FINAL REPORT PROGRAM LEFE

Program LEFE/ action(s) MANU, CYBER	**Project Title** **DL-PIC Deep Learning for Plankton Images Classification**	**Years 2017 – 2018**

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Context

Planktonic organisms are primary components of the Earth's biosphere. New automated imaging instruments allow to study them at both fine resolution and large scale. But these instruments generate large amounts of data that require the interaction of human curators and machine learning algorithms.

Objectives / scientific questions

DL-PIC aimed at using the fairly recent Deep Learning approaches from computer vision to help process this data. The specific objectives were to (1) improve training sets, (2) tune deep networks architecture and settings for plankton, account for organisms (3) size and (4) taxonomy in the classification, (5) include these improvements in a user-friendly interface, and (6) explore deep learning for applications on embedded hardware.

Main results

(1) Improve training sets

We released a curated dataset of 1.4M ZooScan images (https://www.seanoe.org/data/00446/55741/), which has been browsed ~500 times, downloaded ~80 times and cited in three publications in 2019. We have prepared a similar dataset for 7.5M UVP images which is currently being used for tests before being released to the public. More modest datasets have been prepared for other instruments to allow tests and will be released publicly when they reach a critical mass.

(2), (3), (4) Explore deep learning networks for plankton classification

To tackle several questions together, we used a combination of deep and classic machine learning. Deep networks consist of several parts: (i) the convolution + pooling layers, which act as morphological features extractors; (ii) the fully connected layers, which perform dimensionality reduction; (iii) the final softmax classification layer. We chose to fully train our network on various data sets but, then, to cut it short at the time of evaluation and extract ~400 morphological features from it (i.e. the last fully connected layer). Then we re-trained a classic classifier (a Random Forest) with those features, or the handcrafted features we classically extract from images (size, grey level, etc.), or a combination of both.
This mixed approach allowed us to:

- Use a potentially higher performing classifier (Random Forest vs. simple softmax).
- Quickly train custom classifiers without having to recompute the features, which is time consuming.
- Combine different types of features and therefore explore the effect of size, for example, which is a feature commonly computed in handcrafted routines but usually absent from deep networks.
- Use a classifier that is based on trees, on which imposing some structure in the form of a taxonomic tree will be more natural (this, unfortunately, was not achieved within the timeframe of the project).

In addition, several papers and our tests show that the features extracted by deep networks are often generic and can be transferred from one use-case to another. So, we did not spend too much time fine-tuning the

networks and, instead, extensively tested the final Random Forest classifier.
In the end, we achieved classification accuracies from ~70 to ~90% depending on the datasets (Table 1). Deep learning features gave, most of the time, more accurate models than handcrafted ones. Most interestingly, the combination of a few handcrafted features with the many deep learning features always improved the classifier (up to 3.5%); most of this improvement can be tracked down to the inclusion of size.

(5) Include these improvements in a user-friendly interface
The trained deep learning models as well as the improvements of the settings of the Random Forest algorithm were all included in our web application for plankton image classification https://ecotaxa.obs-vlfr.fr/ (Figure 1). They are now available to its 700 registered users and 40 concurrent daily users around the world.

(6) Explore deep learning for applications on embedded hardware
One of our imaging instruments is destined to equip autonomous instruments such as Argo floats. Floats are not recovered and images are too big to be transferred, so feature extraction and classification has to be done onboard. We evaluated (i) the deterministic extraction of features (image moments) followed by classification by Gradient Boosted Trees vs (ii) a minimalistic 4 layers neural network.
Solution (i) requires a few image manipulation steps to compute moments and the training of a model with at most 38k parameters per class (and ~40 classes). Solution (ii) requires ~370k parameters to compute 1.2M values. So, the overall complexity of the approaches is actually similar. Yet, loading the model in memory is the most time and energy consuming step and the tree-based model turned out to be much smaller than its maximum theoretical size (hence faster to load); it also performed slightly better. We are currently fine tuning it.

Table 1

Dataset	*Handcrafted features*	*Deep features*	*Both*
FlowCam	83.2%	82.7%	86.7% (+3.5)
UVP5	86.1%	79.6%	86.7% (+0.6)
ZooCam	87.9%	89.9%	92.2% (+2.3)
ZooScan	71.7%	78.6%	80.2% (+1.6)

Figure 1

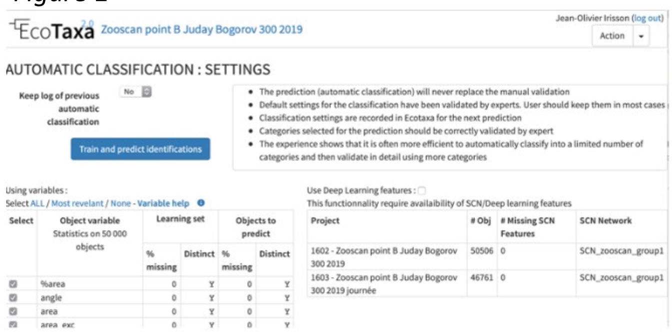

Table 1: Accuracies for four plankton images datasets (from different instruments) using either handcrafted features (size, grey level, etc.), or deep learning features, or both. The combination is always beneficial over the best single model (improvement noted in parentheses).
Figure 1: Screen capture of the automatic classification page of EcoTaxa where the handcrafted features (on the left) are joined with the deep learning features (on the right).

Future of the project:
The initial work in this project gave rise to several larger scale projects (including one funded for 1M€ by the Belmont Forum) that will allow its activities to continue and develop. New training datasets will be released to the community. We will explore further the possibility to join generic network for feature extraction and classic classifiers to benefit from the richness of deep networks and the speed and “simplicity” of classic models. The inclusion of taxonomy in the classifier is the topic of a current PhD thesis, and classification on embedded hardware as well as selective validation of huge plankton datasets are part of two others.

Nombre de publications, de communications et de thèses
Luo JY, Irisson J-O, Graham B, Guigand C, Sarafraz A, Mader C, Cowen RK (2018) Automatic plankton image analysis using convolutional neural networks. Limnology and Oceanography: Methods 16:814-827.
Contribution to the ICES Working Group on Machine Learning in Marine Sciences (WGMLEARN) with 30 participants and 13 presentations. Review paper in writing; Participation to the Ocean Sciences Meeting 2020 with two oral presentations.
Three PhD theses started in Sept 2019, all partially based on the initial findings in DL-PIC.