Norwegian Veterinary Institute

Report 12 – 2026

Precision Fish Farming in land-based recirculating aquaculture systems – State of the art and future perspectives

WHITE PAPER

REPORT 12/2026

Precision Fish Farming in land-based recirculating aquaculture systems – State of the art and future perspectives

WHITE PAPER

Authors

Britt Bang Jensen[1]*, Mogens A. Krogh[2], Matti Pastell[3], Aikaterini Spiliotopoulou[4], Kristoffer Vale Nielsen[1], Vivi M. Thorup[2], Leslie Foldager[2], Hilla Fred[3], Victor H.S. Oliveira[1], Mette Frandsen[4], Martin E.G. Bertelsen[4], Paw Petersen[4]

1: Norwegian Veterinary Institute
2: Aarhus University, Department of Animal and Veterinary Sciences
3: Natural Resources Institute Finland (Luke)
4: OxyGuard International A/S
*: Currently: Technical University of Denmark

Suggested citation

Bang Jensen, B., Krogh, MA., Pastell, M., Spiliotopoulou, A., Nielsen, KV., Thorup, VM., Foldager, L., Fred, M., Oliveira, V.H.S., Frandsen, M., Bertelsen, MEG., Petersen, P.   Precision Fish Farming in land-based recirculating aquaculture systems – State of the art and future perspectives. VI report. Veterinærinstituttet 2026. © Norwegian Veterinary Institute, copy permitted with citation

Quality controlled by

Ingunn Sommerset, Director Department of Aquatic Animal Health, Norwegian Veterinary Institute

Published

2026 on www.vetinst.no
ISSN 1890-3290 (electronic edition)

Colophon

Cover photo: Kristoffer Vale Nielsen
www.vetinst.no

Content

Summary

This white paper presents the findings of the IntelliRAS project, which investigated how Precision Fish Farming (PFF) can be applied to land-based Recirculating Aquaculture Systems (RAS) in Nordic countries. The motivation stems from the growing global demand for sustainable food production and the challenges faced by RAS farms, such as high mortality rates, feed waste, and health issues in fish populations.

PFF is proposed as a solution to improve monitoring, decision-making, and automation in aquaculture, drawing inspiration from Precision Livestock Farming. The report is structured around three core components of PFF: observation of animal variables, development of predictive models, and automatic decision-making and control. It explores how fish growth, feeding behaviour, health, mortality and welfare can be monitored using both manual and sensor-based methods. Technologies such as cameras and hydrophones are evaluated for their potential to automate observations, though challenges like water turbidity and data quality remain significant. The project also tested machine learning models to detect fish behaviour and health indicators, with varying degrees of success depending on data quality and annotation consistency.

Predictive modelling is another key focus, with examples including models for estimating biomass, forecasting mortality, and assessing feeding activity. These models rely heavily on high-quality data, which is often difficult to obtain due to inconsistent data collection practices, lack of standardization, and limited infrastructure on farms. The report emphasizes the need for tailored models that account for the diversity of RAS systems and suggests that dynamic, farm-specific models may be more effective than generic solutions.

The final component—automatic control—remains the most challenging. While theoretical frameworks for automated feeding systems are proposed, practical implementation is hindered by the need for reliable real-time data, validated models, and farmer engagement.

The report concludes that while PFF holds promise for improving sustainability and efficiency in RAS, significant technological, infrastructural, and economic barriers must be addressed. It calls for further development of sensor technologies, standardized welfare protocols, robust data systems, and pilot-scale testing of automated control solutions to move closer to real-world implementation.

1 Foreword

This white paper is an outcome of the research project “Intelligent farming and health control in land-based Recirculated Aquaculture Systems (IntelliRAS)”. In this project, we have studied how variables important for production in RAS can be measured and controlled.

We have used the theory behind the Precision Fish Farming (PFF) concept as an offset for the project and focused on areas where knowledge and practical evaluation were lacking. Specifically, we have tested the possible use of selected sensors for developing automated feedback systems for control. We have evaluated the use of audiovisual sensors for monitoring of health and production of salmonids in RAS farms in three Nordic countries. We have assessed what it would require developing a protocol for standardized welfare assessment, and what information can be gained from frequent weighing of fish for growth control. During the project period, we have collected information and encountered challenges related to the defined requirements for PFF, which we share as examples in each of the chapters of the white paper.

The aim of the paper is thus to describe the state of the art and the possibilities, challenges and scientific advantages of using PFF in RAS-operations, to see whether it is possible to move from the theoretical proposition of a PFF to actual real-life implementation. This is done within the framework of the NordForsk-project “IntelliRAS”, and the focus is therefore on the application for aquaculture in the Nordic countries.

The scope of this white paper is to describe what it would take to implement PFF for different purposes in RAS, and to provide examples of practical applications. We have tested some theoretical approaches towards a more automated monitoring and control of feed, growth and welfare and used this to make suggestions and perspectives for implementation of PFF in RAS.

For structuring this paper, we have used the three tiers of Berckmans’ description of Precision Livestock Farming (PLF; Berckmans, 2006) as a backbone, which we have translated into the following headings:

- Measuring and registration of animal variables (PFF component 1 -Chapter 2)
- Models for decision making (PFF component 2 -Chapter 3)
- Automated feedback systems (PFF component 3 -Chapter 4)

2 Introduction

2.1 Growth of aquaculture and the promise of RAS-farming

The global food demand will increase by approximately 60% by 2050 according to the Food and Agriculture Organization (Dijk et al., 2021). This means that innovations that can deliver sustainable, resilient, responsible, diverse, competitive, and inclusive food systems within the frame of a circular bioeconomy while providing a healthy diet are required. Seafood currently represents 17% of global animal protein production (Costello et al., 2020). Of the overall production of aquatic animals, over 157 million tonnes (89%) were used for human consumption (FAO, 2022). Scientists and policy makers agree that there should be an emphasis on the industry's environmental and societal aspects, including transparency and traceability. The production of salmonids in land-based production systems is associated with narrow production margins and uncertainty in production, especially due to sudden unexplained die-offs and losses due to feed waste. In Norway alone, around 50 million salmonids die annually during the development from larvae to smolt (Moldal et al., 2025).

A sustainable production of fish entails good health and welfare of the animals, in addition to being economically viable and with the least possible environmental impact. Land-based recirculating aquaculture systems (RAS) are closed-containment systems where fish are farmed in reused water (Lekang, 2007). RAS has become increasingly important by making the best use of water, which is a limited resource, while also achieving production continuity. In RAS, the water is re-used multiple times before it is finally led back to the source. RAS is considered the most promising solution and an environmentally friendly technology to produce fish with a relatively low environmental impact (Bregnballe, 2022), but there are some challenges to the RAS production system that needs to be resolved to fulfil its potential.

In RAS, biofiltration is essential to prevent ammonia build-up, and the water must be continuously reoxygenated, aerated and pH, CO2 and temperature controlled, to provide a healthy environment for the fish. Thus, an extensive level of technology is needed to monitor and control the facility, making the construction costs high. In addition, a large degree of technology literacy is required to manage these complex systems.

The biggest hindrances for an economically and biologically sustainable production in RAS is suboptimal feed usage and adverse health problems in the fish. Up to 50% of the production costs in aquaculture is feeding costs, hence optimized feed management would increase the production margins in RAS and make the production more economically sustainable (Asche et al., 2013). Besides the direct cost of the feed, unused feed in the water impairs the water quality in RAS with a detrimental effect on fish health and welfare. System failure and/or changes in water environment often result in sudden die-offs or reduced growth and further have direct animal welfare and economic consequences. Therefore, farmers are looking for ways to monitor and identify risks affecting fish health and prevent aberrations before they occur.

Today, monitoring in RAS is done in different ways; from the simple use of on-site water quality test kits to using state-of-the-art sensors and probes that measure parameters continuously. The most important monitoring is performed by direct observations of the water and the fish by the farm managers. Since RAS facilities are continuously expanding in response to the increased demand for fish proteins, manual observation becomes increasingly more resource demanding.
Data from monitoring and observation are stored in various ways; from manual entering in a paper form to automatic registrations in databases. In addition to these data, farmers have access to a vast amount of data originating from slaughterhouses, veterinary inspection, surveillance and even environmental data. All which can possible be used to gain more information on the production and for risk assessment (Zhou et al., 2025).

2.2 Precision Fish Farming as a solution?

Production of fish in aquaculture is mainly based on the experience of the farmers. Several potentially important production decisions are not necessarily based on factual knowledge and hence have some (small or large) degree of uncertainty. Any information that can reduce this uncertainty will be beneficial from a production point of view, because this will lead to a more predictable production result. Information that the farmer can attain earlier is also beneficial, because it provides an opportunity to react and possibly intervene against the negative effects associated with e.g. disease outbreaks.

To address these challenges and improve decisions concerning both production and health management, Precision Fish Farming could possibly offer a solution. The concept of Precision Fish Farming (PFF) was introduced in 2018 by Føre et al., to stimulate transition from experience- to knowledge-based production. PFF is the subset of precision livestock farming (PLF) that was introduced by Berckmans almost 20 years ago (Berckmans, 2006) and has been widely implemented in terrestrial animal production. PFF focuses on aquaculture and especially the more technological intense production systems including RAS.

Føre et al. (2018) described the aims of PFF as:

1. Improve accuracy, precision and repeatability in farming operations;
2. Facilitate more autonomous and continuous biomass/animal monitoring;
3. Provide more reliable decision support and;
4. Reduce dependencies on manual labour and subjective assessments and thus improve staff safety.

In theory, PFF is based on a variety of sensors that are used to gain insight into the farming environment, make decisions that optimize fish health, growth, and economic return, and reduce risk to the environment. Thus, PFF could potentially solve the challenges faced in RAS. However, in order to implement PFF or PLF, certain requirements must be fulfilled. Berckmans has suggested a three-tier structure to progress to PLF:

1. Animal variables (i.e. parameters related to the behavioural or physiological state of the animal) need to be measured continuously with cost-effective robust sensor technology;
2. A reliable model for predicting (expectation of) how animal variables will dynamically vary in response to external factors at any moment must be available, and;
3. Predictions and online measurements are integrated in an analysing algorithm for automatic monitoring and/or control.

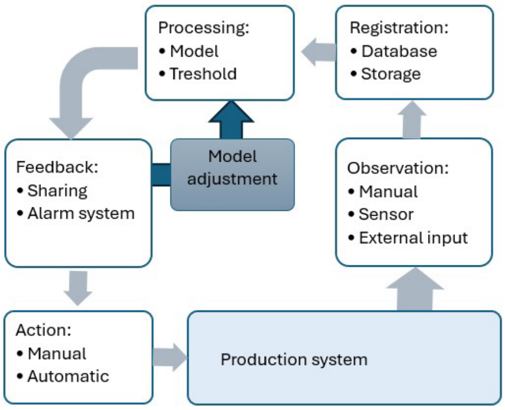

Figure 1. Graphical illustration of the processes involved in a precision fish farming system.

The different components of a PFF system are illustrated in figure 1. In a truly integrated and operational PFF system, the circular process from observation to action illustrated in figure 1 should be automatic and based on sensor technologies. An example can be a sensor that detects a sudden drop in dissolved oxygen levels and trigger automated aeration systems to restore the balance, preventing stress and potential mortality in fish populations.

A theoretical application could also be an intelligent feeding system that automatically adjust feeding schedules and quantities based on real-time camera observations of fish behaviour and biomass. This would ensure that fish receive the right amount of food at the right time, thereby minimizing waste and improving overall efficiency.

2.3 Exploring the state of the art of Precision Fish Farming in RAS

In their paper from 2018, Føre and colleagues provided a description of some of the technologies already implemented that could be used for PFF and gave suggestions for implementation of PFF in four case studies aimed at solving specific challenges related to biomass monitoring, control of feed delivery, parasite monitoring and management of crowding operations.

Since then, there has been a lot of focus on developing systems for automated monitoring of fish growth and health. Many of these solutions are based on using cameras and/or hydrophones for observation, and machine learning for analysis. (Some examples are provided in Chapter 3 of the present report). Most of these solutions seem to have been developed for the production of salmonids in marine farms, which was also the primary focus of the suggestions made by Føre et al. (2018).

3 Observation of animal variables in RAS (PFF component 1)

The first component of PFF is to implement robust and standardized methods to continuously measure and store data on animal variables (i.e. parameters related to the behavioural or physiological state of the animal). Thus, the two main steps are the observation and the registration of variables.

3.1 Animal variables

Simply speaking, the animal variables we want to measure are growth, health and welfare. We can measure these either directly from the animal or we can measure variables that we know are directly correlated with the growth, health and welfare. Direct measures from animals would be visual observations of the fish and their behaviour in the water and of sampled fish. Indirect measures would be water quality, feed usage and slaughter data. This is illustrated in figure 2. Due to the number of individuals and because fish are always housed together in batches, fish would rarely be observed on an individual level, but rather as a group or at tank or cage level.

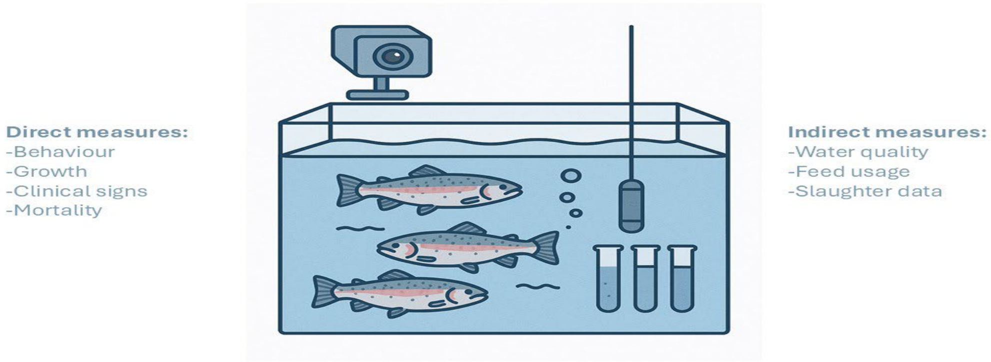

Figure 2. Illustration of animal variables that are measured directly or indirectly. Illustration made partly with ChatGPT.

Practical experience

In the IntelliRAS project we found that RAS farms are very diverse. They use different systems (ponds or raceways), degree of recirculation, water source and type of production (from hatching to slaughter or just a part of the production) and very different management practices. Another aspect of RAS production is the high degree of moving and grading of fish that occurs to assure that the fish within each tank are uniform in size and to avoid a limitation of growth due to excess biomass in the tanks. Figure 3 demonstrates the moving of the fish of in one farm during a one-year production cycle where the fish grew from 350-400 g to 3500-4000 g.

This constant movement of fish between tanks provides a challenge when it comes to observation of the animal variables. Often, it will only be possible to have fragmented measurements of a fish group from each of the tanks they pass through during a production cycle.

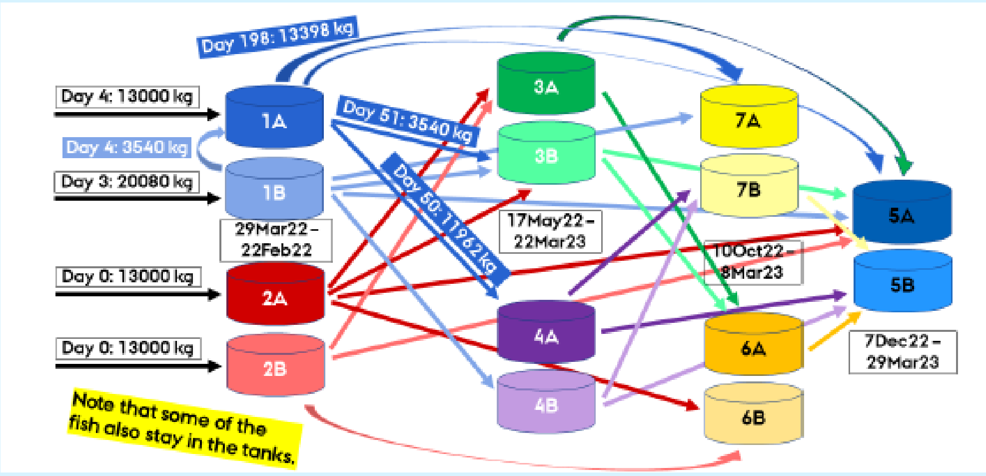

Figure 3. Flow diagram of moving of fish inserted into tank 1a, 1b, 2b and 2b at the same time and followed though a one-year production cycle.

3.1.1 Fish growth

As the output of fish production is kilograms slaughterweight, for the farmer it is paramount to be able to monitor the growth of the fish. Fish follow a species-specific growth curve, which also depends on the temperature and the amount of feed provided. The goal is to reach the maximum growth possible given the amount of feed. A growth curve which is lower than expected indicates a production problem and can be an indicator of adverse health issues. Growth of the fish is determined by the amount of energy from feed that the fish consume. Several internal and external factors influence the efficiency with which the conversion from feed to meat occurs. Internal factors would be species of fish, breed of fish, appetite and behavioural aspects that influence both feed consumption and the ability to convert the nutrients. External factors would be local environment such as temperature, water quality and stocking density. Since these internal and external factors are fairly constant from production cycle to production cycle, this means that if the fish are provided feed with a constant energy concentration, the feed conversion ratio (FCR) should be constant as well. Based on the amount of feed fed to the fish, the biomass of the fish (or tank) can be estimated. However, decreases in health status in the tank (or facility) would negatively influence the FCR because of reduced feed intake and changes in how the nutrients are utilised (from anabolic to catabolic states).

The most common ways to measure growth are listed in table 1, with pros and cons for each method, and an assessment of its suitability for use in a PFF.

Table 1. The most common ways to measure growth of fish.

	How	Pros	Cons	Suitability for PFF
Manual observation (by human)				
Bulk weight at start and end	A group of fish are weighed when they are put in the tank, and when they are slaughtered. They are counted, and average weight gain calculated	-Very little work for farmer -Requires no/little training -Less stress for the fish	-Gives only two timepoints of measures -Gives no variations of the individual fish weight -	No
Average weight when fish are moved between tanks	As above, but happens every time fish are moved, sorted or treated	-Very little work for farmer -No extra stress for the fish -Gives more timepoints	-Gives no variations of the individual fish weight -No regularity -Not continuous	No
Regular bulk weights	As above, but put into system, i.e. once a month, once a week	-Gives regular timepoints -Easy to perform	-Takes time for the farmer -Gives no variations of the individual fish weight -More stress for the fish	Maybe
Regular individual weights	Fish are taken up and weighed individually at certain timepoints	-Gives regular timepoints -Easy to perform -Provides information of variations	-Takes time -Stressful for the fish	Maybe
Automatic observation (by camera)				
Growth monitoring with cameras	Fish are monitored with cameras and weights are estimated	-Gives series of data -No extra work for farmer -No stress for the fish	-Costly to implement -Needs validation	Yes – in the future

Practical experience

In the IntelliRAS project, we found that most farmers used growth curves supplied by the feeding companies to decide the amount of feed that should be supplied to the fish to meet growth expectations. This means that based on the expected growth curve, the weight of the fish is estimated only based on the amount of feed supplied to the fish in that period. As demonstrated in figure 3, many fish farmers grade, sort and split the fish multiple times as the fish grow. Each time, they get some information about real weight. On the other hand, the high degree of grading and moving of fish in relation to size also makes it very complicated to apply or estimate actual growth curves to the production – because it is very difficult to follow the fish inserted into the initial tank or at least it requires very detailed and meticulous recordings of grading and movement.

Other farmers keep the batch of fish constant over the production cycle. These farmers often perform monthly or bi-monthly weighing of a sample of fish from the tank, which, together with the total number of fish, is used to get an estimate of the tank/batch biomass.

3.1.2 Feeding

The biomass of the fish (or tank) can be estimated based on the amount of feed the fish consume. Poor health or impaired welfare often lead to a loss of appetite, and thus measuring feed intake is important both for estimating the economic returns and as an indicator of the health of the fish.

Feed uptake is measured by direct observations of the fish: that is, watching them eat. Fish are normally fed based on appetite, and thus the amount of feed delivered is adjusted to the eating behaviour of the fish. In RAS, uneaten feed pellets will end up at the tank outlet, so observing the uneaten pellets (potentially quantified) is another way of observing feeding. Monitoring feeding behaviour by camera or hydrophone can be a way to move towards a sensor-based observation of feeding. This is described in more detail in section 4.3.

3.1.3 Fish health

As previously described, an important indicator of fish health is its growth and appetite. In addition, fish with a health problem will often display a change in behaviour, for example being lethargic, show disrupted schooling or nervous and erratic swimming. Such changes in behaviour are observed by the fish farmers but can also be observed by either camera or hydrophone, same as for feeding behaviour. This is described in section 3.2.

Most health problems cause the fish to display external signs of injury or disease. Again, the observation of such signs is done by fish farmers, but it could potentially be replaced or supplemented by automatic camera monitoring. In marine salmonid aquaculture, systems for automatic monitoring of external signs like scale loss, wounds, deformities and operculum damage is being developed (for example: createview.ai, stingray.no). So far, these systems are relatively new and thus are still being tested and validated. They have been developed for the marine net pen fish farming and cannot be directly implemented in RAS without considerable modifications. This would include adaptation to above water observation, training on other species and sizes of fish, training on how external deviations looks like on these fish, etc. Further, the systems are often very costly, and thus it might not be feasible for the farmers to implement. It was not within the scope of the IntelliRAS-project to explore such systems.

3.1.4 Fish mortality

Apart from external signs of clinical disease, one of the most used parameters for assessing health and welfare in aquaculture is mortality. Dead fish should be collected (minimum) on a daily basis. This is normally done manually by the fish caretakers. A very crude estimate of the health status of a batch of fish is the mortality rate, i.e. the number of dead fish out of the total population per day, week or month. Farmers can use the mortality rate as an estimate of health, if they already have an estimate of the “normal” or expected mortality, that is, a sort of benchmark. The expected mortality depends on the age and maturity of the fish, the species, the production system and several other factors. The benchmark can either be according to previous batches of fish in the same farm, according to comparable farms, or according to an industry or national standard. The benchmark can be based on models, as described in Chapter 4. Counting dead fish could potentially be done automatically, in a system where the dead fish are picked up by a probe or a robot, but such a solution has not been developed yet. Thus, the registration of number of dead fish is not likely to be automated in the near future.

Measuring the number of dead fish does not provide help for the farmers towards which actions to take to improve health of the fish. For that, death of the fish must be assigned a cause. This is most often done by the fish farmers. The extent to which mortality causes are used varies a lot between farms. The rationale for using mortality categorization and a description of what to consider for this is provided by Aunsmo et al. (2023). Mortality categorization can be on a very overall level, for example the one used by Norwegian authorities for reporting from farmers, where fish losses are assigned to each of five categories: Dead, Escaped, Discarded, Other and Counting error. Most farmers use a more detailed categorization, where the top-level would be main categories based on first visual inspection. The second level would be more specific into background causes of the mortality, and the third level would give a very specific cause, as illustrated in figure 4.

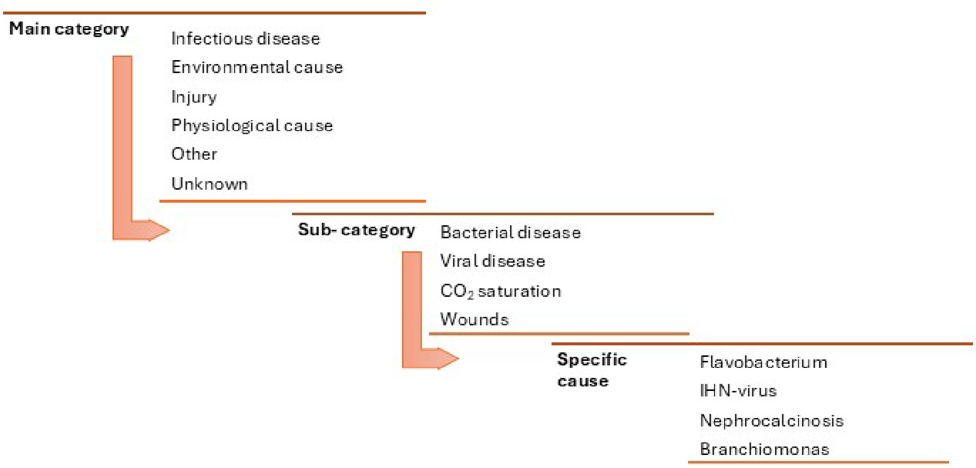

Figure 4. Three levels of mortality categorization. The figure is inspired by the structure also presented by Aunsmo et al. (2023).

Assigning causes at level 2 and 3 would require some background knowledge or additional information that could be obtained either by using skilled personnel for the observations, by including data from the production system (e.g. on CO2 levels or prior diagnoses of diseases) or by laboratory analysis of the fish.

If the cause of disease or mortality is not obvious from inspection, samples of the fish can be sent to laboratories for analyses. Often, the results from such analyses are returned as documents, but some laboratories offer technical solutions for direct transfer of their results electronically. Thus, there is a prospect for automatization of at least some parts of the mortality categorisation.

3.1.5 Fish welfare

Health is closely interrelated with welfare, and in a PFF-framework, fish with impaired welfare will not reach their full potential for growth and feed utilization. In addition, the farmer has a responsibility to ensure good welfare of the fish, and it is also important from a consumer perspective. Thus, monitoring of the welfare of fish should also be part of a PFF. However, performing regular welfare scorings as part of production of fish in RAS is not standard. To a large extent, this is probably due to a lack of standardized and objective ways of scoring welfare.

Currently, several initiatives are looking into what can be used as objective welfare indicators in fish farming. According to the FISHWELL handbook, welfare indicators can either be "...direct animal-based (something you get from the fish), or indirect resource-based (e.g. rearing environment, infrastructure etc.)" (Noble et al., 2018). Thus, in line with the description of direct and indirect observation of animal variables in the beginning of Chapter 3 and figure 2. Welfare indicators that can be used on the farm are termed Operational Welfare Indicators (OWI). The FISHWELL-handbook (figure 2.3-1 in Noble et al., 2018) presents three main groups of RAS-relevant OWIs: Environment based OWIs, Group based OWIs and Individual based OWIs. Observation of environmental parameters is addressed in section 3.2. The group based OWIs include feeding activity, growth, mortality, deviation from normal behaviour and disease, which have been discussed above.

Arguably, the most direct assessment of fish welfare is an individual evaluation of the fish itself. Evaluation of the individual based OWIs requires sampling of the fish. Sampled fish are inspected externally, and welfare indicators like scale loss, fin damage, wounds, eye occluding and bleeding and deformities are registered and graded according to severity. The FISHWELL-handbook provides a scoring system for OWIs, which was developed and evaluated in terms of their relevance, useability, reliability and suitability. This scoring system thus provides a way to observe the welfare of fish, based on manual observations.

In theory, OWIs can be assessed by the camera-based monitoring as described for health evaluation. The technology required would be the same as for health monitoring and is described in section 3.2.

To be able to use welfare evaluation for decision-making, a baseline or benchmark needs to be set, that the welfare evaluations can be compared to. Such benchmarks are lacking for welfare assessment in RAS, as there has been no systematic evaluation of the welfare status in farms using OWIs. Thus, a place to start for moving towards PFF was to perform a study on the occurrence of welfare indicators, which is presented as a practical example experience below.

Practical experience

In the IntelliRAS project, we evaluated the OWIs as an objective assessment of welfare of salmonids in RAS. We sampled 2844 fish from a total of 18 batches of fish from the four case farms. At each sampling point, 30-100 fish were evaluated for the following OWIs: Nose wound, jaw deformity, eye damage, eye opacity, operculum deformity, spinal deformity, scale loss, skin bleeding, body wound and fin damage.

Almost all fish had one or more OWIS, most of them being varying degrees of fin damage. There was a large variation between farms in the prevalence of the different OWIs as illustrated in figure 5. Thus, in two farms, for example, 21-25% of the fish had nose wounds, which was completely absent in the fourth farm. Two farms had >10% prevalence of eye damage, whereas in the other two farms the prevalence was <1%. Similarly, one farm had a consistently higher prevalence of deformities that the other farms.

We also found that the prevalence and severity of the OWIs varied with time within the farms.

Some welfare indicators are easier to detect in a camera system than others; for example body wounds, dorsal fin damage, nose wounds and scale loss. We therefore evaluated whether some of these indicators were correlated with others, which could make it sufficient to register only a subset. However, we found no meaningful correlations between any of these indicators and other indicators and any others.

In conclusion, each farm needs to make some initial assessments of which welfare problems they have and then base their systematic evaluation on indicators that reflects these.

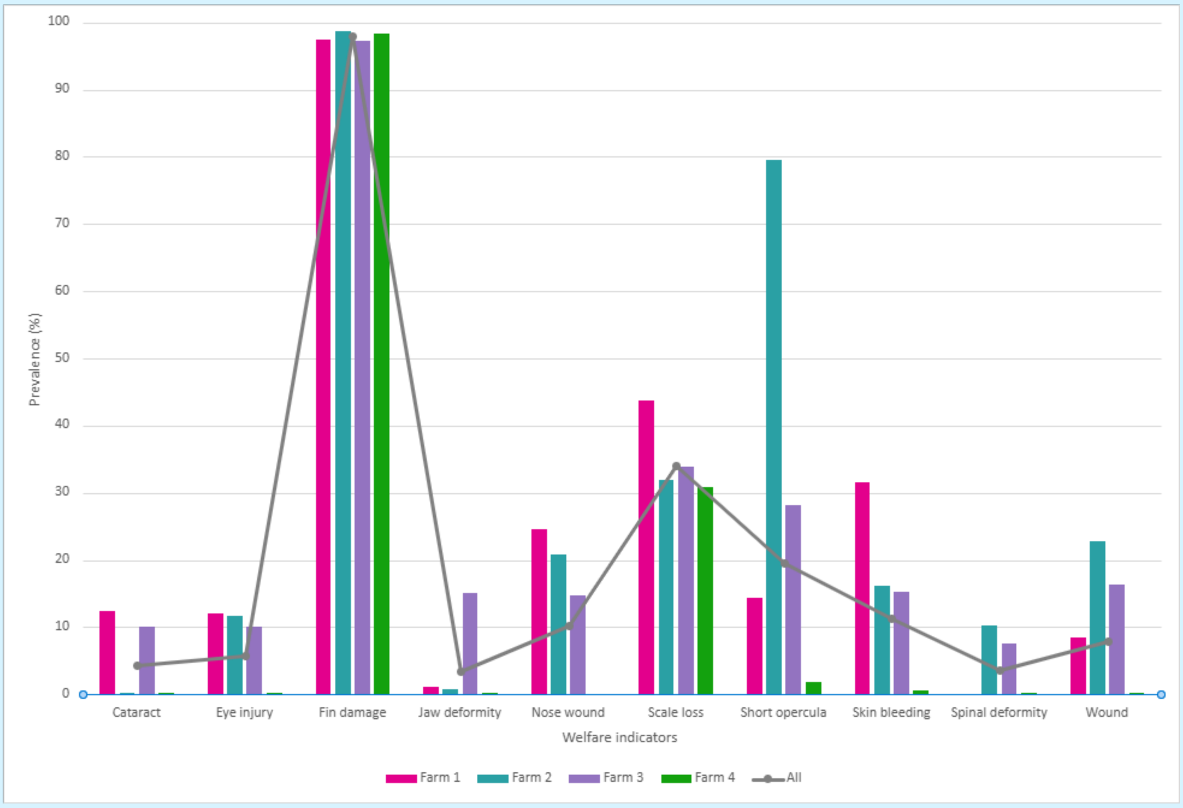

Figure 5. Prevalence of selected OWIs in four RAS farms. Bars show the prevalence of each indicator in the different farms, line shows the overall prevalence across the four farms. A total of 2844 fish were sampled for the study.

3.2 Sensor-based observations

The primary purpose of sensors is either to enable new types of observations — particularly of variables that were previously unmeasurable — or to replace manual, time-consuming observations with automated, real-time data collection. For sensors to be effective, they must deliver consistent results and undergo regular calibration. Despite their advantages, high upfront costs and ongoing maintenance expenses often hinder widespread adoption.

In the following sections, we explore the types of sensors commonly used on farms today, as well as emerging technologies involving visual and audio-based observations. Practical experiences with these systems are discussed in more detail later.

3.2.1 Water quality sensors

In RAS, water quality must be meticulously controlled to ensure optimal conditions for aquatic organisms. This is achieved through a combination of monitoring and control systems, where specialized sensors are integrated with central control units that enable automatic regulation and generate alerts when deviations from predefined threshold values occur. Monitoring is performed in different ways; from the simple use of on-site water quality test kits to using state-of-the-art sensors and probes that measure parameters continuously.

While all RAS facilities continuously monitor oxygen levels and temperature, many other parameters (for example pH and ammonia) are measured only periodically. Some farms have incorporated continuous monitoring of carbon dioxide (CO_2); however, this capability is not universally available across all fish farming operations.

Water quality is relevant for health and welfare of the fish, as both will be impaired by even short-term poor water quality. In the long-term, suboptimal water quality will also impair growth and thus production outcome.

Practical experience

In the IntelliRAS project we had access to production and sensor data from 18 RAS farms. Data from CO2 and Oxygen sensors were only available in the production data of one of these farms. It was not established if this low occurrence of sensor data reflected that sensors were not present in the farms – or that the data were not transferred to the management system. In either case the potential benefits to management are generally not exploited and therefore potential additional value could be gained by incorporating this data type deeper into management and surveillance. Within the project, CO2 sensors were installed in two of the test farms, but we experienced some practical challenges using the data from these sensors. In one farm we experienced that even though 2 sensors were placed in the same tank right next to each other, they measured systematically different levels of CO2. The fluctuation on the sensors were the same, which suggest a level-calibration issue. Generally, calibration and frequent re-calibrations seemed to be required. We also experienced challenges with data acquisition, due to unstable or non-existing internet connection of the sensors and farms.

We used the CO2 measurements for a small-scale implementation test of a warnings system (feedback) which is described in Chapter 4.

3.2.2 Video data

Recent developments in the applications of artificial intelligence (AI) permit the use of video data to gain insight into the behaviour of fish. Accurate estimation of fish activity using computer vision would give the farmers insight into e.g. feeding activity and appetite and provide a basis for automatic continuous monitoring and early warning systems. Neural network models are developed by storing and annotating thousands of pictures or video sequences. When enough training data are available, the method has been shown to be advantageous compared to others.

In marine aquaculture, camera technology is used to a wide extent for observing fish under water. Underwater video cameras allow the fish farmer to observe behaviour of the fish i.e. feeding activity and use this for feed optimization (Zhou et al., 2019). However, below-water monitoring is difficult or even impossible in RAS, as the water in RAS is turbid, creating low visibility as well as clogging the cameras. Another barrier is the high cost of such systems, which is a hindrance for the use in RAS, with their lower production revenues.

Possibilities for the use of computer vision in different applications have expanded vastly in the past years due to the rapid development in neural networks and GPU hardware. Typically, neural networks trained for computer vision tasks require lots of training data, which is based on good quality images that are further annotated by a human expert. The annotation work includes classifying the image or pointing out objects of interest for the model to learn in the training phase. In fish farming, the annotated image data can be used to train a neural network model to e.g. detect and track fish (Wang et al., 2022), classify feeding intensity (Zhou et al., 2019), detect dead fish (Zhao et al., 2022) or detect leftover feed (Hu et al., 2021). The amount of training data needed varies a lot depending on how hard the task is, the model used, and the level of performance expected of the model. As an example, for the model to be able to predict the location of fish in the image, the model needs some training data consisting of images and the annotated locations of the fish in these images. A clear criterion for the annotations is needed for the model to be able to find a consistent solution, especially if there are multiple annotators working together on a dataset.

For example: If only a part of the fish is visible, should it be marked on the image? What is the difference between "weak" and "normal" feeding activity in terms of amount of water disturbance on the surface? What are the criteria for a floating fish close to the surface, if there are strong reflections and it is difficult to determine if the fish is above the surface or not? Outsourcing annotation work is popular, but in this case annotation quality should be very closely monitored. Inconsistencies in annotations, whether it's in choice of class or placement or size of the bounding box will cause unnecessary noise in the input for the model, resulting in a worse performance (Fred et al., 2025).

With a surface camera above the tank, external conditions like lighting, camera placement, animal density and water turbidity affect the quality of the visual data, which can be somewhat mitigated by adjusting camera settings, such as exposure time, gamma correction and how many frames per seconds are recorded. Foam and reflections on the water surface easily occlude the view of the fish, so these should be considered when placing surface cameras. Naturally, camera resolution, cable bandwidth and the choice of video format and possible compression algorithm are also critical for the quality of the recorded data.

It is challenging to obtain high quality data from RAS systems due to water reflection from above surface cameras, and due to low light intensity and high fish density from underwater cameras. Frequent occlusion of the fish due to high stocking density, foam and reflections makes it impossible to track the movement of an individual fish for an extended period. When implementing solutions to production environments, AI should be applied on site due to limited network access in production facilities.

In addition, as mentioned previously, fish are rarely in the same tank for extended periods of time, and individual groups of fish may express different behaviour. This poses a challenge when it comes to obtaining training datasets and can also entail that individual models need to be made for each fish group or tank.

Practical experience

In the IntelliRAS project, we collected video data from a commercial farm environment and used it to train a tracking-by-detection model to estimate the swimming activity of the fish group. We placed cameras above water in two farms (For technical details see "Technical notes").

The collected data was annotated, and the resulting dataset consisting of 2654 images was used to train a YOLOv5 model (Ultralytics, 2021), a fast and lightweight neural network, to detect fish heads, in addition to detecting dead and injured fish. The images were annotated by three different people who worked independently, while following a short guidebook containing visual examples of the classes to be used, written by one of the annotators. All annotators used the open source MakeSense online annotation tool. They would draw rectangular bounding boxes over the fish heads, aiming to mark all or most of the fish in the image. In addition to "Fish", other classes annotated were "Floating", "Injured" and "Dead", as illustrated in figure 6. In real life, reliable identification of all the fish individuals is a challenging task due to lighting conditions and high animal density in the tank. Improving the image quality made the annotation work easier, as the details help in distinguishing the fish from each other in crowded scenes. The work resulted a total of 2654 annotated images and 39020 annotated bounding boxes.

By annotating the fish heads instead of the whole fish, the resulting bounding boxes are less affected by fish orientation and camera perspective, compared to annotating the whole animal. The model was trained on a NVIDIA Tesla v100 GPU. We noticed that the choice of hyperparameters, model and image size had a large impact on the results and decided to use a medium-sized model and a largish image size of 1280 for the training. In addition, we saw that heavy use of different augmentation strategies improved model accuracy on test data. On farm 1, we were able to reach an F1 score of 0.85 on detecting fish heads. For farm 1, the F1 score was slightly lower at 0.77. This is likely due to data from farm 2 having lower quality images, annotations, and a smaller number of training images in total.

Despite having a shared guidebook for all the annotators, we noticed that the resulting annotator agreement was quite low. Differences in the number of annotations and the size of the bounding boxes between annotators were substantial, and improving the quality of the dataset by increasing the size of the bounding boxes and discarding images with many missing annotations improved the performance of the model trained on the improved dataset.

In the training data, the number of dead and injured fish was low. Dead fish are visually easier to recognize and easier for the model to learn, so despite having few training examples we were able to detect dead fish quite accurately, with an F1 score of 0.80. Detecting injured fish is harder both visually and due to having only a handful of examples for training, resulting in an F1 score of 0.71. The examples of the injuries in the training data contained only tail injuries from one farm, and for achieving a more robust model to work across farms more data from different settings would be beneficial.

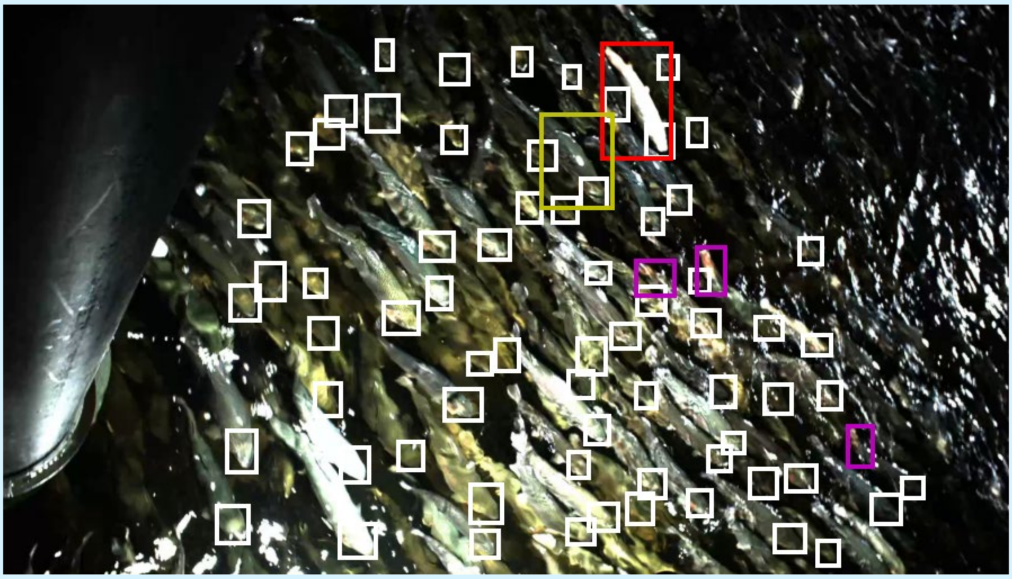

Figure 6. Still-picture from a video-sequence taken by a camera installed over the surface of a tank at a RAS-farm. The squares show annotated fish heads (white), dead fish (red), floating fish (yellow) and tail injuries (purple).

3.2.3 Audio data

Acoustic methods have recently been explored in aquaculture (Li et al., 2024), including passive acoustics (i.e., hydrophone recording) for fish feeding intensity assessment (Cui et al., 2022), and active acoustics (such as sonar imaging or acoustic telemetry), e.g., for fish detection (Kristmundsson et al., 2023), fish counting and size estimation (Gutiérrez-Estrada et al., 2022), and feeding behavior monitoring (Folkedal et al., 2022). While also multimodal methods – combining passive and active acoustics with optical methods – have been employed for fish feeding intensity assessment (Cui et al., 2024), the IntelliRAS project focuses solely on passive acoustic methods, specifically for fish feeding intensity assessment.

Passive acoustics are not yet implemented in RAS facilities, but the technology has recently been explored for fish feeding (Li et al., 2020; Rosten, 2023) and monitoring of stress behavior monitoring in aquaculture (Li et al., 2022; Helberg et al., 2024). For these applications hydrophones are deployed in aquaculture tanks and data is analyzed using machine learning methods, such as deep learning networks (Cui et al., 2022).
Like the case of camera-based methods, sound clips are labeled according to the fish feeding intensity to use for supervised (or semi-supervised) learning. Melspectrograms of the sound clips are formed and are treated as images in computer vision classification models, such as convolutional neural network or vision transformer models.

One of the major challenges in passive acoustic fish feeding behavior assessment is the background noise from pumps, machines, etc., which varies between facilities, and which may obscure the relevant sounds to be used for classification (Li et al., 2020; Li et al., 2024). The intensity of the background noise can affect the classification, since it can reduce the dynamic range of the hydrophone and thereby make the relevant sounds relatively weaker. In the case of fish feeding intensity assessment, the soundscapes of different aquaculture facilities vary, and even within a facility the background noise can vary, depending on human activity, whether a pump or machine is active, or the placement of the hydrophone, etc.
A model fitted to data from one facility may therefore not perform equally well for other facilities, unless measures are taken to generalize the model. To make the model invariant with background noise, a proposed strategy is to use sound separation methods to extract only the relevant features, i.e., the sounds of fish eating (Li et al., 2024). Examples of such regularization or feature extraction methods could be denoising autoencoder models or non-negative matrix factorization.

Hydrophone-based methods have the advantage over video-based methods, that they are not affected by the reduced visibility in the turbid water of intensive RAS facilities, nor by occlusion from high population density fish tanks. They are well suited for fish feeding intensity assessment and potentially for stress behavior monitoring, for which they may serve as an alternative or a compliment to camera-based methods. For other camera-based method applications, such as biomass estimation or fish detection or tracking, hydrophone-based methods are not well suited.

Practical experience

As part of the IntelliRAS project, a fish feeding intensity assessment model based on audio data was employed in an industrial, intensive recirculating aquaculture facility. The feasibility of the method was assessed for industrial applications and challenges of the method were identified.

Hydrophone recordings obtained outside of the IntelliRAS-project by project partner OxyGuard International A/S, were used for the analyses described here. Two days of hydrophone recordings were made in an intensive recirculating aquaculture salmon pre-grow out tank. The fish feeding regime for each day began at midnight, with feed being dispensed for around two seconds every 53-54 seconds, until the feed ration for the day (around 1.2% of fish biomass) was exhausted, sometime in the afternoon. This feeding regime enabled automatic labeling of fish feeding intensity by the time after beginning of feed dispensing, with the reasoning that feeding activity will naturally decrease as the feed gets eaten up and less feed thereby is available.

The hydrophone recordings were partitioned into two second segments of three categories: 4, 6 and 10 seconds after beginning of feed dispensing and melspectrograms were formed, which were fed to a CNN autoencoder-classifier model.

The model was trained on a training set consisting of 2551 training samples, with a validation set of 1275 samples, and tested on the test set consisting of 1280 samples. Testing showed an accuracy of 75 % and F-1 score of 75 %, with the best performances on the classes 4 s and 10 s of accuracy 83 % and 88 %, and F-1 score 79 % and 82 %, respectively, while for class 6 s accuracy of 53 % and F-1 score 60 % were displayed. These results seem promising for future implementation of fish feeding intensity assessment in intensive RAS facilities, although more work is needed to generalize the model between facilities.

4 Reliable detection and prediction models (PFF component 2)

After observing the feature variables, predictive models are the second step for PFF. In terms of PFF, a reliable prediction model would be a model that filter and aggregate the raw sensor data into feature variables. A feature variable is intended to describe a specific biological response from the animals within the production system. A feature variable could for example be 'fish activity' derived from camera observations. This feature variable can then be used for monitoring and/or potentially as the basis for decisions (in which case we call them target variables).

For applications of PFF in RAS; mortality, growth and feeding were discussed in previous chapters and these feature variables are well suited for predictive modeling. The first step in a model is the collection of data: How this can be done has been described in Chapter 3, and in Chapter 5 we explore the needs and challenges for procurement and storage of data. Before the data can be used in a model, it must be organized. All the information must be cleaned and sorted (also known as data curation), so it is ready to be used. This step removes any errors and imputes missing parts.

Next, a model is trained to learn patterns from the organized data. For example, it might learn that fish grow faster when water temperature stays at a certain level. Different models are used for different applications. Some are classical models like ordinary linear regression, partial least squares, and generalised linear models such as logistic regression whereas others are more modern (in some sense) and often referred to as machine learning, e.g., artificial neural network or deep learning, and random forests.
Examples of common models used for prediction are:

- Ordinary Linear and Nonlinear Regression Models: Finds relationships between variables assuming normal distributed residuals. For example, how temperature and feed amount affect fish weight. Can for example be used for predicting fish growth over time.
- Time Series Models: Analysis of data collected over time to make future predictions. This can for example be used for forecasting changes in water temperature or oxygen levels. Dynamic linear model (DLM) is one class of models that may be useful in this context.
- Decision Trees and Random Forests: These models make decisions by asking a series of yes/no questions (like a flowchart) or splitting by thresholds. Random forests use many trees together for better accuracy. This can for example be used for predicting the best feeding times or identifying poor water quality conditions.
- Artificial Neural Networks: These methods take inspiration from how human brain works by recognizing complex patterns in large data sets. This can for example be used for more advanced tasks, like predicting disease outbreaks or fish behaviour based on camera or sensor data, as explained in Chapter 3.
- Support Vector Machines: This method aims at finding the best boundary known as hyperplane that for example separates different classes in the data. A hyperplane is a generalization of a two-dimensional plane in three-dimensional space to arbitrary dimension, i.e., an (n-1)-dimensional part of an n-dimensional space. This could for example be used to classify images and thereby discriminate levels of activity in the water.

- Differential equation models: these are mechanistic models which are built on biological or physical assumptions. For commonly used models for fish growth modeling, for which analytical solutions are readily available, the parameters can be estimated using (nonlinear) regression or maximum likelihood methods. In other cases, e.g., when closed form solutions are unavailable, the model parameters can be estimated using data assimilation techniques, such as Bayesian smoothing, Kalman-type filters or particle filters for state- and parameter estimation.

After the model is developed, it needs to be tested with new data to see how well it predicts e.g., fish growth or the best feeding time. Often, one will divide the available data into a training data set to train the model, and a testing data set to test how well the model performs. Splitting data may also be used for tuning of model parameters like the maximum number of trees, convergence thresholds and more. Nevertheless, validation of the model using a completely new data set should also be done. If the model only predicts well on the batch of data from which the training set was also drawn, it will be useless in practice. It may, however, be necessary to build models within say a farm as the process generating the data might be very different across farms. Changes over time may also necessitate adjustment of the model along the way.

A proposed approach is to use dynamic models that are updated sequentially with new data to smoothen noisy observations such as mortality counts. These models may provide more reliable estimates of the underlying mortality rate and flag unusual deviations. Recent publications have shown how models can be used to monitor mortality in marine environments, using production data from salmonid farms in Scotland and Norway (Merca et al. 2024 a,b; Oliveira et al. 2024). In these studies, models were applied to trigger alarms when mortality exceeded expected levels, which could support farmers in taking timely actions. In Oliveira et al. (2024), the performance of the model was also tested for detecting outbreaks of a notifiable disease (salmon pancreas disease), and it showed promising value for this purpose. These models build on previous studies on mortality patterns and risk factors for mortality in marine salmonid farming (Bang Jensen et al., 2020; Oliveira et al., 2021). Developing similar models for mortality in RAS could provide a useful tool for fish health managers, but such models are still lacking.
As previously mentioned, other possible applications for PFF would be to control growth by modelling and predicting feeding and biomass. An example of predicting feed intake of trout fish (and hence growth) in small groups of 30 based on information of water quality, fish weight and number using neural networks was recently published (Chen et al., 2020). Such results demonstrate the potential, but the number of fish involved also show that a substantial work is needed to make this commercial useful.

Practical experience

In the IntelliRAS project we have worked with 4 specific salmonid farms and been looking into data from multiple additional salmon farms. The insights gained show that these production systems differ greatly in both scope and type. This also indicate that it will be unlikely to provide general PFF tools that do not require substantial training, calibration and customization to accommodate the needs of the individual fish farmers.

4.1 Modelling mortality in RAS

The purpose of modelling mortality is typically to be able to predict the risk of mortality in the near future (days or weeks) and allow the farmer to react if mortality risks increase. It can also be to predict whether certain fish groups or tanks are at a high risk of increased mortality. To design the best model, one needs to understand the production system (for example, species of fish, type of production, number of tanks, number of fish in system,

temperature, etc). It is also important to understand if there are any known drivers of mortality, beyond those that one aims to detect. For example, temperature is known to influence mortality in salmonids (Oliveira et al., 2021; Tvete et al., 2023).
A common management practice of fish farmers is to react to increased mortality by reducing the amount of feed supplied to the fish. However, the fish farmer needs to take this decision (intervention) of reducing feed amount based on uncertainty – with very limited information available to assist in assuring that the reaction is based on a real change in the underlying mortality rate and not simply on truly random variation in mortality. One approach is to apply control charts to the feature of interest — here, mortality. As shown in figure 7 and described in Chapter 3, the frequent movement of fish results in relatively short time series, which makes modelling imprecise and yields only limited additional information; or the modelling requires a substantial number of assumptions that are unlikely to remain constant over time and across batches of fish.

Practical experience

In the IntelliRAS project we worked with mortality in individual tanks. Figure 7 is an example of a control chart, that can be used to detect separate incidents of ordinary and exceptional variation (where the peaks cross the upper dashed line) in mortality.

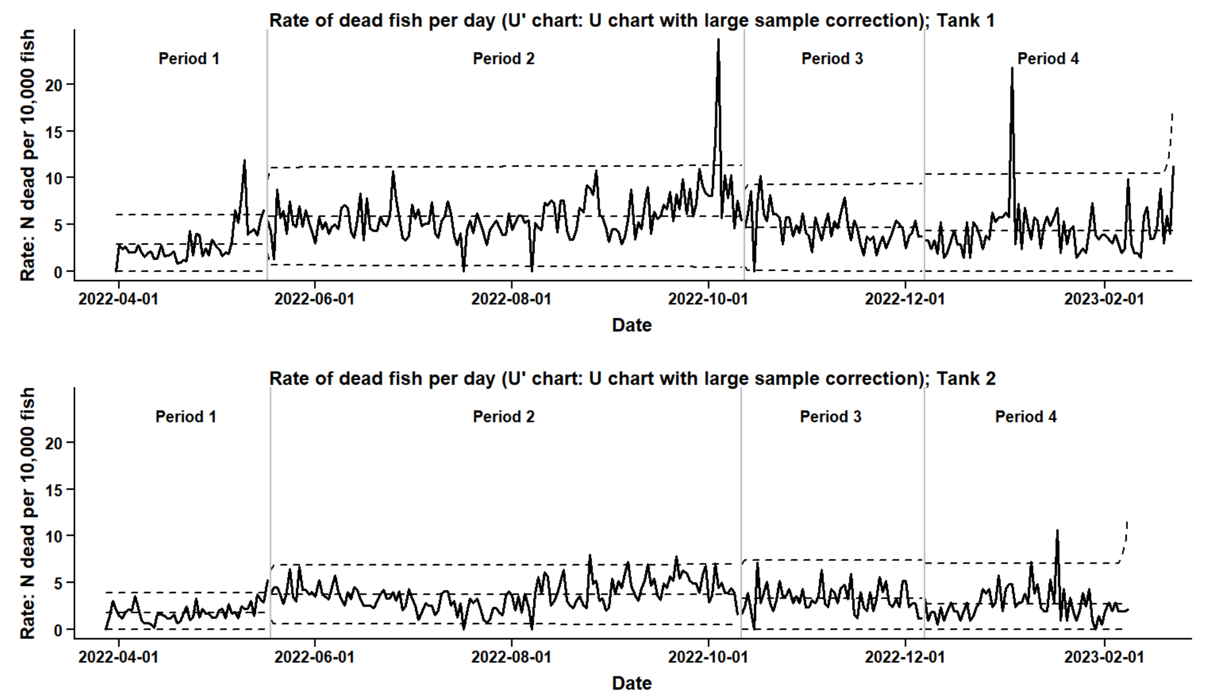

Figure 7. Control charts of mortality rates with Laney's correction for large sample sizes (U'-Chart) in two different tanks in the same farm. The dashed lines represent a mean centre line with lower and upper confidence limits within periods. Periods (1-4) were defined by dates where some of the fish were moved to other tanks.

4.2 Modelling biomass

Estimation of the biomass in a specific tank is essential for production planning. Fish farmers in RAS systems often use samples of the individual tanks to monitor and potentially adjust their expectation of tank biomass. This is done by sampling, for example, 30 kg of fish, counting the actual number of fish and based on these, estimate the average weight. Since the total number of fish (or at least an estimate) is known, the tank biomass can be estimated. However, this approach does not account of the uncertainty associated with sampling nor can information from previous samplings be included in the estimate. This may justify using a modelling approach to estimate biomass. Several commercial companies offer solutions for estimating biomass based on camera inputs and modelling. These have mainly been developed and used in marine farming, but recently, also systems built for RAS-farms have been introduced. Input data can either be manual weighing or video recording, as described in Chapter 3.

Practical experience

In the IntelliRAS project we developed a model structure for integration of information from samplings with the information provided by the supplied feed to the tank. The model is based on Bayesian updating of the sampling estimates and provides probabilities that the growth curve of the fish is either following expectations or deviating below or above them. Figure 8 shows a simulated growth curve of trout that deviated from expectation at 100 days. From the tank, 20 fish were sampled weekly, and the probability of being under track increased and exceeded the probability of being on track.

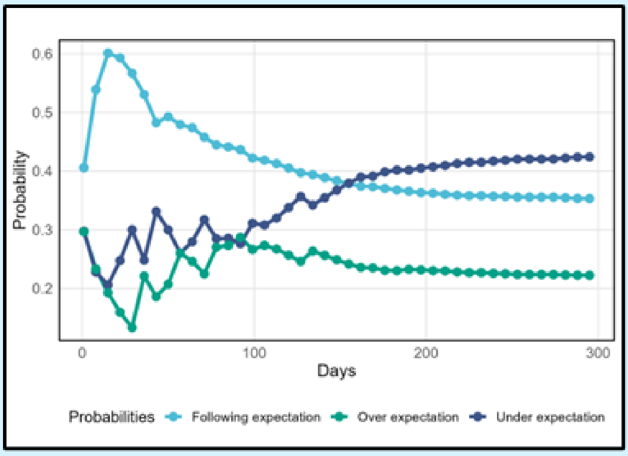

Figure 8. The estimated probabilities of following growth expectation or being over or under expectations in a simulated scenario, where growth decreased after day 100.

4.3 Modelling feeding

Automatic control of feeding could be beneficial for fish farms as efficient use of feed is important economically; in addition, environmental sustainability and feeding are also linked to fish welfare. It is common practise on RAS farms to adjust the feeding settings according to feeding activity. The feeding activity of the fish is assessed visually according to the experience of the farm staff. Computer vision or hydrophone recordings offer an opportunity to automate this process and improve its accuracy. Another way to measure feeding is to monitor the number of uneaten pellets in the tanks, which could also be done by using video cameras.

Several authors have developed models for automatically assessing the feeding activity in small to medium scale RAS systems (Zhou et al., 2019) and automated feeding level control systems have been developed (Atoum et al., 2015). The developed models aim to classify the fish feeding activity as low, medium or high, however, no clearly described and repeatable scoring system for fish appetite has been used and therefore repeatability of the studies is low.

A model on feeding would also require information of biomass, predicting this as part of the model or separately (section 4.2). Moreover, parameters like temperature, dissolved oxygen and CO_2 concentration may be valuable to include in such a model. Further requirements when developing automatic feeding control are considered in Chapter 5.

Practical experience

In the IntelliRAS project, together with a tracking algorithm to estimate moving objects position and velocity, the trained detection model can be used to track fish on video across frames. We used the StrongSort (Du et al., 2023) model together with the detection model to track the fish continuously. From these tracks we can get an estimate of the swimming activity levels of the fish and see how the activity levels change with respect to feeding times, as seen in figure 9.

Parameters chosen for the tracking model were conservative: to avoid identity switches between fish located close to each other, a strict threshold of 0.01 for appearance-based matching was used to filter unlikely matches. To avoid the increase in uncertainty and increase in identity switches due to missing detections, a maximum of missed frames was set to a low value of 3. Even with the careful choice of parameters, some tracking errors were still present. These outliers were filtered by excluding the samples where the value was over 5 times the mean standard deviation during the 24-hour observation time.

The results showed that the automated feeding activity assessment was able to detect the changes in fish behaviour around feeding time, however due to the risk of production losses on the farm we could not study the use of the model for automatic control of feeding levels.

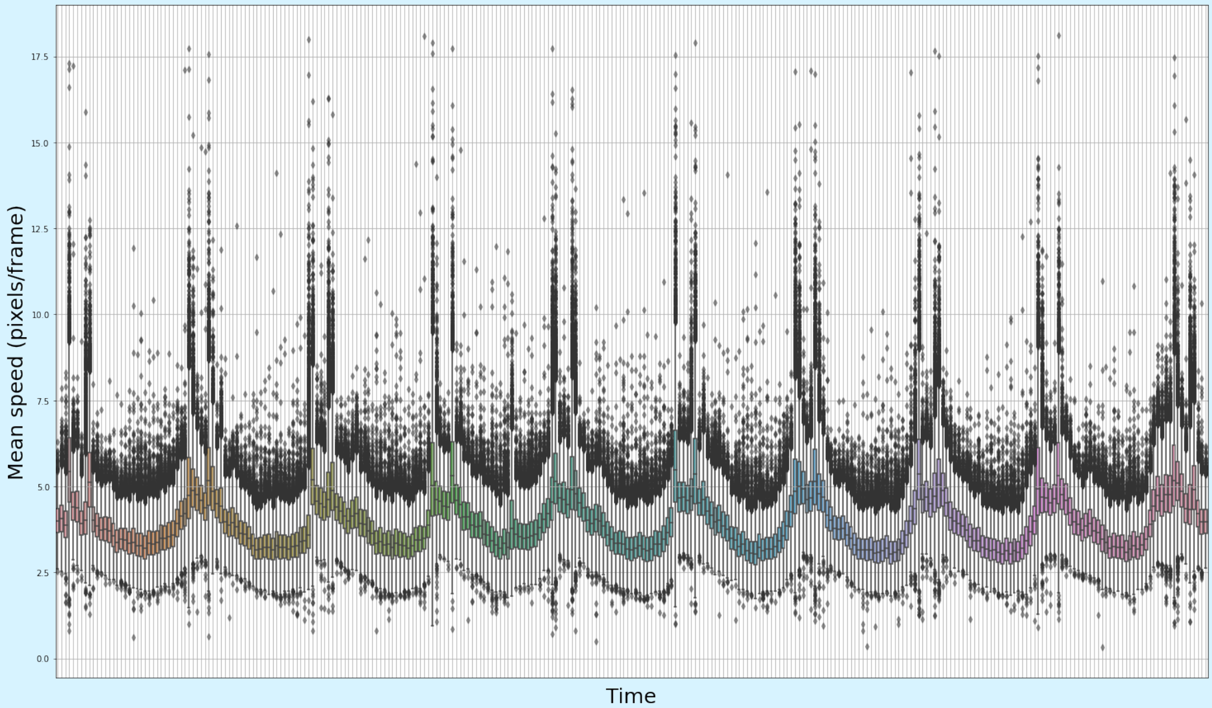

Figure 9. Estimate of the fish group’s swimming activity over a 24-hour timeframe obtained using frame-level aggregation of tracks. The increases in tracked speed correspond to known feeding times.

5 Automatic decision making and control (PFF component 3)

Developing prescriptive and autonomous systems that can automatically control different aspects of production is the most challenging part in precision fish farming. In a prescriptive system a model can predict and optimize the effect of control or intervention on the system, however the final decision and intervention are still done by a human. Ideally the system would be controlled in ways that prevent problems from occurring, however they can also be used to take corrective action in case a monitoring system suggests an anomaly in production such as an increase in mortality.

An autonomous system will make the decision and actuate the system. Such systems need to have real-time access to reliable data from relevant control inputs, such as water quality or fish appetite. In addition, such systems need a reliable prediction model on the expected effect of changing the control variables such as fish feeding rate or schedule. Additionally, the model needs to be able to actuate the system (Verdouw et al., 2021).

To our knowledge there are no validation studies yet that use automated feeding control and demonstrate improvements in feed efficiency or economic outcomes.

A schematic suggestion for a computer vision based automatic feeding control system is illustrated in figure 10. Such a system would need significant commitment from the fish farm during the system development and willingness to tolerate production losses during the development stage. A model for establishing a relationship between the feeding levels, measured activity, fish growth and health needs to be established for the controller to be useful. Developing such a model needs several experiments to establish and tune the model parameters. A way forward could be to develop such a system in pilot scale and if significant benefits can be demonstrated, apply the same principles in real production scale.

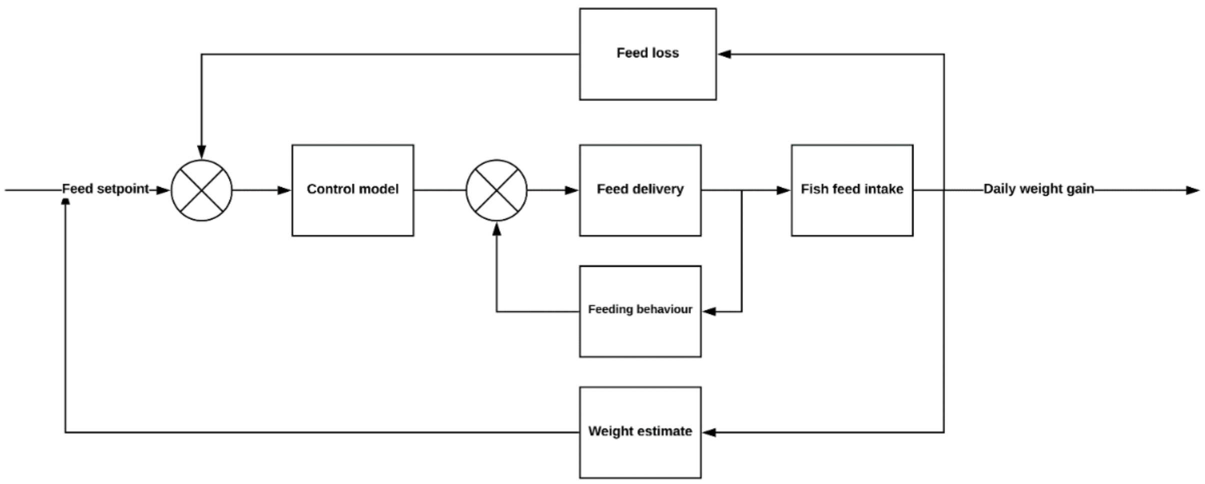

Figure 10. Schematic illustration of a closed loop control system for feeding. The diagram shows a two-level feedback mechanism, that both involves feed planning and feed adjustment based on fish feeding behaviour, feed loss and weight estimates.

6 Registration and storage of data: Needs, quality and quantity

As previously discussed, Precision Fish Farming (PFF) is a data-driven approach, and its implementation in fish farming requires addressing several challenges related to data storage, access, transport, and quality. This chapter focuses on these challenges and explores potential solutions.

A robust control system for PFF relies on effective data management. Data must be collected, stored, secured, and shared in a safe and accessible manner. While many sources outline best practices for data governance, this paper identifies the following key factors for successful PFF implementation: robust data procurement and data standardization. For each factor, we present practical issues to be resolved.

6.1 Data Procurement

Challenges in data procurement can be divided into the subcategories listed in Table 2: This table highlights the main obstacles to effective data procurement in fish farming; each requiring specific strategies to overcome and enable successful PFF deployment. As stated, PFF is data-based, and to implement PFF in fish farming, challenges related to data storage, access, transport, and quality would need to be resolved. In this chapter, we focus on present challenges and the possible solutions for these. In order to have any sort of control system, there needs to be a system for data management. Data must be obtained, stored, secured and shared in a safe and secure manner. While there are many sources that describe principles for good data governance, we have in this paper identified the following key factors for PFF: robust data procurement and data standardization. For each of these factors we present some practical issues to be solved.

Table 2. Overview of challenges in data procurement, and the reasons for issues.

Data Procurement Issues	Reason(s)
Data is not collected at the farm	Fish farmers lack incentives to collect data
Lack of technology for data collection	Fish farmers do not have the necessary technology
Data is not being shared	Fish farmers are reluctant to share data
Lack of data storage	Insufficient infrastructure for data storage
Limited digital access to data	Data is inaccessible outside the farm due to infrastructure limitations
Data is not processed	Data is collected but not processed effectively

To enable effective use of data, it must be readily available, timely, and accessible. It is essential that farms have clear incentives to collect data and understand the importance of standardized, consistent, and timely data management. This need should be reflected in digital tools designed for fish farmers, ensuring that the benefits of engaging in data collection and sharing are apparent.

Additionally, robust infrastructure is needed to manage data effectively, including careful planning for data storage and access controls. Even a basic setup with one or two cameras can generate substantial data volumes, making efficient data storage and accessibility critical—particularly if the data is intended for research or advanced product development. This becomes even more pressing in larger production facilities where complex systems are implemented.

Data transfer presents another challenge. The primary issue is the vast amount of data generated from devices like hydrophones and cameras, which may exceed 100 GB per minute. For production environments, AI processes must operate on-site, as uploading these data volumes to a cloud storage service can be extremely time intensive. Similarly, downloading data is slow, with a four-second video potentially requiring up to four minutes to retrieve.

Remote farm locations add further complexity; some farms rely solely on Wi-Fi for internet connectivity, which may lack the upload/download speed and stability needed for seamless data transfer and cloud storage, especially for video and sensor data.
Moreover, data originates from multiple sources, necessitating a system that can integrate diverse data streams. With numerous commercial solutions available, it can be challenging and time-consuming for farms to identify which system best meets their specific data integration needs.

6.2 Data Standardization

For data to be broadly useful, standardized practices must be in place among those collecting and utilizing it. Data must be collected systematically, with specific units or units that can be easily converted to common metrics. Each data point should include both a value and a timestamp to facilitate cross-farm comparisons. Standards are also needed for managing data outliers and preserving raw data to ensure consistency and reliability.
Several organizations are actively working toward standardizing data practices within the aquaculture sector. Certification bodies such as the Global Aquaculture Alliance (GAA) and the Aquaculture Stewardship Council (ASC) are key players in this effort. Integrating data standards into farm certification processes would create a built-in incentive for compliance. Industry initiatives, such as AquaCloud, are also tackling data challenges in fish farming by focusing on developing platforms for **sensor data standards**, **fish health standards**, and **environmental data standards**. These efforts aim to drive consistency and quality across the industry.

Practical experience

In the IntelliRAS project, we experienced issues with data storage and transfer. Some farms did not have sufficient internet access to allow for transfer of data from camera. Therefore, data had to be procured at the farm and subsequently transferred physically to the model developers. Another issue was farmers not being willing to share data with external institutions, and another was that it was difficult to get all the data needed for the model development from all the farms, as their data registration systems differed.

Upon downloading, the massive data (from continuous measurements from different sensors, images from the videos and sound data from the hydrophones) were collected during several months and were inserted in excel files that had to be stored on hard drives of the size of gigabytes. Partners had to store data in databases or network drives.

7 Needs for PFF and the way forward

In Chapter 2 we introduced Precision Fish Farming, or PFF as a potential solution for a more economically and biologically sustainable production in RAS. As described, the largest gains would be obtained by better control of feeding, growth, and health and welfare. We also described requirements to develop and implement PFF in RAS, specifically in production of rainbow trout and Atlantic salmon in the Nordic countries.

In Chapter 3, we presented different ways to measure animal variables, with most emphasis on methods that could be suitable for PFF. We also relayed the practical experiences we have obtained during our studies in the four test farms in the INTELLIRAS-project.

In Chapter 4, we described what models could be used in PFF, and some advantages and challenges of designing and implementing models for PFF in RAS.

When we set out on the project, one aim was to get to the point where a pilot automatic control system for feed could be developed, and in Chapter 5 we describe the theoretical framework for such a system.

The backbone of any system for production monitoring and control is the data procurement and storage, and during the writing of this report, it became clear that this subject warranted a chapter of its own. Thus, in chapter 6 we described the needs and requirements for data, including what challenges need to be addressed for a PFF to function and the practical experience we obtained during the project.

Based on the current state of the art and the experiences with practical implementation as described in the previous chapters, we suggest focusing the work towards PFF on the issues presented in figure 11

Observation of animal variables

- Camera technology can be used for observing behaviour related to measuring health and feeding. Algoritms based on machine learning are promising for these purposes.
- In theory, camera technology could also be used for measuring growth and biomass, but at present this application is not feasible in RAS.
- The same applies for monitoring external clinical injuries or signs and mortality classification.
- Hydrophones can be used for observing behaviour related to health and feeding.
- For more precise monitoring of growth, new types of animal variables are needed that can predict fish weight or substantially more control weighings.
- In order to use mortality registration for decision making, classification of causes of mortality should be standardized.
- Protocols for standardized monitoring of welfare on farms are lacking. They need to be developed and adjusted according to each farm.

Reliable prediction models

- Reliable prediction models need to be developed that can make the sensor observations into useful information and substantial validation afterwards. The diversity of RAS systems could suggest that such models would need individual calibration.

Automatic decision making and control

- Automated control of feeding could be beneficial for fish farms. A pilot-scale system could be developed and implemented to test and demonstrate the benefits to the farmers.

Data needs

- In order to move towards PFF, data procurement obstacles needs to be resolved.
- Lack of standardization in data registration and storage makes it difficult to develop PFF that could be applicape across different farms.

Figure 11. Technology and knowledge gaps and suggested ways forward towards implementation of PFF in RAS

7.1 Conclusive remarks

There are currently several initiatives towards using big data and automatic monitoring for health, growth and welfare in aquaculture.

Through our investigation of the different components required for implementing PFF in RAS, it is evident that there are some hindrances that must be overcome for implementation to be feasible.

In addition to what is presented here, the costs of investing in automatic monitoring systems and developing models needs to be considered – for many RAS-farmers, the production margins are quite small, and it can therefore be difficult for them to assess if the initial costs of implementing such systems are worth investing in.

It seems that there is still a long way to go for achieving robust and predictable ways to automatically monitor animal variables in RAS, but the research into such systems is ongoing and therefore there is still a promising future for such systems. In addition, equipment costs are decreasing.

Similarly, the challenges of developing useful models can be overcome if more experience is gained, for example by including more examples from actual productions, and with the continuous developments within machine learning.

8 Acknowledgements

We would like to thank the four aquaculture companies that participated in the study. Especially the staff who carried out and helped us with the sampling and inspection of the fish, and those who helped us procure data from production systems and sensors.

9 Reference list

Asche, F., Roll, KH., Sandvold, N., Sørvig, A. & Zhang, D. (2013). Salmon aquaculture: larger companies and increased production. Aquaculture Economics & Management, 17(3), 322–339.

Aunsmo, A., Persson, D., Stormoen, M., Romstad, S., Jamtøy, O. & Midtlyng, PJ., 2023. Real-time monitoring of cause-specific mortality- and losses in industrial salmon farming, Aquaculture, Volume 563, 738969.

Atoum, Y., Srivastava, S. & Liu, X. 2015. Automatic Feeding Control for Dense Aquaculture Fish Tanks. IEEE Signal Process. Lett. 22, 1089–1093.

Bang Jensen, B., Qviller, L. & Toft, N., 2020. Spatio-temporal variations in mortality during the seawater production phase of Atlantic salmon (Salmo salar) in Norway, Journal of Fish Diseases. 43, 445–457.

Berckmans, D. (2006). Automatic On-Line Monitoring of Animals by Precision Livestock Farming. In: Livestock Production and Society; Geers, R., Madec, F., Eds.; Brill. Wageningen Academic, Wageningen, The Netherlands, pp. 287–294; ISBN 978-90-8686-567-3.

Bregnballe, J. (2022). A guide to recirculation aquaculture – An introduction to the new environmentally friendly and highly productive closed fish farming systems. Rome. FAO and Eurofish International Organisation. 2022 Edition.

Chen, L., Yang, X., Sun, C., Wang, Y., Xu, D. & Zhou, C. 2020. Feed intake prediction model for group fish using the MEA-BP neural network in intensive aquaculture, Information Processing in Agriculture, 7, 261-271.

Costello, C., Cao, L., Gelcich, S.,…..& Lubchenco, J. (2020). The future of food from the sea. Nature, 588, 95-100

Cui, M., Liu, X., Z, J., S, J., Lian, G., Chen, T., Plumbley, MD., Li, D., Wang, W., 2022. Fish feeding intensity assessment in aquaculture: a new audio dataset AFFIA3K and a deep learning algorithm. IEEE 32nd International Workshop on Machine Learning for Signal Processing (MLSP)

Cui, M., Liu, X., Liu, H., Du, Z., Chen, T., Lian, G., ... & Wang, W. (2024). Multimodal fish feeding intensity assessment in aquaculture. IEEE Transactions on Automation Science and Engineering.

Dijk, M., Morley, T., Rau, ML. & Saghai, Y. (2021). A meta-analysis of projected global food demand and population at risk of hunger for the period 2010-2050. Nature Food, 2, 494-501.

Du, Y., Zhao, Z., Song, Y., Zhao, Y., Su, F., Gong, T., Meng, H., 2023. StrongSORT: Make DeepSORT Great Again. IEEE Transactions on Multimedia 25, 8725–8737

FAO (2022). The State of World Fisheries and Aquaculture 2022. Towards Blue Transformation. Rome, FAO.

Folkedal, O., Macaulay, G., Fosseidengen, J. E., Mikkelsen, G., Myrland, J., Søvegjarto, B., ... & Stien, L. H. (2022). Deployment of hydroacoustic feeding control in salmon sea-cages; biological and technical considerations. Aquaculture, 561, 738700.

Fred, H., Krogh, MA., Jensen, BB., Ruotsalainen, L., Vielma, J. & Pastell, M., 2025. Automatic Visual Segmentation of Fish in Recirculated Aquaculture Systems Using the Segment Anything Model. 10.2139/ssrn.5281709.

Føre, M., Frank, K., Norton, T., …. & Berckmans, D, 2018. Precision fish farming: A new framework to improve production in aquaculture. Biosystems engineering, 173, 176-193

Gutiérrez-Estrada, J. C., Pulido-Calvo, I., Castro-Gutiérrez, J., Peregrín, A., López-Domínguez, S., Gómez-Bravo, F., ... & De la Rosa-Lucas, I. (2022). Fish abundance estimation with imaging sonar in semi-intensive aquaculture ponds. Aquacultural Engineering, 97, 102235.

Helberg, G. A., Anichini, M., Kolarevic, J., Sæther, B. S., & Noble, C. (2024). Soundscape characteristics of RAS tanks holding Atlantic salmon (Salmo salar) during feeding and feed withdrawal. Aquaculture, 593, 741325.

Hu, X., Liu, Y., Zhao, Z., Liu, J., Yang, X., Sun, C., Chen, S., Li, B. & Zhou, C., 2021. Real-time detection of uneaten feed pellets in underwater images for aquaculture using an improved YOLO-V4 network. Computers and Electronics in Agriculture 185

Kristmundsson, J., Patursson, Ø., Potter, J., & Xin, Q. (2023). Fish monitoring in aquaculture using multibeam echosounders and machine learning. IEEE Access, 11, 108306-108316.

Lagardere, JP and Mallekh, R. 2000. Feeding sounds of turbot (Scophthalmus maximus) and their potential use in the control of food supply in aquaculture: I. Spectrum analysis of the feeding sounds. Aquaculture, 189, 251-258.

Lekang, OI. (2007). Aquaculture Engineering, Aquaculture Engineering. Blackwell Publishing Ltd, Oxford, UK. ISBN:9780470995945

Li, D., Wang, Z., Wu, S., Miao, Z., Du, L., & Duan, Y. (2020). Automatic recognition methods of fish feeding behavior in aquaculture: A review. Aquaculture, 528, 735508.

Li, D., Wang, G., Du, L., Zheng, Y., & Wang, Z. (2022). Recent advances in intelligent recognition methods for fish stress behavior. Aquacultural Engineering, 96, 102222.

Li, D., Du, Z., Wang, Q., Wang, J., & Du, L. (2024). Recent advances in acoustic technology for aquaculture: A review. Reviews in Aquaculture, 16(1), 357-381.

Merca, C., Boerlage, AS., Kristensen, AR. & Jensen, DB. 2024 a Monitoring monthly mortality of maricultured Atlantic salmon (Salmo salar L.) in Scotland I. Dynamic linear models at production cycle level, Frontiers in Marine Science, 11

Merca, C., Boerlage, AS., Kristensen, AR. & Jensen, DB. 2024 b. Monitoring monthly mortality of maricultured Atlantic salmon (Salmo salar L.) in Scotland II. A hierarchical dynamic linear model, Frontiers in Marine Science, 11

Moldal, T., Wiik-Nielsen, J., Oliveira, VHS., Svendsen, JC. & Sommerset, I. (2025) Norwegian Fish Health Report 2024, Norwegian Veterinary Institute Report series #1b/2025, published by the Norwegian Veterinary Institute.

Noble C., Gismervik, K., Iversen, MH., Kolarevic, J., Nilsson, J., Stien, LH &
Turnbull, JF. (Eds.) 2018. Welfare Indicators for farmed Atlantic salmon: tools for assessing fish welfare, 351pp.

Oliveira, VHS, Dean, KR, Qviller, L., Kirkeby, C. & Bang Jensen, B, 2021. Factors associated with baseline mortality in Norwegian Atlantic salmon farming, Scientific Reports, 11, 14702.

Oliveira, VHS., Dórea, FC., Dean, KR. & Bang Jensen, B, 2024. Exploring Options for Syndromic Surveillance in Aquaculture: Outbreak Detection of Salmon Pancreas Disease Using Production Data from Norwegian Farms, Transboundary and Emerging Diseases, 2024, 9861677.

Rosten, C. M., Mathiassen, J. R., & Volent, Z. (2023). Acoustic environment of aquaculture net-pens varies with feeding status of Atlantic salmon (Salmo salar). Aquaculture, 563, 738949.

Tvete, IF., Aldrin, M & Bang Jensen, B, 2023. Towards better survival: Modelling drivers for daily mortality in Norwegian Atlantic salmon farming, Preventive Veterinary Medicine, 210, 105798

Ultralytics, 2021., YOLOv5: A state-of-the-art real-time object detection system. Available at: https://docs.ultralytics.comhttps://docs.ultralytics.com (Accessed: 2 August 2024)

Verdouw, C., Tekinerdogan, B., Beulens, A., Wolfert, S., 2021. Digital twins in smart farming. Agricultural Systems 189, 103046.

Wang, H., Zhang, S., Zhao, S., Wang, Q., Li, D. & Zhao, R., 2022. Real-time detection and tracking of fish abnormal behavior based on improved YOLOV5 and SiamRPN++. Computers and Electronics in Agriculture, 192, 106512

Zhao, S., Zhang, S., Lu, J., Wang, H., Feng, Y., Shi, C., Li, D.& Zhao, R., 2022. A lightweight dead fish detection method based on deformable convolution and YOLOV4. Computers and Electronics in Agriculture 198

Zhou, C., Xu, D., Chen, L., Zhang, S., Sun, C., Yang, X. & Wang, Y., 2019. Evaluation of fish feeding intensity in aquaculture using a convolutional neural network and machine vision. Aquaculture 507, 457–465.

Zhou, X., Boerlage, AS., Bang Jensen, B., Gismervik, K., Oliveira, VHS., Hutchinson, I, Burrell, A., Graham DA., Doidge, C., Kaler, J., van Schaik, G., Siegrist, M. & Bearth, A. 2025. The use of data for health and welfare management of farmed salmons in Norway, Scotland, and Ireland, Preventive Veterinary Medicine 239,106512.

10 Technical notes

Video equipment:
In the IntelliRAS project, we collected video data from a commercial farm environment and used it to train a tracking-by-detection model to estimate the swimming activity of the fish group. We placed cameras above water in two farms (For technical details see "Technical notes"). Video data were collected using Alvium 1800 U-240c RGB cameras above the fish tanks. The cameras were connected to two Jetson Nanos, which in turn stream the video forward to an Intel NUC mini-pc over a PoE ethernet cable located near the fish tanks. From the mini-pc, the video files were continuously uploaded to a cloud storage.

The collected data was further annotated, and the resulting dataset consisting of 2654 images was used to train a YOLOv5 (Ultralytics, 2021) model, a fast and lightweight neural network, to detect fish heads, in addition to detecting dead and injured fish. The images were annotated by three different people. The annotators worked independently during the months, while following a short guidebook containing visual examples of the classes. The guide was written by one annotator, who started the annotation work earlier than the rest. All the annotators used the open source MakeSense online annotation tool in their work. The work consisted of drawing rectangular bounding boxes over the fish heads, aiming to mark all or most of the fish in the image. Other classes than "fish" were marked by drawing the rectangle over the whole fish; floating, injured and dead (figure 6). In practice finding all the fish individuals reliably is a challenging task due to lighting conditions and high animal density in the tank. Improving the image quality made the annotation work easier, as the details help in distinguishing the fish from each other in crowded scenes. The work resulted a total of 2654 annotated images and 39020 annotated bounding boxes.

By annotating the fish heads instead of the whole fish, the resulting bounding boxes are less affected by fish orientation and camera perspective, compared to annotating the whole animal. The model was trained on a NVIDIA Tesla v100 GPU. We noticed that the choice of hyperparameters, model and image size had a large impact on the results and decided to use a medium-sized model and a largish image size of 1280 for the training. In addition, we saw that heavy use of different augmentation strategies improved model accuracy on test data. On farm 1, were able to reach an F1 score of 0.85 on detecting fish heads. For farm 1, the F1 score was slightly lower at 0.77. This is likely due to data from farm 2 having lower quality images, annotations, and a smaller number of training images in total.

Despite having a shared guidebook for all the annotators, we noticed that the resulting annotator agreement was quite low. Differences in the number of annotations and the size of the bounding boxes between annotators were substantial, and improving the quality of the dataset by increasing the size of the bounding boxes and discarding images with many missing annotations improved the performance of the model trained on the improved dataset.

A clear criterion for the annotations is needed for the model to be able to find a consistent solution, especially if there are multiple annotators working together on a dataset. For example: If only a part of the fish is visible, is it marked on the image. What is the difference between "weak" and "normal" feeding activity in terms of amount of water disturbance on the surface? What are the criteria for a floating fish close to the surface, if there are strong reflections and it is difficult to determine if the fish is above or below the surface Outsourcing annotation work is popular, but in this case annotation quality should be very closely monitored. Inconsistencies in annotations, whether it's in choice of class or placement or size of the bounding box will cause unnecessary noise in the input for the model, resulting in a worse performance.

In the training data, the number of dead and injured fish was low. Dead fish are visually easier to recognize and easier for the model to learn, so despite having few training examples we were able to detect dead fish quite accurately, with an F1 score of 0.80. Detecting injured fish is harder both visually and due to having only a handful of examples for training, resulting in an F1 score of 0.71. The examples of the injuries in the training data contained only tail injuries from one farm, and for achieving a more robust model to work across farms more data from different settings would be beneficial.

Audio data:
As part of the IntelliRAS project, a fish feeding intensity assessment model based on audio data was employed in an industrial, intensive recirculating aquaculture facility. The feasibility of the method was assessed for industrial applications and challenges of the method were identified.

Hydrophone recordings obtained outside of the IntelliRAS-project by project partner OxyGuard International A/S, were used for the analyses described here. Two days of recordings were made in an intensive recirculating aquaculture fish tank with a Bruel & Kjar miniature hydrophone of type 8103, with a sampling rate of 192 kHz and with different placement depths of the hydrophone (7 cm, 28 cm and 42 cm below the surface). The hydrophone was submerged in a pre-grow out, high population density fish tank, containing around 31700 juvenile salmon (smolt), at around 285 grams each. The fish feeding regime for each day began at midnight, with feed being dispensed for around two seconds every 53-54 seconds, until the feed ration for the day (around 1.2% of fish biomass) was exhausted, sometime in the afternoon. This feeding regime enabled automatic labeling of fish feeding intensity by the time after beginning of feed dispensing, with the reasoning that feeding activity will naturally decrease as the feed gets eaten up and less feed thereby is available.

An initial analysis was performed on audio recordings from the fish tank, in which fish feeding sounds were manually identified, as well as feed dispensing, splashing and sounds of fish bumping into the hydrophone. Furthermore, machine noises were heard, and to a smaller degree surface sounds as well. Using Fourier analysis, the frequency band of fish feeding sounds were identified to be in the range of 2-10 kHz, peaking at around 2.5 kHz, which is a bit lower than other studies, which have found the frequency band associated with salmon feeding sounds to be 6.5-9.4 kHz (Helberg et al., 2024).

For fish feeding intensity assessment, the hydrophone recordings were partitioned into two second segments of three categories: 4, 6 and 10 seconds after beginning of feed dispensing. The audio clips were resampled to 43.52 kHz and melspectrograms were formed, with 64 mel bins within the frequencies 1.024- 16.384 kHz, a Hann window with length 1024 and hop length 512 and with 1024 fast Fourier transforms. SpecMix (Kim et al., 2021) data augmentation was applied to the melspectrograms, which were fed to a CNN autoencoder-classifier model with 3 layers in the encoder and in the decoder, and with a latent dimension of 128.

The model was trained for 4000 epochs, with a learning rate of 1e-3, on a training set consisting of 2551 training samples, with a validation set of 1275 samples, and tested on the test set consisting of 1280 samples. Testing showed an accuracy of 75 % and F-1 score of 75 %, with the best performances on the classes 4 s and 10 s of accuracy 83 % and 88 %, and F-1 score 79 % and 82 %, respectively, while for class 6 s accuracy of 53 % and F-1 score 60 % were displayed. These results seem promising for future implementation of fish feeding intensity assessment in intensive RAS facilities, although more work is needed in order to generalize the model between facilities.

Health and well-being
for animals and people

Norwegian
Veterinary Institute

Ås ▪ Sandnes ▪ Bergen ▪ Trondheim ▪ Harstad ▪ Tromsø

postmottak@vetinst.no
vetinst.no