# FHF 901871 – Real time detection of free-swimming sea lice: e-lice

**Akvaplan-niva AS Report: 2025 64650.02**

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## Summary

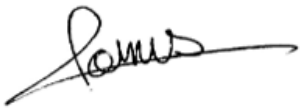
English

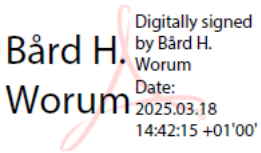
The salmon industry is currently challenged by sea lice infestations (*Lepeophtheirus salmonis*). This calls for a need to develop an in situ early warning system to detect, count and report the presence of free swimming sea lice in the water to stakeholders. Herein, we propose a novel approach based on an in-situ imaging sensor, an underwater vision profiler version 6 (UVP6) and onboard data processing using artificial intelligence for real-time detection and classification. We have developed AI algorithms for free swimming sea lice, adults lice (male and female) and ca. 30 different plankton taxa. The UVP6 was deployed from an autonomous buoy from a winch to collect data across depth and the algorithms were deployed in the UVP6 onboard microprocessor. Data were streamed to a dashboard for end users. The results show that the performance of the AI running in the sensor is not sufficient quality compared to running the AI in the cloud which offers more powerful processing capacity. Overall, a system has been successfully developed, tested, debugged and optimized. This proof of concept points out the need to further improve on the AI component, the data processing pipeline and the sensor hardware in order to offer a robust solution for commercial use.

Norsk

Laksenæringen står i dag overfor betydelige utfordringer knyttet til angrep av lakselus (*Lepeophtheirus salmonis*). Dette skaper et presserende behov for å utvikle varslingssystemer ved oppdrettsanlegg, slik at man kan oppdage, telle og rapportere fritt svømmende lakselus i sjøen tidlig i prosessen. Vi foreslår en ny tilnærming basert på en bildesensor kjent som undervannssynsprofiler versjon 6 (UVP6). Denne enheten overfører og behandler data ombord ved hjelp av kunstig intelligens for sanntidsdeteksjon og klassifisering av lakselus. Vi har utviklet KI-algoritmer for både fritt svømmende lakselus og voksne lus (både hann og hunn), samt for omtrent 30 forskjellige planktontaxa. UVP6 ble plassert på en vinsj festet til en autonom bøye, noe som gjør det mulig å samle inn data fra vannsøylen. Algoritmene ble lastet inn i en mikroprosessor i UVP6, og de prosesserte dataene ble strømmet til et dashbord for visualisering for sluttbrukerne. Resultatene viser at ytelsen til KI-algoritmen som kjøres på sensoren ikke er tilstrekkelig sammenlignet med KI-algoritmen som kjøres i skyen, som gir betydelig bedre prosesseringskapasitet. Totalt sett har vi utviklet, testet, feilsøkt og optimalisert systemet gjennom hele prosjektperioden. Denne "proof of concept " påpeker behovet for å forbedre KI-komponenten, data prosesseringslinjer og sensormaskinvaren ytterligere for å kunne tilby en robust løsning for kommersiell bruk.

## Approvals



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| Lionel Camus | Bård H Worum |
| Project manager | Quality control reporting |

# Content

# 1 Introduction

Since 1980, the production of Norwegian farmed salmon has increased from ca. 4,000 tons to ca. 1.2 million tons. This means that the industry produces on average about 14 million salmon meals every day, throughout the year. Norway experienced an exceptional growth in salmon production, of around 10% annually, in the 20-year period leading up to 2013. Production has since stagnated due to sea lice (*Lepeophtheirus salmonis*) infestation and its consequences. Industrial development cannot occur until environmental challenges, such as sea lice infestations are addressed and effectively managed. Further, it is recognized that by 2030, salmon must be farmed using technologies that eliminate the problems of sea lice. Within this context, the FHF has issued a call for proposals with the aim to develop and systematize knowledge about the prevention and control of salmon lice with the best possible fish welfare. It is a large joint call with a total of six (6) separate themes and sub-goals. In this proposal, we are addressing the sub-goal no. five (5) which deals with developing and documenting a better method for notification, monitoring and registration of sea lice in near real time. To develop such an early warning system for sea lice, we propose to use an advanced high resolution plankton camera, the Underwater Vision Profiler version 6 (UVP 6: Picheral et. al, 2021), with possibilities for on-board data processing. The UVP 6 is an underwater imaging sensor available in the market and produced by the company Hydroptic, invented and developed by the zooplankton research community at CNRS. With the emergence of these high-resolution imaging hardware, the use of Artificial Intelligence (AI) based systems for data processing, animal identification and classification have gained popularity since the last decade (Giering et. al, 2022). In e-Lice, we aim to use this advanced imaging sensor and an AI-based data processing drive for real-time detection and classification of free-living early developmental stages of sea lice as an early-warning system of potential infestations. By using imaging hardware that is available on the market and widely used by the plankton research community with open-source data treatment, we ensure that our proposed solution is non-proprietary, applicable in the field with a broad industrial utility and with an easy upscaling potential.

## 1.1 Sea lice biology

L. salmonis has a direct life cycle (i.e., a single host) with eight life stages (Hamre et al., 2013: Fig. 1). The adult female sea louse extrudes a pair of egg-strings and the planktonic, from which eggs hatch directly into the water column. Lice emerging from hatched eggs moult through three (3) free-swimming stages – two naupliar stages and one copepodid stage (Fig. 1). The copepodid progressively moult into chalimus (I & II), pre-adult (I & II) and then the adult, all of which are parasitic (Boxaspen, 2006). The proposed technology in this project mainly focuses on and distinguish between the free-living early developmental stages (nauplii and copepodid) and to some extent, the parasitic stages as well (Fig. 1). Although the parasitic stage is not supposed to be free swimming in the water column, lice can be released into the water column during delousing processes and can reinfect fish farms in the vicinity.

## 1.2 Earlier systems to detect sea lice

Presently, the most accurate estimates of infestation pressure are acquired through a multidisciplinary effort that includes lice counts on the fish from the aquaculture industry, modelling of sea lice production and dispersal, surveillance of salmon lice on wild salmonids and measuring infection levels on fish in sentinel cages. To our knowledge, scientists have tried via several technological alternatives to detect sea lice in the marine ecosystem with funding from FHF. Krolicka et al (2022) have developed and tested a new specific DNA-based

assay for detection and quantification from seawater samples using an analytical pipeline compatible with the Environmental Sample Processor (ESP) for autonomous water sample analysis of gene targets. Pettersen et al (2019) has achieved the detection and classification of *L. salmonis* using underwater hyperspectral imaging. Skern-Mauritzen et al (2021) developed the fluorolice method to detect presence of free-swimming sea lice in the water column with colorimetric method on samples. Flamarique (2009) showed that a light-based trap can be used to collect and count sea lice. While these approaches appeared promising, none of them can be used for (near-)real-time detection of the sea lice in the water column. Consequently, we propose a novel approach based on an in-situ imaging sensor and onboard data processing for real-time detection and classification.

## 1.3 The optical imaging sensor

The Underwater Vision Profiler version 6 (UVP 6: Picheral et al., 2021) is an in-situ imaging device used for studying the plankton and other particulate matter in aquatic environments. It is equipped with a high-resolution camera that takes images of plankton and particles passing through an illumination field emitted by a laser diode. A dedicated image processing unit analyzes (pre-processes) the captured images for identification and quantification of the imaged targets (Fig. 2). The UVP 6 is power-efficient and has thus been incorporated into biogeochemical Argo floats, gliders and moorings for longer-term observations. The UVP 6 can resolve targets down to 0.1 mm, which is well-within the size range of pelagic early life stages of sea lice (Fig. 1). Akvaplan-niva owns and operate four UVP6.

The overall innovation in e-Lice embraces developing a proof of concept for an early-warning system based on imaging of sea-lice in the water column using an optical sensor with onboard AI-driven data processing capability, which can detect, classify and count (enumerate) various life stages of sea lice in real-time. Data will be visualized on an e-dashboard aimed at end users for decision making in order to mitigate for the risk of infection.

## 1.4 Goals

The main goal of the project is to develop and document methods for early-warning, monitoring and registration of the presence of free-swimming early developmental stages of sea lice in real-time before the infection of farmed fish. The project aims for a "proof-of-concept" in using AI-driven automatically processed digital images (acquired by the UVP 6) for detection and classification of pre-infection stages.

## 1.5 Sub-goals:

- Rearing sea lice early developmental stages and establishing a laboratory set-up for imaging sea lice with the UVP 6 (WP1)

- Training, validating, testing and embedding a deep learning algorithm for automated detection and classification of different sea lice developmental stages (WP2)

- Assembling the UVP 6 on an autonomous mooring for field deployment (WP3)

- Developing a digital early-warning system with data streaming and dashboard for end users (WP4)

- Optimizing and validating the overall concept and technology for operational use (WP5)

- Communicating with end users and organizing outreach activities (WP6)

In order to realize the work, Akvaplan-niva has partnered with several organizations: VESO for their competence in rearing sea lice larva and adults at their facilities. MP Consulting, the inventor of the UVP6 and Hydroptic the manufacturer of the UVP6. Kongsberg Discovery for the cloud-based solution and dashboard fabrication for data visualisation and reporting to stakeholders. NIVA for their expertise in zooplankton classification.

# 2 Benefit of the approach for the industry

In 2022, an all-time high 56.7 million salmonids died in Norwegian fish farms (Sommerset et al 2023). This results in severe ethical, environmental, economic and regulatory issues, and some of the main causes are related to sea lice infestations and the subsequent treatments. Several attempts to develop methods for early warning to reduce sea lice infection have been previously performed without success (see background section). Continuous In-situ optical monitoring around fish farms enables the implementation of early-warning measures when image data processing and transmission are automated and happens on-board and in real-time. Such early-warning systems can lead to quick preventive and/or mitigatory responses by farm owners, which can substantially reduce infestations. In this regard, our proposed solution is not proprietary because the UVP6 is available on the market and the producer Hydroptic opens up possibilities for upscaling whenever needed. During the last three years, about 140 UVP 6 units have been sold to the plankton research community, which is developing competence and knowledge and feeds this back to the manufacturer, which in turn upgrades and develop the sensor further. Many features of UVP 6 are open source to allow the research community to improve the algorithms developed by machine learning software for animal detection and classification. Lice counts from the e-lice system will be a useful tool through several applications.

At a local scale, knowledge about when and where blooms of sea lice are approaching will aid farmers in deciding which preventive strategies to use where, and at which intensity. For instance, skirts can be taken on or off, lasers deployed and pulse frequency or intensity of systems like Harbor Fence and Blue Lice can be adapted. Further it will facilitate a better understanding of the vertical distribution of the lice, which varies with site properties and climatic variables. This is particularly useful when using depth-based strategies, or a combination of methods (Oldham 2023). In addition, logged data on lice levels in the ocean will be very useful when evaluating the effect of new preventive strategies. Overall, resulting reduced numbers of lice and de-licing operations will increase the industry's profitability and reputation. In addition to on-site monitoring, an ambition is to implement a network of the e-Lice monitoring system at strategic locations along the Norwegian coast to collect information on sea lice presence and density, and to share this through the Barents Watch portal. At a regional scale this will be a very useful tool for both research and regulation. Revealing the regional trends will improve the understanding of how lice spread to different areas. This is useful in e.g., the work to set up site structures with better biosecurity, and for improved timing of the intensity of treatments in periods when the environment is particularly vulnerable, e.g., during the migration of smolts from the rivers. The e-lice project using on-line automatic processed digital pictures technology is therefore highly relevant for the entire Norwegian aquaculture community.

# 3 Method

To reach the goals described previously, the work is divided into six work packages (WPs), see detailed description below (and Fig. 3). WP1 involves rearing and imaging of live sea lice in the laboratory, WP2 involves developing an algorithm for automated detection and classification of sea lice from the above imagery, WP3 involves a field program to test the UVP 6 and the algorithm in the real world, WP4 involves developing an e-dashboard for decision-making. In WP5, results of WPs 1,2,3, and 4 are synthesized, validated and optimized. Communication, outreach and stakeholder involvement are taken care of within WP6.

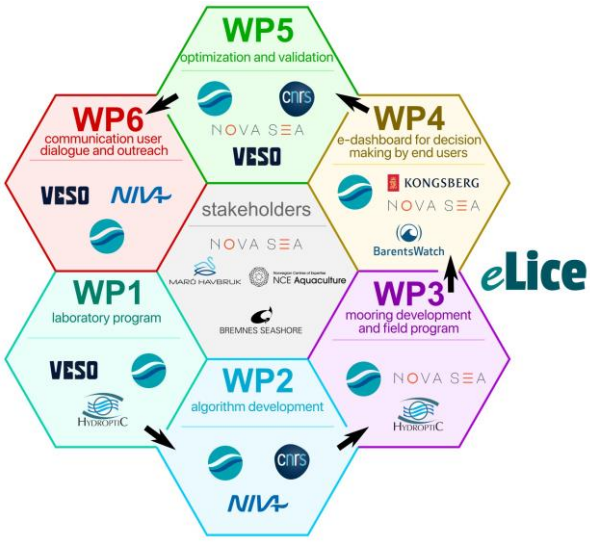


**Fig. 1** The organisation of work-packages within the e-Lice

# 4 Results

## 4.1 WP1 Laboratory program. Lead: VESO | Partners: Akvaplan-niva

### 4.1.1 Collection and hatching of sea lice

Female sea lice (*Lepeophtheirus salmonis*) with eggstrings were collected from a salmon processing plant (slaughterhouse) in Nærøysund municipality, Trøndelag, Norway. Sea lice were picked individually with forceps by trained personnel on the slaughter line shortly after the fish had been killed and before bleeding. Sea lice were placed directly in cold seawater before transport to VESO Aqualab where experiments took place. Pigmented eggstrings (totally approx. 1100) were selected for hatching as pigmentation is a sign of developing embryos. Eggstrings were prepared for hatching by tilting/breaking off strings at the base where they are attached to the female lice. The hatching system consisted of several chambers placed in a system where the volume of each chamber was approx. 0.3 Litre. The water supply was through planktonic mesh at the bottom of each chamber. We used both full strength salinity (32.8 – 33.3 per thousand) and seawater of 12 °C (+/- 0.5 °C) for both hatching of sea lice larvae and tank trial with the underwater imaging sensor UVP6.

### 4.1.2 Experimental set- up

The UVP6 sensor was installed in a test tank holding 430 L seawater (Figure 4). Continuous power supply was secured through power supply in the lab. Planktonic mesh was placed on the outlet and inlet of water and the water flow was reduced to a minimum. The test tank was covered with a dark fabric to avoid surrounding light to interfere with the measurements and the illuminance was measurements to 00.0 LUX inside the tank. The sea lice larvae and mobile stages were added to the tank through a silicon tube to make sure that the lice entered the tank within the water volume and view/focus area of the UVP6 sensor. This was done to make sure the larvae were within the field of view of the sensor at least when they were added to the tank. Especially mobile lice (pre-adults and adults) that are capable of free-swimming will normally not prefer to swim in the water column when no salmonids are present in the tank. They will rather attach and suck to a surface as fast as possible. The laboratory test with sea lice larva and mobile lice respectively were performed at two separate occasions and varied in the duration of the experiment and had the same experimental set up.

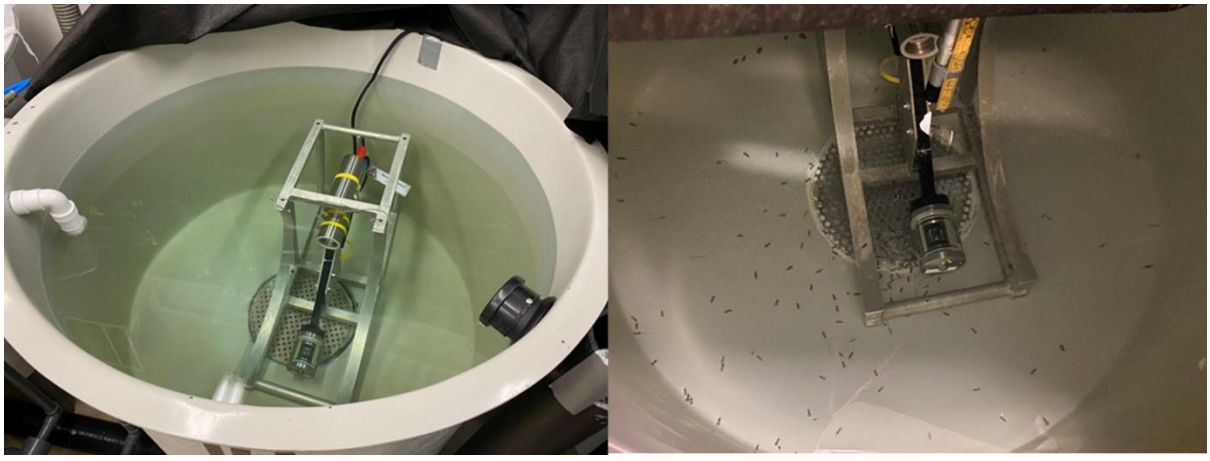

*Figure 4 Experimental set of UVP6 in the test tank. The same set up was used for both sea lice larva's (left image) and mobile lice (right image) (Photo: Ragnhild Pettersen, Akvaplan-niva).*

### 4.1.3 Laboratory study with Nauplius and copepodid stages of sea lice

Nauplius- and copepodid stage sea lice larvae (0.5-0.7 mm) were first added to the test tank the day after hatching start and added (eventually as they hatched) over four days in the following concentrations: 29 300 nauplii (Day 1); 96 700 nauplii (Day 2); 127 000 nauplii + 30900 copepodids (Day 3) and remaining 2500 copepodids were added to the tank on Day 4 (Table 1) (Figure 5). Thus, we estimate that more than 300 000 sea lice larvae were added to the test tank during the test period.

*Table 1 Nauplius and copepodid stages of larva added to the test tank for 4 days*

| Time | Number of larvae | Life stage |
|---|---|---|
| Day 1 | 29300 | Nauplii |
| Day 2 | 96700 | Nauplii |
| Day 3 | 127000 | Nauplii |
| Day 3 | 30900 | Copepodid |
| Day 4 | 25000 | Copepodid |
| Total | **308900** | Nauplii + Copepodid |

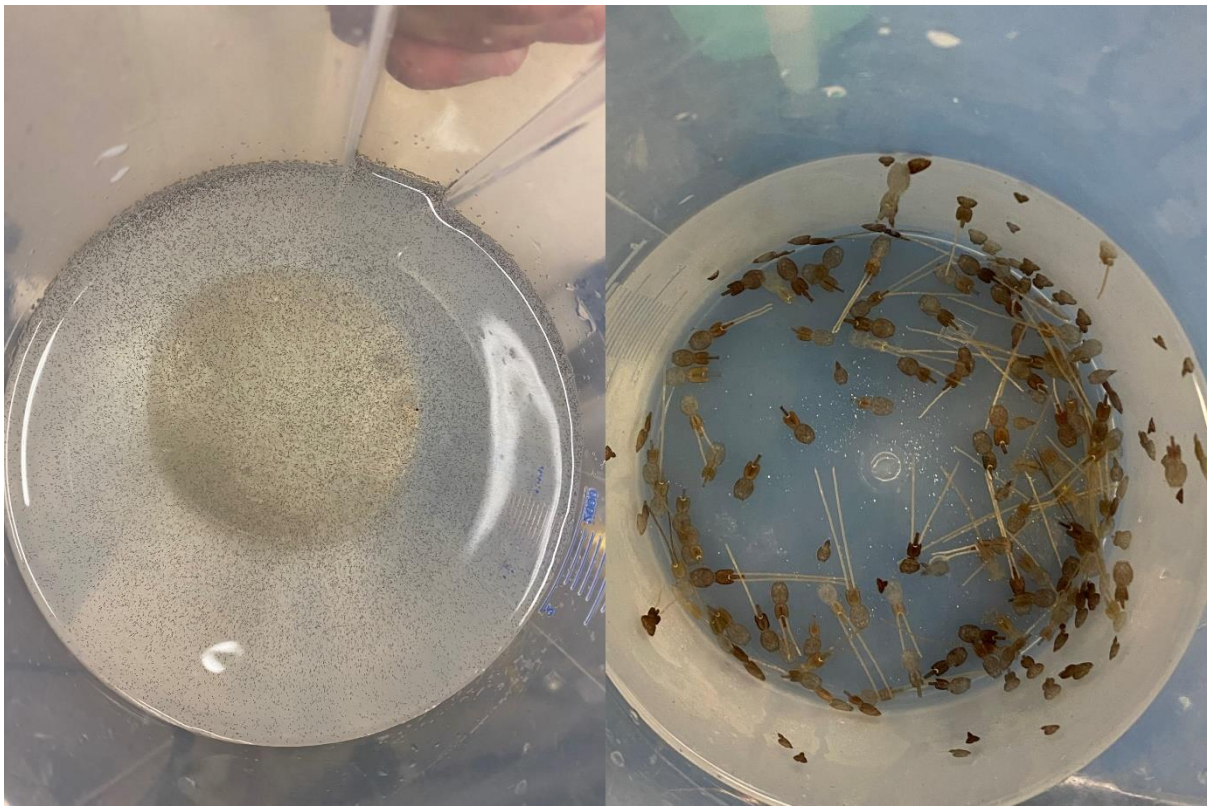

*Figure 5 Sea lice larva (left image) and pre adult/adult (right image) before adding to the tank with the UVP6 imager (Photo by Ragnhild Pettersen, Akvaplan-niva).*

After day 4 the UVP6 continued to acquire images in the tank for 11 more days without any further supply of larvae, resulting in 15 days of imaging sea lice larvae. The development from

nauplii I to copepodids takes approx. 3.6 days at 10 °C, meaning that the test tank was dominated by copepodids from day 7.

### 4.1.4 Collection of mobile sea lice

Adult sea lice of both genders, totally approx. 1150 individuals were collected at the same salmon processing plant and under same conditions as previously described for sampling of egg strings. Collected sea lice were placed directly in cold seawater and transported to VESO Aqualab. Cooling and aeration with aquarium pumps were provided after arrival and before the start of the study.

### 4.1.5 Laboratory study with mobile sea lice

Due to the preference of the lice to settle down on a substrate above of swimming around in the tank, the procedure of applying lice to the test tank and in the field of view for the sensor needed some modifications. A transparent plastic hose with a funnel on the top was mounted on a metal rod, so that the lower end of the hose emptied the imaging area of the UVP6 imager. Lice were gently collected from the tank with a siphon, meaning that each louse was flushed through the hose and into the image area several times over two days. Lice were also left for free-swimming in the tank during night. This resulted in several hundred images.

### 4.1.6 Results

Imaging of sea lice larvae resulted in more than 5000 images of sea lice larvae. Examples are shown in Figure 6

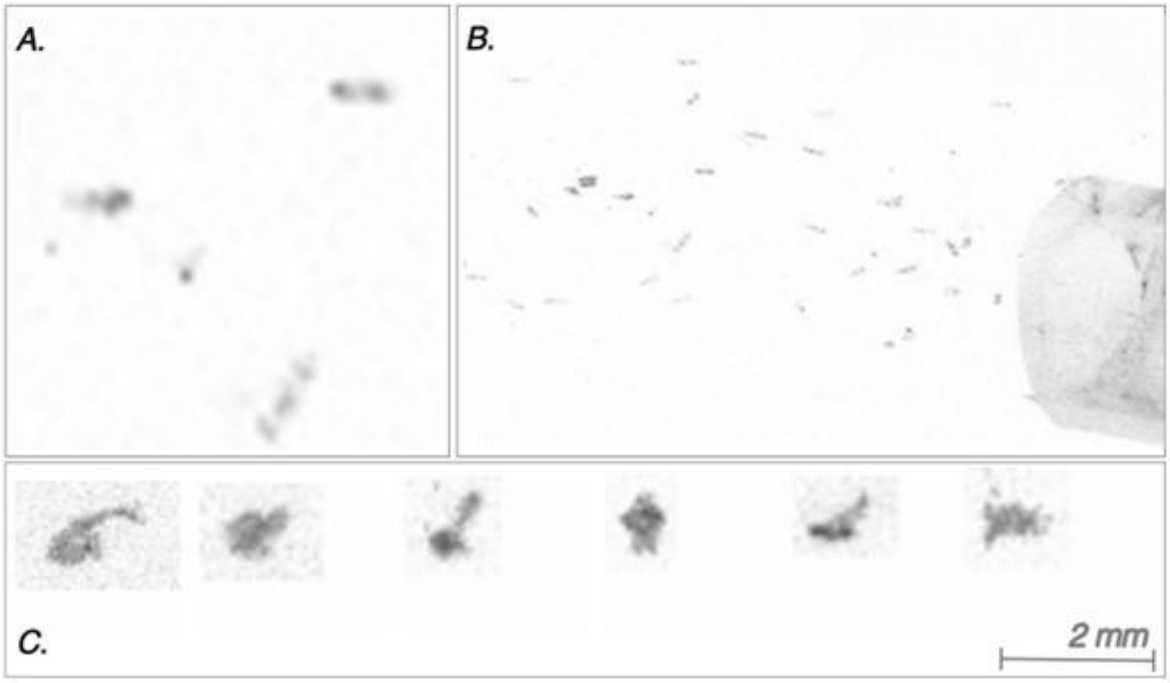


*Figure 6 Images of sea lice larvae and the larvae entering the test- tank (Images by the UVP6).*

Imaging of mobile sea lice resulted in 200 – 300 pictures of mobile sea lice of both genders (Figure 7 and 7)

*Figure 7 Mobile Sea lice (Mostly adult females with eggstrings; without eggstring to the right) (Photo by Ragnhild Pettersen, Akvaplan-niva and the UVP6).*

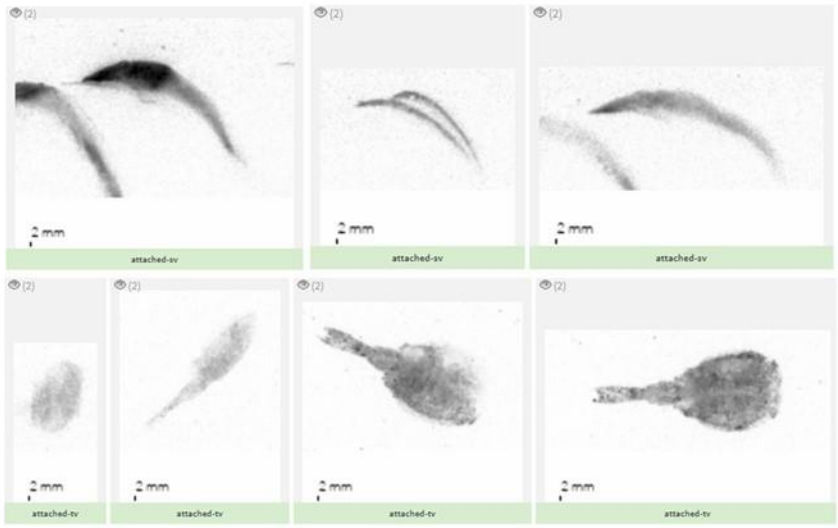


*Figure 8 Male sea-lice from the side (upper row) and from above (lower row) (Images by the UVP6).*

Images were used to develop the algorithm to detect both sea lice larvae and mobile sea lice in the field.

## 4.2 WP2 Algorithm development. Lead: Akvaplan-niva; Partners: MP Consulting, NIVA

### 4.2.1 Objective

Developing an algorithm for automated detection and classification of sea lice.

### 4.2.2 Task 2.1: Algorithm development

One algorithm was developed, and one algorithm was re-used is WP2:

**Real-time (live) image classification algorithm:** For real-time, on-device (embedded) detection and classification, we used the existing Underwater Vision Profiler Embedded Classifier (UVPEC) version 1.5.0.1 (https://github.com/ecotaxa/uvpec). UVPEC is a light-weight machine learning algorithm, primarily based on boosted regression trees, which renders classification outputs within several milliseconds. The lightweight design and fast response time allows the UVPEC to be embedded in the UVP6 image processing unit for real-time, on-device operations.

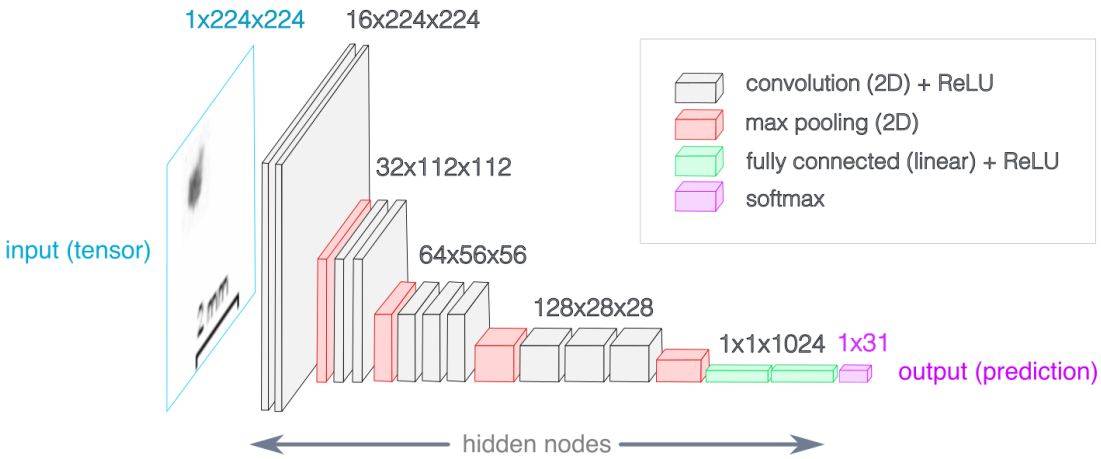


Figure 9: The architecture of the PlanktonVision13 convolutional neural network. UVP6 images (vignettes), that represent the input to the network, gets numerically encoded and transformed through a network of hidden nodes and outputs the most probable final annotation.

**Validation algorithm:** While the UVP6 with the embedded UVPEC algorithm is deployed in the field (see WP3 below), it transmits the classification outputs in text format and saves the images to the UVP 6's SD card, which can only be accessed after its retrieval. To validate and confirm the real-time classifications of the UVPEC algorithm, we developed a deep convolutional neural network (CNN) termed 'PlanktonVision13'. In summary, PlanktonVision13 is a 13-layer-deep CNN, which includes: (i) an input node, (ii) a network of hidden nodes and (iii) an output node (Figure 9). The images input to the PlanktonVision13 are of standard 1 × 224 × 224 pixels in color channels × width × height. Since the dimensions of the UVP6 vignettes/images vary with the size of the objects being imaged, we scaled the images before passing them through the CNN. However, we preserved the original aspect ratio of the images using a custom-built PyTorch image processing pipeline. The UVP6 vignettes are greyscale, and therefore, contains a single colour channel. These greyscale images are then numerically encoded as PyTorch tensors (numerically encoded input

images), which are then normalized using mean and standard deviation of pixel values (grey levels) of the model training datasets (see below). The normalized tensor is passed through a TrivialAugment image augmentation pipeline (https://github.com/automl/trivialaugment) to account class imbalance of the training datasets, e-Lice31 and e-Lice33 (see below)....

The construction of the PlanktonVision13 algorithm commenced in February 2023, and it was completed by early May 2023. Fine-tuning of the model architecture continued until May 2024, which provided improvements of performance (see below).

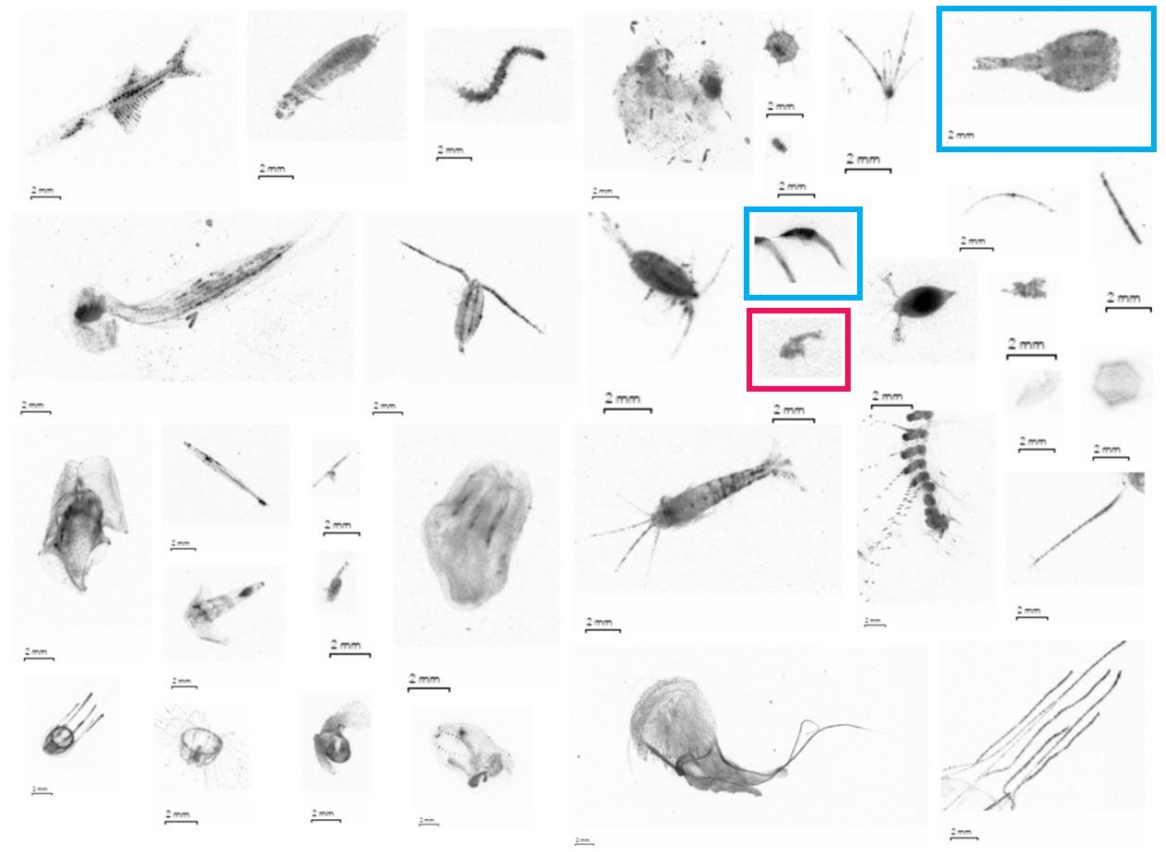

Figure 10: A representative subset of the e-Lice33 model training dataset, containing 33 living and non-living categories alongside free-living (red box) and pre-adult and adult (blue boxes) stages of sea lice.

**Table 2** The 33 categories of the *e*-Lice33 dataset and the number of images of the training and test (70:30) subset under each category. Sea lice images of the controlled imaging experiments (WP1) were included under the 'Caligidae' category including two sub-categories. sv: side view, tv: top view, L: large bell, S: small bell.

| Category | train | test |
|---|---|---|
| Actinopterygii | 77 | 33 |
| Amphipoda | 175 | 75 |
| Annelida | 149 | 64 |
| Antennae | 237 | 102 |
| Appendicularia_alive | 101 | 43 |

| | | |
|---|---|---|
| Appendicularia_dead | 636 | 273 |
| Artefact | 2100 | 900 |
| Calanidae | 614 | 263 |
| Calanoida | 2100 | 900 |
| Caligidae | 2100 | 900 |
| Caligidae > *attached-sv* | 80 | 34 |
| Caligidae > *attached-tv* | 11 | 4 |
| Cavoliniidae | 72 | 31 |
| Chaetognatha | 400 | 172 |
| Copepoda | 2100 | 900 |
| Creseidae | 125 | 54 |
| Crystal | 1400 | 600 |
| Ctenophora | 143 | 61 |
| Detritus | 2100 | 900 |
| Eumalacostraca | 892 | 382 |
| Fiber | 1400 | 600 |
| Fillament | 1400 | 600 |
| Hydrozoa_L | 331 | 142 |
| Hydrozoa_S | 649 | 278 |
| Limacinidae | 29 | 13 |
| Ostracoda | 379 | 162 |
| Pluteus | 60 | 26 |
| Reflection | 1400 | 600 |
| Rhizaria | 1400 | 600 |
| Salpida | 246 | 106 |
| Scyphozoa | 27 | 12 |
| Siphonoporae | 83 | 35 |
| Tentacle | 260 | 112 |
| **Total** | **23269** | **9973** |

**Algorithm training:** To train both the real-time UVPEC algorithm and the validation algorithm PlanktonVision13, we used a standard UVP6 reference dataset based on Picheral et al., 2024[1]. Images in this dataset were arranged into 30 different categories. To this we added images acquired from the laboratory experiments. We added images of free-living sea lice and got the training data set e-Lice31 and we added images of pre-adult and adult sea lice and got the training data set e-Lice33. (Figure 10). The algorithms were trained on both the e-Lice31 and the e-Lice33 dataset. The UVP6 deployed in the field (see WP3), however, only contained the algorithm trained with the e-Lice31 dataset (only including images of the free-living sea lice). The other living and non-living categories of objects and artefacts in the images generally represent some of the common taxa that co-exist with sea lice in the

[1] Picheral Marc, Courchet Lucas, Jalabert Laetitia, Motreuil Solène, Carray-Counil Louis, Ricour Florian, Petit Flavien (2024). UVP6Net : plankton images captured with the UVP6. SEANOE. https://doi.org/10.17882/101948

northern Norwegian Sea (Figure 10). In the end the training dataset contained 33242 images, out of which 23269 were used for training and 9973 for testing (ground truthing) (Table 2).

Training of both algorithms began in May 2023 and continued until May 2024. Through these training exercises, we could improve the performance of both algorithms on the training datasets (Figure 11).

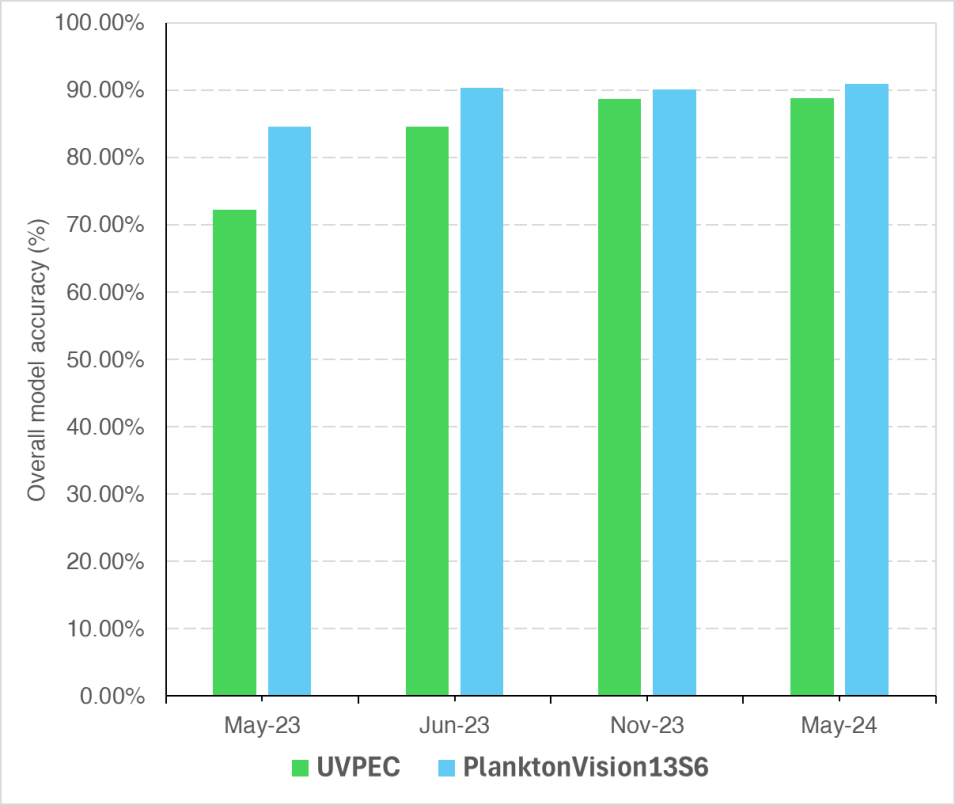


Figure 11: The overall performance of the real-time (live) algorithm (UVPEC) and the validation algorithm (PlanktonVision13) at different times of the project timeline. Performance is indicated by overall (macro-average) % accuracy on the e-Lice31 dataset (May–November, 2023) and the e-Lice33 dataset (May 2024).

Table 3: Summary of performance metrics across the entire training dataset and different sea lice categories in the e-Lice31 and e-Lice33 model training datasets.

| **Performance metric** | **e-Lice31 (November 2023 update)** | | **e-Lice33 (May 2024 update)** | |
|---|---|---|---|---|
| | **UVPEC** | **PlanktonVision13** | **UVPEC** | **PlanktonVision13** |
| Overall model accuracy | 88.7% | 90.4% | 88.9% | 90.9% |
| Overall model F1-score | 0.84 | 0.90 | 0.88 | 0.89 |
| Accuracy Caligidae (free-living) | 87.6% | 98.4% | 87.6% | 98.4% |
| F1-score Caligidae (free-living) | 0.85 | 0.98 | 0.85 | 0.98 |

| | | | | |
|---|---|---|---|---|
| Accuracy Caligidae (adult, top-view) | – | – | 99.4% | 94.5% |
| F1-score Caligidae (adult, top-view) | – | – | 0.98 | 0.92 |
| Accuracy Caligidae (adult, side-view) | – | – | 98.9% | 99.6% |
| F1-score Caligidae (adult, side-view) | – | – | 0.98 | 0.99 |

**Algorithm performance:** The overall and category-specific performance of both algorithms were satisfactory. Based on the training conducted in November 2023 on the e-Lice31 dataset (without pre-adult and adult lice), UVPEC showed an overall (macro average) accuracy of 88.7% and an overall (macro-average) F1-score of 0.84. At this time of the project the PlanktonVision13 algorithm showed an overall accuracy of 90.4% and an overall F1-score of 0.90. However, compared to the PlanktonVision13 algorithm, the UVPEC algorithm tended to misidentify free-living sea lice as detritus and *vice-versa.* The UVPEC had a category-specific accuracy of Caligidae of 87.6% whilst the PlanktonVision 13 had a m category-specific accuracy of Caligidae of 98.4%). By May 2024, on the e-Lice33 training dataset with pre-adult and adult sea lice, the UVPEC algorithm showed an overall accuracy of 88.9% and a F1-score of 0.88. On the same dataset, PlanktonVision13 performed slightly better, with an overall accuracy of 90.9% and F1-score of 0.89. While both algorithms performed well with (pre-)adult sea lice, the misidentification of Caligidae by the UVPEC could not be improved (Table 3). The performance of the two algorithms at the last training exercise in November 2023 (i.e., the algorithms used in the field deployment: see below) is presented in Figures 12 and 13.

### 4.2.3 Task 2.1: Algorithm embedding

In December 2023, the UVPEC algorithm trained on the e-Lice31 dataset (without pre-adult and adult stages) was embedded in the UVP6 SD card for onboard real-time classification of objects. This embedded algorithm was tested in several indoor tests prior to the actual field deployment. The training of the two algorithms based on the e-Lice33 dataset (with pre-adult and adult images acquired in the second laboratory imaging exercise) was done in late-May 2024.By this time, the UVP6 with the e-Lice31-trained UVPEC was already sent for deployment. Therefore, this updated UVPEC algorithm was not deployed in the field. We did sadly not get a second deployment opportunity to re-embed the new e-Lice33-trained UVPEC algorithm.

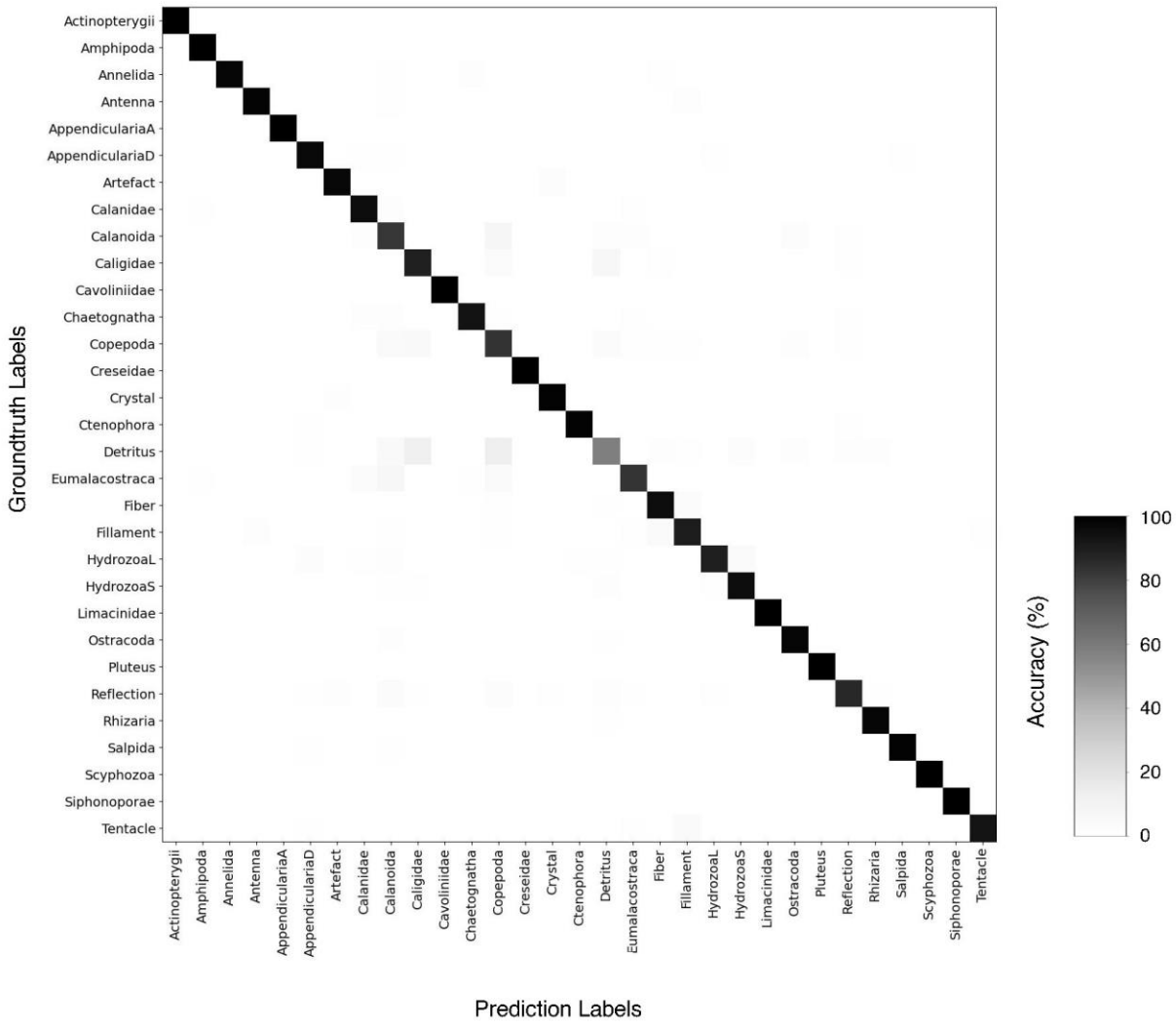


Figure 12: Confusion matrix of category-specific accuracy of the UVP6 embedded classifier (UVPEC) trained on the e-Lice31 dataset (November 2023).

### 4.2.4 Deliverables

**D2.1 AI algorithms for detection and classification of sea lice (software):** Two algorithms, i.e., the real-time (live) image classification algorithm, UVPEC and a validation algorithm, PlanktonVision13 were set-up, trained and tested. The trained UVPEC model parameters were delivered in December 2023 for embedding in the UVP6 SD card for on-board image processing. The trained model parameters of PlanktonVision13 algorithm were saved into an internal repository in December 2023.

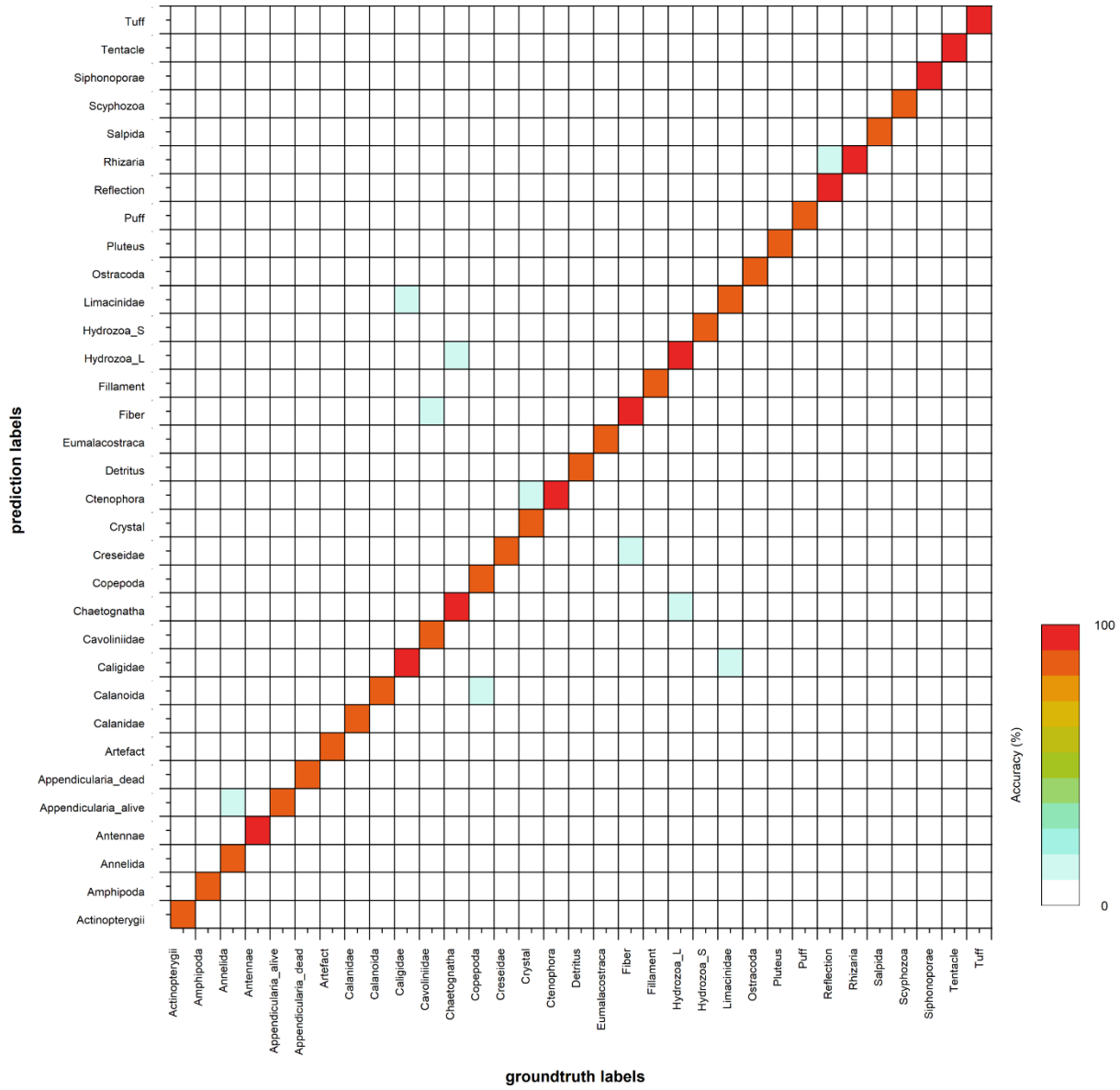


Figure 13: Confusion matrix of category-specific accuracy of the PlanktonVision13 validation algorithm trained on the e-Lice31 dataset (November 2023).

**D2.1 AI algorithms for detection and classification of sea lice (publication):** The work on the research article titled, "*Automated real-time detection of free-swimming and mobile stages of salmon lice (Lepeophtheirus salmonis) using underwater imaging and artificial intelligence*" commenced in June 2024 and the first draft was completed in September 2024. The manuscript is currently pending an update of the results of the field deployment data, which will be completed in Q1, 2025 and submitted to the journal 'Aquaculture'.

**D2.3: Algorithm embedding in compact microprocessors for real-time data processing:** The UVPEC algorithm, trained on the e-Lice31 dataset, was embedded in the UVP6 in December 2023.

**D2.4: Acquired UVP6 images of sea lice and other co-occurring taxa:** All images of sea lice and other co-occurring taxa from laboratory experiments and the field deployment were delivered to the zooplankton imaging database EcoTaxa. EcoTaxa project no. 10791 contains the images of first laboratory imaging experiment of free-living sea lice (https://ecotaxa.obs-vlfr.fr/prj/10791) and EcoTaxa project no. 14015 contains the images of second laboratory

imaging experiment of pre-adult and adult stages (https://ecotaxa.obs-vlfr.fr/prj/14015). The raw (non-quality-controlled images) acquired in the field deployment (see WP3 below) are found in the EcoTaxa project no. 14951 (https://ecotaxa.obs-vlfr.fr/prj/14951) and the quality-controlled images of the above deployment are found in the project no. 15023 (https://ecotaxa.obs-vlfr.fr/prj/15023).

## 4.3 WP3 Mooring development and field program | Lead: Akvaplan-niva | Partner: Nova Sea & MP Consulting

Work Package 3 (WP3) focused on the development, assembly, and field testing of a mooring system equipped with a UVP6 (Underwater Vision Profiler) to facilitate real-time sea lice detection at the Nova Sea aquaculture site "Buktodden NØ" (site number 22035). The goal of the mission was to adapt existing technology, integrate detection algorithms developed in WP 2, and push the live detection data via 4G communication to the e-dashboard in Blue Insight developed in WP4.

### 4.3.1 Task 3.1: Mooring Development

**Objective:** To develop an online mooring solution capable of deploying and controlling the underwater imager UVP6 and push the collected data to an e-dashboard.

**Approach and Implementation:**

This work task included the adaptation of the Automatic Profiling Buoy made by SAIV AS for use with the UVP6 and facilitate for online transfer of data.

The initial plan to use three UVP6 devices suspended statically at pre-set depths was abandoned following the first meeting with the e-Lice Reference Group. In this meeting it was highlighted that it would be beneficial to target ocean temperature layers where sea lice are commonly found. Hence following a workshop with SAIV AS, we found an alternative solution. Instead of static positioning, we decided to utilize the winch system in the buoy to lower the UVP6, along with a CTD (Conductivity, Temperature, Depth) and PAR (Photosynthetically Active Radiation) sensor (Figure 14.). This setup allowed us to profile the water column down to 15 meters and use the profile data to select an appropriate depth for increased sea lice detection by the UVP6.

We also decided to use a cloud solution for handling data instead of an onboard computer, The background for this was that this would preserve a significant amount of energy allowing for an increase in the operation of the winch to target water column layers of interest. This setup also simplified the electronic integration. By utilizing an optional power assembly provided by SAIV AS, the only third-party electronic component needed was a serial-to-ethernet communication adapter to ensure the UVP6 communication protocol (serial) corresponded to the available input of the moorings 4G modem (ethernet). This along with software modifications to the electronic control system of the APB5, we managed to facilitate remote power and communication to the UVP6.

Components (figure 16.) for attaching the UVP6 to the dynamic part of the APB5s winch (Figure 15.) was first designed in a CAD (Computer aided design software) and later 3D-printed using PETG (Polyethylene terephthalate glycol). This allowed for rapid prototyping and final production for further testing.

To facilitate the detection algorithm developed in WP2, the UVP6 was shipped to the production company Hydroptics for upgrading to facilitate onboard processing and implementation of the third-party detection algorithm, PlanktonVision13.


***Figure 14.*** *Complete assembly*

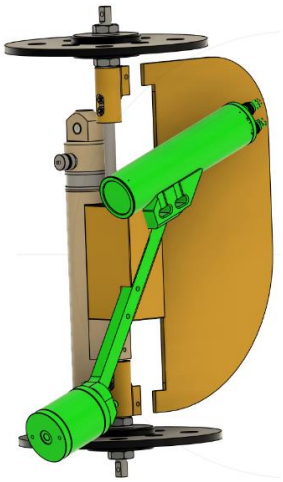

***Figure 15.*** *Dynamic assembly*

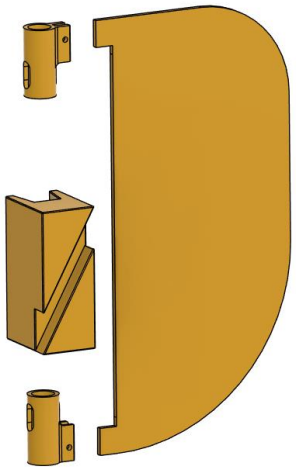

***Figure 16.*** *PETG Components*

**Outcome:**

- Successful design and production of necessary hardware, adaptation and implementation of electronics and bench testing of the complete solution including data transfer via an onboard 4G modem.

### 4.3.2 Task 3.2: Initial Testing

**Objective:** To test and verify the hardware and software solution both on land and in sea to identify any limitations and correct them before deployment at the Nova Sea site.

**Approach and Implementation:**

During this phase, comprehensive testing was conducted at the Akvaplan-niva facilities in Tromsø (Figure 19). Initially we tested on land to stress test the winch over time ensuring that it would withstand the extra load of a UVP6 with associated hardware. The testing revealed that the power distribution circuit board in the buoy needed reinforcement as the original board could not handle the high load and associated power draw (Figure 17).

After the power distribution board was upgraded and tested, we proceeded with testing in the ocean. This testing was performed by a dock for easy access and monitoring. The complete system was operated over an extended time with and without solar charging. The goal of this was to test the long-term functionality of the system, ensure that marine biofouling would not cause any challenges, and establish a baseline for how often we could operate the winch based on available power capacity.

During this testing phase we discovered no biofouling challenges, however the UVP6 needed a solution for facing the current and maximizing the water volume sampled. For this purpose, we designed a “sail” that corrected the direction of the UVP6 and protected it from potential impacts while entering and exiting the APB5 mooring, as illustrated in task 3.1.

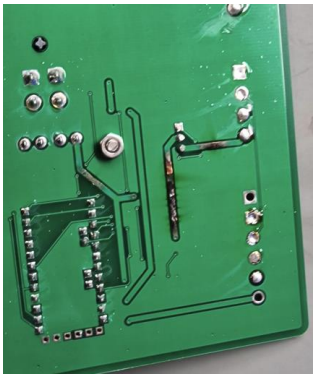

***Figure 17.*** *Burnt Power distribution PCB (Printed Circuit Board)*

***Figure 18.*** *APB5 Mooring deployed at quay*

***Figure 19.*** *APB 5 During workshop testing*

**Outcome:**

- Successful verification of hardware and software functionality.
- Identified minor system improvements, which were incorporated into the final design.
- Development of field procedures for operation and field maintenance.

### 4.3.3 Task 3.3: Field Study

**Objective:** To deploy the mooring system at Nova Sea's Buktodden NØ (22035) site for in-situ sea lice detection.

**Approach and Implementation:**

The buoy was deployed at Buktodden NØ on June 7 by one of the Nova Sea service vessels. In conjunction with Nova Sea and the project group it was decided to deploy the mooring inside an empty fish pen to minimize potential conflict with ongoing operations and assure that there would not be any conflict with the site mooring system.

When the mooring was in place and secured (Figure 20.), we took daily profiles of the water column down to 15 meters depth. Afterwards the UVP6 was positioned at the appropriate depth based on an analysis of the profile data. The UVP6 was submerged for approximately 22 hours per day while the system was operational, with an average of two profiles taken per day to adjust the depth and transmit salinity and temperature data to shore.

During the deployment of the buoy with sensor there were three incidents with the buoy. Two incidents were due to maintenance activities at the site. The third incident was a data corruption issue with the UVP6 internal logging discovered post deployment, which resulted in incomplete data for some of the deployment period. The buoy was retrieved from the site on August 16th.

***Figure 20.*** *APB5 Mooring system deployed at aquaculture site Buktodden NØ.*

**Outcome:**

- Successful deployment and remote operation of the mooring system at the Buktodden NØ aquaculture site.
- Real-time sea lice and CTD data transmitted to the e-dashboard, providing Nova Sea with in-situ data.

### 4.3.4 Deliverables

**D3.1: Assembled Mooring with Vertical UVP6 Array**

- The mooring system was successfully assembled with a UVP6 on a winch allowing for profiling down to 15 meters depth with online supporting parameters of salinity, temperature and depth. Additionally, a PAR sensor was fixed to the UVP6 for post processing.

**D3.2: Deployed and Field-Proven Mooring at Key Location**

- The mooring system was successfully deployed at the Nova Sea aquaculture site Buktodden NØ, operating under real conditions at an active aquaculture facility, where sea lice levels were manually reported by Nova Sea personnel and the live data of the UVP6 were transferred to the e-dashboard and WP4.

## 4.4 WP4 e-dashboard for decision making by end users. Lead: Kongsberg Discovery; Partners: Nova Sea & Akvaplan-niva.

Objectives

The main objective of WP4 was to design a dashboard that could give an enhanced understanding of the measurements of the UVP6 and CTD sensors (Task D4.1). The second objective was to establish a mechanism for data distribution to project stakeholders (Task D4.2).

For both these tasks we worked with the project members to improve the designs in increments. Initially, we worked with WP3 to establish the data formats and protocols, later the project established the information design that would be needed for the dashboard.

### 4.4.1 Task 4.1: data ingestion, storage, processing and visualization

The project team decided a heatmap with sea lice detections and CTD plotted against time and depth would give the best situational understanding. The heatmap shows either live or historic data from the sensor deployed at the test site depending on the user selection. To facilitate reuse of the work, we decided to make component libraries and allow for configurable queries. The drawback of this is that a user can create queries which produce extreme data volumes.

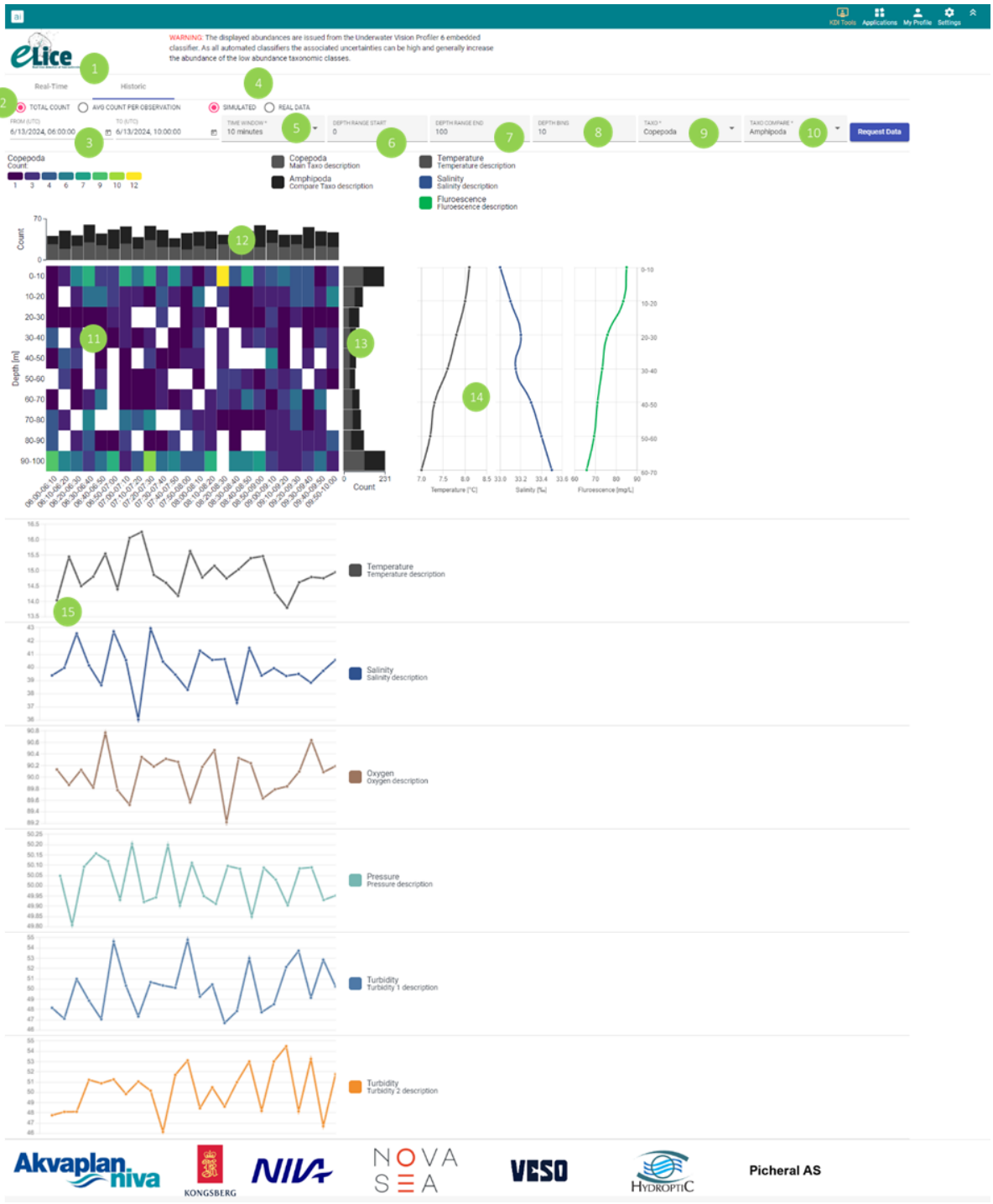


*Figure 21 Dashboard overview with heatmap*

The dashboard components:

1) Real-time vs Historic selector
2) Total count vs Average count per observation
3) Date selector (from-to)
4) Simulated vs Real data
5) Time window (10 min, …, )
6) Depth range start (0m)
7) Depth range end (100m)

8) Depth range bins (10)
9) Taxa: Copepoda
10) Taxa Compare: Amphipoda
11) Heathmap over depth and time dimensions
12) Count per time slot
13) Count per depth bin
14) CTD profiles depth dimension
15) CTD plotted along time dimension

As illustrated in the figure below, if the user selects an element in the heatmap, a more detailed data view is overlayed.

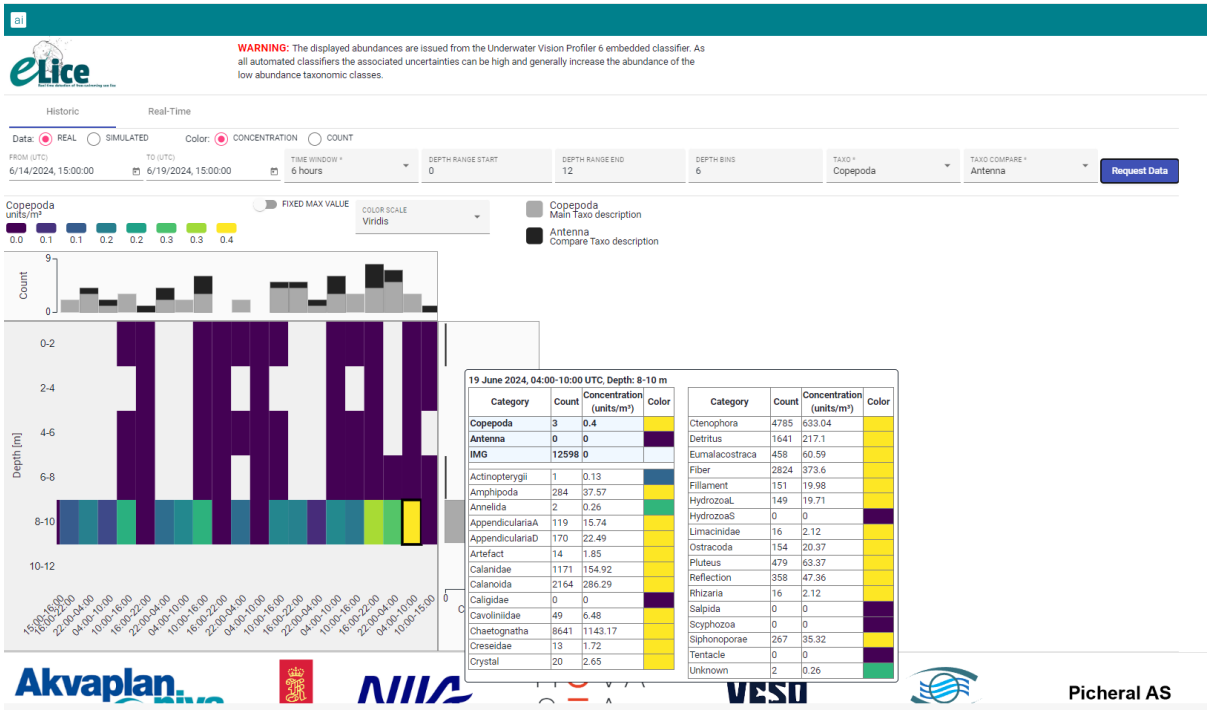


*Figure 22 e-Dashboard with detailed view*

### 4.4.2 Task 4.2: Transferring the data to specific end user.

To be able to forward data to the project partner Nova Sea, we developed an exporter function. This service runs a query into the database system at a configurable schedule and dumps the data in a blob store. The keys to this blob store were shared with Nova Sea and the company can now access the data from their preferred third-party software.

However, this service is not useful if the buoy is not deployed and can be enhanced to offer message-based support in time for new deployments.

### 4.4.3 Task 4.3: Making the mooring data open source.

The integration of e-Lice results to the Barents Watch platform was not implemented but this will not reduce the use of the set up for Nova Sea.

**Architecture**

The diagram outlines the architecture that is developed in the WP4 to run in the Blue Insight tenant for Akvaplan-niva.

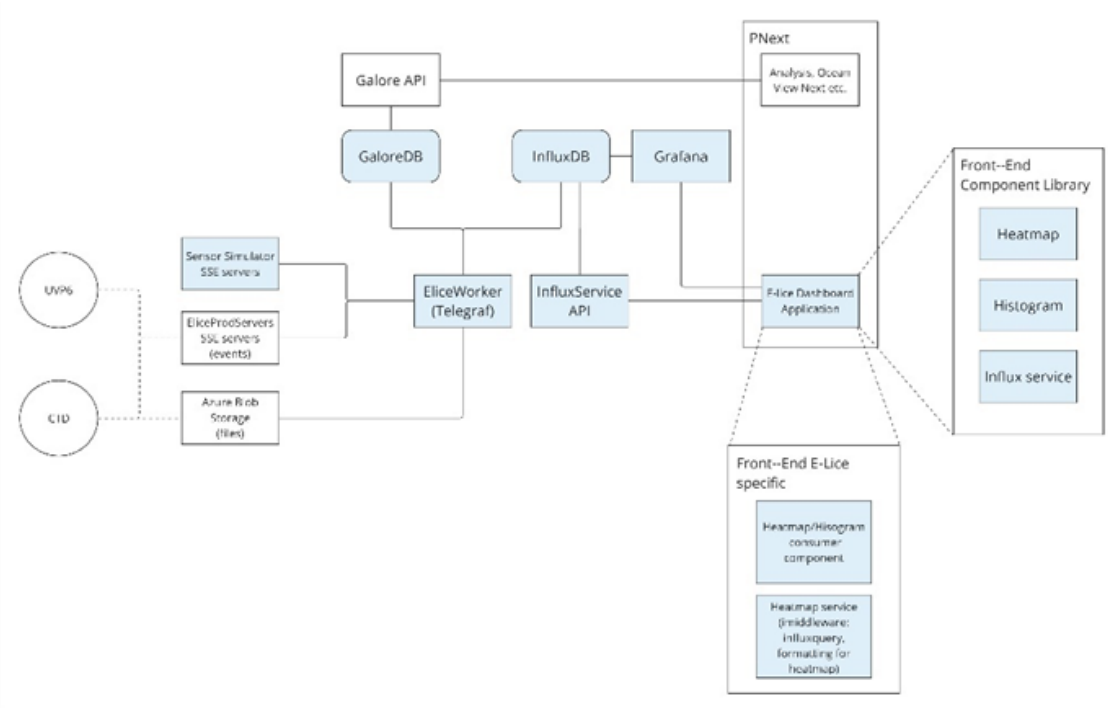


Figure 23. architecture of the e-system to power the dashboard

The sensors are UVP6 and CTD. The UVP6 data is made available via a Server-Side Event server and an EliceWorker process running Telegraf in the Blue Insight tenant is receiving these events. The EliceWorker is also receiving CTD data as files via a blob store. The data is ingested in two time series databases, GaloreDb and InfluxDb. The Elice Dashboard application can get data from either of these databases, the default is InfluxDb. The application uses three front-end component libraries Heatmap, Histogram and an Influx service. The application uses two e-Lice specific components to display the data. The solution includes a UVP6 simulator to help with the tuning of the system.

The e-Lice application is made available in the Blue Insight tenant deployed for Akvaplan-niva. Other users can get access to this specific application upon request.

### 4.4.4 Deliverables from WP4

Deliverables: 4.1: A dashboard for real-time and historic mooring data visualization, reporting and early was successfully developed and deployed in the Blue Insight infrastructure running for Akvaplan-niva.

Deliverables: 4.2: An exporter function was developed which allows data to be fetched in a protected storage account as files. This provides a more generic data access method than the proposed API for Barents Watch and Nova Sea data portals.

## 4.5 WP5 Optimization and validation | Lead: Akvaplan-niva. Partners: CNRS, Nova Sea, VESO, KD

### 4.5.1 Task 5.1 Validation of field deployment data

**Overview:** The UVP6 attached to the Automatic Profiling Buoy (APB5, see WP3 above) recorded data from mid-day of July 5. to morning of August 24. 2024. However, the images and metadata in the UVP6's SD card indicated that the data acquisition was not continuous, and there was a significant gap from July 28 to August 16, 2024. The same data recording and transmission gap was apparent in the live data transmitted to the e-Dashboard of Blue Insight (WP4). Despite this gap, data covering ca. 21 days were extracted from the UVP6's SD card[2]. The validation process began in the last week of November 2024 and was concluded December 13. 2024.

**Approach:** Three types of metadata was transmitted by the UVP6 to Blue Insight as RS232 data frames: (i) LPM frames with metadata of the objects detected in the acquired images, (ii) BLACK frames, which are reference data with the UVP6 lights off at regular intervals and (iii). TAXO frames, that contains the taxonomic annotations (labels) of the detected objects by the UVPEC algorithm. Despite the transmission of LPM, BLACK and TAXO metadata, the underlying images of the detected objects are not transmitted to Blue Insight but saved to the SD card of the UVP6. After the UVP6 was recovered following the field deployment, we extracted the saved images and metadata for validation analyses.

Before the analyses, we implemented two layers of quality control. QC1: It appeared that while the UVP6 was in the upper 5 m of the water column, sunlight had impacted the sensor and caused images of a lot of artefacts. Therefore, as the first quality control layer (QC1) we removed the images that were potentially impacted by light using the UVPApp and UVP toolbox (https://github.com/ecotaxa/UVP_toolbox). The images and metadata that passed the QC1 were uploaded to EcoTaxa (https://ecotaxa.obs-vlfr.fr/prj/15023) and EcoPart (https://ecopart.obs-vlfr.fr/prj/1071). These QC1 images were then downloaded from EcoTaxa and re-annotated using the PlanktonVision13 validation algorithm to compare with the annotations in the live data made by the UVPEC algorithm. The annotations output by PlanktonVision13 was then subjected to a second layer of quality control. QC2: Here, the annotated image data were split into two categories based on their prediction probabilities.[3]We established a prediction probability threshold of 0.90 (90%) and image annotations with a prediction probability greater than or equals to the above threshold were marked as 'confident annotations' and used in the analyses. The others (with a prediction probability < 0.90) were marked as 'dubious annotations', which needed an additional layer of quality control (QC3: manual validation by a taxonomist) to confirm their annotation. However, the QC3 was not implemented in the project due to time and resource limitation. For comparing the effect of different prediction probabilities on the data, we also used a 0.99 (99%) threshold. However, most of the analyses described below are based on the 0.90 (90%) quality control threshold. The numerical impact of QC1 and QC2 on the data are listed in Table 4.

Table 4: The impact of various quality control steps on the size of the image dataset acquired during the field deployment. A visual comparison of QC2 is presented in Figure 24.

[2] The data extraction from the UVP6's SD card was not straightforward, as the card was corrupted and could not be read in full. After more than a month-long data recovery attempt, we were able to recover almost all data from the SD card. Due to some bad sectors of the SD card, approximately 9 hours of deployment data were lost. This data loss duration was estimated after comparing the time tags of the recovered data with those of the live data transmitted to Blue Insight.

[3] In deep learning, prediction probability refers to the likelihood that a model assigns to a particular class or outcome for a given input. It's essentially the model's confidence level in its prediction.

| QC | Description | Number of images and/or metadata | Percentage (compared to original dataset size) |
|---|---|---|---|
| Raw data | Images and metadata saved in the UVP6 SD card; no quality control | 2,146,415 | 100.00% |
| Live data* | Live data transmitted to Blue Insight; no quality control | 1,309,581 | 61.01% |
| QC1 | Removing images impacted by sunlight | 984,568 | 45.87% |
| QC2 | Thresholding (90%) | 670,769 | 31.25% |
| QC2 | Thresholding (99%) | 389,516 | 18.15% |

*Live data cannot be quality controlled because images are not transmitted to the cloud (Blue Insight)

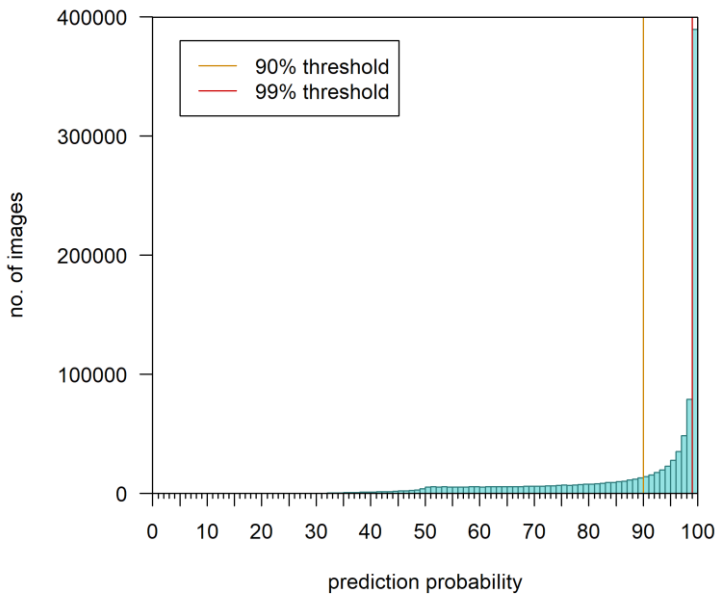


Figure 24: A histogram of the no. of images acquired by the UVP6 based on prediction probabilities rendered in PlanktonVision13 validation algorithm after QC1.

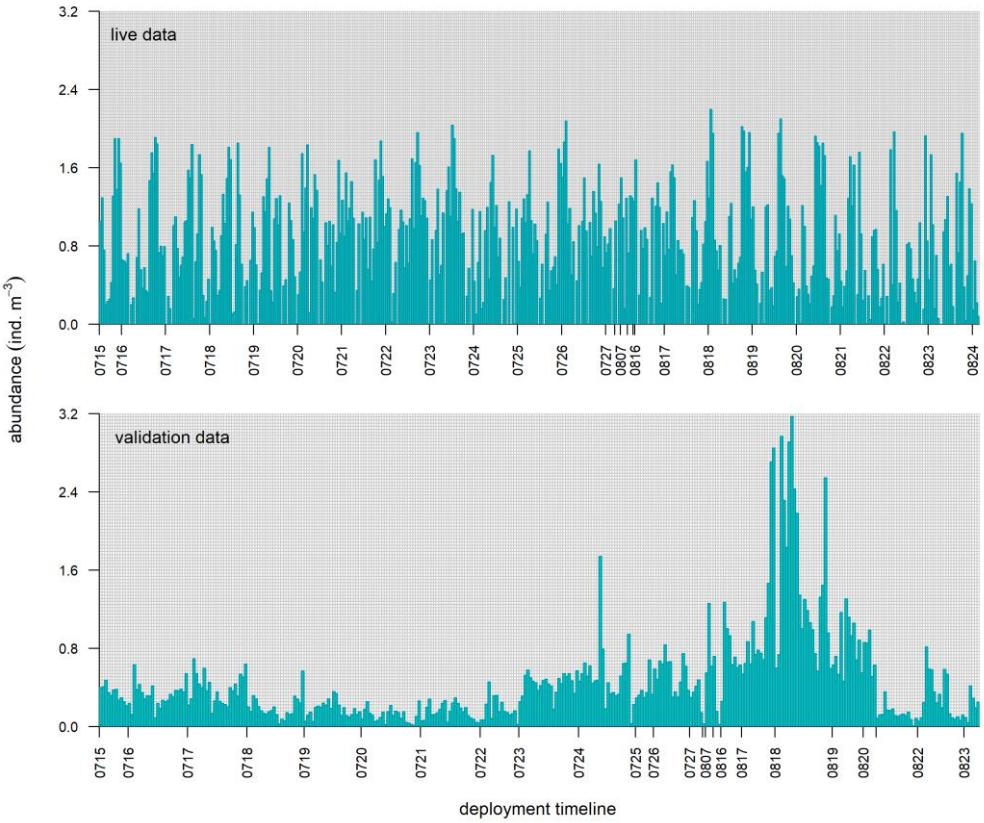


Figure 25: Comparison of estimated abundance of free-living naupliar and copepodite stages of sea lice during the field deployment. Top: live data transmitted to Blue Insight; Bottom: validation data after quality controlling (QC1 + QC2 at 90% threshold).

Compared to the number of images recovered from the UVP 6's SD card (n = 2,146,415: Table 4), the taxonomic annotations found in the archived live data were significantly less (n = 1,309,581: Table 4). This discrepancy is due to a power-saving function of the UVP6, where the UVPEC annotation is arrested when the number of objects detected in a single acquisition exceeds 25. The impact of this arrested UVPEC annotation (among other things) was evident when live data were compared with the validation data (see below).

**Observations:** As per both live data transmitted to Blue Insight and validation data, free-living sea lice nauplii and copepodites (annotated as 'Caligidae') were detected during the deployment. However, the estimated abundance of free-living sea lice differed notably between the live data (0.82 ind.m$^{-3}$) and validation data (0.45 ind.m$^{-3}$) (Figure 25). While the validation data showed a distinct abundance peak between late July and mid-August, no such pattern was apparent in the live data. In the live data, the estimated abundances of free-living sea lice were more or less uniform (Figure 25). The same late July to mid-August peak was apparent when using the 99% threshold QC2 validation data (Figure 26).

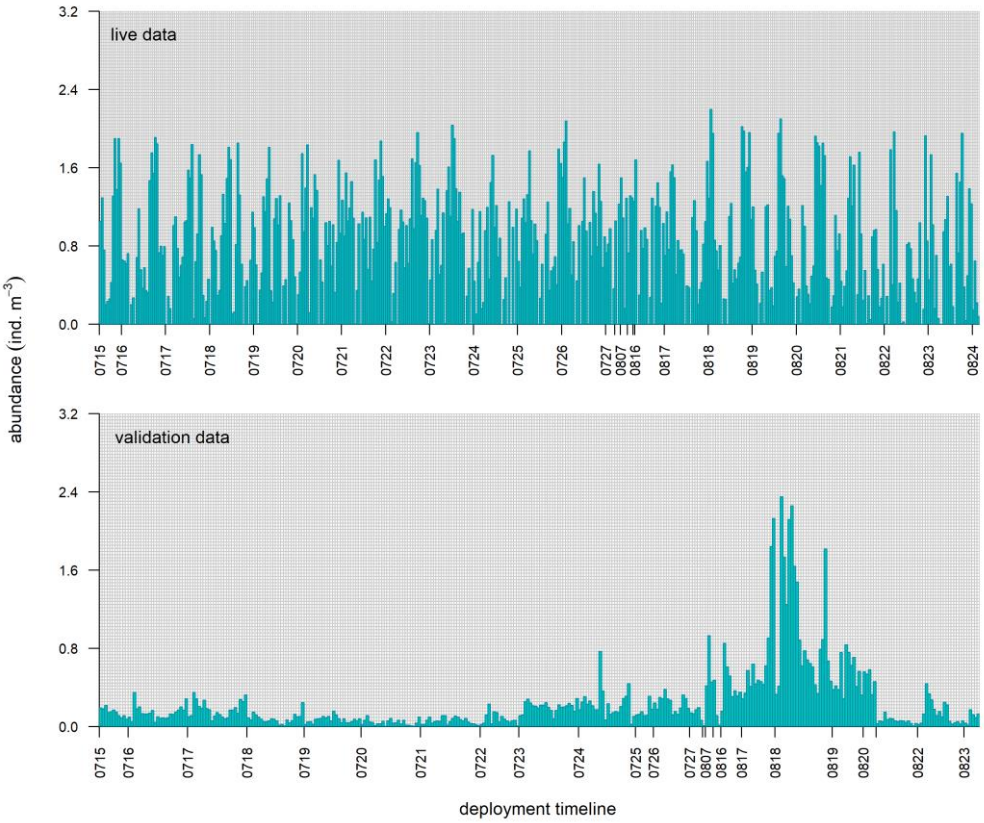


Figure 26: Comparison of estimated abundance of free-living naupliar and copepodite stages of sea lice during the field deployment. Top: live data transmitted to Blue Insight; Bottom: validation data after quality controlling (QC1 + QC2 at 99% threshold).

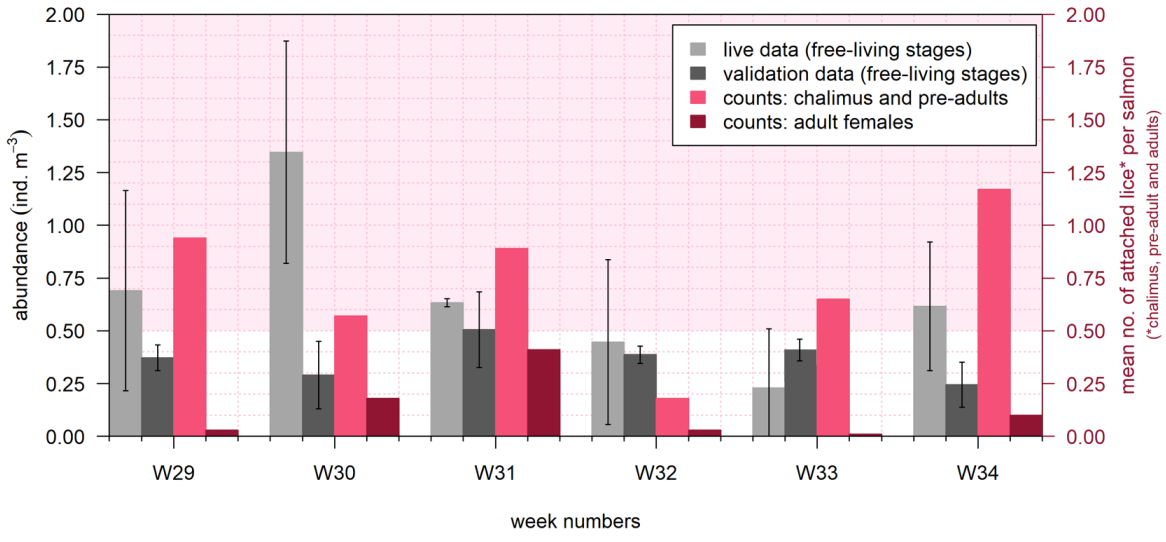


Figure 27: Comparison of estimated abundances of free-living sea lice from the live and validation data *vs.* the manual counts of chalimus, pre-adults and adult female stages at the aquaculture site vicinity of the UVP6 deployment. Delousing treatments were applied when manual counts of adult female sea lice reached > 0.5 per salmon on average (pink shaded area). Dispersion bars indicate standard deviation.

When the weekly means of live data and validation data were compared with the weekly manual sea lice counts made at the aquaculture facility near the deployment site, the

validation data matched the general fluctuation of the manual counts of chalimus and pre-adult stages across 4/5 weeks (80%) except week 34 (Figure 27). Here, the delousing treatment was applied in Week 32 (thermoliser), which explains the drop in attached stages, such as chalimus, pre-adult and adult females (pink and red bars in Figure 27). This decrease was also registered in validation data (free-living stages) in Week 32 (dark grey bars in Figure 27). In the manual count data, the attached lice count increased after the treatment across Weeks 33 and 34. In comparison, the validation data showed an increase in the free-living lice abundance in Week 33 but a decrease thereafter. It should be noted that in Week 34, the validation data was incomplete due to data loss during UVP6 SD card corruption. However, these comparisons should be made with caution, because the manual lice counts were on older developmental stages, but the estimated abundance using the UVP6 data were based on free-living naupliar and copepodite stages. Indeed, we can expect that free swimming stages of lice could be compared to chalimus stages counted on the fish one or two weeks later depending on water temperature and expected development time to chalimus. In addition, the category mentioned as "chalimus and pre-adult stages" in Figure 27 may also contain adult males – thus making direct comparisons with free-living stages further difficult. An alternative approach is to compare the free-living stage abundances with the manual lice counts with a 1-or-2-week time lag, which accounts for developmental time of nauplii and copepodites to chalimus and pre-adults. However, as both "free living stages" category and "chalimus and pre-adults" category (in Figure 27) contain multiple developmental stages, defining a proper lag time is a complication. Also, a time-lag comparison could have been more practical if we had UVP6 data covering a relatively long time period.

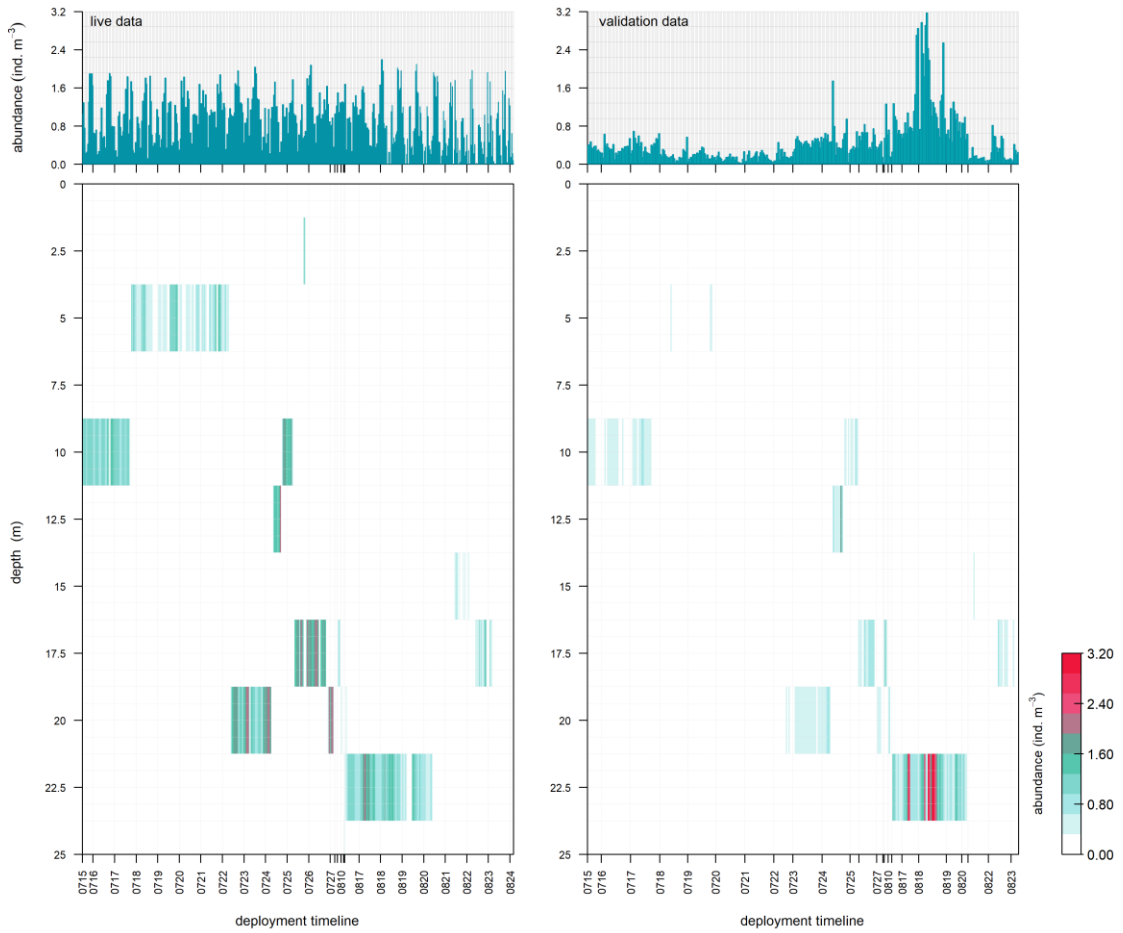

Figure 28 Estimated vertical distribution (binned at 5 m intervals) of free-living nauplii and copepodite stages of sea lice observed by the UVP6. Left: live data; Right: validation data. Top panels indicate the abundance similar to Figure 25, which is also represented in the colour scale to the right.

Despite the differences of abundance between the live data and validation data, the estimated vertical distribution of sea lice remained largely the same (Figure 28). During the first half of the deployment (5–28 July: Figure 28), sea lice free-living stages were distributed across the upper 15 m of the water column. In contrast, they were found below 15 m during the latter part of the deployment (16-24 August).

Alongside sea lice free-living stages, several other copepod developmental stages were observed by the UVP6 during the field deployment. Similar to sea lice, their estimated abundance pattern in the validation data did not match that of the live data (Figure 29). Here, two distinct abundance peaks in the validation data for Calanoida (18-19 July) and Copepoda and Calanoida (16-24 August) were not represented in the live data (Figure 29). However, during much of the deployment period, copepod abundance estimated from the live data was 2-3 times higher compared to validation data.

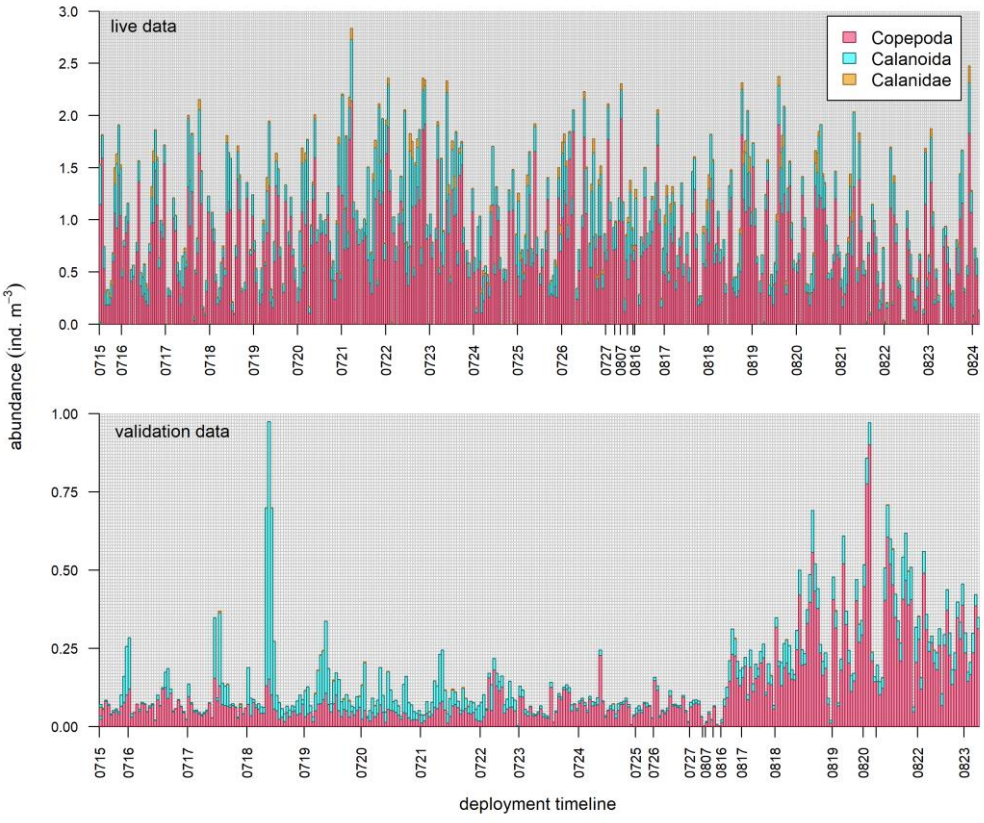


Figure 29: Comparison of estimated abundance of different types of copepods observed by the UVP6 during the field deployment. Top: live data transmitted to Blue Insight; Bottom: validation data after quality controlling (QC1 + QC2 at 90% threshold). Note that Copepoda, Calanoida and Calanidae are categories represented in the e-Lice31 and e-Lice33 training datasets as well as EcoTaxa library.

In our training datasets, in terms of shape and size, detritus is closely related to free-living naupliar and copepodite stages of sea lice. This is because sea lice free-living stages appear in the UVP6 images as blobs, thus resembling detritus. The abundance discrepancy between live data and validation data was also apparent in the detritus (Figure 30). Here also, the live data did not register the peak abundance of detritus observed between 23–27 July.

The estimated abundances for all living and non-living categories in the live data and validation data are compared in Figures 31 and 32. Similar to free-living sea lice (Caligidae), copepods and detritus, the discrepancy between live data and validation data are apparent across many of the remaining categories as well. A notable distinction is the large number of amphipods and annelid larvae detected by the embedded classifier (UVPEC) (Figure 31). However, validation data based on PlanktonVision13 could not confirm the occurrence of large densities of amphipods and annelids in the images (Figure 32).

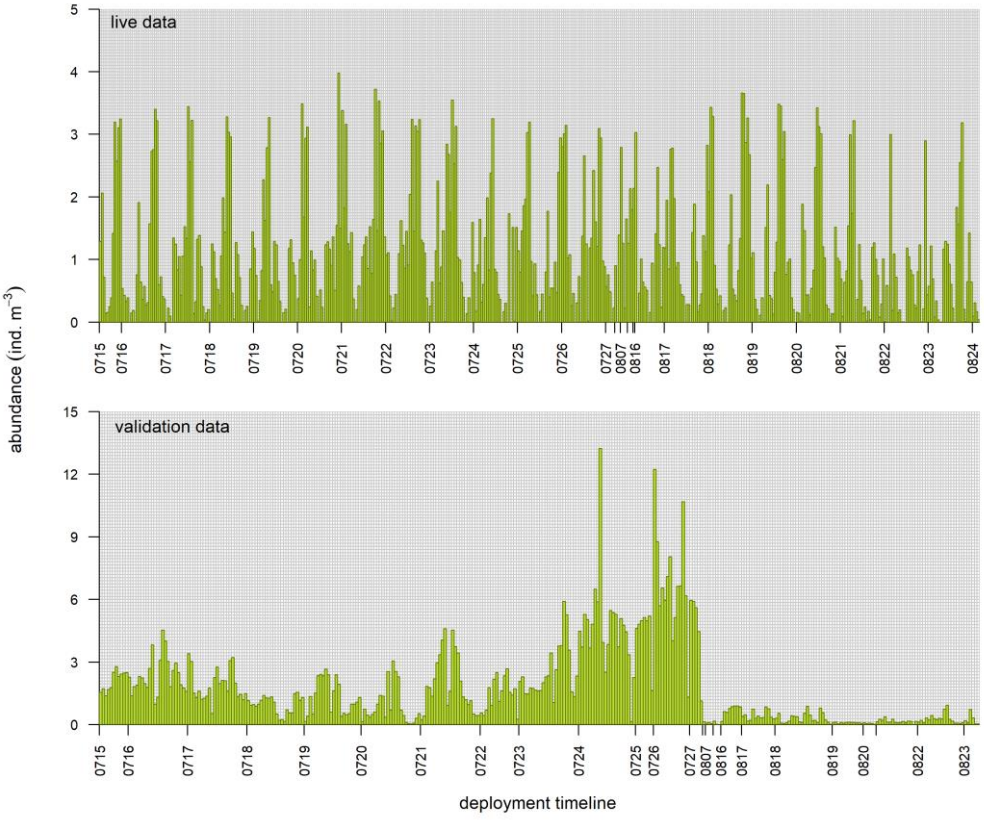


Figure 30: Comparison of estimated abundance of detritus during the field deployment. Top: live data transmitted to Blue Insight; Bottom: validation data after quality controlling (QC1 + QC2 at 90% threshold).

**Summary:** Overall, both the real-time (live) image classification algorithm (UVPEC) and the validation algorithm (PlanktonVision13) were able to detect free-swimming sea lice during the field deployment. These detections remained intact under both 90% and 99% prediction probability thresholds (Figures 25 & 26), indicating higher confidence in the ability of the UVP6 to detect free-living naupliar and copepodite stages of sea lice. However, the abundance estimated based on the live data and validation data differed significantly, where the former overestimated the latter by nearly two folds. For free-living sea lice and other living and non-living categories (such as copepods and detritus), the UVPEC-annotated live data did not

register the temporal trends of abundance, such as abundance peaks. These observations reveal the importance of: (i) validation of the live data before interpretation and (ii) re-training the two algorithms using the field data to span any performance gaps between them.

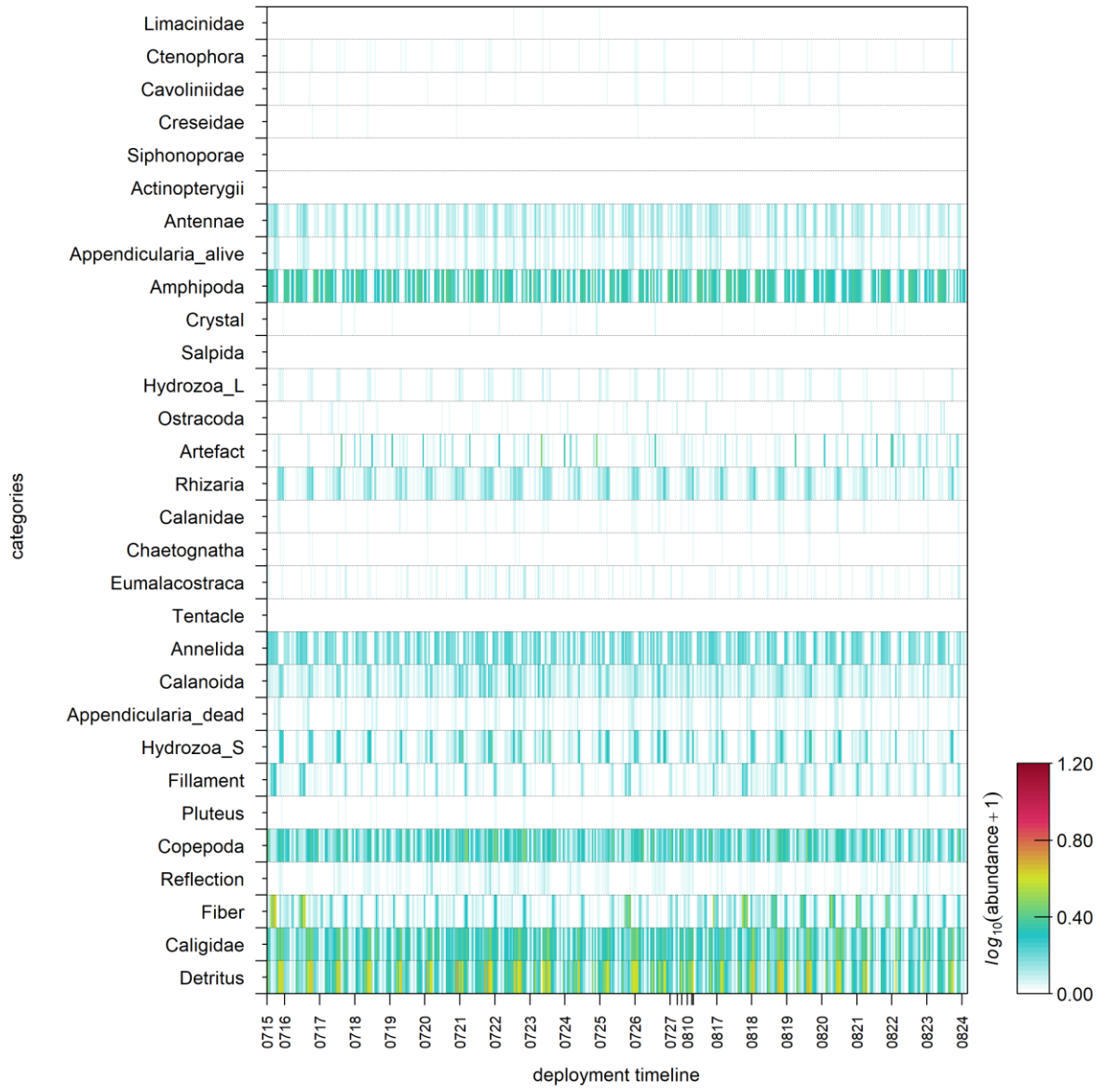


Figure 31: Patterns of estimated abundance of living and non-living categories registered in the live data (Blue Insight), annotated in real-time by the UVPEC algorithm. Note that the abundance is presented after $log_{10}$ transformation for enhancing visualization.

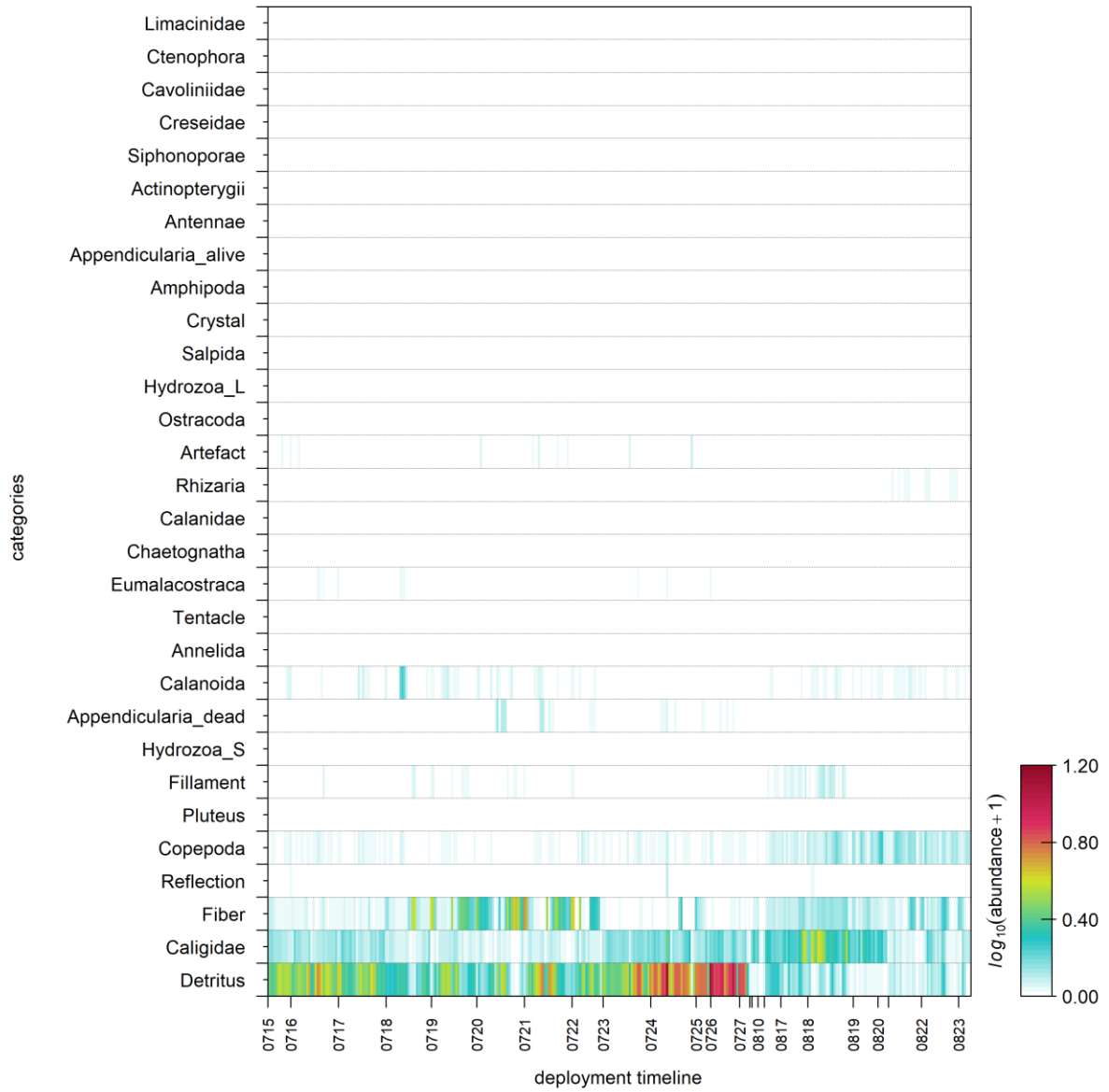


Figure 32: Patterns of estimated abundance of living and non-living categories in the validation data (QC1 + QC2 at 90% threshold) annotated by PlanktonVision13 deep learning algorithm. Note that the abundance is presented after $log_{10}$ transformation for enhancing visualization.

### 4.5.2 Task 5.2 Validation of UVP6 images of free-living sea lice

**Overview:** Validation of image data through human-annotation is a crucial task in AI and computer vision that aids in an accurate ground truthing of the data, on which the interpretation and decision making happens. It also provides the means of iterative refinement and improvement of the AI models implemented. While the images acquired of all other taxa during the field deployment are possible for human-validation, a key challenge that seem to appear in this project is performing a human-annotation on the images of detritus and sea lice free living stages (Caligidae). This is because of their striking similarity in shape and size (cf. Figure 10), which is near-impossible to be distinguished by human eyes. This was caused by the small size of sea lice nauplii and copepodites (0.4–0.6 mm), whose images were not feature-rich in the UVP6 images. However, during the tank experiments, we could easily annotate Caligidae images manually in EcoTaxa (see annotations in: https://ecotaxa.obs-vlfr.fr/prj/10791) because filtered seawater was used in the tanks, which

filtered out the detritus and other particulate matter. However, when it comes to the field data, although the two algorithms did an excellent job in distinguishing detritus and Caligidae, manual re-annotation for validation of these algorithm annotations was near impossible.

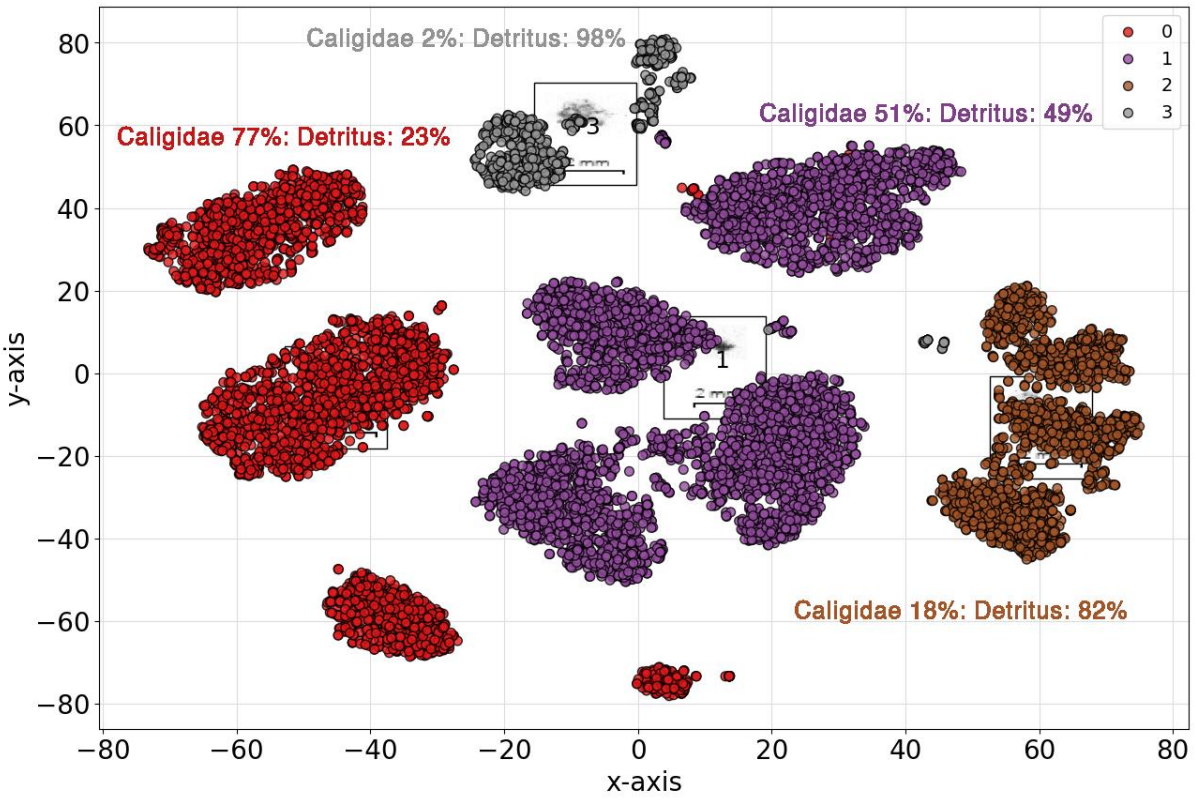


Figure 33: The *t*-SNE applied to the random sample of 10,000 Caligidae and detritus images. The images were pre-processed using Principal Component Analysis (PCA) to extract the most informative features, and then *t*-SNE was employed to reduce dimensionality and reveal the underlying clusters. 'Caligidae' and 'detritus' percentages are the number of images with PlanktonVision13 re-annotation in each cluster.

**Approach:** The optimal way forward until better quality images of free-living sea lice are available to us, is to trust the automated annotations of the two algorithms, and in particular the validation algorithm (PlanktonVision13). Nonetheless, to further test robustness of the convolutional neural network-based feature extractor of PlanktonVision13, we conducted an unsupervised classification on a random sample of 10,000 images composed of detritus (n = 5000) and Caligidae (n = 5000) images. These images were randomly selected from the pool of images following the QC1+QC2 (at 90% prediction probability cutoff). In the unsupervised classification, we used the Principal Component Analysis (PCA) as the feature extractor, which was then put through a dimensionality reduction method based on *t*-distributed stochastic neighbour embedding (*t*-SNE). Based on the clusters identified by the *t*-SNE, we re-sorted the underlying images into arbitrary categories and performed a re-annotation using PlanktonVision13 to see how well detritus images are differentiable from Caligidae.

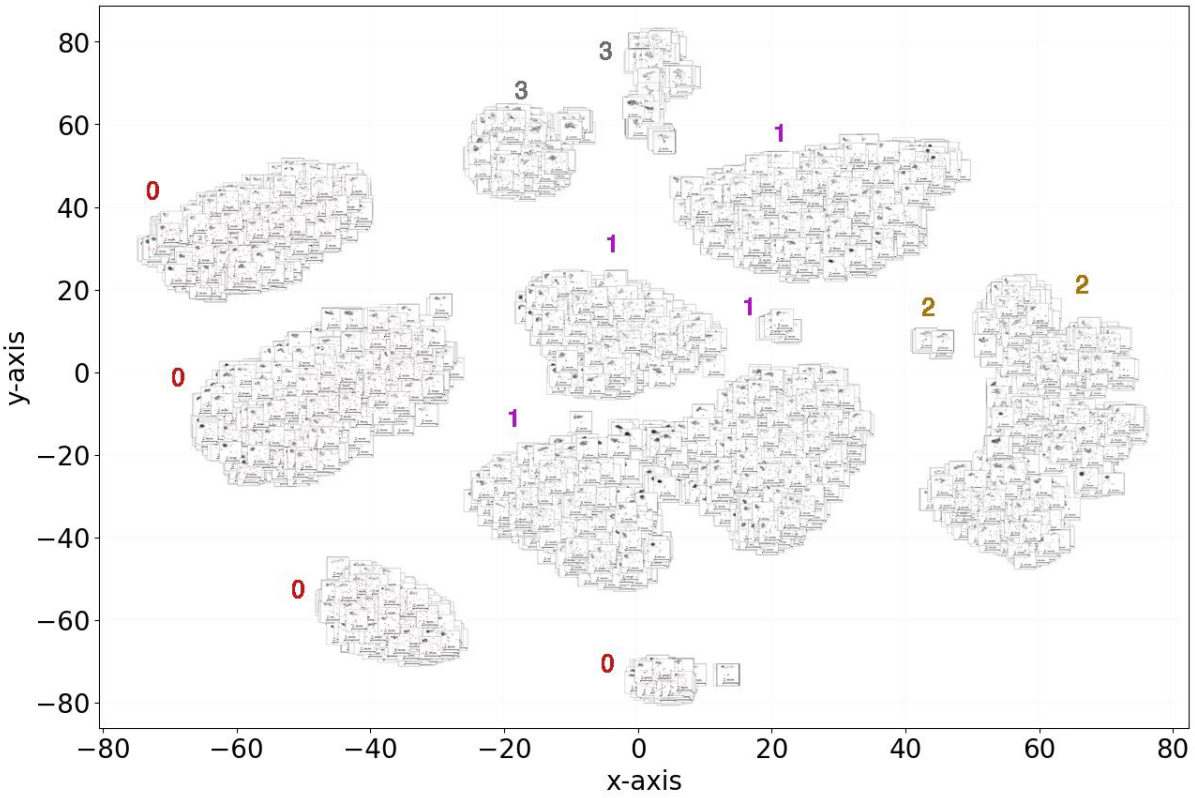


Figure 34: The UVP6 vignettes of the random sample of 10,000 detritus and Caligidae images belonging to the clusters (0–3) defined in the *t*-SNE embeddings in Figure 33.

**Observations:** Based on the *t*-SNE embeddings, the PCA-based feature extractor defined 4 categories (clusters: Figure 33), that include two large clusters; cluster-0 (3183 images) and cluster-1 (4499 images), and two smaller clusters; cluster-2 (1623 images) and cluster-3 (695 images) (Figure 34). Based on the PlanktonVision13 re-annotation of images in each of these clusters, we found that cluster-0 was predominantly composed of Caligidae (77%) and the vast majority of images in clusters-2 (82%) and -3 (98%) were composed of detritus. This indicates that at least part of the detritus and Caligidae images can be objectively differentiated by a non-CNN feature extractor. Since detritus appears in a diversity of shapes and sizes, clustering them into different groups is not surprising at all. However, nearly 45% of the images were clustered into cluster-1, which contained detritus and Caligidae images at a 49:51 ratio (Figure 33). This indicates that despite their differentiating features, detritus and Caligidae share some strikingly similar morphological and morphometric features between them. Without manual validation with human input, we cannot say whether CNN-based PlanktonVision13 feature extractor was better or worse compared to the PCA-based feature extractor. Nonetheless, this analysis shows that at least ca. 55% of the detritus and Caligidae images captured by the UVP6 during the field deployment can be annotated using both supervised and unsupervised techniques.

## 4.6 WP6 Communication, user-dialogue and outreach | Lead Akvaplan-niva | Partners: all

During the project period, we performed many communication and outreach activities. These activities are listed in the table 5.

Table 5. List of communication activity, date and media.

| Time | Communication activity | Platform/arena |
|---|---|---|
| **2023** | | |
| | e-Lice Logo produced | |
| 7.11. | KICK-OFF MEETING | Press release APN |
| Oct | Project page APN web | APN website, SoMe |
| 29.11 | News item from task 1.4 (Ragnhild/Veso) - ENGLISH | APN website, SoMe |
| 1.12 | News item from task 1.4 (Ragnhild/Veso) - NORW | APN website, SoMe |
| 1.12 | News item from task 1.4 (Ragnhild/Veso) - NORW | kyst.no |
| **2024** | | |
| 16.01 | MID-TERM MEETING - | Digital |
| 23.01 | Lionel Camus presents e-Lice at FHF lice conference | FHF Sealice conf |
| 5.02 | FHF lice conference - | Facebook |
| 5.02 | FHF lice conference - | Linkedln |
| 5.02 | e-Lice project news item (pp 50-53) | Fish Farmer |
| 6.03 | BLÅLYS - Nova Sea choice of e-Lice technology | kyst.no |
| 18.03 | e-Lice presented for NCE Aquaculture Miljøforum | Hybrid meeting |
| 1.04 | FishFarmer magazine article | APN SoMe |
| 24.04 | Presentation Norw. Crown Prince Haakon | The Fram Centre |
| 1.06 | Chronicle High-tech havforskning | Fiskeribladet |
| June | Lab experiments movie | APN web, SoMe |
| 13.06 | News item from field mission - smart buoy | Nova Sea website |
| June 24 | WORLD AQUACULTURE AND FISHERIES CONFERENCE | Paris |
| 27.06 | Campaign "Future Ocean Space" | Aftenposten |
| 29.08 | REFERENCE GROUP MEETING | Teams |
| 28.09 | Forskningsdagene - Fritt Fram Tromsø | Polaria/Fram C |
| 23.okt | HAVBRUK FHF and NFR | Tromsø |
| 5.11 | Marine Alliance for science and Tech. for Scotland, Lionel | Oban, Scotland |
| 20.12 | Final report | FHF&partner web |
| **2025** | | |
| 10.01 | End meeting with Ref. Group | Teams |

# 5 Discussion

In WP2, we were able to develop, train and test two AI algorithms for: (i) the UVPEC algorithm for real-time automated detection and classification of free-living naupliar and copepodite stages of sea lice and (ii) the PlanktonVision13 algorithm for validating the real-time annotations made by the above algorithm. The performances of both algorithms were satisfactory, where they reached ca. 90% of overall accuracy and ca. 0.89 F1-score in the two datasets used (e-Lice31 and e-Lice33). The PlanktonVision13 deep learning algorithm outperformed the UVPEC machine learning algorithm both in terms of overall performance and category-specific performance of free-living sea lice. This indicates that PlanktonVision13 was a strong candidate for validating the real-time annotations made by the UVPEC algorithm.

Although both algorithms were trained on free-swimming sea lice (nauplii and copepodites) and attached sea lice (pre-adults and adults), we could not deploy the UVPEC trained on pre-adult and adult stages. The reason for this was that was time constraint, the UVP6 had already been shipped for field deployment at the time of completion of the algorithm training, evaluation and fine-tuning. Therefore, we could not test the ability of the algorithms to detect free-swimming advance stages of sea lice.

Sea lice nauplii and copepodites imaged by the UVP6 sensor in the tank experiments in WP1 appeared as blobs of ca. 0.4-0.6 mm diameter and did not appear as actual sea lice. It was only after a UVP6 live-camera test that we were able to confirm that these blobs were actually representing sea lice free-living stages. From human eyes, these blobs were near-impossible to distinguish from detritus. However, both algorithms were able to readily distinguish these blob-like sea lice images from detritus with surprising accuracy (> 88%). The challenge this poses is that it is near impossible to manually annotate UVP6 images of these free-swimming sea lice larvae in the field deployment raw dataset/live data. Manual re-annotation of data is a key step in the validation and improvement process of the AI algorithms.

During the validation of live data (transmitted to the Blue Insight platform), we observed a considerable discrepancy between the annotations made by the UVPEC algorithm and the PlanktonVision13 algorithm. This was surprising, given that both algorithms had comparable performances during the training exercises. However, it is likely that factors other than the performance differences of the UVPEC and the PlanktonVision13 algorithm contributed to this discrepancy. A major contributor in this regard is the fact that the classifier that is embedded in the UVP6 (the UVPEC) does not perform the real-time classification (annotation) when the number of objects detected per image is greater than 25. This feature is implemented in the UVPEC as a power saving measure. This function seems to have an impact on the abundances estimated in the live data. This is because when there is high abundance of a particular taxon, there is high likelihood that more individuals of that taxon to be detected in a single UVP6 image (corresponding to 690 ml). However, because the UVPEC does not perform the classification in such instances, most abundance peaks are not registered in the live data. As a result, although 2,146,415 objects were detected during the field deployment, only 1,309,514 objects were annotated by the UVPEC in the live data. This accounts for a loss of ca. 40% of objects, especially a loss of objects at high abundances. The explanation for this may be that the abundance peaks observed in validation data for free-swimming sea lice (Caligidae), detritus and copepods were not registered in the live data.

# 6 Conclusion

In the e-Lice project, we realized the following:

- a cutting-edge imaging sensor deployed in a profiling buoy with artificial intelligence, live data streaming and dashboarding to detect free-swimming sea lice in the water column as an early-warning system of potential infestations.
- As proof of concept, this technological integration worked well, and we demonstrated that free-swimming naupliar and copepodite stages of sea lice can be detected by the camera system (UVP6) and can be recognized automatedly by the AI algorithms both in-situ (live data) and ex-situ (validation).
- The trend of chalimus and pre-adult counts made at the aquaculture site near the UVP6 rig deployment was in general agreement with the validation data, thus providing further proof of evidence of the functionality of the system.

Despite the success, there is a need to improve and fine-tune several components of the e-Lice technological integration. Herein, we have identified what to improve in three domains: the artificial intelligence, the data processing pipeline and the hardware.

- The artificial Intelligence component

We suggest to improve the artificial intelligence component by proposing 1) longer deployment of the UVP6 sensor to collect a larger dataset to confirm our findings across seasons and 2) using the images captured by the UVP6 of the local plankton community as a training set to improve the algorithms. This could help in minimizing the class imbalance in the training datasets, which is a key metric that drives the performance of the algorithms and their generalization.

- The data processing pipeline

We suggest streaming the raw data in real time to process them with the high-performance algorithm PlanktonVision13 deployed in a powerful system (cloud or PC) instead of processing the raw data in the UVP6 embedded sensor (UVPEC). This is today possible with the UVP6 sensor which offers the raw data streaming feature via ethernet.

- The hardware:

*Improving the sensor resolution*

As our laboratory imaging experiments showed (WP1), the images of free-living sea lice were difficult to recognize from the human eye because their size bordered the maximum resolution of the UVP6. Although AI algorithms used in this project could readily distinguish these images from other taxa/objects, it created complications in the manual validation process of the field data. A key area for advancing e-Lice's implementation involves utilizing imaging sensors with superior resolution. In collaboration with Hydroptic, Marc Picheral, the inventor of the UVP6 and an advisor to the e-Lice project, is spearheading the development of a next-generation UVP with enhanced resolution down to 10 micrometres. This development promises a potential solution that can be tested in the future with the same data processing pipeline that has been developed in this project in order to catch more and unique features of the sea lice that can improve the algorithm performance substantially.

*Improving the UVP6 deployment*

Further, we suggest tethering the winch of the buoy for improved performance and flexibility of the system in situ.

# 7 Deliverables

## 7.1 Deliverables WP1:

D1.1: Method for rearing sea lice nauplii and copepodids in tanks. Delivered

D1.2: Laboratory setup. Delivered

D1.3: Imaging free-swimming and parasitic stages of sea lice. Delivered

D1.4: Imaging of co-occurring naupliar and copepodid stages of co-occurring zooplankton. Not delivered.

This task was not performed as the copepod planktonic season had passed due to the project start that had been delayed. This task was moved to the field deployment.

D1.5: Post-processing and quality control of images. Delivered

## 7.2 Deliverables WP2:

D2.1 & D2.2: Deep learning algorithm for detection and classification of sea lice: software & publication. Delivered

D2.3: Algorithm embedding in compact microprocessors for (near-)real-time data processing. Delivered

D2.4: Algorithm-tagged (classified) sea lice images (export to EcoTaxa database). Delivered

## 7.3 Deliverables WP3:

D3.1: an assembled mooring with vertical UVP 6 array. Delivered

D3.2: a deployed and field proven mooring at key location. Delivered

## 7.4 Deliverables WP4:

D4.1: a dashboard for real-time and historic mooring data visualization, reporting and early warning within Blue Insight. Delivered

D4.2: an API that enables data push/request to/by the Barents Watch and NOVASEA data portals. Delivered

## 7.5 Deliverables WP5:

D5.1: Algorithm re-testing on a plankton community with a known composition. Delivered

D5.2: Adjusting or altering of algorithm architecture. Delivered

D5.3: Quality control of the field dataset. Delivered

D5.4: Comparing with other available data. Delivered

D5.5: Mooring optimisation. Delivered

## 7.6 Deliverables WP6:

D6.1: Open (kick-off) meeting. Delivered

D6.2: Mid-term meeting. Delivered

D6.3: Closing meeting. Delivered

D6.4: Final report. Delivered

D6.5: Popular scientific outreach. Delivered

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