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An app as a tool for detecting migrant females of *Anguilla anguilla* to support the wild population

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ABSTRACT
The eel (*Anguilla anguilla*) population in Europe has declined dramatically since the 1980s and shows no signs of recovery. There are several threats to this species: migratory barriers, loss of habitats, hydroelectric dams, overfishing, and illegal trade. As a result, the eel has become part of the ICUN endangered species and is protected by various institutions. Information data on the maturation stage is needed to monitor silver eel escapement and assess population trends. In the sampling activities spanning from 2012 to 2022 silver index was calculated on 1852 eels in the northern Adriatic Sea. With the help of machine learning technology, we trained an algorithm in pupil recognition and the calculation of horizontal eye diameter in eels. This study allowed us: a) to identify a single parameter to discriminate the sexual maturity of the eel and thus to know the female with a migratory instinct; b) to use this parameter as a proxy to develop an easy and user-friendly app for all management operators.

Section: RESEARCH PAPER

Keywords: European eel; machine learning; conservation; silver index

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1. INTRODUCTION

The European eel is an important species both economically and ecologically. *Anguilla anguilla* (Linnaeus, 1758) is a catadromous teleost, with a particular life cycle which involves four stages of metamorphosis from an embryo to an adult. The last metamorphosis of the eels before the reproductive event is called "silvering": in fall/winter, eels leave inland waters and prepare for the return to the sea and undergo morpho-physiological changes [1]. One of the most obvious is the change of the livery that passes from a yellowish coloration (yellow-eel/resident) to the migratory one characterized by a silvery coloration (silver-eel/migrant).

The available information indicates that the stock has declined severely in most of its distribution area and the population has decreased dramatically since the 1980s [2], [3]. Now is at a historical minimum and currently to be outside safe biological limits, and fisheries are not sustainable [4]. To date, the European eel is classified as "critically endangered" according to IUCN. Several hypotheses explain the decline of this stock, all linked to its complex life cycle. First of all, overfishing is carried out both on juvenile (glass eel) and older eel (silver eel) [5]. Fishing for eels in these two different life stages leads to major problems for the sustainability of the stock. Another factor to consider is the consumption of European eel in Asian countries, where eels are highly appreciated for human consumption. For this reason, poaching (illegal, unreported, and unregulated fishing (IUU) and illegal export to Asia are becoming major problems. Other causes include freshwater habitat destruction, barriers to up- and downstream migration (including damming of river systems for hydro-electric power), oceanic modification of the North Atlantic drift, physical obstructions to upstream and downstream migrations by dams [6], parasites (e.g. *Anguillicola crassus*) [7], and pollution by domestic and industrial effluents [8], [9].

To address the bad state of this species, the European Union adopted a management plan for the recovery of eel stock through an EU regulation (i.e., Regulation EU 2017/1004), which provides for the release of 40 % silver eel caught. Because the species is a unique stock with a European distribution [10], [11], and its conservation depends on recruitment and emigration from each basin, it is very important to collect the data on the presence of migrating eels and their stage of maturity.

Data on the maturation stage in general is needed to monitor silver eel escapement, to assess population trends, and to provide data as a proxy for spawning stock biomass. The proportion of mature eels (silver eels) can also be used to calculate the production potential of a specific water body. The change of livery in the transition from resident to migrant eels it is not a sufficient element to characterize the silver eel. Researchers noted that eye size increased with maturity [12] and, later, it was found that female eels commencing their migration had longer pectoral fins [6]. From these two studies descended two different indexes, which are the most used to indicate the eel maturation stage.

Both indexes, however useful, are not quick and easy to use for stakeholders, fishermen and farmers who have to manage the release, since both require measurements to be taken implying an expenditure of time and the use of instruments such as a calliper or ichthyometer, which are not at everyone's reach. Another problem of this measurement method is the operator's subjectivity. A study by Sundin et al. [13], shows how the measurement of eel eye diameter performed using computer software can be more precise and decrease subjectivity.

In the last years, machine learning technology is used increasingly and has already been developed to facilitate the annotation and extraction of information from images in various fields, namely medicine [14], ecology [15], agriculture [16], aquaculture and fishing [17]. This technology can extract highly dimensional features and in-depth information into data, thus offering a solution for smart aquaculture and introducing the fishing industry into a new era [18]. A commonly used approach is to train a machine learning algorithm by showing examples of desired inputs and outputs, rather than programming a set of rules for all possible inputs [19], [20]. This approach is advantageous in that the algorithm is less constrained and learns and improves automatically from experience [20], [21].

Based on the nature of the dataset, several algorithms can be used for the detection of image objects, among which we find artificial neural network (ANN) [22]-[25], support vector machine (SVM) [26], logistic regression (LR) [27], dep neural network (DNN) [28], [29] and convolutional neural network (CNN) [30], [31].

The aim of this study is to create a user-friendly and non-invasive tool with the help of machine learning technology, able to identify the migrant eels by taking a picture of the eye using any device (e.g phone, tablet) to support the wild population.

2. MATERIALS AND METHODS

2.1 Animals

The animals used for this study were caught in North Adriatic lagoons from 2012-2022. Morphometric parameters were taken: body length (*BL*, cm), body weight (*BW*, g), horizontal eye diameter (*EDh*, mm), vertical eye diameter (*EDv*, mm), pectoral fin length (*PFL*, mm). The initial stage of eels relative to the silvering process (silver index - *SI*) was determined according to Durif et al. [6], [32] and is summarized below:

SI I-II → *Stage I-II* → *yellow eel* → *resident eel,*

SI III → *Stage III* → *silver eel* → *pre-migrant eel,*

SI IV-V → *Stage IV-V* → *silver eel* → *migrant eel*

Eye index (*EI*) was also calculated using the following formula:

$$EI = 100 \cdot [(EDh + EDv) \cdot 0.25]^2 \, \pi \cdot (10 \cdot BL)^{-1} \, .$$

Efforts were made to minimize animal handling and stress all fish were anaesthetized using a solution (0.2 mL/l) of 1/10 clove oil dissolved in ethanol 70 %. All fish were kept and handled following the guidelines for experimental procedures in accordance with the European Union regulations concerning the protection of experimental animals (DIR 2010/63/UE). This study was approved by the Ethics Committee of Bologna University (ID 1157).

2.2 Training

The training was carried out in Tensorflow [33]. The architecture used is Efficientdet, in which three neural networks work simultaneously: the first is Efficient net (which takes care of extracting the features from the images); the second is BiFPN (which, from the features, determines the main characteristics of the image); and finally, the model (which takes care of determining the position and classification of the object). All three fall under the category of CNNs, the flow chart of the proposed models for the classification of eels is given in Figure 1.

The training was conducted using photos (*n* = 280) captured in the laboratory (Figure 2). Photos were obtained from 70 animals for each silver index (II, III, IV, V). Based on the data obtained from the measurements made in the preventive phase, a test dataset was created which allowed us to use a supervised learning approach. Supervised learning is a training mode where the data used is labelled; each input is known to the respective output which is used to teach the algorithm the rules of the model [34].

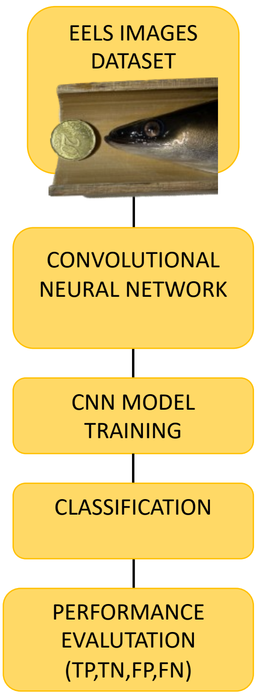

Figure 1. Flow chart of evaluation of classification performances of eels migration stage.

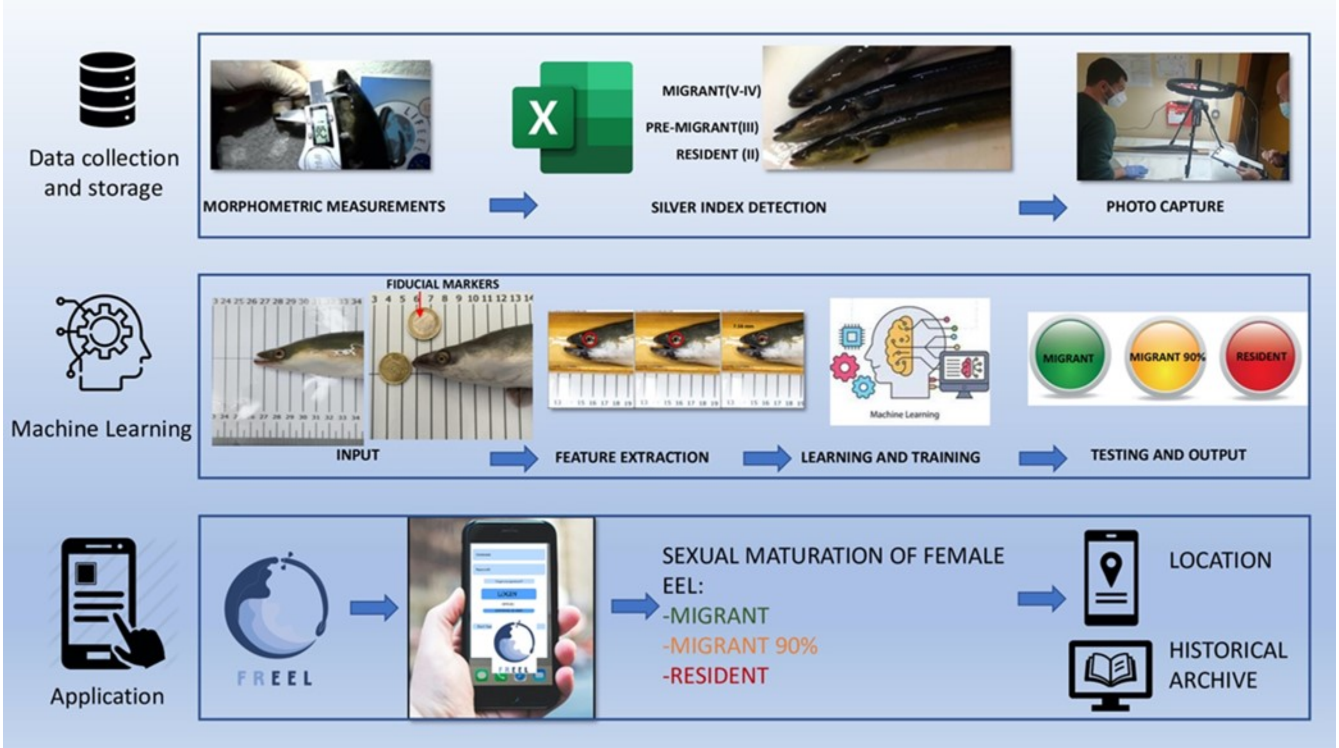

Figure 2. The application structure of machine learning.

2.3 Fiducial marker and image acquisition

Coins were introduced like fiducial markers [35] all with a circular shape but with different diameter (Figure 2). Photographs of the European eel were taken in different locations with different conduction of light and with different non-specialist cameras. Eel horizontal eye diameter was measured and recorded. The marker was placed near the head (Figure 2) and then photographed.

2.4 Performance metrics

The performance of the model was calculated using a confusion matrix, which provides information on the correct and incorrect classification of positive samples and the correct and incorrect classification of negative samples [36] True positive (*TP*), False positive (*FP*), False negative (*FN*) and True negative (*TN*) were calculated in the confusion matrix [37]. These values were used to perform statistical calculations and to analyse the performance of bottom right corner and are updated automatically.

3. RESULTS AND DISCUSSION

As part of sampling activities from 2012 to 2022 and thanks to the LIFEEL project (LIFE19 NAT/IT/ 000851), the silver index was calculated on 1852 eels in the northern Adriatic Sea. In general, both resident, pre-migrant and migrant eels were caught. All morphological parameters observed in Table 1. showed an increase in values from yellow to silver eel. The same trend was evident in the EI values, which increased as the SI increased, thus confirming what has already been observed by other researchers [12], [6], [32], [38], i.e., that the eye horizontal eye parameter it is possible to discriminate a sexually immature adult eel from a mature one. More specifically, a threshold value was identified below which the eel is sexually immature, an intermediate value that intercepts a 90 % migrating eel, and finally, a value above which the eel is sexually mature and ready for ocean migration.

This data combined with machine learning technology made it possible to create a downloadable application on all types of camera devices that precisely allows the detection of circular shapes the comparison with a fiducial marker for a more accurate measurement, which in our case is a coin. The choice of this marker is first and foremost due to the known shape and measurements of the various coins but also due to the ease of availability. The use of markers, in fact, in the various tests carried out managed to decrease the measurement error found in an early version of the application in which only the detection of circular shapes was used. The results of the algorithm performance are shown in Table 2. Regarding the initial trials conducted on a limited selection of images, nonetheless, the

Table 1. Results of morphometric analysis.

	SI-II	*SI-III*	*SI-IV*	*SI-V*
BL **(cm)**	59.46 ± 6.96	69.93 ± 6.31	84.30 ± 5.39	65.91 ± 7.56
BW **(g)**	386.07 ± 137.32	646.83 ± 202.48	1331.92 ± 257.41	538.20 ± 174.99
Edh **(mm)**	5.85 ± 0.79	7.79 ± 0.85	9.65 ± 1.19	9.42 ± 1.31
Edv **(mm)**	5.40 ± 0.69	7.37 ± 0.79	8.99 ± 1.07	8.89 ± 1.15
EI **(%)**	4.29 ± 0.99	6.52 ± 1.14	8.28 ± 1.93	9.96 ± 2.09
PFL **(mm)**	26.60 ± 3.25	33.11 ± 3.26	38.30 ± 3.46	35.76 ± 4.23

Table 2. Confusion matrix.

		Predicted class	
		Positive	Negative
Actual class	Positive	$TP = 263$	$FN = 2$
	Negative	$FP = 1$	$TN = 14$

outcomes are promising. In particular, ACC was 98 %, SNS was 99.89 %, and PRE was 99.24 %. For the future, however, it will be useful to compare different algorithms to see which performs best, as other studies have already done. [39]-[41].

However, what will make the algorithm usable for all, will be the training with a larger dataset that will not only consider the morphometric and photo data of European eels of the north Adriatic but also data from different European migration sites. In fact, this will make it possible to have a standardization on a large-scale sampling, which has already been planned for the next sampling campaigns.

In general, traditional methods [6], [12] although non-invasive methods of detecting the stage of maturity, often cause stress to the animals, which must be anaesthetized to take the measurement. This is not sustainable in the field. Thus, the use of ML technology seems to be the key to a smarter future in managing the conservation of this species.

From early field tests of the app, it appears to be a convenient, efficient, and user-friendly tool. In the final version of the app, archive and location functions will be added. Thus, with each find and shot in addition to the output that will be given to the field operator (fishermen, farmers, state, and conservation agencies), there will also be the possibility to create an important data collection with images, measurements, and the location where that eel was found. The latter function could be a valuable tool for stock management to know any changes in the migration period.

4. CONCLUSION

This study allowed us:

a) to identify a single parameter to discriminate the sexual maturity of the eel and thus to know the female with a migratory instinct.

b) to use this parameter as a proxy to develop an easy and user-friendly app for all management operators.

In the future, the algorithms behind the app should also be trained on *A. anguilla* from different parts of Europe; only in this way we will achieve a standardized tool with high potential in the conservation management of this species.

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