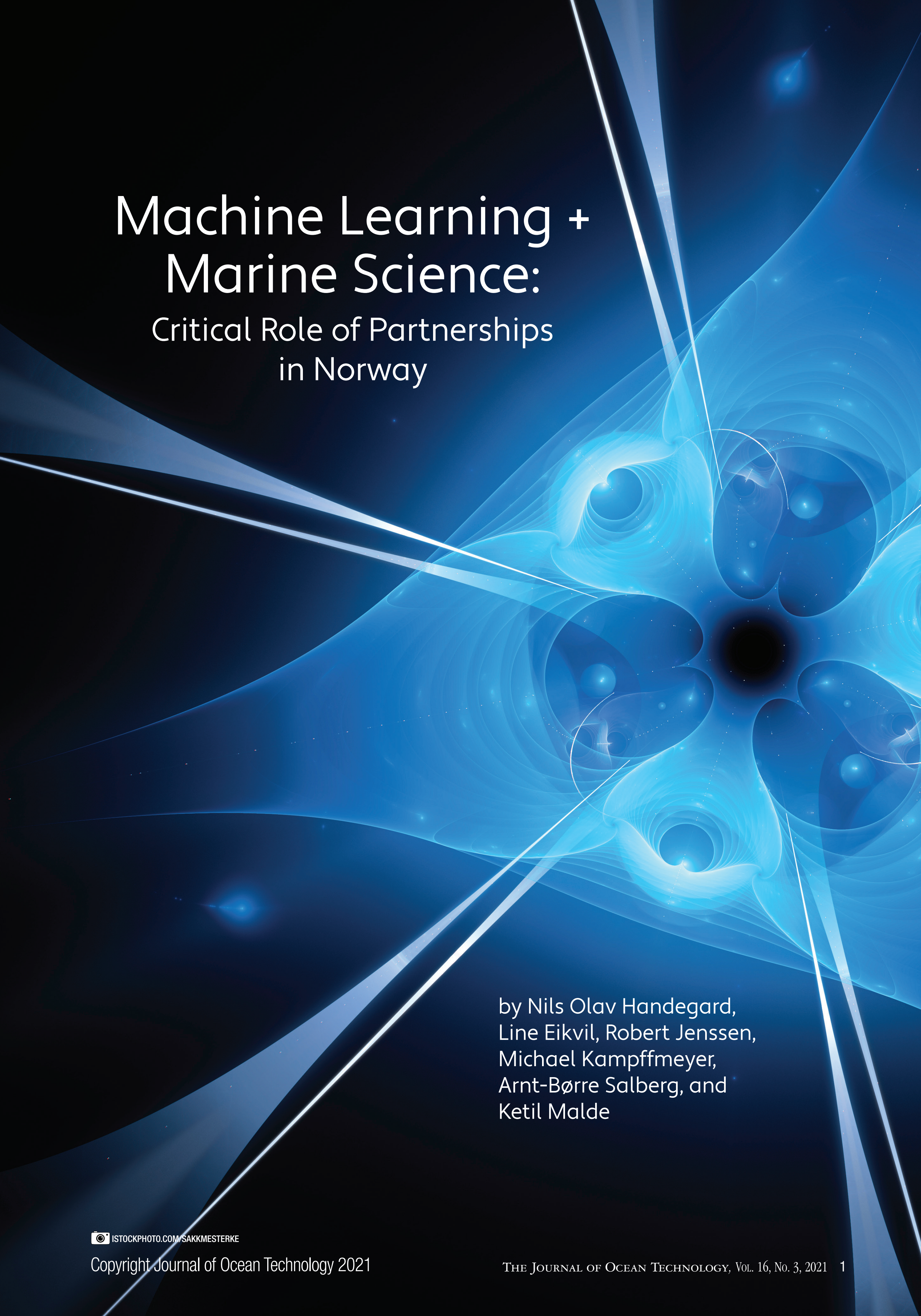

Machine Learning + Marine Science:

Critical Role of Partnerships in Norway

by Nils Olav Handegard, Line Eikvil, Robert Jenssen, Michael Kampffmeyer, Arnt-Børre Salberg, and Ketil Malde

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In this essay, we review some recent advances in developing machine learning (ML) methods for marine science applications in Norway. We focus mostly on deep learning (DL) methods and review the challenges we have faced in the process, including data preparation, (lack of) labelled training data, and interpretability. We also present the partnerships that have been formed between e-science institutions and marine science institutions in Norway. These partnerships have been instrumental in moving this effort forward and have been fuelled by grants from the Norwegian Research Council. The last addition to this collaboration is the recent centres for research-based innovation in Marine Acoustic Abundance Estimation and Backscatter Classification (CRIMAC) and Visual Intelligence (VI).

An Ocean of Data

Extensive data collection forms the basis for managing the human pressures on the marine ecosystem, and new platforms and new sensors are emerging and are being deployed that augment existing monitoring programs. However, turning data into knowledge is challenging, and the process often includes manual or semi-manual steps. This is time-consuming, and automated processing is necessary for scaling up the monitoring programs.

The traditional approach in automating processing pipelines involved a lot of trial and error; often using a range of different methods, algorithms, and software. As the manual processing steps often rely on tacit expert knowledge, developing a precise specification necessary for automating them can be difficult. Also, the resulting code can be difficult to maintain, since it requires the maintainer to have both programming skills as well as specialist domain knowledge.

To be able to realistically handle the data from the sensors and provide input to the subsequent steps in the processing pipelines, a more flexible approach that can be applied to a wider range of problems is needed.

Figure 1A: Automatic interpretation of Greenland Halibut otoliths using deep learning. Example image of an otolith.

Machine Learning

ML are algorithms that learn from data. Conventional ML methods have a long history, but over the last decade DL models have gained a lot of attention since they can extract information directly from the raw data. When adequate training data are available, supervised DL methods have been successfully applied to a large variety of tasks.

An appealing aspect of these supervised methods is that they can be trained end-to-end, learning both the representation (features) and the output (prediction). With enough training data, they can use raw acoustic or image data as input and provide predictions. Although the network architecture will be task dependent, off-the-shelf (pretrained) models are often repurposed for new tasks, accelerating the development. With rudimentary programming skills, it is possible

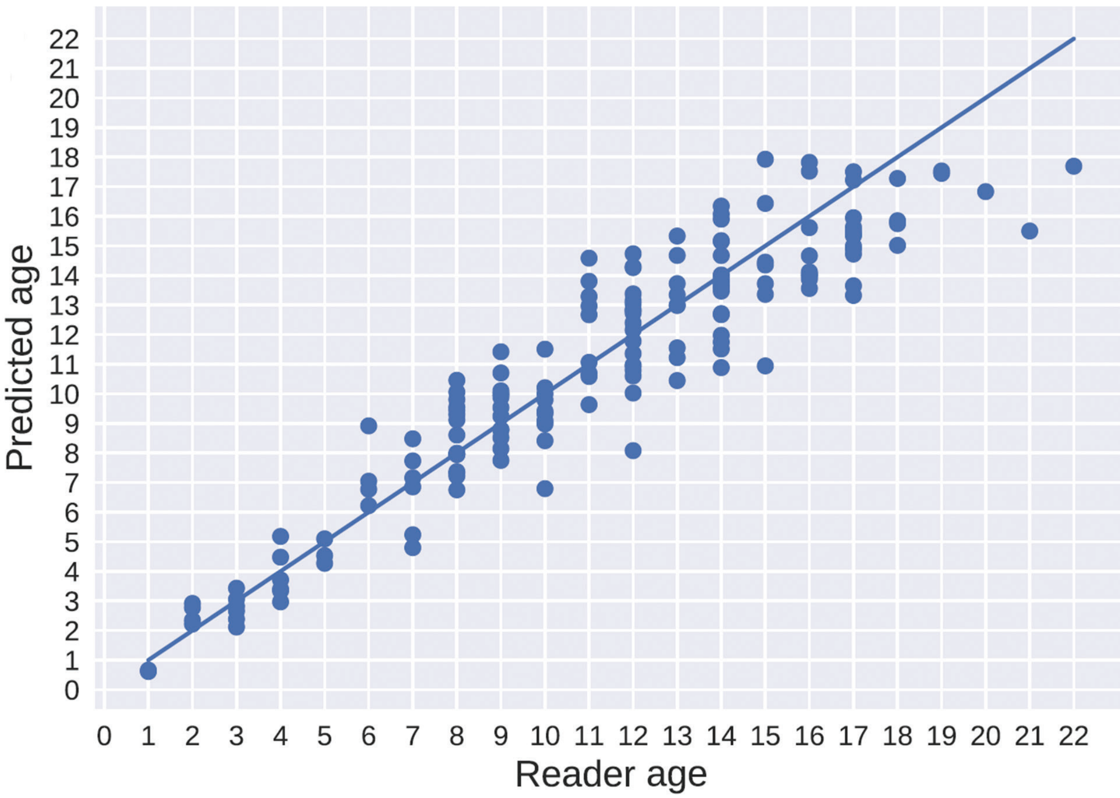

Figure 1B: Comparison between manually age reading and the algorithm.

to train a model to perform standard tasks like recognizing hand-written numbers from images (such as the MNIST dataset example).

Applications

Image and video data are extensively used in marine science applications, and the data are typically manually processed. Images and videos from benthic habitats, fish behaviour, in-trawl cameras, otoliths, or scales for fish aging are examples where cameras are used for data collection. These cases are good candidates for DL, and we have successfully trained convolutional neural networks (CNNs) to predict age from fish scales and otolith images (Figure 1A,B) and predict species and fish counts from in-trawl camera systems (Figure 2).

Acoustic surveys are used to aid fisheries assessments, and the Institute of Marine Research (IMR) together with the Norwegian Computing Center (NR) published the first DL classifier on multifrequency acoustic data (Figure 3). With the recent introduction of commercially available broadband echo sounders, the more comprehensive echo spectrum of the objects in the water column is available. We are still learning how to utilize the rich detail in these data, and DL methods are currently being explored for this task.

Challenges

Although off-the-shelf models are easily available in open-source libraries for supervised DL, there are still several challenges that make the transition to modern data processing methods challenging.

Data availability, data organization, and data versioning are major bottlenecks. Data have traditionally been collected and organized manually, leading to inconsistencies in

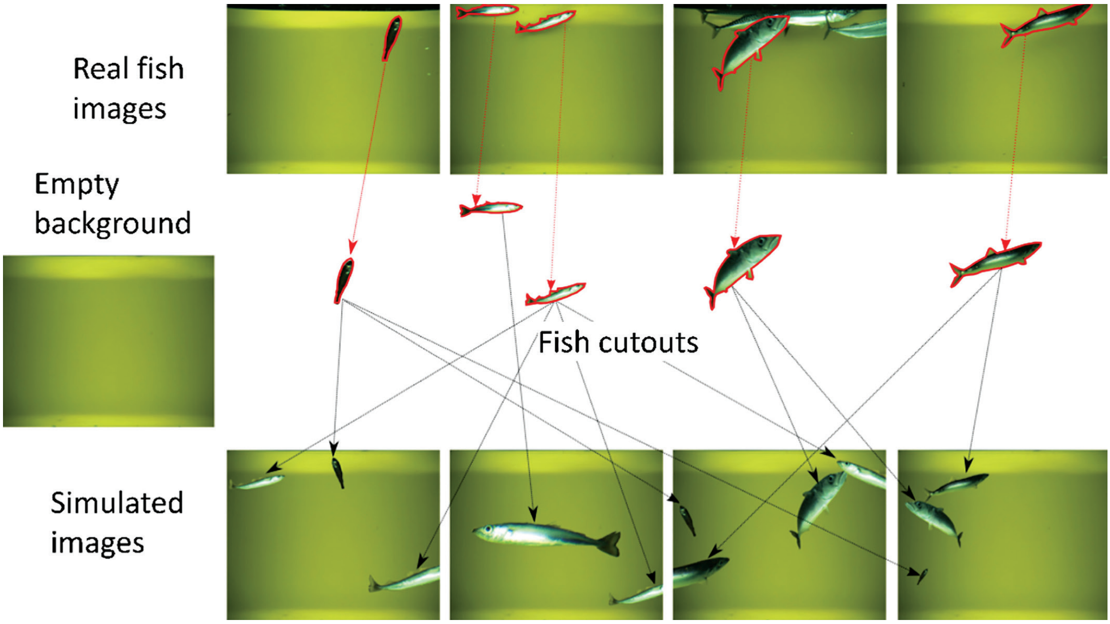

Figure 2: Images from an in-trawl camera system (Deep Vision). A deep convolutional neural network (CNN) (Inception 3) was trained to identify the species. To address the lack of training data, the method was trained on simulated images and validated on real data.

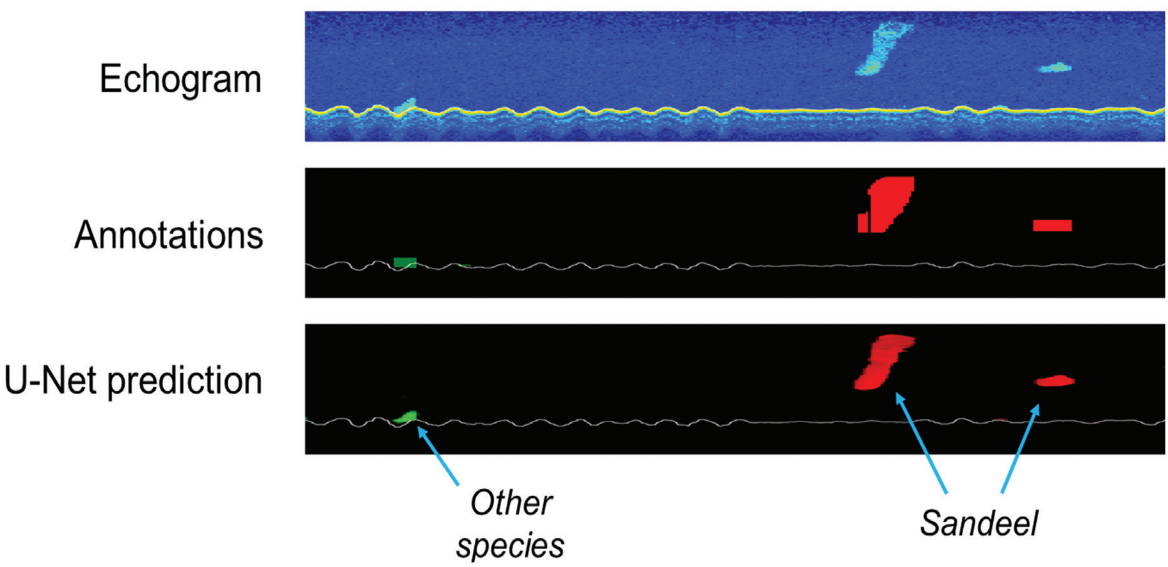

Figure 3: Acoustic target classification using a deep convolutional neural network (CNN). A U-Net algorithm was used for semantic segmentation of the echogram (pixel-wise segmentation).

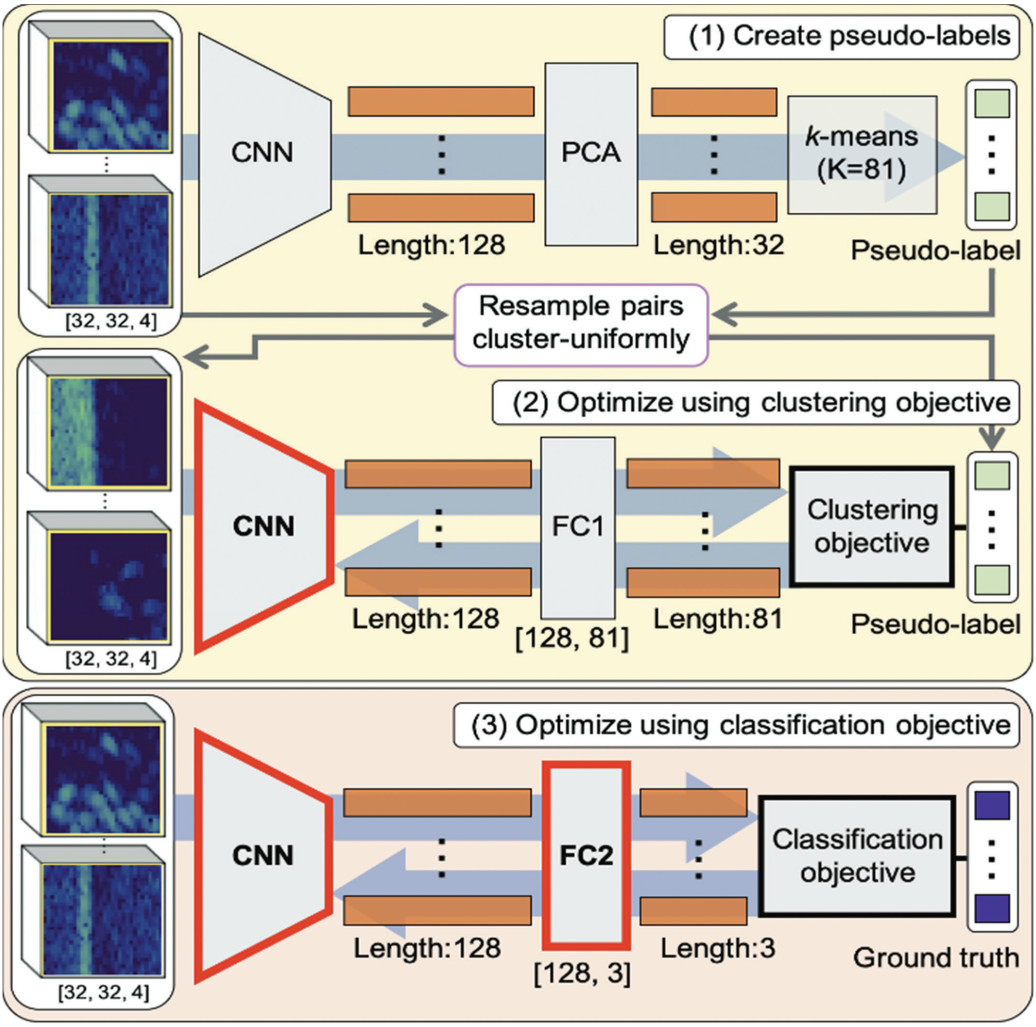

Figure 4: A semi-supervised method used on acoustic multifrequency data. The first step clusters the data without training data and generates "pseudo labels." Pseudo labels are pixels that possess similar properties but lack a "human" interpretation. The second step trains the convolutional neural network (CNN) based on the pseudo labels (red outline denotes training), and the last step includes the actual labelled data for interpreting the labels.

data organization that prevents automation. In addition, labels suitable for supervised training are usually not part of the metadata standards. The solution is to ensure that the necessary data and metadata are available through the data centres, and scripting the process is, in our opinion, the only way to ensure that everything is in place.

Supervised deep learning methods require substantial amounts of annotated training data. In many cases these are not available. Due to the manual labour required or the complexity and the veracity of the data, this is a major bottleneck. This can, to some extent, be mitigated using data augmentation schemes, transfer learning, or simulating data (for example, Figure 2).

Semi-supervised learning is an approach that addresses the lack of annotated data by utilizing the properties in the unlabelled data. The Arctic University of Norway (UiT), together with IMR and NR, used this approach for semi-supervised target classification from multi-frequency echo sounder data (Figure

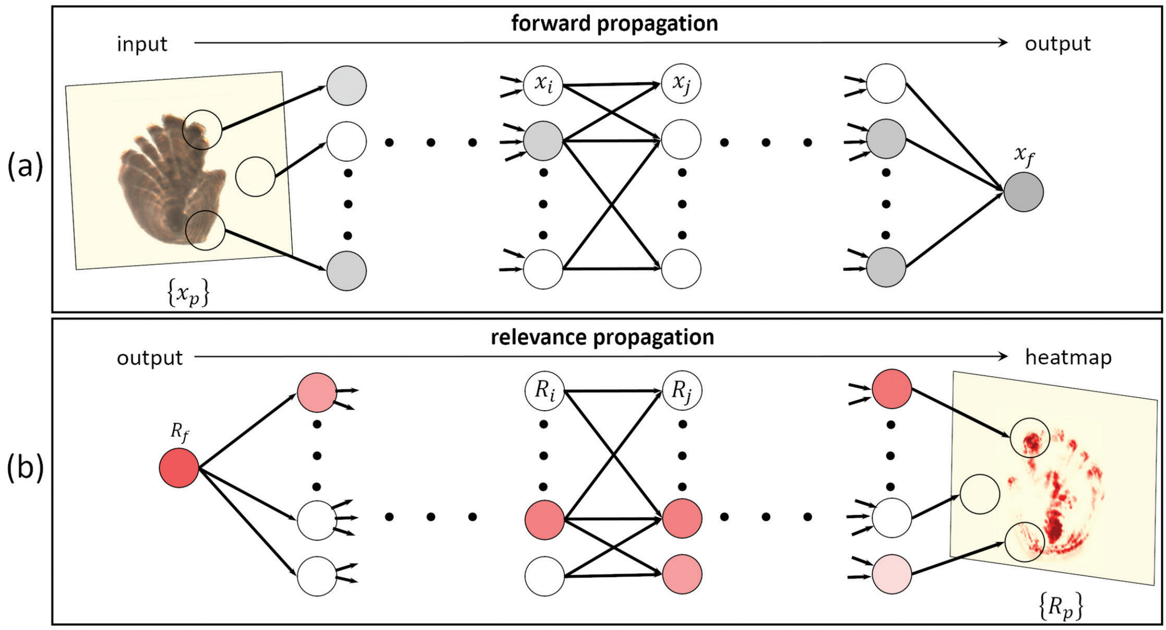

Figure 5: Illustration of the layer-wise relevance propagation (LRP) method. (A) The age (xf) of a fish is predicted using a deep learning model. (B) The relevance propagation phase of all the pixels visualized as a heatmap. The part of the image the model is using for the prediction is highlighted in red.

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4). With only a tenth of the data annotated, the method achieved 67.6% accuracy, outperforming a conventional semi-supervised method by 7.0 percentage points.

Most machine learning algorithms work best when the number of samples in each class are about equal. When the number of samples in each class differs, the training set becomes imbalanced and the network will be biased to the most abundant class. To handle class imbalance, we often modify the cost function and emphasize the samples from the classes with the fewest labels. This can work, but there is a risk that the model is overfitted to those samples.

Weak labels may refer to overall counts of organisms in a video instead of the complete annotations of the organisms within each video frame. Recent DL works on weak-label learning are emerging, e.g., based on label-propagation schemes. These methods are still developing and are lacking for several of our applications.

Deployment and building trust in the models can be challenging. DL models are perceived as black-box models, and several approaches exist that attempt to identify what parts of the data the model uses for its decisions. One method is "layer-wise relevance propagation" (LRP) that can be used to visualize what the model uses (Figure 5). Another approach to build trust is to demonstrate that the results remain the same as the ones obtained with the existing processing pipeline.

Partnerships

Access to personnel with the appropriate skill set is important for developing and implementing machine learning methods. The IMR, NR, and UiT together span this skill set. IMR has a solid base in marine science and marine monitoring programs and has links to international marine science organizations like the International Council for Exploration of the Seas and others. NR has a long record of accomplishment in computational

Figure 6: The Kongsberg Maritime autonomous surface vehicle *Sounder*.

mathematics, including statistical analysis, image analysis, and machine learning. UiT has a group in machine learning with links to international ML communities. In concert, these institutions cover the bases required for developing and implementing ML in marine science. It is also important to note that the ML experts need a rudimentary understanding of the marine science field and that the marine science experts must understand the basics of the ML methods.

Recently, the Research Council of Norway awarded the consortia with two centres on research-based innovation. The Visual Intelligence centre is working on DL methods for complex image data and addresses four research challenges within DL: learning from limited data, exploiting context and dependencies, quantifying uncertainties, and building explainable artificial intelligence (AI). The CRIMAC centre will exploit the data from broadband echo sounders, aided by image data and modern sensor platforms, and has ML as a key component for the data analysis.

Deployment and Further Developments

The marine monitoring programs worldwide are currently undergoing a transformation. Sensors are being deployed on new and more cost-efficient autonomous platforms. This enables the research vessels to focus on more complex tasks but poses challenges in how to control the new platforms and manage their data. Current plans involve modern sensors and platforms for data collection, and platforms include unmanned surface vehicles (Figure 6), autonomous underwater vehicles, gliders, and observatories.

An important part of this transformation is the onboard processing capabilities on the new platforms, where machine learning plays a critical role. The onboard data processing is important for supporting adaptive survey strategies, transfer of processed data to shore-based data centres, in addition to the time saved for manual data processing.

In order to deploy software on a variety of systems and platforms, we use container technology. The container embeds the necessary libraries and supporting software, and frees the user from conflicts between library versions or programming language choice, etc. Typically, several containers are chained together, with the output of one step forwarded as input to the next. A major challenge is to standardize the data models between the processing steps.

The combination of new platforms, sensors, and modern processing methods will support marine management and provide a better basis for understanding our marine ecosystems. The use cases are many, including imaging from drones to count seals and blue mussels, river cameras to monitor salmon runs, benthic images from autonomous underwater vehicles for counting crabs and benthic habitats, unmanned surface vehicles to support the decision phase in fishing operations, and in-trawl camera systems for active selection.

ML methods will be an important and integral part of these systems, and through the VI and CRIMAC centres we will continue to develop these methods.

Dr. Nils Olav Handegard has a PhD in applied mathematics and is leading the CRIMAC centre for research-based innovation. He has been working on sensors to observe behavioural responses in fishes, and how to apply these techniques on the assessment of anthropogenic stressors. More recently he has been working with machine learning and deep learning algorithms, and how these methods can be applied to ecology and fisheries oceanography. Dr. Handegard has leadership experience from international organizations as well the Norwegian Institute for Marine Research, and has been involved in the International Council for Exploration of the Sea (ICES) through a range of working groups, including leading the Fisheries Acoustics Science and Technology group and the steering group overseeing ICES coordinated scientific surveys. He has been part of the science leadership group in the organization and has actively contributed to the ICES strategic plan.

Line Eikvil is the research leader for the image analysis group at the Norwegian Computing Center. She has more than 30 years' experience from contract research in image analysis and machine learning for a wide range of applications, with experience from both research and project management for R&D projects funded by industrial customers and public service organizations. Ms. Eikvil is also co-director of Visual Intelligence, a recently funded centre for research-based innovation on deep learning and AI to extract knowledge from complex image data. Her current research focus within image analysis is on deep learning for applications with complex image data, such as medical images, seismic data, and marine observation data, to solve problems such as learning from limited training data, incorporation of context and prior knowledge, estimation of confidence, and explaining of predictions.

Dr. Robert Jenssen is the director of Visual Intelligence, a centre for research-based innovation funded by the Research Council of Norway and partners from industry and the public sector. He is a professor in the Machine Learning Group at the Arctic University of Norway, as well as an adjunct professor at Copenhagen University and at the Norwegian Computing Center, Oslo, Norway. His research interests include deep learning, kernel machines, graph-based learning, and information theoretic learning. He has had several long-term research stays abroad, at the University of Florida, at the Technical University of Berlin, and at the Technical University of Denmark. He is an associate editor of the journal *Pattern Recognition*. He has served on the IEEE MLSP Technical Committee and on the general board of International Association for *Pattern Recognition*. Dr. Jenssen is general chair of the annual Northern Lights Deep Learning Conference.

Dr. Michael Kampffmeyer is an associate professor at the Machine Learning Group, the Arctic University of Norway (UiT), as well as a senior researcher at the Norwegian Computing Center. He received a PhD from UiT in 2018. His research interests include the development of deep learning algorithms that learn in the presence of limited labelled data and their interpretability. He has had long research stays at the Machine Learning Department at Carnegie Mellon University and the Berlin Center for Machine Learning at the Technical University of Berlin.

Dr. Arnt-Børre Salberg has more than 20 years' experience as a research scientist within data analysis, computer vision, machine learning, and artificial intelligence. He started his career as a PhD scholar at University of Tromsø in 1999 focusing on signal analysis for digital communication. In 2003 he joined the Institute of Marine Research, working on computer vision in underwater images and statistical modelling. Then in 2006 he stepped into the role as chief scientist at tech startup DolphiScan AS, where he had a key role in developing an ultrasound camera. Since 2008 he has been a senior research scientist at Norwegian Computing Center, supporting numerous companies over the years with complex data analysis challenges and research funding. His main focus area today is developing AI-models to perform data analysis within the fields of marine science and Earth observation.

Dr. Ketil Malde has a background in computer science and bioinformatics and has contributed to genomics and population genetics for several important marine species. Recently, his main interest has turned to machine learning. New ecosystem observation platforms and sensors increase the volumes and complexities of data, and he leads the effort at the Norwegian Institute for Marine Research to develop new deep learning models and methods to realize the potential of this data. He helped to initiate and is still a member of the Machine Learning Group at the University of Bergen, where he has developed and taught introductory and advanced courses in machine learning. He is chair of the ICES working group for machine learning in marine science.