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A Deep Learning method for accurate and fast identification of coral reef fishes in underwater images

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Abstract

Identifying and counting fish individuals on photos and videos is a crucial task to cost-effectively monitor marine biodiversity, yet it remains difficult and time-consuming. In this paper, we present a method to assist the identification of fish species on underwater images, and we compare our model performances to human ability in terms of speed and accuracy. We first tested the performance of a convolutional neural network (CNN) trained with different photographic databases while accounting for different post-processing decision rules to identify 20 fish species. Finally, we compared the performance of species identification of our best CNN model with that of humans on a test database of 1197 fish images representing nine species. The best CNN was the one trained with 900 000 images including (*i*) whole fish bodies, (*ii*) partial fish bodies and (*iii*) the environment (e.g. reef bottom or water). The rate of correct identification was 94.9%, greater than the rate of correct identification by humans (89.3%). The CNN was also able to identify fish individuals partially hidden behind corals or behind other fish and was more effective than humans to identify fish on smallest or blurry images while humans were better to identify fish individuals in unusual positions (e.g. twisted body). On average, each identification by our best CNN using a common hardware took 0.06 seconds. Deep Learning methods can thus perform efficient fish identification on underwater images and offer promises to build-up new video-based protocols for monitoring fish biodiversity cheaply and effectively.

Keywords: marine fishes, convolutional neural network, underwater pictures, machine learning, automated identification

Introduction

Coral reefs host a massive and unique biodiversity with, for instance, more than 6,000 fish species (Mouillot et al., 2014) and provide key services to millions of people worldwide (Rogers et al., 2017). Yet, coral reefs are increasingly impacted by global warming, pollution and overfishing (Graham et al., 2011; Robinson et al., 2017; Scott and Dixson, 2016; Hughes et al., 2017; Cinner et al. 2018). The monitoring of fish biodiversity through space and time on coral reefs (Halpem et al., 2008; Jackson et al., 2001) is thus a critical challenge in marine ecology in order to better understand the dynamics of these ecosystems, predict fisheries productivity for dependent human communities, and improve conservation and management strategies to ensure their sustainability (Krueck et al., 2017; Pandolfi et al., 2003).

Most surveys of coral reef fishes are based on underwater visual censuses (UVC) carried out by scuba divers (Brock, 1954; Cinner et al., 2016, 2018; Thresher and Gunn, 1986). While non-destructive, this protocol requires the identification and enumeration of hundreds of individuals belonging to hundreds of species so it can only be performed by highly trained scientific divers while being time consuming. In addition, the accuracy of such visual-based assessments is highly dependent on conditions (depth, dive duration) and divers experience while the presence of diver biases the detection of some furtive species (Chapman and Atkinson, 1986; Harvey et al., 2004; Sale and Sharp, 1983; Watson and Harvey, 2007; Willis, 2001).

Over the last decade, underwater cameras have been increasingly used to record fish individuals on fixed videos, along belt transects (Cappo, 2003; Langlois et al., 2010; Mallet and Pelletier, 2014), or around baits to attract predators (Harvey et al., 2007; Watson et al., 2005; Willis and Babcock, 2000). Video-based surveys provide estimations of fish abundance and species diversity similar to UVC-based surveys (Pelletier et al., 2011). Video-based methods can be used to overcome the limitations of human-based surveys (depth, time underwater). They also provide a permanent record that could later be re-analyzed. However, assessing fish biodiversity and abundance from videos requires annotation by highly trained specialists and is a demanding, time-consuming and expensive task with up to several hours required to identify fish individuals per hour of video (Francour et al. 1999). There is thus an urgent need to develop new tools for automatic identification of fish individuals on photos and videos to provide accurate, efficient, repeatable and cost-effective monitoring of reef ecosystems.

Automatic and accurate identification of organisms on photos is crucial to move toward automatic video processing. In addition, automatic identification of species on photos is especially relevant for citizen science. For instance, the application pl@ntNet (https://plantnet.org/) automatized the identification of 13,000 species of plants. For fishes, some public tools like inaturalist.org or fishpix (http://fishpix.kahaku.go.jp) offer the possibility to upload images that will be manually identified by experts. These valuable initiatives would benefit from the support of automatic identification algorithms to save time of experts.

The performance of recent methods dedicated to the automatic identification of objects on images has drastically increased over the last decade (Siddiqui et al, 2017; Lowe, 1999). However, some of these methods have been tested only on images recorded in standardized conditions, in terms of light and/or fish position (e.g. only lateral views) (Levi, 2008; Alsmadi et al, 2010). Identification of fish individuals on 'real-life' underwater images is more challenging because (*i*) color and brightness are highly variable between images and even within a given image, (*ii*) the environment is textured and has a complex 3-dimentional architecture, (*iii*) fish can be recorded in various positions and are often hidden behind other fish or corals, and (*iv*) the acquisition camera and its internal parameters can be variable.

Recently, an accurate automation of detection and identification of fish individuals has been obtained (Shortis et al., 2016) using machine-learning methods such as support vectors machines (Blanc et al. 2014), nearest neighbor classifiers (Levi, 2008), discriminant analysis classifiers (Spampinato et al., 2010) or Deep Learning (Li et al., 2015). The latest competitions (Joly et al., 2106) and comparisons (Villon et al., 2016) show that Deep Learning based methods, which are a type of neural network combining simultaneously automatic image descriptor and descriptor classification, tend to achieve the highest performance, particularly convolutional neural network (CNN) that add deep layers to classical neural networks (Lecun et al., 2015).

However, the accuracy of CNN methods is highly dependent on the extent and the quality of data used during the training phase, i.e. the set of images annotated by experts for all classes to identify. The effects of the extent of the training database (i.e. the number of images per class) and associated post-processing decision rules on the performance of the whole identification process remain untested. Since real-life videos of coral reef fishes and thus images extracted from those videos are highly diverse in terms of surrounding conditions (environment, light, contrast) and fish positions, the performance of identification methods must be carefully tested using an independent dataset to assess its robustness over changing conditions.

Furthermore, the performance of models should be compared to the performance of humans to determine whether machine-based assessment of fish biodiversity provides an advantage over traditional human processing of images (Matabos et al., 2017). Here we tested the performance of 4 models, built with the same CNN architecture, for automatic identification of fish species on coral reefs. Specifically, we assessed the effect of several training image datasets and several decision rules, with a particular focus to identify fish partially hidden behind the coral habitat. We then compared the performances of the best CNN models to those of humans.

Methods

Image acquisition for training and testing CNN models

We used GoPro Hero3+ black and GoPro Hero4+ black cameras to record videos at 30 fps over 50 reef sites around the Mayotte island (Mozambique Channel, Western Indian Ocean) including fringing and barrier reefs, and at depth from 1 to 25m. Videos were recorded from April to November 2015. Recording conditions varied between sites and days, especially in term of light and environment (i.e. proportion of hard and soft corals, sand and water visible). All videos were recorded with a resolution of 1280x720 (HD) and 1920x1080 pixels (full HD) with default settings for color temperature and exposure (i.e. no use of protune or automatic color balance adjustment).
For all recordings, the cameras remained stationary and no artificial light or filter were used. We recorded 116 videos representing a total of 25 hours.

For all videos, 5 frames per second were extracted leading to a database of 450,000 frames. Fish individuals were delineated and identified by undergraduate, master degree students and PhD students in marine biology trained for fish identification on videos with the support of identification keys and under the supervision of experts (Froese and Pauly, 2000; Taquet and Diringer, 2007). Each annotation consisted in drawing a rectangle bounding box around a single fish individual, including only its very close context as illustrated on Fig.1.a, and associating a label (i.e. species name) to this individual. We call those specific images “thumbnails”.
The criteria for the annotation were:
1) Annotate a fish only if there is no more than 10% of its surface covered by another object (fish, coral, or substrate).

2) Annotate a fish only if it can be identified at the species level in the frame (i.e. independently from previous or next frames where the same fish could have a better position for identification).
3) Annotate a fish only if its apparent size is larger than 3,000 squared pixels, i.e. ignoring fish individuals too far from the camera.
4) Annotate images from different habitats and depths to represent a broad range of light conditions and environment, and target at least 1,200 thumbnails per species.

We did not consider thumbnails of individuals in positions where they are hard to identify (such as fish seen from front) since they would bring more noise than relevant information for the algortihm as the discriminating parts of the fish are hidden (specific color pattern, marks, etc). We did not process the image with background subtraction for 2 reasons:
1) We did assume that in our case the context helps to identify fish species, as some species tend to be associated with some particular environment such as Amphiprion in sea anemone, Chromis viridis on Acroporas, Caesionidae in plain water etc...
2) We wanted our process to be used on full images. In such context, separating fish individuals from their background would be either manual or not reliable.

This annotation procedure yielded a training dataset (T0) with 44,625 annotated fish thumbnails belonging to 20 species (Table 1). The 20 species present in the training dataset represent the most common species appearing in the videos and belong to 12 families among the most diverse and abundant on coral reefs worldwide (e.g. Pomacentridae, Acanthuridae, Chaetodontidae, Labridae). Models were then tested using a set of images independent from the ones used for the training phase to ensure a cross validation procedure and that model performance reflects real-life study case. More specifically, the test dataset was built using 6 videos recorded in contexts different from those of videos used for training (i.e. sites or days not included in the training database). Annotations of these videos were made like the training dataset except that it included fish individuals partially hidden by other fish or by corals as well as fish individuals viewed from front or back (their identity being checked using when necessary previous or next frames). As our goal is to identify fish species on images and photos, the test without any filter allows to assess to which extent our algorithm is performing to help users to take a picture good enough for fish identification.

We obtained a test dataset of 4,405 annotated fish thumbnails belonging to 18 out of the 20 species present in the training dataset (Table S3). We then randomly selected a subset of 1,197 fish thumbnails belonging to 9 species to compare the performance of humans vs. obtained models (Table S3).

Deep-learning algorithm

We used a convolutional neural network (CNN) architecture to build a fish identification model (Schmidhuber, 2015). CNNs are a class of deep learning algorithms used to analyze data and particularly to classify objects from images (Krizhevsky et al., 2012).

CNNs are made of layers of interconnected neurons and each neuron includes a 'convolutional kernel' that computes a set of mathematical operations (defined by 'weights') on the matrices of values describing the image (i.e. values for each color channel for each pixel).
Convolutional features are combinations of pixel values that encode information about target classes. Low level features can detect edges or color patterns, while, high level features might differentiate different fish shapes.

This process yielded 'feature maps', i.e. a vector describing image characteristics (shapes, colors, statistical information of the image).

The main difference between CNNs and other classifiers is that CNNs build the "feature extractors" (convolutions in the case of CNN) and the classifier conjointly.
Then the last layer of the network classifies those feature maps with a soft-max method and gives as output scores corresponding to the "probability" that each image belongs to each of the learned classes (Lecun et al., 2015). More precisely, the training phase of the network consists in iteratively modifying the weights of the convolutional kernels (hence features maps) to optimize the classification score of all classes.

We used a GoogLeNet architecture as it was the winner of the 2015 competition imageNet (Szegedy et al., 2015), an identification challenge on 1,000 different classes. This CNN is composed of 22 layers. It uses inception modules. Inception modules allow the network to use convolutions of different sizes (1*1, 3*3 and 5*5 pixels) and to weight each of these convolutions. This network could thus account more or less strongly for the context of each pixel, which increases the range of possibilities to improve its performance during the training.

A link to a depository with architecture details is given at the end of references. We stopped the network training after 70 epochs (i.e. a complete scope of the dataset where each image is used only once), to prevent overfitting. We used a learning rate of 10^{-5}, an exponential learning decay with a Gamma of 0.95, a dropout of 50% and an Adam Solver type as learning parameters. Those are classic hyper-parameters for a fast convergence of the network without over-fitting (Srivastava, 2014). The weight initialization is also classic with a random Gaussian initialization. The training lasted 8 days on our configuration; we trained and ran our code on a computer with 64GB of RAM, an i7 3.50GHz CPU and a Titan X GPU card for 900,000 images.

We used at least 2200 thumbnails per fish species class, and batches of 16 images to train our network. We ran this architecture on Caffe (Jia et al, 2014). To focus on the impact of the training data, we used the same CNN architecture for our training and test procedures.

Building the training datasets

Using the raw training dataset of 20 fish species (Table S1) we built 4 different datasets to assess the influence of the dataset building on classification results (Table S2).

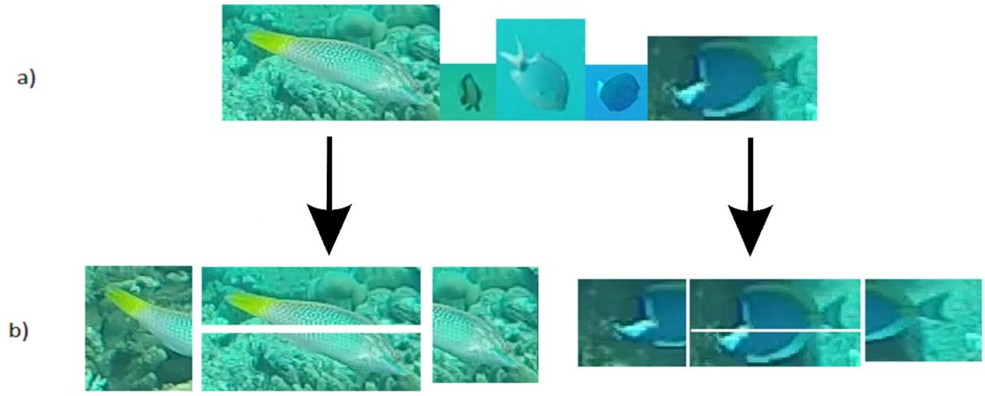
The first training dataset T1 contained raw fish thumbnails (T0) and their respective mirror images. More precisely, we doubled the number of thumbnails per fish individual by flipping each thumbnail with respect to the vertical axis. Such a procedure homogenizes the proportion of left-oriented and right-oriented individuals in the database and we hypothesize it could improve the average identification rate since fish individuals are seen in all positions.

The second training dataset T2 contained fish thumbnails from T1 plus "part of fish" thumbnails. Thumbnails of this class were obtained by splitting each thumbnail of T0 into 4 parts: upper part, lower part, right part, and left part as shown on Fig.1. b. We hypothesized that this class can prevent from misidentification of partially hidden individuals. For instance, if a black and white fish is partially hidden so that only its dark part is visible it would likely be confounded with a full dark fish.

The third training dataset T3 contained fish thumbnails from T2 plus thumbnails of a single class "Environment". Environment thumbnails were extracted at random in portion of frames where no fish was detected. We hypothesized that such a procedure can help distinguishing between fish species given the high diversity of environments present around them, i.e. allowing CNN models to find more efficiently features discriminating fishes whatever the background around them.

The fourth training dataset T4 contained thumbnails from T3 minus the "part of fish", which is replaced by 20 classes "part of species" obtained by splitting thumbnails from each species. The difference between T3 and T4 was that T3 contained only one global class "part of fish" whereas T4 contained as many "part of species" classes as there were "fish" species.

Figure 1: Thumbnails samples.
a) Examples of thumbnails of whole fish individuals from the training database and b) examples of thumbnails extracted from whole fish picture to build "part of fish" and "part of species" classes.



Testing the performance of models

We first compared the performance of the 4 models trained using each of the 4 training datasets. In addition, we tested the performance of models after correcting their raw outputs using two *a posteriori* decision rules. First, since the networks trained with T2, T3 or T4 are likely to recognize environment samples with a high confidence score (over 99%) they could thus classify some fish as an environment class (i.e. false positive). We therefore defined a decision rule (r1): when the first proposition of the network was 'environment' with a confidence lower than 99% we provide, as final output, the fish class with the highest probability.
Similarly, as "part of species" classes present in T4 were just a methodological choice to improve model performance (and hence were absent from the test database), we defined a second decision rule (r2): when the result given by the network is "part of species X", we provide, as final output, "species X".

We then compared the performance of the best model with the performance of humans, in terms of accuracy and time needed to identify fish thumbnails. This experiment aimed to compare the results obtained by humans to those obtained by the CNN using a fair method. This means that during the comparison procedure both CNN and humans were shown thumbnails without any contextual information (there was no general view of the scene), and the thumbnails were never seen before the test procedure. The procedure could even be slightly in favor of humans because they knew that there were only 9 species to classify, whereas the CNN worked from the 21 species learned and misclassification could occur with a higher probability.

Our goal was to allow humans to identify species as fast as possible in this particular context. For this purpose, we developed an online survey tool operating in Chrome web browser which allowed users to easily and quickly identify a fish on a picture displayed at the center of the window by either writing the name of the species (with auto-completion) or to select it from a list. A "help" sheet showing a reference picture of the fish species to identify was available in the same window (Fig. S1). Once a user selected a species, time to perform the identification was saved and a new randomly chosen fish picture was displayed.

This comparison was performed on 1197 randomly chosen thumbnails of only 9 species present in the test thumbnail dataset (Table S3) to ease the test for humans. The test lasted 20 minutes with the help of 10 undergraduate students, 2 Master Degree and 2 PhD student in biology from the University of Montpellier who were previously trained to identify these fish species. Such a short test duration for humans reduces tiredness that could decrease identification accuracy and rapidity. We then compared the answers to the ground truth (i.e. identification made by experts in fish taxonomy) and computed the time needed to perform each identification. We finally compared correct identification rate and time per fish individual between humans and the best CNN model.

Results

Influence of the training database and of post-processing on model performance

The 4 CNN models obtained with 4 different datasets (T1, T2, T3, T4) had similar mean identification success rate, close to 87% (Table 1). However, there were marked differences in correct identification rate between models for several species. For instance, *Dascyllus carneus* was correctly identified in only 4% of the cases by model trained with only whole fish thumbnails (T1) while it was correctly identified in more than 90% of cases by the three other models. Conversely, *Pomacentus sulfureus* was more often correctly identified by the models trained with T1 than by models trained with environment thumbnails (T3 and T4).

Table 1:

Raw success rate (%) of the 4 CNN models trained with different thumbnails datasets for identifying 18 fish species. See details about training databases in Table S2.

Species	Only whole fish (T1)	Whole fish and part of fish (T2)	Whole fish, environment and part of fish (T3)	Whole fish, environment and part of species (T4)
Abudefduf sparoides	80.8	94.9	85.8	82.8
Abudefduf vaigiensis	94.5	89.0	89.0	80.0
Chaetodon trifascialis	94.7	90.4	91.0	85.1
Chromis weberi	98.8	96.6	92.9	98.8
Dascyllus carneus	4.0	91.5	92.3	91.5
Monotaxis grandoculis	90.0	68.0	77.7	79.1
Myripristis botche	100	80.0	75.0	95.0
Naso elegans	96.2	92.4	89.7	95.1
Naso vlamingii	92.6	95.3	89.1	95.8
Nemateleotris magnifica	100	98.2	99.5	99.1
Odonus niger	79.5	91.4	92.6	81.8
Plectroglyphidodon lacrymatus	100	100	74.2	94.0
Pomacentrus sulfureus	97.8	67.6	82.5	73.8
Pterocaesio tile	100	100	100	99.5
Pygoplytes diacanthus	84.2	91.5	84.2	86.8
Thalassoma hardwicke	83.9	82.7	88.0	87.3
Zanclus cornutus	93.3	84.3	86.4	89.0
Zebrasoma scopas	89.0	88.8	88.8	92.7
Mean identification success rate	87.6	87.9	87.7	86.9

Post-processing raw outputs of the model T4 following decision rule r1 (i.e. environment not considered as a correct result), improved correct identification rate from 86.9 to 90.2% (Table 2). Adding decision rule r2 (i.e. identification of a part of a species considered as a correct answer) increased this success rate to 94.1% (Table 2). Hence, post-processing raw outputs of the model trained with the most complete dataset provided the best identification rate. Among the 18 species, success rate ranged from 85.2 to 100%, with only 3 species being correctly identified in less than 90% of cases and 9 species being correctly identified in more than 95% of cases, including 3 with a correct identification rate >99%.

Confusions between 2 fish species were lower than 4% (Table 3). Confusion between a fish and the environment was common when no post-processing was applied with for instance up to 20.9% of *Pomacentrus sulfureus* individuals misidentified as environment (Tables S4, S5). However, applying decision rule r1 decreased this error rate to less than 4% (Table 3).

Table 2:
Success rate (%) of 3 CNN models for identifying 18 fish species. First column presents accuracy based on raw output of a deep-learning model trained with thumbnails of whole fish, part of species and environment (as last column of Table 2). Second column presents accuracy after applying a decision rule 'r1' keeping most likely fish class if 'environment' was the most likely class. Third column presents results after applying decision rule 'r1' plus decision rule 'r2': "part of species X" is equivalent to "species X". Numbers are percentages of correct fish identification.

Species	Raw output	Decision Rule r1	Decision Rules r1 and r2
Abudefduf sparoides	82	88	91.9
Abudefduf vaigiensis	80	89	98
Chaetodon trifascialis	85.1	87.8	91.5
Chromis weberi	98.8	98.8	99.2
Dascyllus carneus	91.5	91.5	91.5
Monotaxis grandoculis	79.1	83.3	86.1
Myripristis botche	95	95	95
Naso elegans	95.1	96.7	97.8
Naso vlamingii	95.8	96	96
Nemateleotris magnifica	99.1	100	100
Odonus niger	81.8	81.8	85.2
Plectroglyphidodon lacrymatus	94	94	96
Pomacentrus sulfureus	73.7	78.1	87.9
Pterocaesio tile	99.5	100	100
Pygoplytes diacanthus	86.8	89.4	92.1
Thalassoma hardwicke	87.3	89.6	94.2
Zanclus cornutus	89	95.3	98.4
Zebrasoma scopas	92.7	92.7	92.7
Average success rate	86.9	90.2	94.1

Table 3:

Performance and confusion rates of CNN model for 9 fish species.The CNN was trained with dataset T4 (see Table 1), including thumbnails of whole fish, part of species and environment. Raw CNN outputs were post-processed with following decision rules:

'r1': If the highest probability is lower than 99% and is for class "environment" then the fish class with the second highest probability is kept.

'r2': Outputs "part of species X" are considered as equivalent to "species X" (i.e. the scores of *A. sparoides* and *part of A. sparoides* were merged).

Columns indicate the species to classify, and rows indicate the results (most probable species) given by the model (i.e. percentages on the diagonal indicate success rate). Only values over 1% are shown. Full names of species are in Table 1

Species	*A.sparoides*	*A. vaigiensis*	*C. Trifascialis*	*N. elegans*	*P. sulfureus*	*P. diacanthus*	*T. hardwicke*	*Z. cornutus*	*Z. scopas*
A.sparoides	91.9						1.3		
A. vaigiensis	1.1	98.2							
C. Trifascialis			91.5				1.0		
C. Weberi	2.2						1.1	1.5	
D. caruleus									3.9
N. elegans				97.8					
P. sulfureus	1.0	1.8	1.0		87.9	2.5			
P. diacanthus					3.8	92.1			
P. lacrymatus						2.6			
T. Hardwicke	2.0		1.5				94.2		
Z. cornutus	1.0							98.5	
Z. scopas									92.7
Environment					3.6	2.6			1.0

Performance of CNN models vs. humans

On average, each human identified 270 fish thumbnails during the 20-minute test. Mean rate of correct classification for humans was of 89.3% with a standard deviation of 6% (Table 4). Rate of correct classification achieved by the best model on the same thumbnails was of 94.9% with a standard deviation of 3.3%. Correct classification rate by the best model ranged from 88.2% (*Abudefduf sparoides*) to 98.2% (*Abudefduf vaigiensis*). For only one species (*Zanclus cornutus*), the best model had a lower performance than humans but both were higher than 97%. The mean time needed to identify a fish by humans was 5 seconds, with the fastest answer given in 2 seconds and the longest in 9 seconds. On average, each classification by our final model took 0.06 seconds with hardware detailed above.

When tested against humans using a challenge with only 9 potential species, the network was more effective on smaller or blurrier thumbnails, while humans were better to recognize unusual positions (Fig. 2). There were only 2% of fish individuals which were neither identified by humans nor by the network (Fig. 2).

However, experts with more than 10 years of experience in the field may have outperformed the CNN model in terms of correct identification particularly for hidden or unusually positioned fish.

Table 4: Accuracy (success rate in %) of fish identification by humans and by the best CNN model for 9 species. The model was trained using thumbnails of whole fish, part of fish species and environment (T?). Raw outputs were post-processed applying two decision rules: (r1) keeping most likely fish class if "environment" was the most likely class, and (r2) considering "part of species X" equivalent to "species X".

Species	Number of thumbnails tested	Deep-learning model	Humans
Abudefduf sparoides	88	93.4	87.7
Abudefduf vaigiensis	47	97.3	84.7
Chaetodon trifascialis	149	95.1	89.4
Naso elegans	165	98.4	94.8
Pomacentrus sulfureus	443	97.9	93.2
Pygoplites diacanthus	35	90.4	77.4
Thalassoma hardwicke	73	96	91
Zanclus cornutus	53	97.1	97.8
Zebrasoma scopas	144	96.2	88.3
Average success rate	1197	95.7	89.3

Discussion

Assessing the performance of the same CNN trained with four different datasets demonstrates that correct identification rates were all close to 87% . Thus, a training dataset made of more than 1300 thumbnails of each species could yield a success rate similar to the ones obtained in image identification challenges in more controlled conditions (Siddiqui et al., 2017). Beyond their number, thumbnails of each species used to train the network were extracted from different videos and different sites to include as many orientations of fish as possible and to embrace a strong environmental variability in terms of light, colors and depth. However, our best CNN model may perform more poorly with a broader range of species across other locations and environments. Our 18 species belong to 12 different families so are likely to differ in shape or color. With much more congeneric species these differences would make the identification much more challenging.

Despite a similar mean success rate, the performance of the four models differed markedly for some species. Ten out of the 18 species were more often correctly identified when CNN models were trained using thumbnails of part of fish or environment, and eight other species were better identified by the model trained with only whole fish picture. Additionally, some species were often misidentified as environment (Table S5), even if the probability of this class was lower than 99%.Such confusion could be explained by the fact that some small species are always close to corals and of similar colors, e.g. the yellow benthic fish *Pomacentrus sulfureus.* Similarly, for the small *Dascyllus carneus* case, which is often misclassified with almost all fish species when background was not included in the training dataset, the addition of environment thumbnails certainly helps the network to focus on features unique to the fish body rather than to its surrounding.

We demonstrate that the best results were obtained after applying two *a posteriori* decision rules on raw outputs from the neural network trained with the most complete set of thumbnails. This model reached a success rate of 94.1% for the 18 species tested, with only 3 species being correctly identified in less than 90% of cases. Therefore, training a neural network with thumbnails from surrounding environment and thumbnails of part of each fish species is important to reach a high correct identification rate in real-life cases. The class "Environment" adds versatility to the training and hence helps the network to select features that are robust to the context around fish. Including classes "part of species" allows the network to classify correctly individuals partially hidden by other fish or corals. Such situations were common in the test dataset as illustrated by the fact that up to 9% of individuals of *Abudefduf vaigiensis* were classified as "part of *A. vaigensis*" rather than "whole *A. vaigensis*".

The success rate of the best model is similar to that of the model of Siddiqui et al. (2016) which reached a success rate of 94.3% on 16 species. This latter model was trained on a much smaller training dataset of 1309 thumbnails than our model (> 900 000 thumbnails). However, Siddiqui's model was designed to identify fish on videos recorded in partially controlled conditions (i.e. fish swimming close to a baited camera) while in our case we tested the ability of the model to identify fish partially hidden by corals as well as shot in all positions and orientations. The few misidentifications by our best model mostly occurred when only the face or back of fish was visible. Such an issue could be easily circumvented in practice when analyzing videos because it is likely that each fish will be seen from the side on at least one frame (out of the 25 frames recorded per second by most cameras).

Figure 2: Samples of thumbnails recognized by the CNN model and not recognized by humans (a), samples of thumbnails recognized by humans and not recognized by the CNN model (b) and sample of thumbnails misidentified by both humans and the CNN model (c).

Identification methods such as the ones presented here pave the way towards new ecological applications. First, such methods can work continuously and their performance is constant through time and hence reproducible, contrary to human experts who work discontinuously and are likely to perform differently through time. Given the high rate of correct identifications, the best model could be used to pre-process a massive number of thumbnails: up to 1 million thumbnails per day. Furthermore, additional post processing procedures could be used. For example, under a certain threshold (e.g. 98% certainty), human experts could be asked to check the thumbnails identified by CNN models. Such a two-step workflow would ensure a very high identification rate while saving time of experts in fish taxonomy who will not have to identify “obvious” fish that can be accuratly identified by models. In addition, identification methods could also be used as a tool to initiate citizen science programs, for example where divers upload images of fish and obtain the most likely taxonomic identification from a CNN model. Therefore, the continued development of these identification tools could potentially offer benefits for both professional scientists collecting massive raw data from the field, and for citizens to improve their awareness and knowledge about biodiversity (e.g. Bradley et al., 2017)

The method tested here is one step towards the identification of hundreds or thousands of fish species that occur on coral reefs (Kulbicki et al., 2013). Since the performance of CNNs is known to increase with the number of classes (i.e. the 1000 classes of ImageNet) (Krizhevsky et al., 2012), there is no theoretical limit to such upscaling, the main challenge being to increase the size of the training dataset and the computer power. However, the identification of rare species will remain challenge given the difficulty to collect enough thumbnails of such species in different conditions to train the model. Future work is also needed to broaden the range of conditions where the model is efficient for most of species. In this paper, we considered only fixed videos recorded between 1m and 25m for both our training and testing datasets. It would relevant to include deeper videos as well as videos recorded with other protocols (e.g. baited remote underwater videos, transects).

Ultimately, the goal of automatic identification is not only to classify fish into species, but also to localize and count them, and estimate their size (body length) on videos. The detection task in underwater videos remains challenging as the context is particularly complex. Towards this aim, including “environment” and “part of species” classes in the training of models will enhance the accurate detection of fish inidividuals partially hidden behind corals or other fish, for instance using a sliding windows approach over a video frame. We could also associate a classifier with a detector (Weinstein et al., 2015, Price Tack et al, 2016). Such algorithms focus on the detection of objects of interest (such as fish individuals) in images. Ultimately, deep-learning based methods could help marine ecologists to develop new video-based protocols for a massive monitoring of increasingly imperiled reef fish biodiversity, in the same way as next-generation sequencing of DNA has revolutionized several research domains including biodiversity monitoring (Deiner et al., 2017).

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SUPPLEMENTARY TABLES

Table S1. Raw fish thumbnails training dataset

Classes	Number of thumbnails
Abudefduf sparoides	1241
Abudefduf vaigiensis	5674
Chaetodon trifascialis	1456
Chromis weberi	3576
Dascyllus carneus	2276
Lutjanus kasmira	1652
Monotaxis grandoculis	1239
Myripristis botche	1264
Naso elegans	2068
Mulloidichtys vanicolensis	1264
Naso vlamingii	1789
Nemateleotris magnifica	1189
Odonus niger	2986
Plectroglyphidodon lacrymatus	652
Pomacentrus sulfureus	5176
Preocaesio tile	3088
Pygoplytes diacanthus	1106
Thalassoma hardwicke	1579
Zanclus cornutus	1886
Zebrasoma scopas	1835

Table S2. The four thumbnails datasets used to train the four models, with for each the number of thumbnails per class in the training datasets, with class “environment” gathering thumbnails of water and substrate (sand, corals) while “Part of fish” gathers all thumbnails of half of a fish individual and the "part of species" classes contain thumbnails of half of individuals for each species.

Species	Only whole fish (T1)	Whole fish + “Part of fish” (T2)	Whole fish + Environment + “Part of fish” (T3)	Whole fish + environment + “Part of species” (T4)
Abudefduf sparoides	2482	2482	2482	2482
Abudefduf vaigiensis	11328	11328	11328	11328
Chaetodon trifascialis	2912	2912	2912	2912
Chromis weberi	7152	7152	7152	7152
Dascyllus carneus	4552	4552	4552	4552
Lutjanus kasmira	3300	3300	3300	3300
Monotaxis grandoculis	2478	2478	2478	2478
Mulloidichtys vanicolensis	2528	2528	2528	2528
Myripristis botche	2528	2528	2528	2528
Naso elegans	4138	4138	4138	4138
Naso vlamingii	3578	3578	3578	3578
Nemateleotris magnifica	2378	2378	2378	2378
Odonus niger	5972	5972	5972	5972
Plectroglyphidodon lacrymatus	1304	1304	1304	1304
Pomacentrus sulfureus	10352	10352	10352	10352
Preocaesio tile	6176	6176	6176	6176
Pygoplytes diacanthus	2212	2212	2212	2212
Thalassoma hardwicke	3158	3158	3158	3158
Zanclus cornutus	3772	3772	3772	3772
Zebrasoma scopas	3670	3670	3670	3670
Part of *Abudefduf sparoides*				4964
Part of *Abudefduf vaigiensis*				22656
Part of *Chaetodon trifascialis*				5824
Part of *Naso elegans*				14304
Part of *Pomacentrus sulfureus*				20704
Part of *Lutjanus kasmira*				6600
Part of *Pygoplites diacanthus*				4424
Part of *Thalassoma hardwicke*				6316
Part of *Zanclus cornutus*				7544
Part of *Zebrasoma scopas*				7340
Part of *Chromis weberi*				14034
Part of *Monotaxis grandoculis*				4956
Part of *Plectroglyphidodon lacrymatus*				1304
Part of *Dascyllus carneus*				9097
Part of *Myripristis botche*				5056
Part of *Naso vlamingii*				7156
Part of *Nemateleotris magnifica*				4744
Part of *Odonus niger*				11944
Part of *Pterocaesio tile*				12352
Part of *Mulloidichtys vanicolensis*				7528
Part of Fish		521555	521555	
Environment			862174	862174

Table S3: Number of thumbnails of each fish species present in test datasets used in this study

Class	Dataset for testing models performance	Dataset for testing model performance vs human performance
Abudefduf sparoides	103	88
Abudefduf vaigiensis	59	47
Chaetodon trifascialis	208	146
Chromis weberi	269	
Dascyllus carneus	269	
Monotaxis grandoculis	72	
Myripristis botche	20	
Naso elegans	189	165
Naso vlamingii	358	
Nemateleotris magnifica	246	
Odonus niger	176	
Plectroglyphidodon lacrymatus	150	
Pomacentrus sulfureus	1567	443
Pterocaesio tile	215	
Pygoplytes diacanthus	39	35
Thalassoma hardwicke	111	73
Zanclus cornutus	64	53
Zebrasoma scopas	184	144
Total	4405	1197

Table S4. Performance of CNN model trained with T4 thumbnails set to identify nine fish species with no post processing; species are identified in columns and rows refer to whole fish and parts of fish present in the training dataset.
Part of species X means that some individual were recognized as part of a fish species.
Only percentages of over 1% are shown.

Species	*A.sparoides*	*A.vaigiensis*	*C.trifascialis*	*N.elegans*	*P.sulfureus*	*P.diacanthus*	*T.hardwicke*	*Z.cornutus*	*Z.scopas*
A. sparoides	82.8								
A .vaigiensis	1.1	80.0							
C. trifascialis			85.1						
C. weberi							1.1		
N. elegans				95.1					3.9
P. sulfureus					73.8	2.6			
P. diacanthus							86.8		
T. hardwicke								87.3	
Z. cornutus									89.0
Z. scopas									92.7
Part of *A. sparoides*	6.0								
Part of *A. vaigiensis*	1.0	9.1							
Part of *C. trifascialis*			2.6						
Part of *N. elegans*				1.6					
Part of *P. sulfureus*			1.1		4.3				
Part of *P. diacanthus*									
Part of *T. hardwicke*							2.6		
Part of *Z. cornutus*								6.2	
Part of *Z. scopas*									
Environment	8.0	10.9	9.5	2.2	20.9	7.9	9.2	4.6	2.8

Table S5. Performance of our final CNN model to identify 9 fish species. Raw model output was post-processed with following decision rule: outputs " part of species X" and "species X" are considered the same (i.e., the results of *A. sparoides* and *part of A. sparoides* are added together*);* *s*pecies are in columns with rows indicating the percentage of good identification for each species and only values over 1% are shown.

Species	*A. sparoides*	*A. vaigiensis*	*C. trifascialis*	*N.elegans*	*P.sulfureus*	*P.diacanthus*	*T.hardwicke*	*Z.cornutus*	*Z.scopas*
A. sparoides	89.0								
A. vaigiensis	2.1	89.1							
C. trifascialis			97.7						
C. weberi							1.1		
D. caruleus									3.9
N. elegans				95.7					
P. sulfureus			3.1		78.1	2.6			
P. diacanthus						86.8			
T. hardwicke						89.4			
Z.cornutus								95.2	
Z. scopas									92.7
Environment	8.0	10.9	9.5	2.1	20.9	7.9	9.2	4.6	2.8

SUPPLEMENTARY FIGURES

Supplementary Figure 1. Screenshot of the online application used for testing human performance in identifying fish on thumbnails. Picture of fish to identify is displayed on the left part. Name for species should be typed in the bottom text bar (with auto-completion). The help box with examples of the 9 species to identify is visible on the right.