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Using deep-learning for automatic identification of images of marine benthic macro-invertebrate bycatch: a proof of concept

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Abstract

We applied a deep-learning approach in order to develop a neural network able to detect and identify macro-invertebrate organisms within images of benthos bycatch collected in the Southern Ocean. We used the Faster RCNN architecture and fine-tuning approach. To perform the transfer-learning, we used an annotated dataset of 59,756 images of organisms identified within 1,845 images of lots, covering eleven taxa: Echinodermata, Asteroidea, Arthropoda, Annelida, Chordata, Hemichordata, Cnidaria, Porifera, Bryozoa, Brachiopoda and Mollusca. The resulting network, not yet efficient enough to obtain precise identifications, is able to provide detection and classification of organisms with a good level of accuracy considering the limited quality of the images used for training. We present this study as a proof of concept for teams involved in the management of collections of macro-invertebrate images.

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Using deep-learning for automatic identification of images of marine benthic macro-invertebrate bycatch: a proof of concept

by

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Abstract. – We applied a deep-learning approach in order to develop a neural network able to detect and identify macro-invertebrate organisms within images of benthos bycatch collected in the Southern Ocean. We used the Faster RCNN architecture and fine-tuning approach. To perform the transfer-learning, we used an annotated dataset of 59,756 images of organisms identified within 1,845 images of lots, covering eleven taxa: Echinodermata, Asteroidea, Arthropoda, Annelida, Chordata, Hemichordata, Cnidaria, Porifera, Bryozoa, Brachiopoda and Mollusca. The resulting network, not yet efficient enough to obtain precise identifications, is able to provide detection and classification of organisms with a good level of accuracy considering the limited quality of the images used for training. We present this study as a proof of concept for teams involved in the management of collections of macro-invertebrate images.

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Résumé. – Utiliser l'apprentissage profond pour l'identification automatique d'images de macro-invertébrés marins issus de captures accessoires de benthos : une preuve de concept.

Nous avons utilisé une technique d'apprentissage profond pour développer un réseau de neurones capable de détecter et d'identifier des macro-invertébrés au sein d'images de lots d'organismes. Nous avons retenu l'architecture Faster RCNN. Pour réaliser le transfert d'apprentissage, nous avons utilisé une collection de 59756 images annotées d'organismes détectés et identifiés au sein de 1845 images de lots. Cette collection comprend onze groupes taxonomiques : Echinodermata, Asteroidea, Arthropoda, Annelida, Chordata, Hemichordata, Cnidaria, Porifera, Bryozoa, Brachiopoda et Mollusca. S'il n'est pas encore suffisamment performant pour permettre des identifications fines, le réseau que nous avons obtenu est capable de détecter et classifier les organismes avec un bon niveau de précision compte tenu de la qualité limitée des images de la base d'entraînement. Nous présentons cette étude comme une preuve de concept pour les équipes impliquées dans la gestion des collections d'images de macro-invertébrés et souhaitant implémenter des techniques d'intelligence artificielle.

Key words
Deep-learning
Benthos
Macro-invertebrates
Kerguelen
Southern Ocean
Bycatch
Fisheries
Automatic identification
Images
Annotated image collection

INTRODUCTION

The use of deep-learning approaches in bio-computing has considerably increased in the last few years because of strong improvement of calculation facilities and availability of massive datasets. This new approach is part of the machine-learning family of algorithms, *i.e.* techniques which commonly used in ecology for modelling species and community distributions (*e.g.* Elith *et al.*, 2008). The main point distinguishing deep-learning techniques from other artificial intelligence approaches is the capacity to handle massive datasets with no need to control the learning process. The modeller provides the solution to the machine and the machine recreates an algorithm which is able to find the solution. The implementation is processed by training artificial neural networks whose design is inspired by the functioning of real biological neural networks. This approach is suitable to build predictive tools in scientific contexts where explanatory parameters of a series of observations are unknown or extremely complex, preventing the possibility to use supervised algorithms (for more information see Goodfellow *et al.*, 2016).

The use of deep-learning in ecology covers various fields, such as population dynamics, landscape ecology, functioning of ecosystems or conservation biology (Christin *et al.*, 2019; Borowiec *et al.*, 2022). Their scale ranges from the individual level to global, including applications such as molecular data (Derkarabetian *et al.*, 2019) or the classification and analysis of massive bio-acoustic (Mac Aodha *et al.*, 2018) and image datasets (Hansen *et al.*, 2020). In the context of the scientific monitoring of the French fisheries of the Southern Ocean (Martin *et al.*, 2021), we have

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Figure 1. – Image of a batch of macro-invertebrate bycatch organisms from Kerguelen Exclusive Economic Zone (Poker 4 survey, 2017), including various species of sponges, ascidians, corals and echinoderms.

developed a database including 92,447 images of epibenthic marine macro-invertebrate bycatch organisms (Martin *et al.*, 2023). This database has been fully annotated, with the recording of organism identification (varying from species to phylum level) and a storage structure including images of lots (Fig. 1) and images of organisms, which have been obtained by cropping the images of lots (Fig. 2). We decided to use this original dataset to test the possibility of developing a neural network able to detect and classify automatically macro-invertebrates in images of lots. The main issue of this project was to assess the possibility of using this technology in a context characterized by the limited quality of raw data and the complexity of forms to be identified. Various deep-learning projects demonstrated the possibility of developing networks able to identify images of organisms (Joly *et al.*, 2016; Körschens *et al.*, 2018; Norouzzadeh *et al.*, 2018; Willi *et al.*, 2019; Guo *et al.*, 2020). In our project, we had to face three specific constraints:

– the large diversity of anatomical structures, shapes and general aspect of the benthic marine macro-invertebrates, due to the huge diversity of taxa (Fig. 1);

– the possibility of observing strong similarities in the aspect of organisms belonging to different taxa, due to evolutionary convergence affecting their anatomical structures (Fig. 2);

– the field constraints not allowing controlled conditions for the photographic capture of organisms, which induces important limitations for the quality of the images: overlap between organisms, non-standardized layout of the organisms, limited definition of the images, limited conditions of lighting, and non-standardized distance, focus and angle (Fig. 3).

Figure 3. – Image of a batch of macro-invertebrate bycatch organisms from Kerguelen Exclusive Economical Zone (Poker 4 survey, 2017), including corals, a crinoïd, an ophiurid, a sea urchin and a brachiopoda; organisms are incomplete and have been quickly spread out over a small plate to take the picture.

Here, we present the technique we used to address these issues and the results we have obtained as a proof of concept for further developments, for the benefits of teams involved in the curation of databases including images of macro-invertebrates such as the SeaLifeBase project (Palomares and Pauly, 2021).

MATERIALS AND METHODS

The detection network

We performed transfer learning through the fine-tuning of an existing detection network, namely the Faster RCNN (Region based Convolutional Neural Network) architecture

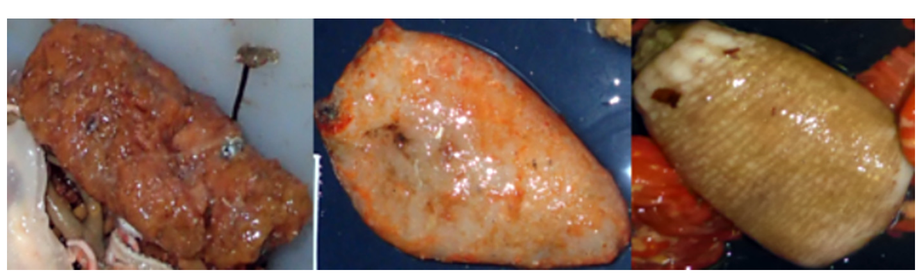

Figure 2. – Three images of organisms obtained by cropping images of lots; from left to right: Chalinidae (Porifera), Polyclinidae (Chordata), Hormatidae (Cnidaria).

(Ren *et al.*, 2015). It was retained due to its efficiency for objects detection and its flexibility (Ren *et al.*, 2015). A convolutional neural network is used to extract features from input images. Then, proposals (bounding boxes) are generated by another network (Region Proposal Network, RPN). Features corresponding to these proposal regions are then fed to a fully connected classification network for final object (organisms in our case) identification. Before this classification step, the sizes of the bounding boxes proposed by the RPN are standardized by a ROI (Region Of Interest) pooling layer. By including the RPN, Faster RCNN constitutes an improvement compared to the first generation of RCNN networks using selective search algorithms to generate propositions to be classified.

Training of the network

Fine-tuning is a classical approach to adapt a network trained on generic object databases to databases that are more specific and may exhibit structures and acquisition conditions that strongly differ from the initial training database. Such approaches have been regularly used to classify medical images (Zhou *et al.*, 2017) or specific object types (Chu *et al.*, 2016).

Training is processed using the PyTorch (Paszke *et al.*, 2019) framework and the Torchvision library (Marcel and Rodriguez, 2010). The library contains a Faster RCNN network already trained on the dataset COCO (including 330 K images and 80 classes, see Lin *et al.*, 2014) to the detection of an important diversity of basic shapes and forms. Mean values and standard deviation are used for normalization (three for each colour channel).

The database Bendima (Martin *et al.*, 2023) was used for the transfer learning. To train the network, we selected a set of images collected during scientific surveys in the Kerguelen Exclusive Economic Zone. We consider this to be the best available dataset of Bendima regarding quantity of organisms, diversity of taxa, diversity of shooting conditions, precision of the identifications and ecological representativity. The dataset resulting from this selection consists in 59,756 images of single organisms or colonies (Fig. 2) obtained by saving crops extracted from 1,845 images of lots (Figs 1, 3). Eleven taxa were considered, including ten phyla and one taxonomic class: Echinodermata, Asteroidea, Arthropoda, Annelida, Chordata, Hemichordata, Cnidaria, Porifera, Bryozoa, Brachiopoda and Mollusca. For the computing process on which the network training was based, such grouping provided object classes including enough contents.

Images from 1,600 lots out of 1,845 were used for the training. Two classification strategies were investigated. A first network (network 1) was based on the use of the Cross entropy as a loss function. Optimization was obtained with an Adam gradient descent (initial learning rate = 0.0001, during 50 epochs). A second network (network 2) was obtained with a weighted loss function to compensate the imbalance of classes, with the same gradient descent strategy, also during 50 epochs.

Evaluation

To evaluate performances, images from a randomly selected sample of 245 lots out of 1,845 were used as a testing dataset. Assessment was performed by calculating the precision and the recall. Precision indicates the proportion of correct classifications of predicted bounding boxes. Recall indicates the proportion of well-detected objects. Indices are calculated as follows: Precision = TP / (TP + FP) and Recall = TP / (TP + FN), where TP = True positive, FP = False positive, FN = False negative.

RESULTS

The two trained convolutional networks presented contrasting detection and classification results. The network 1 reached the highest mean precision value (0.57 *vs* 0.55) when the network 2 reached the highest mean recall value (0.52 *vs* 0.41).

Checking the indices for each class of object revealed also strong divergences in the performance of the two networks depending of the taxon which was considered (Table I). Network 1 and network 2 both presented the highest performance for the Echinodermata and Asteroidea object classes (excepted the mean recall of Echinodermata, which dropped to 0.38 for network 1, when network 2 reached 0.9). For both networks, performance then decreased for Arthropoda, Annelida and Chordata. Mean precision and mean recall of network 1 drop to 0 for Hemichordata, Cnidaria, Porifera,

Table I. – Mean values of Precision and Recall obtained for each object class of network 1 and network 2.

	Network 1 Mean precision	Network 1 Mean recall	Network 2 Mean precision	Network 2 Mean recall
Echinodermata	0.74	0.38	0.73	0.90
Asteroidea	0.62	0.78	0.67	0.85
Arthropoda	0.28	0.40	0.51	0.15
Annelida	0.22	0.15	0.5	0.60
Chordata	0.05	0.04	0.28	0.26
Hemichordata	0	0	0.25	0.60
Cnidaria	0	0	0.17	0.25
Porifera	0	0	0	0
Bryozoa	0	0	0	0
Brachiopoda	0	0	0	0
Mollusca	0	0	0	0

Figure 4. – Example of detection and classification obtained with an image of sea stars with network 2; red squares and annotations have been provided by the computer with no human action.

Figure 5. – Example of detection and classification obtained with an image including Ascidians and a sea star with network 2; red squares and annotations have been provided by the computer with no human action.

Bryozoa, Brachiopoda and Mollusca. Network 2 presented a low performance for Hemichordata and Cnidaria, with low mean values of precision and recall, which dropped to 0 for the four remaining groups. Despite a relatively high variability in classification accuracy depending on the taxon, these results showed that the fine-tuned networks indeed had the ability to reasonably classify images from the Bendima dataset, provided that annotated images of the considered taxon are abundant enough.

Figure 4 shows an example of the use of the network 2, with detection and classification performed on the image of a lot containing six Echinodermata organisms from different species, presenting various forms, sizes and colours: one fragment of an Ophiuroid (the body and basal part of the arms of a *Gorgonocephalus chilensis* (Philippi, 1858)) and five Asteroidea. The network did not detect one of the Asteroidea (*Pteraster* cf *affinis* Smith, 1876) but well detected the four others (*Porania antarctica* E. A. Smith, 1876, *Hippasteria* cf *phrygiana* (Parelius, 1768), *Bathybiaster loripes* Sladen, 1889 and *Diplasterias meridionalis* (Perrier, 1875)). *Diplasterias meridionalis* was over-detected, with a second region partly covering the organism. *Gorgonocephalus chilensis* was also over-detected, with two detections of the full fragment, one detection of the body only and one detection of the base of one arm. All the detected Asteroidea were well attributed to the Asteroidea object class. Three detections of *Gorgonocephalus chilensis* were rightly attributed to the Echinodermata. One detection of the full fragment was false and attributed to the Cnidaria object class.

Figure 5 shows an example of the use of network 2 on the image of a lot containing one fragment of an Asteroidea (the body of a sea star, *Labidiaster annulatus* Sladen, 1889) and 28 Polyclinidae ascidians. Network 2 over-detected *Labidiaster annulatus* with two detections, both attributed not to the Asteroidea object class but attributed to the Echinodermata object class, which was less accurate. Only one Ascidian was not detected, and four of them were detected two times. All the Ascidians were well attributed to the Chordata object class, excepted three of them resulting from over-detection: one was attributed to the Cnidaria object-class and two were attributed to the Echinodermata object class.

Figure 6 shows an example based on the image of a lot containing only three organisms, with no overlap: the fragment of an ophiuroid of the genus *Ophiura* (body and basal part of the arms), a fragment of a coral and a fragment of

Figure 6. – Example of detection and classification obtained with an image including an Ophiuroid, a piece of coral and a sea star with network 2; red squares and annotations have been provided by the computer with no human action.

Figure 7. – Example of detection and classification obtained with an image including Crinoïds, a Gastropod and pieces of seaweed with network 2; red squares and annotations have been provided by the computer with no human action.

an Ophiuroid, *Gorgonocephalus chilensis* (body and basal part of the arms). All three organisms were well detected by the network. *Gorgonocephalus chilensis* was detected two times, both regions covering only a part of the organism. The three organisms were rightly attributed to the Echinodermata and Cnidaria object classes.

Figure 7 shows an example based on the image of a lot containing 15 real organisms of epibenthic macro-invertebrates, but with also two pieces of sea weed, one fixed on a stone. Invertebrates were composed by one Mollusca, *Provocator pulcher* R. B. Watson, 1882, and 14 Crinoids, *Promachocrinus kerguelensis*. *Provocator pulcher* was well detected, but mistaken for an Ascidian and attributed to the Chordata object class. Only two Crinoids were undetected by the network, and four of them were over-detected. All of them were rightly attributed to the Echinodermata object class, except the over-detections, attributed to the Cnidaria object class. Moreover, the network has not been confused by seaweeds and stones, which were not detected as epibenthic macro-invertebrate organisms.

DISCUSSION

This first experiment is a success, and a proof of concept for the use of deep-learning for the treatment of images of marine macro-invertebrate bycatch. Given the limited quality of the images used for the training of the networks, the results in terms of detection and classification are both encouraging. For now, only detection could be used to develop a tool for automatic cropping of massive sets of images and to perform data mining to obtain a preliminary estimation of the number of organisms (especially for the most common and abundant species, for instance the sea stars). The quality of detection and classification is not yet sufficient enough to extract automatically reliable identifications.

From this experiment, we can first conclude that deep-learning methods can perform detection and classification of specimens of marine invertebrates, but under two conditions: the examples of crops representing a given group has to be numerous and diverse enough. The increase of the size of Bendima could be a first goal to address this issue (Shorten and Khoshgoftaar, 2019). Improvements in the learning strategy should be explored. The available dataset would be easily enriched without the need of new records by applying transformations on the images, for instance by rotating or flipping the crops. This would quickly increase the diversity of the training dataset, in order to make the deep-learning process more powerful (Perez and Wang, 2017; Mikolajczyk and Grochowski, 2018; Pacheco and Krohling, 2021). Moreover, strategies taking advantage of the nested structure of the classes should be explored. Here, images have been pooled without considering the nested structure of the data resulting from the taxonomic ranks. Improvement of the learning process should be based on the use of the Phylum/Class/Order/Family/Genus/Species information attached to each image of organism. Furthermore, additional information could be implemented in the learning process, with complementary annotations of the images (Lopez-Fuentes *et al*., 2017; Pritt and Chern, 2017; Ellen *et al*., 2019). This may include information about the quality of the images (*e.g*. if the organism is complete or not); anatomical structures (*e.g*. which anatomical parts of each organism are visible); or geographical location and depth, to weight detection probability by the known distribution of the species.

We believe that the main interest of the deep-learning approach is the possibility of recording the "human brain-based" process of taxa identification, which is performed without a computer, just with knowledge and naturalist skills, by any author of a study. In the future, when such approach will be improved enough, authors could provide the recording of their brain-based taxa identification process within the 'supplementary materials' section of an article, in the form of a trained network stored in a computer file, contributing to improve reproducibility of the research. Such recording could be shared with other scientists, to be applied to other datasets, allowing comparison studies. This possibility would be of interest when recording the brain-based identification process performed by a specialist in the field of taxonomy, so that it may be used in the field of ecology. This could be a suitable solution to complete the barcoding approach (Hebert *et al*., 2003; Ratnasingham and Hebert, 2007) in response to the lack of experts in systematics (Costello *et al*., 2013).

Finally, the recording of a collective brain-based identification process, based on combined identifications from many contributors, may allow two primary improvements:

1 – Improved reliability of automatic identification tools based on such recordings.

2 – The possibility to base organism identifications on a consensus, which could be an achievement in conservation contexts involving divergent stakeholders such as conservation planning studies or protected areas design (Yates and Schoeman, 2015).

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