Towards Low Cost Automated Monitoring of Life Below Water to De-risk Ocean-Based Carbon Dioxide Removal and Clean Power

Devi Ayyagari
Dalhousie University
Halfiax, NS 15213
devi.ayyagari@dal.ca

Corey Morris
Department of Fisheries and Oceans
St. John's, Canada
corey.morris@dfo-mpo.gc.ca

Joshua Barnes
National Research Council Canada
St. John's, Canada
joshua.barnes@nrc-cnrc.gc.ca

Christopher Whidden
Dalhousie University
Halfiax, NS 15213
cwhidden@dal.ca

Abstract

Oceans will play a crucial role in our efforts to combat the growing climate emergency. Researchers have proposed several strategies to harness greener energy through oceans and use oceans as carbon sinks. However, the risks these strategies might pose to the ocean and marine ecosystem are not well understood. It is imperative that we quickly develop a range of tools to monitor ocean processes and marine ecosystems alongside the technology to deploy these solutions on a large scale into the oceans. Large arrays of inexpensive cameras placed deep underwater coupled with machine learning pipelines to automatically detect, classify, count and estimate fish populations have the potential to continuously monitor marine ecosystems and help study the impacts of these solutions on the ocean. In this proposal, we discuss the challenges presented by a dark artificially lit underwater video dataset captured 500m below the surface, propose potential solutions to address these challenges, and present preliminary results from detecting and classifying 6 species of fish in deep underwater camera data.

1 Introduction

Oceans and seas cover more than 70% of the planet. They directly employ 56 million people, host 80 percent of the planet's biodiversity, regulate our climate and are responsible for at least 50% of oxygen on Earth. Despite their vital role in our climate, oceans have so far remained largely unobserved and not understood on a large scale owing to the extremely high costs and complexity involved in studying such a large ecosystem. Precisely because of their vastness and complexity, they play an outsized role in regulating our climate[1, 2, 3].

Many studies indicate that oceans act as a buffer against climate change[4, 5]. Strategies to increase the alkalinity of the oceans and accelerate the weathering processes that naturally consume CO2 from the atmosphere[6] or harvest tidal energy to generate greener alternative energy [7, 8, 9] are proposed as potential solutions to harness oceans to mitigate climate change. Despite careful efforts by researchers to assess the risks involved with adopting these solutions, the long-term consequences of these strategies on the ocean ecosystem are not very well understood[10]. With aggressive targets needed to prevent average global temperature from rising more than 2°C in the next few decades[11], we will need to adopt some or all of these strategies to be able to address this climate emergency

Tackling Climate Change with Machine Learning: workshop at NeurIPS 2022.

before fully understanding the risks these strategies might pose[12, 13]. It is thus critical that we develop affordable, scalable and automated ocean monitoring solutions with low carbon footprints to closely monitor the effects of these solutions on the oceans and the marine ecosystems.

We explore placing cheap underwater cameras along with a light source and bait deep underwater to acquire a dataset with different species of fish and apply machine learning techniques on this dataset to monitor marine ecosystems. The primary objective of this research is to detect and classify different species of fish in underwater video data. A secondary objective of this research is to determine the number of samples of different species of fish required to develop an efficient and accurate deep learning model to inform data collection and annotation efforts. In this proposal, we present the results from training a model to classify and detect 6 species of fish and argue that 2000 samples of each class are sufficient to train a model successfully. Additionally, we identify the challenges involved with detecting and classifying the rarer species in the dataset and propose strategies to address the challenges involved with this dataset. Finally, we identify the challenges and opportunities that must be solved to scale such a system worldwide to meaningfully tackle climate action.

1.1 Related Work

Traditionally, ocean and marine ecosystems have been monitored using high frequency radar, ocean gliders and animal tagging[14, 15, 16]. These techniques are invasive, human resource intensive, expensive and will not scale to meet the climate emergency[17]. Much research is underway to replace these traditional monitoring techniques with different forms of electronic monitoring using audio and video devices like cameras, satellites, echosounders, and other acoustic devices[18, 19, 20, 21, 22, 23]. However, image-based machine learning research for life underwater has been limited to deploying cameras on fishing vessels, shallow waters, aquariums or aquaculture establishments, with very limited work extending these camera monitoring systems to deep underwater because of the challenges involved in acquiring and analyzing underwater video data below the sunlight zone. To our knowledge, marine ecosystems at these depths have not been captured by cameras with these resolutions, and machine learning applications to analyse this data have not been explored. Continuous and automated video monitoring pipelines to estimate fish abundance will be an invaluable tool in assessing the impact of climate change on marine ecosystems.

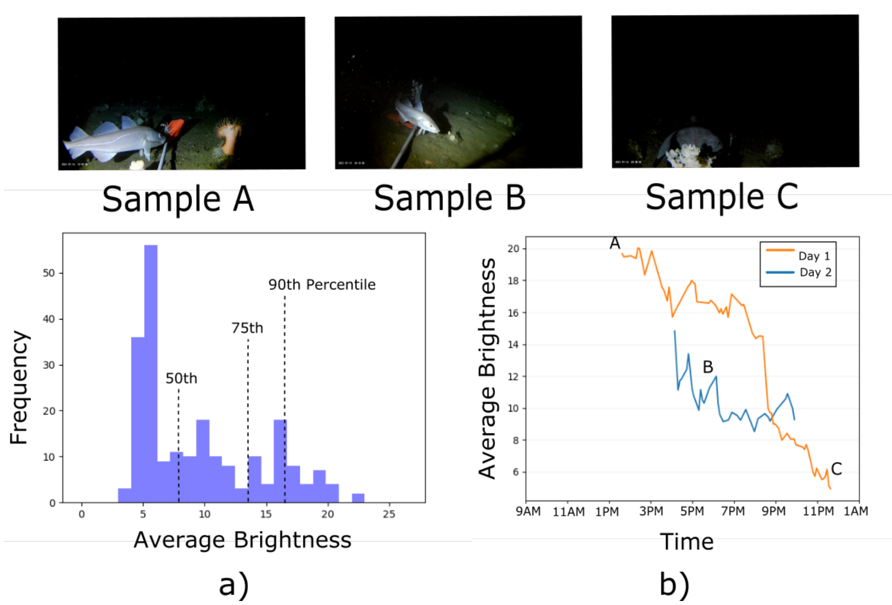

Figure 1: a) Variation of brightness in the dataset. b) Variation of average brightness over time. Brightness measured by the average "Value" channel in HSV color space across frames of each video.

2 Data and preliminary results

Inexpensive cameras with bait to attract fish and a battery-powered light source were placed and later recovered from an approximate depth of 450-500m along the marine slopes of the Northeast Newfoundland marine refuge to determine the impact of nearby seismic testing on fish in the marine protected area[24]. There is no meaningful light past 200 meters[25] due to limited sunlight penetration and the 6V battery depletes over time resulting in low and decreasing average brightness (Fig. 1). .5221 videos, recorded at 30fps, with an average video length of 5 minutes, were annotated by a fish expert at DFO using the VIAME[26] platform. The annotated dataset has 11 species of fish, with unbalanced sampling. Six species are well represented but some appear in only a single video.

2.1 Preliminary results

The 221 videos were partitioned into training, validation and test splits with a a 70-15-15 ratio based on the distribution of the frequency of frames with fish in each video. Balanced subsets of 200, 500, 1000 and 2000 frames from the 6 species with at least 2000 distinct training objects were randomly sampled from the training set. Detection and classification models based on YOLOv4[27] architecture were trained on each subset to quantify the number of annotated samples required to train an effective model. We found that 2000 samples, representative of the larger test set, at an IoU threshold of 0.4 are sufficient to train a classification and detection model on this dataset(Fig . 2).

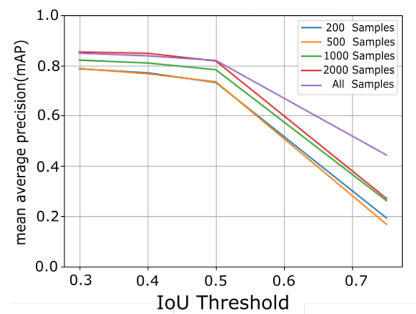

Figure 2: Performance comparison of models trained on balanced subsets of 200, 500, 1000, 2000, all samples for 6 species of fish on the ocean floor.

3 Future work

We demonstrated that YOLO-based models can detect and classify fish species 500m underwater given a sufficient number of training examples. However, such datasets naturally have large class imbalances (e.g. our other 5 species) because the ocean floor is sparsely populated by fish and fish species are unevenly distributed. An automated system for monitoring rare at-risk species will require models that can a) efficiently classify species with as little as a single unique instance and b) detect and catalogue species the model has not previously seen. Towards this goal, we propose exploring an R-CNN family[28, 29] model to train classifiers and detectors separately: training the detector to segment fish, freezing the detector's layers; and training classifiers using small balanced subsets from identified species. Furthermore, we propose experiments augmenting the sample size of rarer species using generative models[30, 31, 32], optimizing training by subsampling efficiently to use all the training data while using balanced subsets, using statistical methods like joint probabilistic data association filters[33] to track and count fish across frames, and training with water frames to develop an efficient population estimation algorithm. Marine conservation research using deep underwater video data has incredible potential if the enormous and expensive manual effort can be reduced by machine learning strategies like one-shot or few-shot learning, leveraging large foundation models for Imagenet and using acoustics alongside video to aid classification and detection.

In addition to machine learning model development, there are several large challenges that must be solved to deploy automated analysis and continuous monitoring camera systems deep underwater on a large scale: replenishing/circumventing using bait to attract fish to the camera; limited on-chip data storage, resources to store and process large amounts of data; trained interdisciplinary scientists and operators to acquire and process the data; verification and generalisability to variations in habitat, camera resolutions, to name a few. Although this research focused on classifying and detecting different species of fish and estimating population, we see this as the first step towards the larger goal of worldwide monitoring of life underwater which will require a concerted effort from multiple diverse groups including experts in machine learning, biology, and oceanography as well as social scientists and Indigenous peoples. If successful, such research will enable the safe development of tidal power, safe development and application of carbon removal technology, better monitoring of at risk fish in marine protected areas, and other upcoming solutions to help address our climate threat.

References

[1] UN Environment. The first global integrated marine assessment: World ocean assessment i.

[2] Hans-Otto Pörtner, Debra C Roberts, Valérie Masson-Delmotte, Panmao Zhai, Melinda Tignor, Elvira Poloczanska, and NM Weyer. The ocean and cryosphere in a changing climate. *IPCC Special Report on the Ocean and Cryosphere in a Changing Climate*, 2019.

[3] Grant R Bigg, TD Jickells, PS Liss, and TJ Osborn. The role of the oceans in climate. *International Journal of Climatology: A journal of the Royal Meteorological Society*, 23(10):1127–1159, 2003.

[4] Callum M. Roberts, Bethan C. O'Leary, Douglas J. McCauley, Philippe Maurice Cury, Carlos M. Duarte, Jane Lubchenco, Daniel Pauly, Andrea Sáenz-Arroyo, Ussif Rashid Sumaila, Rod W. Wilson, Boris Worm, and Juan Carlos Castilla. Marine reserves can mitigate and promote adaptation to climate change. *Proceedings of the National Academy of Sciences*, 114(24):6167–6175, 2017.

[5] Jean-Pierre Gattuso, Phillip Williamson, Carlos M Duarte, and Alexandre K Magnan. The potential for ocean-based climate action: negative emissions technologies and beyond. *Frontiers in Climate*, 2:575716, 2021.

[6] Phil Renforth and Gideon Henderson. Assessing ocean alkalinity for carbon sequestration. *Reviews of Geophysics*, 55(3):636–674, 2017.

[7] R H Charlier. Tidal energy.

[8] Mehmet Melikoglu. Current status and future of ocean energy sources: A global review. *Ocean Engineering*, 148:563–573, 2018.

[9] Alistair GL Borthwick. Marine renewable energy seascape. *Engineering*, 2(1):69–78, 2016.

[10] Lennart T Bach, Sophie J Gill, Rosalind EM Rickaby, Sarah Gore, and Phil Renforth. Co2 removal with enhanced weathering and ocean alkalinity enhancement: potential risks and co-benefits for marine pelagic ecosystems. *Frontiers in Climate*, 1:7, 2019.

[11] Christopher J Rhodes. The 2015 paris climate change conference: Cop21. *Science progress*, 99(1):97–104, 2016.

[12] Sarah R Cooley, Brittany Bello, Daniel Bodansky, Anthony Mansell, Andreas Merkl, Nigel Purvis, Susan Ruffo, Gwynne Taraska, Anna Zivian, and George H Leonard. Overlooked ocean strategies to address climate change. *Global Environmental Change*, 59:101968, 2019.

[13] Ordinary Things. The case for carbon dioxide removal: From science to justice • carbon dioxide removal primer.

[14] Mingwei Lin and Canjun Yang. Ocean observation technologies: A review. *Chinese Journal of Mechanical Engineering*, 33(1):1–18, 2020.

[15] Tim P Bean, Naomi Greenwood, Rachel Beckett, Lauren Biermann, John P Bignell, Jan L Brant, Gordon H Copp, Michelle J Devlin, Stephen Dye, Stephen W Feist, et al. A review of the tools used for marine monitoring in the uk: combining historic and contemporary methods with modeling and socioeconomics to fulfill legislative needs and scientific ambitions. *Frontiers in Marine Science*, 4:263, 2017.

[16] Benoit Beauchamp, H Benoît, and N Duprey. *Review of catch monitoring tools used in Canadian fisheries*. Canadian Science Advisory Secretariat, 2019.

[17] Brian Polagye, James Joslin, Paul Murphy, Emma Cotter, Mitchell Scott, Paul Gibbs, Christopher Bassett, and Andrew Stewart. Adaptable monitoring package development and deployment: Lessons learned for integrated instrumentation at marine energy sites. *Journal of Marine Science and Engineering*, 8(8), 2020.

[18] M Rizwan Khokher, L Richard Little, Geoffrey N Tuck, Daniel V Smith, Maoying Qiao, Carlie Devine, Helen O'Neill, John J Pogonoski, Rhys Arangio, and Dadong Wang. Early lessons in deploying cameras and artificial intelligence technology for fisheries catch monitoring: where machine learning meets commercial fishing. *Canadian Journal of Fisheries and Aquatic Sciences*, 79(2):257–266, 2022.

[19] Muhammad Ather Iqbal Hussain, Zhi-Jie Wang, Zain Ali, and Shazia Riaz. Automatic fish species classification using deep convolutional neural networks. *Wireless Personal Communications*, 116, 01 2021.

[20] Dian Zhang, Noel E. O'Conner, Andre J. Simpson, Chunjie Cao, Suzanne Little, and Bing Wu. Coastal fisheries resource monitoring through a deep learning-based underwater video analysis. *Estuarine, Coastal and Shelf Science*, 269:107815, 2022.

[21] Vishnu Kandimalla, Matt Richard, Frank Smith, Jean Quirion, Luis Torgo, and Chris Whidden. Automated detection, classification and counting of fish in fish passages with deep learning. *Frontiers in Marine Science*, 8, 2022.

[22] Jia-Hong Lee, Mei-Yi Wu, and Zhi-Cheng Guo. A tank fish recognition and tracking system using computer vision techniques. In *2010 3rd International Conference on Computer Science and Information Technology*, volume 4, pages 528–532, 2010.

[23] Brian Polagye, James Joslin, Paul Murphy, Emma Cotter, Mitchell Scott, Paul Gibbs, Christopher Bassett, and Andrew Stewart. Adaptable monitoring package development and deployment: Lessons learned for integrated instrumentation at marine energy sites. *Journal of Marine Science and Engineering*, 8(8):553, 2020.

[24] Joshua Barnes Dustin Schornagel Christopher Whidden Morris, Corey and Phillippe Lamontagne. Measuring effects of seismic surveying on groundfish resources off the coast of newfoundland, canada. *Journal of Ocean Technology*, 16(3):57–63.

[25] National Oceanic US Department of Commerce and Atmospheric Administration. How far does light travel in the ocean?, Jun 2013.

[26] VIAME Contributors. VIAME: Video and Image Analytics for Marine Environments, 5 2017.

[27] Alexey Bochkovskiy, Chien-Yao Wang, and Hong-Yuan Mark Liao. Yolov4: Optimal speed and accuracy of object detection. *ArXiv*, abs/2004.10934, 2020.

[28] Ross Girshick, Jeff Donahue, Trevor Darrell, and Jitendra Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2014.

[29] Peize Sun, Rufeng Zhang, Yi Jiang, Tao Kong, Chenfeng Xu, Wei Zhan, Masayoshi Tomizuka, Lei Li, Zehuan Yuan, Changhu Wang, and Ping Luo. Sparse r-cnn: End-to-end object detection with learnable proposals. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 14454–14463, June 2021.

[30] Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, and Yoshua Bengio. Generative adversarial nets. In *Advances in neural information processing systems*, pages 2672–2680, 2014.

[31] Chanho Eom and Bumsub Ham. Learning disentangled representation for robust person re-identification. In *Advances in Neural Information Processing Systems*, pages 5298–5309, 2019.

[32] Tero Karras, Samuli Laine, and Timo Aila. A style-based generator architecture for generative adversarial networks. In *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 4396–4405, 2019.

[33] Shaoming He, Hyo-Sang Shin, and Antonios Tsourdos. Joint probabilistic data association filter with unknown detection probability and clutter rate. In *2017 IEEE International Conference on Multisensor Fusion and Integration for Intelligent Systems (MFI)*, pages 559–564, 2017.