

## RESEARCH ARTICLE

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# Automated identification of invasive rabbitfishes in underwater images from the Mediterranean Sea

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## Abstract

1. Coastal ecosystems of the Mediterranean Sea are among the richest in non-indigenous species, mostly due to the establishment of species coming from the Red Sea through the Suez Canal. Two herbivorous rabbitfishes, *Siganus rivulatus* and *Siganus luridus*, are already invasive in the south-eastern part of the Mediterranean Sea where they cause ecological damage by overgrazing algae.
2. The early detection and the counting of these non-indigenous species in the rest of the Mediterranean Sea is thus a major challenge for scientists and ecosystem managers. However, analysing images from divers or remote cameras is a demanding task.
3. Here, a dataset of 31,285 images of *Siganus* spp. and of six common native fishes to the Mediterranean Sea was built from 40 underwater videos recorded at three reef habitats. A deep learning algorithm was then trained to identify *Siganus* spp. on images containing the eight Mediterranean species. Finally, the algorithm and a post-processing filtering were tested with an independent dataset of 2024 images.
4. The model had a recall of 0.92 for the *Siganus* genus (i.e., two *Siganus* species combined). After a confidence-based post-processing, the recall increased to 0.98 with only 4 out of 272 images of *Siganus* spp. being misclassified. Accuracy reached a score of 0.61 meaning that experts would have to discard false positives. Images of five native species not present in the training dataset yielded similar false positive rates than species present in the training dataset. Overall, the automatic processing of images by the model and then the checking of putative *Siganus* images by experts required up to five times less effort than a full processing by experts.
5. The algorithm can help to efficiently detect these two invasive fishes in underwater images to evaluate progress towards conservation objectives and accelerate citizen-based monitoring of coastal ecosystems.

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## KEYWORDS

coastal ecosystems, deep learning, image analysis, Mediterranean Sea, non-indigenous species, *Siganus* spp

## 1 | INTRODUCTION

Biodiversity has been increasingly impacted by global change in all ecosystems (Jaureguiberry et al., 2022). Among those impacts, climate warming and introduction of non-indigenous species (NIS) are acting synergistically in many regions (Bennett et al., 2021; La Sorte & Jetz, 2010). Mediterranean coastal ecosystems are an emblematic case of such marked changes in biodiversity (Albano et al., 2021). Indeed, the opening of the Suez Canal in 1869 and its recent expansion have permitted the entry of more than 150 NIS fish species from the Red Sea into the Mediterranean Sea (Azzurro et al., 2022). The northward and westward geographic range expansion and the increase in abundance of those tropical NIS have been favoured by the rapid warming of Mediterranean Sea surface waters (>1°C since 1980) (Shaltout & Omstedt, 2014).

Rabbitfishes *Siganus rivulatus* and *Siganus luridus* have become the most abundant herbivorous fishes along the south-eastern coast of the Mediterranean Sea since their establishment in 1927 and 1956, respectively (Bariche et al., 2004; Ben-Tuvia, 1964; Sala et al., 2011). They now contribute to more than 50% of the herbivory activity (Magneville et al., 2023). Importantly, in many of these coastal habitats, *Siganus* spp. have overgrazed macroalgae to the point that the diversity of other organisms has decreased and ecosystem functioning has been disrupted (Peleg et al., 2019; Vergés et al., 2014). *Siganus* spp. have been colonizing northwards into the Aegean Sea and westwards to Sicily over the last two decades (Azzurro & Andaloro, 2005). Some individuals have even been observed along the coast of France (Daniel et al., 2009) and Croatia (Dulčić et al., 2011). Yet, their long-term establishment and new colonization pathways are still under scrutiny.

In this context of accelerating NIS expansion, it is thus of utmost importance for scientists and ecosystem managers to be able to detect the arrival of such potentially invasive species as early as possible and then to monitor their settlement and abundance dynamics. Monitoring non-indigenous marine fishes has been mostly carried out using standardized surveys by scuba divers (Brock, 1954; Holland et al., 2020; Thresher & Gunn, 1986) and opportunistic records from fisheries landings (e.g., Kleitou et al., 2022). Yet, underwater visual census of fish requires trained divers who may still miss elusive species, such as *Siganus*, especially when they are rare. As an alternative, monitoring NIS based on underwater remote cameras and underwater pictures from divers have been increasingly applied (Peters et al., 2019). However, the identification of target NIS on such images is a demanding task in terms of time and expertise in fish taxonomy.

Owing to the recent development of artificial intelligence and especially Deep Learning algorithms (DLAs), there is a growing effort to

automate the identification of fish species in underwater images (Ditria et al., 2021). DLAs have been demonstrated to efficiently identify indigenous reef fishes in several coastal ecosystems (Lopez-Marcano et al., 2021; Villon et al., 2018), but none addressed the key issue of detecting NIS in the Mediterranean Sea. As *Siganus* spp. can change colour rapidly from olive green to dark brown with a mottled pattern, training an algorithm able to identify them remains challenging. In this study, images of the two *Siganus* spp. and six common native fish species were collected across the Mediterranean Sea. Then, a DL was trained to identify polymorphic *Siganus* spp. in underwater images, and its performance was tested in various conditions.

## 2 | MATERIAL AND METHODS

### 2.1 | Image datasets

DLAs require two independent image datasets: the first one used to train the model, that is, to find the optimal parameters discriminating the species of interest, and the second one used to test the trained model reliability in the various conditions of application. To build those datasets, underwater remote videos were recorded during three field campaigns in Northern Crete (Greece) and the Gulf of Lion (France) in 2017, 2019, and 2020 (Table 1).

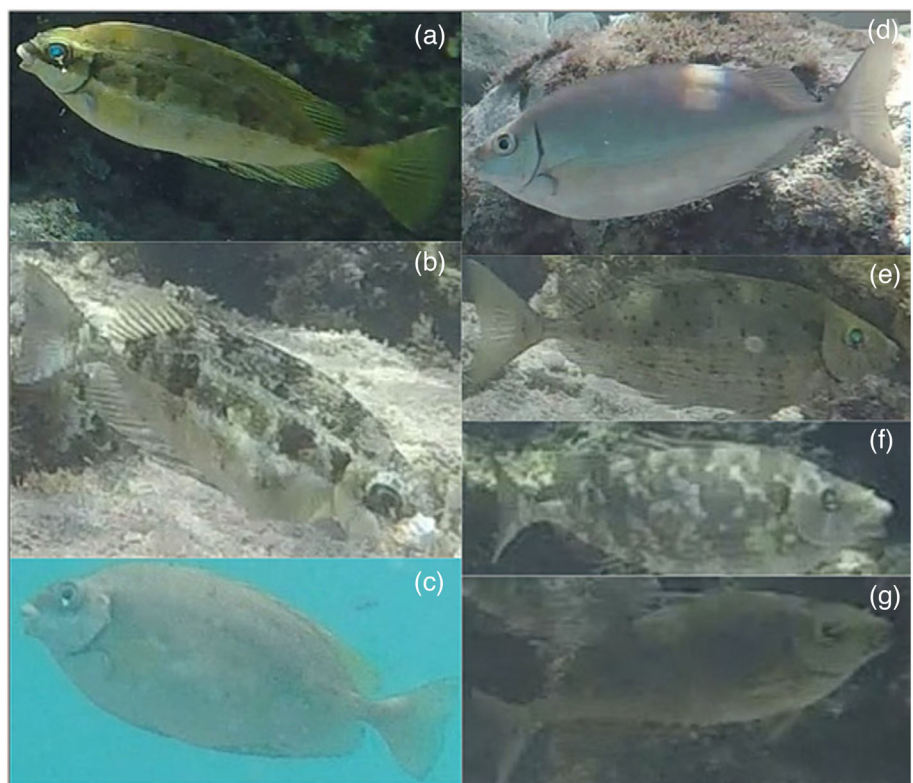
All videos were recorded with GoPro HERO5 Black (GoPro Inc., USA) set with “linear” angle-of-view, full high-definition (HD) resolution (1920 \* 1080 pixels) and 25 frames per second. The cameras were set up on the sea floor in shallow (1–5 m deep) coastal habitats dominated by seagrass, macroalgae, bare rock, or sand (Table 1).

To ensure that the test of the algorithm was performed independently from the training, the two datasets were built using videos recorded in different locations or seasons (Table 1). The training dataset was built with images from 40 videos for a total of 140 h recorded between the 2 and 10 of October 2019 in Crete. For the testing dataset, nine videos recorded in France (July 2017 and May 2020) and in Crete (June 2019) were used.

Videos of different lengths were extracted from the raw recordings based on the presence of fish, and images were extracted at the rate of one or three images per second yielding 11 to 1064 frames from a video. On each of these frames, individual fish whose body was entirely visible (i.e., not hidden by another fish, rocks, or algae and not facing camera or recorded from the face or behind) and which could be identified to the species level were annotated using a bounding box encompassing the body and labelled with the species name. Because of these rules, most of the annotated fish individuals were not present on temporally successive frames. Furthermore, as fish individuals were of various sizes and were at various distances

**TABLE 1** Summary of underwater videos and fish images used to train and test the deep learning classifier.

Use	Territory	Site	Date (year-month)	Habitat	Number of videos	Number of annotated images of fishes	Presence of <i>Siganus</i> spp.
Train	France	Frontignan	2019-09	Macroalgae/bare rocks/turf	1	134	
Train	Crete	Hersonissos	2019-10	Macroalgae/bare rocks/sand	26	5247	X
Train	Crete	Kokkini Hani	2019-10	Macroalgae/turf/seagrass	13	4636	X
Test	France	Banyuls	2017-07	Macroalgae/bare rocks/turf/seagrass	2	114	
Test	Crete	Hersonissos	2019-06	Macroalgae/bare rocks/sand	3	292	X
Test	Crete	Kokkini Hani	2019-06	Macroalgae/turf/seagrass	1	831	X
Test	Crete	Bali	2019-06	Macroalgae/turf/seagrass	1	139	X
Test	France	Carry le Rouet	2020-05	Macroalgae/bare rocks/turf/seagrass	2	783	

**FIGURE 1** Examples of the different body shapes and colours of *Siganus luridus* (a–c) and *Siganus rivulatus* (d–g) in the test dataset.

from the camera, the annotated images had variable sizes and length/depth ratios. Given the diversity of sea floor in the videos (i.e., rocks, algae, and seagrass), varying hydrological conditions (turbidity and light), and the movement of filmed components (i.e., algae and other fishes), the images displayed different backgrounds even within a single video (Figure S1). Additionally, considering the mobility of the target fish species, the images exhibited a range of fish body orientations. Special attention was given to ensuring that images of *Siganus* spp. represented the diversity of colourations encountered in the wild (Figure 1).

For this study, images of the two NIS—*S. luridus* and *S. rivulatus*—were used along with images of the six most common native fish species in the videos (*Chromis chromis*, *Diplodus sargus*, *Diplodus*

*vulgaris*, *Sarpa salpa*, *Sparisoma cretense*, and *Thalassoma pavo*), which are also prevalent throughout the Mediterranean Sea. Each species represents a class learned by the deep learning classifier.

A total of 31,285 images were annotated from videos of the training dataset. For each class, 1250 to 1256 unique images were randomly selected among those available and horizontally flipped to augment the representativity of the dataset (Villon et al., 2018). For the test, 2159 images (Table S1) of the eight species common with the training dataset (i.e., two *Siganus* spp. and six common fishes) were used, along with 100 images of five species not present in the training dataset (i.e., *Diplodus puntazzo*, *Oblada melanura*, *Mullus surmuletus*, *Lithognathus mormyrus*, and *Trachurus mediterraneus*,  $N = 20$  individuals for each species).

## 2.2 | Training of the classifier

The classifier involved fine-tuning a ResNet50 model that had been previously trained on the ImageNet dataset using PyTorch (torch 1.8.1). At the beginning of the training, all images were resized to  $224 \times 224$  pixels. The batch size was set at 16. The Adam algorithm was employed as the optimizer, and the negative log-likelihood loss function was used. To prevent overfitting, it was ensured that the loss was decreasing after each epoch. If this was not the case for 20 consecutive epochs, the training was stopped. The algorithm was trained using an Nvidia Quadro RTX 3000 GPU card on a Dell Precision 7550 laptop with an Intel® Core™ i7 processor and 62 GiB RAM.

## 2.3 | Testing the classifier

For each class, the number of true positive (TP) images, representing correctly identified images, was computed. In addition, the number of false negative (FN) images, indicating images belonging to a given class but missed by the classifier, and the number of false positive (FP) images, representing misidentified images in a given class, were also calculated.

The model efficiency was assessed using the recall and precision metrics for each class. The recall is the proportion of correctly labelled individuals among all individuals of this class and is computed as  $\frac{TP}{TP + FN}$ . It is maximal (and equals 1) when all individuals of the class are correctly identified, and it decreases when some individuals of the analysed class are misidentified as fish species from other classes.

The precision is the proportion of correctly labelled individuals among the items identified as this class and is computed as  $\frac{TP}{TP + FP}$ . It is

maximal (and equals 1) when there are no individuals belonging to another class and decreases when some individuals of other classes are misidentified as the analysed class.

Metrics were also computed for the two *Siganus* spp. combined, considering that, in most applications, the goal was to detect the presence of this non-indigenous genus. For this purpose, a new class “siganus” was created that bundled the classes “siganus\_luridus” and “siganus\_rivulatus.”

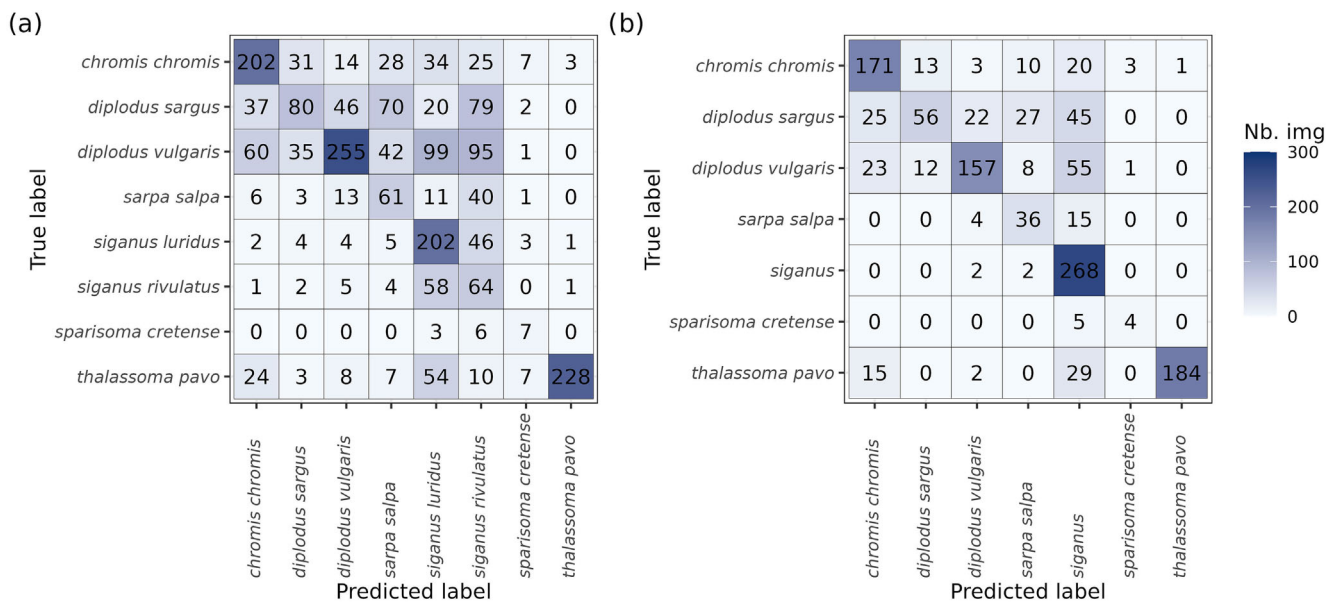
In the context of automated identification of NIS, the priority was to ensure that NIS individuals were not missed, hence to maximize recall (i.e., few FN). However, the time of experts required for checking the images classified as NIS has also to be as low as possible; hence, precision should remain as high as possible (i.e., few FP).

For each image processed by the DL, the most likely class returned had an associated confidence score ranging from 0 to 1, with values close to 1 indicating the most reliable classes. Thus, images with a confidence score lower than 0.8 were transferred to an “unsure” class. The recall was computed after removing these “unsure” images.

Image size may play an important role in fish identification. Indeed, a smaller image can be indicative of an individual which is far away from the camera and difficult to identify. Thus, the influence of image area (height  $\times$  width in pixels) on TP and FP rates was analysed.

## 3 | RESULTS

The training lasted 31 min and ran 36 epochs at which point the early stopping procedure stopped the training as the loss did not change over the last 20 epochs.



**FIGURE 2** Performance of the Deep Learning algorithm in identifying fish species in underwater images using a confusion matrix where correct classifications are on the diagonal. Largest numbers of individuals are highlighted. Comparison between the initial confusion matrix (a) and the confusion matrix after merging the two *Siganus* classes and removing the images for which the confidence score was lower than 0.8 (b). Each row of the matrix represents an actual class, while each column represents a predicted class.

The average recall was 0.62 among the eight classes (Figure 2). The recall for the classes *S. luridus* and *S. rivulatus* were 0.74 and 0.47, respectively. When merging the two *Siganus* species in a single class, the recall reached 0.92. The precision was 0.42 for the class *siganus\_luridus*, 0.18 for the class *siganus\_rivulatus*, and 0.44 when considering the merged class “*siganus*.”

After the post-processing removal of unsure predictions, the recall for the class *Siganus* increased to 0.99 and the precision increased to 0.61. On the four videos with at least one *Siganus* individual, the *Siganus* genus was detected in at least one frame (84% up to 100% of *Siganus* spp. were detected per video).

Among the 100 images of the species not present in the training database, only 17 (five *D. puntazzo*, five *L. mormyrus*, three *M. surmuletus*, three *O. melanura*, and one *T. mediterraneus*) were misidentified as *Siganus* spp. among which seven remained misidentified as *Siganus* spp. after the post-processing removal of unsure predictions.

None of the correctly identified *Siganus* images had an area <4900 pixels, while all the 13 images with area <4900 pixels, which were labelled as *Siganus*, were in fact one of the six native species (Figure 3). Choosing a cut-off at 10,000 pixels removed 62 FP (36%) and 9 TP (3%) increasing the precision to 0.71 while marginally decreasing the recall for the class *Siganus* to 0.98.

## 4 | DISCUSSION

The recall of 0.92 for the class “*siganus*” demonstrates the reliability of the trained DLa because only 32 out of 402 images of *Siganus* spp. were misclassified as images of indigenous fish species (Figure 2a). Among those 32 incorrectly labelled images (FN), 28 had a confidence score lower than 0.8 and only four (Figure 2b) had a confidence score greater than 0.8 so were retained in the final model outputs after post-processing. Those four FNs were images of *Siganus* individuals shot in turbid water, exposed to direct sunlight, and of an individual masked by a *S. salpa* (Figure 4). If an expert was to check the 28 unsure images (7% of the images analysed) and identified all of them as *Siganus*, only 1% (4 out of 272) of *Siganus* spp. images would be missed (FNs). Besides, ignoring the 28 unsure images had no impact on the detection of *Siganus* at the scale of the video sequence as each of the videos contained at least 10 images of *Siganus* spp. So, the classifier coupled to long running videos would most likely detect rabbitfish presence even when elusive or rare.

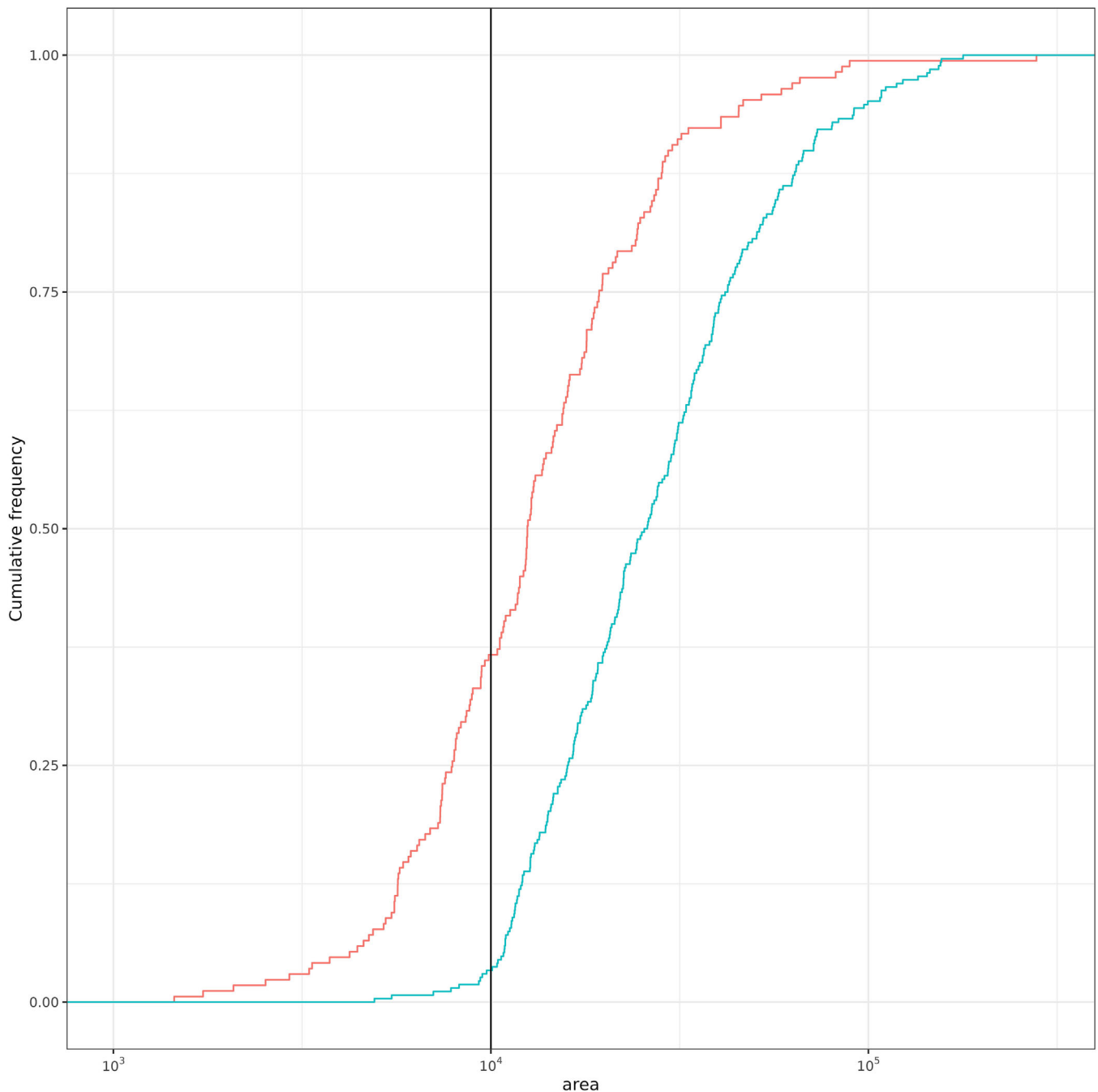
The precision of 0.44 for the class “*siganus*” means that 56% of images labelled as “*siganus*” were actually indigenous species. The confidence-based post-processing removal of unsure predictions increased the precision for the “*siganus*” class to 0.61, meaning that among the 437 images labelled as *Siganus*, 169 were actually images of native species. This model's performance level is within the average performance level of existing models. The recall for *Siganus* obtained by this model is lower than other studies on a single fish species (Ditria et al., 2020; Lopez-Marcano et al., 2021). The overall performance on the eight species is higher than for the classification

algorithm by Catalán et al. (2023) for nine Mediterranean indigenous fishes (recall: 0.76, precision: 0.37) and for 47 species of tropical sharks and rays, which proposed a combination of three models (a detection model, a binary sorting model, and a classification model), achieving an overall accuracy of 70% (Jenrette et al., 2022). The two species most commonly misidentified as *Siganus* spp. were the two seabream *D. vulgaris* (194 FP) and *D. sargus* (99 FP) (Figure 2a). Yet, these two species have a shape and colour pattern different from *Siganus* spp. Visual inspection of these confidently misclassified images revealed that they mostly depict individuals in the background or with their body partially hidden (because of their orientation relative to the camera or movement of the tail) making them more difficult to identify even by humans (Figure 4). Meanwhile, the *Diplodus* individuals close to the camera and not masked were correctly classified (i.e., among the 921 *D. vulgaris* and *D. sargus*, 44% were classified as a *Diplodus*). Hence, the confusion between *Diplodus* and *Siganus* is context dependent.

As a consequence, not accounting for *Siganus* identified in images of less than 10,000 pixels discarded more than one third of FP *Siganus* identifications while keeping recall above 98% (i.e., only nine images of *Siganus* would be misidentified as a native fish species). Such small images correspond to individuals filling less than 5% of a full HD video frame (1920 × 1080, >2 million pixels). Hence, as in all the remote underwater videos, it is likely that present *Siganus* individuals will be recorded with an apparent size >10,000 pixels.

The processing of the 2024 images belonging to the test dataset took 10 s on a laptop computer and the optional checking of the 28 predictions of *Siganus* with low confidence threshold would take less than 3 min for an expert (assuming 5 s per image). Checking only the 437 images identified as *Siganus* would take 36 min and would allow FPs to be discarded. Hence, as the analysis of the 2024 images by an expert would take 168 min (assuming 5 s per image with no break), the DLa thus provides at least a fivefold gain of time.

One limitation of the DLa classifier is the identification of *Siganus* only in images containing a single individual at its centre. Thus, in practice, raw videos or pictures from underwater cameras must be cropped to focus only on fish individuals, which requires no expertise in taxonomy and is fast using any software able to save a screenshot (e.g., VLC media player). A future priority will be to couple this identification model with a general fish detection model able to segment all fish individuals from a video frame or a picture (e.g., Knausgård et al., 2022) for the model to subsequently process those extracted images. Even if current detection models are only able to identify a single species (Lopez-Marcano et al., 2021), recent advances in other taxa show encouraging results such as DeepFaune (Rigoudy et al., 2023) for French terrestrial fauna or for insects (Teixeira et al., 2023). However, these detection models require images with all individuals annotated, which is time-consuming as underwater images could contain >100 fish. Another limitation is that classifiers are only able to identify species in the training dataset, which requires the collection of more than 1200 images per species

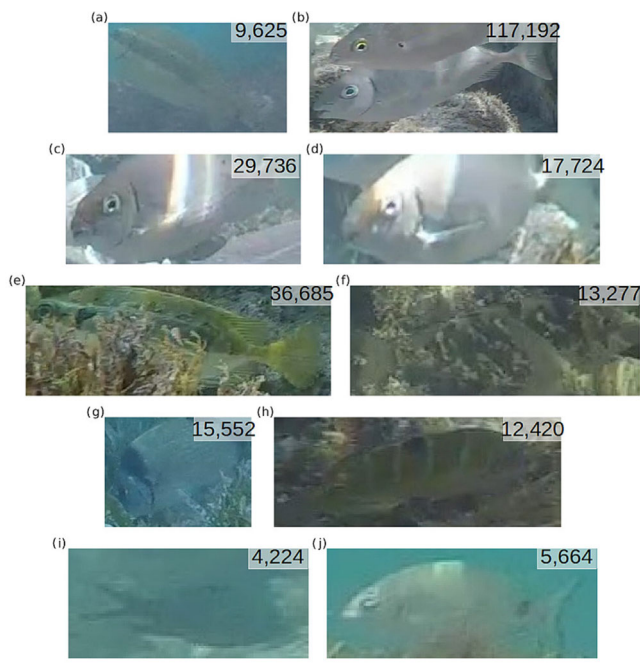


**FIGURE 3** Effect of image area on algorithm output. Cumulative frequency distribution of *Siganus* images correctly identified by the algorithm as *Siganus* (i.e., true positive in blue) and of native species images misidentified as *Siganus* (i.e., false positive in red) along the gradient of image area (log10 scale). The vertical black line illustrates the cut-off at 10,000 pixels.

or applying few-shot learning techniques that usually results in a decrease in recall and precision (e.g., Villon et al., 2021). In this case, among images from the five indigenous species not present in the learned classes, only 7% were confidently classified as *Siganus* spp., which was lower than the FP rate for the six indigenous species present in the training dataset. Hence, the model would likely not misidentify individuals as *Siganus* species that are not present in the training dataset.

## 5 | CONSERVATION PERSPECTIVES

Developing rapid and robust knowledge on the distribution and density of NIS is crucial to evaluate progress against international agreements, including the UN Sustainable Development Goals, Convention on Biological Diversity Targets, EU Biodiversity Strategy, and the Green Deal. Towards this goal, improving the capacity to automate data collection and processing is needed to dramatically



**FIGURE 4** Illustration of automated identification of fishes by the Deep Learning algorithm. *Siganus luridus* (a) and *Siganus rivulatus* (b), partially masked by the head of a *Sarpa salpa*, misidentified as *S. salpa*. *S. rivulatus* (c, d) misidentified as *Diplodus vulgaris*. Individuals of *S. luridus* (e) and *S. rivulatus* (f) correctly identified by the model despite their partially masked bodies. Individuals of *D. vulgaris* (g), *Thalassoma pavo* (h), *Chromis chromis* (i), and *Diplodus sargus* (j) misidentified as *Siganus* spp. The number in the top right corner of each image is the image area in pixels.

increase the amount and quality of information and knowledge available to scientists and decision-makers.

Remote or diver-operated underwater videos have been increasingly used by scientists and ecosystem managers to monitor fishes for the last decade across the Mediterranean Sea (Nalmpanti et al., 2023). We believe that our DLAs will be useful for ecosystem managers to accelerate the analysis of videos collected during those NIS monitoring programmes, ensuring detection of *Siganus* spp. Towards this aim, the DLAs are available in a public repository ([https://github.com/valentine-fleure/Siganus\\_identifier](https://github.com/valentine-fleure/Siganus_identifier)). The classifier applied to long underwater videos will pave the way to high-frequency monitoring of rabbitfishes throughout the Mediterranean basin. Such massive data are needed to describe the geographic expansion of rabbitfishes through time to ultimately unravel its driver (climate and connectivity) and test the potential benefit of marine protected areas (MPAs) on lowering their abundance through increased level of predation by large fishes.

In addition, as the Mediterranean coastal ecosystems are a popular place for underwater activities (snorkelling, freediving, and scuba diving) and because many of these recreational users own underwater cameras, there is a high potential to collect a large number of images from many places. As most recreational users have no to little ability to identify all fish species, the publicly available algorithm will favour current citizen science monitoring of NIS.

Indeed, the algorithm will favour the participation of new users to those programmes as well as help them improving their identification skills so that fewer individuals of rabbitfish will be missed. Ultimately, these recorded and validated new occurrences could be integrated in the Global Biodiversity Information Facility and the Ocean Biodiversity Information System to reveal the rabbitfish's geographic range size and provide an estimate of the invasion rate.

Given the increasing number of NIS entering the Mediterranean Sea as well as the expansion of those already present in the south-eastern part (Azzurro & Andaloro, 2005; Azzurro et al., 2022), video-algorithm based monitoring programmes should be able to monitor more species. Towards this aim, it would be important to upgrade the model by identifying more indigenous species as well as more NIS. Among the NIS that should be prioritized to be added to the training database, lionfish (*Pterois miles*), silver-cheeked toadfish (*Lagocephalus sceleratus*), yellow-spotted puffer (*Torquigener flavimaculosus*), and sweepers (*Pempheris* spp.) are of the highest priority given their abundance in the Eastern Mediterranean and their rapid northward and westward expansion (Zenetos et al., 2022). These Lessepsian species are morphologically distinct from one another and from indigenous species and should thus be easily identified by algorithms.

One step further, artificial intelligence algorithms may unlock the potential of video-based monitoring beyond the case of NIS detection through automated identification of all fish species, including endangered ones, as well as estimating their size and behaviours (Ditria et al., 2021) to assess a large set of indicators as envisioned by the Essential Biodiversity Variable framework (Kissling et al., 2018). These variables would deliver multiple indicators of coastal ecosystem status, climate change effects, and spatio-temporal trends in fish biodiversity, as required to meet the monitoring requirements of the EU Water Framework Directive and the Marine Strategy Framework Directive.

#### AUTHOR CONTRIBUTIONS

Valentine Fleuré, David Mouillot, and Sébastien Villéger conceived and designed the study; Camille Magneville and Sébastien Villéger collected the data. Valentine Fleuré wrote the first draft of the manuscript. All authors contributed to subsequent revisions and approved the final version.

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## CONFLICT OF INTEREST STATEMENT

The authors have no conflict of interest to declare.

## DATA AVAILABILITY STATEMENT

Research data are not shared.

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## SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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