Developing Artificial Intelligence (AI) Tools for Electronic Monitoring (EM) Applications

AFSC Electronic Monitoring Innovation (EMI)

Goal – Automate some EM monitoring processes

Example applications:

- Review longline videos for species (and measurement)
- Validating handling and reporting of salmon bycatch in trawl deliveries to plants
- Camera chutes to monitor at-sea discards

Validating handling and reporting of salmon bycatch in trawl deliveries to plants

- Project started for rockfish deliveries (SK funded project with AGDB)
  - Can EM validate salmon counts in plant reports? (auxiliary to full retention at sea)
  - Four Kodiak plants
- Initially tested with human video review
- AI trials added through collaboration with the AFSC EMI project – Included pollock deliveries

Validating handling and reporting of salmon bycatch in trawl deliveries to plants

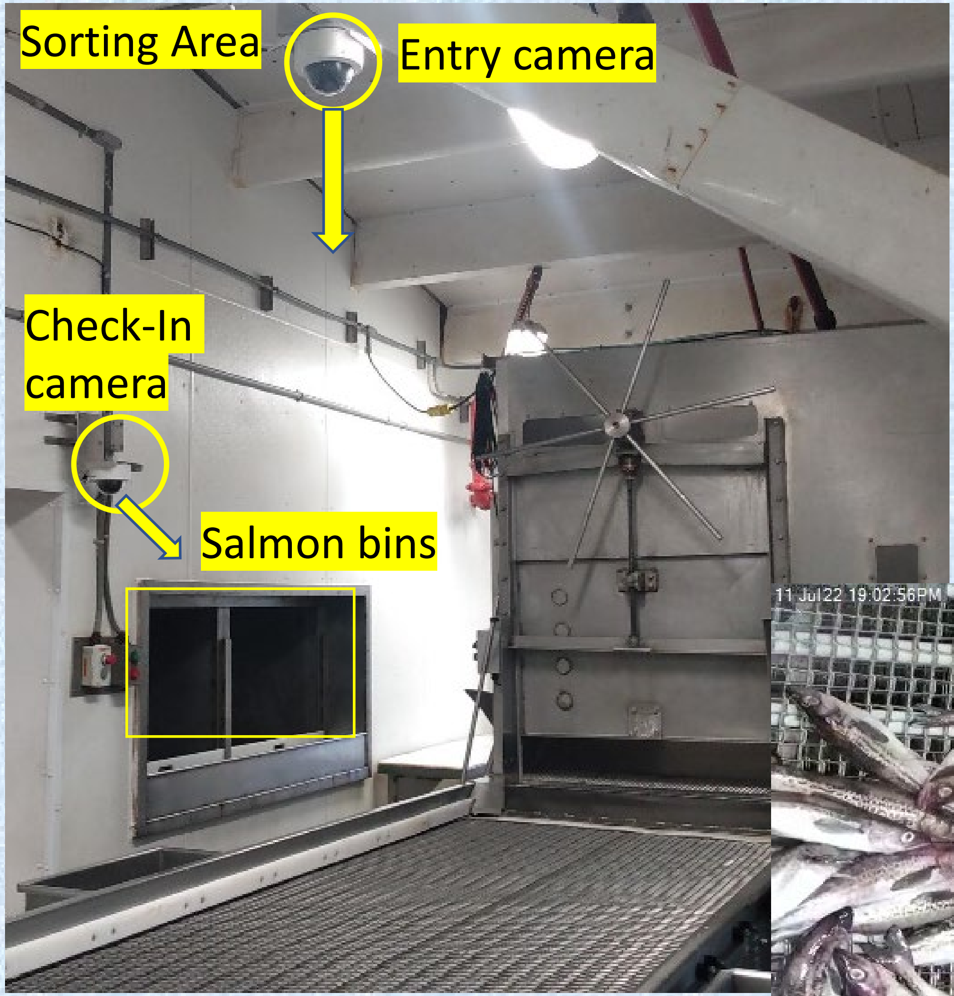
Can an automated EM process replace or relieve the need for constant observer monitoring of the sorting process throughout deliveries?

Concept: Detect most salmon entering the sorting area and confirm each of those were found by sorters and properly retained

Data collection equipment and process

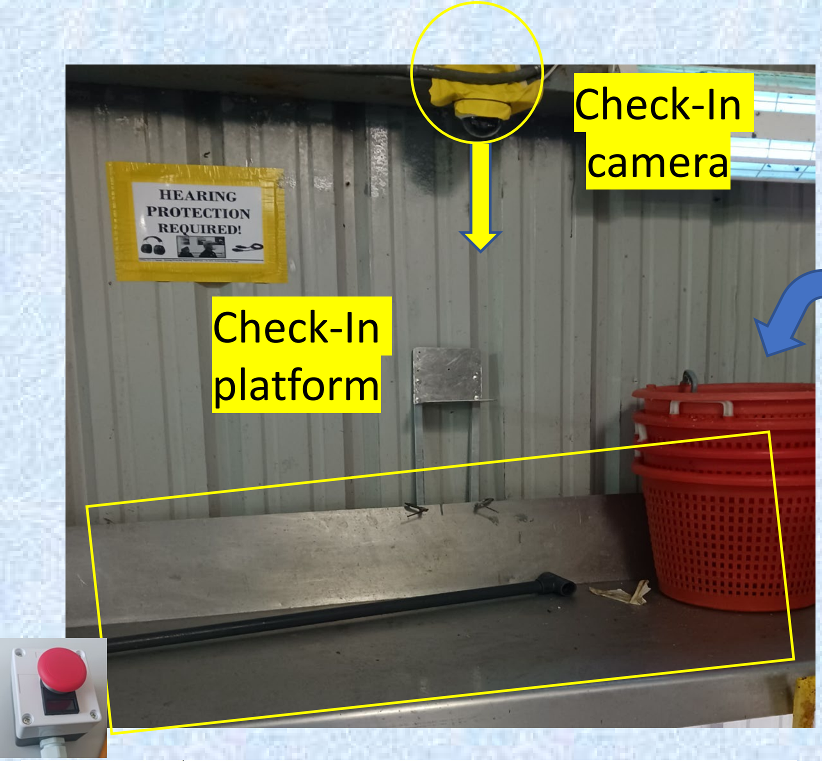
- Camera records fish entering the sorting area (Entry camera)
- Detect and record times when salmon are separated from the delivery (Check-In)
    - Camera views the holding location with motion detection
    - Sorting crew displays salmon to camera before storage
    - Sorting crew activates a Check-In switch

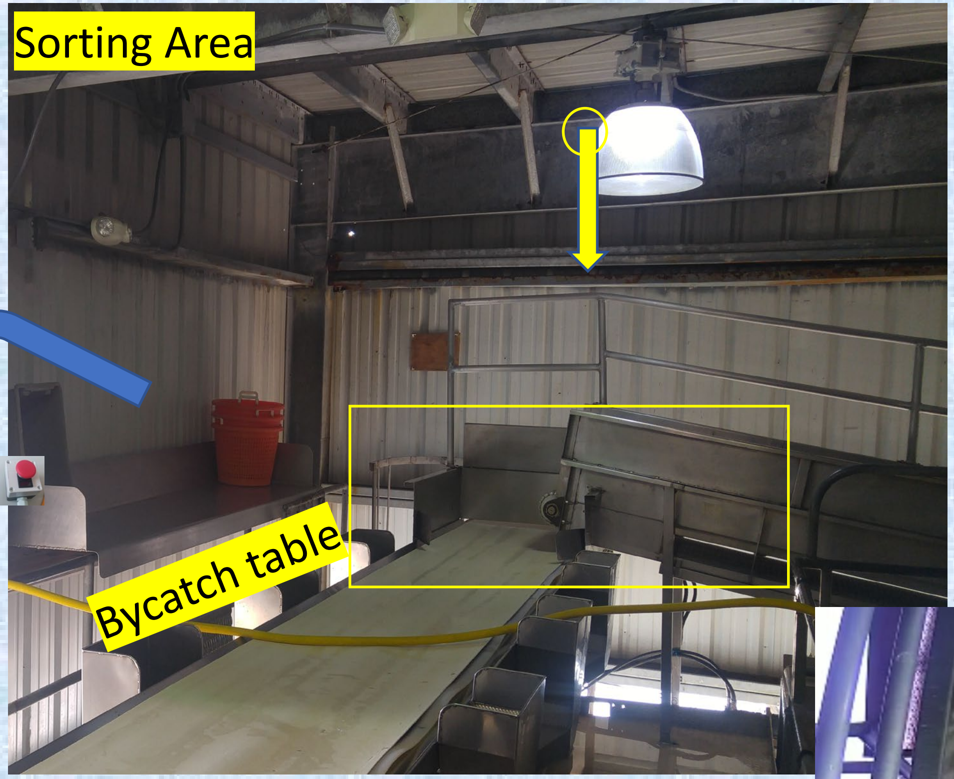
Westward Seafoods Alyeska plant (Dutch Harbor)

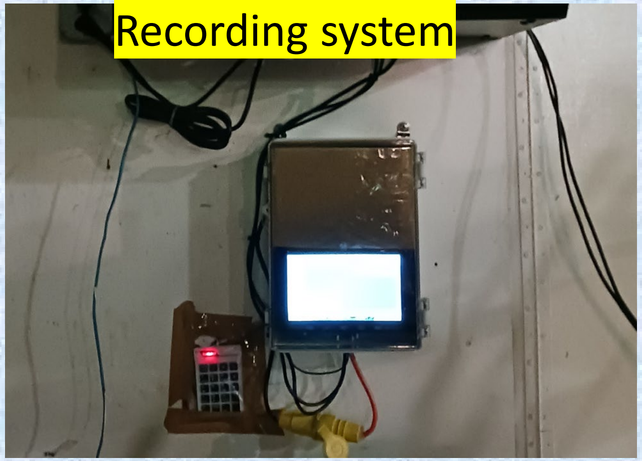


Recording system in adjacent office

North Pacific Seafoods (Kodiak)







Process – Analysis

- Video analysis detects times most salmon enter sorting area

- All detections should be shortly followed by a Check-In event
  - Proportion matched should approach 100%

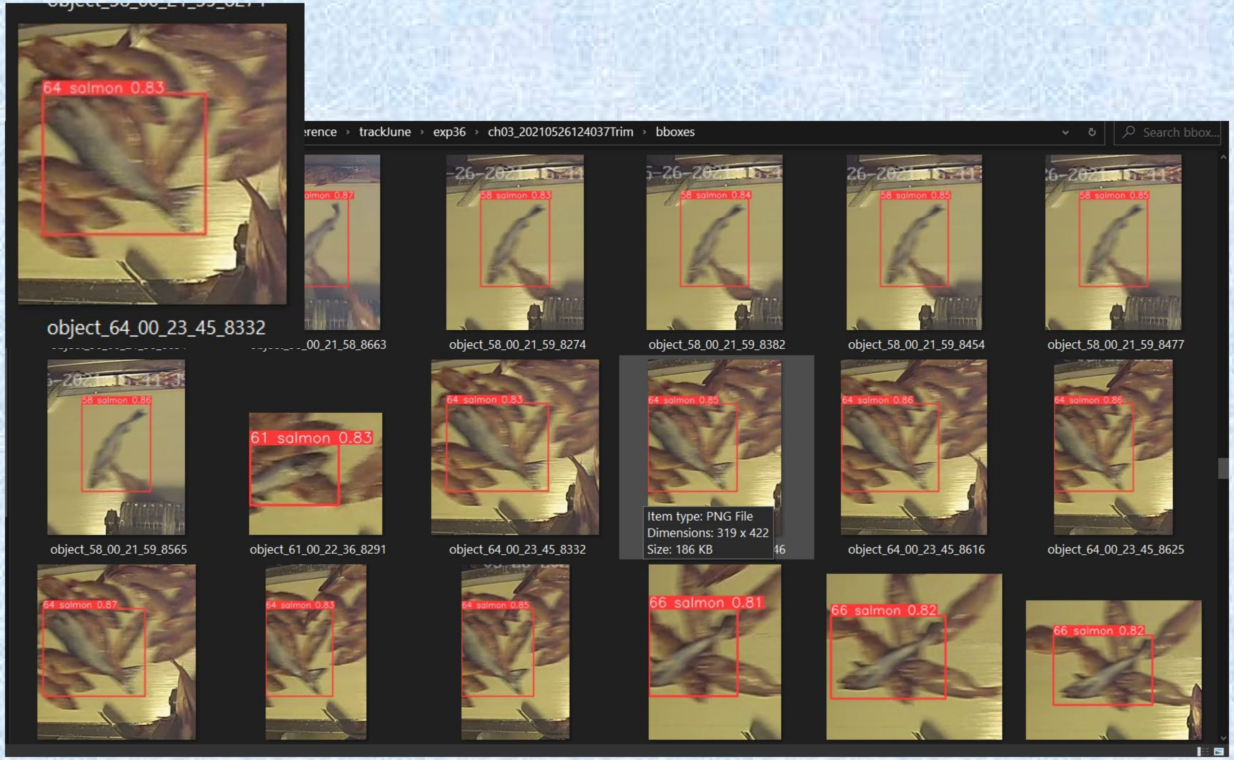
- The number of Check-In events should match the salmon numbers
  - Numbers on plant report or observer count

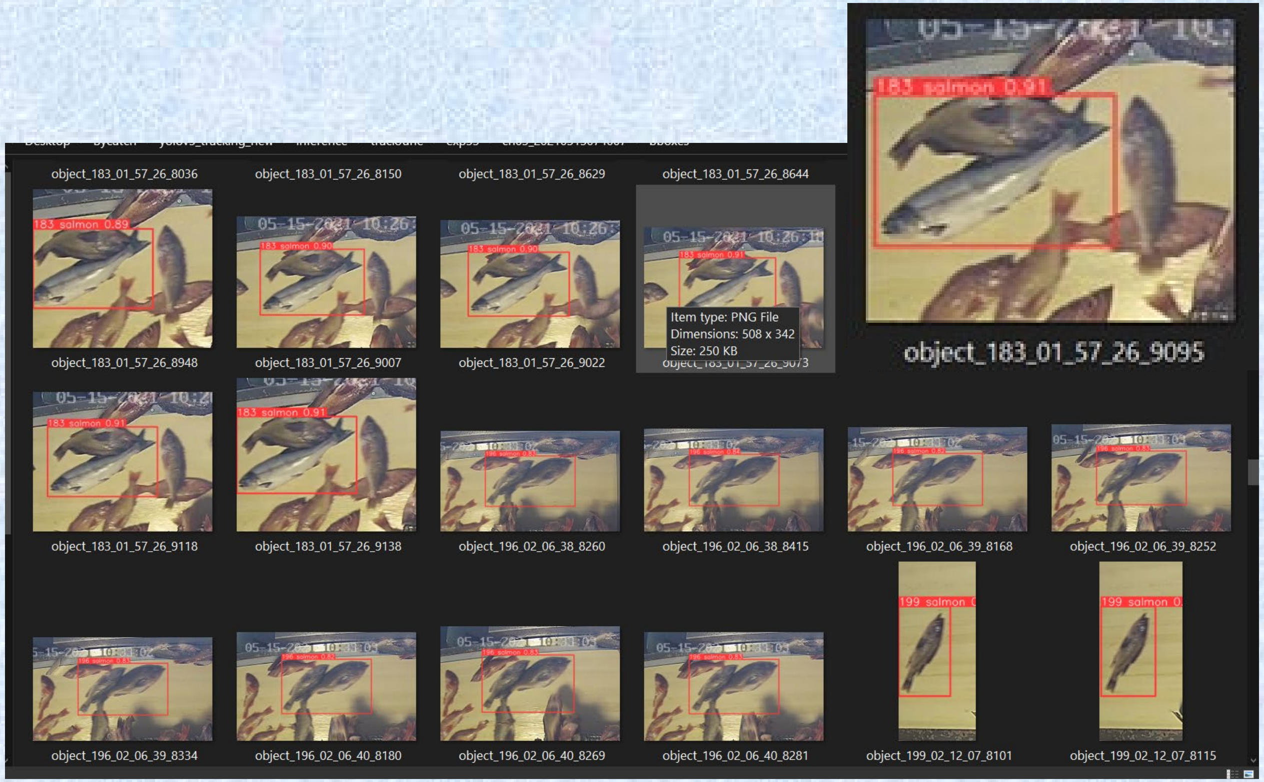
Detector performance

- Program runs in roughly the same time that the delivery took
- Initial training statistics were very promising (91% of salmon detected, with only 1.3% of the detections were not salmon)
- HOWEVER, when applied to the volume of real deliveries, the false positives were greatly multiplied (mostly other non-target species)
    - About 200 detections per hauls averaging only 3.5 salmon
- So far, additional training with identified ‘false positives’ has not improved performance
- Requires an additional step to find salmon among the detections

Review for false positive salmon detections

- Program outputs several cropped images per detection
- Scan these detection images to find true salmon detections
- This takes several minutes for each delivery, so still much less time than current situation
- Could sampling be used? How many salmon detections are enough?





Issues and Potential Improvements

- **Effective Check-In system**
  - **Must be easy for crew, especially when there are many salmon**
  - Motion detection – small area, convenient to belt, with no movement artifacts
    - (e.g., shadows or parts of passing people)
  - Switch – must be easily accessible – maybe on the sorting line or pendant?

- **Separating deliveries**
  - Matching delivery to data requires start/stop separation times

- **Monitoring and maintaining recording system and function**
  - Confirmation that system is operating and cameras are clear

Implementation Issues

- Who runs the analysis and where?
  Onsite in real-time or disk swap for off-site processing

- How to deal with many false positives?
  Better model training (AI) has failed so far
  Human review –
    Should take minutes per delivery
    Who does this?

- How is validation communicated to data managers?

- What happens when salmon are being missed?

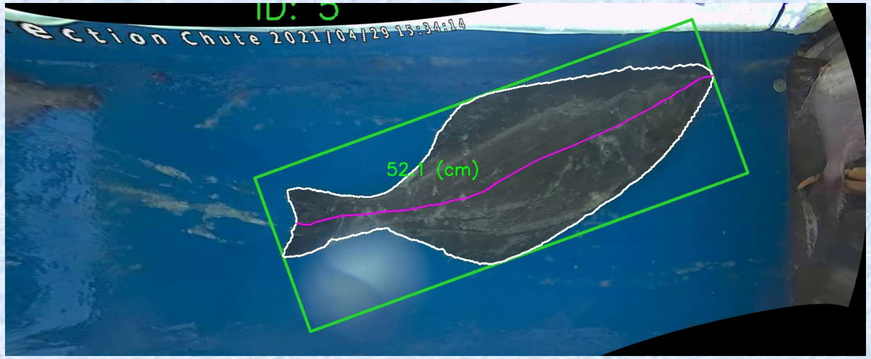
Summary

- This system could replace a very time-intensive observer task
- Not fully automatic – some human review will be necessary
- Will require adaptation for each plant, especially the Check-In system

Questions on Salmon Count Validation

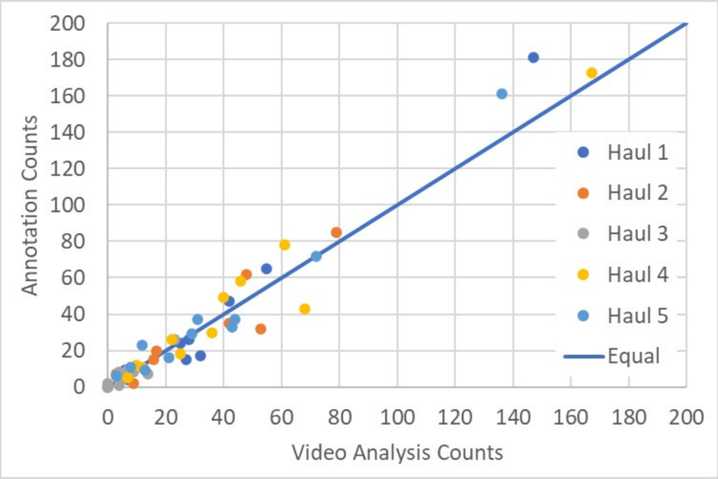
Camera chutes for discard monitoring

- Enclosures with controlled lighting and background
- Software tracks, classifies, and measures fish passed through
- Applications:
    - Halibut discard accounting
    - Mixed discards from trawlers
    - Discards from pot vessels
    - Check-In for plant monitoring



Camera chutes for discard monitoring

- Extensive set of fish images collected from Alaska and West Coast
- Classifier performed well when trained from the same dataset
- Performance drops when applied to new data
- Scene differences including lighting and slime clearance affect classification models



Recurring lesson for practical AI applications to fisheries EM

Standard performance statistics from initial model trainings (performance on a testing set randomly segregated from the training set) overestimate performance when applied to new data

Issues:

- Domain differences: e.g., differences in lighting, background
- Label shift: species distribution in new data very different than training
- Long-tail distributions: Rare species results are more error-prone than common species
- Novel species: Species not in the training set are not recognized, so will be forced into a known species

Questions?