

A deep learning-based method to identify and count small pelagic and mesopelagic fishes from trawl camera images

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PICES 2024



INSTITUTE OF MARINE RESEARCH
HAVFORSKNINGSINSTITUTTET

Institute of Marine Research (Norway)

Ensure sustainable harvest
of marine resources in Norway

Main activities

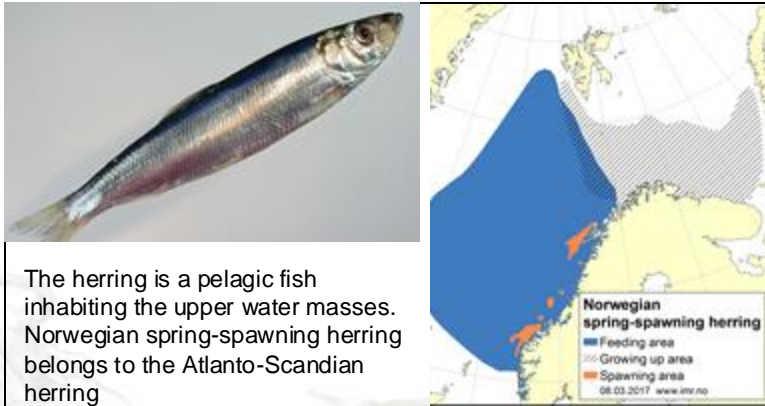
- Monitoring
- Research
- Advisory work

Provide yearly quotas to fisherman

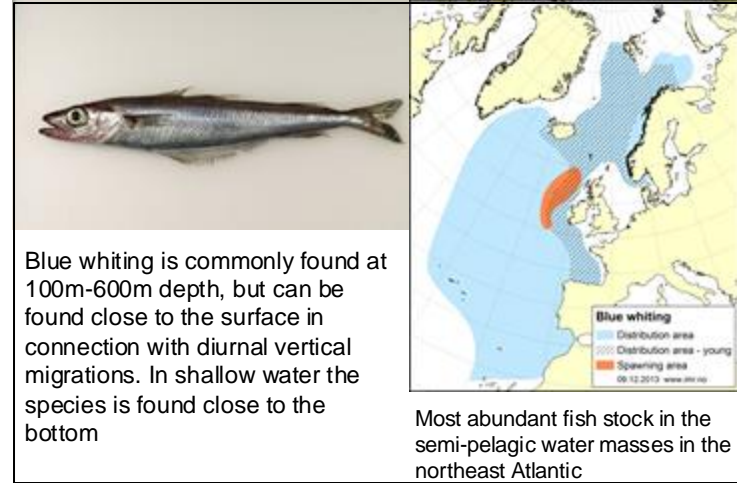
Main
areas



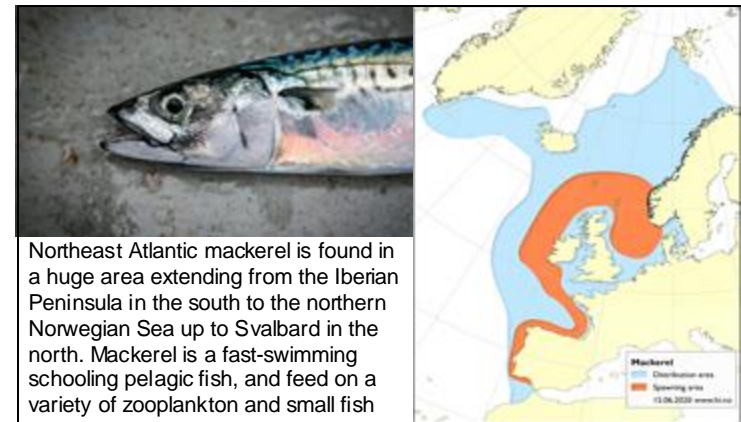
Norwegian sea: Dominant pelagic stocks



Norwegian spring-spawning herring (*Clupea harengus*)

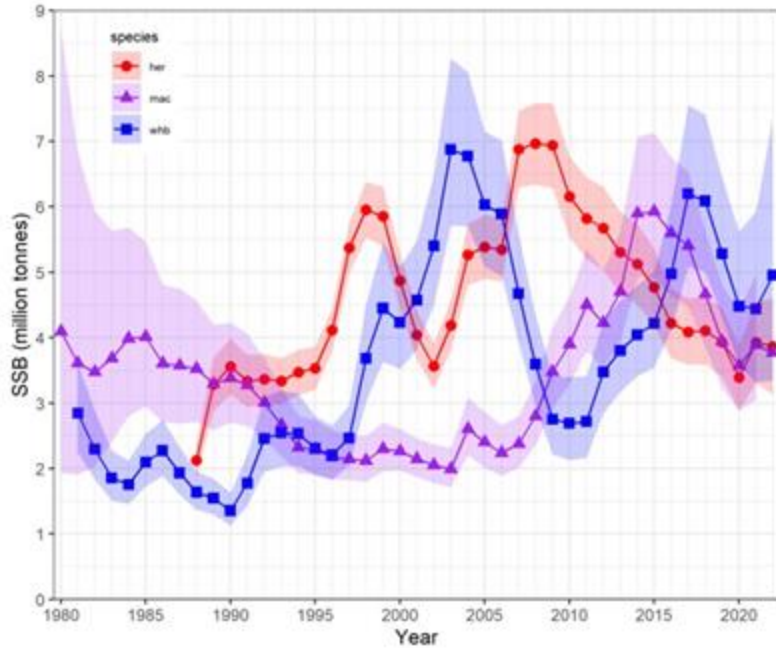


Blue whiting (*Micromesistius poutassou*)

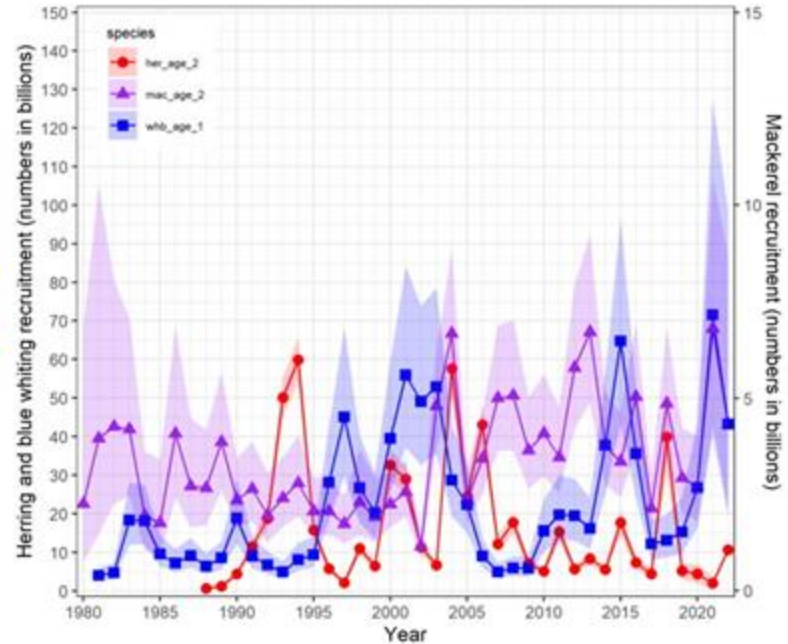


Mackerel (*Scomber scombrus*)

SSB of dominant pelagic stocks since 1980

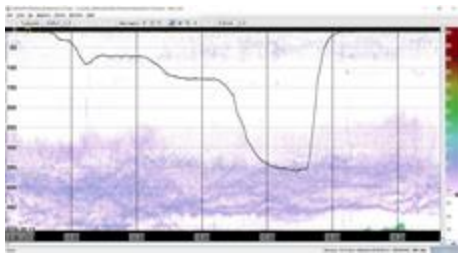
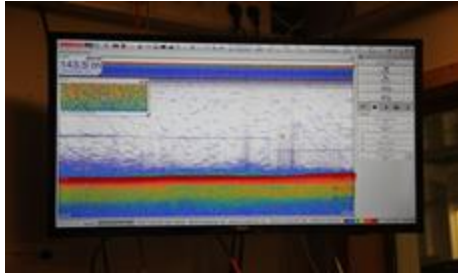


Estimated spawning stock biomass for Norwegian spring-spawning herring (red), mackerel (purple) and blue whiting (blue)



Estimated year-class size at recruitment for Norwegian spring-spawning herring, mackerel and blue whiting

Acoustic trawl survey

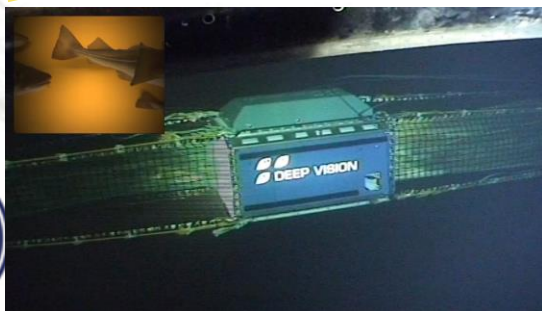
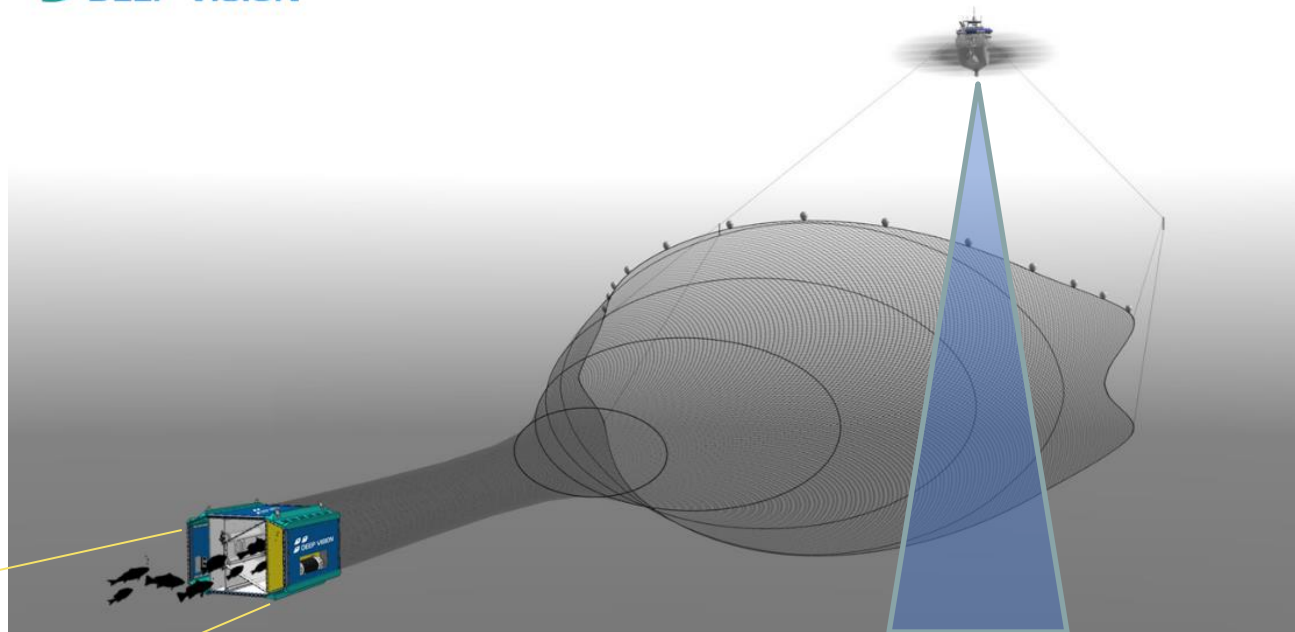


Acoustic data

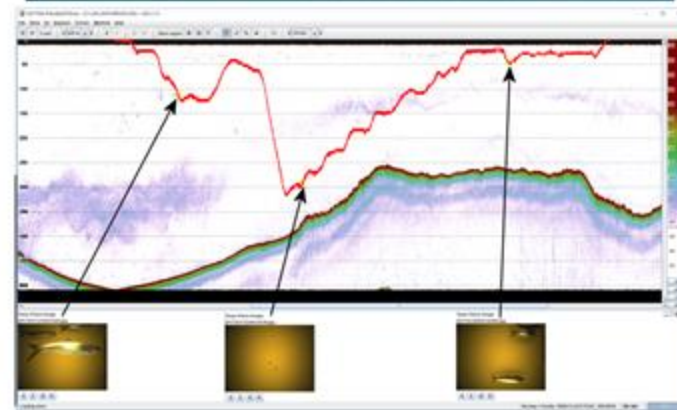
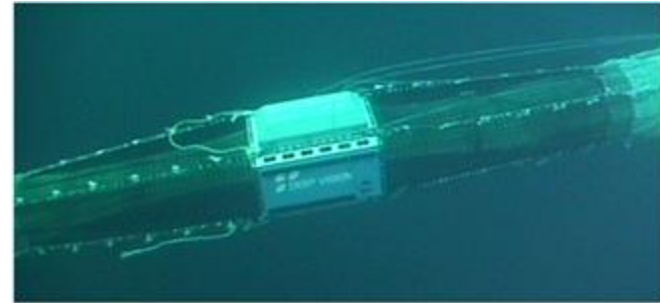
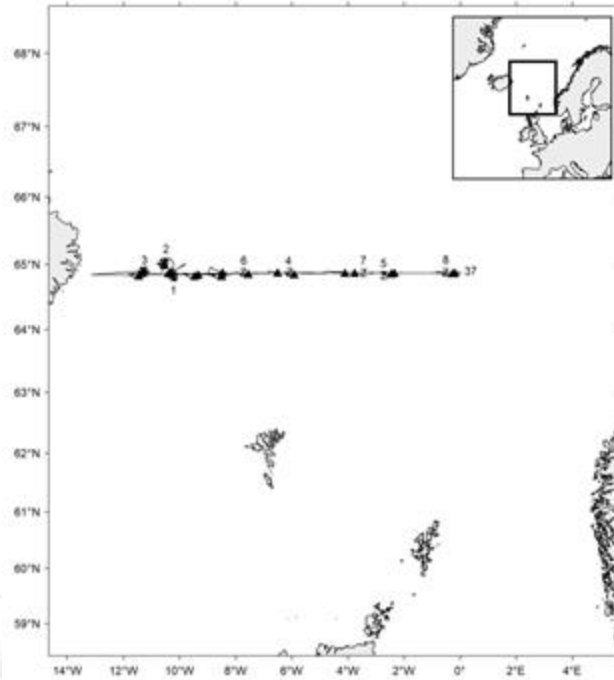
Trawl sampling

Deep Vision

In-trawl cameras



Deep Vision in trawl surveys

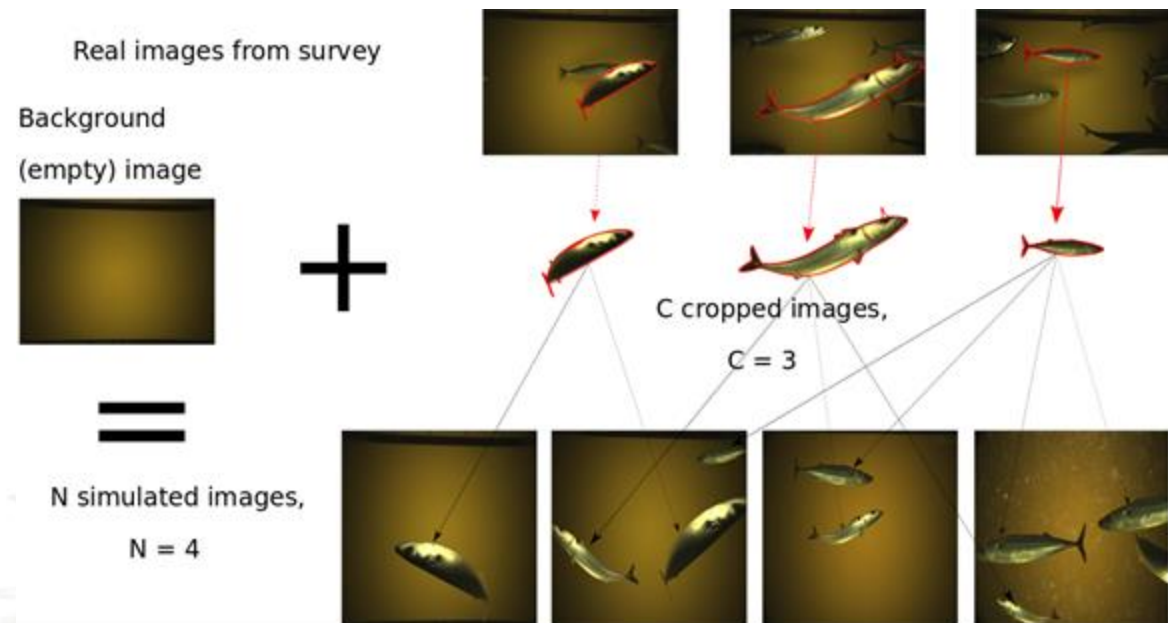


Automate image classification

- Images at 100 ms interval
- Millions of images
- Need for automation



Dealing with limited annotated data



Model performance: image classifier

- Classification model
 - Training dataset:
 - 5000 synthetic images
 - 70 real images
- } per species
- Accuracy on test dataset: **94 %**

Confusion matrix

Blue whiting	0.966	0.020	0.014
Herring	0.034	0.890	0.077
Mackerel	0	0.026	0.974

Blue whiting


Herring

Mackerel



ICES Journal of
Marine Science

ICES Journal of Marine Science (2018), doi:10.1093/icesjms/fsy017



Fish species identification using a convolutional neural network trained on synthetic data

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Ailam, V., Handegard, N. O., Rosen, S., Schreyeck, T., Mahoux, T., and Malde, K. Fish species identification using a convolutional neural network trained on synthetic data. – ICES Journal of Marine Science, doi:10.1093/icesjms/fsy017.

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Acoustic-trawl surveys are an important tool for marine stock management and environmental monitoring of marine life. Correctly assigning the acoustic signal to species or species groups is a challenge, and recently visual camera systems have been developed to support interpretation of acoustic data. Learning images from trawler positions in the trawl track provides high resolution ground truth for the presence of species. Here, we design and deploy a deep learning neural network to automate the classification of species present in images from the Deep Vizion visual camera system. To remedy the scarcity of training data, we developed a novel training regime based on realistic simulation of Deep Vizion images. We achieved a classification accuracy of 94% for blue whiting, Atlantic herring, and Atlantic mackerel, showing that automatic species classification is a viable and efficient approach, and further that using synthetic data can effectively mitigate the all too common lack of training data.

Keywords: acoustic-trawl survey, deep learning, fish image classification, machine learning, trawl camera

Introduction

Sustainable exploitation of marine natural resources requires effective management based upon ongoing monitoring of the marine environment. Acoustic-trawl surveys (MacLennan and Simenstad, 2002) are one of the most important tools for assessing fish abundance. These are typically used for pelagic stocks, providing important input to the fisheries assessment models. When using calibrated echo sounders, fish density is related to backscatter strength (Enebo, 1981) through the target strength (TGS; 1987). As target strength varies by species, correctly identifying the species detected acoustically is critical to correctly estimating fish density.

Acoustic-trawl surveys typically use trawl sampling to identify the species or species groups present. Trawl sampling only provides an aggregate collection of fish along the trawl path, and if different fish species are collected, assigning each species to specific locations can be challenging. Using remote equipment in the trawl is one way to increase the resolution along the trawl path.

The Deep Vizion (SeaView Deep Vizion AS, Bergen, Norway) system (Rosen and Hain, 2017) (Figure 1) houses the trawl catch over a high resolution stereoscopic camera chamber, before it is collected in the codend. Image pairs are taken with a focal length of 3 or 10 frames per second, resulting in millions of images from a typical acoustic-trawl survey. Classification is challenging due to partial visible fish, fish at different orientations and shapes, and similarities between the species in terms of shape size and coloring. Each image is accompanied by information about GPS position, time, and depth.

Machine learning and computer vision techniques can be used to automate image processing, and tailored image recognition techniques have traditionally been developed to solve specific problems (Lacort et al., 2015, and references therein). This is also the case for fish images, where specific techniques have been developed for species identification (Whitey et al., 2009) and fish age estimation (Chuang et al., 2012), among others.



Adapting model to new datasets

Drop of around 40% in accuracy when tested on new dataset (from 94% to 53%)

Performance does not generalise across datasets



Image from 2017



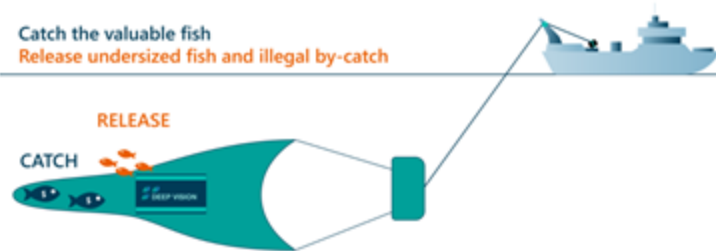
Image from 2018

Options

- Combine data from 2017 and 2018 and train network on the larger combined dataset
- Finetune model trained on 2017 dataset on data from 2018

Idea

- Step 1: Develop fish detection model
- Step 2: Deploy for automatic counting (?) /species distribution
- Step 3: Open cod-end. We (and fish) live happily ever after



Building the datasets

- 1879 annotated images from 2017 and 2018 surveys
- Generated 20000 synthetic images from 343 “real” images
 - Composition of synthetic training dataset:
 - Random
 - Reflect composition of real images
 - 4000 of each fish species
 - Blue whiting
 - Herring
 - Mackerel
 - Mesopelagic fish
 - 4000 mixed species images



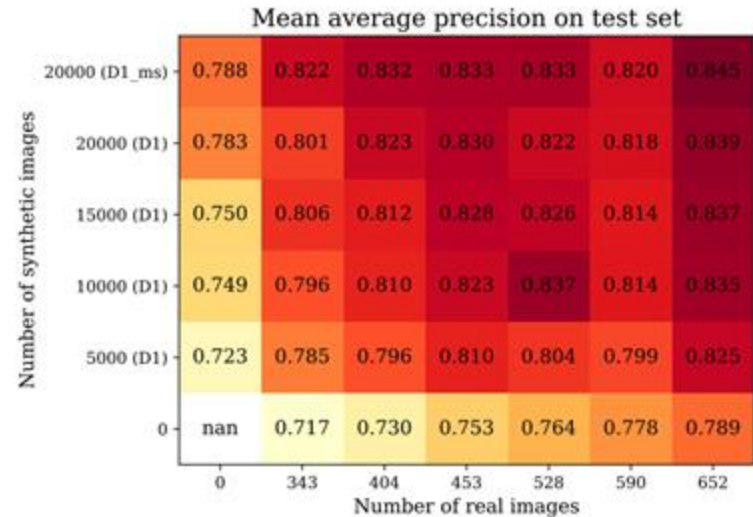
Manually annotating fish for object detection

Allken V., Rosen S., Handegard N. O., Malde K. 2021. A real-world dataset and data simulation algorithm for automated fish species identification. *Geoscience Data Journal*, 00: 1–11, <https://rmets.onlinelibrary.wiley.com/doi/abs/10.1002/gdj3.114>

Object detection model: Model performance

- Object detection model (RetinaNet)
 - Best training dataset
 - 20000 synthetic images
 - 652 real images
 - Performance on test dataset
 - Best mAP = **0.85**

} per species



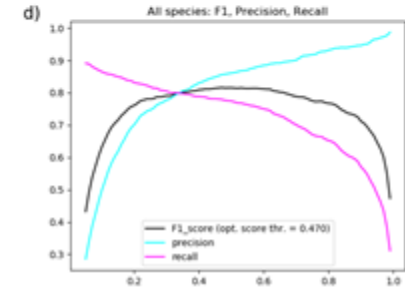
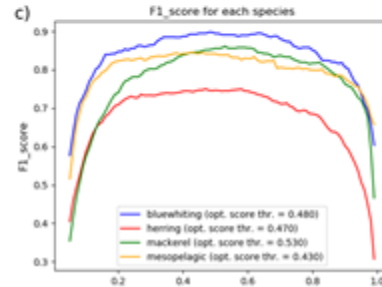
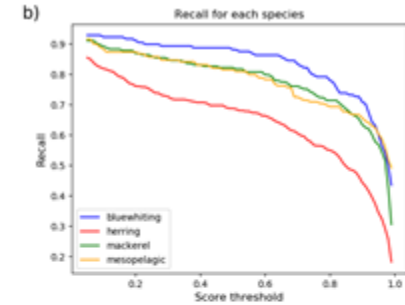
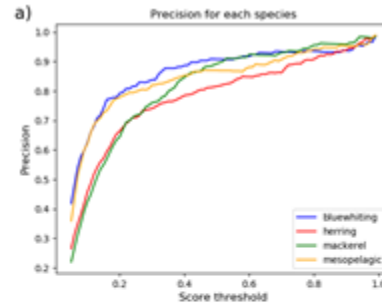
Optimal score threshold

For predictions, we use the score threshold corresponding to the maximum F1 score

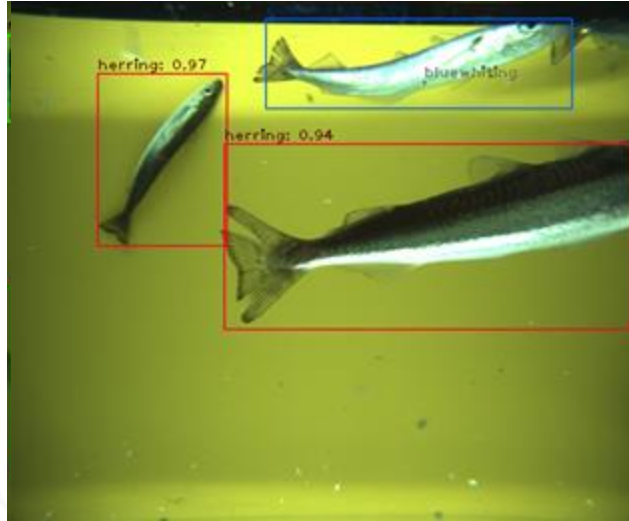
$$F1 = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} = \frac{2TP}{2TP + FP + FN}$$

Optimal score threshold for:

- Blue whiting : 0.48
- Herring: 0.47
- Mackerel: 0.53
- Mesopelagic: 0.43
- All species: **0.47**



Application to the real-world



Model predictions



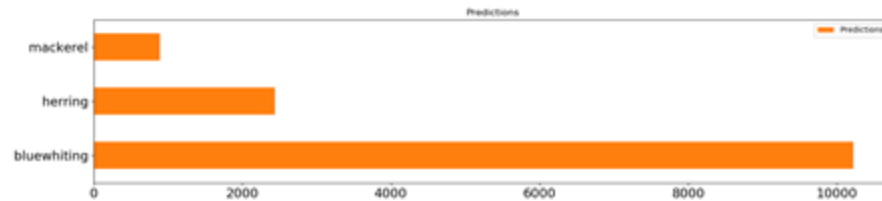
Catch data

Challenge in automating count

Catch

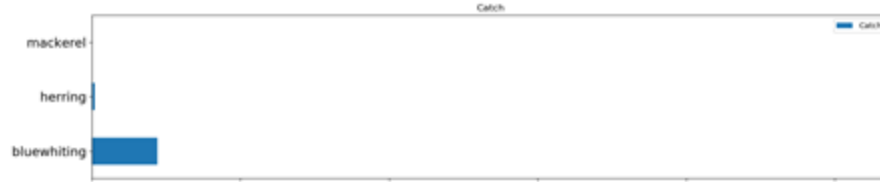


Predictions

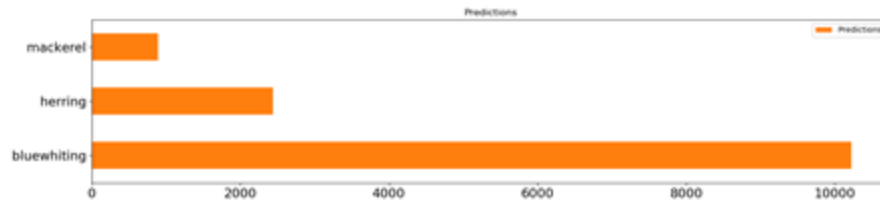


Challenge in automating count

Catch

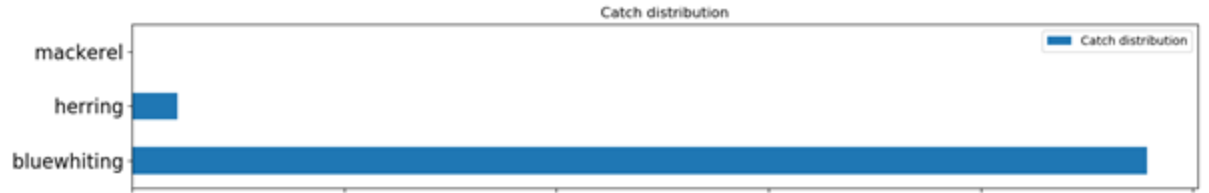


Predictions

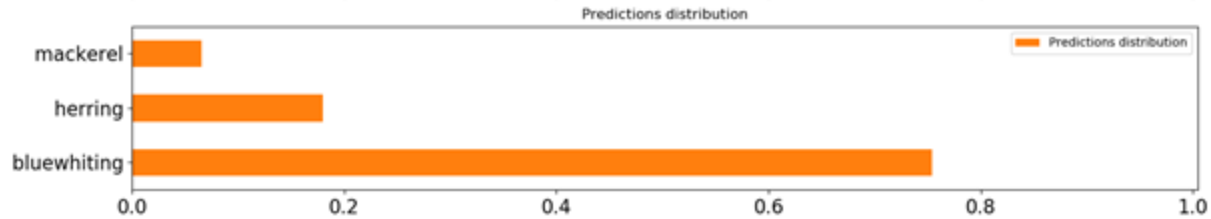


Fish distribution?

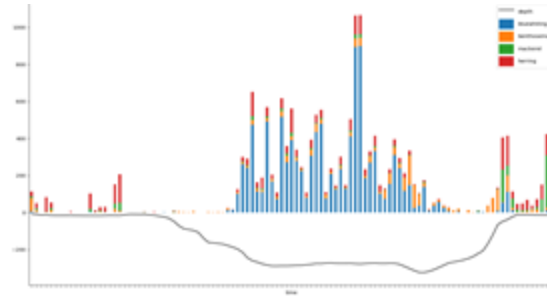
Catch



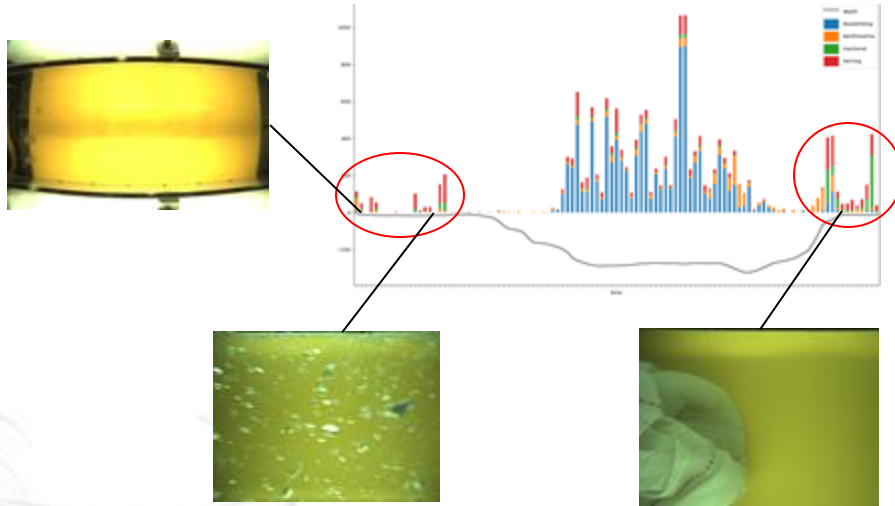
Predictions



Fish distribution as a function of time



Empty/non-fish images

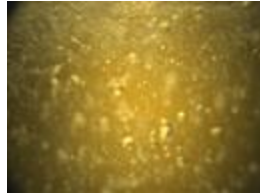


Most images do not contain fish

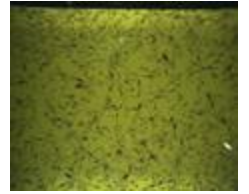
- Large number of false positives
 - Images on deck
 - Images containing artifacts

Filtering algorithm

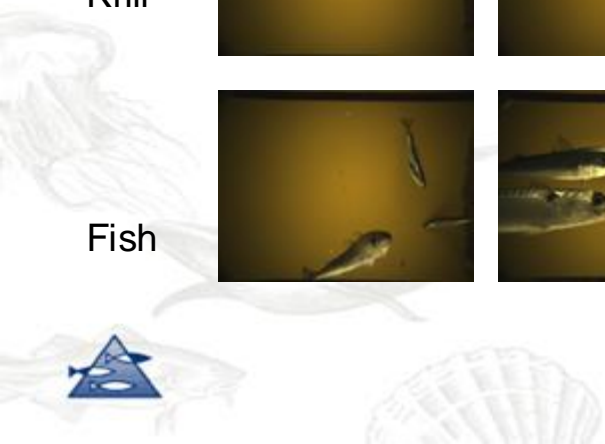
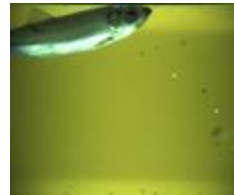
Empty



Krill



Fish

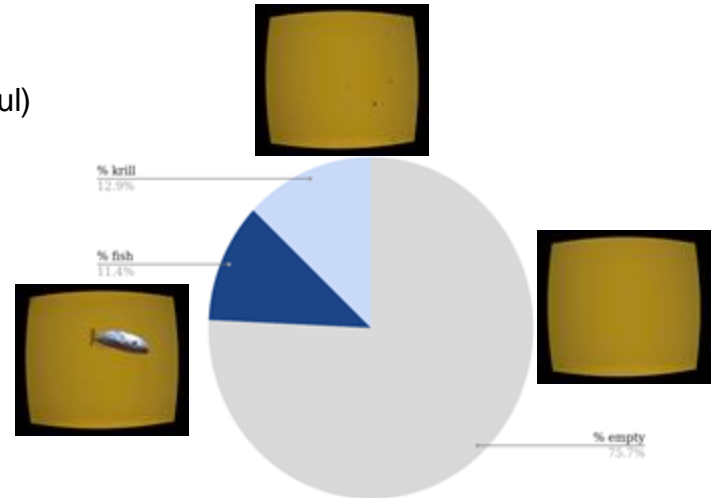


Empty/non-fish images

- Challenge: Most images do not contain fish
 - Long processing time (> 100 000 images/trawl haul)
 - 10 stereo pairs per second



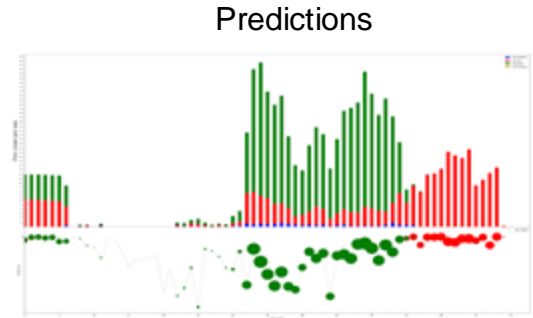
- 75% images are empty



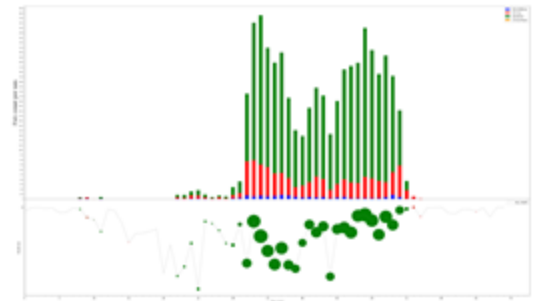
Empty/non-fish images

- Filter out empty images in Deep Vision system
- Run model only on active images
 - Fewer false positives
 - Faster processing time

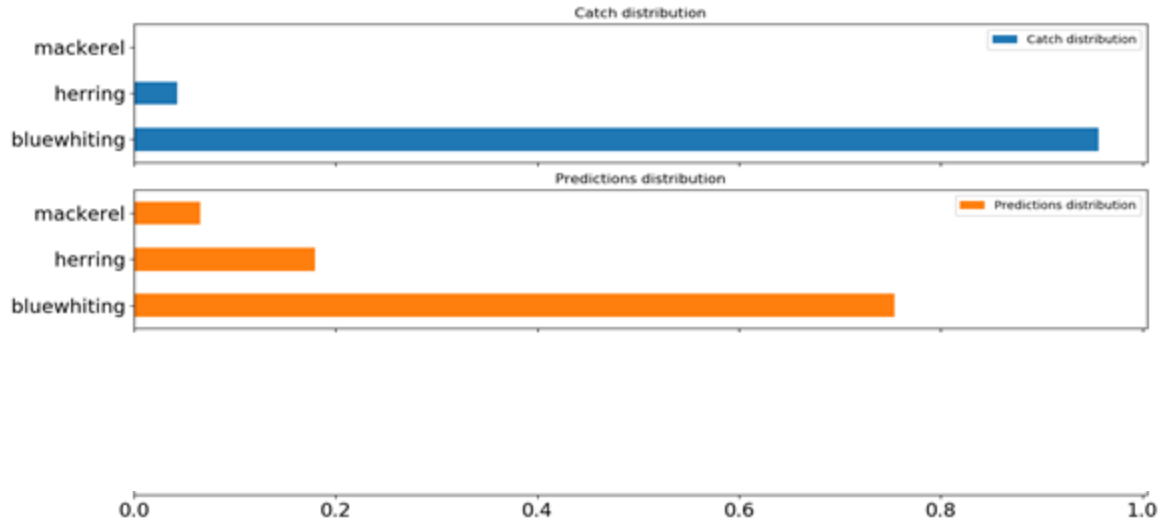
Without filter



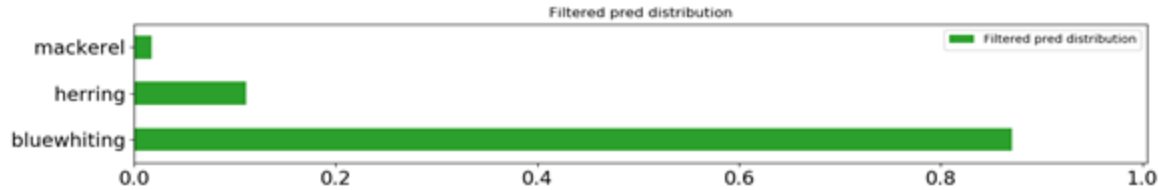
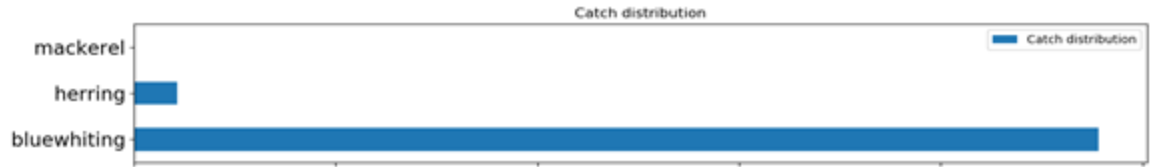
With filter



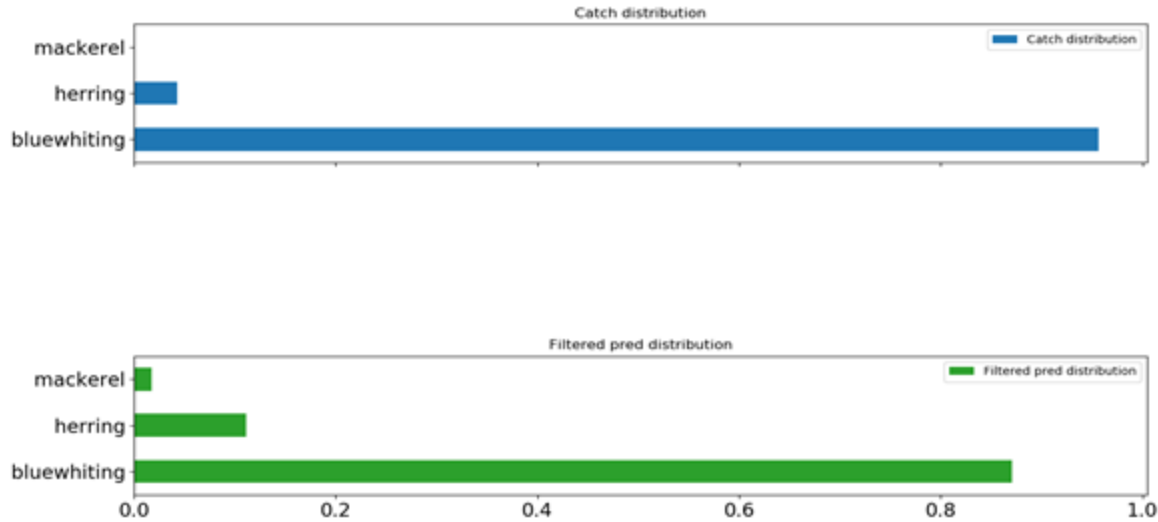
Before applying filter



After applying filter



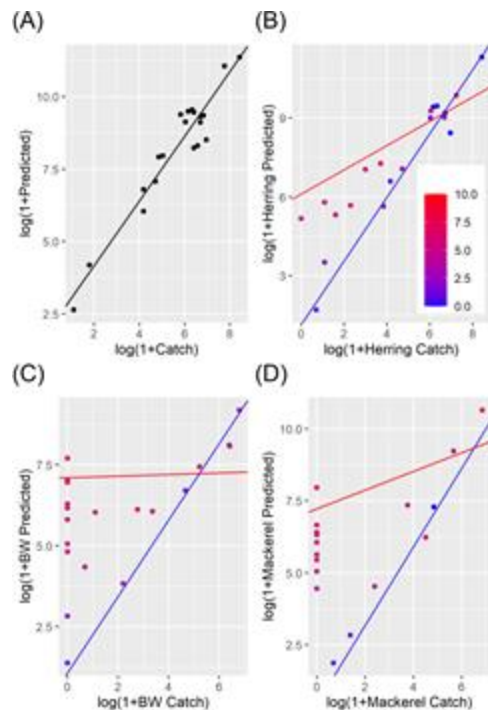
After applying filter



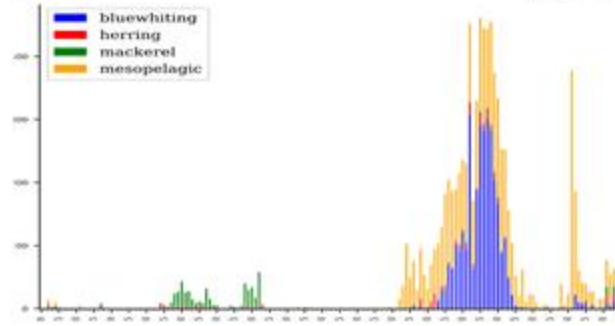
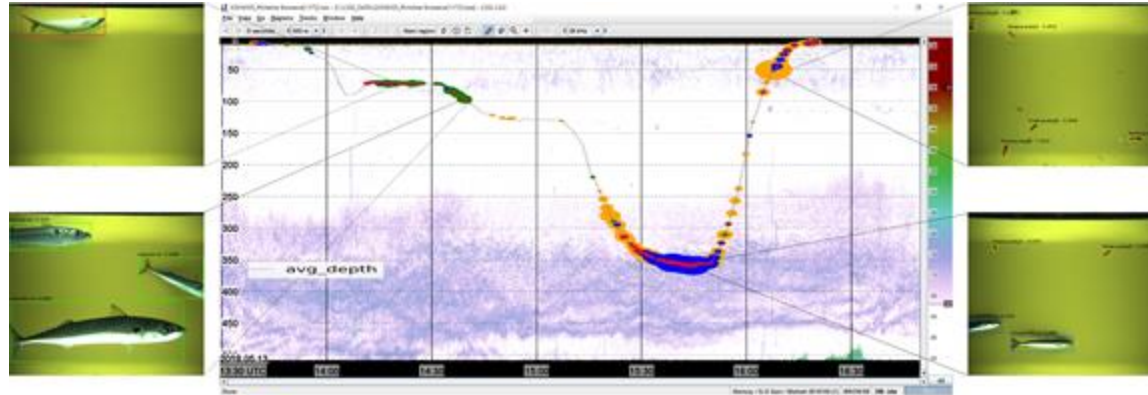
Different species have different average swimming speeds
=> Overcount slower fish (appears in more consecutive images)

Automating count: comparison with catch data

- Compare catch and prediction counts
 - Catch data not available for all species
 - Species-dependent duplicate images
 - Counts/catch
 - Blue whiting: 10.4
 - Herring: 15.4
 - Mackerel: 40
 - Regression model can be used to estimate overall catch



Prediction on entire trawl haul



Allken V, Rosen S, Handegard NO, Malde K, **A deep learning-based method to identify and count pelagic and mesopelagic fishes from trawl camera images.** *ICES J Mar Sci.* 2021; 78(10): 3780-3792. doi:[10.1093/icesjms/fsab227](https://doi.org/10.1093/icesjms/fsab227)

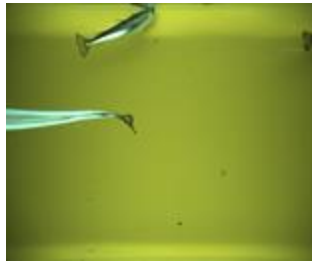
Data drift: variations in image quality

Evolution of Deep Vision system

- Changes in resolution, geometric calibration, colour-correction



2017



2018



2021



2022

=> Reduced performance of machine learning model

Data drift: variations in image quality

Continuously improve model with new data

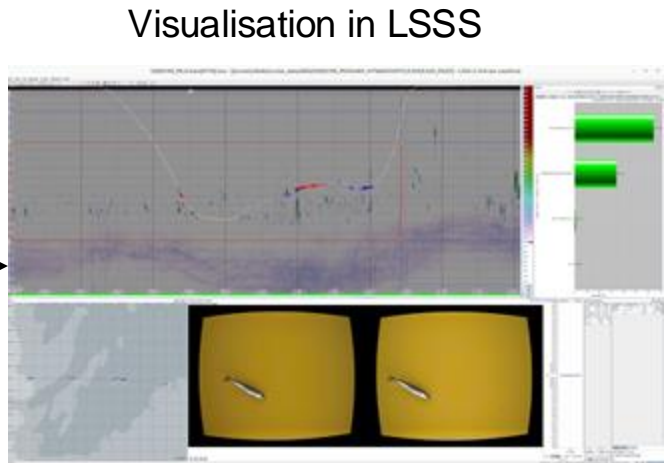
- If labelled
 - Train/test on a variety of datasets
 - Finetune on sample of annotated data every year
- Not labelled
 - Semi-supervised learning
 - Run model on new images
 - Build new training set with images where
 - Prediction scores is high
 - Left prediction = Right prediction
 - Fine-tune on new training dataset



Deep Vision pipeline



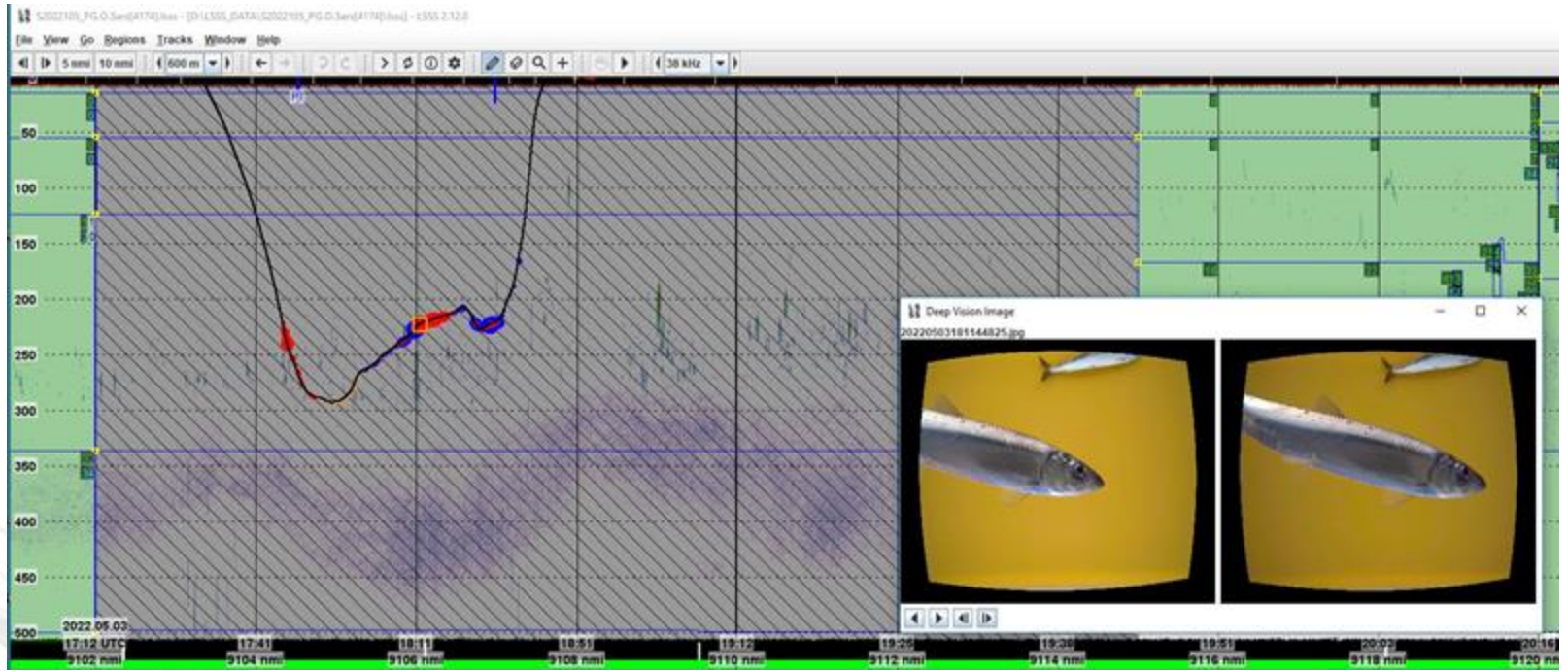
Processing and object detection (1-2h)



Download (5 - 30 min)

DV can be set out again after download

Acoustic herring survey 2022



Acoustic herring survey 2022



Methods used for stock assessment at IMR

Task	Method	Acoustic	Trawl catch (regular mesh)	In-trawl cameras (since ~2015)	
				Visualise img	Automatic (ML) predictions
Norwegian spring-spawning herring & blue whiting					
Abundance estimate		X	X	X	X
Length distribution			X	X	X
Age distribution			X		

X : done/ongoing

X : future work



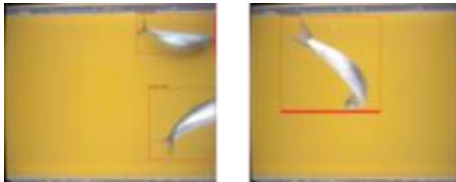
Length distribution

Challenges

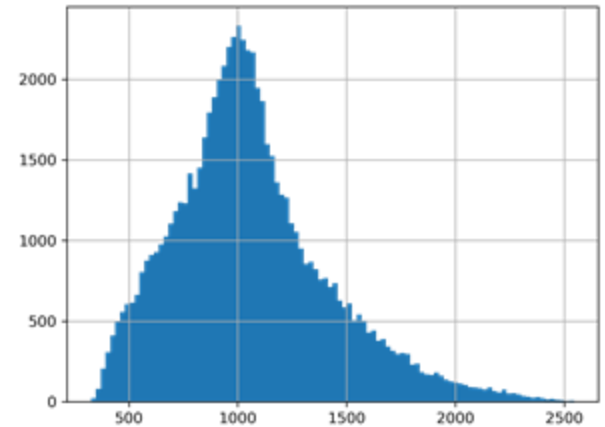
- Same fish appears in several images



- Fish not always captured whole or in ideal position



- Tracking could help but only few frames per second



Predicted fish length distribution (by pixel)

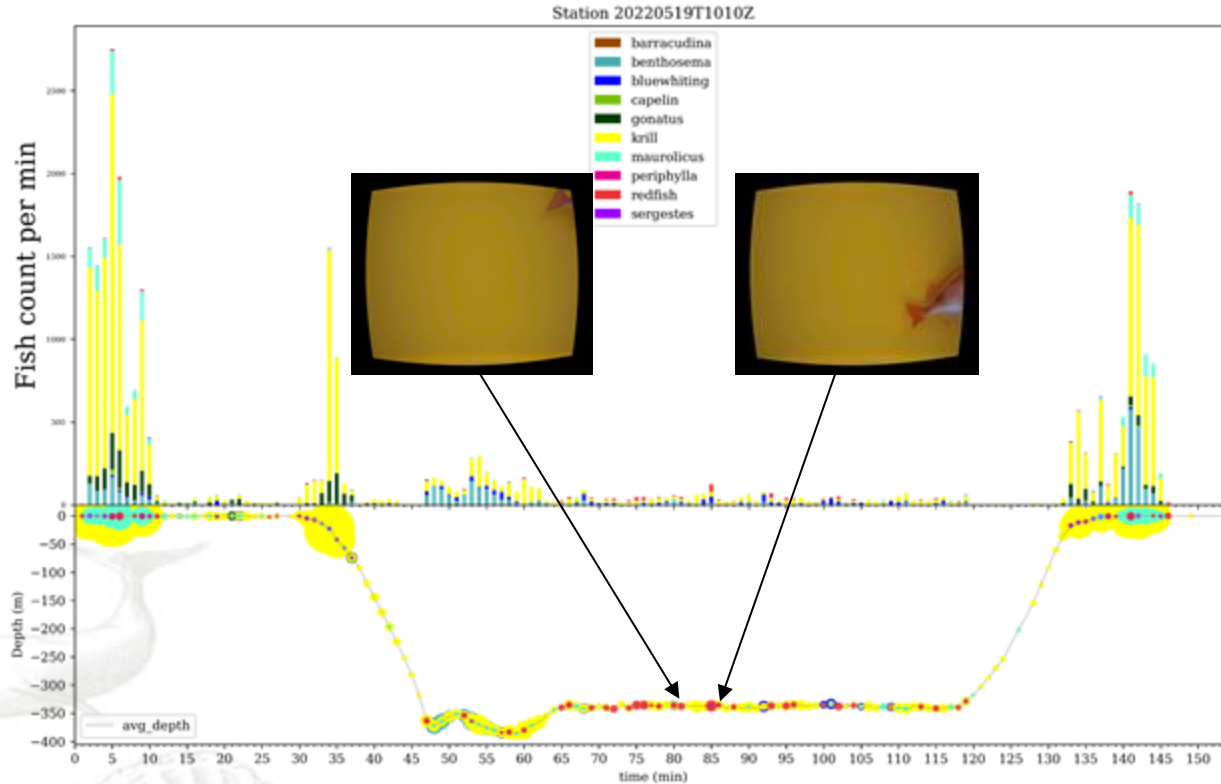
Methods used for stock assessment at IMR

Method	Acoustic	Trawl catch (regular mesh)	In-trawl cameras (since ~2015)	
			Visualise img	Automatic (ML) predictions
Norwegian spring-spawning herring & blue whiting				
Abundance estimate	X	X	X	X
Length distribution		X	X	X
Age distribution		X		
Redfish				
Stock monitoring	X	X	X	X

X : done/ongoing
X : future work



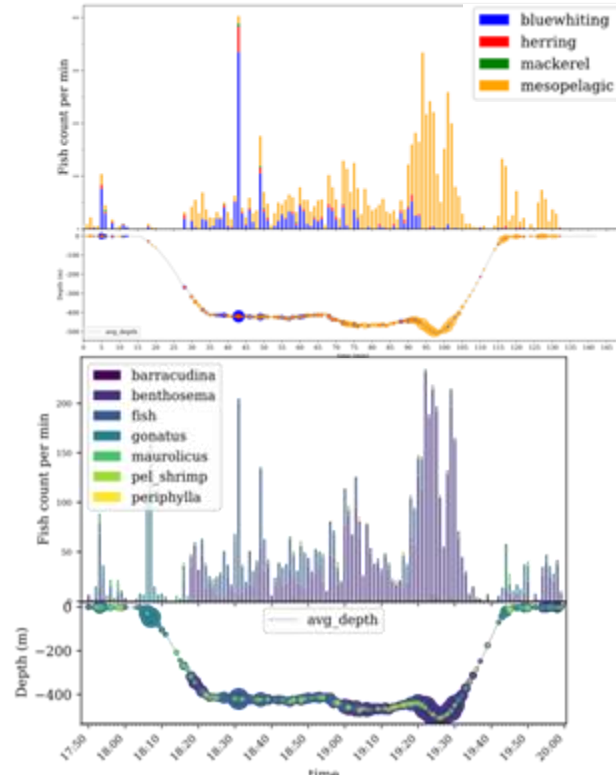
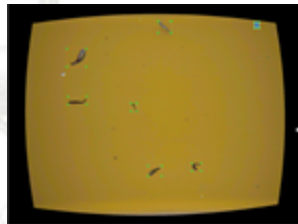
Redfish model



Mesopelagic fish distribution

- Growing interest in mesopelagic species
 - Gap in knowledge
- Trawl catch
 - Small organisms escape regular-sized mesh
 - Small mesh liners specifically developed
- Relevance of images from in-trawl cameras
 - Manual analyses prohibitively time-intensive

=> developed object detection model (YOLOV8)



Methods used for stock assessment at IMR

Task	Method	Acoustic	Trawl catch (regular mesh)	In-trawl cameras (since ~2015)	
				Visualise img	Automatic (ML) predictions
Norwegian spring-spawning herring & blue whiting					
Abundance estimate		X	X	X	X
Length distribution			X	X	X
Age distribution			X		
Redfish					
Stock monitoring		X	X	X	X
Mesopelagic fish					
Relative abundance		X		X	X
Depth distribution		X		X	X

X : done/ongoing
X : future work

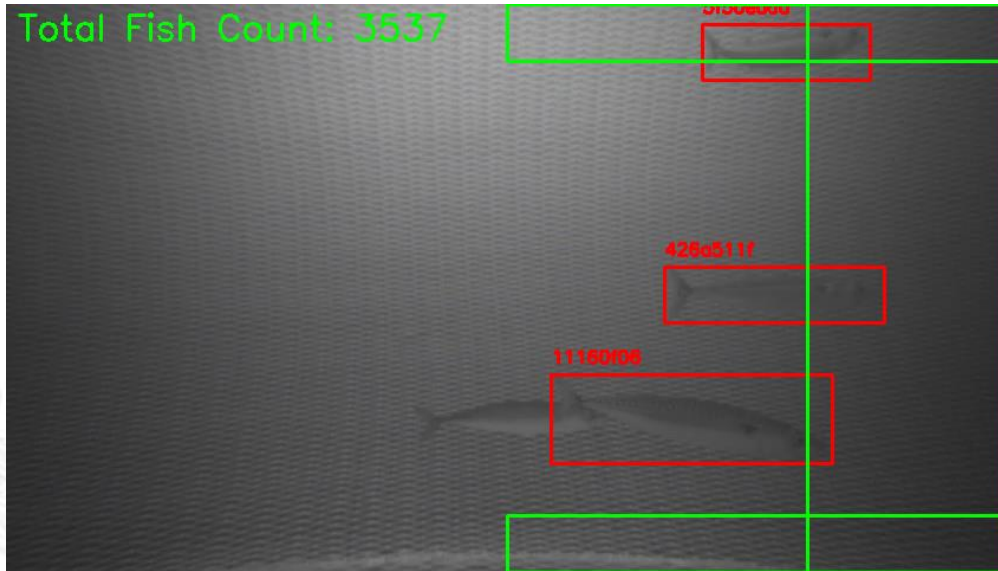
Mackerel abundance estimation

Challenge:

- Shallow distribution of mackerel
 - In blind zone of echo sounder
- High-density images
 - Undercounted by previous object detection model



Mackerel abundance: recent experiments



Work & video by Jørgen Høyer

Methods used for stock assessment at IMR

Task	Method	Acoustic	Trawl catch (regular mesh)	In-trawl cameras (since ~2015)	
				Visualise img	Automatic (ML) predictions
Norwegian spring-spawning herring & blue whiting					
Abundance estimate		X	X	X	X
Length distribution			X	X	X
Age distribution			X		
Redfish					
Stock monitoring		X	X	X	X
Mesopelagic fish					
Relative abundance		X		X	X
Depth distribution		X		X	X
Mackerel (swept area survey)					
Abundance estimate			X		X

X : done/ongoing

X : future work



IMR Team

Machine Learning



Vaneeda Allken

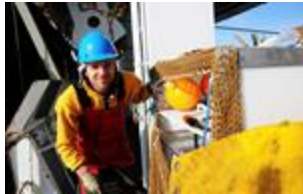


Ketil Malde



Nils Olav Handegard

Biologists



Shale Rosen



Taraneh Westerglering



Maria Tenningen

Funding by CRIMAC

(Center for **R**esearch-based
Innovation in **M**arine **A**coustic
Abundance Estimation and
Backscatter **C**lassification)



Thank you for your attention!

Contact: **vaneeda@hi.no**

- **Fish species identification using a convolutional neural network trained on synthetic data**, Vaneeda Allken, Nils Olav Handegard, Shale Rosen, Tiffanie Schreyeck, Thomas Mahiout, Ketil Malde, *ICES Journal of Marine Science*, Volume 76, Issue 1, January-February 2019, Pages 342–349, <https://doi.org/10.1093/icesjms/fsy147>
- **A real-world dataset and data simulation algorithm for automated fish species identification**, Vaneeda Allken, Shale Rosen, Nils Olav Handegard, Ketil Malde, *Geoscience Data Journal*, Vol 8, Issue 2, March 2021, Pages 199-209, <https://doi.org/10.1002/gdj3.114>
- **A deep learning-based method to identify and count pelagic and mesopelagic fishes from trawl camera images**, Vaneeda Allken, Shale Rosen, Nils Olav Handegard, Ketil Malde, *ICES Journal of Marine Science*, Volume 78, Issue 10, December 2021, Pages 3780–3792, <https://doi.org/10.1093/icesjms/fsab227>

