Deep Learning Object Detection

for Counting Fish

...

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July 2020

Agenda

- Background
- Challenge
- Data
- Model
- Evaluation
- Conclusion

Background: Pacific Northwest Salmon

Salmon hatch in freshwater streams

Migrate to the saltwater ocean

Return upstream to their natal streams

Spawn and die

Salmon hatch in freshwater streams

Migrate to the saltwater ocean

Background: Pacific Northwest Hydroelectric Power

Columbia & Snake River Dams

Background: Power *and* Salmon

Built fish ladders

Adjust dam outflow

Fishing guidelines (daily limits, season duration)

Q: How do we know how it's going?

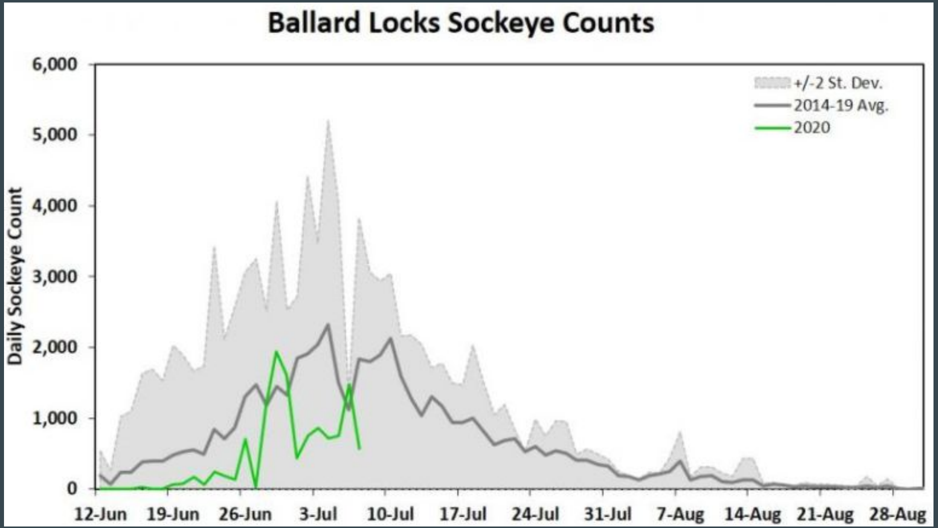
A: Monitor fish migrating upstream through the ladders

Challenge: Accurate Fish Counts

1. Estimate from a daily sample (Ballard Locks)
2. Real-time count (Bonneville Dam)
3. Video count (Rock Island Dam)

Challenges:

- Sampling error
- Human expertise
- Accuracy affects commerce, fishing



Is machine learning for object detection ready to assist in this challenge?

Data: Good Images

Public Viewing Windows

Web scraped images

- Lighting
- Depth of tank
- Obstructions

Detect:

- Fish or no fish (count)
- Fish details (count species)

Chelan PUD Fish Count Window

Snapshots from video

Data: Label, Augment

Object detection models require labeled images

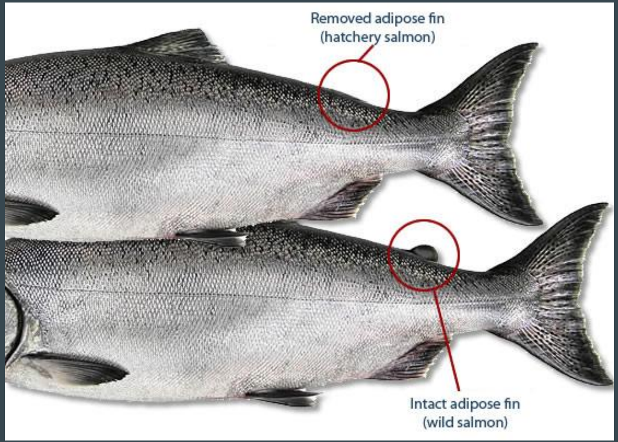
3 classes:

- adipose
- no_adipose
- unknown

Sockeye Coho Chinook

Steelhead Lamprey

Adult / Jack Clipped / Unclipped

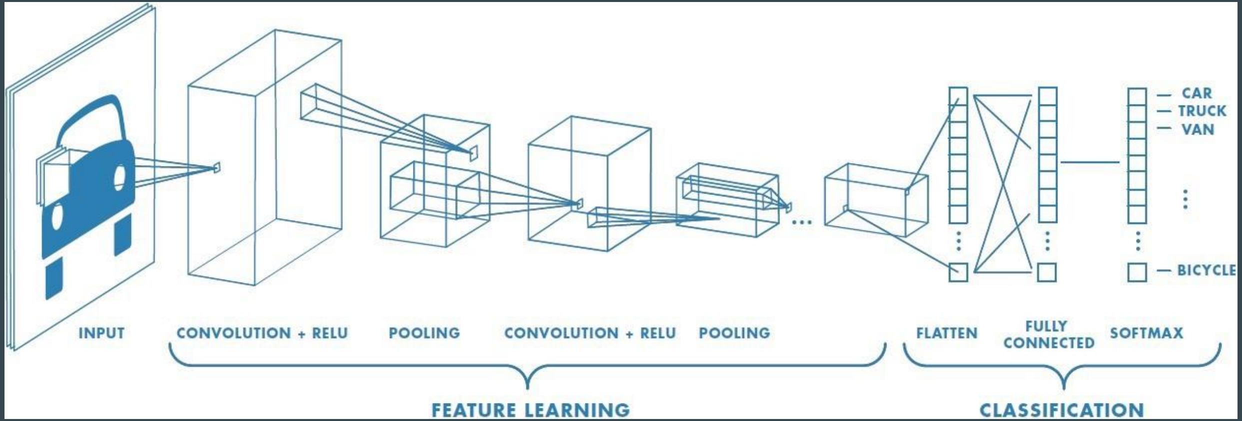


Final:

- 317 snapshots from video
- 1025 annotations (~3.2 per image)
- 15 null examples (no fish)
- Augmented by flip, blur, brightness -> 951 images

Model: Object Detection by Convolutional Neural Network

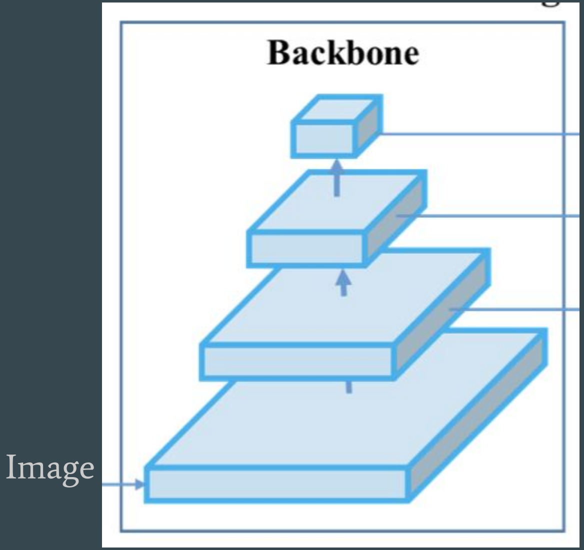
also called "Deep Learning"



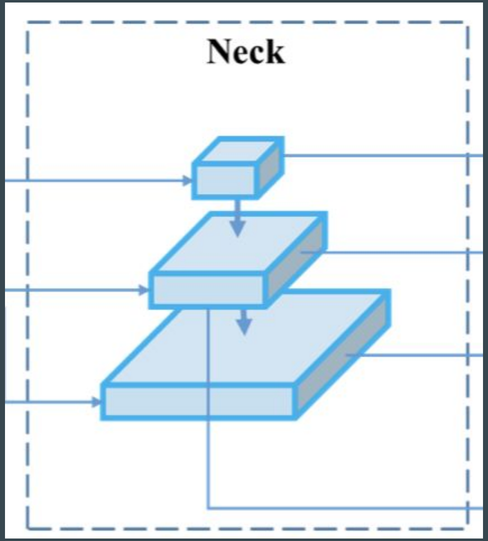
- Break down an image into pieces
- Predict what it is based on pieces

'Guitar and Violin', c. 1912 →

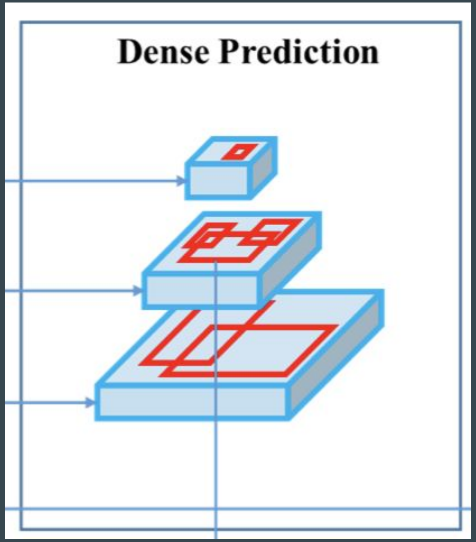
Model: Convolutional Neural Network (CNN) - YOLOv5



- Classification task:
- VGG16
- Darknet

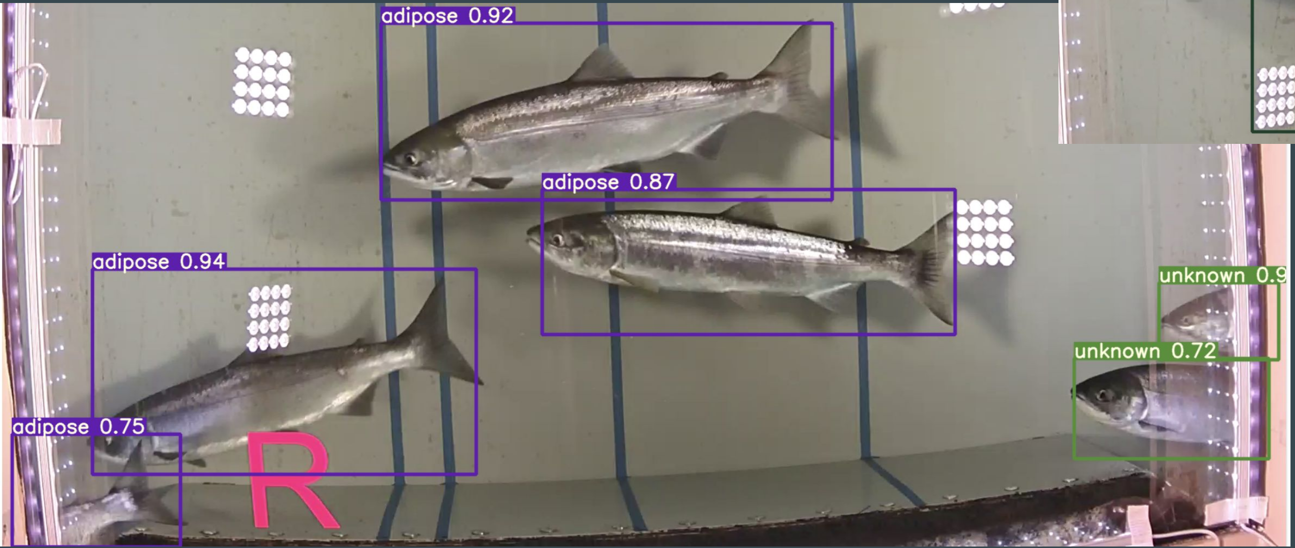


- Collect feature maps from different stages
- More ‘pieces’ for the final layer to use

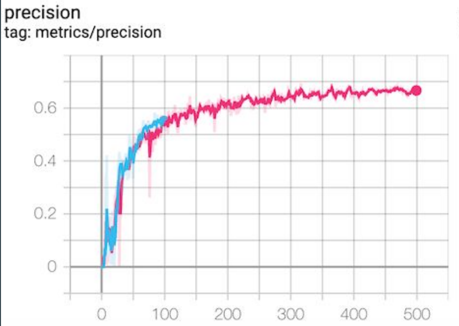


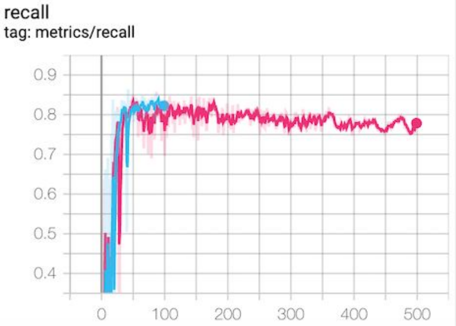
- One shot final step:
- Predict class
- Predict bounding box

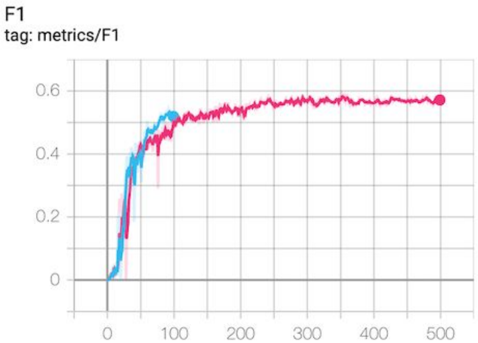
Evaluation: Example Output



Evaluation: Accuracy of Predictions







IDEAL in all cases = 1 or "100%"

Precision: "If you say it's a fish, what percentage of the time is it really a fish?" ~70%

Recall: "If there's a fish in there, what percentage of the time do you find it?" ~80%

F1 score: 2*Precision*Recall / (Precision + Recall)

Evaluation: Accuracy of Predictions mAP@0.5

mAP

Average Precision for 1 class:

- Calculate the BEST Precision at each level of Recall, then AVERAGE these

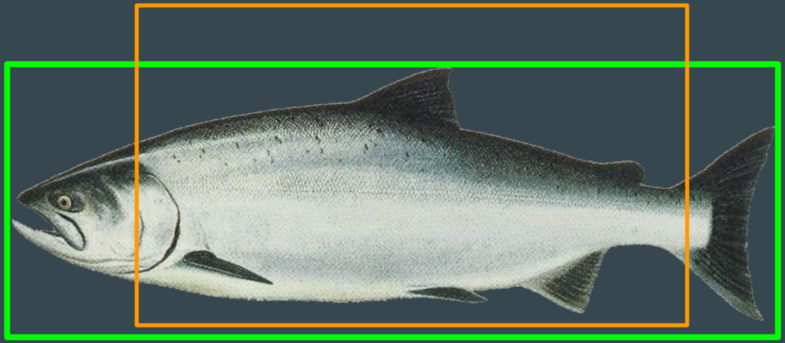
$$\frac{\#TP(c)}{\#TP(c)+\#FP(c)}$$

mean Average Precision for 3 classes:

- Find the Average Precision for each class, take the mean of those

@0.5

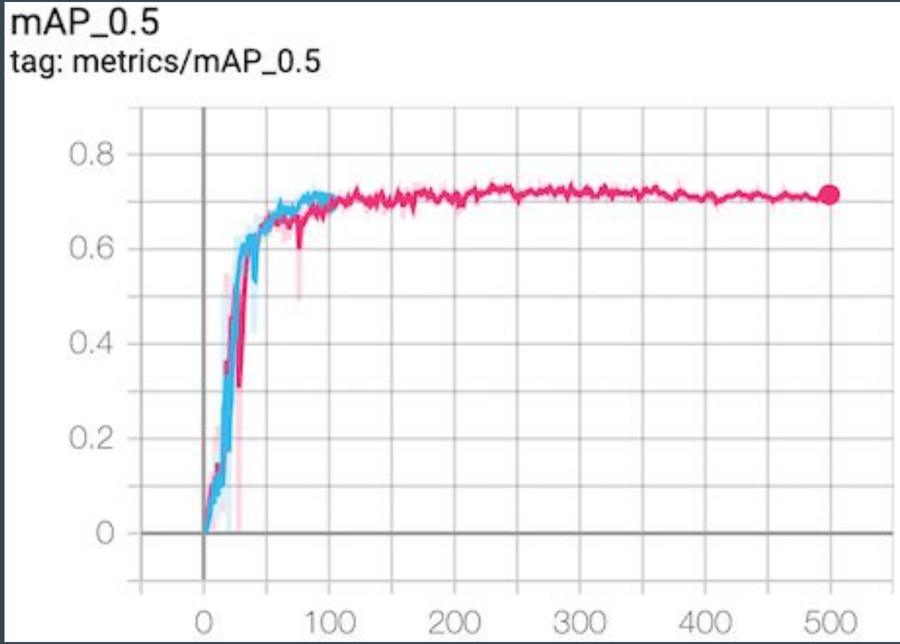
IoU = intersection over union



Common definition of “@0.5”:

IoU > 0.5, it’s a good detection.

Evaluation: Accuracy of Predictions mAP@0.5



mAP@0.5 ~ 70%

Common metric, but...

- Classes are not of equal importance
- Bounding box is not critical
- Count is more important than details of the species

Evaluation: Training and Inference

1 hour 12 mins (fast!) - Training time for 500 sessions with all 951 images (epochs)

13 MB (small!) - Size of model weight file

12 msec (fast!) - Time required for inference (object detection) on a simple image

This translates to a nearly 1 - 1 ratio for video processing -- a 1 minute video can be run through the model in about 1 minute.

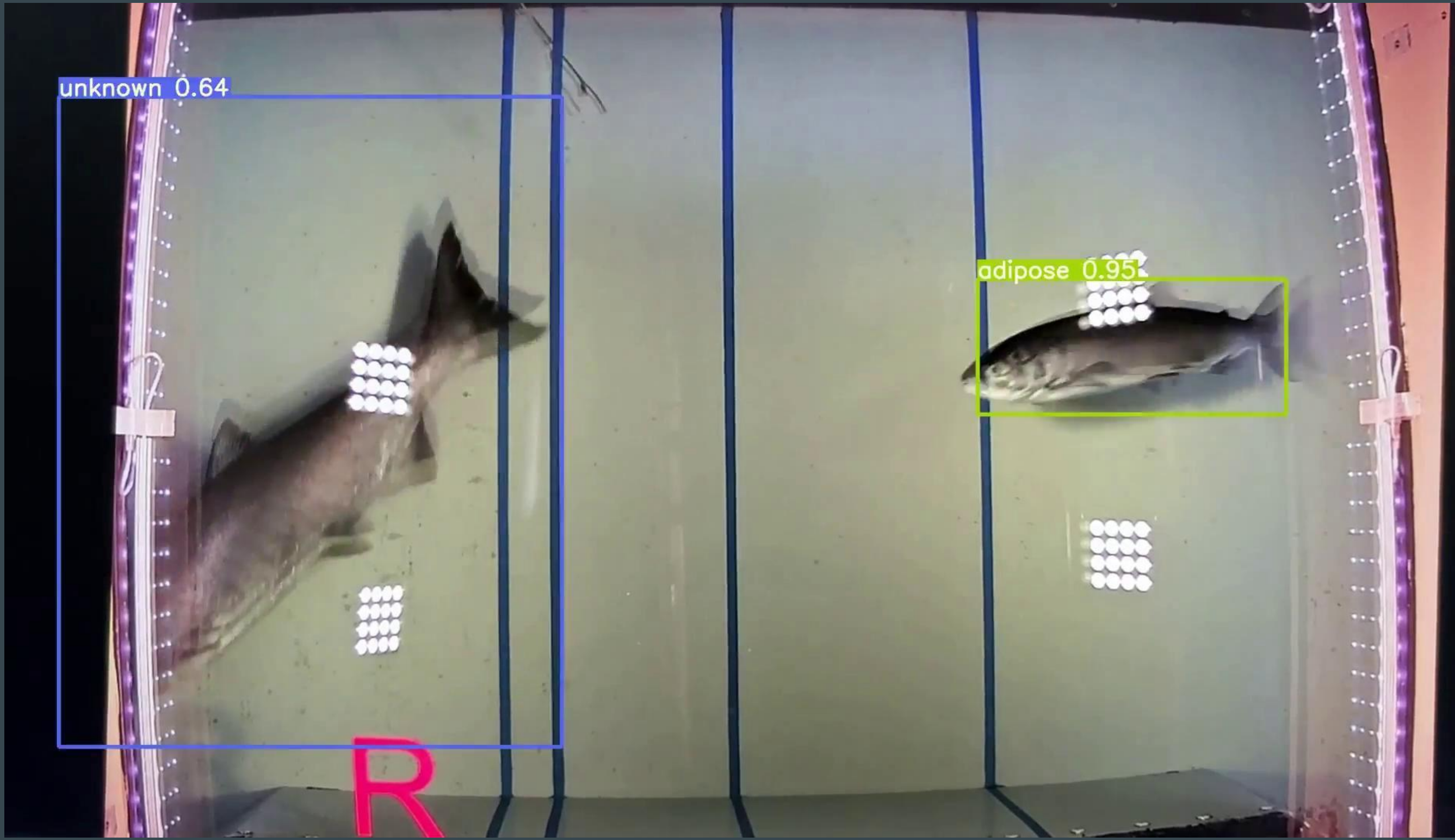
*Times are from Google Colab with GPU enabled.

Conclusion:

The model presented today is not ready for production. It needs:

- Expert labeled images (more classes, fewer errors)
- More images (trained only on images from sockeye run, no chinook or coho)
- Object counting (e.g. implement the SORT method)
- Handling of difficult cases (salmon exit the frame and return, crowded conditions)

Technology and expertise exist for all of these, indicating that modern machine learning object detection methods -- e.g. Deep Learning networks like YOLO -- may soon be ready to assist in this challenge.



Questions?

Acknowledgements

Special thank you to the staff at the **Chelan County PUD** for providing information on salmon counting methods and for a 1-hour video clip.

D. Patterson, T. Mosey, T. West

https://www.chelanpud.org/environment/fish-and-wildlife/fish-counts

Team Roboflow.ai

Image augmentation tools & template notebooks for YOLO models

Sources

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https://thefisheriesblog.files.wordpress.com/2013/05/de1de-two_fins2.jpg

https://static.seattletimes.com/wp-content/uploads/2018/10/Lower-Snake-River-Dams

CNN diagram

https://towardsdatascience.com/a-comprehensive-guide-to-convolutional-neural-networks-the-eli5-way-3bd2b1164a53

YOLOv5 architecture figures are from the YOLOv4 paper

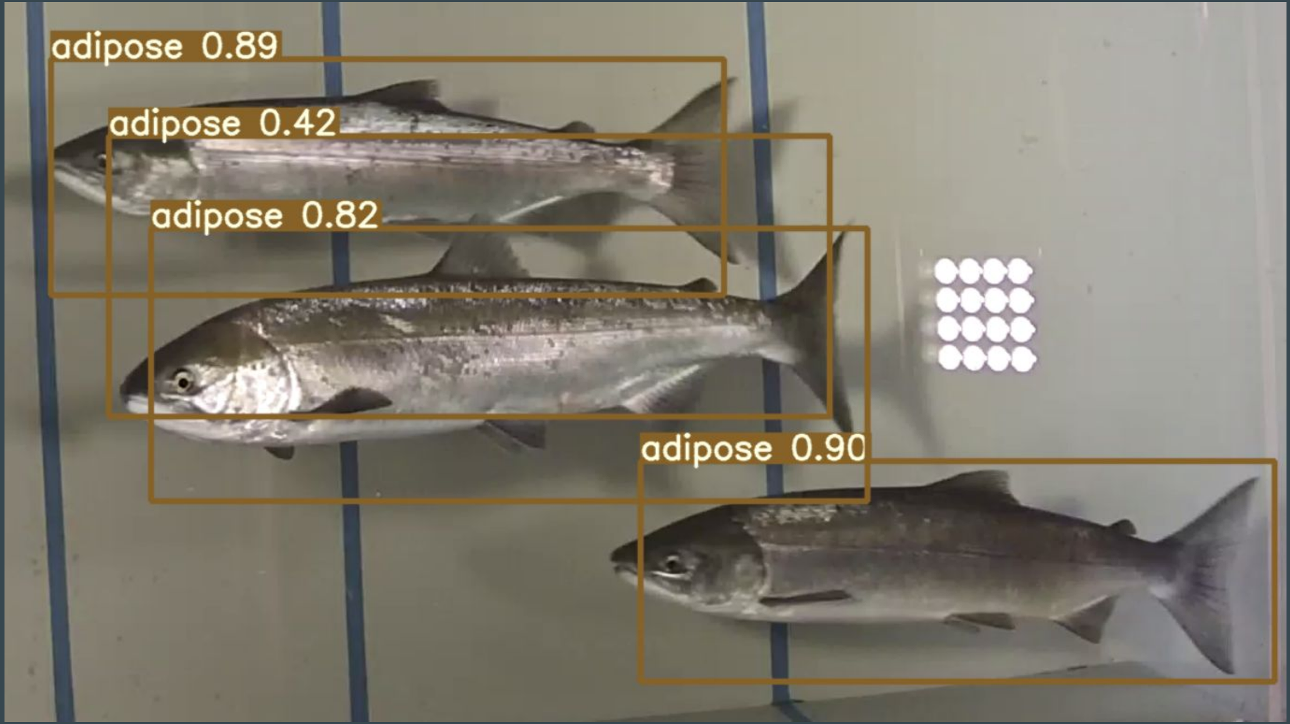
https://arxiv.org/pdf/2004.10934.pdf

Addendum

Difficult Images

Shadows
Object overlap
Crowded conditions

-- there's an extra box in this image @0.42



Difficult Images

Crowded conditions

2 or 3 fish were not found