shared to a folder accessible to the AI models. Five-minute video clips were supplied in series to this folder and processed individually by the AI.

The Ai.Fish software was deployed on one participating vessel. Onboard processing results were obtained from three trips taken by this vessel from January to March 2024.

AI MODELS: OnDeck

Overview

OnDeck produced a system with two primary components for training and inference. Training consisted of cloud-based machine learning infrastructure for data management and labeling, AI model training and software on GPU-accelerated compute , and MLOps frameworks to manage and track training tasks and artifacts.

The project followed a long waterfall cycle, with short turnaround once real domain data was available. As a result, certain capabilities had to rely on heuristics and added parameters to mitigate the waterfall cycle constraints and ensure the best possible recall.

The inference system was deployed on the edge system, and included custom serving software to manage, perform, and expose inference results. The software required optimizations and conversions to run AI models in real time on edge devices, as well as reasonable robustness measures to handle exceptions, especially on edge hardware. There was also a small pipeline for securely deploying software to edge devices.

Component Requirements

Near real time performance and prediction outputs were in line with expectations given available compute, and the AI component had clear responsibilities.

Specific operational and technical details were left vague under the assumption that they would be discussed and finalized as project progressed, and in general OnDeck found this agile approach effective. Some operational issues occurred between the different components (hardware, EM, deployment) but were handled well.

Training

AI model development was guided by the core CV tasks: object detection and object tracking. OnDeck trained state-of-the-art AI models to detect different fish and implemented tracking and reidentification algorithms to associate real-time detections across video frames. As part of tracking, OnDeck trained a secondary embedder model used internally to associate objects; however, this second model was ultimately discarded due to performance tradeoffs. To produce catch counts, static polygon boundaries were implemented in tracking algorithms to identify catch and discard interactions.

The AI model chosen for object detection was a state-of-the-art single-shot detector with 6 million parameters. The chosen tracking algorithm implemented a deep appearance descriptor and a Kalman filter to track unique objects. The detection model and the tracking system's internal embedder model were trained on OnDeck proprietary datasets and on labeled data generated by this project.

SYSTEMS: AI Model – OnDeck

Training was performed on AWS GPU-accelerated cloud servers. The final object detection model was trained for 140 epochs , which took 1.5 days on a p3.16xlarge instance . The training reached a mAP at IoU 0.5 score of 0.909, which is one metric to measure how accurately the model is performing.

The project required real-time AI model performance on limited-compute edge devices, achieving targets at 25–30 fps. The single shot detector model was chosen over other architectures for better performance and proven edge optimizations. For tracking, using a simple feature extractor instead of deep appearance descriptors achieved the required speed with very little accuracy degradation.

Inference System

The serving software consisted of a containerized inference service that exposed an HTTP API to the local edge network. This software facilitated the scheduling of inference tasks on locally available videos transferred from the EM system on the boats. Users specified the input path, output JSON path, and relative timestamps to queue footage for inference, based on an asynchronous design following the producer-consumer pattern . The software targeted the edge devices provisioned for the project: Nvidia Jetson AGX Xavier and Orin devices with the Jetpack 5.1 SDK installed.

The producer-consumer pattern and data flow design allowed the software to balance speed and accuracy by dropping frames, skipping inputs, or swapping larger or smaller models to maintain real-time processing. Deployment involved building Docker images and distributing them through a secure registry, with manual transfers via encrypted drives when network bandwidth was limited.

Output Format

OnDeck produced a per video JSON object structure with per frame results. An example is shown in the figure below.


```
{"overallCount": 10,
 "overallCatches": 2,
 "overallDiscards": 1,
 "overallRuntimeSeconds": 255.5401,
 "frames": [
   {"frameNum": 1,
    "timestamp":
"2023-06-13T19:44:17.302580+00:00",
    "bbox": [
       [
         923.3727416992188,
         454.06427001953125,
         1279.0,
         538.3589477539062
       ]
     ],
     "confidence":[0.513396680355072],
     "class": [0.0],
     "trackingIds": ["1"],
     "allActiveTrackingIds": ["1","2"]
   },
   ...
```

EDGE SYSTEM

Edge System Overview

The targeted system for the edge computer was the Jetson Xavier NX 8GB. productOps sourced five reComputer J2021 systems from Seeed Studio, an IoT hardware vendor. The Xavier NX was picked following input from AI partners; it is a highly capable model within the established Jetson product family.

Two upgraded Orin NX 8GB machines were sourced as additional edge computers. This enabled comparison of generational hardware improvements.

- Orin NX - 100 TOPS - released 2023
- Xavier NX - 21 TOPS - released 2020

All edge computers ran Nvidia's L4T 35.3 Linux distribution, which is based on Ubuntu 20.04.

Software

The software stack was developed as a set of microservices written as Python 3.8 scripts. The lifecycle of each microservice was managed by a systemd unit. Each microservice had independent inputs and managed its own state in a local PostgreSQL 12 database.

This architecture allowed each microservice to automatically resume tasks after unexpected errors or interruptions.

Processing AI Models

Both AI models were fully contained in a Docker image. The Nvidia Docker runtime provided full access to the GPU.

The AI models differed in their lifecycle and input interface, though they both input five-minute video clips in near real time.

Both AI models output JSON files, but their data structures were significantly different.

OPERATIONAL

The edge computer functioned as a practical and useful point for monitoring and operational tasks. A VPN granted remote access to an SSH terminal for live diagnostics. Data, updates, and raw video were copied from and to the edge computer with USB drives.

NVIDIA Jetson Orin

Edge AI devices are diverse, and the technology is advancing rapidly. It can be difficult to compare these devices, but the field is best sorted by total power and AI performance in TOPs. Very low power devices (<5W) are still too weak for good AI vision. The 15W range is healthy, and includes the Jetson devices used in this project and laptop APUs, driven in part by handheld gaming devices. Microsoft is expected to push a new AI PC device category, which would create even more capable Edge AI devices.

EDGE SYSTEM: Vectors

Vectors – Term & Overview

The term “vector” in this project refers to a small computer program or process that generates or transforms data in real time on the vessel. The term is derived from “threat vector” in the computer security field, where specific aspects of a broad space can be evaluated independently and combined in novel ways to achieve a goal.

Multiple vectors were built for this project. Each vector is independent and covers a unique aspect of data on the boat. Vectors access recent data, analyze the data, and output a score.

Architecture

- Vector code is built in Python 3
- The Vector type is built on a database ORM layer to store configuration values.
- Vectors are instantiated from database rows.
- Vectors have a time-parameterized “execute()” function.
- Vector instances are executed by a scheduler.
- A vector execution outputs a score between 0.0 and 1.0.

Implemented Vectors

GPS Fence	Outputs a high score when the vessel leaves Costa Rica’s exclusive economic zone.
THALOS connectivity	Outputs a high score when the edge system cannot connect to THALOS’s network storage.
Internet connectivity	Outputs a high score when the edge system cannot connect to the public internet.
Equipment outage (aggregate)	Aggregates the THALOS and internet connectivity vectors into one score.
Catch count correlation	Runs a Pearson correlation on haul times (from eLogs) vs. AI catch counts and outputs a low score when the two are highly correlated.
eLog gaps between hauls	Outputs a high score when there is a long time between hauls (based on eLogs).

Vector Types

The vectors generally fall into two categories: data generation for downstream use and data analysis for human interests.

The “connectivity” vectors, for example, are data generation vectors. Their purpose is to continually check the status of connectivity and store a representative value. Data analysis vectors, on the other hand, are designed to help answer a question of human interest. Catch count correlation, for example, is a running analysis that can be used for set prioritization.

EM ANALYSIS

Data Transfer

Initial transfer of the EM footage for review involved removing and replacing hard drives on vessels, followed by shipping the physical drives to the EM provider. To improve efficiency, the process was updated before the trial trips to transmit data over the internet.

Review Process

The review of EM footage was done by Bureau Veritas. Once video footage is received an analyst at Bureau Veritas does an initial check to ensure the video is complete and of sufficient quality for each camera.

Departure Identification: Using a map of the vessels gps data, the departure time and corresponding video are used to identify the vessel leaving port.

Fishing Set Analysis:

- **Start of Set:** Identify the beginning of a fishing set by observing the crew deploying the beacon.
- **Setting Review:** Review footage at accelerated speeds until the longline is fully deployed.
- **Start of Hauling:** Identify the start of the hauling process when the crew retrieves the beacon.
- **Hauling Review:** Review footage, slowing down during catch identification to examine each catch. Record data for each catch in an Excel document and create a note in OceanLive Analyst.
- **Collaborative Review:** Reviewers collaborate on any uncertainties, documenting them for later validation.

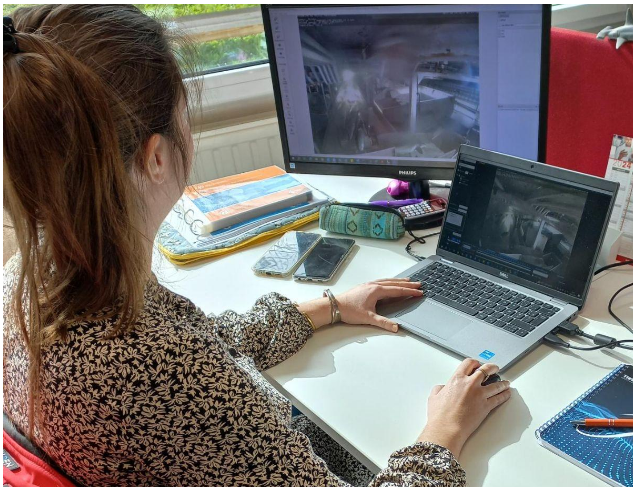
Return Identification: Infer the vessel's return to port using the map, noting that the camera signal cuts before arrival.

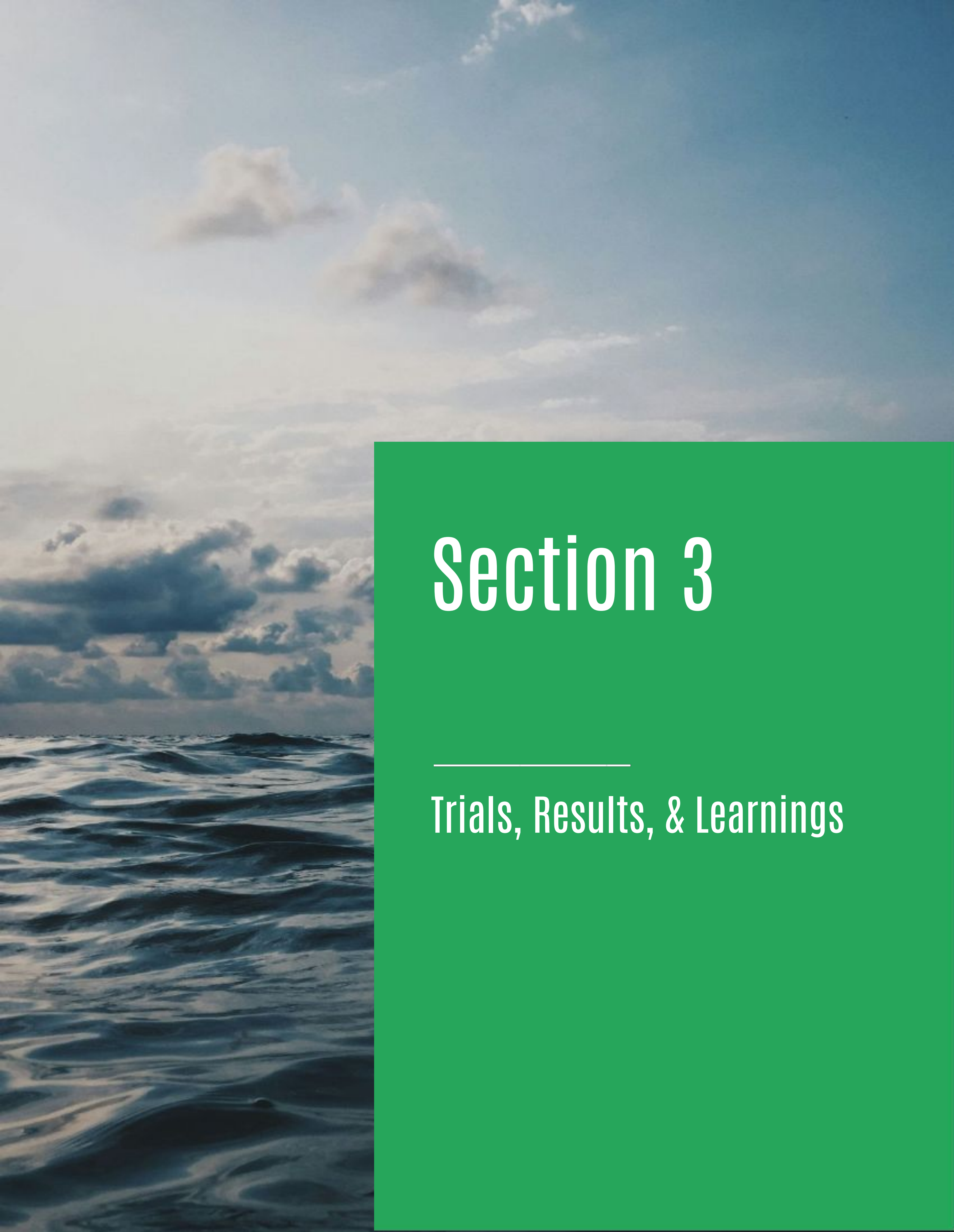
Data Validation

Logbook Comparison: Compare the date, time, and location data with logbooks.

- **Match:** Validate if data matches.
- **Missing Fishing Set:** Note and inform productOps if the fishing set is not in the logbook but observed in the video.
- **Unobserved Fishing Set:** Conduct further review if the fishing set is in the logbook but not observed in the video.

Catch Verification: Verify the logic of catch information, ensuring completeness of discard data and accurate species identification. Cross-verify identified species and review random samples of the catch, with a thorough check of all tuna catches and discarded species.





Section 3

Trials, Results, & Learnings

TRIALS AND TESTING

Unlike the approximately 5 months of initial systems testing to gather video for AI training and test systems and integration, the actual trials required very little development work from partners. The trials were largely self operational with logistic and technical support as needed. productOps monitored the trips for issues and made several adjustments for critical issues that occurred.

productOps also supported the electronic transfer of all video footage from Costa Rica to France for EM review. This is the first time that the project used this method instead of sending hard drives.

Results Summary

For edge based prioritization to be truly successful, more development work will need to be done in AI models for catch count and species identification. These are not simple challenges and will likely require more funding in AI.

Even without AI however, this project has shown that data can be collected, aggregated, and scored to determine useful outputs that can be used in prioritization.

Running the Trials

The trials ran from January 2024 through March 2024. Because of vessel operational issues with Vessel C, only two vessels were included in the actual trial. These vessels each ran 3 trips for a total of 6 trips.

Primary Project Evaluation: Results & Learnings

The development for this project was based on evaluating the success criteria mentioned earlier.

Evaluation Result 1	
EM SYSTEM	**Evaluation:** EM components will work on Costa Rican longline fishery vessels.
	Result: Success - Camera uptime was improved for trials. Power source issues on the vessels prevents 24/7 coverage. The captains' proclivity to turn the system off remained as a small barrier to uptime
	Learning: Power is critical on vessels in these fisheries; there is not enough spare power to run EM as-is. Adding generators to the vessels gave us the greatest benefit for EM system on-time.

Evaluation Result 2	
ONBOARD NETWORK	**Evaluation:** Systems can connect to the network and access the other systems as needed.
	Result: Success. Systems on the vessel communicated through the EM provider's local network with minimal issues.
	Learning: Tapping into the EM provider's network is a viable alternative to building a separate network for edge computing.

Evaluation Result 3	
ELOG IMAGES	**Evaluation:** Captains can use workflow to take pictures. Data is sent to the network.
	Result: Success: the eLog system was modified to take in required data points including images. Captains successfully took gear photos for each trip.
	Learning: As a required step in the workflow, gear photos were taken consistently, while optional event documentation with images may be underutilized due to unfamiliarity or perceived difficulty.

Evaluation Result 4	
EDGE INTEGRATION	**Evaluation:** Edge device can connect to systems and get data as needed.
	Result: Success: The edge device was able to integrate with all systems and access data. Integration delays caused by system shutdowns were found in all integration types.
	Learning: System coordination across the various teams was involved. Errors or delays in integration are unavoidable, especially around system shutdowns. Connecting integration results back to the partner teams is necessary for an edge product lifecycle.

Primary Project Evaluation: Results & Learnings

Evaluation Result 5a & b **AI MODEL**	**Evaluation:** Existing AI model can detect and count fish on the edge
	Result: Success.
	Learning: As expected, further training and algorithm fine tuning is required. Key improvements include enhancing training data for better species representation and more challenging object classification, experimenting with contextual tracking, and exploring supplementary counting methods. Constraints like limited R&D time with real data, operational challenges, and reliance on heuristics impacted performance, suggesting the need for iterative ML development.

Evaluation Result 6 **PROCESS VECTORS**	**Evaluation:** Edge device can process vectors and record results on the device
	Result: The vectors were run with a success rate of 90% or above, excluding downtime from an out-of-disk-space event. Vectors run on longer time intervals were more likely to be interrupted by system-off events.
	Learning: The scheduler worked reliably. More frequent runs would address the interruptions for long-period vectors.

Evaluation Result 7 **CATCH COUNT VECTOR**	**Evaluation**: Catch count vector can compare AI catch counts to Elog catch counts to determine correlation.
	Result: Partial. Without an initial model defining the expected relationship between elog counts and AI counts, there was nothing to measure the at sea results against.Because elog catches were submitted in a single batch rather than incrementally, catch count values were compared in aggregate for the entire haul.
	Learning: To enable the use of AI catch counts for evaluating the accuracy of elog counts, a statistical model can be built from the existing data to provide a benchmark for scoring.

Evaluation Result 8 **EDGE TO CLOUD**	**Evaluation:** Edge device can send results to cloud account
	Result: Success - The uploader successfully uploaded all internal data to the cloud without any unrecovered errors, demonstrating effective data transfer and cloud integration. However, the 1GB monthly data limit was insufficient for transferring raw AI model outputs.
	Learning: Future projects should consider adding cloud uploads for internal program logs to aid in operations and debugging. Additionally, more efficient data compression methods or larger data plans are needed to handle the volume of AI output data.

Primary Project Evaluation: Results & Learnings

Evaluation Result 9 **SYSTEM RESILIENCE**	**Evaluation:** Run trials and only monitor - how many times was intervention needed and what type?
	Result: Success. Vast majority of major issues were worked out on Pre-trial trips.
	Learning: Pre-trial trips required a lot of intervention, other trips still required a some monitoring and adjustments. More hardening would be required to reduce reliance on the technical support team.

Evaluation Result 10 **KEY EVENTS**	**Evaluation:** Can the Edge detect events (start/stop of fishing, equipment issues, etc - compare with EM analyst
	Result: Success. While not conducted on the vessel during trials, key events were detected using the data and computational efforts available on the edge.
	Learning: Additional modeling, built on the results of the AI catch count models has the ability to detect key events,, focus reviews, and streamline video processing, showing promising future capabilities even with minimal training.

Secondary Project Evaluation: Results & Learnings

The development for this project was based on evaluating the success criteria mentioned earlier.

Evaluation Result 11 **ELOG USE BEHAVIOR**	**Evaluation:** Are captains using the elog system as intended?
	Result: Success for reported set times, partial success for catch reports. Both the set times and catch counts reported on the elogs closely matched those observed by reviewers, with minimal deltas. The catch reporting is labeled as a partial success because captains reported catches in one batch at the end of the haul rather than incrementally, as requested.
	Learning: Captains found it challenging to report catches incrementally during hauling, due to their focus on fishing activities, leading to batch reporting instead. However, the consistency in start and end times for sets and hauls indicates that captains could record these events with relative ease as part of their workflow.

Evaluation Result 12 **ELOG-BASED PRIORITIZATION**	**Evaluation:** eLog behavior can be used to help determine prioritization.
	Result: Partial. The Elog Time Gap Vector produced mixed results, with point-in-time scores showing expected peaks during elog gaps, but the final vector scores did not accurately reflect these gaps. Improvements can be made by using project data to create a more representative function, similar to the recalculated vector score.
	Learning: The Elog Time Gap Vector's calculations need refinement, as the original scores did not accurately reflect elog gaps. Using data from this project to develop a more representative function, like the recalculated vector score, could improve accuracy.

Evaluation Result 13 **REMOTE SUPPORT**	**Evaluation:** Support team can monitor and log into systems to resolve issues. Includes radio coms with captain.
	Result: Success - ignoring hardware issues, most software issues were resolved remotely.
	Learning: Remote support is critical and is part of the current landscape of EM systems. Even with automation, remote support will be needed. AI vision models are very large and present a barrier to remote updates.

Secondary Project Evaluation: Results & Learnings

Evaluation Result 14 **EM DATA TRANSFER**	**Evaluation**: Send data from EM drives over the Internet reducing hard drive shipments.
	Result: Success (eventually) - Data transferred in about 2 days per trip
	Learning: EM electronic data transfer can greatly reduce the time to get data to analysts to review. Slow international transfer speeds may be fixed with relay servers.

Evaluation Result 15 **INCENTIVE EVALUATION**	**Evaluation**: Did participants find value in the incentives? Did incentives encourage participation?
	Result: Regular communications with captains and vessel owners indicate that incentives like internet connectivity, which enabled valuable WhatsApp communication, and the Comms video highlighting EM benefits, were well-received.
	Learning: These incentives helped alleviate initial fears about EM, were seen as valuable, and mitigated opposition from other vessels. An incentive model is recommended for the first phase of similar projects to reduce friction, increase alignment, and make EM a "win" for both captains and crew.

Evaluation Result 16 **EDGE HARDWARE**	**Evaluation**: Which edge hardware worked best and what are the recommendations for future projects.
	Result: Both devices performed well, with the Jetson Orin NX device the more capable and expensive.
	Learning: Close collaboration with AI modelers needs to be considered when choosing hardware.

Evaluation Result 1

EM Systems

Success Criteria:

Systems are installed and operational as intended while at sea.

Success Metric:

Systems check and supporting data. Possible values: **success**, **fail**, or **intermittent.**

Results: Success

Details

The output of video from the EM System shows when the system was on and working. The output video is downstream of several EM systems, including the cameras, the EM network, the EM video processing pipeline, and the EM storage. A lack of output video shows at least one part of the EM system was not working.

In an ideal environment, the EM System will produce output 24/7. But on these boats in this fishery, 24/7 video is not feasible. Most EM downtime is when the captains turn off the system overnight.

Results

Evaluating uptime with 24/7 as a baseline, the six trips had both cameras producing video 64.2% of the time. As mentioned above, 24/7 is not a reasonable baseline for this project.

Evaluating with sunrise/sunset as a baseline, the six trips produced video 91.0% of the time. Evaluating with THALOS's internal system logs as a baseline, video was produced 97.3% of the time.

Figure 2 demonstrates that most video outages are very short. We manually checked four of the longer outages and found they line up well with the vessel finishing its activity for the day. These longer outages are likely caused by the captain turning off the EM system.

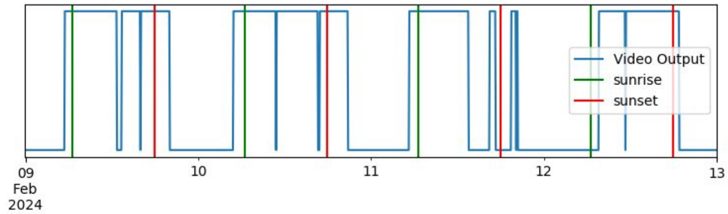


Figure 1. Video output during four working days on the vessel. Three days show typical EM System uptime. The 11th shows a significant outage in the evening.

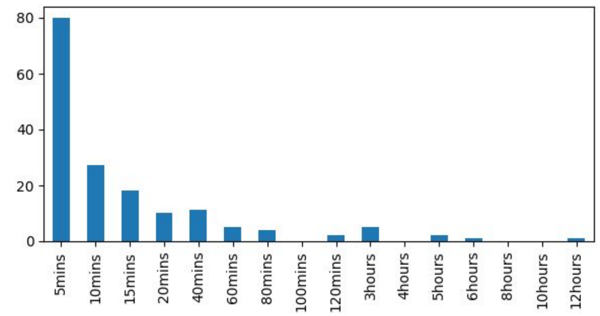


Figure 2. Distribution of video outage length for all 6 trial trips.

Learnings

On the pre-trial fishing trips, there were numerous issues with too much power being used on these vessels at sea. Originally captains were manually turning off the power to the systems at night. Additions of solar arrays and generators helped with power. The captains did not report power issues during the six trial trips, and 91.0% uptime during the day proves the power issues had been resolved.

With power issues resolved, captain behavior is the second leading cause of downtime. The EM system itself provides good uptime. Power is critical in these fisheries, vessels have barely enough electric power as it is, using systems 24x7 drains the batteries and causes a safety risk. Alternate power and storage is needed to run the systems for longer periods of time (i.e, beyond fishing practices).

Evaluation Result 2

Onboard Network

Success Criteria:
Systems can connect to the network and access the other systems as needed.

Success Metric:
Systems check and supporting data. Possible values: **success**, **fail**, or **intermittent.**

Results: Success

Details

Instead of building our own edge network, this project tapped into the EM provider's (THALOS's) network onboard the boat. This solution required extra system configuration changes from THALOS. The edge computer had access to THALOS's video box and access to the cloud. The eLog iPad had access to the edge computer.

Results

Figure 1 shows the distribution of elog submission delays, from when the captain pressed "submit" to when the edge computer received the data.

Most elogs were transferred over the network within 30 seconds.

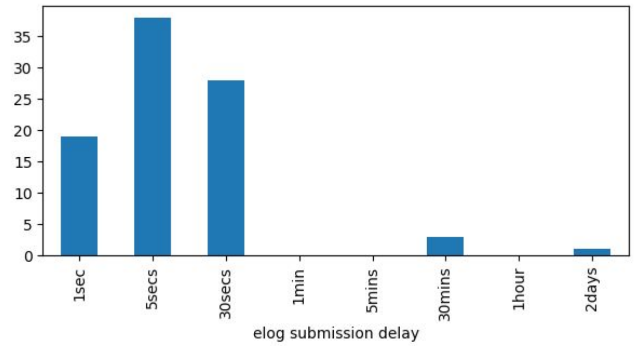


Figure 1. Distribution of eLog submission delays.

The data contains one obvious outlier. During a trip in January, one elog submission was delayed for 2 days because the edge computer had run out of disk space. The network is not implicated in this case, and elog submission recovered automatically.

Internet connectivity succeeded 96.6% of the time.

Learnings

Using THALOS's network was a success, saving time, effort, and complexity compared to building a custom network.

The project relied on static local IPs, which are not recommended for future implementations.

Allowing full internet access to iPads is not advisable when data plan is restrictive, as background systems in Apple's ecosystem, such as updates, backups, iCloud, and maps, can silently consume excessive data.

Evaluation Result 3

eLog Images

Success Criteria:
eLogs system can be modified to allow captains to annotate events with images.

Success Metric:
QA test on eLog systems to match requirements. Possible values: **success, fail, or partial.**

Results: Success

Details

Traditionally, captains on fishing vessels reported their gear through physical landing reports filled out upon arrival and/or in electronic logs (eLogs). To enhance transparency, a new feature was added to the eLogs allowing captains to include photos of their gear, particularly hook types which vary in their impact on bycatch. An unskippable step was developed in the eLog trip workflow that requires a photo of the gear to be taken. This photo is saved by the eLog program and submitted at the beginning of the trip.

An optional step was added, allowing captains to take a picture at any time. This feature enables captains to document any interactions with endangered, threatened, or protected (ETP) species or other events of interest to fisheries managers.

Results

As a result of these developments, images of the gear were successfully submitted for every trip. However, none of the captains utilized the optional step of taking a photo at any time to document additional events or interactions. Examples of the gear photos are shown in figures 1 and 2.

Figure 1 and 2. Examples of gear photos submitted at the beginning of trial trips.

Learnings

Including images of gear types allows for the verification of reported gear, ensuring transparency and building trust between fishermen and fisheries management. Images are quick to scan and can aid in the prioritization of fishing sets. The fact that the optional step of taking images at any time was not utilized could be due to captains not being familiar with the tool or finding it challenging to use.

Evaluation Result 4
Edge Integration

Success Criteria:
The edge system will be able to access the raw data from EM cameras as well as e-logs.

Success Metric:
Data validation and systems check. Possible values: **success**, **fail**, or **intermittent**

Results: Success

Details

The edge computer is the central collection point for all data sources on the boat. eLog data is submitted to the edge computer via HTTP API. The EM video data is polled and fetched by the edge computer from a SMB network fileserver. GPS data from the EM system is polled and fetched from the same fileserver. AI model outputs are written asynchronously to the local filesystem, which the edge computer monitors for changes.

All data is stored in raw format, either on the edge filesystem or in a local postgres database. Some data types are parsed, amended with metadata, and/or transformed depending on the raw format and expected use cases.

Results

Of periods where the edge system was powered on and expected video, video could not be found 27.3% of the time. The root causes are unknown, but the out-of-disk-space error might contribute up to half of the no-video instances.

Figure 1. Status of Video (top) and AI (bottom) integration on the edge. 1 block = 100 instances; Each instance occurs at a 5 minute interval.

Edge Integration: Results

Results Cont.

The edge system had a 98.9% success rate of copying videos after finding them on the network files server. 1.0% of videos were copied significantly later than expected. The video integration pipeline runs in near-real time; video copies are expected within about 10 minutes. Delays varied from a few minutes to several hours.

When the AI model was started, it produced an empty file as output 20% of the time. Empty outputs could be caused by two scenarios: 1. the AI model was successful and did not detect anything for the duration of the video 2. the AI model errored and/or quit early. This category cannot be wholly classified as success or failure because the two scenarios are indistinguishable in our post-analysis data. Manually checking a handful of the source video for these scenarios showed that most scenarios were successful runs with no detections. A few scenarios were errors such as out-of-memory or video file parsing errors.

When the AI Models produced output, they produced reliable output. A very small percentage of AI output (0.1%) went unused.

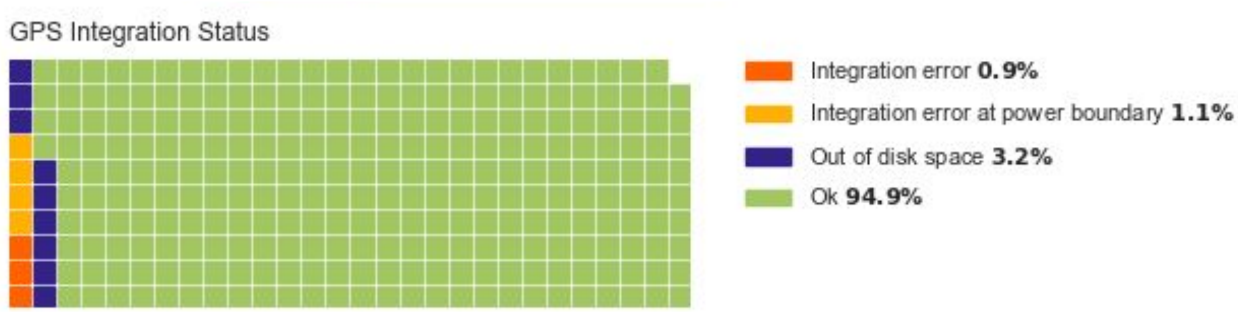


Figure 2. Status of GPS integration on the edge. 1 block = 500 instances; Each instance occurs at a 1 minute interval.

The largest source of integration errors for GPS data was the out-of-disk-space outage from Jan 5th to Jan 8th. The data was not lost, but 4377 data points (3.2% of all data points) were delivered late, after the disk-space outage was resolved.

A significant percentage of integration errors appear on the boundary of system-power-on or system-power-off events. About half of GPS integration errors occurred near when the system was powered off. For integration systems that use polling, these errors are unavoidable, emphasizing the need for resilient systems that can recover the data later.

Learnings

Overall, integration of data in this project was a huge success. All systems were integrated to a level that achieved the project goals. One high level challenge of quantifying integration errors is separating them categorically from discrete component errors. The AI models were the largest source of component errors, but it's difficult to prove that AI model errors weren't caused by an error during integration.

In future projects, greater attention and resources should be given to relaying logs and errors between the integrator and the product vendors. For the integrator, opaque error conditions and a lack of tools for debugging leaves the integrator unable to affect change when seeing a problem. For the product vendors, the nature of edge computing leaves them disconnected from their product without the integrator's help. Thus it is not only the integrator's job to build the primary integration workflow, but also to build the out-of-band communication channels for logs, errors, and fixes.

Evaluation Result 5a
Ai.Fish Model

Success Criteria:
Process fish detection using AI on EM videos.

Success Metric:
AI Models run and produce results. Result output of fish counts can be used as an input for other systems.

Results: Success

Authored by Ai.Fish

Operational Results

Following installation on the participating vessel, Ai.Fish artificial intelligence was reliably operational (running) and produced results. The installation was in place from December 2023 to March 2024 and 3 separate trips were taken where EM video was processed by the AI onboard. Results were transmitted to Ai.Fish approximately one month after each trip and therefore there was limited opportunity to perform ongoing analysis or adjustment to the algorithms during the project.

AI Performance

Object Detection

With respect to object detection, the AI experienced an unexpectedly large number of false positives. This is the key contributor to counting errors seen in onboard data analysis. Many of these errors were novel for the existing algorithm and had not been seen in past work. Compared to the environment in which the existing algorithm was developed there were some distinct behaviors and circumstances that we believe contributed to these false positives and which further algorithm training or fine-tuning would correct. Specifically interesting differences included:

- Fishermen seated on deck with legs outstretched. In prior work the algorithm had been used for fishermen were typically standing when in the camera view.
- Non-fishing objects on deck. Examples include things like coffee mugs; bowls for food; garbage bags, clothing hanging to dry.
- Unattended PPE on deck. For example, gloves, and boots left on deck after cleaning to dry.

These differences indicate some of the variables that need to be considered during AI development for commercial fishing and are also representative of practices on different sized boats as well as circumstances related to the local environment.

Object Tracking

A challenge with false positives in detection is that it will also generate false positive tracks. Since counting was achieved through the identification of unique tracks associated with fish objects this resulted in inflated counts. Generally object tracking performed well across frames. Due to the use of an existing algorithm designed for continuous video, tracking did not take into account the need for tracking across clips. This was a minor contributor to inflated counts.

AI Performance Cont.

Object Classification

Generally speaking, object classification worked well when examining the application of the correct species label to a true positive detection in target catch. (i.e. if a tuna was detected, reliably the "tuna" label was applied). However, while a number of sharks and other bycatch or non-target species were caught, none of these were correctly classified. We believe this to be a facet of the limited training data available for bycatch and non-target species.

Learnings

- Enhance training data to be more representative across catch and non-target species and improve classification.
- Enhance training data with "difficult" non-fishing objects and human positions to reduce false positive detections.
- Highly consistent fishing routines onboard the vessel suggest opportunities for experimentation with contextual tracking.
- Supplementary counting methods should be explored to improve the ability to use AI counts in comparison with Logbooks.

Evaluation Result 5b

OnDeck Fisheries AI Model

Success Criteria:

Process fish detection using AI on EM videos.

Success Metric:

AI Models run and produce results. Result output of fish counts can be used as an input for other systems.

Results: Success

Authored by OnDeck Fisheries AI

Operational Results

The final model was running on the vessel for most of January - April 2024, processing footage when it was provided into the containerized system. The model did not have insight into any operational status beyond it's input requests and internal status. Overall, there were limited opportunities to tune prior to the report, thus further improvements are analysed as much as possible in this section.

Deployment Timeline

Deliverable	Delivered Date	Details
Project Start	*May, 2023 Start*	Proposal, Capability Demo, Project Requirements and Discussion, Operational setup and development of Jetson Xavier device
First Release V0.1	June 15th, 2023	• Optimize and refactor baseline object detection model for edge deployment • Develop and integrate counting algorithm • Develop containerized serving software and release ○ Documentation and deployment
Hot Fix	July 11th, 2023	• Provided compatible models for Jetson Orin devices
V0.2	October 4th, 2023	• New API Architecture to expose the service • Polygon support for tracking and counting • Performance management functionality
Receive high quality footage	November 18th, 2023	Received high quality footage, OnDeck begins internal labelling since accurate evaluation and improvement of model requires high quality labelled data.
Final Release V1.0	December 12th, 2012	• Retrained AI with high quality data and OnDeck labelling • Improved performance of tracking and inference service • Packaged final trained models, polygons, and device support.

NOTE: Project architecture has a separate Risk Assessment component which takes outputs of the AI component and processes them for system output (see "Defining the Project - Edge assessment activities & system architecture” on page 33). However, this section is purely a discussion of the AI Component and its raw AI outputs which are *intermediary outputs* of the overall system, and thus evaluated differently from the Risk Assessment outputs.

AI Model vs Human Review Results

Human review results for trials run in January and part of February 2024 were made available for analysis, alongside summary results from the AI model outputs. AI Models were not consistently run 24/7 due to external issues in the wider system and thus only certain days contain comparable data. While we do us human review counts as a baseline, it is important to keep in mind that this project does not have statistics on human review accuracy.

“BV” refers to human review data while “ML” refers to OnDeck’s AI model output data. OnDeck’s system outputs do not compare directly to human annotated fields, and instead are defined as follows:

Active Track, or Track: An component of the tracking algorithm where a detected fish is re-identified successfully across consecutive frames in a video.
Count: Overall count of detections identified consistently by unique active track. This increments each time an active track is created by the tracking system, thus is largely inflated compared to human counts based on occlusions or missed detections.

Catch: Total catch interactions detected, where a catch is an active track transitioning from outside the polygon to inside.

Discard: Total discard interactions detected, where a discard is an active track transitioning from inside the polygon to outside. Human review discard counts will account for non-target species discards as well.

There are 3 types of data that were available for analysis:

- Re-encoded footage (converted to a different data type, meaning it will behave differently when locally testing the model),
- Summed/aggregate model outputs (catch and discard count for each 5 min video), and
- Full model outputs (all the outputs our model generated, including the detections and track information). Only available for 2 days: 2024-01-17 and 2024-01-24.

Either full/raw footage or full model outputs with re-encoded videos are needed to perform a complete, defensible analysis of model performance and the AI lifecycle, thus presents an restriction on all the analysis performed in this report. No full/raw footage was able to be used (original footage recorded off the camera).

OnDeck Fisheries AI Model: Results

Analysis and Visualizations

Due to project logistics, only compressed video copies are available from vessels, limiting the potential for analysis and visualization. Inference was run again post-trial on an onshore Jetson Xavier to produce visual analysis for the models outputs. Only footage from 2024-01-17 and 2024-01-24 could be analysed at a granular level since original model outputs (necessary for accurate analysis) were only available from these dates due to limited outgoing bandwidth availability from edge systems. Any visual analysis henceforth uses compressed video unless stated otherwise.

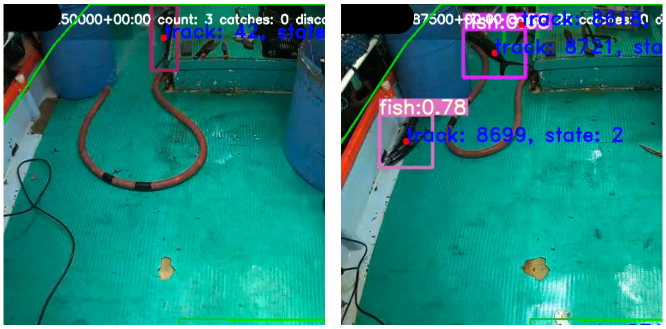
While the compressed video copies are largely similar to raw edge footage visually, fine-grained ML analysis on them yields different results. Comparing model outputs, we see approximately two-thirds of re-created inference detections match with original model outputs, where detections are classified as matches if the four bounding box coordinates have a sum difference of less than 40 pixels to original model outputs.

Confidence

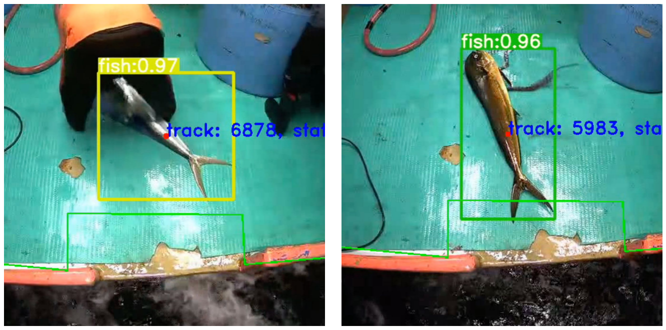
Statistics on inference confidence values from 2024-01-17 and 2024-01-24 re-created visualizations. Inference results have a lower bound of 0.65 on confidence as the model uses non maximum suppression to discard lower confidence detections.

Set	# Detections	Average	Median	Min (NMS)	Max
2024-01-17 (11:25:00 - 16:10:00)	345414	0.8377	0.8513	0.6500	0.9737
2024-01-24 (00:00:00 - 00:55:00)	25685	0.8061	0.8098	0.6500	0.9628
2024-01-24 (07:35:00 - 10:55:00)	148532	0.8135	0.8276	0.6500	0.9715

Minimum Confidence Examples



Maximum Confidence Examples



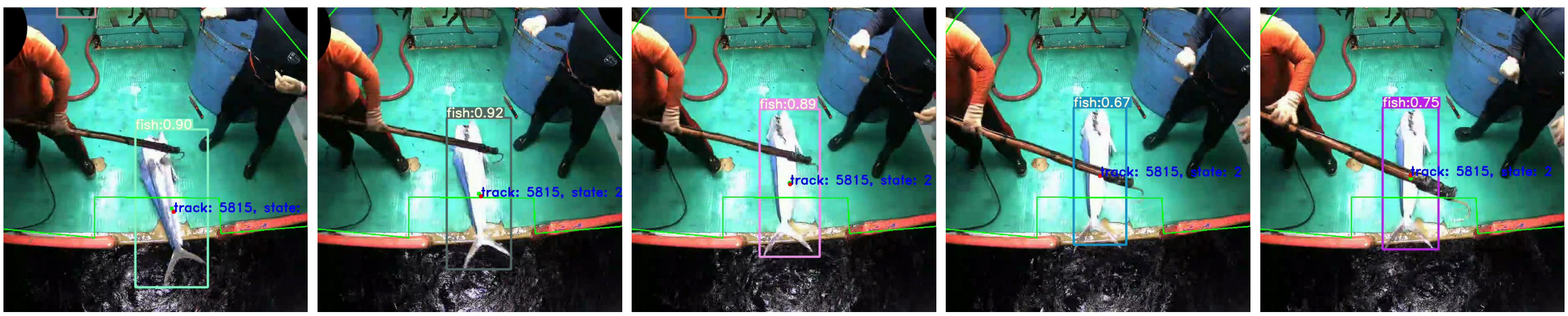
OnDeck Fisheries AI Model: Results

Catch and Discard Visual Analysis

Successful Catch Detection (Sampled at 8 FPS)

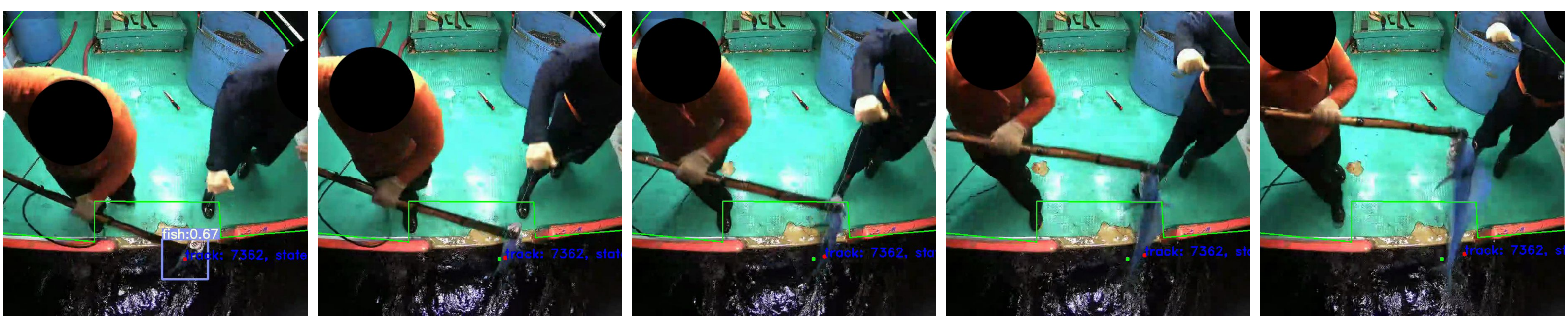
1 | 2 | 3 | 4 | 5

6 | 7 - Catch Detected | 8 | 9 | 10

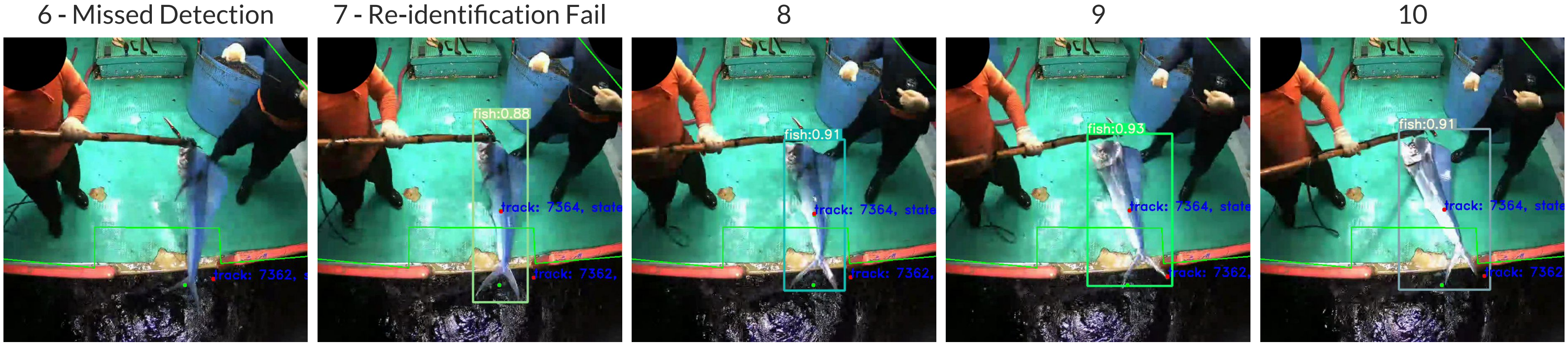


Unsuccessful Catch Detection - Missed (Sampled at dynamic FPS)

1 | 2 - Missed Detection | 3 - Missed Detection | 4 - Missed Detection | 5 - Missed Detection

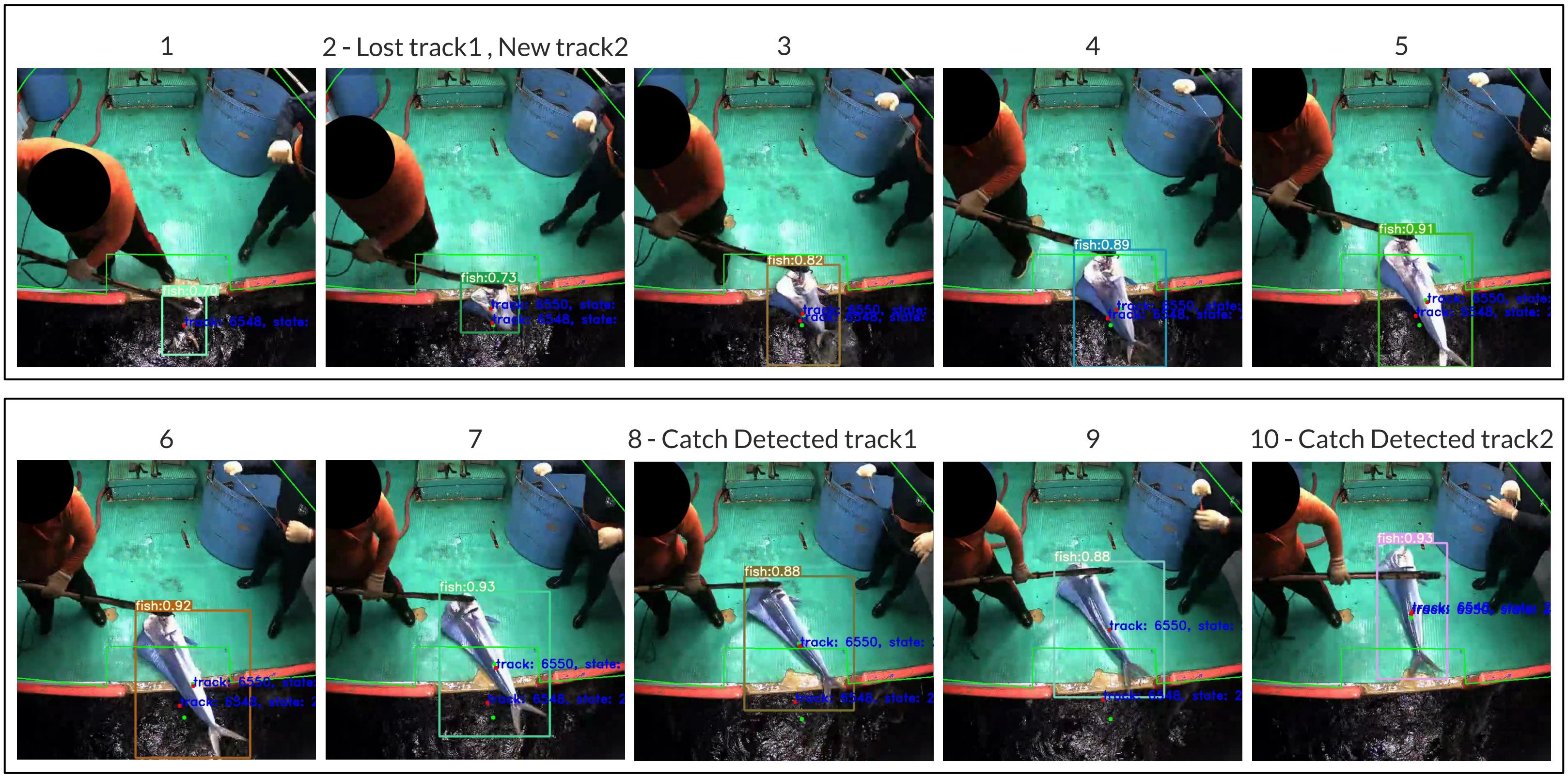


6 - Missed Detection | 7 - Re-identification Fail | 8 | 9 | 10

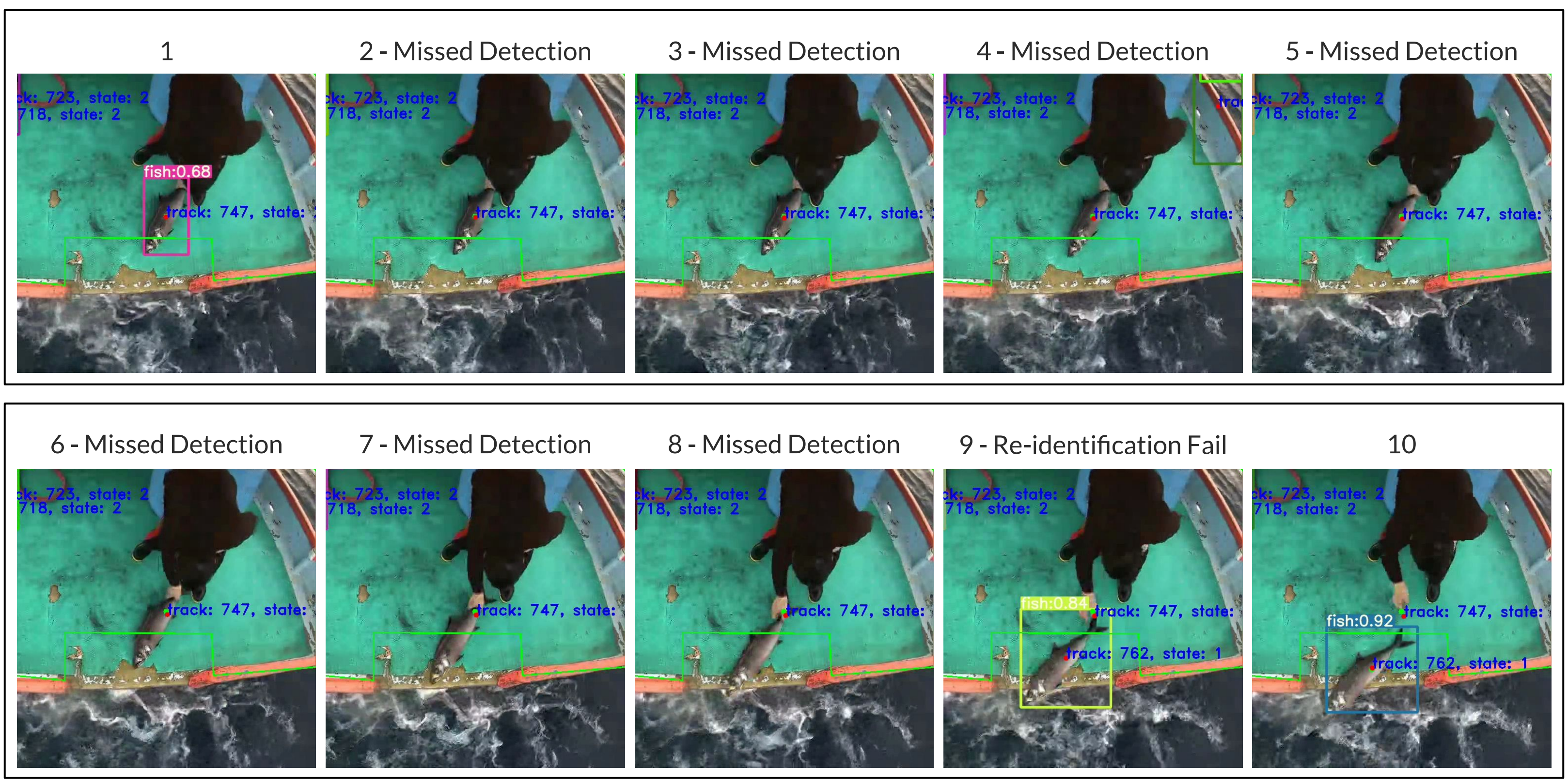


OnDeck Fisheries AI Model: Results

Unsuccessful Catch Detection - Double Count (Sampled at 5 FPS)



Unsuccessful Discard Detection - Missed (Sampled at 16 FPS)

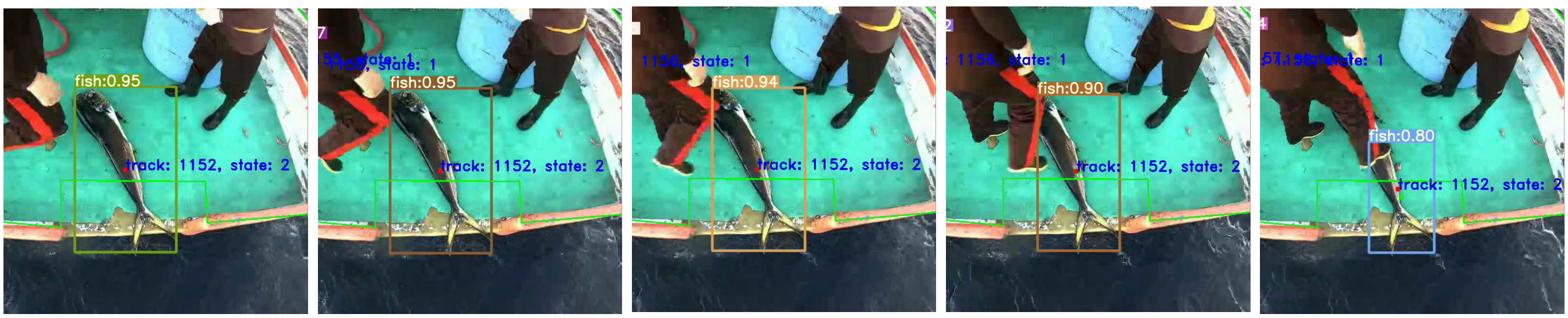


Unsuccessful Discard Detection - False Discard (Sampled at 16 FPS)

The Catch/Discard systems' behaviour assumes a fish is only caught once, and only discarded once or not at all. In practice, fish are often brought on board but kept close to the boats edge while being processed, causing this "boundary" problem where it crosses the polygon border multiple times. Furthermore, this is often caused by a partial occlusion where the bounding box gets resized.

This issue is easily mitigated by a small functionality change where we track all transition interactions, and calculate the difference to obtain the number of retained fish. This change is analyzed later in the data learnings section.

1 | 2 | 3 | 4 | 5 - Discard Detected



6 - Catch Not Detected | 7 | 8 | 9 | 10

Improvements

Through the project, in particular after receiving high quality footage just before final deployment, we identified potential improvements that could be made to the overall system. Each improvement has a different cost of engineering, and due to the research nature of many of these and their dependencies, experimental work is required to determine their prioritization.

Improvements Cont.

Classes of Further Improvements

- Higher fidelity re-identification, particularly using memory
- Underlying inference runtime optimizations
- External dependency variability detection
- Distribution shift and out of distribution detection
- Post-processing, can act as verification of edge AI outputs and Risk Assessment
- More compute onto model preparation
- Model design improvements

Other improvements we identified have a larger proportion of non-model involvement, thus are not listed here. Also, failure modes and improvements that address them are not independent either causally or laterally (between each other). For example, a change in the model's detection and identification fidelity can significantly impact tracking performance indirectly.

Examples of an Experiment Needed to Identify Further Improvements

To address double counting of catches across two contiguous videos, a small code change enables consistent counting of unique catches between videos. This results in more accurate catch counts, addressing one of the improvement points to reduce inflated number of catches by the model.

A second counting change modifies the assumption of one catch/discard count per fish. Instead, we track all interactions for a more accurate catch count following Risk Assessment definitions. This change outputs an additional catch count which better represents the number of fish caught.

After these example improvements we saw a closer agreement between the ML model output and human review (when tested on re-encoded video). However, we noticed that the time from 15:00-16:00 on January 17, 2024 still sees a high number of false positives due to 2 significant challenges for the model.

Challenge 1: A cascading combination of

- Partial occlusions by human gutting the fish while standing in front of it (losing track of a fish),
- Re-identification failure after occlusion & gutting (guessing it is a new fish),
- Being near the edge of the boat (belief that the new fish is also being caught),
- Throwing pieces removed from fish overboard (appears like little fish being discarded).

Result: Algorithm overcount, contributing to both discards and catches. This cascade occurs several times.

Challenge 2:

- Fish sitting on deck partially occluded by hose and water (losing track of a fish),
- Re-identification failure after occlusion (guessing it is a new fish)
- Being near the edge of the boat (belief that the new fish is also being caught)

Result: algorithm overcount, contributing to catches. This cascade occurs several times.

These are examples of improvements that fall under the class: "*Higher fidelity re-identification, particularly using memory*" from the list on the previous page. Details on the steps necessary in this case include:

- Improve performance of inference engine. →Allows running larger, better models. →Allows for stricter tracking params. →Which improves re-identification.
- Improve tracking capabilities with memory component. Requires significant engineering effort. →Allows for better re-identification with occlusions.

LIDAR and other sensors can provide a physical understanding of a scene to boost performance in the face of occlusion & dismemberment, since fish become a fundamentally different object after dismemberment.

This example of two basic counting changes that quickly improved counts and identified root causes are meant to highlight:

- potential improvements areas for the project,
- the benefits of post-processing raw outputs for analysis,
- and the need for iteration to identify and execute improvements to ML systems.

Examples of Non-model Improvements

An example of a non-model issue is visible when a discard event outside of the vessel is not detected by the model, but are recorded in BV data. Visualizations of this cannot be shown due to sensitive content. A fundamental issue is video quality and camera angle makes it difficult to see objects partially in the water, behind hands/tools, moving too quickly, and moving in the same direction as the camera (in & out of the plane of vision). Addressing this would require:

- Additional camera angle.
- Higher FPS with set stricter tracking parameters

OnDeck Fisheries AI Model: Learnings & Recommendations

Learnings

Overall, we were impressed by the The Nature Conservancy and productOps' ability to navigate substantial logistical challenges that emerged during this project, and we learned a lot from their leadership. For those interested or skeptical of using computer vision in fisheries, please consider the following.

Key Recommendations

- It is critical to engage AI partners at the onset of program design, and allow for AI providers to be involved in product design.
  - Direct lines of communication between the AI developers and the end users is key for delivering valuable outcomes.
- A different product structure is needed to deploy effective machine learning tools.
  - Iteration allows for capabilities that cannot be achieved with a waterfall approach.
  - Full sharing of data to allow for proper AI capabilities.
- More isolated evaluation of AI for EM is required to find desired conclusions about AI.
  - It is difficult to fully disentangle challenges unrelated to the ML component. These challenges should not be confounded with AI for EM as a whole.
  - This project attempted a very specific approach for risk assessment, not monitoring as a whole where significant opportunities are available.

Additional Future Opportunities

- In order to reach reliable performance, ML model development requires:
  - Representative Data → ML R&D → Deployment → Repeat, in a tight loop.
  - Due to logistical challenges, this project had little to no R&D time available with representative data from initial deployment. A larger focus is needed on data quality and timely gathering, to ensure high quality outcomes of data-driven AI.
  - Earlier and continuous access for AI providers to representative data.
- Minimized layers of separation between ML R&D and others.
  - Provide more input opportunities for control and collaboration with software providers and EM providers (e.g. input format, camera angles, etc).
  - Clarification and control over labelling by ML providers.
- There are numerous opportunities to improve ML systems, dependent on the above.
  - Software with ML is one of the best tools we have to solve challenges in EM.
  - There is a tradeoff between tool capabilities and approaches to the problems we want to solve with those tools. The correct balance lies in optimizing the intersection between AI capabilities and the goals of the project.

Evaluation Result 6

Process Vectors

Success Criteria:

Edge device can process vectors and record results on the device

Success Metric:

Verify that the edge compute program created a result based on these two value sets. Possible values: success, fail, intermittent

Details

The project implemented and ran six vectors on the edge for the full trial trips.

Vectors for this project were developed without any pre-existing data. Several concepts for vectors could not be implemented because they depend on pre-existing data that can be used to build a model.

Each vector was configured to run on a 10 minute, 30 minute, 1 hour, or 4 hour interval. The vector scheduler started when the was system turned on. The scheduler does not run the vectors immediately on boot; the scheduler runs the vectors after their interval on boot. The scheduler runs relative to boot time and does not align intervals to fixed times or to a global clock.

Results

To evaluate the performance of vector processing in Table 1, the vectors' outputs were compared to times when the schedule was expected to run. This excludes downtime from the out-of-disk-space event.

Table 1

Vector success, evaluated per interval

10 min	30 min	1 hour	4 hour
96.6%	98.8%	95.0%	90.5%

For longer time intervals, the system was more likely to be interrupted by a system-off event.

Learnings

The scheduler worked well and reliably as expected.

One of the consequences of the scheduler restarting after the system is turned on is a significant increase in the the space between run times for long period vectors. All vectors should be run frequently, even when the window of data the vector evaluates is very long. The size and compute savings of running infrequently is not worth the tradeoff of having fewer data points.

The scheduler is dependent on a persistent clock. It's important to ensure the edge device has access to a correct clock on every boot.

Evaluation Result 7

Catch Count Vector

Success Criteria:

Edge computing is able to compare AI, eLog data, and other data at the level of catch count per set.

Success Metric:

Verify that the edge project created a result based on these two value sets. Possible values: success, fail, intermittent

Results: Fail

Details

The the initial intention of the Catch Count Correlation Vector was to asses the relationship between catch counts reported in the elogs and catch counts recorded by AI and provide a score based on the accuracy of the elogs. Evaluating elog/AI count relationship for accuracy requires some expected value to evaluate against. Without initial modeling to define the expected relationship, there is nothing to compare the at sea results to. Additionally, as elog catches were reported in one batch at the end of the haul, AI counts could only be compared to the entire haul.

The vector developed runs a Pearson Correlation on AI Catch Counts vs elog haul times (using 1.0 as the value during the haul and 0.0 outside of haul times) from the last 24 hours. A high correlation outputs a low vector score. Conversely, a higher vector score is produced when there is little correlation between elogs and AI catch counts.

Results

Two significant issues impacted the accuracy of the vector calculations. Firstly, network delays caused some elogs to be excluded from the vector's calculations if the elogs were received more than 24 hours later. Secondly, in several instances the absence of elog data resulted in the vector producing no result. This was due to the inability to calculate the Pearson Correlation when elog values were uniformly zero, as there was no variability to correlate with the AI Catch Counts.

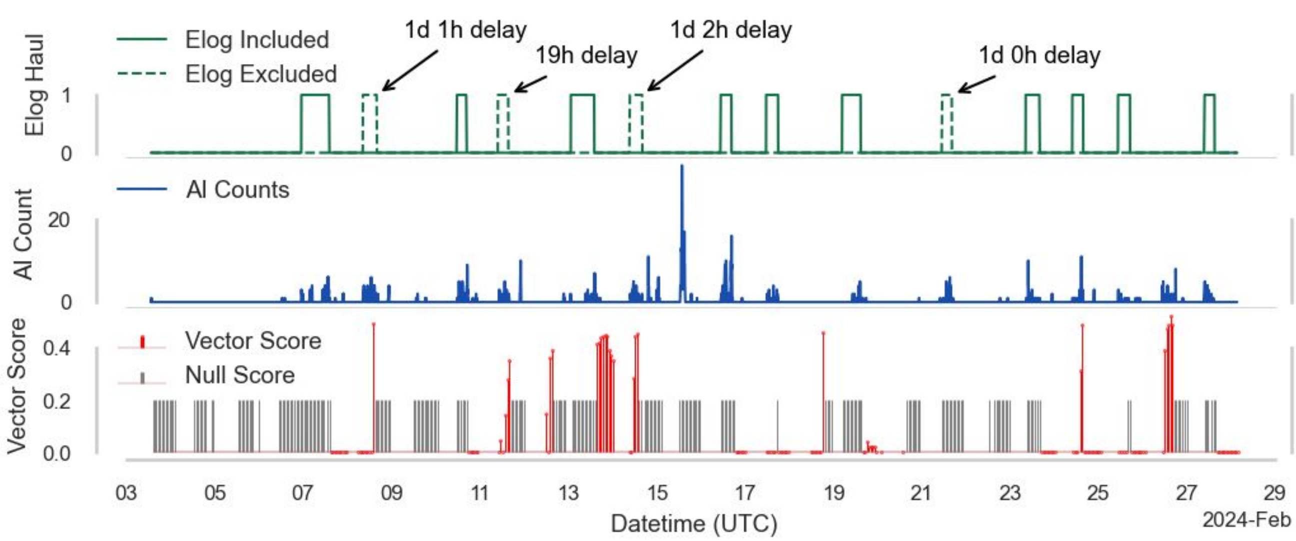


Figure 1. The Catch Count Vector score and the data included in its calculation, for Vessel B, trip 2. Excluded elogs were the result of network delays, causing data to be received outside the 24-hour window used for the vector calculations.

Catch Count Vector: Learnings

LEARNINGS

To produce vector score based on correlation between AI catch counts and reported eLog counts, incremental catch reports from the eLogs and a baseline model for the expected relationship are necessary. To address potential delays in the data, a practical solution would be to include a larger time frame in the calculations.

Evaluation Result 8

Edge to Cloud

Success Criteria:
Data is sent to the cloud and processed in a data lake for data analysis.

Success Metric:
Verify that the data is in S3. Possible values: **success, fail, intermittent**

Details

The edge system had internet access through satellite while powered on. As discussed in section 2, this project selected a data plan larger than what a mature project might need. The plan granted 1GB of data transfer each month, upload and download combined. While too low to transfer all video data, this limit is large enough to transfer a some selected video when deemed useful. The 1GB limit was also enough to transfer all internal edge data tables, with spare for updates, operations, and more. The 1GB limit was not enough to transfer the raw AI model output.

The cloud uploader ran every hour and selected all new data from 9 internal data tables and uploaded them directly to Amazon S3 as a CSV file. After a successful upload, the uploader marked its progress. The 9 data tables included: eLog data, gps data, vetcor output, video metadata, and a subset of all AI model output data. After uploading to the S3 bucket, the cloud platform automatically ingested the CSVs into a queryable Amazon Athena service.

Results

The uploader uploaded 10346 CSV files, totalling 255.046 MB. There was no evidence of any unrecovered upload errors.

Learnings

Perhaps the least novel aspect but still critically important piece of the system is the cloud integration for sending data. This works as expected, however the larger size of the AI model output (JSON) makes sending raw AI inferencing results impractical without a larger broadband account. There may be some ways to minimize and compress this data.

The edge system did not upload program logs from its internal processes. Future projects should strongly consider adding a cloud upload to its program/process logs because it is usefulness for operations and debugging.

At a high level, uploading edge computation outputs is analogous to lossy data compression. A very large data source (video) is fed to an algorithm (models and vectors) which outputs a much smaller representation of the original data. The original video cannot be reconstructed from the “compressed” output, but the models and vectors are designed to keep the most useful parts in a smaller size. In a scenario where upload limits are not a constraint (next-generation satellite internet, perhaps), this advantage for edge computing is lost and uploading video data becomes more attractive.

Evaluation Result 9

System Resilience

Success Criteria:

Successfully run trials with no direct intervention from support team.

Success Metric:

Record of trips that require support. Possible values: **success, fail, intermittent**

Results: Success

DETAILS

Below is a list of issues requiring technical support after initial installation. The list may not be exhaustive. The impact of each issue varies greatly, but they are broadly categorized as major and minor: major define as the system on the boat cannot function or accomplish project goals until the issue is resolved and minor defined as the system can function and accomplish project goals, but with some reduced function.

RESULTS

Table 1

List of issues

	Impact	Time to Fix	Date	Remote solution?
undesired data usage (remote desktop)	major	6 days	7/11/23	yes
undesired data usage (ipad)	minor	5 days	7/17/23	yes
power issues at sea	major	22 days	7/13/23	no
bad video recording config	major	13 days	8/15/23	yes
camera positioning	minor	4 days	8/16/23	yes
camera failure	major	7 days	9/19/23	no
software update	minor	2 days	10/2/23	no
computer failure	major	7 days	11/16/23	no
camera failure	major	2 days	11/27/23	no
camera mount bent	minor	2 days	12/21/23	no
software update	minor	3 days	12/27/23	no
edge out of disk space	major	6 days	1/5/24	yes
video transfer issue	minor	16 days	2/4/24	yes
ipad charging cable broken	major	2 days	2/6/24	no

LEARNINGS

Pre-trial trips required a lot of intervention, primarily because this was a new fishery with no EM, eLogs, or Sat data experience. Other trips still required some monitoring and adjustments. More hardening would be required for better automation.

Three boats were at sea for a combined 486 days since system installation. With 6 cameras, 2 camera failures, 3 edge computers, and 1 edge computer failure, the worst case MTBF* (Mean Time Between Failures) for primary equipment is 151 days. The project ended with working equipment, so the actual MTBF is likely much higher. Not enough data to classify failures as "infant mortality".

***MTBF** is a measure of the reliability of a system or component, indicating the average time between failures. For this project, MTBF is used to assess the reliability and expected operational lifespan of the equipment used in electronic monitoring and data collection.

Evaluation Result 10

Key Event Detections

Success Criteria:
Be able to detect key events with only on-vessel technology and data (fishing activity, missing elogs)

Success Metric:
Comparison of data from edge to EM analysts list of events.
Possible values: **success, fail, partial**

Results: Success

Details

The goal of this evaluation is to determine if "Key Events" can be detected using on-vessel technology. For this evaluation, Key Events refer to **fishing events** (sets and hauls) and observations from BV analysts of events that deviate from regular fishing activities. These observations have been aggregated from the review notes, and organized into these categories:

Unreported eLog: the fishing event was missing from the elogs.
eLog incorrect: the start and end times of fishing events were incorrect in the eLog.
No Video: There is video available
Camera Hidden: Video is available but view is blocked.
Haul Break: Haul is stopped, usually because of gear issues but also for breaks or other operations.
Abnormal Catch: something about the catch or catch amount is abnormal
Abnormal Haul: The haul as a whole is abnormal
Other Gear: Other gear was used aside from the usual long line gear
SSI Interactions: Interactions with species of special interest
Transhipment: A transhipment occurred.

On-vessel technology encompasses the on-vessel devices and their resulting data, including AI models run on the edge, metadata from the EM (Electronic Monitoring) system such as stored video and system status, GPS, and eLog data. While some of the detection methods used in this evaluation were not computed on the vessels, all have the potential to be implemented on the edge device.

Results

The Key Event categories that will be evaluated for detection in this evaluation are fishing events, unreported or inaccurate eLogs, haul stops, gear issues, and abnormal hauls.

Camera covering events and SSI (species of special interest) interactions were not detectable with the current set of data. However, this could be incorporated into the categories of object classification in future AI catch count models. Identification of other gear usage or transhipments were also not possible.

Table 1. *Number of Analyst Observations by Category for all six trial trips.*

Category	Observations
Haul Break	76
No Video	40
Camera Hidden	12
Other Gear	6
No eLog	6
eLog Incorrect	5
Abnormal Catch	4
Gear Issue	3
Abnormal Haul	2
SSI Interaction	3
Transhipment	1
Other	2

Results Cont.

Fishing Events

While further training and algorithm fine tuning are required to obtain accurate catch counts, the results produced by the AI models still provide valuable insights into when fishing activity occurred. Using AI counts as input and haul times recorded by BV as the "source of truth" a classification model was built to label 5 minute intervals* as "haul" or "no haul". The AI model was trained on the data from Vessel A, trip 1 and tested on Vessel A, trip 2 and trip 3. The performance values from the test results are displayed in Table 2 and Figure 1.

Table 2

Model Performance Metrics for Vessel A, Trip 2 and Trip 3

Metric	Trip 2	Trip 3
Recall	0.70	0.47
Precision	0.81	0.83
Accuracy	0.87	0.87

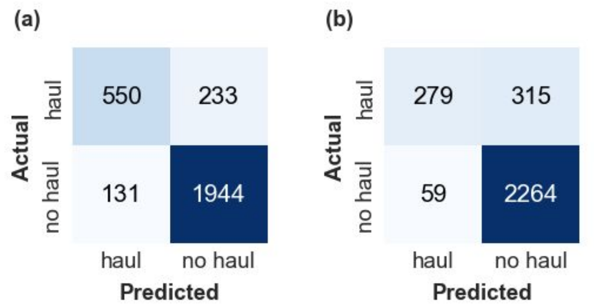


Figure 1. Confusion matrix for haul classification on (a) Vessel A, Trip 2 and (b) Vessel A, Trip 3

When examining the predicted hauling events in comparison to the analyst hauls, it is evident that, in aggregate, the predicted hauls are well aligned with the analyst hauls, as seen in figure 2 and 3.

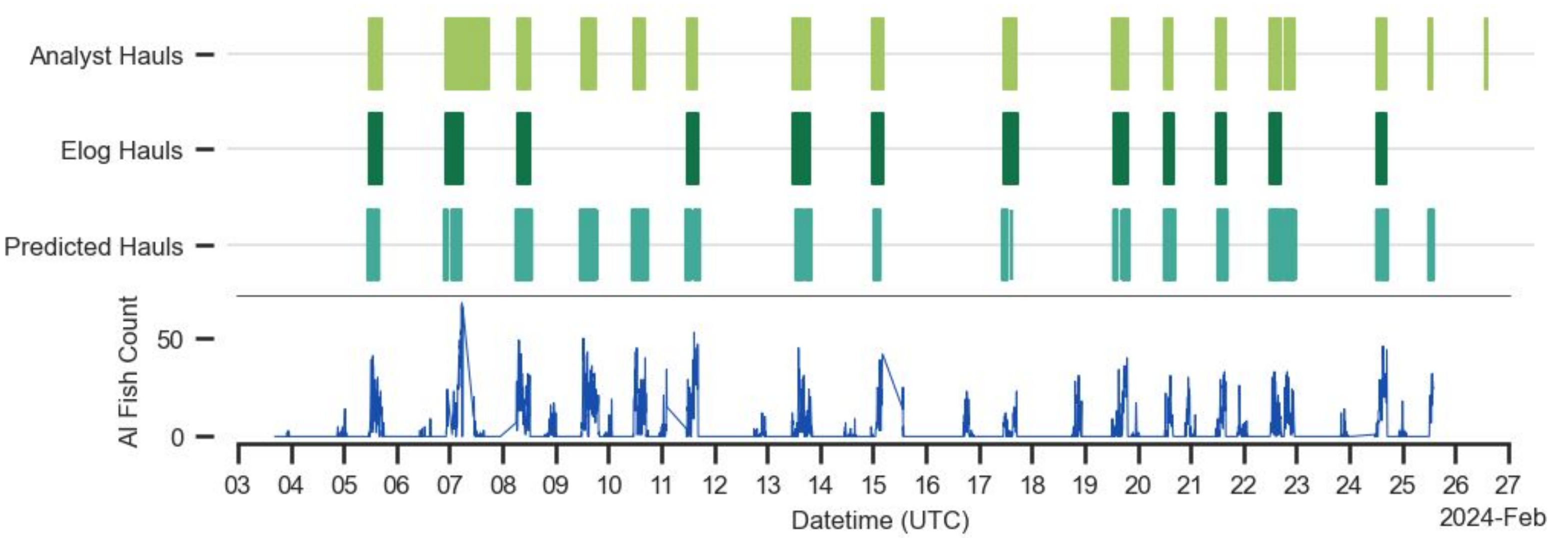


Figure 2. Comparison of Trip 2 Haul Events: Analysts, E-Logs, and Predicted Hauls with AI Fish Counts Used for AI Model Input.

*Five minutes is the interval at which the AI model analyzes the video and outputs results.

RESULTS cont.

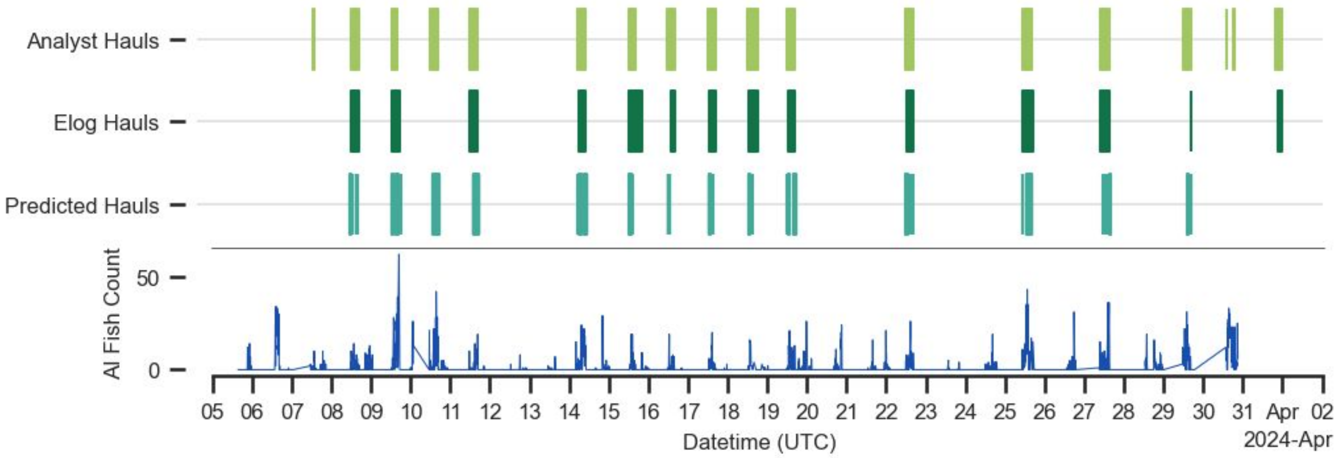


Figure 3. Comparison of Trip 3 Haul Events: Analysts, E-Logs, and Predicted Hauls with AI Fish Counts Used for AI Model Input.

Unreported or Inaccurate eLogs

The evaluation of "eLog Behavior Risk Assessment" details the efforts done on the edge device to determine the likelihood of a missed elog. For the purposes of detection, the previously discussed haul classification model can also be used to identify unreported e-logs. Figure 2 and 3 demonstrate that in instances where e-logs are missing, the haul classification model successfully predicted hauls during those periods.

Identifying inaccurate e-log times is more challenging, as the predicted haul times are often very close but not exact. As the AI model uses the AI fish counts as input, the false negatives occur during hauling periods when the AI fish count was low, and false positives occurring when there are spikes in fish counts outside of the hauling period. This is likely the result of fishing remaining on deck and in view of the camera after hauling is completed. However, it seems likely that this method could be used to detect larger discrepancies in elog times, especially if there fish being caught during the unreported time.

Haul Stops, Gear Issues, and Abnormal Hauls

One of the most common observations noted by analysts was a stop during hauling, often to resolve gear issues such as tangled lines. Other observed reasons for haul stops were for cleaning or breaks. Stops ranged from a couple of minutes to a few hours.

Upon first glance at the results from the classification model previously discussed, it appeared that there was a relationship between the gaps in the haul predictions and the haul stops recorded by analysts. Figure 4 illustrates a few of the sets, shown in (a),(b), and (c), where the haul stops seem very much in line with the prediction gaps. However, as demonstrated by (d) in figure 4, there were several other sets where there did not appear to be a visual relationship.

Key Event Detections: Results & Learnings

Results cont.

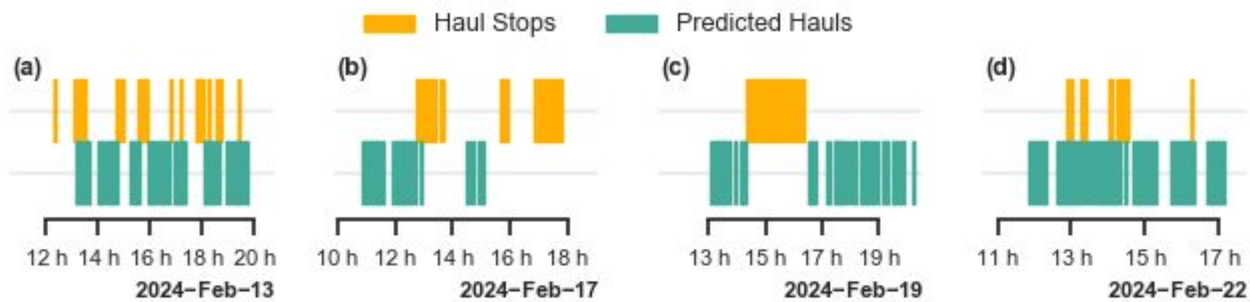


Figure 4. Select set comparison of haul stops to gaps in predicted hauls. **(a)** Set 7 was labeled as "a difficult [haul] because of numerous knots." There were 11 stops in total, 8 of those were for knots. **(b)** Set 9 included a stop for a lunch break, followed by stops to resolve line knots. **(c)** Set 10 had 3 haul stops in a row, the last for a lunch break and to fish with additional gear. **(d)** Set 13 had 5 total haul stops for knots, cleaning, and a lunch break.

When examining the overlap of hauls stops with haul prediction gaps in aggregate, using Pearson correlation and Chi-squared tests, no significant relationship was found. The venn diagram in figure 5 illustrates the total time overlap. For haul stops, 44.5% of the duration of all haul stopping events lined up with the gaps in the haul predictions. While this doesn't provide any major insights, it does suggest that a classification model, like the one developed here, can increase the value of the AI output, by recognizing patterns in fishing activity. Additional training could be done to include haul stops as a classification.

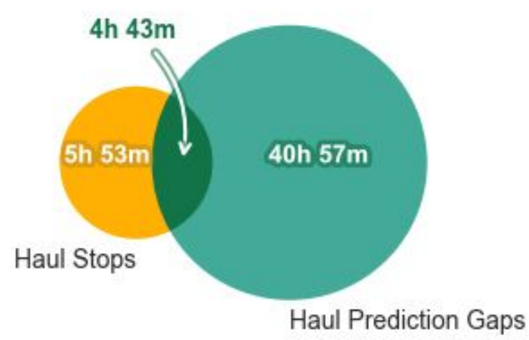


Figure 5. Co-occurrence of haul stops and haul prediction gaps, compared to the total durations of each occurring independently.

Learnings

This evaluation highlights the potential for enhancing the on-vessel AI catch count models through simple classification models. Additionally modeling on the vessels can be used to recognize patterns in the output from the catch count models, and classify key events and irregular behaviors. Additional classification can guide analysts to specific segments of trips, making the review process more focused and efficient. A classification model such as this could also be used to detect and trim EM video around fishing activity, reducing transmission needs and simplifying the reviews process.

The model demonstrated here, trained on only one trip and without hyperparameter tuning, provides promising evidence of future capabilities. While these assessments were not conducted on the vessel, on-vessel technology is already capable of doing so.

Evaluation Result 11

eLog Use Behavior

Are captains using the elog system as intended?

<u>Success Metric:</u>

Verify elog set times and catch counts with results from EM analysts. Possible values: **success, fail, or partial**

Details

The start and end times of sets and hauls are recorded in the log by the captain. Species and catch counts, including target and bycatch, are also recorded by captains in the elogs. Upon completion of the each trip, the video was reviewed by a human reviewer at Bureau Veritas (BV), who recorded the set times and catch counts observed from the recorded video.

Results

Of the 83 sets recorded by BV reviewers across 6 trips, 71 were recorded in the Elogs. Of those 45 sets, the deltas between start and end times were fairly low. Figure 1 displays the distribution of those deltas in minutes. The outline of each box represents the interquartile range (IQR) and the center line represents the median value.

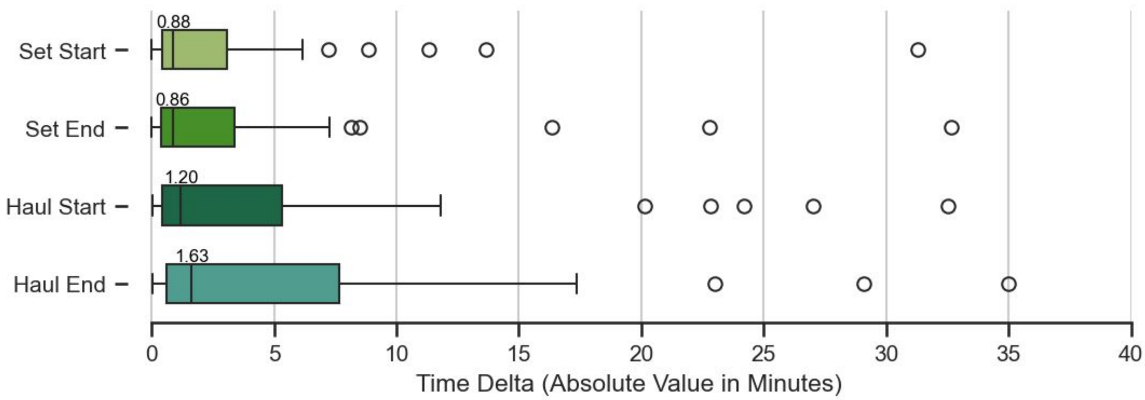


Figure 1. Distribution of the time deltas discrepancies between eLogs and BV reviewers.

For all except Haul End, the IQR of the elog time was within just a few minutes of times reported by BV. Haul End times had a larger range of values, with a few outliers exceeding 60 minutes.

Although captains had the ability to record catches incrementally as they came in, all of the catch counts were reported at the end of the haul. The deltas between elog and BV catch counts are represented by figure 2 on the right. Negative values mean the elog count was less than the BV count. The IQR is between -4.5 and 0, with a median of -1 and a mean of -2.07.

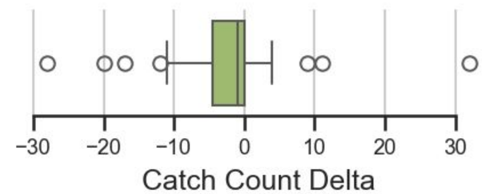


Figure 2. Distribution of the catch count deltas between eLogs and BV reviewers.

eLog Use Behavior: Learnings

Learnings

Early on there was a request to increment catches as they came in, however captains are not using it in this way. Post project discussions with captains and vessel owners indicate that recording catch incrementally is difficult to do, as their full attention is needed on the hauling activities. This aligns with findings from the deltas in Haul End times, which were generally submitted several minutes later. Still, the overall consistency between the start and end times of both sets and hauls, indicate that captains were able to record these events with relative ease as part of their workflow.

Evaluation Result 12

eLog-Based Prioritization

Success Criteria:

eLog behavior can be used to help determine prioritization (i.e., are captains using the system).

Success Metric:

Systems check and supporting data. Possible values: success, fail, or intermittent

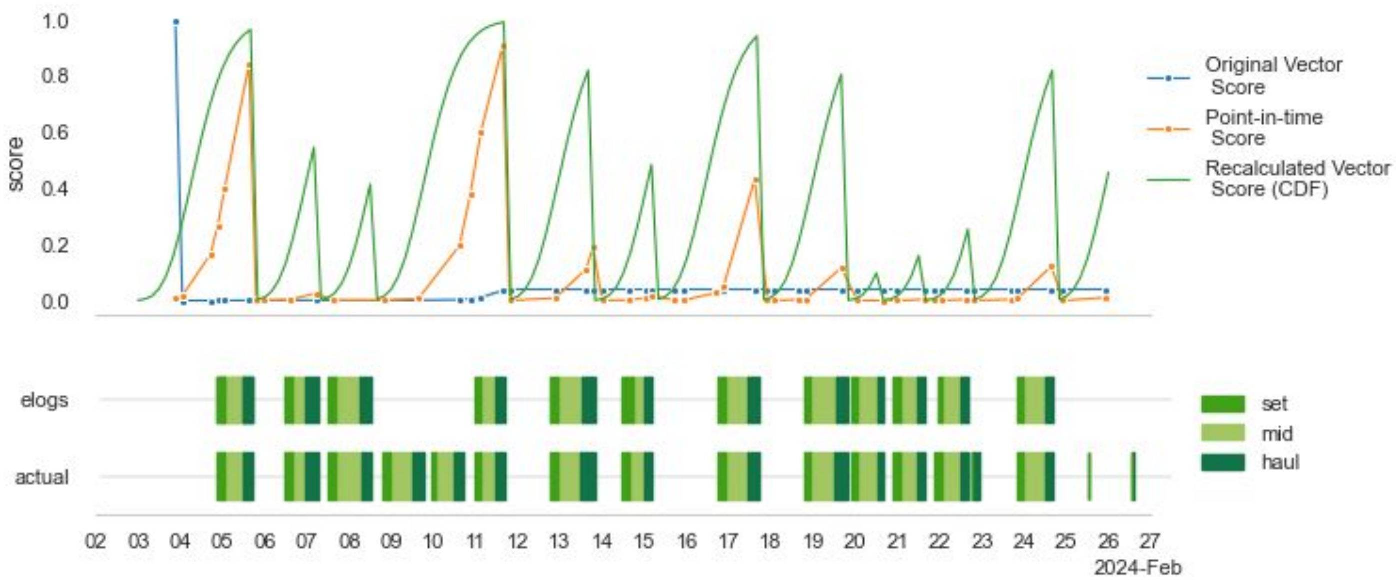
Results: Partial

Details

The start and end times of sets and hauls are recorded in the log by the captain. The elog system shares the details of the set and haul at one time, once the haul is marked as finished on the ipad. The intention of the Elog Time Gap Vector is to assess risk based on how long it's been since the last logged set/haul. The elog system shares the details of the set and haul at one time, once the haul is marked as finished on the ipad. The vector uses a logistic function that hits its midpoint at 60 hours and peaks after about 3 days. On the edge device, the vector is run every 4 hours. Each time it runs, it re-evaluates all of the previous points based on the events it has received from the elog since the last run, and outputs the max score from the entire trip.

Results

The results of the Elog Time Gap Vector were mixed. The figure below is an example from one trip. The blue line, represents the Original Vector Score, calculated at sea, for a completed trip. The lack of peaks is a result of that re-evaluation step, when all of the elogs have been submitted. The orange line, Point-in-time Score, is a rerun, to demonstrate how the vector is assessing risk at each of these points when it has not yet received the next elog. The green line, Recalculated Vector Score, is based on a cumulative distribution function (cdf) calculated from the data we have post-project.



Results Cont.

On Feb 9 and Feb 10 there was a gap in elogs. There Point-in-time score (orange) displays a large spike during this gap, yet the resulting Original Vector Score (blue) displays only a small increase following this gap. This could be the result of the vector giving a smaller weight to this time gap, or a bug in the calculations. The Recalculated Score (green) produces a higher score earlier than the orange line.

Learnings

Vector outputs on the edge should not be aggregate functions of data across the whole trip. Aggregation functions in vectors should be run on rolling windows during the trip. Aggregation across the entire trip can happen off of the edge.

Although the Point-in-time vector score resulted expected peaks during elog gaps, the resulting Original Vector Score did not accurately represent the gap that had occurred. The Elog Time Gap Vector calculations can be improved by using the data gathered from this project to create a function more representative of the data, like the Recalculated Vector Score.

Evaluation Result 13

Remote Support

Success Criteria:

When there are system issues they are resolved without having to wait until vessels are in port.

Success Metric:

Review support activity for resolutions that did not require action at port. Value: number of trips that did not require in port resolutions (not including standard EM data).

Results: Success

Details

The system failures, listed System Resilience, were each resolved independently. Each resolution is classified as a "remote" resolution in a separate column.

Results

At a high level, 6 out of 14 issues were resolved fully remotely. In 5 of the remote resolutions, the problem was fully encapsulated in software, thus the resolution was resolved with remote management. One issue was camera positioning. We resolved the issue by radioing the captain.

Of the 8 issues that required in-person resolution, 6 of them were hardware issues of some kind. The power issue was the longest time to fix, with the most back-and-forth troubleshooting, and with the most expensive resolution. The issue was resolved by installing a new solar panel on the boats.

The "out of disk space" issue deserves special mention. Thanks to linux's design and resilience, the edge system was bootable, connectable, and recoverable fully remotely while having zero available disk space.

Learnings

Remote support is critical and is part of the current landscape of EM systems. Even with automation, remote support will be needed. Supporting a complicated set of systems that all produce large volumes of data may not be practical initially for vessels with very low data plans. More robust systems with health alerts could help automate and reduce remote system monitoring.

Remote Software Updates

There are 2 issues labeled "software updates" that seem resolvable remotely, but in practice they required an in-person technician. The software updates included full AI vision models, approximately 15GB of data each. These updates were too large to be transferred over satellite, so the updates were loaded onto USB storage devices and plugged in in-person.

Smaller software updates are not listed in the issues table. Git logs show 53 commits after the edge computers were installed, and before the primary trials started. These 53 commits were all transferred to the edge computers remotely over the satellite connection.

In conclusion, the size of AI models is the only significant barrier to completely remote software updates.

Evaluation Result 14

EM Data Transfer

Success Criteria:

The data is sent from local network to a server accessible by the EM provider.

Success Metric:

Compare number of days to upload to EM analysts to average number of days to mail and customs. Value: **number of days difference**. Positive number is success.

Results: Success

Details

Shipping physical hard drives to the EM provider involves coordinating the removal and replacement of drives on vessels, as well as managing the logistics of shipping. This process is time-consuming, tedious, and expensive. On two occasions, technicians ran out of spare drives, highlighting the inefficiencies of this method.

Before the trial trips, the process was switched from shipping physical hard drives to transmitting data over the internet. The initial steps were the same: the vessel arrived at shore, and a technician removed the hard drive, replacing it with an empty one. The technician took the hard drive and connected it to a computer on shore where the data was transferred to the EM provider. Once the upload was complete and the data was delivered to the EM provider, there was an interim step for data conversion on the EM provider side. When this was complete, the hard drive was erased.

Starting on the second trial trip, an internet transfer relay was added to increase performance.

Results

The initial internet transfer from Costa Rica to France took approximately 14 days per trip. While technically fast enough, this time frame did not leave room for any unexpected issues or errors. Both teams in Costa Rica and France had anticipated much faster performance given their network connectivity, making the slow internet speeds unexpected. After introducing a transfer relay through a server in the US, transfer times significantly improved, reduced to about 2 days per trip.

Table 1

Data Transfer Speeds

Transfer Route	Upload Speed
Costa Rica to France	1732 Kbps
Costa Rica to US Relay	62038 Kbps
US Relay to France	5901 Kbps

Learnings

EM electronic data transfer can greatly reduce the time to get data to analysts to review. Initial issues included slow transfer times from CR to France due to a routing issue through slow points. Routing the data to a server in US East then to France sped up the process greatly.

When transferring data over the internet, 3rd party internet companies (ISPs) are sometimes automatically added as hops along the way. For international transfers, these 3rd party hops are a certainty. Unfortunately, 3rd party ISPs provide these hops as “best effort”, which often makes them deprioritized and slow. By adding a transfer relay, 3rd party hops are effectively replaced by the ISP of the transfer relay. For international transfers, adding relay points may be the only way to improve transfer speeds.

The interim step of waiting for data conversion was necessary because electronic data transfer was a new development for this EM provider. It is expected that this step can be optimized in future projects.

Evaluation Result 15

Incentive Evaluation

Success Criteria:

Incentives motivate vessel participation and compliance to project guidelines.

Success Metric:

Feedback from owners and captains, EM results demonstrate compliance with instructed practices.

Results: Success

Details

To encourage project participation and guideline compliance, participating vessel owners and captains were provided with a variety of incentives, In addition to economic incentives, participating vessels received upgrades including solar panels, generators, and internet hardware that will stay with the vessel post project.

Results

Evidence to support the assessment of these incentives comes from the regular communications with captains and vessel owners. The captains have indicated that the use of data connections at sea, specifically for WhatsApp text communications, is incredibly valuable. They are using it to keep in touch with families and to get updates on conditions.

Another powerful motivator, is the Comms video, which highlights the positive impacts EM can have on the fishery. This video gives vessel owners the opportunity to share their reasons for adopting EM with the fisheries community, where many are still critical.

The three incentives—internet on the vessel, $250 per trip for the crew, and internet hardware that stays with the vessel post-project—helped alleviate initial fears about "opening the door to EM" during the first few months after installation.

Learnings

There are several win-win aspects to the project that serve both the project's operational needs and the participants. Vessel enhancements, are kept by the vessel owners, creating value long term. Internet connectivity, used for the transmission of data, supplied captains a way to communicate updates and with families while at sea. Video, promoting the benefits of EM, also supports participants in sharing their experience with the community, enhancing understanding.

These incentives were seen as valuable by the participants and also helped mitigate opposition from other vessels that believe EM will negatively impact their fishery. An incentive model is recommended for the first phase of similar projects to reduce friction, increase alignment, and make EM a "win" for both captains and crew. Additionally, the project's mutual benefits, including vessel enhancements and improved communication, highlight the potential for EM technologies to improve industry practices and individual success.

Evaluation Result 16

Edge Hardware

Success Criteria:

Edge devices can be compared on performance and usage

Success Metric:

Review the performance of two different edge devices on their capabilities and performance. Determine recommendation of future projects.

Results: Success

Details

This project utilized two different Jetson edge hardware devices for a couple of primary reasons. The powerful newer model (Jetson Orin) was used in case the standard model (Jetson Xavier) was not sufficient for new models. This also provided the opportunity to do an analysis of what type of hardware will be sufficient for edge processing of AI and prioritization scoring

Results

The Jetson Xavier NX was a good performer that met the expectations for this project. AI partners did not feel unduly constrained by the hardware performance.

Learnings

Working with the AI model partners and collaborating on the specifications for the hardware device was critical to the success of this project. Ai.Fish confirmed early on that the Jetson Xavier NX was sufficient to run their AI models.

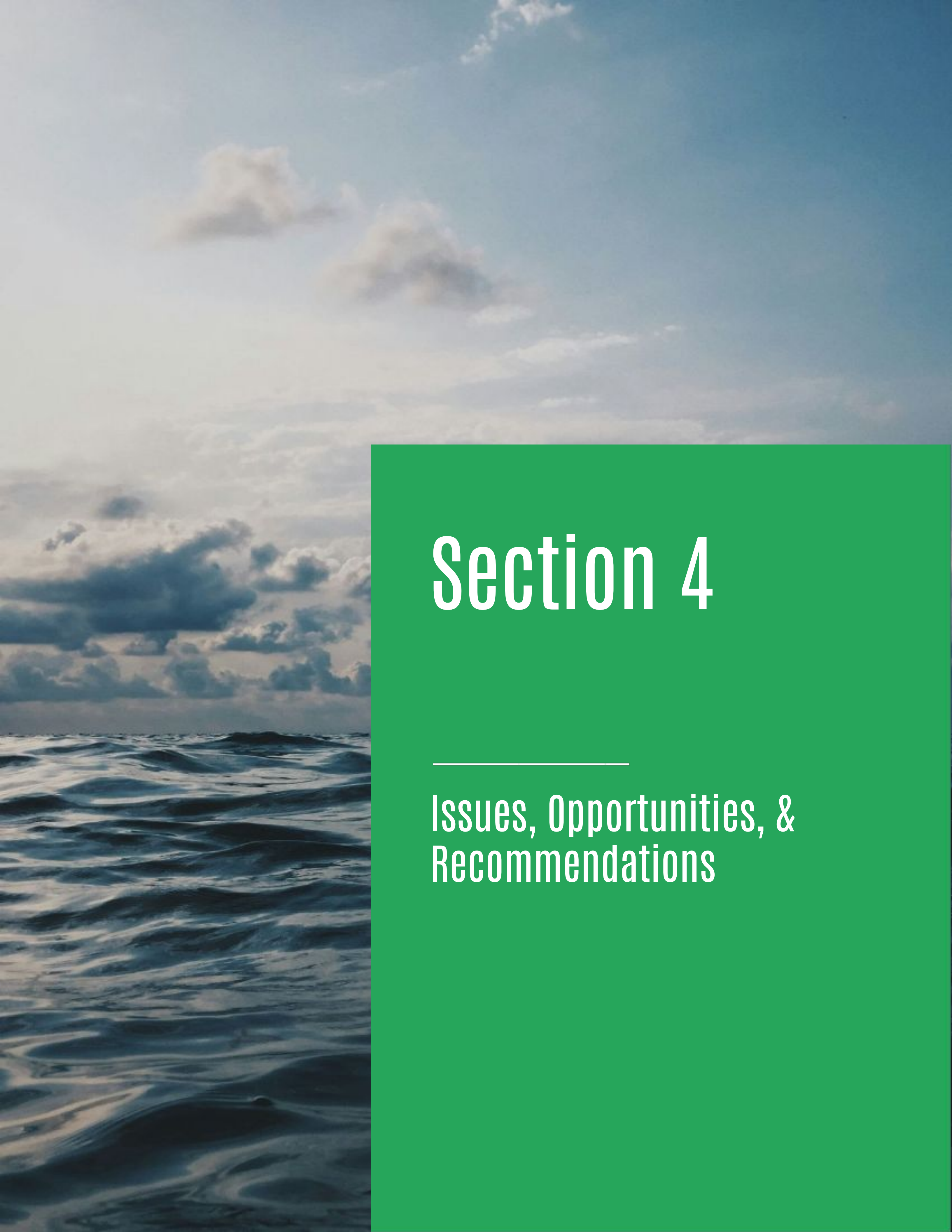
Given the nature of computing advancements, future projects should not lock-in to Xavier NX, but should follow the Jetson generational upgrades . Older AI compute devices or devices under 5 watts are not suggested for future projects.

Future projects should always collaborate with the AI model provider regarding hardware. Future projects could require more powerful hardware due to the following:

- Generational AI model improvements might use more computing as a baseline
- Significant new features in the model might use more computing. For example, in one AI model the detections we not the most computational demanding, it was tying detections together into tracked fish. Features like classification in a future project will likely require more compute power.
- Adding a new models for distinct project features might require multiple AI models to run concurrently. Things like pose-detection for cutting lines off the side, or GlobalFishingWatch's 2018 model for turning GPS data into fishing activity, or prediction models for fishing activity detection.

Learnings Cont.

This project never used both models on the same physical device at the same time. If a future project requires running models concurrently, there needs to be significant planning into how to time-share the GPU. AI Models (and their underlying frameworks) are generally built assuming they have full control of GPU resources and can use all available RAM. They're also not time bounded. Runtime targets for AI models are generally engineered by trial-and-error which could be a risk in future projects.



Section 4

Issues, Opportunities, & Recommendations

SUMMARY OF CONCLUSIONS

After several months of trials at sea, we have evaluated the primary and secondary goals of the project and determined the following conclusions:

Potential for reduced EM program costs, long term

Early indicators show that to get Edge prioritization to a scalable solution will require significant investments in edge and AI development, however many of these benefits will likely be transferable to other fisheries, potentially reducing the overall costs over a longer period of time. There may be an opportunity to do another study that includes edge based prioritization of EM review efforts in a fishery with a more mature EM program (which would require less effort and costs).

Reduced amount of time to get the highest priority data to where it needs to go

Early indications show that this is probable. Highly prioritized events can indeed be selected with edge analysis and sent to analysts for early review (via Internet or prioritized shipment of drives). This may also reduce the amount of data that needs to be sent for review, thus reducing the time it takes to send the data.

AT A GLANCE

This project has shown that analysis on the edge holds a lot of promise, though it requires a lot more investment in technology and program development in order to be a tool that can be deployed at scale.

Areas that show success today include:

- A centralized module and data platform to process data from multiple systems and partners
- Successfully running AI models from multiple partners.
- Near real-time analysis
- Selected transmission of important data to review while at sea
- Added eLog functionality to capture valuable data points

Areas that require further development and investment:

- AI model development for catch counts
- eLog UX and data improvements
- More detailed program guidelines on determining prioritization

SUMMARY OF CONCLUSIONS

Creating New Data Sets

Evaluations have shown that it is possible to process complex data from multiple systems and partners to determine new data elements using edge systems. While programs do not currently exist to use edge prioritization data for fisheries management purposes, edge systems create new capabilities that fishery managers and other stakeholders will need to assess to see how they may be able to use edge analysis to their advantage.

Keeps Providers and Participants Engaged

Monitoring efforts including analysis of eLog usage appears to be a promising element affecting how participants behave. Additional pilots could be done in fisheries with existing eLog programs to see if edge-based analysis significantly affects a captain's eLog behavior.

Impacts on Traceability Programs

While edge analysis may not provide accurate counts yet, edge prioritization scoring could impact traceability programs.

Comparing detailed eLogs with edge analyzed data and prioritized EM review can be used to add significant data points to traceability data, adding much needed first mile credibility. Prioritization efforts would need to be improved and tested before this would be a reliable data source, however it could help bridge the gap between EM and traceability programs.

ADDITIONAL LEARNINGS	
VESSEL TRIP LENGTH	The time that vessels are out at sea is highly dependent on the fishing conditions. Several times during this project, vessels were at sea for much longer than anticipated because the fishing was so bad they did not have enough money for fuel to get back. The time they are in port may also be variable due to vessel repairs and updates.
VESSEL CAPTAINS	Captains are a significant variable in project operations. How they use the eLogs, their fishing practices, and even their tenure are all elements that create a more volatile operational environment.
EQUIPMENT REDUNDANCY / SPARES	As might be expected, several devices failed during the trip including two camera controller boards and the eLog (iPad) charging cable.

ISSUES & OPPORTUNITIES

OVERVIEW

This project highlighted several important issues and opportunities in creating edge analysis systems on vessels , as well as challenges to executing a research and development proof of concept in fisheries with no pre-existing EM programs.

CHALLENGES

The following is a list of some of the potential challenges of running a similar project, especially in a new fishery:

- Introducing the concept of monitoring to owners, captains, and crew.
- Logistics related to the installation of hardware, as well as the vessel infrastructure to support it, (i.e. communication and power supply).
- Creating a timeline that allows for the iteration of models and algorithms.

OPPORTUNITIES

This project has numerous side benefits and we have identified a few key broad opportunities in running similar future projects.

- Positive introduction of EM to fishery managers, vessel owners, and captains and crew.
- Solving data transmission of video not required but will facilitate change
  - The amount of human work needed at port
  - The time to get to an analyst

ON THE HORIZON: TRUSTED TRACEABILITY

Traceability in commercial pelagic fishing refers to the ability to track and trace the movement of fish from the point of capture to the final consumer. It involves collecting and sharing key data elements throughout the supply chain, such as:

- Vessel information
- Fishing locations
- Catch date and methods
- Species interactions
- Species and quantity caught
- Handling and storage conditions
- Chain of custody information

While traceability is an important tool in sustainability, it often lacks verifiable information at the time of species interactions.

Traceability and EM programs are rarely integrated together, even when they are both installed and operating on the same vessel.

There is an opportunity to explore the possibilities for near real-time EM validation and verification of traceability data.

Traceability Programs

There are a few common traceability programs that aim to help reduce IUU and increase sustainability by tracking seafood product through the supply chain including:

The Marine Stewardship Council (MSC): An international non-profit organization that sets standards for sustainable fishing and seafood traceability, providing certification for fisheries that meet their criteria.

The Global Dialogue on Seafood Traceability (GDST): A global platform that develops industry-wide standards for seafood traceability to ensure interoperability and efficiency across the supply chain.

ISSUES & OPPORTUNITIES SUMMARY

PRIMARY ISSUES AND OPPORTUNITIES	
Issue 1 **Power Management**	How do we increase the power or reduce the use of power so that equipment can be used when needed and the safety of crew is not jeopardized?
Issue 2 **Crew Privacy**	How do we protect the privacy of the crew and still obtain relevant and trusted data.?
Issue 3 **Camera Settings**	Resolution of training video may be lower than desired leading to poorer performance of AI models.
Issue 4 **Camera Mounts**	In order to get the best camera angle, cameras must extend past the outside of the boat and point in, however, due to physical conditions, this can put the camera in danger of being knocked around by other vessels and equipment.
Issue 5 **eLog Usage**	Captains did not always use eLogs to record sets (reported by the EM analysts)
Issue 6 **AI Result Output**	AI results create large files making it difficult to transmit raw results over data connections at sea.
Issue 7 **AI Catch Count Results**	AI models that ran on the edge device were not able to reliably count fish with confidence to be used effectively to compare with eLog counts.
Opportunity 8 **Cloud Data Platform**	The cloud data platform is an ideal place to store all data from this project, including raw video and EM results. The data lake can scale easily and the platform can be extended for new features and stakeholders without expensive trials and research.
Opportunity 9 **Data Sharing**	The EM data captured and sent to the cloud in the edge project could be added to other EM data sources to enrich other systems such as the EM data platforms
Issue 10 **Automation**	This proof of concept was not intended to be completely automated and cannot currently scale to be hands off for operations.

ISSUES & OPPORTUNITIES SUMMARY

PRIMARY ISSUES AND OPPORTUNITIES (cont)	
Issue 11 **Key Event Detection**	Key events can be difficult to infer and/or confirm from current sensors and AI models.
Issue 12 **eLog Features for Captain Participation**	Captains are not recording catch events as they happen but rather later in aggregate losing fidelity of catch times to correlate with AI and EM analysts.

Issue 1

Power Management

How do we increase the power or reduce the use of power so that equipment can be used when needed and the safety of crew is not jeopardized?

OPTIONS

- Perform a detailed study of power usage on small vessels like these.
- Add secondary power generation and storage
- Add advanced power saving features such as sleep modes and power saving modes

<table>
<tr><th>Option 1</th><th colspan="3">Perform a detailed study of power usage on small vessels like these.</th></tr>
<tr><td>Reason</td><td colspan="3">Power management and limitations on smaller vessels new to EM programs such as the Costa Rican Vessels is not well understood. Having a baseline power profile will help technical providers understand the constraints on board to make operating vessels safer. It will also help set EM program policies and guidelines (e.g., 24x7 monitoring may not be feasible)</td></tr>
<tr><td>Response</td><td colspan="3">• Determine hardware and systems necessary to record power profiles on the vessel.
• Solicit vessels to participate in project
• Run on vessels for one or two trips each
• Systems should be inexpensive and allow for transfer to other vessels for additional power profiling</td></tr>
<tr><td>Participants</td><td>• Vessel owners and operators
• Fishery managers
• Project sponsor
• Technical partner</td><td>Level of Effort</td><td>Medium
Power management recording is not new and there should be some solutions that would require less development.</td></tr>
<tr><td>Outcomes</td><td colspan="3">A clear set of power requirements for technical providers and fishery managers. This will reduce issues of power on smaller vessels that do not currently have experience with EM and other systems.</td></tr>
</table>

Power Management: Issues (cont)

<table>
<tr><th>Option 2</th><th colspan="3">Add secondary power generation and storage</th></tr>
<tr><td>Reason</td><td colspan="3">While exact power management specifications may not be well understood, adding additional power generation and storage is a simple (though perhaps more costly) solution.</td></tr>
<tr><td>Response</td><td colspan="3">• Create an estimate of power needed to run project systems
• Procure and install systems and train captains
• Monitor results</td></tr>
<tr><td>Participants</td><td>• Project sponsor
• Vessel owners and operators
• Installers</td><td>Level of Effort</td><td>Low-Medium
The effort is pretty low though installations can take a couple of days.</td></tr>
<tr><td>Outcomes</td><td colspan="3">Vessels that can operate systems safely for longer periods of time. Additionally vessels would have a secondary source of power should primary systems fail. This could improve the overall quality of working environment for fishers.

Additionally, with solar systems there could be an overall environmental benefit reducing the use of generators and gas.</td></tr>
</table>

<table>
<tr><th>Option 3</th><th colspan="3">Add advanced power saving features such as sleep modes and power saving modes</th></tr>
<tr><td>Reason</td><td colspan="3">Systems do not necessarily need to consume as much power, especially when little or no activity is happening</td></tr>
<tr><td>Response</td><td colspan="3">• Discuss issue with technical partners to look into costs and feasibility
• If feasible, create requirements for updated systems
• Include specifications when procuring new systems</td></tr>
<tr><td>Participants</td><td>• Technical EM partners</td><td>Level of Effort</td><td>Low for discussions
Undetermined for implementation.</td></tr>
<tr><td>Outcomes</td><td colspan="3">EM and related equipment on board may be able to use less power, putting less of a strain on vessel power systems. This may have a larger up front cost but an overall cost savings in the industry, especially on smaller and artisanal vessels.</td></tr>
</table>

Issue 2

Crew Privacy

How do we protect the privacy of the crew and still obtain relevant and trusted data.

<table>
<tr><th>Option 3</th><th colspan="3">Create a simple way to "pause" camera recording</th></tr>
<tr><td>Reason</td><td colspan="3">Privacy is a big issue on these smaller vessels in Costa Rica and for vessels new to EM, recording 24x7 can be a trust issue. The project utilized manual coverings for the camera, but that introduces other issues including possible bumping of the camera, and it was not recorded. Having an automated way to do this for the captain would make turning the camera off trackable and safer.</td></tr>
<tr><td>Response</td><td colspan="3">• Function should log action in a log - ideally with the ability to log a reason
• Bonus if could be an API and integrated with eLog</td></tr>
<tr><td>Participants</td><td>• EM Companies</td><td>Level of Effort</td><td>Medium
Explicit pausing of video should be tracked and logged, ideally with a comment from the captain.</td></tr>
<tr><td>Outcomes</td><td colspan="3">EM system that can pause easily to protect privacy and preserve power while still recording other data points such as GPS.</td></tr>
</table>

Issue 2

Camera Settings

Resolution of training video may be lower than desired leading to poorer performance of models.

OPTIONS

- Create a standard set of video specifications for both AI training and inferencing
- Establish metrics for video quality

<table>
<tr><th>Option 1</th><th colspan="3">Create a standard set of video specifications best practices for both AI training and inferencing</th></tr>
<tr><td>Reason</td><td colspan="3">There is often a disconnect on what EM systems provide and what AI developers want. Having a consistent guide and best practices may help standardize the process and remove missed assumptions and understandings.</td></tr>
<tr><td>Response</td><td colspan="3">• Meet with AI companies on considerations
• Draft AI video standards and best practices
• Review with EM companies</td></tr>
<tr><td>Participants</td><td>• AI companies
• EM companies
• Project Sponsor</td><td>Level of Effort</td><td>Low
Biggest issue is coordination</td></tr>
<tr><td>Outcomes</td><td colspan="3">Video standards for EM industry</td></tr>
</table>

<table>
<tr><th>Option 1</th><th colspan="3">Establish metrics for video quality</th></tr>
<tr><td>Reason</td><td colspan="3">Standards are essential, however having a clear set of metrics will make the standards more robust and based on data.</td></tr>
<tr><td>Response</td><td colspan="3">• Using the data from the trip, compare two AI models trained with lower res and higher res video to determine a significant differential threshold.</td></tr>
<tr><td>Participants</td><td>• AI companies
• EM companies
• Project Sponsor</td><td>Level of Effort</td><td>Medium
This requires applying data science and cooperation from EM and AI partners</td></tr>
<tr><td>Outcomes</td><td colspan="3">Data to determine what standard settings should be</td></tr>
</table>

Issue 4

Camera Mounts

In order to get the best camera angle, cameras must extend past the outside of the boat and point in, however, due to physical conditions, this can put the camera in danger of being knocked around by other vessels and equipment.

OPTIONS

- Research other programs, projects, and solutions
- Design or purchase new mount system to scale

Option 1	**Research other programs and projects to see what other solutions may be available**		
Reason	Camera mounts can be a difficult and bespoke process and lead to extra costs if there are issues, including installation delays and costs of fabricating custom mounts on site		
Response	• Interview various EM companies and installers. Include captains/owners to discuss what mounts may be better to enhance EM programs.		
Participants	• Lead Researcher • EM Companies • Installers	**Level of Effort**	**Low** The research should be fairly simple - this is intended to gather information only.
Outcomes	A guide to camera mountings in different fisheries and vessel types.		

Option 2	**Design or purchase standard swivel mounts for camera with locking positions**		
Reason	The mounts used in this project were custom made and did experience some issues. Having a standard set of industrial mounts that meet the needs of these smaller vessels could improve installation and operation and reduce costs.		
Response	• Based on research, determine if there is a solution available • Design a solution using easy to acquire parts with best practices guide of no out-of-the-box solution is available		
Participants	• EM Companies • Industrial designer (maybe)	**Level of Effort**	**TBD on research findings**
Outcomes	Easy to install moveable mount for consistent camera angles and to protect the camera in various conditions such as docking.		

Issue 5

eLog Usage

eLogs are not always used to record sets as reported by the EM analysts

OPTIONS

- User workshop on eLog UX
- Create a completely digital log and landing tool to reduce work for captains

<table>
<tr><th>Option 1</th><th colspan="3">Workshop with captains to determine why they enter catches at the end of a set and see if the UX can be improved to make them adopt new behavior.</th></tr>
<tr><td>Reason</td><td colspan="3">Fishers want a simple system for entering catch, and the better the data, the better we can determine prioritization - including the day/time of each catch.</td></tr>
<tr><td>Response</td><td colspan="3">• Create a user experience workshop that focused on making captains' lives easier and generating better eLog catch data</td></tr>
<tr><td>Participants</td><td>• Vessel owners
• Captains
• eLog providers
• User experience expert
• Data strategist</td><td>Level of Effort</td><td>Medium
Finding a solution may take some back and forth, trials, and compromises, as well as development work from eLog companies</td></tr>
<tr><td>Outcomes</td><td colspan="3">Updated eLog procedure that captures a catch when it happens.</td></tr>
</table>

<table>
<tr><th>Option 2</th><th colspan="3">Create a full featured eLog that includes landing reports to simplify work for the captains.</th></tr>
<tr><td>Reason</td><td colspan="3">Captains have a lot of paperwork to do. This work could be mostly automated with the use of eLogs to create landing reports.</td></tr>
<tr><td>Response</td><td colspan="3">• Determine requirements for landing reports in fishery
• Prototype of landing report from eLog company
• Trial with captains to get feedback
• Improve product</td></tr>
<tr><td>Participants</td><td>• Fishery managers
• Captains
• eLog providers</td><td>Level of Effort</td><td>How
This will require development, trials, and refinement</td></tr>
<tr><td>Outcomes</td><td colspan="3">A fully digital landing report.</td></tr>
</table>

Issue 6

AI Result Output

AI results create large files making it difficult to transmit raw results over data connections at sea.

OPTIONS

- AI output workshop

<table>
<tr><td>Option 1</td><td colspan="3">Research and discuss minimization efforts to see how small the files can get for transmission</td></tr>
<tr><td>Reason</td><td colspan="3">If there is a way to minimize, results could be sent in near real-time for analysis and potential intervention and correction leading to new ways of monitoring and management as well as rapid development.</td></tr>
<tr><td>Response</td><td colspan="3">• Analyze existing files
• Make recommendations to simplify
• Trial</td></tr>
<tr><td>Participants</td><td>• Analyst
• AI Providers</td><td>Level of Effort</td><td>Low</td></tr>
<tr><td>Outcomes</td><td colspan="3">There are two possible outcomes:
1) A path forward to refactoring the files for smaller transmission
2) A determination that minimization efforts will not bring the files to a small enough size for transmission without broadband</td></tr>
</table>

Issue 7

AI Catch Count Results

In this project design, AI was not able to reliably detect fish with confidence to be used effectively with Edge Automation

OPTIONS

- Further investment in AI research and development.
- Restructure the program design to allow for effective AI development and iteration.

<table>
<tr><th>Option 1</th><th colspan="3">Add more training to AI models based on fishery</th></tr>
<tr><td>Reason</td><td colspan="3">Fish detections are highly susceptible to the data in which they were trained on. Using more images of species and vessels that match the fishery may yield better results.</td></tr>
<tr><td>Response</td><td colspan="3">• Use additional footage from trips to train AI models.
• Get more footage as necessary
• Run trial trips through new AI models to look for improvements.</td></tr>
<tr><td>Participants</td><td>• Image Labeler
• AI partner</td><td>Level of Effort</td><td>Labeling: Low
Training: Low
Testing model: Medium-High
Analyzing data: Low</td></tr>
<tr><td>Outcome / Impact Level</td><td colspan="3">New AI models with better detection results that can replace initial models</td></tr>
</table>

<table>
<tr><th>Option 2</th><th colspan="3">Restructure the program design to allow for effective AI development and iteration.</th></tr>
<tr><td>Reason</td><td colspan="3">Given the constraints of this project, it was impossible to do full machine learning research and development.</td></tr>
<tr><td>Response</td><td colspan="3">• Obtain video from other programs and projects to run through project AI models.
• Process videos with same AI models and hardware (or simulated hardware) as used on vessels in the project.
• Compare with EM analyst results for those trips.
• Compare accuracy with Costa Rica Edge project</td></tr>
<tr><td>Participants</td><td>• Other fishery
• Partner to process data through existing AI models
• AI partner</td><td>Level of Effort</td><td>Obtaining video for use: Low-Medium
Obtaining permission to use AI models for tests: Low-Medium</td></tr>
<tr><td>Outcome</td><td colspan="3">Better AI model generalizability and understanding of requirements to adapt to a fishery. Identifies steps needed to deploy in each diverse program and fishery.</td></tr>
</table>

Opportunity 8

Cloud Data Platform

The cloud data platform is an ideal place to store all data for the pilot, including raw video and EM results. The data lake can scale easily and the platform can be extended for new features and stakeholders without expensive trials and research.

OPTIONS

- Make the data platform open to other stakeholders for research
- Migrate to another data platform

Option 1	Expand on the platform and make it open and accessible to others		
Reason	The data setup can be used for future programs and the data can be shared reducing costs and increasing value of the program. Concerns about privacy issues and any IP restricted information should also be considered.		
Response	• Transfer data to a new account • Create governance rules • Update APIs		
Participants	• Project sponsor • Data engineer	**Level of Effort**	**Low-Medium** Depends on the level of sharing and access rules
Outcomes	A reusable data platform for other pilots.		

Option 2	Use another platform to migrate all the data into and add governance to allow others to use it.		
Reason	Using an established platform may reduce technical skills and costs of meaning project data, though less custom data science may be available depending on features.		
Response	• Evaluate project data uses and potential future project requirements • Evaluate data platform vendors • Migrate data		
Participants	• Project sponsor • Data engineer	**Level of Effort**	**Medium**
Outcomes	A reusable data platform for other pilots.		

Opportunity 9

Data Sharing

The EM data in the cloud could be added to other EM data sources to enrich other systems such as the EM and fisheries data platforms.

OPTIONS

- Integrate EM data with existing data program

Option 1	Import project data into GEMA data platform		
Reason	GEMA is a great data platform tool for visualizing and comparing EM data sets. This could be used for the data in this project as well as future projects. Additionally it could be a step forward for integrating edge work with other programs.		
Response	• Create a new GEMA project account • Import EM data into project • Allow APIs to be used for future pilot programs		
Participants	• Data engineer • Project sponsor	**Level of Effort**	**Medium** GEMA is set up to do this already, so the effort would be more on coordination and long term platform costs.
Outcomes	Standard for viewing EM data across pilot projects		

Issue 10

Automation

This proof of concept was not intended to be completely automated and cannot currently scale to be hands off for operations.

OPTIONS

- Harden the applications and make them more robust/automated
- Migrate proven concepts to a more mature platform/product

<table>
<tr><th>Option 1</th><th colspan="3">Harden the applications and make them more robust/automated</th></tr>
<tr><td>Reason</td><td colspan="3">Several parts of this program required manual monitoring and intervention which is not scalable. Hardening the application to automatically monitor key events and respond accordingly would reduce costs and allow for the system to get closer to full automation and scalability.</td></tr>
<tr><td>Response</td><td colspan="3">• Determine which parts of the program need monitoring
• Determine the metrics to monitor and action thresholds
• Set up a workflow based on monitoring and metrics</td></tr>
<tr><td>Participants</td><td>• Data engineer
• Project sponsor
• EM provider (optional)</td><td>Level of Effort</td><td>High
While necessary for scaling, making the program more robust and automated requires a fair amount of engineering.</td></tr>
<tr><td>Outcomes</td><td colspan="3">A more robust edge system.</td></tr>
</table>

Automation: Issues (cont)

<table>
<tr><th>Option 2</th><th colspan="3">Migrate proven concepts to a more mature platform/product</th></tr>
<tr><td>Reason</td><td colspan="3">Some of the requirements are standard and do not require much customization. These could be offloaded to other systems (such as an IoT monitoring or workflow system) to increase scalability.</td></tr>
<tr><td>Response</td><td colspan="3">• Determine which elements can move out of proof-of-concept
• Research existing tools/platforms for these elements
• Integrate into new project</td></tr>
<tr><td>Participants</td><td>• Data engineer
• Solutions architect
• Project sponsor</td><td>Level of Effort</td><td>High
While necessary for scaling, making the program more robust and automated requires a fair amount of engineering.</td></tr>
<tr><td>Outcomes</td><td colspan="3">A more scalable and repeatable platform</td></tr>
</table>

Issue 11

Key Event Detections

Key fishing events are determined by analysts and fisheries managers as important to the monitoring program. Key events can be difficult to infer and/or confirm from current sensors and AI models.

OPTIONS

- Detection workshop

Option 1	Workshop that includes a comprehensive list of things to detect and how to detect them		
Reason	This project proved the concept that data can be gathered and new insights can be made from that data in near real-time, however to actually apply this to a specific fisheries management program would require deeper insights into what a specific fishery manager is looking for.		
Response	• Identify fishery for workshop • Determine workshop agenda and format • Conduct workshop • Publish results (used in future programs)		
Participants	• Project sponsor • Fishery manager • Data analyst • EM provider (optional) • AI engineer (optional)	**Level of Effort**	**Low-Medium** The coordination is the largest hurdle. This is likely a two day workshop with a couple of follow-ups
Outcomes	Clear sense of valuable data elements, how they can be used, what actions they might trigger, and a pathway to gather and analyze identified data.		

Opportunity 12

eLog Features for Captain Participation

Create eLog features, e.g. a button press on the eLog app triggers a snapshot from the EM cameras and a system health report from the EM system to record key events the captain wants to record

Overview

Vessel captains would be a great asset to reviewers and fisheries managers if given additional tools. Captains have the domain specific knowledge and the awareness to be very helpful, but their only tool to help is submitting landing forms. With the eLog (iPad) as the captains' primary point of interaction, there is broad opportunity to create additional features in the eLog app that captains can use to inform and assist reviewers and fisheries managers.

Option 1	Integrate eLog/edge events with EM Systems. Create spec for API in Edge device to trigger events.		
Reason	This is an opportunity to flip the incentive structure from adversarial (captains vs reviewers) to collaborative (captains assisting reviewers).		
Response	• Engage with eLog provider and EM provider • Design and publish an edge API for eLog/EM integration • Develop working implementation(s) of edge API		
Participants	• eLogs provider • EM prodiver	**Level of Effort**	**Medium**
Outcomes	A published API for eLog and EM product Integration can drive industry change, moving towards including captains as part of review and management.		

Option 2	Create test pilot program with new eLog communication features, connecting captains to reviewers and fisheries managers.		
Reason	This is an opportunity to add social connections to an otherwise dry process of data form entry.		
Response	• Communicate with Fisheries Managers, EM Reviewers, and vessel owners to define define project structure, expectations, and boundaries		
Participants	• eLogs provider • Multiple vessel captains • Fisheries managers • EM Reviewers	**Level of Effort**	**High** Organizing the pilot, multiple months of execution, evaluating results
Outcomes	Results will enumerate the types of contributions made by captains, with evaluations of each's benefit. Additionally, pilot provides qualitative evaluation of relationships between captains and fisheries managers.		

RECOMMENDATIONS

OVERVIEW

Advancing edge-enhanced fisheries management will require prioritizing the research and development of AI models to improve their effectiveness and utility on edge devices. Additionally the edge-based technology needs to be hardened to allow for less human monitoring of systems while at sea.

Primary Recommendations	
Improve AI object counting	While current metrics offer some prioritization and event detection, reliably comparing AI-derived catch counts to eLogs would have a much greater impact the accuracy and efficiency of fisheries management. Improvement and reliability in this technology would greatly improve the value of edge enhancements.
eLog catch timestamps	If captains were to enter catch in eLogs close to when they actually caught the fish, this would greatly improve functionality and comparison testing of catch counts. What changes would need to be made to the eLog UX to make this feasible for captains?
Secondary Recommendations	
Event workflow workshop and testing	Work with fisheries managers to determine how to best determine prioritization and what events should send an alert. Use project data as examples and include speculation of new vectors as needed. Run a new pilot with modified parameters and include fisheries manager alerts. This should be done in a fishery with an existing EM program.
AI Species identification	Support the development of AI models for key species identification. This can be used to update vectors and send alerts if certain species are detected as probable.
Verification workflow	Work with EM providers on a hybrid program to automatically send small packets of images/videos on high prioritization vector scores (such as detection of ETP species) where an EM analyst can verify.
Modify eLogs to produce landing reports	Work with eLog company, captains, and fishery managers to make landing reports electronic and use data from eLogs to prepare reports.
Integrate edge processing, EM, and traceability	Work with traceability partners to determine methods of integrating EM date, eLogs, and edge processing with traceability systems. This is best used in longline fisheries with large species.

BEST PRACTICES

Based on research of other EM programs and this project's learnings, the following is a list of best practices and considerations for future similar projects:

- Set up a data pipeline before installing systems
- Gathering data requires power to the systems to be consistent. Make sure power systems are tested and adequate including:
    - Verify power consumption and monitor usage
    - Before installing systems, install a power meter to track usage and limits of power source
    - Verify use of equipment in lab as close to entire system as possible
    - Do not forget about extra consumption for troubleshooting and errors.
    - Set up alerts and possibly shut down systems automatically when power is low and set it to recover once power returns. Examples could be to cut one camera as power gets to a certain level. Make sure that the vessel always has power for critical safety functions.
    - Consider installing other power sources such as solar, generators, and additional batteries.
- When considering AI for EM programs, engage early with AI partners to create a project structure that allows for full AI development, and maximized impact on the EM program goals.

NEXT STEPS

Based on the recommendations above, the following are strategies on next steps:

- Workshop with stakeholders to discuss issues, opportunities, and recommendations for further development of new data workflows and potential policies based on the results of this program
- Summit or workshop on the best vectors to create for a program based on the results from this program.
- Work with AI partners to create better AI models to track and count fish using the data from this project

FINAL CONCLUSIONS

This project began as an exploration of how fisheries observation can be made more effective in terms of cost, time, and impact by leveraging Electronic Monitoring (EM), Artificial Intelligence (AI), and edge-based technologies. Our approach focused on utilizing mostly existing products and services.

Current regulations, data policies, management programs, and observation methods have often slowed the pace of innovation and the adoption of data-driven fisheries management. However, our work with partners and stakeholders has shown that new edge technologies and advancements in computer vision AI models hold significant potential for improving the tools available to fishery managers. All stakeholders stand to benefit from these advancements.

The results of this project highlight the possibilities for innovative fisheries management by prioritizing data sets and integrating new workflows into the monitoring and management process. By exploring these new monitoring and management possibilities, further research and development can target both technological and management improvements.

One key finding is the potential for near real-time alerts and decision-making. This approach can help prioritize reviews that need the most attention, allowing for rapid review of monitoring data. For example, high-priority partial data sets can be reviewed on the same day by sending smaller data samples into a review workflow while the vessel is still at sea.

Future innovation programs aiming to enhance review prioritization should involve full engagement with fishery managers to ensure that the results meet their needs and support the innovation of management practices and policies.

APPENDIX A

Partner profiles

PROFILE: productOps

Founded in 2008, productOps, Inc. advises a broad spectrum of organizations in industries including sustainability, higher education, publishing, finance, aeronautics, transportation, leisure, and energy. We develop practical data strategies and implement operational solutions at scale.

Partnering with a diverse range of clients allows productOps to leverage knowledge and experience across multiple industries to improve data solutions and drive change for every client. Our team is experienced and ready to integrate an extensible data platform solution to retain and exploit valuable data so your team can operationalize valuable solutions at scale.

WHAT IS OUR GOAL?

Improving sustainability relies on partnerships, not just projects. Our sustainability work comes from trusted partnerships with non-governmental organizations (NGOs), domain experts, and solutions providers. First and foremost, we serve as seasoned, independent advisors; the cornerstone of all our engagements in strategy, engineering, and operations.

PROFILE:
Ai.Fish

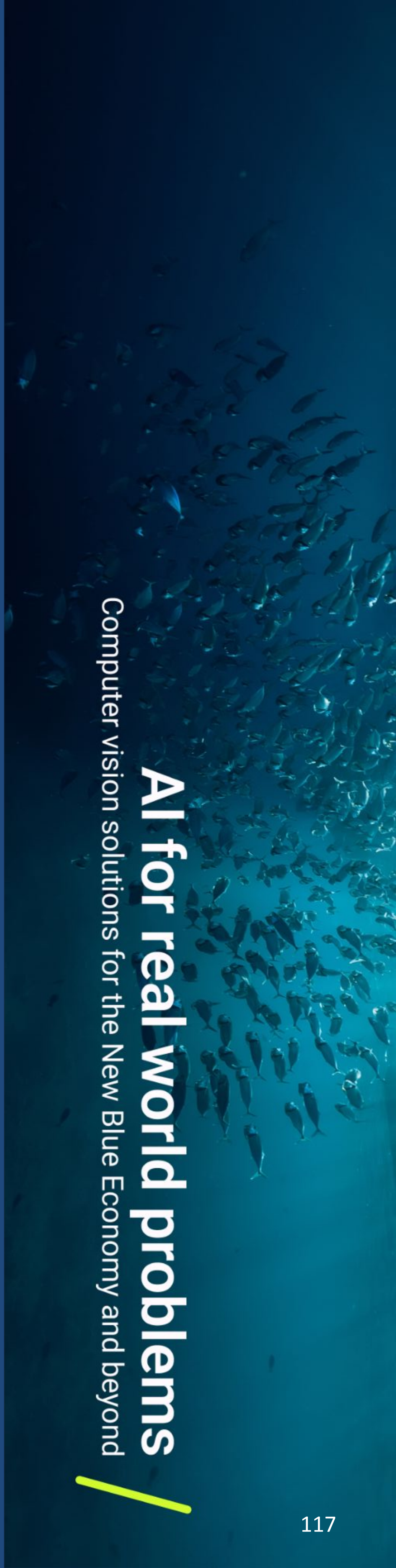
Founded in 2019, and headquartered in Hawaii, Ai.Fish LLC is solely focused on the opportunity of artificial intelligence (AI) in fishery management and ocean conservation. Our team is motivated to solve problems with scale and global impact through computer vision approaches.

Our work is a mix of bespoke product and software development for the commercial fishing industry and R&D activities. Our passion is exploring and perfecting artificial intelligence techniques that solve for key challenges in electronic monitoring and other fisheries opportunities for AI.

WHAT IS OUR GOAL?

Our goal is to realize the Fishery of the Future. We believe that technology like computer vision is ready for industries like fishing but isn't accessible. We believe that the commercial fishing industry has an appetite for great software that isn't currently fulfilled. We aim to fill those gaps to support a world where fish remain a critical food, a beneficial livelihood, and a sustained tradition for generations to come.

AI.FISH



PROFILE:
OnDeck Fisheries AI

OnDeck is driving global marine conservation by making a new generation of AI software accessible and scalable in fisheries. OnDeck specializes in making AI useful to the seafood industry, pioneering new methods of AI and computer vision that allow for companies to practically benefit from productivity lifts in their organization.

Among other work, OnDeck is leading a $3.5M project from the Government of Canada to deploy AI in Electronic Monitoring across Canada, and scale up internationally. OnDeck is working with commercial fisheries, technology partners, Indigenous communities, and governments to make critical marine conservation tools more affordable and effective. The impact of OnDeck's work has been heralded by awards from National Geographic, the Environmental Defense Fund, the Sustainable Ocean Alliance, the Ocean Impact Organization and many more.

WHAT IS OUR GOAL?

As an impact driven, for-profit software company, OnDeck is bringing a new level of software talent that the fishing industry deserves. With a growing team of engineers, product managers, and fisheries experts, we are always looking for exceptional people who love tackling big challenges to shift global behaviour.

OnDeck fisheries AI

info@ondeck-ai.com
www.OnDeck.fish

PROFILE:
Deckhand (Real Time Data)

DECKHAND®
ELECTRONIC LOGBOOK

Real Time Data (RTD) was co-founded by a fisherman in 2010 in Adelaide, Australia. Looking for a better way to handle paper logbook data in his fishery, the Deckhand platform was born. 14 years later, Deckhand is used across dozens of fisheries in four countries.

The Deckhand team learned early that no two fisheries are alike. That's why Deckhand is the world's first workflow-driven logbook platform. The workflow approach enables both internal *and* third-party developers to build workflows that suit the needs of specific regions, fisheries, companies, or causes around the world – all using the core Deckhand logbook engine.

Deckhand's flexibility also lies in its ability to integrate with virtually any endpoint. From offline APIs on board vessels in the Edge project, S3 buckets for oceanographic data, to integrations with state, federal, and international fishery management agencies, Deckhand can send data anywhere.

WHAT IS OUR GOAL?

Our goal is to contribute to the prosperity of fishers and the sustainability of the resources they depend on through providing a flexible and powerful data collection platform that is designed for the salty front lines.

PROFILE: THALOS

Founded 22 years ago, THALOS has established itself as a leader in the development of innovative connectivity and analytical tools for the maritime industry. THALOS equips all types of vessels globally with advanced technological solutions, enhancing operational efficiency and sustainability.

THALOS Core Services

Data Connectivity Management: Cutting-edge solutions ensure precise management, monitoring, and security of data traffic, providing seamless connectivity all around the world and data integrity tailored to the maritime industry.

Operational Efficiency: In the field of fishing operations, where operational efficiency is critical, THALOS offers advanced services designed to boost the performance and sustainability of fleets. Our solutions streamline operational processes, refine decision-making, and add value to fishing campaigns.

Cybersecurity: Developed with a keen awareness of cybersecurity stakes, our network architecture is crafted to manage and secure all data flows between ship and shore.
Sustainability: We are committed to developing solutions that contribute to a sustainable future for the industry and our oceans.

WHAT IS OUR GOAL?

THALOS is dedicated to advancing maritime operations through technology that not only enhances efficiency and safety but also supports sustainable practices and scientific research. Our solutions are tailored to meet the unique needs of maritime operations, ensuring seamless connectivity and robust data management at sea.

As THALOS continues to expand its influence across the oceans, we remain committed to our clients, providing them with reliable, efficient, and innovative solutions to navigate the complexities of modern maritime operations.

PROFILE:
Bureau Veritas

Since 1828, Bureau Veritas is an international leader in **certification, inspection and audit.**

Thanks to our experience of almost 200 years, our "Business to Business to Society" company is operating worldwide (140 countries) for 400,000 clients who trust us for our **independence, impartiality and integrity.**

Aware of the current challenges, we are fully committed in an ambitious **sustainability strategy.**

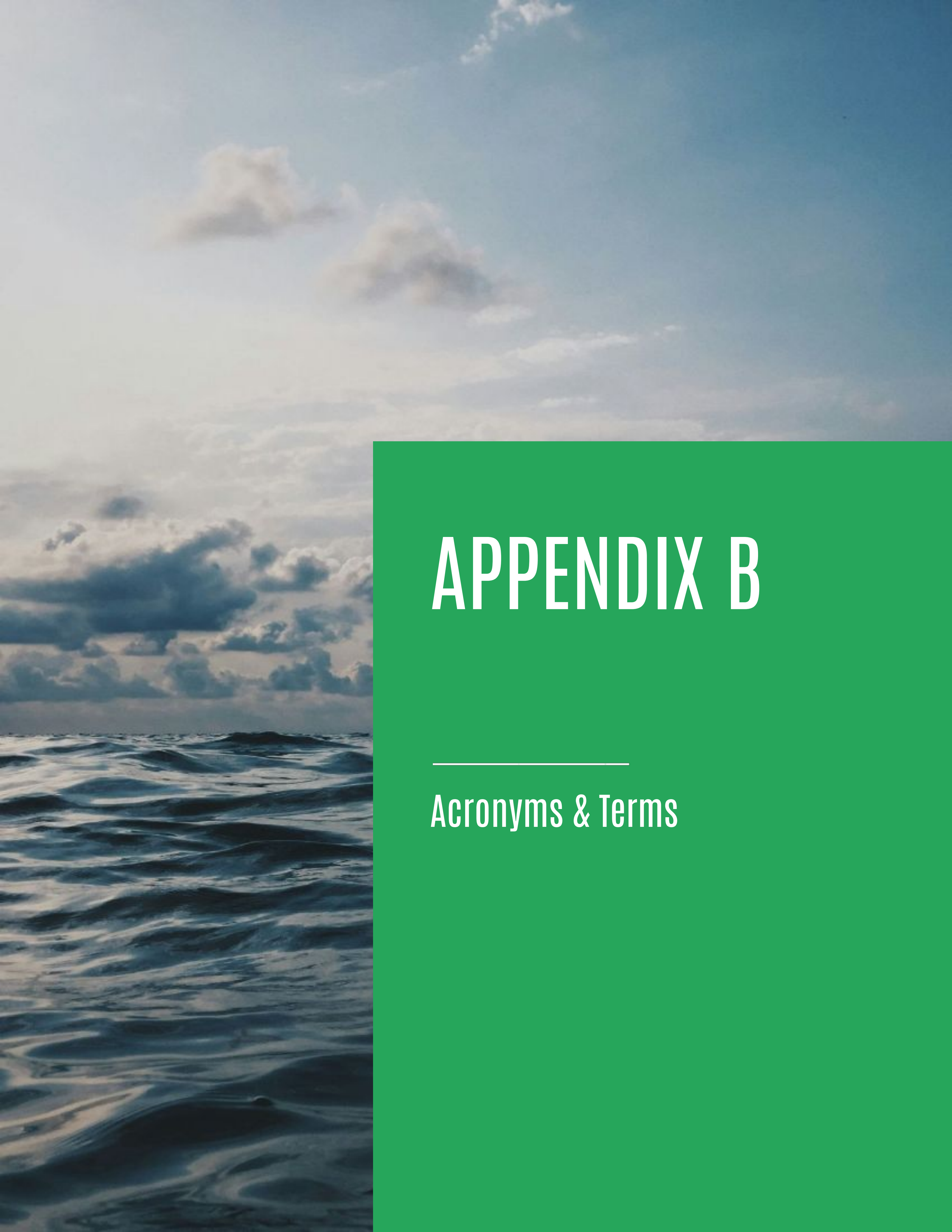
Bureau Veritas Living Resources is a subsidiary of Bureau Veritas specialized in marine and terrestrial living resources.

As an engineering consultant with 20 years of experience in fishing and aquaculture, we propose studies, technical assistance, and observation services (onboard and video review) to fishing companies, national administrations, or NGOs worldwide.

WHAT IS OUR GOAL?

Bureau Veritas Living Resources is dedicated to the **sustainability of marine resources** thanks to consultancy regarding the monitoring of fisheries, the sustainable management of resources, the sustainable supply plans, and the socio-economic assessment of fisheries.

As we increase our expertise in all the oceans, we are eager on developing state-of-the-art services for our clients regarding the new challenges fishing and aquaculture are facing.



APPENDIX B

Acronyms & Terms

Acronyms & Terms

Related to fisheries and fisheries management

AIS (Automatic Identification System) – An automatic tracking system that uses transponders on ships and is used by vessel traffic services. AIS helps in identifying and locating vessels by electronically exchanging data with other nearby ships, AIS base stations, and satellites.

EM (Electronic Monitoring) – Systems that use various technologies, including video cameras, gear sensors, and navigational tools, to automatically record all fishing activities. EM systems are crucial for ensuring compliance with regulations and sustainability practices in fisheries.

ETP (Endangered, Threatened, and Protected) – Species that are recognized as at risk of extinction and are protected under various environmental laws and regulations. **ETP Interactions** are occurrences where fishing activities have an impact on species that are legally protected due to their endangered or threatened status. Monitoring these interactions is crucial for ensuring the protection of these species.

Exclusive Economic Zones (EEZs) – Areas of the ocean where a sovereign state has special rights regarding the exploration and use of marine resources, including energy production from water and wind. EEZs extend from the baseline out to 200 nautical miles from the coast of the state.

First Mile Traceability – A system that tracks the origin of fish from the point of capture to ensure legality and sustainability, providing transparency in the supply chain, particularly in the initial stages of seafood processing.

Fishing Sets – The deployment of fishing gear, such as nets or longlines, into the water and its subsequent retrieval, along with the catch. Each set is an operation ranging from deployment to haul-back.

IUU Fishing Practices (Illegal, Unregulated, and Unreported Fishing Practices) – Activities that do not comply with regional, national, or international fisheries conservation or management laws. These practices are a major global issue as they undermine sustainable fisheries management.

Key Event – Key fishing events are determined by analysts and fisheries managers as important to the monitoring program. Examples include species interactions, catch events, setting and hauling events, and branch line cutoffs.

Longline Vessels – Fishing boats equipped with long lines bearing many baited hooks, used primarily for catching large fish like tuna and swordfish. The project assesses the impact of fishing practices by longline vessels on marine biodiversity.

NGO (Non-Governmental Organization) – An organization that is independent from government involvement and is typically focused on addressing social, environmental, or humanitarian issues. NGOs involved in this project may be focused on conservation and sustainable fishing practices.

Acronyms & Terms

Related to fisheries and fisheries management

On-shore – Pertaining to or located on the land as opposed to at sea. In this document, 'on-shore' might refer to processing, analysis, or decision-making activities that take place away from the actual site of fishing.

VMS (Vessel Monitoring System) – A satellite-based monitoring system used by regulatory authorities to track the location and movement of fishing vessels. This helps in enforcing fishing laws and regulations and in monitoring fishing activities for compliance and sustainability.

Acronyms & Terms

Related to AI and ML for electronic monitoring of fisheries, published by The Pew Charitable Trusts

www.em4.fish/our-library/glossary-artificial-intelligence-and-machine-learning-for-electronic-monitoring-of-fisheries

Accuracy – A measurement of the performance of a machine learning algorithm or model that measures the proportion of correct predictions. It is calculated as the sum of the true positives and true negatives as a percentage of all the items in the dataset. Example: For an algorithm that classifies images into two species of fish. If we had 10 images, 5 of trout and 5 of salmon and 4 images were predicted to be of salmon and 6 of trout, our accuracy would be 90% as 9 predictions were correct.

Algorithm – A set of instructions or rules that a computer follows to perform a task. Machine learning algorithms are designed to learn from data and improve their performance over time on specific tasks, predictions, or decisions.

Artificial Intelligence (AI) –A science and engineering approach to solve problems using a digital computer performing tasks that are generally carried out by intelligent beings.

Audit – An assessment of a machine learning system and its performance, accuracy and compliance with procedures or standards. Audits should consider the wider system in which the AI algorithm is integrated, quantify any bias that may be present, and inform stakeholders of shortcomings or limitations.

Bias –A systematic directional error in a machine learning model that results in incorrect predictions or decisions. Bias can occur when a model is trained on a dataset that is not representative of the population or system modeled.

Bootstrapping – A technique used to estimate the variability of a statistical measure or to create multiple datasets with slight variations for training and evaluation purposes. Bootstrapping involves repeatedly choosing different sets of data points from an original dataset to create new samples that are similar but not identical to the original data. These new samples are used to train and test machine learning models.

Classification – Assigning data to one or more predefined categories or classes, which are then used to train a machine learning algorithm. Example: Assigning an image to the 'fish' category if the image contains fish and assigning an image to the 'no fish' category if no fish are present.

Confidence – A measurement of the relative certainty of a prediction by a machine learning algorithm or model. A high confidence is generally associated with a better prediction. Example: For an algorithm that classifies images into two species of fish, trout, and salmon, if an image is classified as a trout with a 0.95 confidence and as a salmon with 0.30 confidence, it can be determined that the model has predicted the image to contain a trout and not a salmon.

Acronyms & Terms

Related to AI and ML for electronic monitoring of fisheries, published by The Pew Charitable Trusts

www.em4.fish/our-library/glossary-artificial-intelligence-and-machine-learning-for-electronic-monitoring-of-fisheries

Confusion Matrix – A table that shows the performance of a model or algorithm that classifies items into multiple categories, by comparing the model's outputs to the true values. A confusion matrix can be used to visually display which categories are commonly misclassified by the model.

Convolutional Neural Network (CNN) – A type of deep learning algorithm that is often used to recognize, analyze, and process image data and separate images into distinct categories using multiple filters. For example, to detect a fish in an image a CNN would first use a filter that finds the eye of a fish and then a filter that extracts textures to find scales.

Cross-validation – A technique used to evaluate a model's performance by dividing the dataset into training and validation sets and training the model on different combinations of the data. Cross-validation can help reduce overfitting when splitting the data into a single training set would inadequately represent the overall distribution of the data.

Data Retention – Preserving data for a specified period of time after it has been used for its original intended purpose. Data is often retained to meet regulatory requirements and allows systems that were developed from the data to be audited.

Deep Learning – A subset of machine learning that uses algorithms with multiple layers to extract patterns and features, which allow the model to determine which features are the most important when classifying data. Example: A deep learning model could determine which features (i.e., fin or head shape) are most important when classifying an image of a fish as either a trout or a salmon.

Edge Processing – The application of machine learning algorithms by a device close to where the data was gathered, like onboard a fishing vessel.

False Positive/Type I Error – A false positive occurs when a model or algorithm incorrectly identifies an object or event. False positives can lead to the model raising a false alarm or recommending an unnecessary intervention. Example: An algorithm Identifying a fish as a trout when it is actually a salmon.

False Negative/Type II Error – A false negative occurs when the model does not identify an object or event that actually exists. This could lead to the model missing an actual event or failing to take appropriate action. Example: An algorithm not Identifying a trout when it appears in an image.