ICES Journal of
Marine Science

ICES CIEM International Council for the Exploration of the Sea Conseil International pour l'Exploration de la Mer

ICES Journal of Marine Science (2020), 77(4), 1267–1273. doi:10.1093/icesjms/fsaa084

Introduction to the Themed Section: '*Applications of machine learning and artificial intelligence in marine science*'

Introduction

Setting the stage for the machine intelligence era in marine science

Cigdem Beyan [1*] and Howard I. Browman [2]

[1] *Pattern Analysis and Computer Vision, Istituto Italiano di Tecnologia, Via Enrico Melen 83, Genova 16152, Italy*
[2] *Institute of Marine Research, Ecosystem Acoustics Group, Austevoll Research Station, Sauganeset 16, Storebø N-5392, Norway*

**Corresponding author: tel: +39 346 7664 779; e-mail: cigdem.beyan@iit.it.*

Beyan, C. and Browman, H. I. Setting the stage for the machine intelligence era in marine science. – ICES Journal of Marine Science, 77: 1267–1273.

Received 18 April 2020; revised 18 April 2020; accepted 20 April 2020; advance access publication 18 June 2020.

Machine learning, a subfield of artificial intelligence, offers various methods that can be applied in marine science. It supports data-driven learning, which can result in automated decision making of *de novo* data. It has significant advantages compared with manual analyses that are labour intensive and require considerable time. Machine learning approaches have great potential to improve the quality and extent of marine research by identifying latent patterns and hidden trends, particularly in large datasets that are intractable using other approaches. New sensor technology supports collection of large amounts of data from the marine environment. The rapidly developing machine learning subfield known as deep learning—which applies algorithms (artificial neural networks) inspired by the structure and function of the brain—is able to solve very complex problems by processing big datasets in a short time, sometimes achieving better performance than human experts. Given the opportunities that machine learning can provide, its integration into marine science and marine resource management is inevitable. The purpose of this themed set of articles is to provide as wide a selection as possible of case studies that demonstrate the applications, utility, and promise of machine learning in marine science. We also provide a forward-look by envisioning a marine science of the future into which machine learning has been fully incorporated.

Keywords: analysis of underwater acoustics data, artificial intelligence, computer vision, data processing, deep learning, machine learning, surveillance and inspection of fish catch, underwater image analysis

Background and motivation for this themed article set

Artificial intelligence (AI) is increasingly being applied to all kinds of data. Some applications of AI are face recognition systems, natural language processing (e.g. speech recognition, language understanding, language generation, and language translation), disease detection systems, video surveillance, quality inspection in manufacturing, product design and creation, robotics, and self-driving cars (Dargan *et al.*, 2019). It is accurate to say that AI is now everywhere, from our smartphones, to web-browser, to cars.

Machine learning (ML), which is a subfield of AI, implements dynamic models resulting in data-driven decisions. ML techniques can be applied to high-dimensional (Fan *et al.*, 2009), nonlinear, complex, and big data. Further, the ML approach is effective even in cases where the data are noisy (e.g. Frenay and Verleysen, 2014; Xiao *et al.*, 2015) or some identification labels are missing (McKnight *et al.*, 2007; Aste *et al.*, 2015). ML is also able to address the small sample size problem: so-called zero or few-shot learning (Huo *et al.*, 2019). What makes ML most appealing is its capacity to handle problems that are impossible or too challenging for traditional approaches, which require many people and considerable time and resources to produce the desired accuracy. In other words, ML provides not only effective solutions, robustness, and accuracy but also efficiency as it can rapidly process huge amounts of data.

Deep learning (DL), inspired by the structure and function of the human brain, is a subfield of ML that involves the use of artificial neural networks (ANNs). ANN can take several forms, including recurrent neural networks (Hochreiter and Schmidhuber, 1997) and convolutional neural networks (CNNs) (Krizhevsky *et al.*, 2012). Although ANNs are not new, their wide use only became practical after the development of massively parallel graphical processing units (GPUs). GPUs provide computation power and fast processing so that DL architectures running on GPUs can analyse huge amounts of data quickly and efficiently. In 2012, Krizhevsky *et al.* (2012) proved that CNNs can achieve a high level of accuracy in image classification. The success of CNNs has been extended to other computer vision tasks, for example object localization (Ren *et al.*, 2015; Redmon *et al.*, 2016), semantic segmentation (Long *et al.*, 2015; Badrinarayanan *et al.*, 2017), natural language processing for speech recognition (Hinton *et al.*, 2012), machine translation (Sutskever et al., 2014), optical character recognition (Goodfellow *et al.*, 2014), face recognition and verification (Taigman *et al.*, 2014), object recognition (Xiao *et al.*, 2015), and so forth. All of these will, in due course, be applied to data analysis in many branches of research, including marine science.

Studying and sustainably managing marine ecosystems presents special challenges because they are three dimensional, expansive, very dynamic, and complex. These characteristics require data collection over a wide range of spatiotemporal scales, which has been a major challenge (Godø *et al.*, 2014; Janzen *et al.*, 2019). Rapid progress in sensors, information, and communication technologies now allows marine scientists to collect large volumes of data at ever lower cost.

> "Cruises now regularly return to port with terabytes of data, high temporal resolution coastal time series contain billions of measurements, and water samples are parsed into millions of DNA sequences." (POGO Workshop, 2019)

Moored buoys support long-term monitoring and high resolution measurements of physical, chemical, and biological variables, as well as acoustics, at fixed locations and transmit their data in real-time via satellite uplink or cabled connection to shore (e.g. Aguzzi et al., 2015; Van Engeland *et al.*, 2019). However, they are limited to monitoring depths from the seabed to the ocean surface. Sophisticated and heavily instrumented towed observation platforms, and autonomous drones, are collecting large volumes of data of many types (e.g. De Robertis *et al.*, 2019; Lombard *et al.*, 2019; Verfuss *et al.*, 2019). However, the capacity of human experts to filter, curate, and analyse all of these data is limited. This is where ML and AI will be making greater-and-greater contributions as methods improve and are implemented more broadly.

ML can be applied to automate various routine tasks in marine science. The prediction of ocean weather, for example detecting sea surface temperature (Tanaka *et al.*, 2004; Wu *et al.*, 2006), habitat modelling (Krasnopolsky, 2009; Thessen, 2016), modelling monsoons (Cavazos *et al.*, 2002), forecasting sea level fluctuations (Makarynskyy *et al.*, 2004), wind and wave modelling (Forget *et al.*, 2015; James *et al.*, 2018), and the detection of acute situations, for example oil spill and other point sources of pollution (Kubat *et al.*, 1998) are just some of the applications. Continuous underwater video and acoustic surveillance systems are rapidly developing tools to monitor marine life while computer vision and ML techniques contribute by automatically analysing the massive data streams from these platforms (e.g. Fisher *et al.*, 2016). These data can already be used to extract higher-level interpretations by automatically detecting and tracking fish underwater (Spampinato *et al.*, 2008), identifying fish species (Joly *et al.*, 2015; Siddiqui *et al.*, 2018; Villon *et al.*, 2018; Allken *et al.*, 2019), and estimating swimming trajectories and speeds (Beyan *et al.*, 2018). Eventually, it will be possible to use time series of these data streams to assess changes in species abundance and distribution, environmental change, predator–prey relationships, and more (Fisher *et al.*, 2016). Baited cameras and camera traps allow data to be collected without disturbing animals, which produces high volumes of images that can be analysed by using DL techniques (e.g. Tabak *et al.*, 2019). There is also great potential to apply DL to automatic fish identification, counting, and sizing on fishing vessels (e.g. Bartholomew *et al.*, 2018).

In this context, the objective of this themed set of articles was to bring together contributions on the broad theme of the applications of AI, ML, DL, and advanced data systems (e.g. block chains) to research, monitoring and management of marine organisms and ecosystems. We sought contributions on the following topics, among others,

- Automatic marine ecosystem monitoring based on visual and/or acoustic data;
- Automatic fish detection;
- Automatic coral reef state detection (e.g. health, dead/alive);
- Underwater measurement of fish length;
- Automatic fish counting, for example to analyse the effect of global warming;
- Automatic fish tracking (e.g. swimming speeds and trajectories);
- Automatic fish species classification/recognition/identification;
- Characterizing interactions between fish (e.g. predator–prey relationships);
- Fine-grained automatic object recognition in underwater visual data (e.g. substrate classification, plankton);
- Applications of block chain technology/systems;
- Automatic detection/classification of acoustics produced by marine animals (e.g. whales, dolphins, and fish); and
- Automatic systems for fisheries management.

We received 30 submissions in response to the call for papers. The 15 that made it through the peer review process are described below. The articles that appear in this themed set, and the many relevant articles that they cite, demonstrate that AI is already a very helpful tool in a wide variety of applications in marine science.

The articles in this theme set

With the exception of Semmar and Vaz-dos-Santos (2019), Liu *et al.* (2020), and Proud *et al.* (2020), all of the articles present methods based on DL (mainly CNNs), or at least mention the advances in DL and its great potential. The articles can be categorized in terms of (i) the environment that has been examined, that is unconstrained underwater (Mahmood *et al.*, 2019; Salman *et al.*, 2019), observing fish catch on fishing trawlers (French *et al.*, 2019; Garcia *et al.*, 2019; Tseng and Kuo, 2020), fishing vessels (e.g. Lu *et al.*, 2019), and fish caught in a box (Álvarez-Ellacuría *et al.*, 2019); (ii) the type of marine organisms investigated, that is fish (Álvarez-Ellacuría *et al.*, 2019; French *et al.*, 2019; Lu *et al.*, 2019; Malde *et al.*, 2019; Probst, 2019; Salman *et al.*, 2019; Brautaset *et al.*, 2020), lobster (Mahmood *et al.*, 2019), and plankton (Li *et al.*, 2019; Campbell *et al.*, 2020); (iii) the type of data used, that is images (Álvarez-Ellacuría *et al.*, 2019; French *et al.*, 2019; Garcia *et al.*, 2019; Lu *et al.*, 2019; Mahmood *et al.*, 2019; Malde *et al.*, 2019; Salman *et al.*, 2019; Campbell *et al.* 2020; Lu *et al.*, 2020; Tseng and Kuo, 2020) and video or audio (Brautaset et al., 2020; Proud *et al.*, 2020). These articles are summarized below.

Malde *et al.* (2019) review recent developments in ML, mainly DL, and stress the opportunities and challenges associated with integration of DL into marine science. Probst (2019) focuses on how blockchains, data mining and AI can improve trust between producers, wholesalers, retailers, consumers, management authorities, and scientists by increasing transparency and availability of information throughout the supply chain. It is claimed that these digital technologies can make the flow of money associated with the global stream of seafood products more visible and transparent.

Salman *et al.* (2019) propose a method that relies on region-based deep CNNs to detect freely moving fish in unconstrained underwater environments. Motion images obtained by applying Gaussian Mixture Models (Stauffer and Grimson, 1999; Zivkovic and Heijden, 2006) and the optical flow method (Beauchemin and Barron, 1995) are combined with raw greyscale video images. The resulting three-channel image is input to a CNN model, which detects fish. The proposed method was tested on two datasets composed of 42 493 and 1328 labelled fish and produced a state-of-the-art performance for underwater fish detection. The experimental analysis was performed on videos that included several real-world challenges such as blurred images, complex and dynamic backgrounds, crowded scenes, and luminosity changes. Mahmood *et al.* (2019) also focus on automatic underwater image analysis, although the focal species was western rock lobster (*Panulirus cygnus*). The method proposed by Mahmood *et al.* (2019) is also based on DL. The authors note that detection of the rock lobster faces the challenge of having little annotated data available. To handle this, a synthetic dataset was generated that was used to fine-tune the state-of-the-art object detector, YOLOv3 (Redmon and Farhadi, 2018), for detection of rock lobster. Unusually, the individual body parts rather than the whole animal were synthesized. YOLOv3 was trained using the synthetic data only and the resulting model was tested on real-world images. This training scheme showed significantly improved results compared with using real-world images in training and testing. Mahmood et al. (2019) highlight the fact that, for many marine animals, the amount of labelled data is still limited. Despite that, they demonstrate that DL technology can be effective even when the amount of data available is limited.

Lu *et al.* (2019) propose a method that models the images of fish on the decks of fishing vessels to identify them to species. The species included in their study were albacore (*Thunnus alalunga*), bigeye tuna (*Thunnus obesus*), yellowfin tuna (*Thunnus albacares*), blue marlin (*Makaira nigricans*), Indo-pacific sailfish (*Istiophorus platypterus*), and swordfish (*Xiphias gladius*). A pre-trained VGG-16 model (Simonyan and Zisserman, 2015) was fine-tuned for fish species identification and showed a high overall accuracy. Besides the quantitative results, the image regions detected as informative for the classification task were also characterized. Performing such qualitative analysis is important because it provides an explanation and interpretation of the function of the trained CNN model. Another DL-based method applied to fish catches, with the aim of measuring fish length automatically, is presented by Álvarez-Ellacuría *et al.* (2019). Conventionally, fish lengths have been manually calculated for a small number of randomly selected fish. The method proposed by these authors first applies Mask R-CNN (He *et al.*, 2017) to the images of European hake (*Merluccius merluccius*) displayed in boxes (containers used at points of sale holding many fish inside) to segment the fish heads. Image segmentation is the process of partitioning an image into multiple segments (e.g. image objects) that are composed of sets of pixels. A statistical model is then used to estimate the total fish length from the length of the segmented fish heads.

French *et al.* (2019) developed a computer vision system designed to monitor and quantify the fish that are discarded on fishing trawlers. The system is accurate and robust even when the orientation of the fish is variable, when there are occlusions among fish and when there are occlusions in the working area (e.g. from fishers processing the catch). The instance segmentation (the task of detecting and delineating each distinct object of interest in an image) component is based on separate Mask R-CNN models (He *et al.*, 2017), a different one for each conveyor belt. The segmented fish are passed to a CNN-based species classifier. The system was evaluated in four different settings: (i) using only the research samples composed of a large number of training samples, uniform lighting, uniform appearance, and less occlusions. This setting provides an upper bound for the performance of the system; (ii) using only the commercial samples such that training and testing samples are considerably fewer but the conditions are more challenging than the previous scenario, that is resulting in worse performance; (iii) applying leave-one-belt-out cross validation such that training was applied on samples from some commercial belts and the research samples, whereas testing was performed using samples from a never seen commercial belt. This is the case that is closest to the real-world scenario; and (iv) training on research samples and testing on commercial samples. This is the most challenging scenario for a classifier because of the domain gap (the situation that arises when the data distribution across different domains are dissimilar). However, it is also the most ideal scenario to prepare training data because little effort is required for annotation. Additionally, a comparison between the species identification component and human experts was conducted. Human experts achieved a mean class accuracy of 74–86%, whereas the DL classifier achieved ∼58%, which is slightly better than the poorest human expert.

Garcia *et al.* (2019) also present a method to perform automatic fish segmentation and fish size measurement, although they use stereo images acquired using an imaging system placed in the trawl. Assuming that stereo imaging can increase the robustness and accuracy of fish length measurements (French *et al.*, 2019), a Mask R-CNN model (He *et al.*, 2017) is used to localize and segment individual fish in an image. Unlike French *et al.* (2019), the proposed pipeline applies a preprocessing step, which tries to reduce domain gaps that might arise from, for example those resulting from variability in the background illumination and differences in appearance of the fish in different datasets. Additionally, a post-processing step, which performs a gradient-based boundary estimation given the Mask R-CNN's results as the inputs, is applied to provide more accurate boundaries. The proposed fish localization pipeline performs well even in highly cluttered images containing overlapping fish.

Tseng and Kuo (2020) propose an approach for pre-screening harvested fish in videos from electronic monitoring systems (EMS). Using a Mask R-CNN model (He *et al.*, 2017), the harvested fish in the frames of the EMS videos are segmented from the background. The fish are counted using time thresholding (to remove false-positive detections) and distance thresholding (if the distance is less than a threshold the candidate fish identified are considered the same in order to avoid recounting the same fish in sequential frames). Subsequently, the types and body lengths of the fish are determined using the Mask R-CNN model's confidence score. The videos were acquired under uncontrolled weather conditions (e.g. sunny days, rainy days, and dark nights). A total of 500 videos were used for training and validation of the Mask R-CNN model (He *et al.*, 2017) for fish detection and segmentation. The remaining 200 videos were used for assessing the proposed fish counting method. The trained Mask R-CNN model resulted in a recall of 97.58% and a mean average precision of 93.51% for fish detection. For fish counting, a recall of 93.84% and a precision of 77.31% were obtained. Additionally, for fish type identification, an overall accuracy of 98.06% was obtained.

Proud *et al.* (2020) apply an automated method to identify echoes from Dagaa schools (*Rastrineobola argentea*) in echo sounder data collected during fish stock-assessment surveys in Lake Victoria. Only the acoustic data collected between sunrise and sunset were analysed. A random forest (RF) classifier was constructed using school and environment metrics [i.e. length of school, depth of school, height of school, image compactness, the average amount of echo energy produced by the school per m^2 of lake surface (nautical area scattering coefficient (NASC)), lakebed depth, temperature, dissolved oxygen concentration, pH, turbidity, Chla concentration, and longitude]. This classifier showed a test classification accuracy of 85.4%. Evaluating the importance of each school metric showed that school length is the most important metric, followed by school height, school NASC, school depth, lakebed depth, and school image compactness. Environmental variables other than lake depth contribute very little to the overall classification performance and when all environmental information is removed, the overall RF accuracy is reduced by only ∼1%.

For segmenting and classifying echo sounder data collected during acoustic trawl surveys, a DL-based method is presented by Brautaset et al. (2020). A slightly modified version of the U-Net architecture (Ronneberger *et al.*, 2015) is used as the classifier, which takes four frequency channels and a range-time subset of the echogram in the image format, resulting in the following classes: background, sandeel school, or other schools. The proposed method achieved significantly better results compared with non-DL methods when applied to a multifrequency dataset collected between 2007 and 2018 during the Norwegian sandeel survey.

Semmar and Vaz-dos-Santos (2019) present a simplex-based simulation approach developed to investigate growth regulation processes in fish populations, which was applied to *Merluccius hubbsi* stocks in the Southwestern Atlantic sampled in 1968–1972 and 2004 from six geographical areas. Using this approach, the authors were able to show that the growth regulation of different body parts is related to the geographic origin of the fish. Liu *et al.* (2020) compared the performance of ensemble learning models—bagging trees (Johnson, 2001), RFs (Breiman, 2001), and boosting trees—using a dataset of 256 records of *Chondrichthyes* and *Osteichthyes* to predict fish natural mortality rate. The maximum age, growth coefficient, and asymptotic length were used as the features. The results show that tree-based ensemble learning models significantly improve the accuracy of fish natural mortality rate estimates compared with statistical regression models as well as the basic regression tree model (Breiman *et al.*, 1984). Among tested ensemble learning models, boosting trees and RFs performed the best, whereas the classification performance of boosting trees was slightly better.

Li et al. (2020) report on a publicly available dataset, PMID2019, containing 10 819 microscopic images of phytoplankton from 24 different categories. PMID2019 includes high resolution colour images with instance level annotations (manually labelled bounding boxes and corresponding species in each image) that can be used for phytoplankton detection. In order to generalize the dataset, Cycle-GAN (Zhu *et al.*, 2017) was applied to differentiate between images of dead and living cells so that images of dead and living cells can be inter-converted without losing their original features. This resulted in a synthetic phytoplankton living cell image dataset created from the original dead cell images that could be applied to detect phytoplankton *in situ*. PMID2019 was benchmarked by applying several state-of-the-art object detection algorithms: faster R-CNN (Ren *et al.*, 2015), feature pyramid network (Lin *et al.*, 2017a), single shot multiBox detector (Liu *et al.*, 2016), YOLOv3 (Redmon and Farhadi, 2018), and RetinaNet (Lin *et al.*, 2017b). Fast R-CNN produced the best results: average precision between 70.27 and 96.30% for different scenarios (e.g. various lighting conditions and complex background).

Campbell *et al.* (2020) present a novel plankton camera and propose a CNN-based classification system that was applied to the images collected. The plankton camera includes a 0.137 mm × 143 mm telecentric lens mounted on a 12-MP colour camera inside a large pressure housing with a sapphire glass optical port. The camera takes 12-bit colour images at a maximum frame rate of seven frames per second. This imager also incorporates an on-board computer system to segment each image and retain regions of interest that contain images of individual plankton using various image processing algorithms. The CNN architecture fine-tuned to classify the collected images was "Inception v3" (Szegedy et al., 2015). The training set was composed of 18 868 images of 43 separate classes. Classification performance obtained on test data varied among the different classes.

ML and the future of marine science

The articles included in this themed set, and those that they cite make clear that there is great potential for ML to contribute to rapid advances in marine science. DL has already supported impressive advances by changing the way that experts analyse and interpret data, as well as in the amount of data that can be processed rapidly. However, the volume of data produced in marine science continues to increase and this introduces new challenges. Possible solutions follow.

- ML has to be more fully integrated, not only in processing marine data but also in the collection and management of data and, therefore, ML scientists should collaborate more closely with marine scientists in data collection and infrastructure design.

- Communication between ML experts and marine scientists should be improved such that both sides become aware of the range of potential applications. There should be constant engagement between ML experts and marine biologists. ML experts should meet with stakeholders to develop and ensure a mutual understanding regarding the challenges of data analysis. On the other hand, marine experts should try to gain ML knowledge to better understand the potential and limitations of ML methods. This would serve to better define the desired accuracy of any ML pipeline.
- The transparency and intuitiveness of ML methods should be improved so that ML is more than a black box for marine scientists.
- Preserving and sharing ML knowledge and expertise within the marine science community: the size of marine data is huge, however, the size of data used to evaluate ML methods is generally very limited. This is because datasets contain an insufficient amount of labelled data. One solution could be establishing a common online repository in which researchers can share their data as well as their trained models and ML codes that would be aligned with their data.

We encourage submissions to this Journal that follow-up on these and related topics.

Acknowledgements

We are grateful to the authors for their enthusiasm and engagement in this initiative.

Funding

HIB's contribution to this article themed set was supported by Project # 83741 (Scientific publishing and editing) from the Institute of Marine Research, Norway.

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