Northumbria Research Link

Is the use of deep learning an appropriate means to locate debris in the ocean without harming aquatic wildlife?

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ABSTRACT

With the global issue of marine debris ever expanding, it is imperative that the technology industry steps in. The aim is to find if deep learning can successfully distinguish between marine life and synthetic debris underwater. This study assesses whether we could safely clean up our oceans with Artificial Intelligence without disrupting the delicate balance of aquatic ecosystems.

Our research compares a simple convolutional neural network with a VGG-16 model using an original database of 1644 underwater images and a binary classification to sort synthetic material from aquatic life. Our results show first insights to safely distinguishing between debris and life.

1. Introduction

1.1. Background

Marine debris has a devastating effect on marine life. Mammals, sea birds and larger fish are frequently found to have ingested litter or have become entangled within nets and other materials, such as plastics (D'Aurelio, 2019, McAdam, 2017, Day, 1980, Bjornadal et al., 1994). This results in lethal consequences as plastic fragments absorb toxic materials and are highly contaminated with biphenyl polychlorinated (PCB), heavy metals and other noxious substances. Often leached out of common plastics are organophosphate esters (OPEs), particularly organophosphate flame retardants (OFPRs), though the effects are still not fully understood, this group of additives has been associated with a toxic effect on animals and humans, corresponding with different carcinogenic properties, diabetes and reproductive issues (Sala et al., 2021). OPEs have been detected within marine vertebrates; such as in studies with loggerhead turtles *(Caretta caretta)* and the first evidence of OFPRs has been detected within fin whales *(Balaenoptera physalus)* as well as their main diet source, krill *(Meganyctiphanes norvegica)* (Garcia-Garin et al., 2020a).

Once ingested, plastic consumption will likely cause other repercussions including reproductive disorders, hormone changes, higher disease risk or most commonly; obstructing the gastrointestinal tract; resulting in starvation and fatality (D'Aurelio, 2019, Mato et al., 2001, de Stephanis et al., 2013). Additionally, entanglement causes a serious threat to marine ecosystems (Stelfox et al., 2016, Tekman et al., 2022).

As well as an "inestimable number of birds, turtles, fish and other species" (WAP, 2018, WAP, 2014). At least 136,000 pinnipeds and whales; are killed every year by discarded fishing equipment (France-Presse, 2011). The consequence of high whale fatalities is that they are key contributors to the ecosystem of phytoplankton. This is crucial, as phytoplankton "contribute at least 50 percent of all oxygen to our atmosphere" and capture "an estimated 40 percent of all [Carbon Monoxide] CO produced." Acting as the equivalent of 1.7 trillion trees or four Amazon rain forests; our environment depends on phytoplankton populations (Chami et al., 2019).

This global dilemma not only impacts marine life and the environment but human health also, as micro plastics are now being discovered within all water systems (McAdam, 2017, Viehman et al., 2011) and ultimately, human consumption (Luo et al., 2020; Liu et al., 2021; Sharma and Chatterjee, 1987). The level of health risks are rising in correlation with fish consumption, as a study by Garcia-Garin et al. (2020b) concludes that by consuming contaminated, edible fish such as the bogue species *(Boop boops)*, OFPRs are ingested, with their potential toxic effects and a recent discovery has even now detected nano plastics in our blood (Vethaak and J, 2021). Even though this is an accelerating issue, a solution has not yet come to fruition. Therefore, it is critical we begin to use technology to address the above challenges.

Although our piece of research is a very small aspect of the bigger picture, it has the potential to be a vital part of the first application of deep learning to clean up our oceans and water systems. By successfully

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distinguishing between waste and fauna, an artificial intelligence framework could eventually be applied to automation, protecting our rapidly declining marine life and improving the negative impacts on human health.

The application of machine learning to detect and classify litter, is still very minimal but far outweighs the efficiency of current methods which are hugely time consuming and extremely limited. They also require manual labour and are susceptible to human error. Being "one of the most pervasive and solvable pollution problems plaguing the world's oceans and waterways" (Sheavly and Register, 2007), it is critical we invest more research into deep learning as a progressive solution.

The aim is to successfully use deep learning methods to distinguish between synthetic debris and aquatic life by using the following objectives:

• Collect a coloured (RGB) image database, that includes underwater debris and marine life in a variety of settings.

• Compare the train and test results of two CNN frameworks against this new database, to categorise synthetic waste and marine fauna successfully.

2. Gaps in the current literature

Most studies on the application of Artificial Intelligence [AI] have neglected to consider the appropriate safety measures involved with clearing the ecosystem without causing further harm.

Interestingly, popular categories studied in the oceans are plastic bottles, bags and food packaging, however, disregarded fishing nets cause a high fatality and are responsible for the greatest percentage of plastic in the ocean and one of the categories responsible for the highest fatalities (Lebreton et al., 2018, WAP, 2018). Furthermore, many studies including (Garcia-Garin et al., 2021) only considered floating plastics, which contributes to a very minimal percentage of marine litter.

Although the problematic debris is found near the surface where creatures mistake it for food or something to play with, therefore ingesting it (D'Aurelio, 2019, McAdam, 2017), most of the ocean's plastic is in micro form and found in the deepest parts (Peng et al., 2018). Moreover, only 1 % of marine litter floats (Ferries, 2021).

Most algorithms in current research are only looking at three or four separate categories. These categories (usually including plastic bags, bottles and straws) represent only a tiny portion of the vast quantity of synthetic debris currently polluting our oceans (Jambeck et al., 2015) that is continuing to rapidly expand (Lebreton et al., 2018). Additionally, the image databases used to identify and categorise these specific objects do not account for varying degrees of degradation and subsequent distortion to captured imagery from wear, being underwater and sea conditions (light, density, turbulence).

There are also a plethora of conditions that such an algorithm would have to work under, with visibility being the most important factor. The authors in some of the papers are in fact currently testing this problem in real life ocean scenarios; however, current prototypes will still need further development, particularly in rivers which have completely different conditions and are responsible for approximately 1.15–2.41 million tonnes of plastic entering our oceans (Lebreton et al., 2017).

Recent work on the Great Garbage Patch by de Vries et al. (2021) has proven to successfully use AI to track parts of the patch by collecting photographic data with a GPS enabled GoPro from above the waterline. Using a convolutional neural network [CNN] to detect debris, they were able to survey the litter and map out the garbage patch in better detail.

3. Related work

The paper on using deep learning to detect floating debris by Kylili et al. (2018) used VGG-16 pretrained on ImageNet to successfully train their own data set (after having applied transfer learning), to classify their research with a success rate of 86 %. Their paper focused on floating debris and to collect their data, they had to use a large amount

of augmentation to create a dataset consisting of 12,000 images, which were classified into three different categories: bottles, buckets and straws at a testing accuracy of 99 %.

Fulton et al. (2019) compared training four object detection methods (including R-CNN, YOLOv2, Tiny-YOLO & SSD) and concluded that Faster R-CNN had the highest accuracy, at the compromise of speed. YOLOv2 had an accuracy that was close to the R-CNN results, but it performed faster. They discovered that marine debris can be detected in real time using deep learning visual object detection methods - although this was from the surface and the authors do express their belief that it could be used underwater if the data limitations are overcome.

de Vries et al. (2021) recently studied whether they could trace macro debris location and transportation. They used a two-fold approach, testing both the Faster RCNN and YOLOv5 architectures. The authors found that YOLOv5 outperformed FRCNN with the quantity of objects detected and with the smallest object size, however, they report this could be due to the hyper-parameter settings they applied. They go on to explain that YOLOv5 only needed minimal changes for better performance and that both network architectures could have been further improved with more optimization. They successfully produced, what they describe as "the first real-world demonstration of a large-scale automated camera transect survey of floating marine litter"; however due to limitations (such as that they are currently unable to detect anything smaller than macro debris), they believe their work is a strong framework for a method ology, rather than an example of findings.

An alternative experiment aiming to track and identify floating marine debris compared the use of CNN with a 'bag of features' method (Sreelakshmi et al., 2019). The CNN used convolutional and bottleneck layers achieving 77.5 % accuracy when classifying. However, the bag of features method only achieved a 62.5 % accuracy (using MatLab & SURF features).

Comparing the two results clearly indicates that CNN was more accurate with an added benefit of speed - it took half the computational time that the Bag of Features needed.

Another application of AI to detect marine debris was explored by Wang et al. (2019) using Long Short Term Memory Network (LSTM) with Cross Correlations and Association rules (Apriori) to identify characteristics of water pollutants. They discovered that the water quality correlation maps they produced were in fact able to accurately identify fluctuations effectively. Whilst this is useful to detect where large quantities of litter are within the ocean, this would work better as a technology used in addition to a Deep Learning algorithm, to encourage accurately pinpointing our largest problematic areas (Wang et al., 2019). Particularly as they have claimed that their AI scheme could potentially work within aquatic systems.

The paper by Chazhoor et al. (2021) bench marked the three widely implemented architectures on the WaDaBa data set to find out the best model with the support of transfer learning. To ease the recycling process worldwide, seven different types of plastic have been categorised based on their chemical composition. These are Polyethylene Terephthalate (PET or PETE), High Density Polyethylene (HDPE), Polyvinyl Chloride (PVC or Vinyl), Low-Density Polyethylene (LDPE), Polypropylene (PP), and Polystyrene (PS or Styrofoam). PET, HDPE PP and PS dominate the household waste and segregating them into their respective types will allow the reuse of certain types and recycling of other types of plastics. The paper is the first benchmark paper aimed towards classifying different types of plastics from the images using deep learning models, and this has stimulated the research in this area and serve as a baseline for future research work.

To conclude, the current algorithms available are successful and effective; however, comparing the studies, the results clearly indicate that CNN was the most accurate and fastest approach. Convolutional Neural Networks (CNN) can train themselves on debris and continue to learn using transfer learning, concluding in highly accurate and efficient results (Kylili et al., 2018).

Within this research, we have collated an extensive and original

database of not only litter but also aquatic life with an emphasis on submerged imagery that covers a diverse and comprehensive range of data. Incorporating different sea conditions, light levels and depths, as well as all varieties of synthesised materials and in various stages of degradation (or other distortions). This is important to ensure that the CNN does not just learn what is correct but also what is incorrect.

Our paper is especially unique in its binary classification - we split all the data into two simple categories of what is 'living' and what is not - putting the protection of the ecosystem and of life as the priority and trained the system how to differentiate between the two with a current accuracy of 89 %. Therefore, picking up most synthesised matter and avoiding (protecting) aquatic life. It also covers a broader spectrum of items rather than focusing on specific categories at a specific depth. Therefore, training it to recognize properties of either debris or life, rather than single items. We have used data augmentation to diversify the different aspects of images as well as increasing the number of images to deal with class imbalance issues.

4. Materials and methods

4.1. Database collection

A diverse range of organisations and dive centres collaborated with us by providing their images.

We clearly outlined a list of requirements including:

- In colour and as high quality as possible.
- Dimensions for objects photographed would need to be larger than microplastics and smaller than roughly $16''^2$.
- Preferably, they would also have some general labels

We also specified including any of the following within their imagery:

- Underwater Litter
- Underwater Nets
- Underwater Animals (this can include fish, crustaceans, cnidaria etc)
- Underwater Plants
- Anything else miscellaneous that is ecological and shot underwater

The main database acquired was obtained from Japan Agency for Marine-Earth Science and Technology (JAMSTEC). JAMSTEC has a huge database of sub marine images and footage of deep-sea debris in Japan called J-EDI. Their imagery was suitable for different depths, density and light but also for the variety of objects within the photos, with different levels of degradation.

The dataset we obtained included a vast array of marine fauna as shown in Fig. 1 including but not limited to (fish, jellyfish, shells, starfish, anemone) as well as an even wider selection of synthetic debris as shown in Fig. 2 (nets, masks, cardboard, plastic bags, plastic sheets, cloth). As we wanted diversity in our database, it was particularly useful to receive this wide selection of objects.

4.2. Data augmentation process

On our data set, only a small amount of data augmentation was used by manually cropping and rotating any images that were particularly rich in information; mostly in instances where both categories (such as a fish and a plastic bottle) were in one image; that image would then be split into two separate images, individually cropping the items. We started with 1318 photos, after augmentation was applied, our training set consisted of 1644 images and 100 images for the testing set.

4.3. Sorting data

Our first task was to ensure a high-quality collection (Fig. 3). Poor quality images were therefore removed to benefit the system. (This process was subjective. In future research, we could use benchmarks based on a set of predefined parameters.)

Furthermore, imagery containing subject matter deemed irrelevant were also manually removed, to determine clear parameters and prevent confusion within the algorithm. In the case of our dataset, it was mostly the JAMSTEC sub marine machinery parts that were in the way, which was resolved by manually cropping the images.

The biggest issue that arose was the strange (yet incredible) phenomenon of how much aquatic life had chosen to inhabit pollutants. An ethical dilemma therefore arises, as to not disturb the sensitive and delicate balance of the ecosystem, by removing these items (Fulton et al., 2019). We chose to remove any such images to prevent confusion when training the network architectures. From sorting the dataset, it was often questioned whether the Convolutional Neural Networks would be able to safely distinguish between very commonly confused items. For example, a jellyfish and a plastic bag closely resemble each other. There were also cases of starfish that we ourselves found difficult to distinguish whether they were real or plastic. Therefore, there is a very real danger that a neural network could make the same mistake.

4.4. Training a model for a binary classification task

In this study, classes are defined as follows: an image which has man-made debris in it ('Litter' or '1'), or it has natural aquatic life in it ('Animals' or '0'), this class can include plants or any variety of marine biology.

For now, we chose not to use subclasses, in order to test this version first and see if it is successful. In further tests, a training set of multiple categories would be valuable to improve the detail and accuracy of the system.

4.5. Network architecture

We chose convolutional neural networks as they can handle a large quantity of data and have a high-performance rate in the ever-developing machine learning industry. CNN algorithms are the

Fig. 1. Examples of marine life images. Photo Credit: JAMSTEC.

Fig. 2. Examples of synthetic debris images. Photo Credit: JAMSTEC.

Fig. 3. Examples of database images. Photo Credit: Maria Shokouros-Oskarsson.

strongest neural network for image recognition. The system learns to strategically, on different layers, detect the lines and edges in the input image. It is then able to distinguish between them, identifying segments of an image resulting in feature extraction.

A major disadvantage to deep learning algorithms having many parameters, and the use of max pooling, is the higher risk of overfitting (Guo et al., 2016). As one of our models is an entirely new architecture with a brand new, untrained data set, it required a large amount of trial and error of adjusting the different parameters to avoid overfitting. To closely monitor the progress of the architecture, TensorBoard was used, so that we could frequently compare graphs on where overfitting was occurring and make appropriate adjustments. All images were resized, to a width and height of 140px, using Python to maintain a uniform size throughout all images and ensure that parts would not be cropped out. Additionally, 140px when tested, showed enough detail to recognize the shapes and patterns within the image but was not too high to slow down the run time.

In the case of using such a vast variety of underwater debris and aquatic life, it was felt that the most information necessary should be used, even if it compromises speed; so, three channel values RGB were used, instead of one. To eliminate the issue of class imbalance, the data set has been split to have exactly 50 % of each category. Therefore, out of the 1644 training images, 822 were in each category. An additional precaution taken, was to randomly shuffle the data, as the system would otherwise learn that the data is in order and again, guess accordingly.

This system was created on a Dell Inspiron i7-7700HQ CPU 2.8GHz, 16GB RAM, 64-Bit with a Nvidia GeForce GTX graphics card, using Windows 10. The algorithm was programmed using Python in PyCharm and the specs of the system used were: Tensorflow, Keras and ReLU. Using cv2, we imported the collected and built a data set, created 2×2 windows, extracted the max pooling value and used the Adam optimization.

This resulted in the architecture having the following parameters: Three convolutional layers with 32 nodes and no dense layers, the second kernel size was reduced to a (2,2) window, the validation split had to be reduced to 0.1 and it ran 95 epochs. As shown in Fig. 4. We used the Rectified Linear activation Unit (ReLU) as the activation function and the last layer used the logistic sigmoid function to enable binary classification. The validation split is usually optimised at 20 % (0.2) of the set, however, this architecture would favour one of the classifications, if at this setting.

When the final architecture was confirmed, we ran it 10 times to take an average of the Training Loss and Training Accuracy shown in Table 1, intermittently between rerunning the architecture, we continued to run Tests against Training Images and Test Images, periodically testing for correct classification. To train the VGG-16 model, we imported the VGG model using Keras and then applied transfer learning from the ImageNet weights. We used softmax activation and only 2 dense layers to keep our model close to the framework that (Kylili et al., 2018) had promising results with. To train the model on our data set, we then ran 50 epochs on a model checkpoint function, so that the highest accuracy model would be saved.

5. Results, analysis and evaluation

The original aim of this research was to test if we could successfully train a CNN framework to distinguish between underwater debris and aquatic life, safely and to an accuracy of at least 85 %, as we collected a new database.

The test results have shown that from a set of 100 tested images, 89 % were 13 correctly classified. When we ran evaluation metrics on this test (Fig. 5), we calculated a set of strong results such as 0.9 F1 score for 'Animal' detection and 0.88 F1 score for 'Litter', as shown in Table 2. When running a 95 % confidence interval on our results, we found that the classification error of the model is 86 % ± 0.061. Given these results, the true classification error of the model is between 80 % and 92 %.

The obtained result shows promising signs of being able to adapt to a much larger scale database, with more detail and a stronger CNN
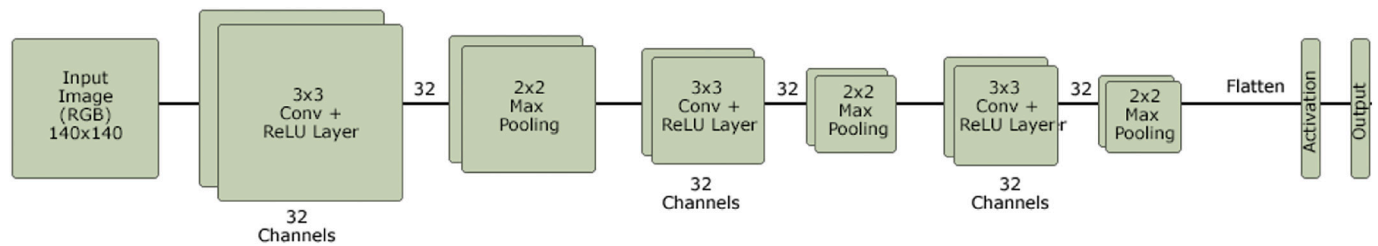
Fig. 4. Block diagram of simple CNN classifier.

Table 1
Training result comparisons.

CNN		VGG-16	
Train loss	Train accuracy	Train loss	Train accuracy
0.23	0.90	0.0093	1.00
0.21	0.90	0.0224	1.00
0.19	0.92	0.0064	1.00
0.22	0.90	0.0055	1.00
0.16	0.93	0.0054	1.00
0.18	0.92	0.1132	0.9844
0.20	0.92	0.0013	1.00
0.19	0.93	0.0136	1.00
0.21	0.90	0.0052	1.00
0.21	0.91	0.02	1.00
0.20	0.91	0.02023	1.00

Fig. 5. Confusion matrix of CNN model.

Table 2
Evaluation metrics of CNN.

	Precision	Recall	f1-score	Support
Animal	0.85	0.94	0.90	50
Litter	0.93	0.84	0.88	50
accuracy			0.89	100
macro avg.	0.89	0.89	0.89	100
weighted avg.	0.89		0.89	100

architecture. Furthermore, we compared our simple CNN model with the VGG-16 architecture by training our dataset onto the framework and using transfer learning and the final output layer of softmax (as suggested by Kylili et al., 2018) (Fig. 6). Our train had a loss of 0.0093 and accuracy of 1.0000, with test results achieving a 95 % accuracy in predictions. Also shown in Table 3 the VGG-16 model achieved an F1 score of 0.95 for both categories, additionally the classification error is 95 % ± 0.043. Therefore, the true classification of the model is between 91 % and 99 %. This shows promising signs that CNN models can be used to successfully classify all types of debris without disturbing marine life, particularly when using transfer learning on VGG-16. Overall, we conclude that transfer learning with a VGG-16 framework is more accurate and though these are our initial findings; with a larger data set and finer tuned parameters, we could have very positive results.

Fig. 6. Confusion matrix of VGG model.

Table 3
Evaluation metrics of VGG-16.

	Precision	Recall	F1-score	Support
Animal	0.92	0.98	0.95	50
Litter	0.98	0.92	0.95	50
Accuracy	0.95	0.95	0.95	100
Macro avg.			0.95	100
Weighted avg.	0.95	0.95	0.95	100

There were limitations to this study, as finding publicly accessible underwater images of debris proved particularly difficult, and the images that were donated to us were not already labelled, so we had to complete this manually, which was time consuming.

We also found similar challenges with de Vries et al. (2021), that many images were not of a high enough quality, consequently reducing our database to a size that was not suitable for CNN training. However, after the use of data augmentation, we were successfully able to create a new database that had a high accuracy level. From here we believe this research is therefore, a strong preliminary methodology for future research in this field with a larger database and a more powerful solution that can allow further depth and contain more classification groups.

As mentioned previously, other papers have strived to identify marine debris using neural networks and have encountered relevant challenges. Similarly to our paper, Fulton et al. (2019)'s study produced their own dataset, which heavily drew from JAMSTEC's imagery and far outweighed our own as it consisted of 5720 images. They had a trinary classification of plastics, man-made debris and other bio matter, their separation of classifications is close to our binary system and can be quite fairly compared. Much like ours, their dataset was designed to challenge the deep learning algorithm to maintain an accurate representation of a real-life scenario. We followed in similar footsteps by trying to vary our data as greatly as we could. Though this reduces the performance as Fulton et al. (2019) mentioned; it is "a better evaluation of what the detector's performance would be in the field", to which the authors of this study concur with. Their study produced promising results by comparing four different models; though they looked into object detection, whereas our paper compares image recognition models. With object detection; (including transfer learning on YOLOv2); their strongest results were using Faster-RCNN which detected plastics at an

average precision rate of 83.3 %. de Vries et al. (2021) were able to capture their own dataset of over 18,000 images of floating debris and chose to compare object detection results of YOLOv2 with Faster-RCNN; yet they concluded that YOLOv2 obtained stronger results. However, their study only focused on surface level debris, so their database would have been far less complex for the neural network to predict.

Other studies looked into using image recognition on surface level marine debris such as Kylili et al. (2018), who also produced their own dataset (12,000 images) and used VGG-16 transfer learning which concluded in strong test results of 99 % and a validation accuracy of 86 %. It is interesting to note that their paper focuses on three specific categories of litter, whereas our study consists of much broader and less focused classifications; including data affected by degradation, wear and visibility, therefore as expected, our study should be producing less accurate results.

When comparing with relevant neural network studies, the authors of this paper strongly believe that, when introduced to a larger dataset, the use of image recognition methods such as VGG-16, underwater to detect marine debris will perform very positively.

This research is unique in its type; that it is one of the first papers that not only is looking for a feasible solution for our polluted water crisis but also has an emphasis on the perspective of animal welfare and ecological conservation. Additionally, our paper has reported some insight into progressive steps that using CNNs could successfully distinguish between any debris and any marine fauna. The paper has therefore, collated a large quantity of thoroughly thought-out scenarios and information that future papers will hopefully prioritise their studies and development with.

6. Conclusions and recommendations

This research sets out to answer the question: can deep learning successfully distinguish between marine life and man-made debris underwater? From the research we conducted, the authors believe that with a larger data set, the possibility of using image recognition to safely remove debris underwater without disrupting aquatic ecosystems is strong. Fulton et al. (2019) quite rightly expressed concern about using image recognition underwater with the vast variety of debris available, however we have proven that subclasses are possible to use as a base to start with, and with future development on this research, we believe this could develop into a working large-scale prototype.

While this research scratches the surface of potentially using artificial intelligence to distinguish successfully and safely between life and man-made debris; there are plenty of other factors that should be considered and researched moving forward.

Our paper has been unique by comparing the effects of trained CNNs on a wide variety of categories, as opposed to three or four groups of objects. In particular, we have taken our study below the surface to detect debris and marine fauna underwater, as well as training the models to distinguish between the two.

Although part of the novelty of this research was the diversity of data in its nature of depth, geographic location, and sea conditions, it did not cover a wide enough variety and would need to comprise of a database that includes these variables or considers fresh waterways and the aquatic life that lives there. Additionally, these algorithms were only trained on matter that exceeded the size of micro plastics (micro plastics are <5 mm). Therefore, it remains untested on any debris or living creatures under that size.

Future research should be tested for image segmentation (or retest object detection) to ensure that biological entities (such as plants or animals) attached onto debris, are not categorised as litter.

Other variables would be to diversify the nature of species of all underwater creatures, such as how would this algorithm specifically respond to stingrays embedded within the sand or coral with plastic wrapped on it. Additionally, an entire classification could be dedicated to entangled sea creatures and plants, which if applied to automation

could be used to alert users to the finding of an endangered life.

Further considerations include asking if it would be able to handle more complex situations? Such as accurately pinpointing floating plastic in a sea of jellyfish. Although de Vries et al. (2021) at Ocean Cleanup are doing a fantastic job of mapping patches of debris within the gyre, could we test our method on retrieving large quantities of underwater debris without picking up small life within something as vast and compact as the Great Garbage Reef?

It would also be valuable for the algorithms to be combined with unsupervised learning using positive and negative reinforcement, so that they constantly train themselves and continue to improve their accuracy.

Programming and architecture building

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CRediT authorship contribution statement

Zoe Moorton: Conceptualization, Methodology, Formal analysis, Investigation, Resources, Software, Validation, Data curation, Writing – original draft, Visualization. **Zeyneb Kurt:** Validation, Writing – review & editing, Supervision. **Wai Lok Woo:** Writing – review & editing, Supervision.

Declaration of competing interest

We confirm that all authors and co-authors are aware of the current submission and consent to its review by the Marine Pollution Bulletin, and that there are no conflicts of interest or any overlapping publications by any of the authors. Additionally, the draft is not under review by any other journal and is our own work.

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