ID16- ADVANCES IN ELECTRONIC MONITORING OF FISHING CATCHES BASED ON ARTIFICIAL INTELLIGENCE

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Abstract
Monitoring plays a key role in all aspects of fisheries management, including those related to sustainable management of resources, the economic performance of the fishery, and the distribution of benefits from the exploitation of the fishery and environment. In this work, software improvements made on the remote electronic monitoring (REM) device iObserver are described towards the improvement of fisheries monitoring by precisely identifying and quantifying fishing catches on board commercial vessel´s. To this aim, we exploit deep learning and convolutional neural networks (CNNs) capabilities and potential.

Keywords
Remote Electronic monitoring systems (REMs), catch identification, species quantification, deep learning, convolutional neural networks.

INTRODUCTION
Sustainability is a basic premise for the economic and social future of fisheries and the main objective of fishing policies, such as the Common Fisheries Policy of the European Union [1]. An immense challenge faced by sustainable fisheries management and policies is that of finding cost-effective monitoring methods. The digital revolution must contribute to guarantee accurate data on the record of total catches, including landings, discards, as well as by-catches, verification of fishing effort and fishing capacity applicable to the engine power of the vessels, better traceability of the fishery products and better catch certification systems. So, digitization and advanced tools applied to fishing, such as remote electronic monitoring systems (REM), artificial intelligence tools, machine and deep learning, data from different sensors and high-definition satellite images resolution, have enormous potential to optimize fishing operations and improve our ability to collect and analyse data, as well as to improve monitoring and control capabilities and ultimately support the sustainable management of marine biological resources. Several REM systems are available to that purpose [2]; however, many of them exhibit a number of drawbacks that prevent its generalization among fleets (e.g. off-line evaluation of catches by the so-called dry observers in land, crew interferences and distrust, etc.). To overcome these drawbacks, robust and reliable innovative technologies for registering captures are required.

In this regard, we have developed the iObserver [3], an electronic device for real-time, automatic identification and quantification of the whole catch on board fishing vessels. The iObserver is installed in the fishing park, over the conveyor belt, just before the fishing separation zone. The system takes images of everything that crosses this conveyor belt during the separation process. The recognition software automatically analyses every image, identifies all the individuals, estimates their length and generates a report containing the results. Identification/quantification results are sent to the RedBox application that we also developed. This software is connected to the vessel's instrumentation (from which it receives data such as position, speed, time or depth) and to the iObserver (from which it receives the composition of each haul). It processes all the information and can send it to land via satellite or GPRS/3G/4G network, practically in real time, in a very small file (300-500 Kb) that contains the amounts caught of each of the species above and below the minimum conservation reference size (MCRS) together with its geolocation.

In this work, and in the framework of the SICAPTOR project (co-funded by the EMFF through the Pleamar Programme of Fundación Biodiversidad), a very significant improvement of the iObserver was carried out on the recognition and quantification software, as presented in the next section.

RESULTS
The very first prototype of the iObserver (fully described in [3]) uses morphological and colorimetric parameters to carry out the identification and quantification of main target species of Galician trawling fleets operating in ICES areas 6, 7, 8c and 9a, failing when the specimen of each haul passing through the conveyor belt of the fishing parks are slightly overlapped or without a minimum separation among them. To overcome this issue, we tried to take advantage of the enormous potential that artificial intelligence, and more precisely deep learning (DL), offers to improve the recognition and quantification capacities of our REM system. As a reminder, deep learning is a class of machine learning algorithms that uses multiple layers to progressively extract higher-level features from the raw input [4]. For example, in image processing (that is the case of our work), lower layers may identify edges, while higher layers may identify the concepts relevant to a human such as digits or letters or faces. The deep learning algorithms for species recognition algorithms included in the iObserver use Convolutional Neural Networks (CNNs). Two models were created with transfer learning and data augmentation techniques:

1) an instance segmentation model for specimen detection and classification, i.e., identification of the area occupied by each object instance (fish individuals) in the photograph. The implementation of the Mask R-CNN algorithm in Keras and Tensorflow has been chosen with FPN and ResNet101 base network pre-trained with the MS COCO data set. This implementation uses images resized to 1,024 pixels tall. Advantages of these new algorithm include: i) greater precision, ii) the ability to segment the image and; iii) the ease of manipulating and applying geometric data augmentation techniques with the help of the segmentation masks of each instance. Its main disadvantages are: i) the greater labelling effort since it involves outlining the contour of each fish for the training images and; ii) the slowest inference.

2) a regression model for fish length estimation based on a convolutional network MobileNet-V1 trained from scratch and modified to include as input the results of the segmentation algorithm.

To train and test both models, a set of about 6,000 images (like the one presented in Figure 1) were labelled with mask, species and length of each individual for a selection of 14 of the most relevant species for the local fisheries (see their FAO 3-alpha codes on the axis of Figure 2). Obtained results are very promising since precision and recall of 98% and 95% respectively for species recognition (as it can be stated in the confusion matrix presented in Figure 2) and 3.2% mean absolute percentage error for length estimation in the test data set, where individuals exhibit a low or medium level of overlapping. In Figure 2, the rows show the results of the predictions, that is, the precision. The number that appears in parentheses, next to the name of the species, indicates the number of times that the algorithm has identified the objects in the images as that species. For example, BIB (54) indicates that the algorithm has identified 54 objects as pout (Trisopterus luscus). Moreover, columns show the real data, that is, data obtained by a human observer. The number that appears in parentheses, next to the species name, indicates the number of times that species appears in the images according to the human observer. The number below indicates the percentage of times the algorithm has correctly identified the species, that is, the recall. For example, in the images there were 55 specimens of pout (BIB) and these specimens have been correctly identified 96.4% of the time (53 out of 55).

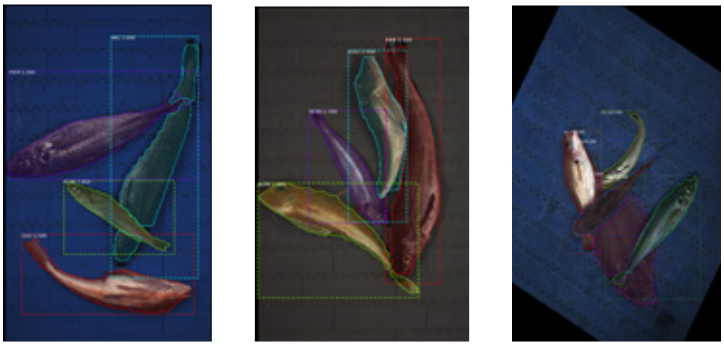

Fig 1. Species identification results in the test set for the final detection algorithm.

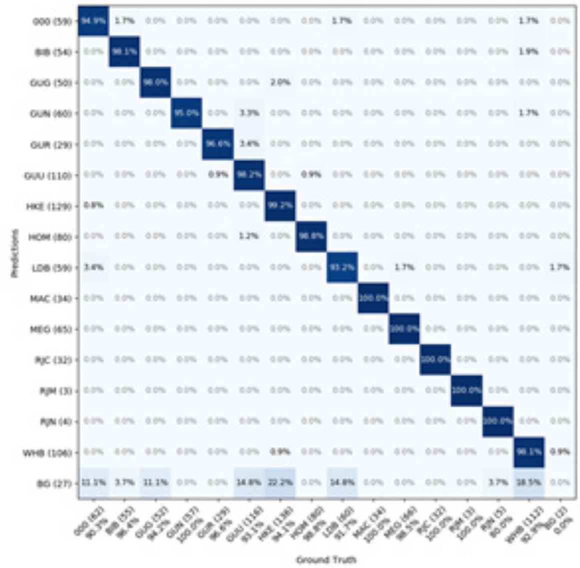

Fig 2. Confusion matrix resulting from the comparison between the measurements of the human observers and the predictions of the model for the set of test images.

CONCLUSIONS

Size estimation and species identification results were satisfactory improved by the developed DL algorithms, even when fish on the conveyor belt are moderately overlapping. Additional images will be obtained and processed in order to improve the capabilities of the algorithms. However, improvements are still required for the case of high levels of overlapping, that could demand the analysis of implementing additional mechanical solutions (acting also over the hardware level) in the fishing park (like vibrating devices, flexible barriers or variable-speed segments in the conveyor belts) to avoid it and maximize the performance of the algorithms and, therefore, or the iObserver. In addition, work on minimizing the equipment size in order to not disturb fishermen activity and to generalize its use in other fisheries or small-scale fleets should be also considered in the near future.

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