COMPUTER VISION BASED COUNTING OF SHIRMP IN REAL FARM CONDITIONS

AWI

AQUACULTURE EUROPE 2022 - "Innovative Solutions in a Changing World" September 27-30, 2022

Sander

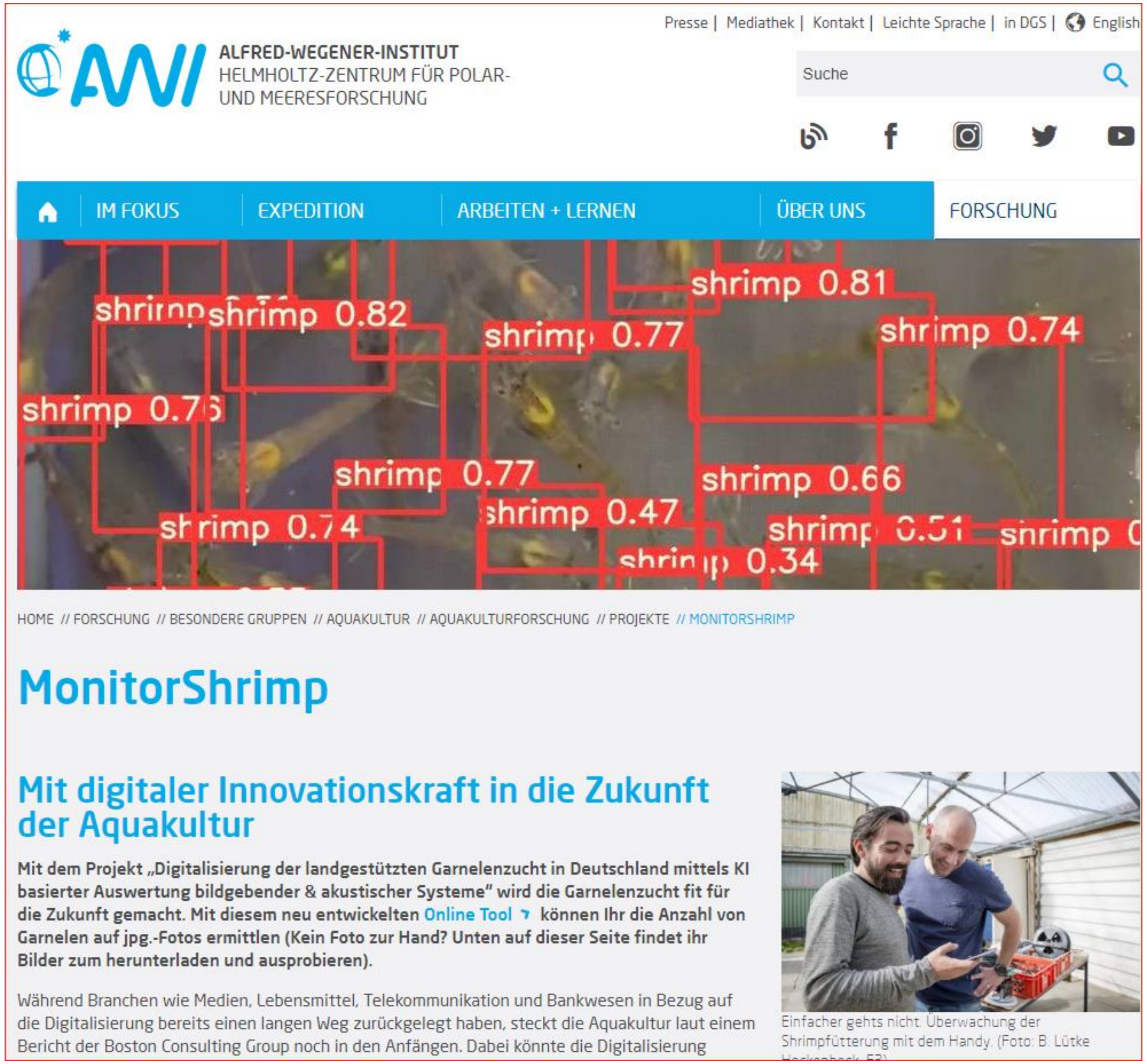
Bundesanstalt für Landwirtschaft und Ernährung

MONITORFISH

FÖRDE GARNELEN

Questions to the audience after the session for open discussion

- Free access to demo tool online on AWI Website
- Invitation last week via EuroShrimp to test the tool
    - Did you test the demo tool?
    - What system type to you use? (biofloc, clear water)
    - How big is your error rate in manually assessing stocking density?
    - In what way would e.g. biofloc system profit from accurate biomass measurement, and, would you use this tool if it works in your system?



COMPUTER VISION BASED COUNTING OF SHIRMP IN REAL FARM CONDITIONS

- Why is automation in counting needed?
  - Because we don‘t know the actual biomass in the system
    - (manual counting error at 20%)
    - Important because………..

- Current knowledge and failure?
  - Automated counting only work in good conditions
    - Current models developed in lab environment fail in real life

- Present approach
  - Go directly into farm environment and ID potential challanges
    - Dimlight
    - Low background contrast
    - Distance to object
    - Shrimp size

Figure 1: top) Images taken under experimental conditions with camera (type unspecified) just above a small beaker and white background (Source Kaewchote et al., 2018) b) right) image taken on the commercial shrimp farm with smartphone taken at practical light conditions, at commercial stocking density and horizontal nets ‘mangroves’. Image was taken at 80 cm above water (Source, AWI/Fördegarnele).

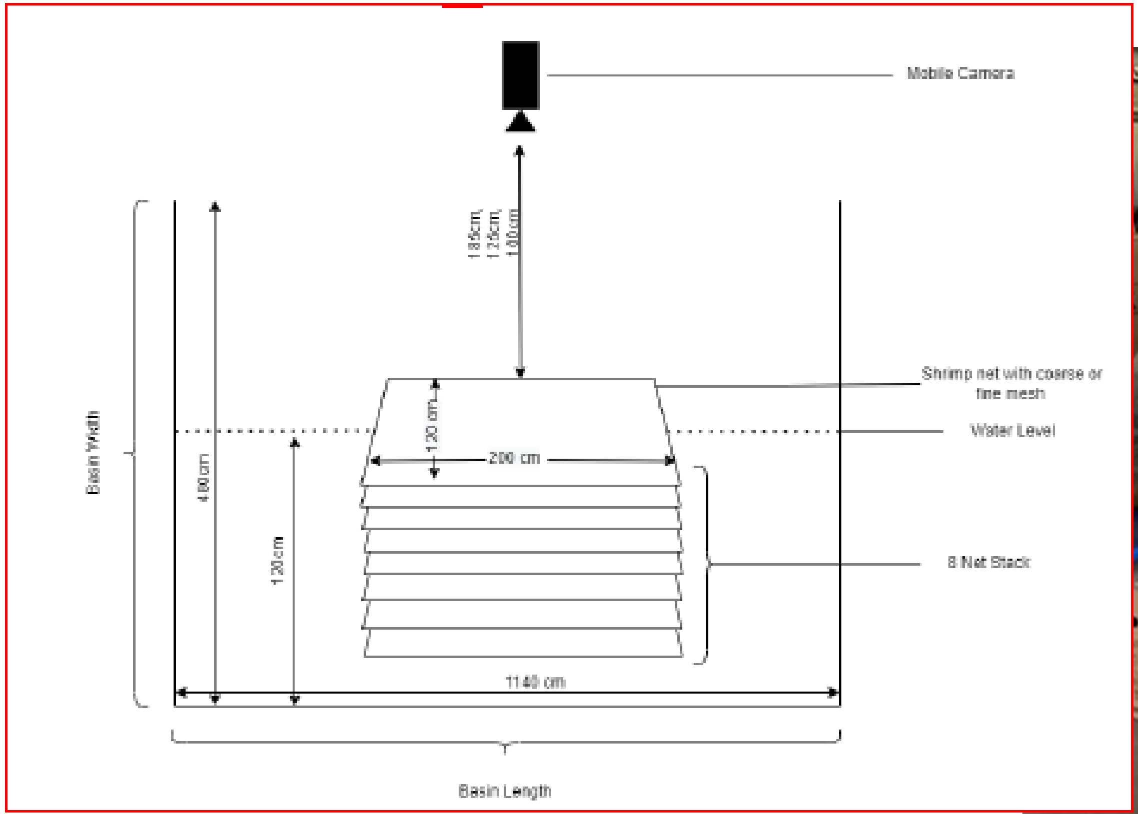


Fig. Camera position above tanks (Image S. Ur Reman, AWI)

Fig. Horizontal shrimp systems at Fördegarnele (Image B. Wecker)

- How to count between horizons?
- Special case for one farm only, not representative for all shrimp farms

How do we measure accuracy?

MAE or mean absolute error, we also used relative errors - taking into account the multiplicity of given predictions and the ground-truth counts: MAPE(mean absolute percentage error) and sMAPE(symmetric mean absolute percentage error).
Mean absolute error (MAE) represents the number of miscounts:

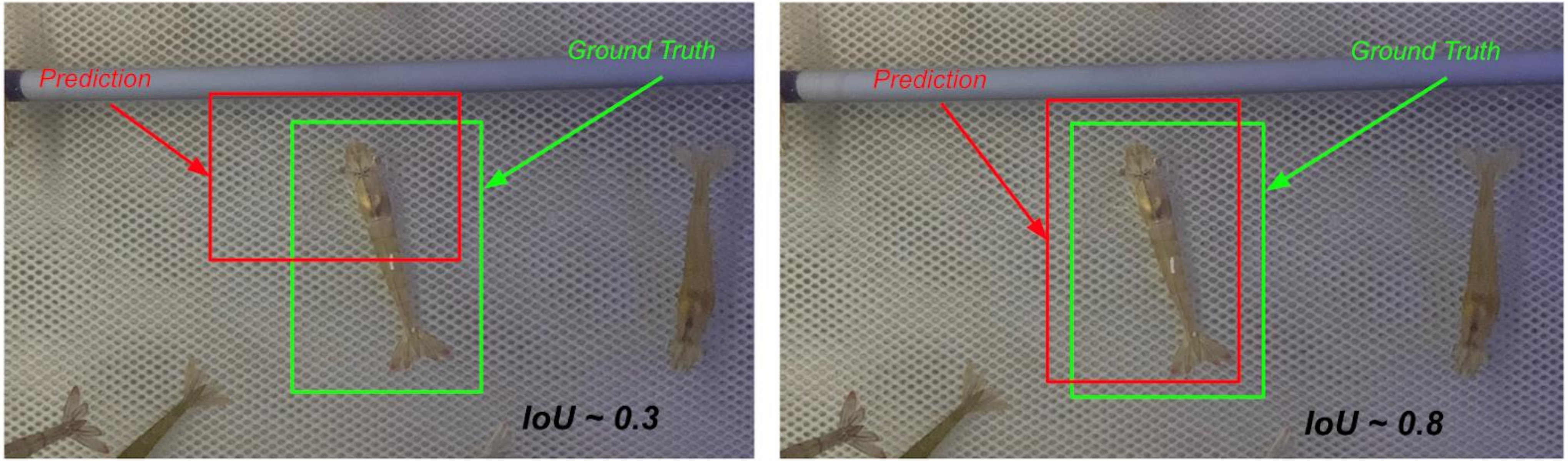
$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - x_i\right|$$

where xi is the true number of shrimps (as annotated by human), yi is the predicted number of shrimps, n stands for the size of the test dataset.

Mean absolute percentage error (MAPE) represents the miscounts relative to the total number of shrimps:

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - x_i}{y_i}\right|$$

Example for likelyhood of positive ID



Intuitive comparison of Intersection over Union on bounding boxes

model's confidence how likely it is that an object (a shrimp) is present inside that bounding box
Confidence thresholds reject bounding boxes with confidence scores that are below confidence threshold

Examples of different detectors tested

- Density Maps
  - A neural network autoencoder architecture to estimate a density map (DM) that represents objects on a given image
  - This approach is commonly used for crowd counting but also for biological objects

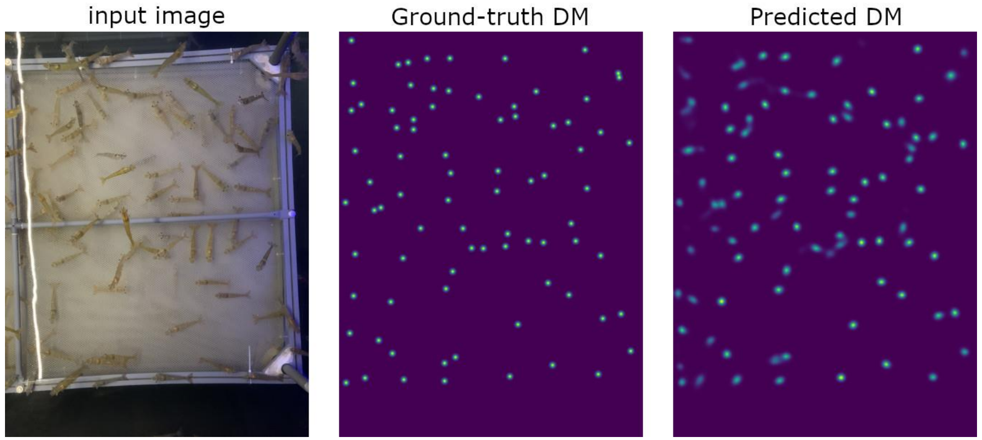


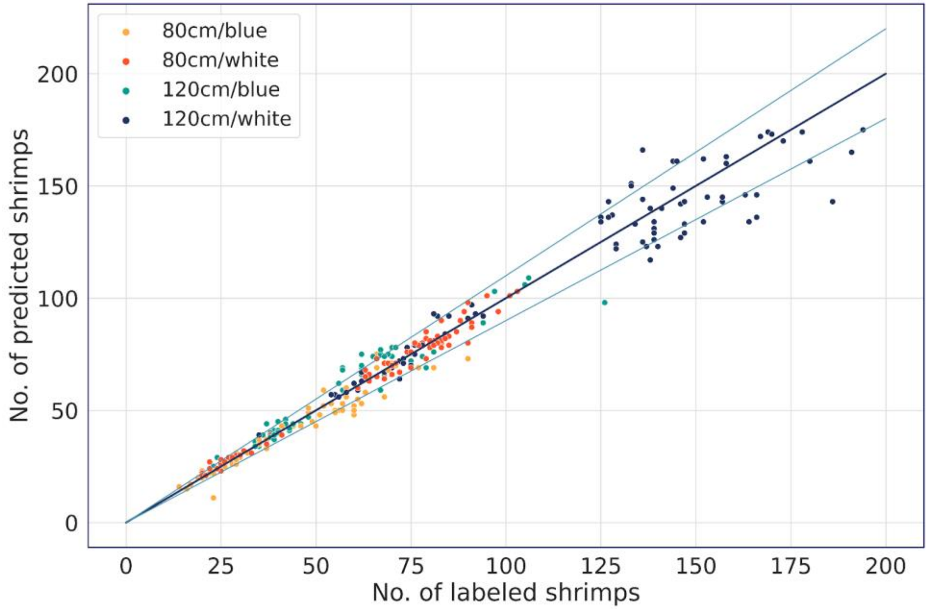
Fig.. Example of density maps output in the shrimp dataset. A generated ground-truth DM (middle) that perfectly represents objects on the input image (left), and DM predicted (right) using trained autoencoder network.

This is where we are in clean water 2-D real farm

Predicted count vs. ground-truth count

Results

counting performance of RCNN on test-dataset and test-dataset with sharp images only (after filtering out the blurred images) are only slightly better(MAE=4.85, MAPE=6.2, sMAPE=6.11) in comparison to the full test dataset (MAE=5.48, MAPE=6.46, sMAPE=6.59)



Faster RCNN performance on test dataset - adjusted NMS thresholds per class

Conclusion

- model copes well with more difficult samples
- The model is accurate in the range of shrimps counts up to 100 and less accurate for higher numbers of ground-truth counts
- Model tends to underestimate shrimps in the case of white light and a distance of 120cm.
- The model copes well with the 80cm distance category for both conditions: white and blue light.

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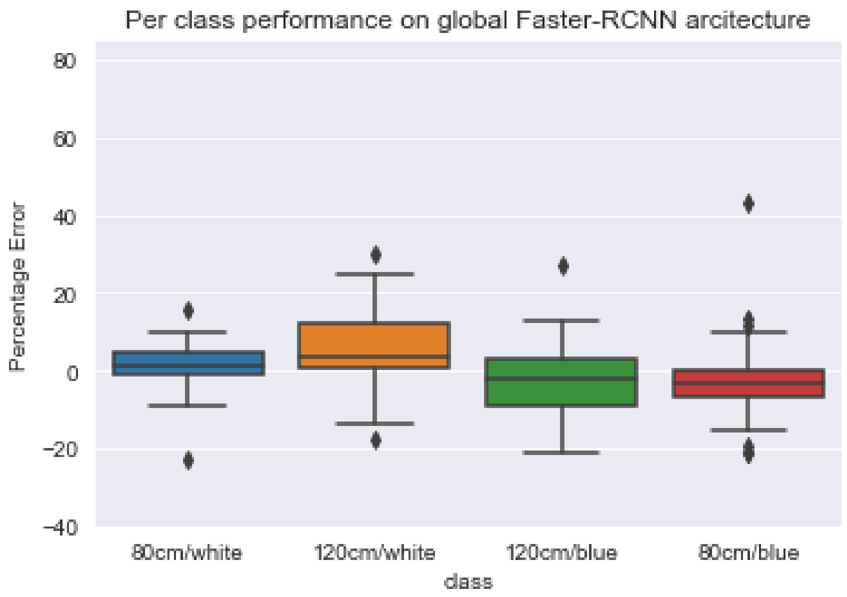

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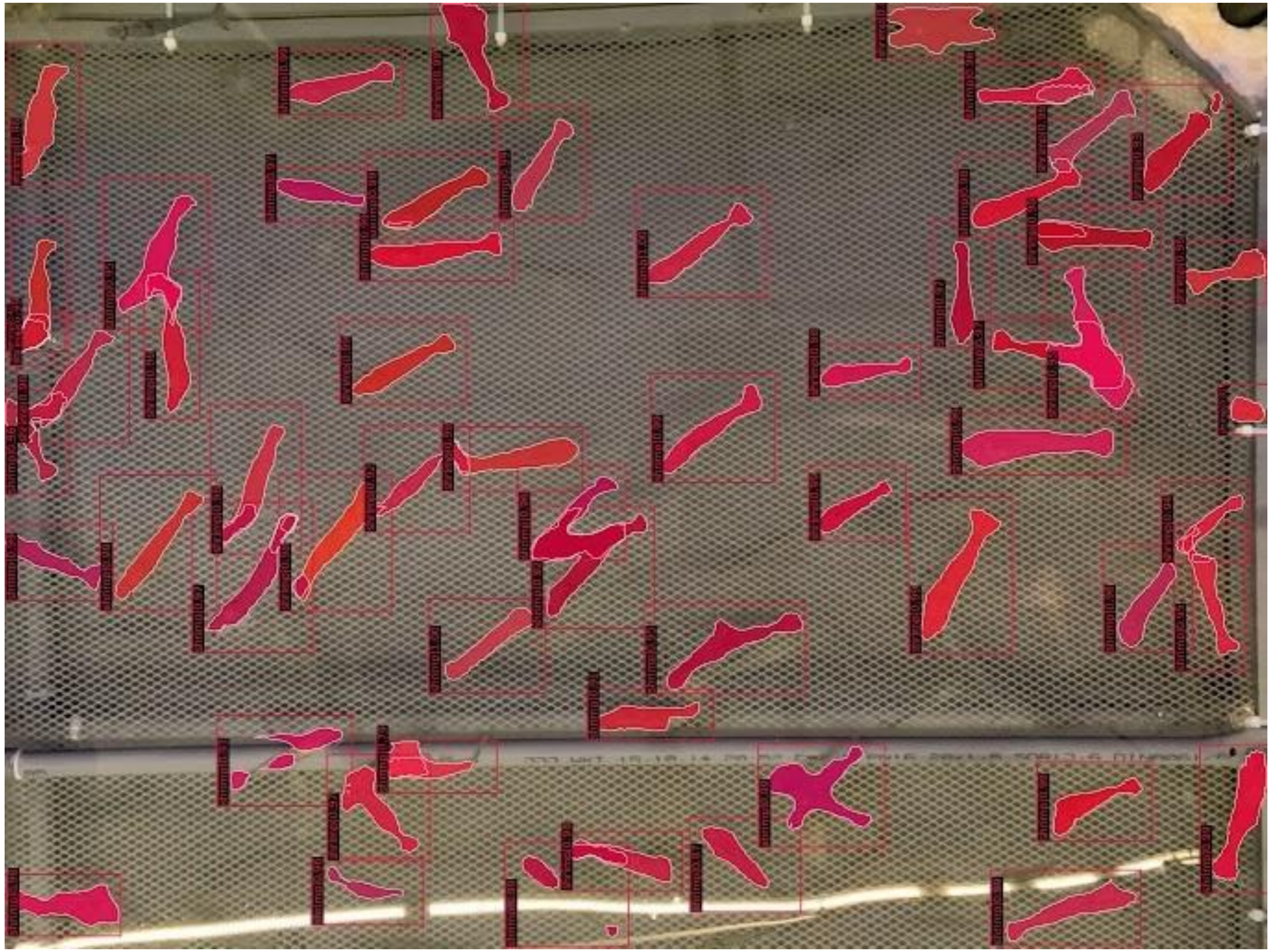
Same model can be used for the estimation of shrimps' length. There are two different approaches in my mind at the moment about how predicted bounding boxes could be used, current approaches under investigation:

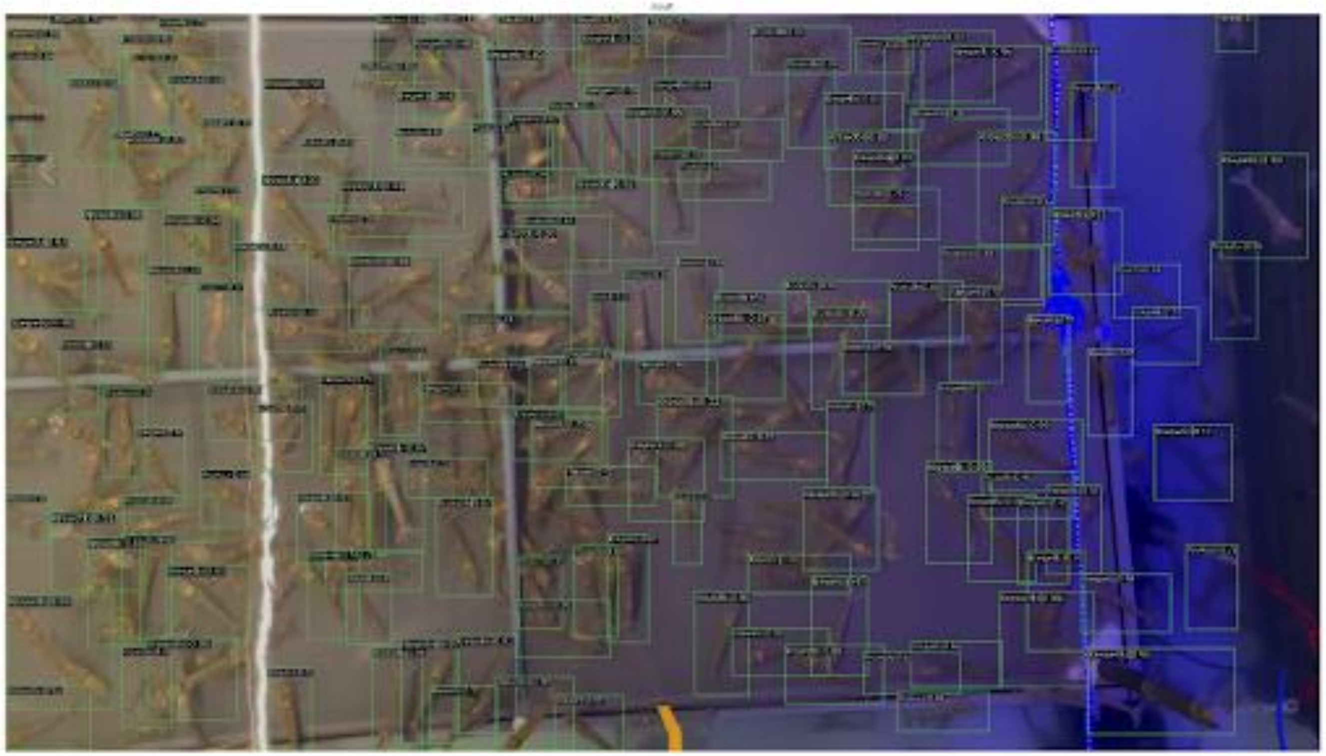
- directly to estimate the length.
- use bounding box dimension and position to extract a patch of an image with a single shrimp and perform e.g. semantic segmentation to get a shrimp's contour



How does our current model trained in clean water 2-D real farm environments work in other conditions

At higher untrained camera distance (185cm)

- ‘fails’ for very crowded areas
  - MAE at 38%



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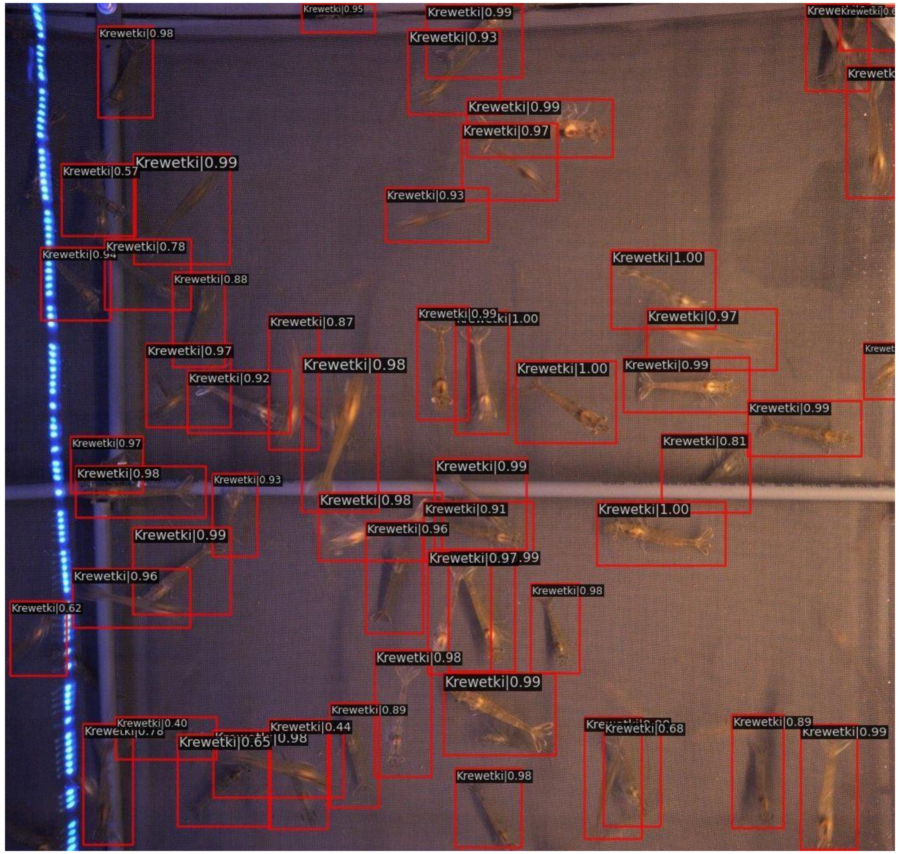
Current model has high accurcy with new hardware camera (untrained)



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Current model does not perform well on turbit 3-D real farm images

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Current model successfully detects unknown shapes such as microalgae and fish

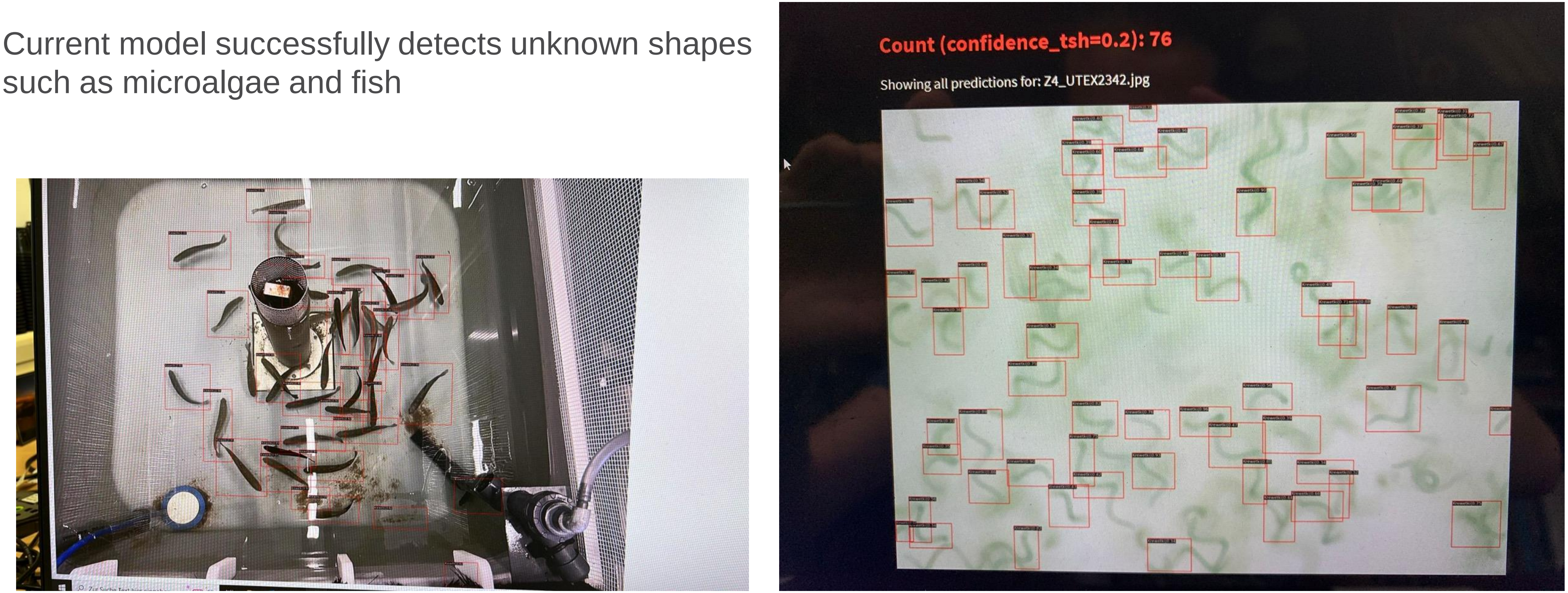


Fig. Left, recognision of trout in a low density system, right, recognision of Spirulina (source AWI)

Solutions which may help transfering current models to work also in other farm condtions

- Training the model in these conditions
    - Remember current model was only trained in 2-D clear water

- Use of turbidity filters

- Subsampling functions to extrapolate numbers identified to absolute numbers

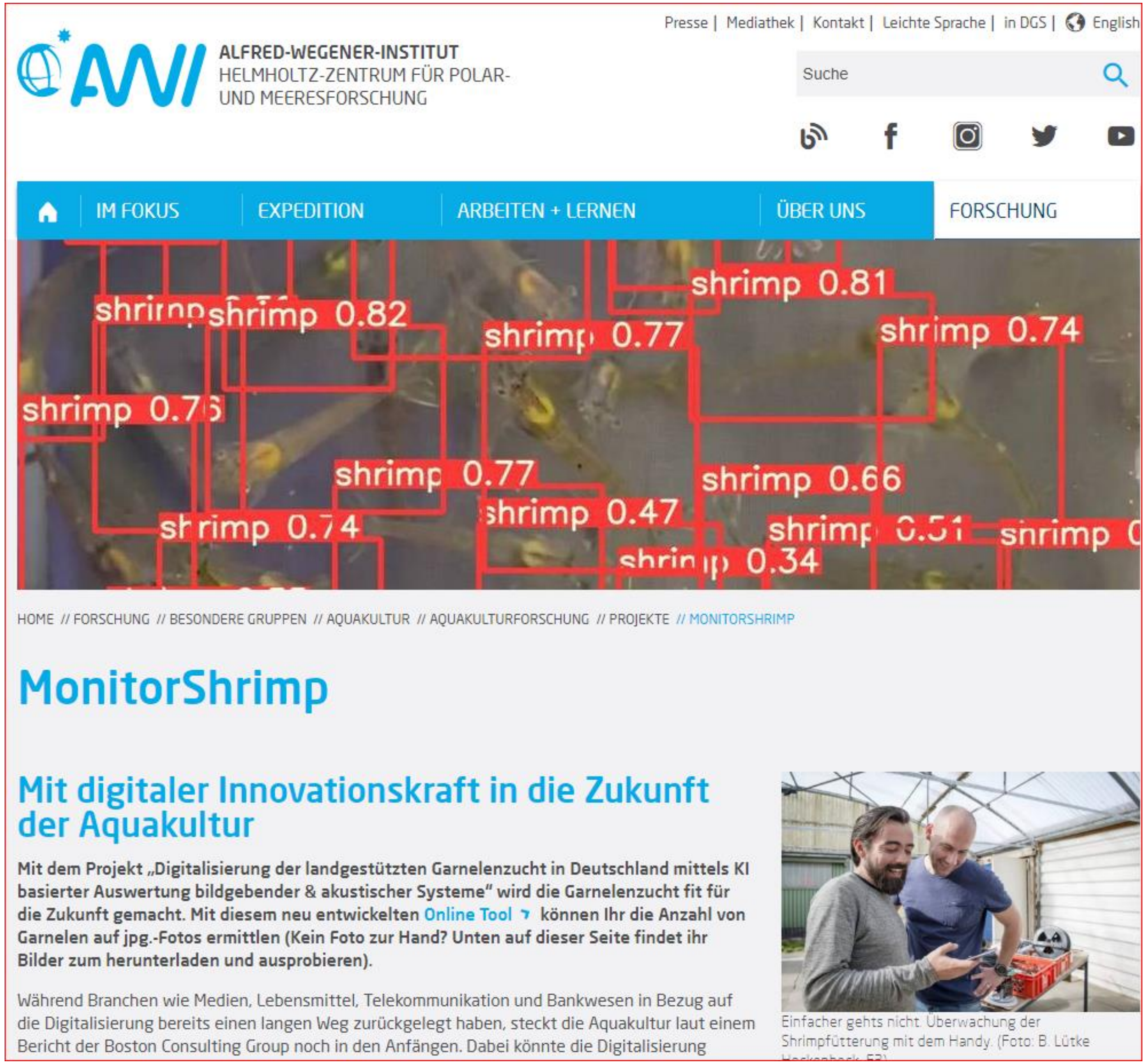
Fig. Example of the use of MonitorFish's vision algorithms as a turbidity filter in the detection of fish in an aquarium

Aimes for June 2023

- Development of a user interface with the output parameters biomass, recommendation for feed quantity, welfare alert (through early detection of e.g. discoloration)

- Project proposals towards application in all RAS aquaculture

- First tests and model adaptation for application in different shrimp systems, without horizons



Questions from the audience?

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Thank you for your attention

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