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

Vaneeda Allken

30th of October 2024

PICES 2024

INSTITUTE OF MARINE RESEARCH
HAVFORSKNINGSINSTITUTTET

Institute of Marine Research (Norway)

Ensure sustainable harvest
of marine resources in Norway

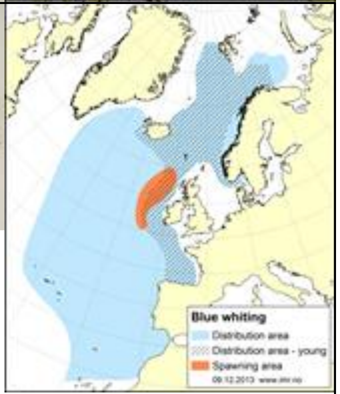
Main activities

- Monitoring
- Research
- Advisory work

Provide yearly quotas to fisherman

Main areas

Norwegian sea: Dominant pelagic stocks



Blue whiting is commonly found at 100m-600m depth, but can be found close to the surface in connection with diurnal vertical migrations. In shallow water the species is found close to the bottom

Most abundant fish stock in the semi-pelagic water masses in the northeast Atlantic

Blue whiting (Micromesistius poutassou)

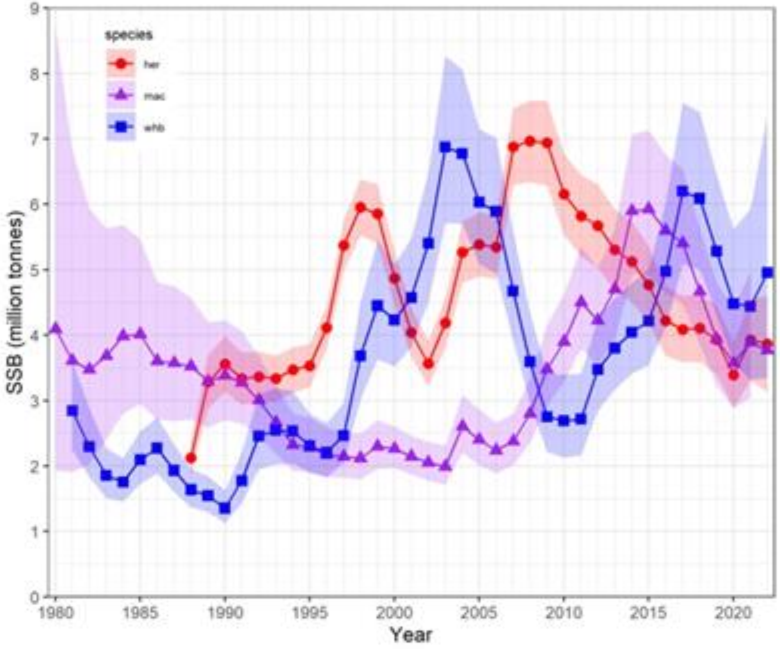
The herring is a pelagic fish inhabiting the upper water masses. Norwegian spring-spawning herring belongs to the Atlanto-Scandian herring

Norwegian spring-spawning herring (Clupea harengus)

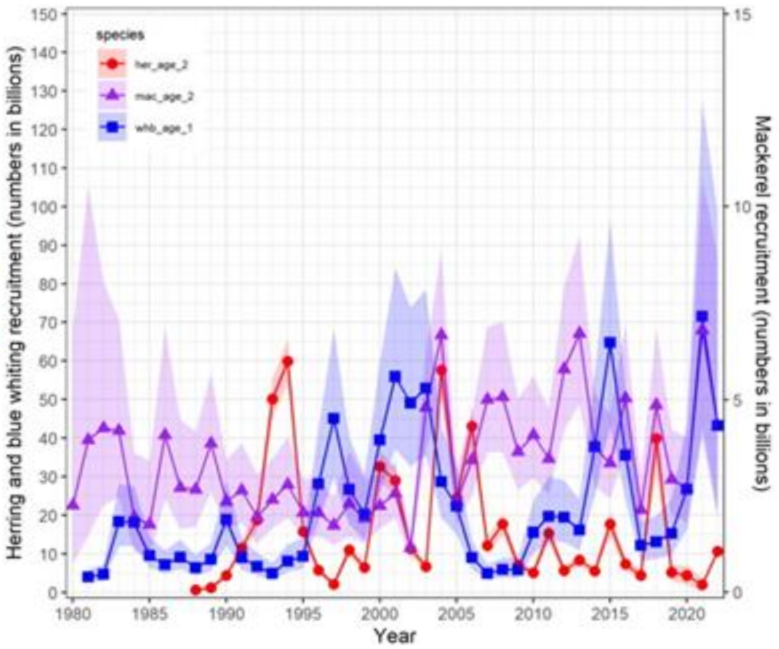
Northeast Atlantic mackerel is found in a huge area extending from the Iberian Peninsula in the south to the northern Norwegian Sea up to Svalbard in the north. Mackerel is a fast-swimming schooling pelagic fish, and feed on a variety of zooplankton and small fish

Mackerel (Scomber scombrus)

SSB of dominant pelagic stocks since 1980

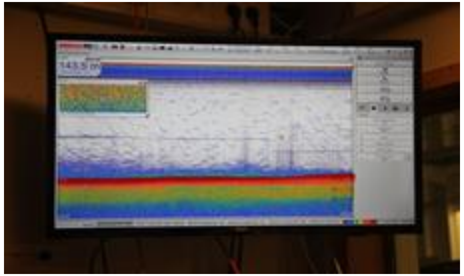


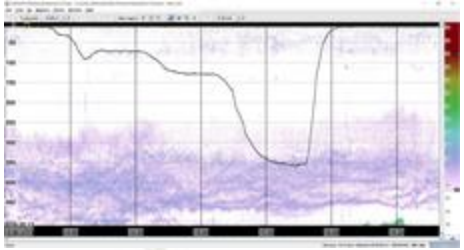
Estimated spawning stock biomass for Norwegian spring-spawning herring (red), mackerel (purple) and blue whiting (blue)



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

Acoustic trawl survey



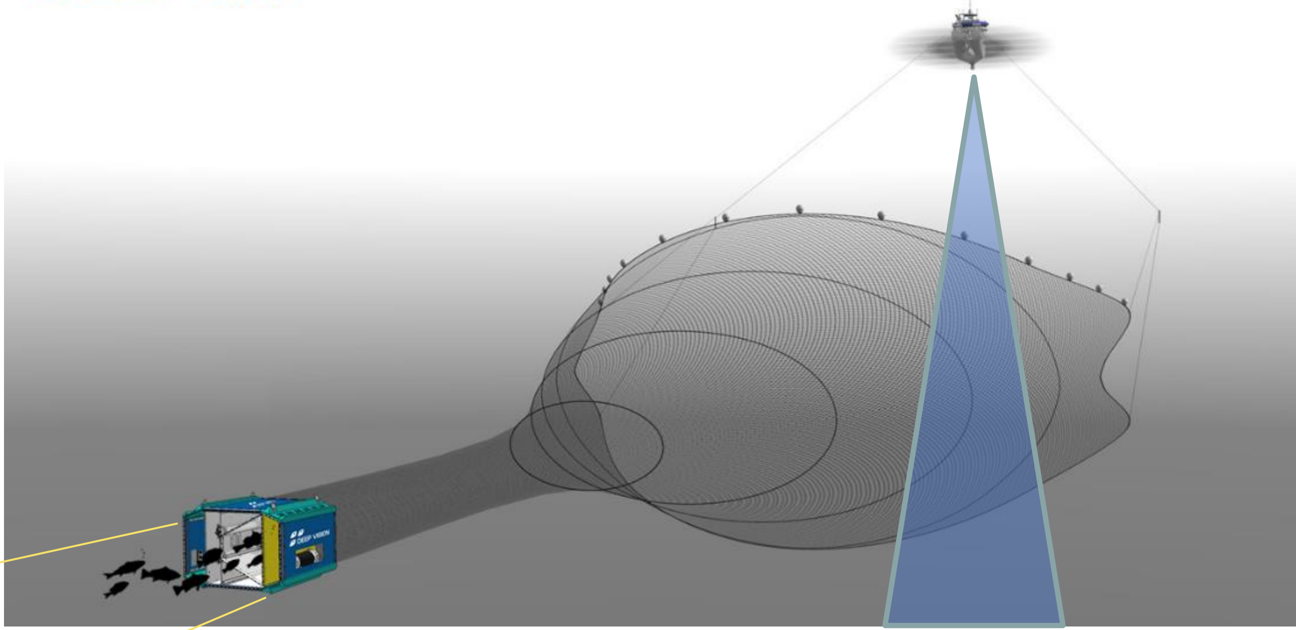


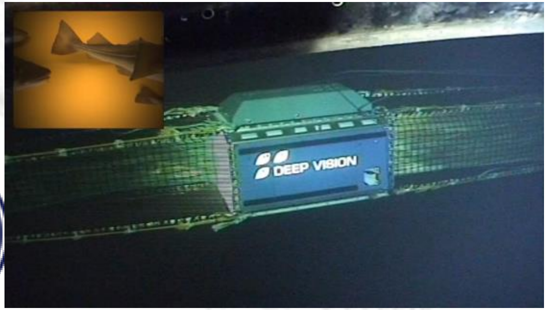
Acoustic data

Trawl sampling

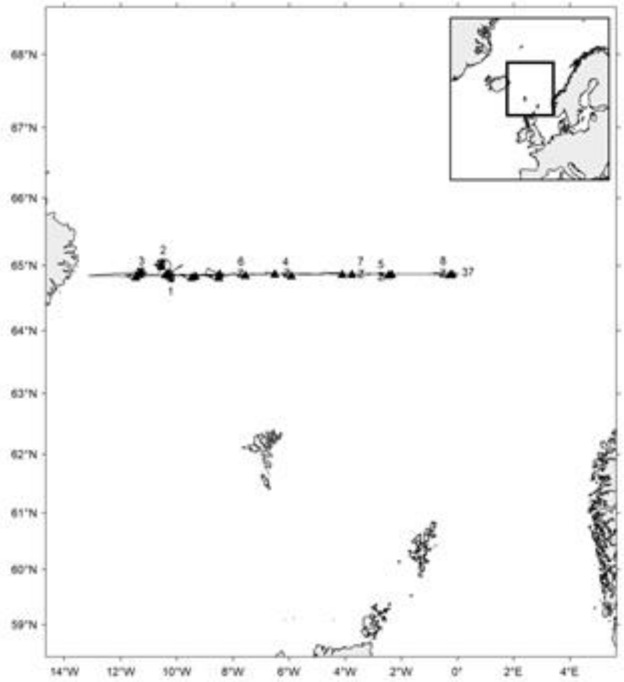
Deep Vision

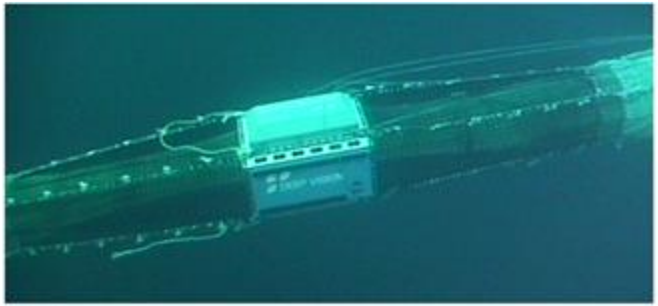
In-trawl cameras

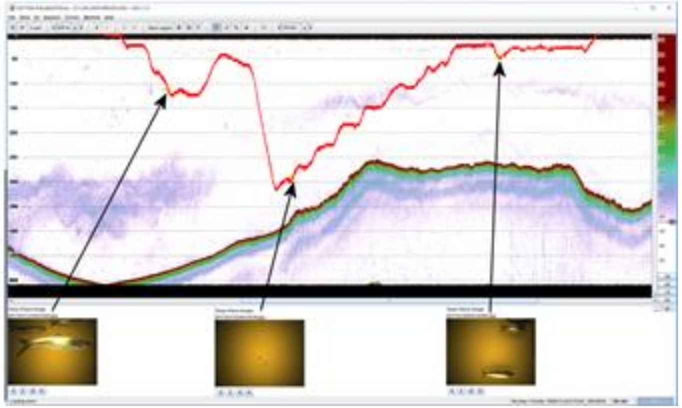




Deep Vision in trawl surveys



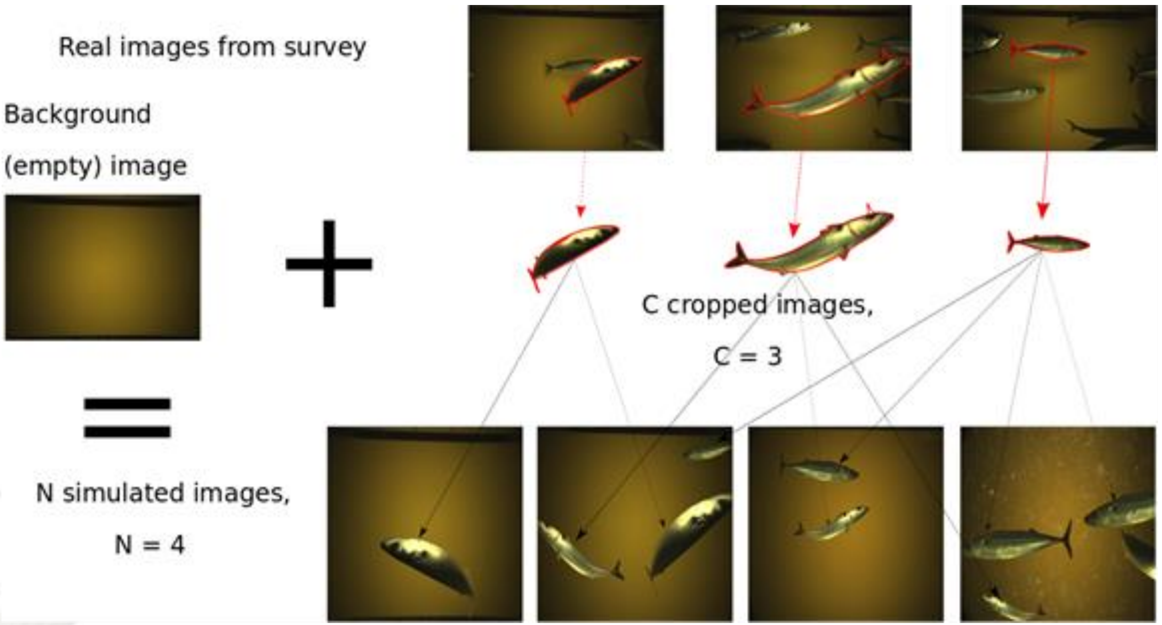




Automate image classification

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

Dealing with limited annotated data

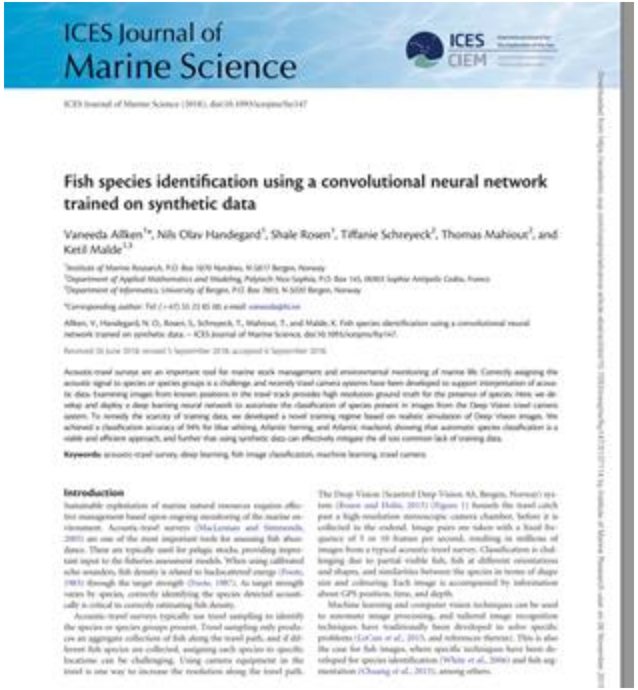


Model performance: image classifier

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

Confusion matrix

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


ICES Journal of Marine Science

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

Vaneeda Allken[1]*, Nils Olav Handegard[1], Shale Rosen[1], Tiffanie Schreyeck[2], Thomas Mahiout[2], and Ketil Malde[1,3]

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

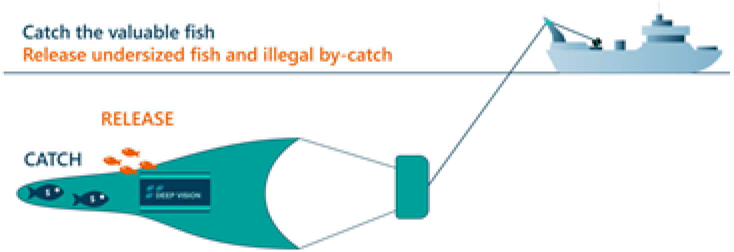
Image from 2018

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

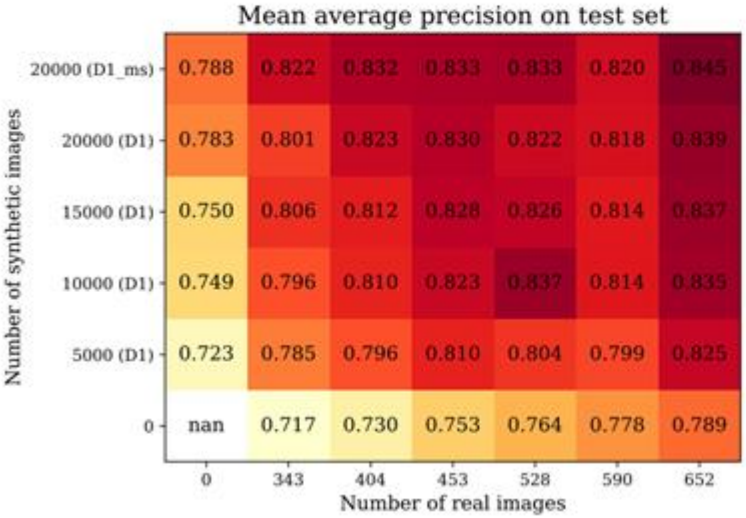
Manually annotating fish for object detection

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

    per species
  - Performance on test dataset
    - Best mAP = **0.85**



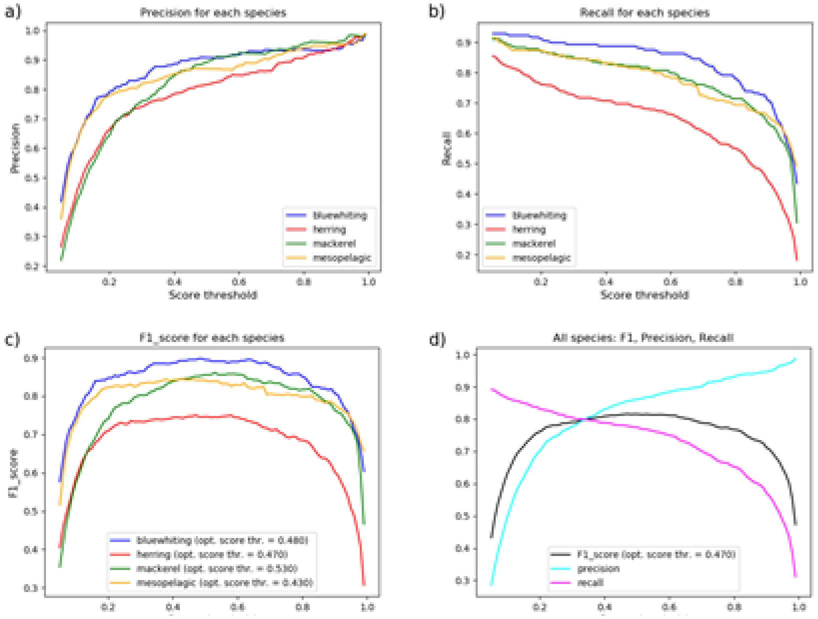
Optimal score threshold

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

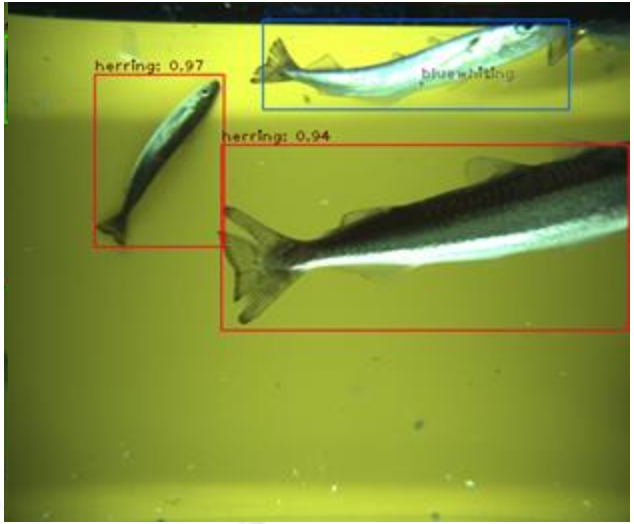
$$F1 = 2 \times \frac{precision \times recall}{precision + recall} = \frac{2TP}{2TP + FP + FN}$$

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



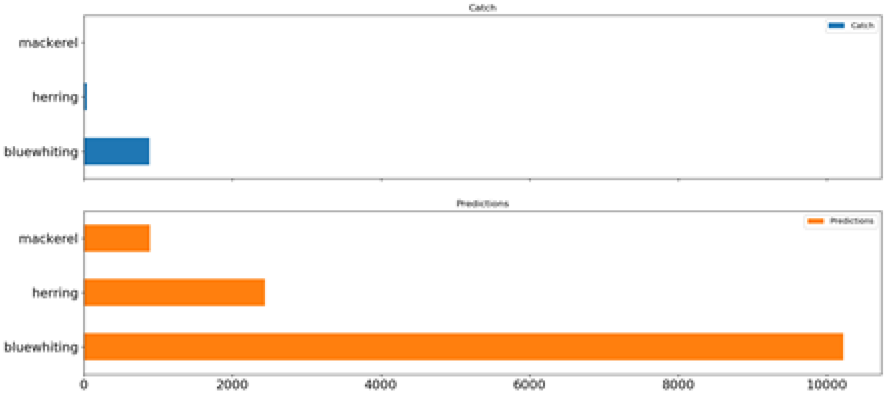
Model predictions

Catch data

Challenge in automating count

Catch

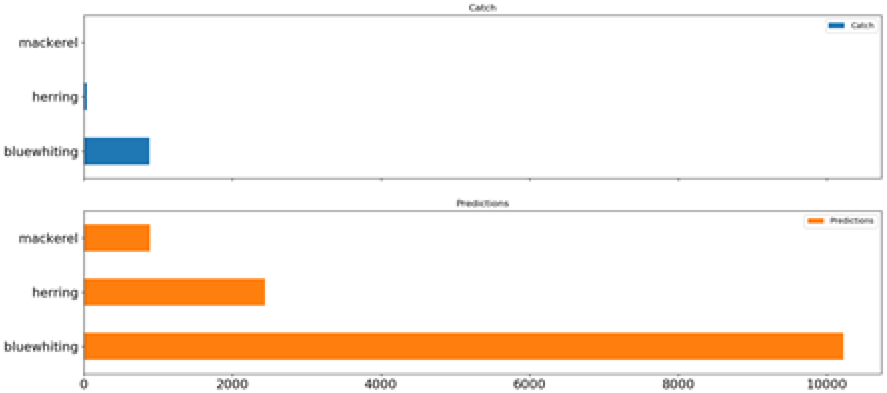
Predictions



Challenge in automating count

Catch

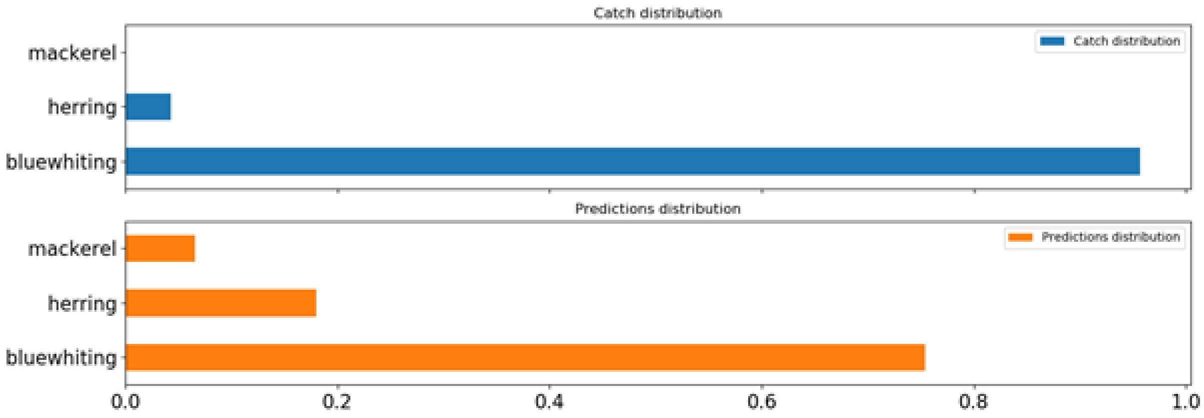
Predictions



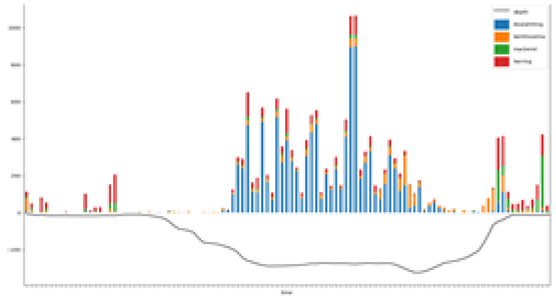
Fish distribution?

Catch

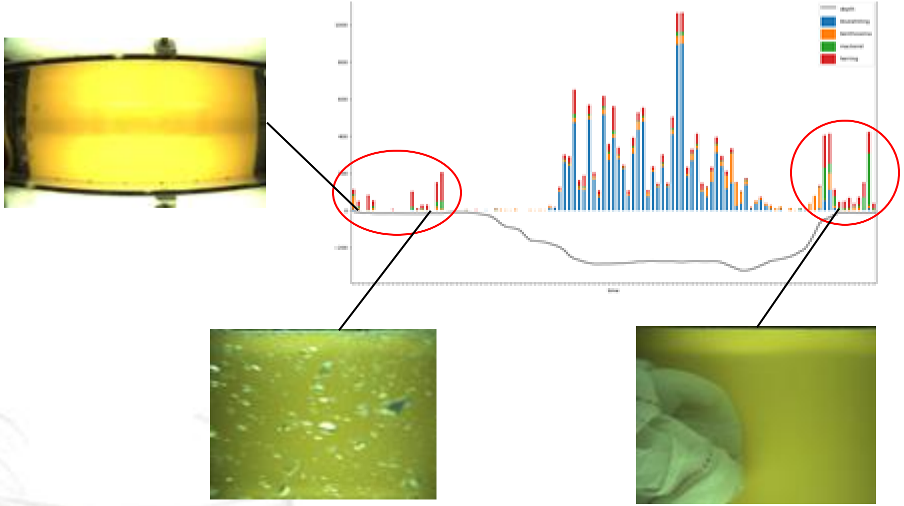
Predictions



Fish distribution as a function of time



Empty/non-fish images



Most images do not contain fish

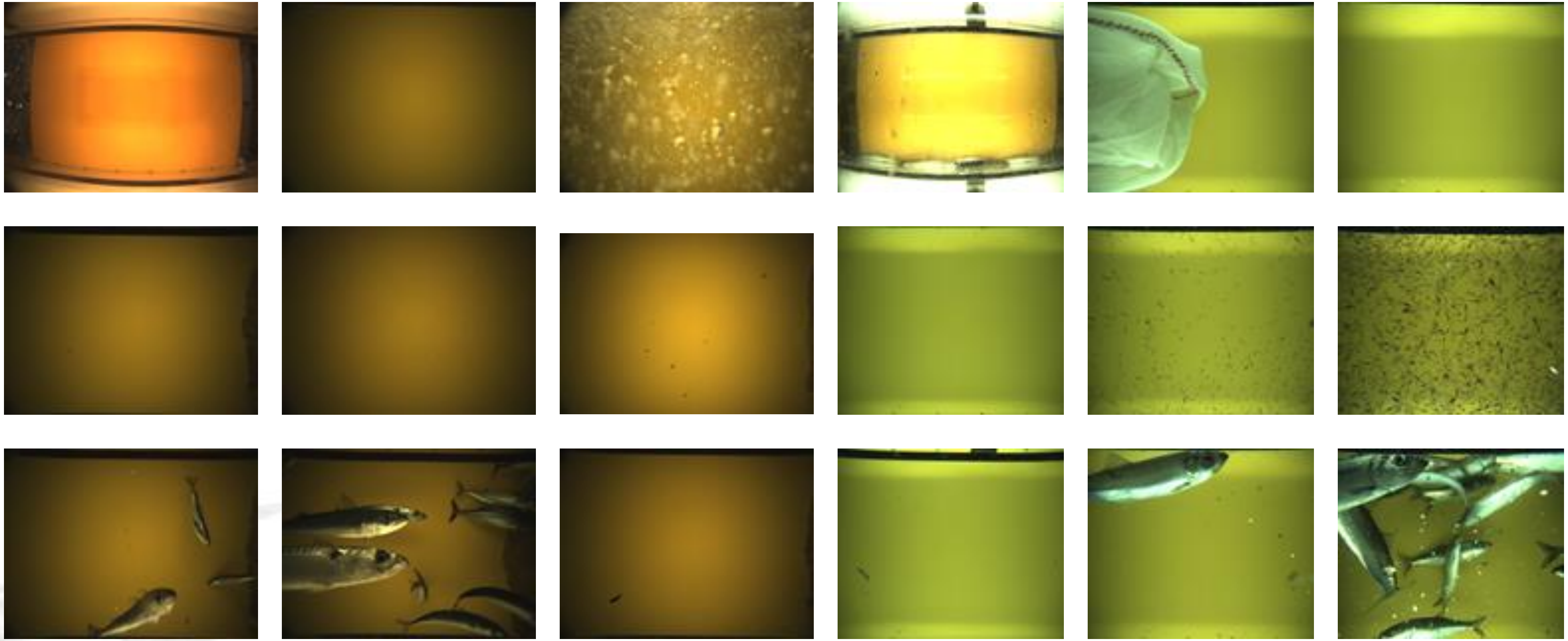
- Large number of false positives
  - Images on deck
  - Images containing artifacts

Filtering algorithm

Empty

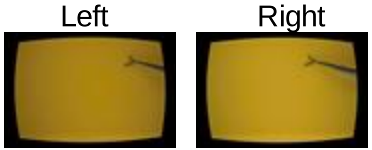
Krill

Fish

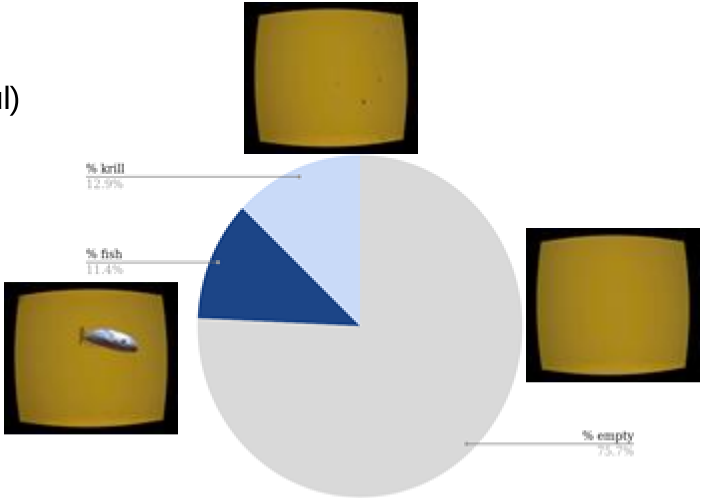


Empty/non-fish images

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



    - 75% images are empty

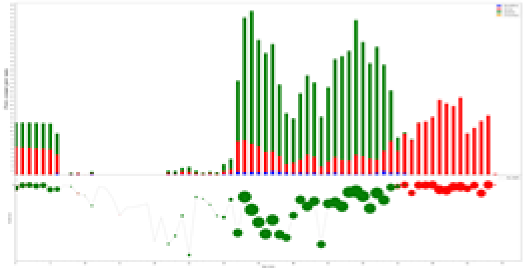


Empty/non-fish images

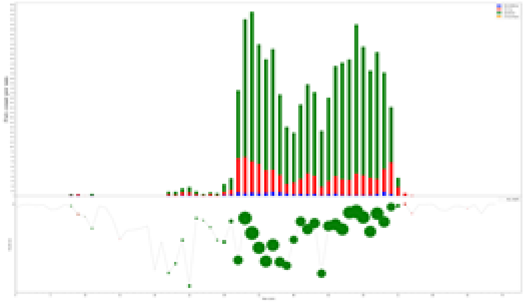
- Filter out empty images in Deep Vision system
- Run model only on active images
  - Fewer false positives
  - Faster processing time

Predictions

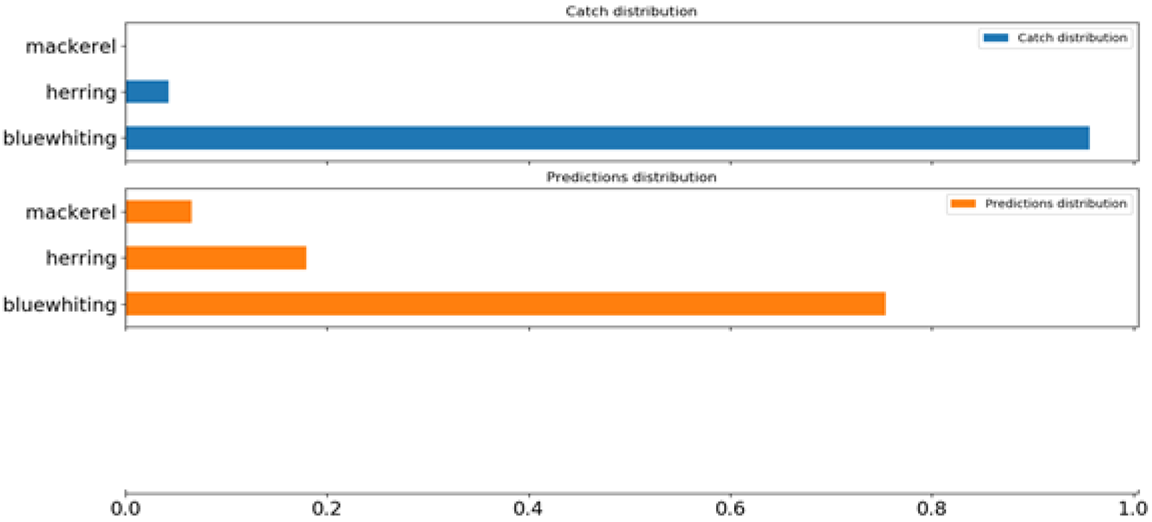
Without filter



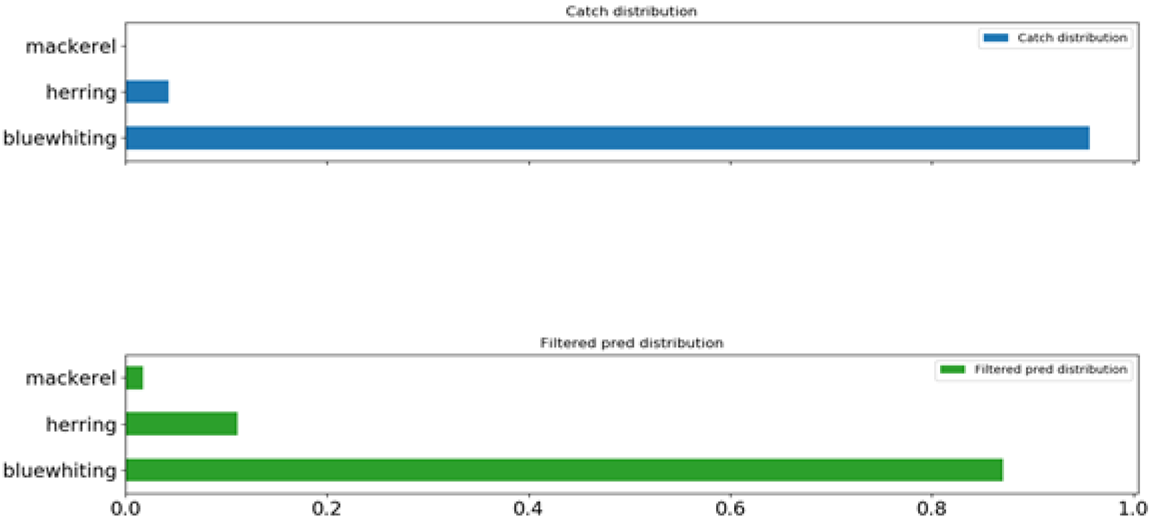
With filter



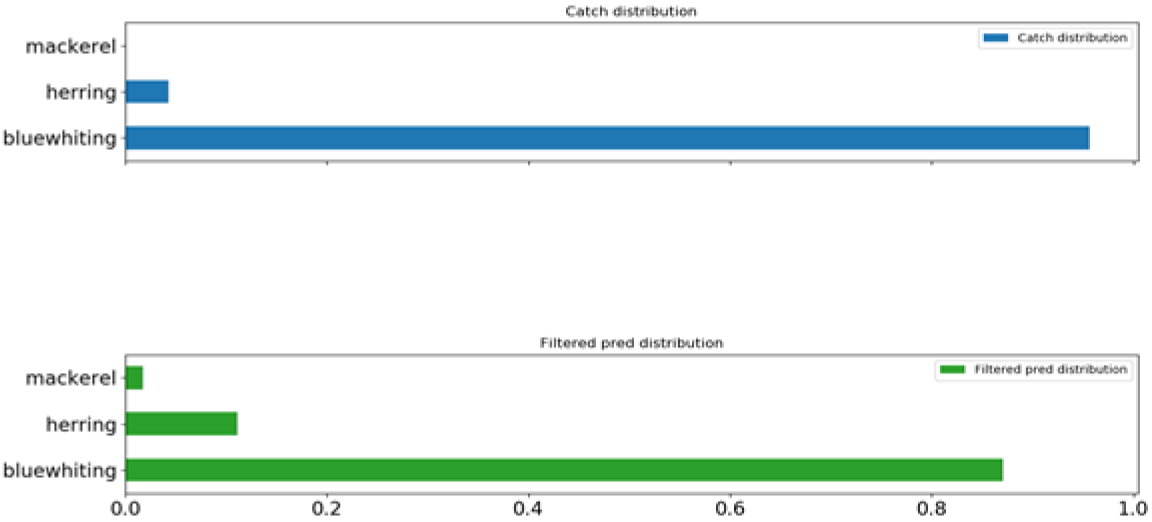
Before applying filter



After applying filter



After applying filter

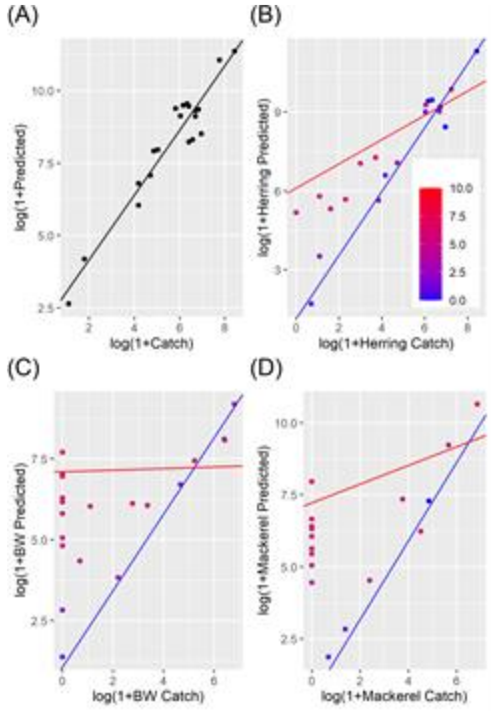


Different species have different average swimming speeds

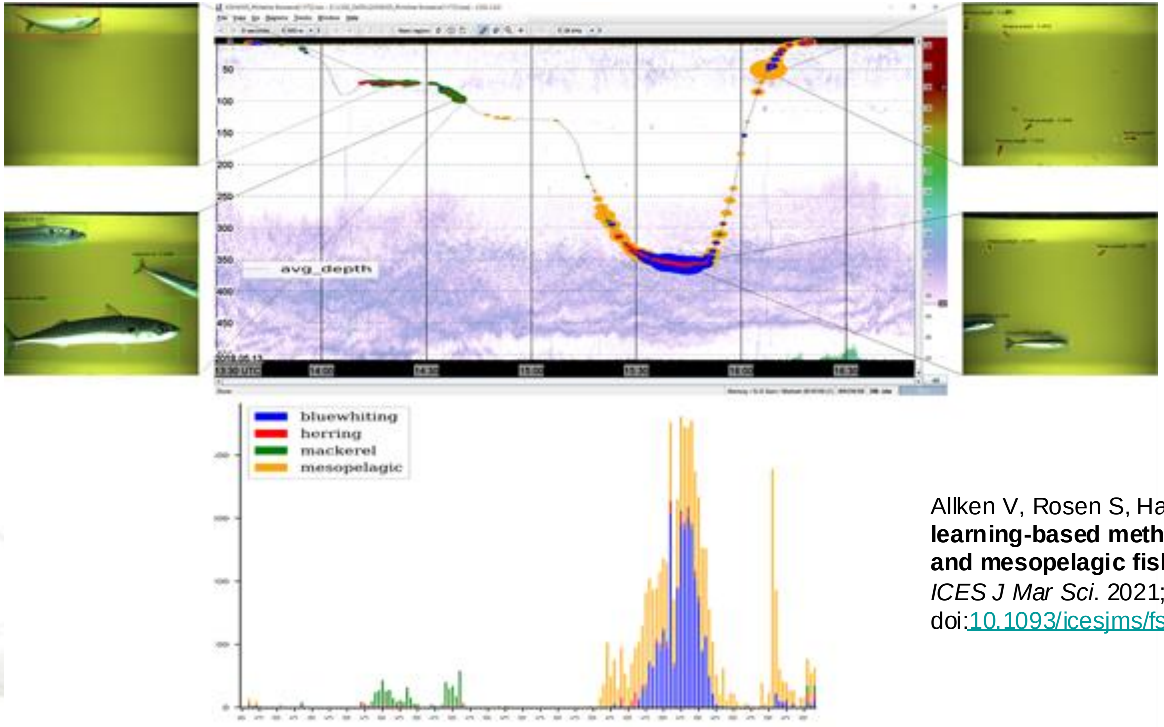
=> Overcount slower fish (appears in more consecutive images)

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



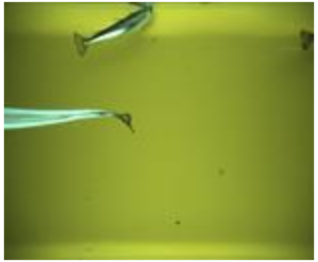
Allken V, Rosen S, Handegard NO, Malde K, **A deep learning-based method to identify and count pelagic and mesopelagic fishes from trawl camera images.** *ICES J Mar Sci*. 2021; 78(10): 3780-3792. doi:10.1093/icesjms/fsab227

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

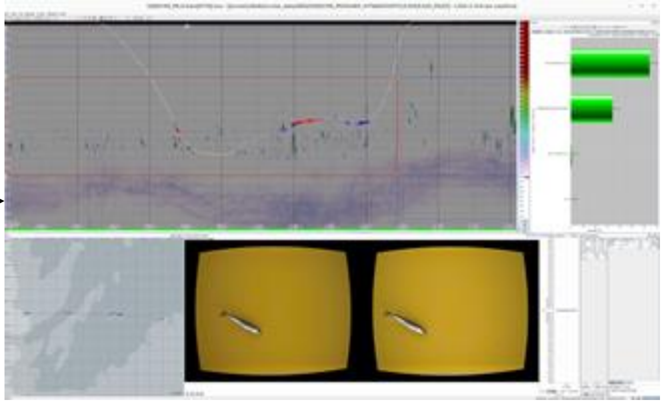
Continuously improve model with new data

- 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

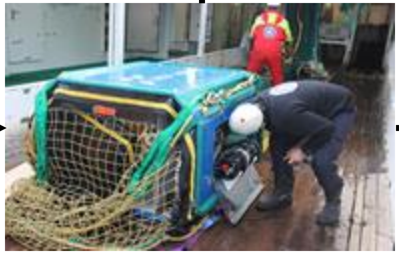
Processing and object detection (1-2h)

Visualisation in LSSS

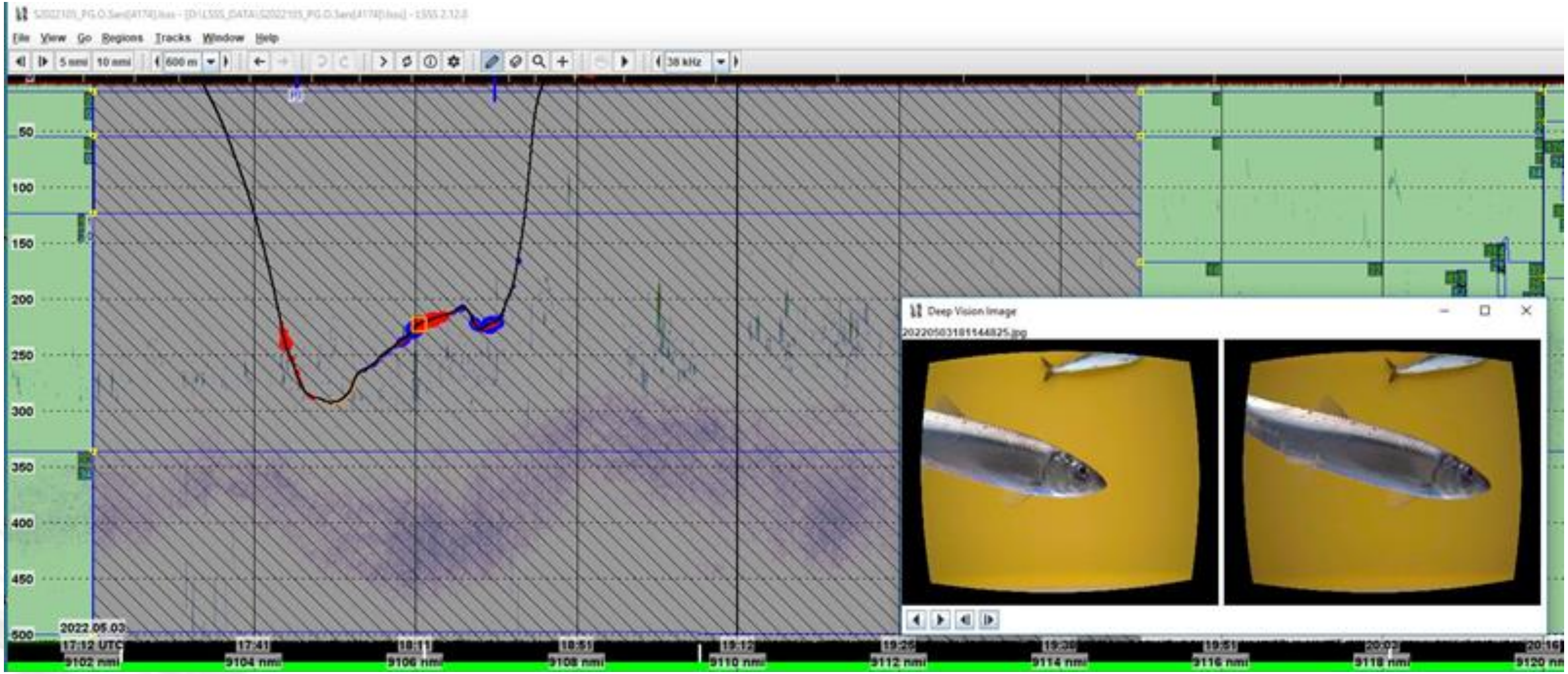


Download (5 - 30 min)

DV can be set out again after download



Acoustic herring survey 2022



Acoustic herring survey 2022

INSTITUTE OF MARINE RESEARCH

CRIMAC

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		

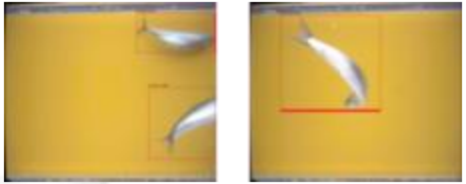
X : done/ongoing
X : future work

Length distribution

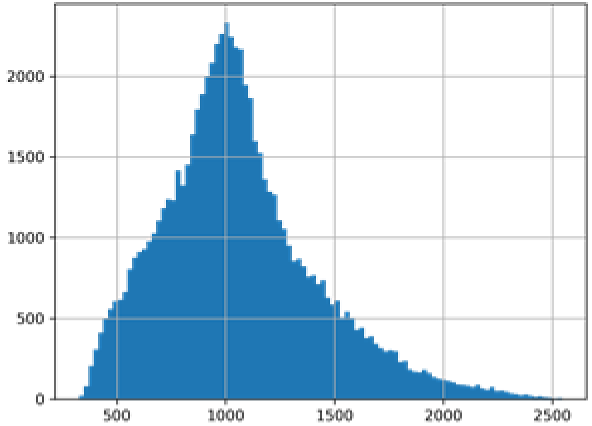
Challenges

- Same fish appears in several images

- Fish not always captured whole or in ideal position



- Tracking could help but only few frames per second



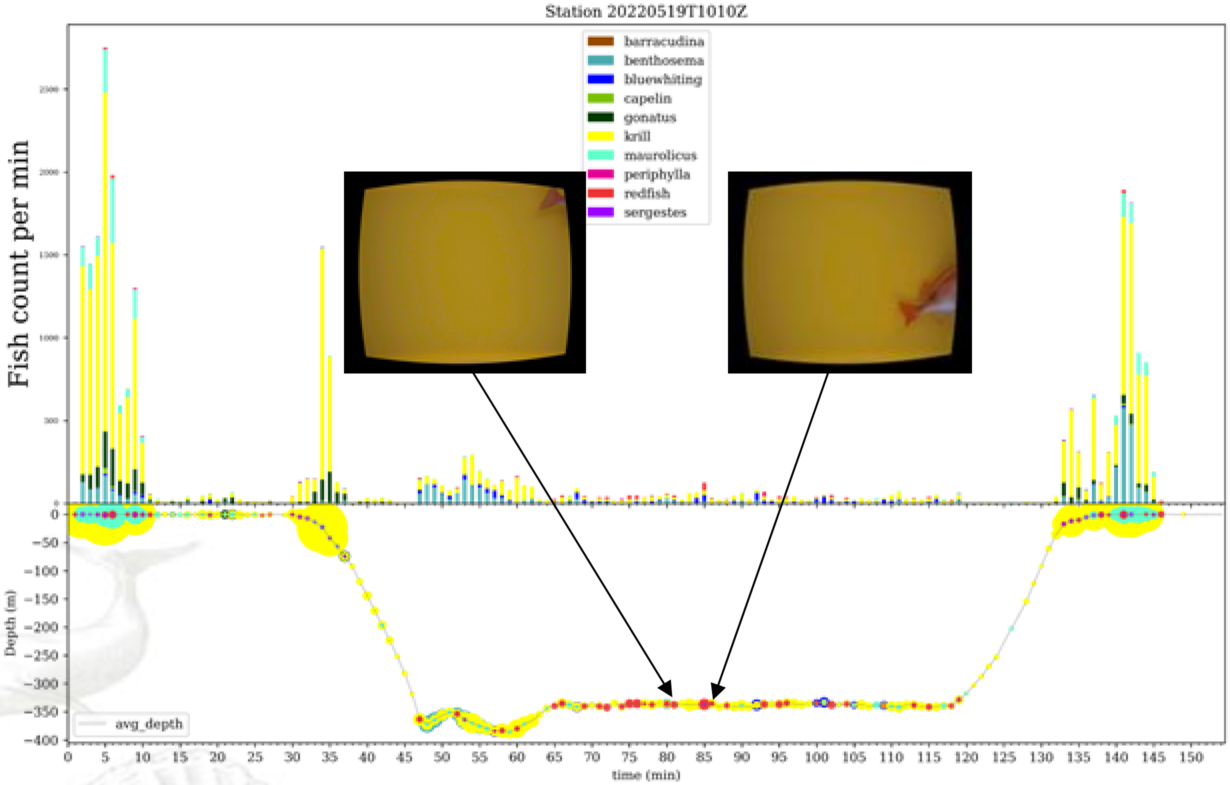
Predicted fish length distribution (by pixel)

Methods used for stock assessment at IMR

Task \ Method	Acoustic	Trawl catch (regular mesh)	In-trawl cameras (since ~2015): Visualise img	In-trawl cameras (since ~2015): 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

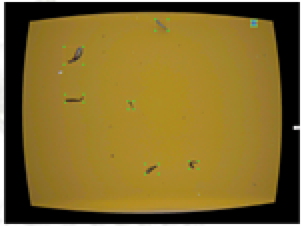
Redfish model

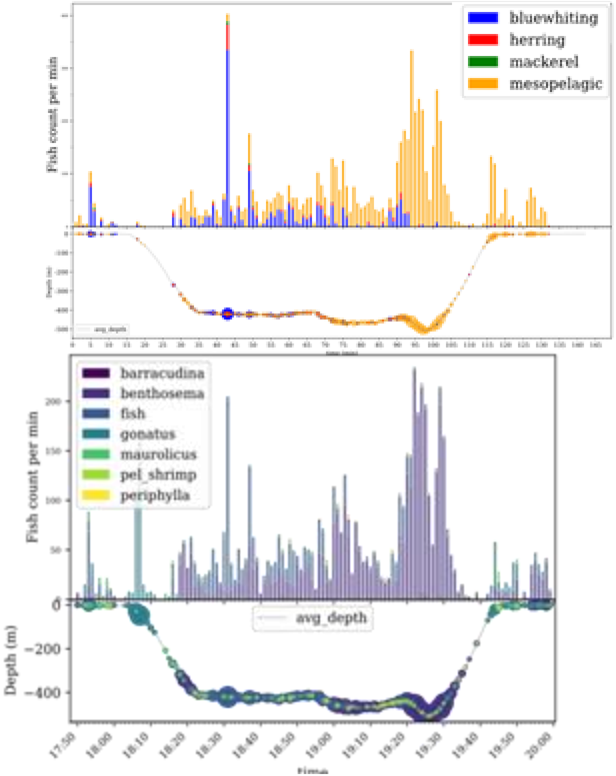


Mesopelagic fish distribution

- 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	In-trawl cameras (since ~2015): 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 Westergerling

Maria Tenningen

Funding by CRIMAC

(**C**enter for **R**esearch-based **I**nnovation 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