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SURVEY

Machine Learning and Image Processing Methods for Cetacean Photo Identification: A Systematic Review

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ABSTRACT Photo identification is an essential method to identify cetaceans, by using natural marks over their body, and allows experts to acquire straightforward information on these animals. The importance of cetaceans lies in te fact that they play a crucial role in maintaining the healthiness of marine ecosystems, however they are exposed to several anthropogenic stressors, under which they could collapse with extreme consequences on the marine ecosystem functioning. Hence, obtaining new knowledge on their status is extremely urgent for the marine biodiversity conservation. The smart use of technology to automate the individual recognition can speed up the photo identification process, opening the door to large-scale studies that are manually unfeasible. We performed a systematic review on systems based on machine learning and statistical methods for cetacean photo identification, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses statement. This review highlights that interest has been increasing in recent years and several intelligent systems have been presented. However, there are still some open questions, and further efforts to develop more effective automated systems for cetacean photo identification are recommended.

INDEX TERMS Machine learning algorithms, convolutional neural networks, feature extraction, reviews, oceanic engineering and marine technology, image processing.

I. INTRODUCTION

Photo Identification (photo ID) is a noninvasive technique devoted to the identification of individual animals using photos, and it is based on the hypothesis that each specimen has unique features useful for recognition [1], [2]. One of the main fields where photo identification has been applied is related to marine fauna, particularly cetaceans. These animals play a key role in marine biodiversity conservation, because they maintain the stability and healthiness of marine ecosystems due to their control roles as top predators or consumers in food webs. The information obtained with photo identification studies is useful for acquiring new knowledge on their abundance estimation, social dynamics, pattern migration and site fidelity of the species under study. However, manual photo identification is time-consuming and impractical in case of large datasets.

Computer-aided systems have been developed to support researchers during photo identification studies, to reduce the user effort and the time required to perform the study. Data used for cetacean photo ID studies are images containing well-exposed dorsal or caudal fin (depending on the species to be photo-identified) of the animal. However, fin images acquisition during a marine survey is not a trivial task, due to the unavailability of a static subject to be pictured, to the dynamic nature of the background, and to lighting effects. In fact, subjects in the foreground of the images are cetaceans in continuous movement, so the images may

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contain the fin of the animal but also other parts of the body, not useful for its photo identification, and the distance of the animal can vary a lot. Moreover, often in the photos two or more dolphins are captured while swimming together. In addition, the images may also contain other moving objects or parts thereof, such as vessels, other animals (i.e. birds or turtles), and fixed structures during sightings in ports or near the coast. In marine images there are also trails, foams, splashes of water, clouds which can be qualified as background. In case of manual photo ID, experts can effectively manage these images, selecting useful information to solve the task. When a large amount of images needs to be analyzed or when a huge number of already known and catalogued individuals is available, the manual task of going through photographs becomes tedious and human resource demanding. Hence, using advanced techniques can support users and accelerate the process of individual photo identification. The automated processing of these images involves several steps: an object detection phase, a cropping of the part of the animal useful for its recognition, the segmentation and extraction of the mask. Successively, feature extraction can be performed, if requested, followed by the individual recognition. Approaches for pattern analysis, recognition, and classification of cetaceans images can help to extract knowledge and to develop innovative models for animal photo identification.

In addition, photo identification methods depend on distinctive marks that are stable over time. However, natural marks on cetaceans can change, making photo identification difficult. This issue could be handled by human intelligence; in fact, experience gained by experts in the field can support them. Instead, in the case of statistical and machine learning models, a tailored training of algorithms should be necessary to study the evolution of natural marks over time.

The main stakeholders in the use of these systems are marine biologists, ecologists and marine mammal observers as well as nonexpert users, such as students and people passionate about the field. Computer-aided systems devoted to photo identification are generally based on computer vision, machine learning and statistics, which provide a variety of methods devoted to acquiring, processing and understanding digital images and information that are widely applied in several application domains [3]–[8]. Machine learning is a subset of artificial intelligence that is concerned with creating systems that learn or improve performance based on the data they use. One of the main drawbacks of machine learning is that there is the need to explicitly express all the knowledge formally, addressing data preprocessing, including cleaning, normalization, scaling, transformation and feature extraction. Automated photo identification systems also exploit the recent concept of deep learning, a part of machine learning, which enables computers to learn and understand the world in terms of a concept hierarchy [9]. With the use of deep learning techniques, it is possible to reduce the data preprocessing impact while increasing the classification performances in multiple domains, including speech and language processing, autonomous driving, health care and medical image processing [10]–[15]. Underlying the deep learning revolution, there are some neural network architectures, particularly Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), such as long short-term memory, which are the basis of the actual empowering of different application domains. Neural networks are a subset of machine learning algorithms, inspired by the human brain, made by layers of artificial neurons, connected to each other, and having an associated weight and threshold. Convolutional neural network is a class of neural networks, most commonly applied to analyze visual imagery [16], [17], while recurrent neural networks are largely employed in handwriting and speech recognition [18], [19]. The main advantage of these techniques is the ability to learn directly by analyzing raw data, without the need to extract discriminating characteristics in advance. Despite its benefits, neural network training requires a large quantity of data and significant time; moreover, it is a resource-intensive task.

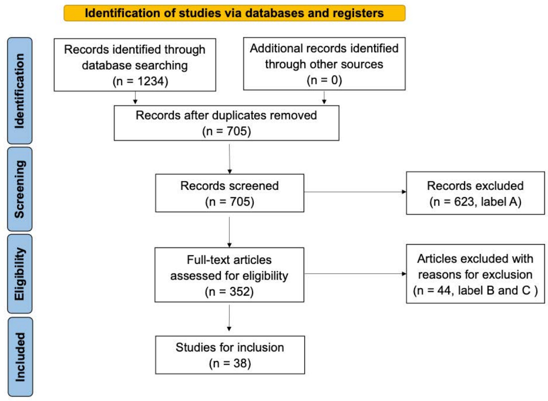

FIGURE 1. Preferred reporting Items for systematic reviews and meta-analyses (PRISMA) flow diagram depicting the process undertaken for the review with the inclusion of the number of studies that were screened and assessed for eligibility. Off-topics papers were tagged with label A, label B refers to reports whose full text was not available and label C was assigned to articles that were not peer-reviewed.

In recent years, employing statistics and learning techniques in the photo identification task has increased, leading to advances in the field. The main novelty of this paper is a systematic review which aims to inform on the state-of-the-art application of computer-assisted photo identification for marine mammals, with a specific focus on cetaceans. It aims to identify, analyse and compare the pull of semiautomated and fully automated photo identification systems presented in the modern literature. To the authors' knowledge, there are no previous literature reviews on this topic. This article will also be useful for readers, not experts in statistical learning, who want to try the current state of the automated photo identification of cetaceans.

II. METHODS

This study was performed following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses

(PRISMA) [20], [21], which is an evidence-based minimum set of items aimed at helping authors improve the reporting of systematic reviews. The PRISMA Statement consists of a 27-item checklist, listed in figure 2 (see also Table 1 of [21]), and a flow diagram of the process depicting four phases: *identification*, *screening*, *eligibility* and *inclusion* (Figure 1 shows the flow diagram of this systematic review). In particular, PRISMA requires that authors should report the total number of records identified from electronic bibliographic sources (including specialized database or registry searches), hand searches of various sources, reference lists, citation indices, and experts. Authors should delineate for readers the number of selected articles that were identified from the different sources so that they can see, for example, whether most articles were identified through electronic bibliographic sources or from references or experts. The flow diagram and text should describe clearly the process of report selection throughout the review. Authors should report: unique records identified in searches; records excluded after preliminary screening; reports retrieved for detailed evaluation; potentially eligible reports that were not retrievable; retrieved reports that did not meet inclusion criteria and the primary reasons for exclusion; and the studies included in the review. Indeed, the most appropriate layout may vary for different reviews. Authors should also note the presence of duplicate or supplementary reports so that readers understand the number of individual studies compared to the number of reports that were included in the review [21].

In this systematic review, the literature search was performed using two online expertly curated abstract and citation databases: Elsevier's Scopus and Thomson Reuters' WoS. The research was performed using a panel of fourteen search strings that use relevant keywords:

- photo identification marine mammals
- automated photo ID marine mammals
- photo identification cetaceans
- photo identification dolphins
- photo ID dolphins
- photo identification whales
- feature detection marine mammals
- feature detection dolphins
- automated feature detection whales
- neural network dolphins
- neural network whale
- artificial intelligence marine mammals
- machine learning cetaceans
- deep learning cetaceans.

These search strings were combined using Boolean operator OR. Furthermore, other constraints were added in the research phase to obtain only results that matched inclusion criteria: publications written in English, publications from 2016, selection of reviews and articles, papers not containing the word *acoustic* in the title. The last restriction is useful to discard papers discussing acoustic methods, which are used for studying cetaceans. In both databases, the search was performed by searching the strings in the title, abstract and keywords of the publication. This review was focused on studies applying automated or semiautomated photo identification techniques for the recognition of cetaceans, so studies that apply manual photo identification methods, studies without a peer review and studies whose topic was not about marine mammals were excluded.

Section/Topic	#	Checklist Item	Reported on Page #
TITLE			
Title	1	Identify the report as a systematic review, meta-analysis, or both.	
ABSTRACT			
Structured summary	2	Provide a structured summary including, as applicable: background; objectives; data sources; study eligibility criteria, participants, and interventions; study appraisal and synthesis methods; results; limitations; conclusions and implications of key findings; systematic review registration number.	
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known.	
Objectives	4	Provide an explicit statement of questions being addressed with reference to participants, interventions, comparisons, outcomes, and study design (PICOS).	
METHODS			
Protocol and registration	5	Indicate if a review protocol exists, if and where it can be accessed (e.g., Web address), and, if available, provide registration information including registration number.	
Eligibility criteria	6	Specify study characteristics (e.g., PICOS, length of follow-up) and report characteristics (e.g., years considered, language, publication status) used as criteria for eligibility, giving rationale.	
Information sources	7	Describe all information sources (e.g., databases with dates of coverage, contact with study authors to identify additional studies) in the search and date last searched.	
Search	8	Present full electronic search strategy for at least one database, including any limits used, such that it could be repeated.	
Study selection	9	State the process for selecting studies (i.e., screening, eligibility, included in systematic review, and, if applicable, included in the meta-analysis).	
Data collection process	10	Describe method of data extraction from reports (e.g., piloted forms, independently, in duplicate) and any processes for obtaining and confirming data from investigators.	
Data items	11	List and define all variables for which data were sought (e.g., PICOS, funding sources) and any assumptions and simplifications made.	
Risk of bias in individual studies	12	Describe methods used for assessing risk of bias of individual studies (including specification of whether this was done at the study or outcome level), and how this information is to be used in any data synthesis.	
Summary measures	13	State the principal summary measures (e.g., risk ratio, difference in means).	
Synthesis of results	14	Describe the methods of handling data and combining results of studies, if done, including measures of consistency (e.g., I^2) for each meta-analysis.	
Risk of bias across studies	15	Specify any assessment of risk of bias that may affect the cumulative evidence (e.g., publication bias, selective reporting within studies).	
Additional analyses	16	Describe methods of additional analyses (e.g., sensitivity or subgroup analyses, meta-regression), if done, indicating which were pre-specified.	
RESULTS			
Study selection	17	Give numbers of studies screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally with a flow diagram.	
Study characteristics	18	For each study, present characteristics for which data were extracted (e.g., study size, PICOS, follow-up period) and provide the citations.	
Risk of bias within studies	19	Present data on risk of bias of each study and, if available, any outcome-level assessment (see Item 12).	
Results of individual studies	20	For all outcomes considered (benefits or harms), present, for each study: (a) simple summary data for each intervention group and (b) effect estimates and confidence intervals, ideally with a forest plot.	
Synthesis of results	21	Present results of each meta-analysis done, including confidence intervals and measures of consistency.	
Risk of bias across studies	22	Present results of any assessment of risk of bias across studies (see Item 15).	
Additional analysis	23	Give results of additional analyses, if done (e.g., sensitivity or subgroup analyses, meta-regression [see Item 16]).	
DISCUSSION			
Summary of evidence	24	Summarize the main findings including the strength of evidence for each main outcome; consider their relevance to key groups (e.g., health care providers, users, and policy makers).	
Limitations	25	Discuss limitations at study and outcome level (e.g., risk of bias), and at review level (e.g., incomplete retrieval of identified research, reporting bias).	
Conclusions	26	Provide a general interpretation of the results in the context of other evidence, and implications for future research.	
FUNDING			
Funding	27	Describe sources of funding for the systematic review and other support (e.g., supply of data); role of funders for the systematic review.	

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FIGURE 2. PRISMA statement: checklist of 27 items to include when reporting a systematic review.

III. RESULTS AND DISCUSSION

The process undertaken for this review, following PRISMA protocol, has been represented in Figure 1. The article research was completed on 2021/09/10, and it has given a total of 1,234 papers, 621 on Elsevier's Scopus (www.scopus.com) and 613 on the Thomson Reuters' Web of Science (WoS, https://clarivate.com/webofsciencegroup) database. Among them, 529 papers were duplicates in both databases, 92 were found only by Scopus and 84 were found only by WoS; hence, 705 (= 529+92+84) articles and reviews were analysed. The full list of the 705 records is available as a supplementary file. The article screening shows that among the 705 records, 667 papers must be excluded with the following justifications:

- 623 papers were considered off topic, meaning that these does not discuss database based, semi-automated or automated systems for marine mammal photo ID (label A);
- for 41 articles full text is not available (label B);
- 3 publications were not peer-reviewed (label C).

TABLE 1. Breakdown of the thirty-eight articles in the international scientific journals. N denotes the article number, among the thirty-eight, published in the journal.

Journal Name	N	References
Frontiers in Marine Science	3	[22]–[24]
Marine Mammal Science	3	[25]–[27]
PLoS ONE	3	[28]–[30]
Scientific Reports	2	[31], [32]
Aquatic Mammals	2	[33], [34]
Ecological Informatics	2	[35], [36]
Electronics	2	[37], [38]
Journal of the Marine Biological Association of the United Kingdom	2	[39], [40]
Mammal Research	2	[41], [42]
African Journal of Marine Science	1	[43]
Behavioural Ecology and Sociobiology	1	[44]
Conservation Biology	1	[45]
Ecology and Evolution	1	[46]
Endangered Species Research	1	[47]
Eurasip Journal on Image and Video Processing	1	[48]
Gulf and Caribbean Research	1	[49]
IEEE Access	1	[50]
Integrative Zoology	1	[51]
International Journal of Geographical Information Science	1	[52]
Journal of Cetacean Research and Management	1	[53]
Journal of Computer Science & Technology	1	[54]
New Zealand Journal of Marine and Freshwater Research	1	[55]
Ocean and Coastal Management	1	[56]
Peerj	1	[57]
Polar Biology	1	[58]
Southeastern Naturalist	1	[59]
total	38	

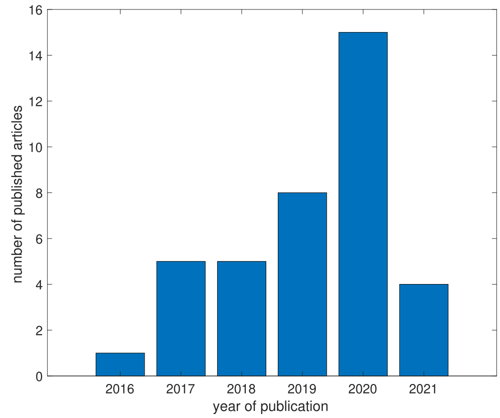

FIGURE 3. Number of articles, among the thirty-eight items selected using the PRISMA protocol, published per year in the period 2016-2021.

The remaining thirty-eight papers are discussed in this review study and the scientific journals to which these papers refer are listed in Table 1. Figure 3 illustrates the number of articles among the thirty-eight items published per year in the period 2016-2021. This highlights an ever-increasing interest in the field; in particular, from 2019 to 2020, the number of published papers almost doubled, while 2021 data are still partial because the search stopped on 2021/09/10.

A. FIELD OF APPLICATION OF AUTOMATED AND SEMIAUTOMATED PHOTO IDENTIFICATION SYSTEMS

The applications of intelligent photo identification systems on vagrant species can be categorized into the following main topics: occurrence and migration patterns, site fidelity and residency patterns as well as population abundance and social dynamics. In particular, several studies have evaluated the site fidelity of cetaceans in the study area [24], [27]–[29], [41], [43], [46], [52] as the tendency of an individual to occupy or return to a previously known area. This concept is relevant because odontocetes are at the top of the food chain, and their presence indicates resilient ecosystems and high-quality habitats. Strictly related to site fidelity, the concept of residency patterns analyses the temporal variation in habitat use by marine mammal species [29], [34], [39]–[43], [47]. Finally, photo identification can be efficiently applied to provide a baseline on species population abundance. A large part of these studies is related to animals ranked as data deficient, vulnerable or threatened by the International Union for Conservation of Nature (IUCN Red List) [23], [24], [46]. These studies are very important to evaluate the risk of their extinction and in that regard we refer to the Indo-Pacific humpback dolphins (*Sousa chinensis*) [29], Guiana dolphin (*Sotalia guianensis*) [33], Australian humpback dolphin (*Sousa sahulensis*) [47], Southern right whale (*Eubalaena australis*) [58], common (*Balaenoptera acutorostrata*) and Antarctic (*Balaenoptera bonaerensis*) minke whales [22], Ringed seal (*Pusa hispida*) [28], as well as the cosmopolitan bottlenose dolphins (*Tursiops truncatus*) [27], [40], [42], [49], [53], [59]. Finally, social dynamics is mainly focused on behaviours with photo ID tools that can recognize groups of individuals and their social evolution over time [26], [31], [34], [43], [44], [52], [57], and it can be particularly helpful with gender recognition. Studies involving social dynamics analyse calving intervals [55], calving success rates [31] and calving areas [58].

B. DISCUSSION ON PHOTO IDENTIFICATION SYSTEMS

In the recent literature, as highlighted by the pull of the thirty-eight selected articles by the PRISMA protocol, intelligent systems for cetacean photo identification have been published and can be clustered into three groups: semiautomated, fully automated and database (see table 2 and table 3), which will be discussed in the following sections. These systems are dedicated to supporting photo-analysts during their studies. Photos of entire dolphins or cropped images of animal dorsal or caudal fins (see Figure 4) are used as input to the photo ID system.

1) PHOTO IDENTIFICATION SYSTEMS BASED ON DATABASE

- FinBase [60], published in 2006 but still widely used, is a customized Microsoft Access database system that stores and manages textual and numerical data from photo identification surveys and performs many of the tasks associated with image management and analysis (https://www.fisheries.noaa.gov/national/

TABLE 2. Photo ID system details. The column **Name** indicates the name of the software. The column entitled **Species** reports the species on which the software has been applied, in particular cetaceans, while marine mammals different from cetaceans are marked with *symbols, and species different from marine mammals are marked with **symbols. The type (D means Database, S means Semiautomated and A means Automated) of system and its output are listed. The column **References** indicates the articles, among the thirty-eight, where the software is described or applied. The mark - means that no reference was found for the category.

Name	Species: Cetaceans Other marine mammals (*) Not marine mammals (**)	Type	Output	References
Finbase	Bottlenose dolphin Adaptable on a variety of other species	D	Catalogue searches for a new sighted individual	[49], [52], [53], [59], [60] (*) - (**) -
DISCOVERY	Humpback dolphin Bottlenose dolphin Spinner dolphin Ringed seal*	D	Catalogue searches for a new sighted individual	[24], [29], [31], [44], [46], [47], [51], [61] (*) [28] (**) -
BigFish	Southern right whale	D	/	[55], [58] (*) - (**) -
DARWIN	Bottlenose dolphin Guiana dolphin Dusky dolphin	S	Ranked list of the possible matches	[23], [26], [27], [33], [40], [43], [57], [59], [62] (*) - (**) -
Finscan	Bottlenose dolphin Dusky dolphin Spinner dolphin Long-finned pilot whale Sperm whale White shark** Basking shark **	S	Ranked list of the possible matches	[34], [39], [42], [63] (*) - (**) [64]
D. Policelli *et al.*	Commerson's dolphins	A	Individual identification	[54]
SPIR	Risso's dolphin	A	Best match individual	[32], [36], [37], [41], [50] (*) - (**) -
R. Bogucki *et al.*	North Atlantic right whales	A	Individual identification	[45]
N.G. Blas *et al.*	Humpback whales	A	Individual identification	[38]
FinFindR	Bottlenose dolphin	A	Ranked list of possible matches, dendrogram of distances between individual fins	[25] (*) - (**) -

FIGURE 4. Example of cropped images of cetacean fins used as input to automated or semiautomated systems for photo ID. The first column refers to the caudal and dorsal fins of sperm whales (*Physeter macrocephalus*), and the second and third columns refer to full photos and cropped dorsal fins of bottlenose dolphins (*Tursiops truncatus* and Risso's dolphins (*Grampus griseus*), respectively. Images refers to different animals.

marine-mammal-protection/ finbase-photo-identificatio n-database-system). Data entry and display forms allow users to interact with their data and images. FinBase maintains a catalogue where individuals can possess multiple attributes (e.g., chopped dorsal fin, apex dorsal fin notch, lower dorsal fin notch, peduncle scar/notch, etc.), and any combination of these attributes can be selected to sort the catalogue. FinBase helps analysts, during photo identification studies, sort the entire catalogue based on the similarity of each existing catalogue individuals' attributes to those of a newly sighted individual [49], [52], [53], [59]. This system, while created for a bottlenose dolphin research application, can be adapted to accommodate photo identification research on a variety of other species. FinBase provides a tool to explore and interact with photo ID data, reducing the time and effort required from the researcher. However, attribute assignments, on which the matching is based, may vary among photo-analysts, so it depends on his experience. Moreover, FinBase can process only one image per time, and for this, it is not suitable for large-scale photo ID studies.

- DISCOVERY (https://www.biosch.hku.hk) and BigFish (https://www.skadia.com.au) are two software programs applied in some studies [24], [28], [29], [31], [44], [46], [47], [51], [55], [58]. Unfortunately, to the best of our knowledge, no papers describing these systems have been published in peer-reviewed journals. DISCOVERY provides users with a freely curated platform and a detailed manual describing its functioning. It is a system platform that assists photo-analysts with filtering raw data and individual matching, in particular

TABLE 3. Main features, strengths and limitations of photo ID systems.

Name	Main features	Strengths	Limitations
Finbase	Database system with specific fields for the identification of cetaceans	- it can be adapted to a variety of other species - It allows researchers to quickly explore the photo ID data within a GIS environment	- Attribute assignments, on which the matching is based, may vary among photo-analysts - It can process only one image per time
DISCOVERY	Assists with filtering raw data and all levels of individual-ID matching	- It can verify "new" individuals (e.g., those that have not verified previously) or already matched individuals - It provides users with a freely curated platform and a detailed manual describing its functioning	- Strong interaction of the photo-analysts with the system - It can process only one image per time - No scientific paper describing its functioning published on peer-reviewed journals
BigFish	It uses code-based profiles to match individual images to an existing catalogue	/	- Poor available documentation - No peer-reviewed journal articles describing its functioning
DARWIN	It uses the fin outline chain code representation to identify fins' salient points	- It can be applied to several species	- It requires human intervention - It analyses one image per time -Poor identification performance in the first place of the ranked list
Finscan	Identification using pattern of nicks and notches on the dorsal fin; it uses the Livewire algorithm for tracing the fin outline	- Flexible, it can be applied on many species - Fairly accurate in individual identification when considering up to the third or fourth position of the ranked list	- it requires human intervention - Poor identification performance in the first place of the ranked list
D. Policelli *et al.*	It uses metadata to train machine learning classifiers	- High identification accuracy	- Collecting metadata requires a great effort and must be done manually - Animals with few pictures cannot be identified
SPIR	It uses either SURF or SIFT feature for matching individuals	- It can reidentify animals with only one previous sighting - It can handle photos where the cetacean is not frontally pictured - Good performance in real scenario - It can process many images in a single run	- Its application cannot be extended to species different from Risso's dolphins
R. Bogucki *et al.*	Pipeline with 3 CNN to identify RoI, key points and correct individual	- Study done inside a competition - A CNN automatically defines an RoI - High identification accuracy	- many images per individual are necessary to improve accuracy -CNN requires quantity of data to be trained
N.G. Blas *et al.*	Image preprocessing with "zero mean", "unit variance normalization" and photo ID using a CNN with 11 layers	- Study done within a competition - Good identification performance	- Each whale is a separate class and whales need multiple photos -CNN requires quantity of data to be trained
FinFindR	Identification performed using 3 CNNs to isolate the fin, to extract the trailing edge and to compute a matching score	- Good performance when using high-quality photos - It can be freely downloaded and used	- It is not clear its performance on a real use scenario

with processing, storing and managing digital images. It provides file naming routines and links sighting information with environmental, geographic, numerous user-defined parameters, graphic displays of data and basic analytical tools [24], [28], [29], [31], [44], [46], [47], [51]. To ensure that the identity and/or other image information (e.g., category/subcategory, quality, distinctiveness) has been correctly entered into the database, all newly catalogued images, either as new or previously matched individuals, should be checked and verified. Using the Verify menu in DISCOVERY, an individual can be considered "new" if no images for a defined ID have been verified, or it can be considered a "matched individual" if at least one image has been verified. Therefore, users should first verify the earliest image of all-new IDs, which then become matched, and the remaining images are verified together with the previously matched individuals. To verify new individuals, users could go through the existing verified catalogue to ensure that there are no matches to the proposed new IDs using the platform. Successively, the new individual will be inserted into the catalogue. DISCOVERY provides the photo-analysts with a verify match form of the platform, allowing them to verify the newly matched ID images that are verified in the existing catalogue. The query images are compared with the type specimen image(s) of that particular individual. Users can either verify or reject the match. If the match is rejected, the ID of the query image should be changed to a new ID, and the image is moved to the new ID folder and the ID, filename and directory updated in the data database so that the rejected image enters the procedure of verifying new individuals, which might result in a new individual or another match to the verified catalogue. DISCOVERY requires strong interaction of the photo-analysts with the system and can process only one image per time. Instead, poor documentation was found on BigFish, a desktop computer-assisted image matching and data management system, which has been used in two studies [55], [58]. It was developed for southern right whales (*Eubalaena australis*), and it uses code-based profiles to match individual images to an existing catalogue and manage associated data.

2) SEMIAUTOMATED PHOTO IDENTIFICATION SYSTEMS

- DARWIN [62] is an open-source computer vision system designed to identify individual bottlenose dolphins (*Tursiops truncatus*), facilitating the comparison of the contour of the dorsal fin of an unknown individual with a catalogue of known dolphins. DARWIN works semiautomatedly and has been used in several studies with some species of cetaceans, not only bottlenose dolphins [23], [26], [27], [33], [40], [43], [57], [59]. In fact, using fin contours to compare dolphin identities can be easily applied to a variety of species. DARWIN stores an approximation of the fin outline, which is obtained by a semiautomated process, and textual information (i.e., sighting data). It uses a variety of image processing and computer vision algorithms to execute the matching process. Consequently, it presents to the researcher an ordered list of obtained fins. In practical terms, the user has to import a photo of the fin and trace an approximation of the leading and trailing edges of the dorsal fin. Afterwards, DARWIN calculates the effective edge of the fin using an active contour algorithm that can be manually modified by the user. The extracted contour is approximated by a sequence of evenly spaced points. During this process, a one-dimensional representation of the fin, called chain code, is created. By using the chain code representation, it is possible to identify salient fin points. DARWIN automatically locates the start and end of the leading edge, the tip of the dorsal fin, the most prominent notch and the end of the trailing edge. To identify the dolphin, a quadratic spline wavelet decomposes the chain code and produces some coefficients: the tip of the dorsal fin is identified by the maximum coefficient, and a backtracking process is used to precisely identify the position of the tip in the chain code. Prominent notches in a fin outline appear as valleys in the plot of a fin absolute chain code and as local minima in wavelet decomposition. Finally, the obtained contour of the unknown fin is compared with all the outlines available in the referred catalogue to find the best-matching contours. DARWIN output is a ranked list of possible matches between the unknown dolphins and those collected in the catalogue. J. Stewman *et al.* in [65] tested the system using a test set of 50 unknown individuals compared to a catalogue of 200 individuals, and the system obtained only 21 times the correct match at the first place of the list, highlighting the poor identification performance of the system when using the first place of the raked list. Moreover, this tool can analyse only one image per time, is not suitable for large studies, and requires human intervention because it is semiautomated software. The major limitation of DARWIN is that, using fin contours to compare dolphin identities, it does not consider at all natural marks over the fin, such as tooth rakes, skin disorders, withe or dark patches and so on, which can be very useful for the individual recognition.
- Finscan is a software system initially developed for identifying bottlenose dolphins [39], [42], and then it was tested on dusky dolphins (*Lagenorhynchus obscurus*), spinner dolphins (*Stenella longirostris*), long-finned pilot whales (*Globicephala melas*), sperm whales (*Physeter macrocephalus*), white sharks (*Carcharodon carcharias*) and basking sharks (*Cetorhinus maximus*), making it extremely flexible [34], [63], [64]. This software allows the identification of marine animals matching an input image with some previously identified pictures. The matching process is based on the pattern of nicks and notches commonly found among the dorsal fin of many species of dolphins. The output of the system is made of a series of images from the database, ordered by similarity with the query image. Afterwards, the user can confirm the match. When you give an image to the system, the user can trace the fin outline with the Livewire algorithm [66]. This interactive algorithm is chosen because it allows the user to supervise the segmentation process; however, this semiautomated approach slows the entire process. When the contour is extracted, two methods are executed to describe the shape: curve matching and string matching, to compare it with the database. The user can choose the matching method that is more accurate for the data. After a catalogue query is made, a search is started through the database using curve matching or string matching. The results are classified according to the similarity to the query image. Then, the user can confirm

the match with a click on the correct image. In 2003, Hillman *et al.* [63] presented one of the first applications of the Finscan system in the literature and showed that, in approximately the 50% of cases, the first suggested match was the correct match; instead, around the 75% of times, the correct match appeared in the third or fourth position.

3) FULLY AUTOMATED PHOTO IDENTIFICATION SYSTEMS

- In [54], Pollicelli *et al.* evaluated the opportunity to use image metadata as a tool for photo identification because it can reduce the number of possible matches in the identification step. Metadata consisted of a set of manually taken annotations, one record per picture, that described different aspects of the animal's fin and surrounding appearance, together with ancillary information regarding the place and time where the picture was taken. The metadata was arranged as a set of attributes. Machine learning techniques were applied over the metadata of 869 pictures taken of 223 different Commerson's dolphin (*Cephalorhynchus commersoni*) images taken over seven years. Four different supervised classification algorithms were used: neural network, Bayesian classifiers, decision tree and K-nearest neighbour algorithms. Preliminary results showed that animals with few pictures (below 5) were almost impossible to identify with only this metadata. Therefore, the learning algorithm was focused only on animals with greater than or equal to 5 recapture records for each individual. A decision tree classifier trained with identifications made by the researchers was able to correctly identify the 90% of the individuals on the validation set using only the metadata present in the image files. This reduces the number of images to be manually compared and therefore the time and errors associated with the assisted identification process. Limitations of this approach are that research must collect metadata, which obviously requires much manual work, and before each new identification session, the algorithm should be retrained to include new photographed individuals. Moreover, the seldom captured animals (less than four captures) cannot be analysed using this method.
- SPIR is an acronym of smart photo identification of Risso's dolphin (*Grampus griseus*), representing a fully automated system initially developed to study the presence of Risso's dolphin in the Gulf of Taranto [32], [36], [37], [41], [50]. Data used in this study were collected thanks to the citizen science activities made by the authors, with general public involvement in research activities, side by side with experts. This species is characterized by several distinctive scars over the dorsal fin and the entire body of the animal, which represent a useful pattern for automated analysis. In the first step of the procedure, the input image is properly preprocessed to extract the fin segmentation using Otsu's thresholding technique and morphological operators. The core of the algorithm is feature detection and extraction performed using either Speeded Up Robust Feature (SURF) [67] or Scale-Invariant Feature Transform (SIFT) [68], which are widely adopted methods able to identify and describe local characteristics in images. Hence interest features, detected by SIFT or SURF, are stored in a proper data structure; these features are invariant to rotation and translation of the fin in the image, and for this, SURF and SIFT are useful in the real case of cetacean photo ID, where the individual is not posed, while they may appear in any position. To predict the identity of the new dolphin, a model comparison step is required comparing the input image with all of the images available in the database. The model with the highest number of matching features with the query image is selected as the best-matching dolphin. SIFT and SURF features are used to perform the photo identification task, and the results highlight that SIFT outperforms the SURF feature detector, showing better performances and achieving a 90% accuracy in the validation experiment [36]. SPIR requires no user interaction and can process multiple images in a single run of the system, thus overcoming the constraints of manual and semiautomated approaches. The SPIR algorithm enables the user to automatically perform the photo ID processing of fin images from Risso's dolphins, reducing the computational time when large quantities of data are analysed. Interestingly, SPIR can photo-identify animals with only one sighting in the catalogue and even only one photo of it. The application of SPIR cannot be extended to other species, especially if these are not characterized by scars over the fin. Moreover, acting as a best-matching algorithm, the peculiarity of SPIR is that it still provides an answer in terms of probability, even if the dolphin in the query image is unknown, that is, it has never been sighted before, and for this reason, its photos are not included in the reference catalogue. Maglietta *et al.* proposed in [50] a novel methodology, called NNPool, devoted to the automated photo identification of unknown vs. known Risso's dolphins with an accuracy of 87% measured on a validation dataset, which can be used as preprocessing of SPIR to detect the unknown dolphin before performing the photo identification of known dolphins. Finally, SPIR, similar to the other systems, required a cropped image of each fin, and the crop was manually created. The same authors proposed a solution to the problem of automatically cropping cetacean images with a hybrid technique based on domain analysis and deep learning [37]. Domain knowledge is applied to propose relevant regions to highlight the dorsal fins, and then a binary classification of fin vs. no-fin is performed by a convolutional neural network. This fin cropping technique can be efficiently inserted into the photo identification pipeline, supporting experts with an increased automation level of the process.

- Bogucki *et al.* introduced a fully automated system based on three Convolutional Neural Networks devoted to the photo identification of North Atlantic right whales (*Eubalaena glacialis*) [45]. This work was developed inside a data science challenge, launched on the Kaggle platform in 2015, on the automation of the right whale recognition process using a dataset of aerial photographs of animals (https://www.kaggle.com/c/noaa-right-whale-recognition). The proposed system uses an original high-resolution aerial photograph of North Atlantic right whales as input. The training dataset provided for the competition consisted of 4,544 images that contained only 1 single right whale and was labeled with a correct whale identification. In addition, a set of 4,111 images, for which a team could submit their predictions during the contest to obtain an aggregated score as feedback to inform algorithm development. Submissions were evaluated on a test set of 2,493 images used to determine the winners at the end of the competition. This data set is large by the standards of the wildlife research community but relatively small by the standards of deep learning algorithms. Moreover, the number of images per whale varied considerably, i.e., six individuals had only one photograph, whereas there were two whales with eighty-two images. This is challenging for machine learning, whose training depends on the number of images available for each individual. First, a CNN roughly selects the region of interest (RoI) in a scaled-down image (down to size 256×256) and outputs a bounding box around the head of the whale, which is then used to crop the high-resolution image. Successively, the authors developed a network that automatically scales, rotates and crops the input image, producing what they call a passport photo of a whale, that is, a standardized right whale photo with uniform size and orientation, which was used for the final photo identification. This was achieved by identifying 2 key points on the top of the whale's head (at either end of the callosity: the tip of the bonnet and just below the blowholes), and a CNN was trained to locate these key points using already labelled data. Data augmentation was applied, adding rotated and rescaled versions of the images in the original dataset, as well as random perturbations of the colour space. Finally, a CNN was used to perform actual whale identification, obtaining an accuracy of individual right whale recognition of 87.44%. The authors highlighted that the wide variability in the number of images per individual whale impacted the performance of the last CNN devoted to individual recognition. In fact, having more images per individual can improve recognition accuracy. In addition, in case of smaller dataset, a compensation can be obtained using data augmentation techniques, which are employed in deep learning framework to expand the available dataset without acquiring new elements: in fact, data augmentation applies random changes to existing data, creating modified copies of them. Accuracy can likely be improved by excluding challenging images such as those where the whale was only partially visible or with particular lighting conditions. However, this improvement in accuracy comes at the cost of designing a system with more stringent photograph quality requirements, which may not be as desirable for the user.
- In 2020, Blas *et al.* presented a model based on a CNN able to identify humpback whale specimens [38]. This work refers to a data science challenge on humpback whale automated identification, launched on the crowdsourcing platform Kaggle (https://www.kaggle.com/c/humpback-whale-identification) in 2018. This work uses a dataset of approximately 25.000 whale tail images. A neural network, using the TensorFlow framework, was trained to deal with the problem of identifying humpback whale specimens, and if there is no record of it, the system must catalogue the specimen as a new whale with a new label. In fact, each whale is a separate class, whales were photographed multiple times and attempts were made to identify a whale class in the testing set. Image preprocessing is considered part of the analysis, which includes greyscale conversion and image downsampling to increase the identification performance of recognition and reidentification. Authors used data augmentation, such as rotation, translation and noise reduction, to reduce the problem of data unbalancing. The proposed method aims to optimize the use of resources and to speed up network training, which can be embedded in a small computing device, even if its performance, 78.5% accuracy, cannot be considered excellent.
- FinFindR [25] is a fully automated photo identification software, which after the extraction of dolphin fins from the input images, tracks their outline and produces a ranked list with the top 50 most likely matching identities, allowing users to view side-by-side image pairs and make the final identity determinations. In detail, the finFindR workflow consists of four steps: fin isolation, isolation of the trailing edge, computation of a score based on distinguishing features and computation of the proximity of the query image score to the scores of other fins in the catalogue. The first step relies on a neural network, with an architecture loosely based on the ResNet architecture. This algorithm can handle both colour and greyscale images. The network outputs a pixel-based continuous value between 0 and 1, representing the likelihood that the pixel is a part of the fin or body. Subsequently, a neural network is used to automatically detect the trailing edge of each fin, standardizing its size and characterizing its distinguishing features. These features are a smart elaboration of red-blue-green color values along the trailing edge, embedding information on the natural marks of the trailing edge. In the third step, a score is assigned to the query image using

another neural network. This neural network computes a score vector based on the distinguishing features of the fin. In the final step of the workflow, the score of the query image is compared with the scores of other images in the catalogue, and an ordered table displaying the 50 closest images to the query image is generated, with a dendrogram of distances between the fin in the query and the fins in the catalogue. During the assessment, finFindR assigns the correct match to the top-ranked position in 88% of the time. In addition, finFindR placed the correct individual among the 10 top-ranked matches in 94% of tests and among the 50 top-ranked matches in 97% of tests. However, these results were obtained using only high-quality photos, making this assessment poorly consistent with a real use scenario. In fact, 149 noncontrast, blurry, water obscured photos, or images representing scenes in which the individual was not frontally photographed or did not have distinct fin features were discarded and not included in the study. FinFindR consists of an R- and C++-based library for photo recognition, and the authors made available a freely downloaded app providing an interface to the core library functionality (https://github.com/haimeh/finFindR). Similarly to what just mentioned for DARWIN, an important limitation of FinFindR is that it uses fin outlines, ignoring the valuable information contained in the natural marks on the fin.

4) AROUND INDIVIDUALS PHOTO IDENTIFICATION

In the literature, photo ID software has also been developed to facilitate the task of identifying a diverse set of species [69], [70]. The focus of this paper is automated individual photo identification. We also consider species photo identification an interesting task that can offer interesting ideas, so we briefly include it in the following discussion. Two of the thirty-eight papers discuss tools for blue whale photo identification [30], [48]. An identifying characteristic of this species is the shape of its dorsal fin observed on both the right and left flanks. The dorsal fin of the blue whale can be grouped according to its shape using three classes: triangular, hooked, and falcate. In [48], Carvajal-Gamez *et al.* presented an automated program of blue whale photo identification for mobile devices. The system uses input images of whale dorsal fins, and allows segmentation of the fin of the blue whale using clustering algorithms and estimates the colour local complexity on mobile devices. The preprocessing step is crucial because it removes characteristics such as posture and structural components of the image (i.e., sea, sky and other elements in the image), occlusion and environmental conditions. The photographic catalogue used in this work contains 771 images in digital RGB colour image format, of which 621 images were acquired with the Canon camera and 150 images were obtained with different mobile devices. The performance results of these proposed methods were good and seemed to exceed those of other well-known tools, such as DARWIN. An app for mobile devices has also been proposed, offering a real-time solution to blue whale photo identification.

In [30], Ramos-Arredondo *et al.* introduced a method to classify blue whale fins into 6 different classes: falcate right and left, hooked right and left, triangular right and left. This is very helpful for simplifying the successive photo ID process. After the preprocessing of the input image, which includes the manual selection of the region of interest, the fin is automatically extracted using the method described in [48]. To extract the features from the fin, the SIFT [68] algorithm is used. Finally, a classifier produces the fin class.

In recent years, crowdsourcing and citizen science activities have been increasing, and the use of nonprofessional photographs taken by the general public is being enlarged by many scientific projects, specifically in photo identification studies, as highlighted in one paper of thirty-eight [35]. This obviously represents a great opportunity to enlarge catalogues, but innovative information technologies are required to analyse them, both in preprocessing data tasks and photo ID analysis. In [35], Policelli *et al.* explore and develop multicriterion RoI detection for Commerson's dolphin pictures taken in the open. They do not face the problem of individual photo identification directly, but this work is still important because the automation of RoI extraction reduces the further burden of the identification process, either assisted or unassisted. A CNN and a multifractal classifier based on colour and texture features were developed, and the resulting RoIs were considered robust. The application of CNN to the RoI extraction task seems again to be promising; in fact, the proposed method achieved better performance than those obtained with the other two methods, Haar cascade object detection and pixelwise classification using colour and texture: the intersection over union (IoU) measure between the ground truth (manually obtained) and the RoI detected was equal to 0.797 ± 0.216.

IV. CONCLUSION AND FUTURE WORKS

This review highlights that in the period 2016-2021, there was a growing interest among data scientists in developing intelligent systems devoted to supporting experts when conducting cetacean photo identification studies, opening new frontiers and opportunities respect to the manually performed studies. The main advantage of manual photo identification is that it exploits human intelligence and experience acquired by experts in the field. For example, a photo scientist trivially solves the problem of having several dolphins in the same photo, as well as of handling the evolution of the distinctive marks of cetaceans that naturally occur in some species over time. On the other hand, manual photo identification of cetacean depends on the experience of those who perform the task, and, in case of large numbers of images, is likely to become tedious and very time consuming. To support photo scientists and general users during photo identification process, some interesting approaches, based on advanced statistical methods and machine learning strategies, have been proposed and showed good accuracies in the individual identification of several species of dolphins and whales, with a degree of automation variable among studies. In some cases, the proposed systems are semiautomated or the best performances are achieved on the n-top-ranked predictions, so these tools still rely on a manual inspection of the potential comparisons. Among the discussed systems, finFindR is a valid tool for cetacean photo identification, based on the outline of the dorsal fin. It is widely employed in the photo ID of bottlenose dolphin with very good accuracy, but it can be applied also to different species. In addition, a freely downloaded version of this system, designed for easy use, is available. Another noterworthy system is SPIR, which uses distinctive marks on the dorsal fin of Risso's dolphin, whose natural scars are particularly evident in adult individuals. Unfortunately, no user friendly version of SPIR is available, and for this its use is limited to scientists and experts. These systems are generally customized for a specific species, and their application to other cetaceans, different from that for which these were built, is not investigated. Further studies should be devoted to this aim, and most important, it will be desirable to have a more inclusive system which uses both the dorsal fin outline and distinctive marks inside it to photo identify individuals.

Moreover, future research could be focused on the comparison of some of the cited automated systems of cetacean photo ID over the same dataset, discussing how system performances are influenced by several factors, such as image quality, distance to the animal, device used for the image acquisition, using cropped fin image or full image. In particular, a special focus of these studies could be devoted to the evaluation of the ability of those systems of identifying dolphins or whales whose natural markers, used as features of recognition, change quickly. In fact, to the best of our knowledge, the problem of evaluation on how the temporal evolution of natural markers of an animal affects the system performance, during the photo identification process, has not yet discussed in the literature.

For whale photo identification, CNNs provides interesting solutions to this task. However, no advanced system can be here recommended, and further studies on this topic are surely desirable. This can be also attributable to the fact that whale sightings are rarer than dolphin sightings in many study areas, and for this few data on whale are available for training machine learning systems. Fortunately, two competitions on automated recognition of right whale and humpback whale individuals was launched, and a high number of competitors participated. This was very interesting because competition obviously stimulates researchers to apply on that theme and, most importantly, provides them with datasets. We want to focus attention on the benefits that open data can lead to marine biodiversity conservation, as well as in many other fields. Sharing data gives a strong impulse to research, facilitating data scientists to analyse them because data are essential to developing machine learning strategies, particularly in the case of deep learning algorithms that need a large number of samples to be trained. Open data can open new opportunities to create networks among research groups, thus covering broader geographical areas of study. Although we are aware of the great efforts required to collect data on cetaceans, due to the costs of marine surveys, to the high skills required to find animals and to the intrinsic hostility of the marine environment, we strongly recommend that researchers share their data on cetacean sightings to boost innovative studies in this field. Moreover, CNNs have been successfully applied to automated recognition of whale species with a good degree of automation and performance. Additionally, in this case, freely accessible data should increase the number of studies on this matter, which is now limited.

Finally, our study highlights that some benefits come from citizen science activities, which provide researchers with a larger amount of data, particularly nonprofessional images acquired by the general public, which can successfully be used in photo identification studies.

Another future direction on which we suggest to invest is developing apps and web interfaces to automated photo ID software, which can be very useful for making automated photo ID accessible to a broader and/or nonexpert audience.

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