Bipolar contrast in phytoplankton size structure revealed from deep learning

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Area being submitted to: *3. Artificial Intelligence;*

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Abstract

Phytoplankton size plays an important role in regulating primary production, carbon cycling, and sustaining upper trophic levels in the global ocean. However, it is still under debate how phytoplankton size structure is affected by environmental factors such as temperature (Marañón et al. 2012, 2015; López-Urrutia et al. 2015). While Ward (2015) suggested that the temperature effect was only pronounced in polar waters, a number of studies showed that small phytoplankton dominated in Arctic waters (e.g., Zhang et al. 2015). In addition, although size fractionation of chlorophyll *a* is one of the most widely used method to quantify phytoplankton size structure due to its ease of sampling, we still lack a global dataset and associated statistical model to predict global phytoplankton size structure based on these measurements.

Here we assembled the largest ever dataset on size-fractionated chlorophyll *a* measurements in the global ocean and analyzed the relationships between multiple environmental factors, including temperature, nitrate, mixed layer depth, dissolved iron etc., and phytoplankton size using a deep-learning algorithm by taking advantage of the *keras* package in the R programming environment. Our results suggest that at the same temperature, the fraction of small phytoplankton increases significantly with ambient nitrate concentration. Our work contributes to solving the long-lasting debate in phytoplankton ecology as to how temperature affects phytoplankton size and highlight the difference in phytoplankton size structure between Arctic and Antarctica waters due to contrasting nutrient supply.

Acknowledgements

We thank E. Marañón for sharing his data and the Leverhulme Trust Research Project Grant (RPG-2020-389) for financial support.

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Simple and accessible machine learning for automatic classification of broad-benthic habitats

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Identification of benthic habitats from imagery is fundamental to marine spatial planning. Automation through Machine Learning, particularly transfer learning, has proved to be a powerful way to overcome time and resource limitations. Here, pre-trained and general convolutional neural networks (CNNs) are used with an additional domain-specific tuning step. However, these techniques are complex. They are often left inaccessible to a non-specialist, as they require large investments in time (for comprehension by the user and for training) and computational resources.

We demonstrate that we can use transfer learning, for classifying benthic habitats, in a much simpler framework. Specifically, we take an 'off-the-shelf' CNN (VGG16) (Simonyan & Zisserman, 2015) and use it to extract features from benthic images (without further training) (Razavian et al,. 2014, Yosinski et al., 2014). The default outputs of VGG16 are then fed in to a Support Vector Machine (SVM), a classical and simpler method than deep nets. We explore the discriminative power of our VGG16+SVM classifier on three benthic datasets (574-8353 images) from Norwegian waters; each using a unique imaging platform. Benthic habitats are broadly classified as soft substrates (sands, muds), hard substrates (gravels, cobbles and boulders) and reef (*Desmophyllum pertusum*). Each dataset was split into 80\% training and 20\% testing and SVM hyperparameters tuned using 5-fold cross validation of the training set. For comparison, we also train the remaining classification layers of VGG16, a more complex approach.

Final training time of the SVM classifier ranged from 0.57-15.6 minutes; around half the time of the CNN classifier (1.7-35.5 minutes). Both approaches performed well, however the simpler of the two (SVM) performed best with test accuracy ranging from 0.86-0.96 (average= 0.9 (±0.05)). Whereas test accuracy with the CNN classifier ranged from 0.82-0.95 (average=0.87 (±0.06). Performance in both cases increased with dataset size. Average recall and precision results were also good across datasets, with 0.82 (±0.09) and 0.87 (±0.08) for the SVM and 0.8 (±0.12) and 0.83 (±0.1) for the CNN, respectively.

This framework is simple, fast and consistent. It's usage is particularly suited for offshore use; offering near real-time decision making, development of sampling protocols, triaging data collection and providing quick, albeit crude, insights into habitat presence. It can also support automation by grouping images into similar categories, for annotation or model selection, and be used to screen old-datasets.

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From data to decisions: innovations to support the Blue Economy Vision

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Area being submitted to: *Artificial Intelligence;* **Preferred presentation medium**: oral

We may have one of the e-poster sessions as part of a wine reception on Tue 8th Nov. Would you be available for this? Yes. **Are you a student?**: No.

At a high level, the Scottish Blue Economy vision, (incorporating the Scottish Aquaculture vision), is an easy sign-up: it is consistent with "A marine environment, which is clean, healthy, safe, productive and biologically diverse, managed to meet the long-term needs of nature and people"(1). Who could argue with that!? Looking in more detail, though, raises issues of scale and perspective; there is a growing awareness to consider the 'system' as a whole: "negative impacts on marine ecosystems [should be] minimized and, where possible, reversed" (2).

Addressing ecosystem-scale questions benefits from ecosystem-scale sampling and that has posed challenges to previous generations of scientists. However, we live in an age where the decreasing cost of getting data is being matched by the amount of data gathered. Whilst generating data from the marine environment is getting easier, interpreting, and acting on those data, remain a challenge, partly because decision making frameworks are variously based on 'previous' technologies.

Two technologies that are revolutionizing the way we assess our environment are DNA-based 'omics' and image analysis. These technologies, which are reliant on machine learning (ML) and artificial intelligence (AI), give insights into assemblage structure and function, covering all organismal scales (viruses to whales), and can be utilized at virtually any scale in any ecosystem. The power of these systems includes their capacity for highly efficient scale-up including robotization in both data acquisition (sampling), sample processing (e.g., wet-lab robots) and number crunching. Machine-based data-crunching (interpretation) offers society a wealth of potential advantages, including consistency, accuracy, speed, and low cost. Within the same budget, data intensity (sampling effort) can increase giving us a much higher resolution, in space and time, at relevant ecosystem scales. Surely, then, we are on the road to delivering the 'vision'?

Possibly, but there is a slightly unnerving aspect to ML and AI– and that is we don't fully understand how they work. Random forests (RF), for example, are an increasingly ubiquitous ML tool utilized to great effect to classify samples (e.g, a sediment is degraded/not-degraded), based on its 'big-data' characteristics which can include thousands of attributes (predictors). Furthermore, the RF algorithm will tell you which of those thousands of predictors are the most important, information that, you'd hope, enables you to interpret the observed data, linking cause and effect. However, even while the RF delivers on predictions, by its very 'random' nature it varies in the identification of those key predictors between iterations with the same data – we know it works, we are less sure how. The RF algorithm is, conceptually, much simpler than the convolutional neural nets (CNNs) that underpin many of the best computer vision algorithms. CNN training involves the machine creating a complex architecture of millions of inter-connected 'neurons', and the setting of billions of parameters ('axons') connecting them all; again, the output is often remarkable, but we don't understand the detail of how a particular machine (algorithm) works. Assigning confidence in our ML/AI predictions is also quite a different process when compared to model-based predictions (e.g. around linear-regression).

Does this matter? I'm not sure, after all, I don't know how my phone works, let alone my own eyes and I still make decisions based on what I hear and see. If we do accept machines into data generation and interpretation, we are faced with the next challenge, which is societal and cultural as much as scientific. As our capacity to monitor impacts is enhanced, we will need to focus more on what it is we want from our ecosystem and how much change or 'damage' we are willing to live with – defining that 'vision' might be more challenging.

Acknowledgments

My thanks to Thorsten Stoeck, John Halpin, Joe Marlow, Shraveena Venkatesh, Victoria Ashley-Wheeler and many more for their thoughtful insights into these concepts.

References

(1) and (2) https://www.gov.scot/publications/blue-economy-vision-scotland/pages/5/ and page 6 respectively.

Smartrawl "Eye": a vision-based technique for fish detection and species identification

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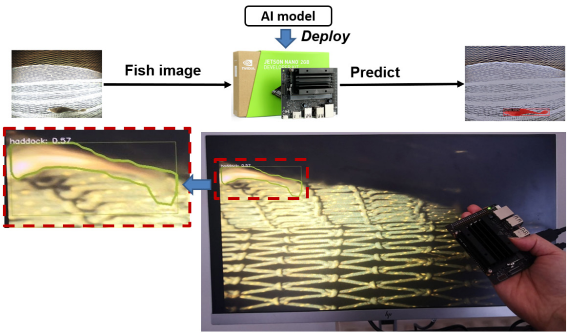
Tweetable abstract

The Smartrawl eye is a vision-based AI technique fitted to fishing trawls, enabling the detection and identification of fish species. Combined with other elements of the Smartrawl, this "eye" can contribute to eliminate discards and bycatch, which are a global problem threatening fisheries sustainability. #MASTSasm2022 @DeweiYi @PaulFer13180972.



Abstract

Two of the leading causes of unsustainable fishing are bycatch and discards (Fernandes *et al.*, 2011), where unwanted marine life and fish, respectively, are caught in commercial fishing trawls and thrown back, dead, to the sea. To help tackle this global issue, we propose a novel vision-based technique to enhance the performance of detecting and identifying fishes prior to capture in the fishing apparatus. In particular, our developed technique can improve both the generalisation ability and stability for detecting fish and identifying their species.

This presentation describes a technological solution for accurate fish detection and species identification, which is a key component of Smartrawl system. That is, the developed technique gives an "eye" to our Smartrawl system[1]. Due to compelling progress in the success of deep learning in computer vision, it is now possible to monitor marine fauna automatically by camera images (Yi *et al.*, 2022). To achieve fish detection and species identification, an advanced object detection and recognition method (Yi *et al.*, 2021) is introduced and developed in our technique. To evaluate the performance this technique in a comprehensive way, our method is evaluated on various underwater scenarios. Experimental results indicate that our method is promising for fish detection and species identification in terms of accuracy and generalisation performance. The method paves the way for only wanted fish to be selected and caught, whilst other fish and marine life can be released in-situ unharmed.

The technique has been deployed and tested in the Jetson Nano[2] platform, a low-cost and small form factor computing unit. The presentation highlights the next steps and plans for further trials to test the system in the field.

Acknowledgements

The Smartrawl project has been funded by Fisheries Innovation Scotland, through their membership organisations, chief amongst which was Marine Scotland: all of their support is gratefully acknowledged. The vision-based technique was developed with the assistance of Yiren Li and Sean Flinn (University of Aberdeen). Shaun Fraser (UHI) is thanked for running field trials and data collection.

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