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BRITISH ECOLOGICAL SOCIETY Methods in Ecology and Evolution

REVIEW

Conservation, Ecology and Artificial Intelligence: Advances and Symbiotic Solutions

Reviewing seas of data: Integrating image-based bio-logging and artificial intelligence to enhance marine conservation

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Abstract

1. Conservation of marine ecosystems can be improved through a better understanding of ecosystem functioning, particularly the cryptic underwater behaviours and interactions of marine predators. Image-based bio-logging devices (including images, videos and active acoustic) are increasingly used to monitor wildlife movements, foraging behaviours and their environment, but generate complex datasets needing efficient analytical tools.
2. We review advances in image-based bio-logging technology for ecological studies on marine fauna. Emphasis is placed on the diversity of data collected, merging research questions, challenges in image processing, and integration of Artificial Intelligence (AI) methods. Image-based system issues, such as exposure, focus, blurriness, colour balance, moving background, perspective and scale variability are even more challenging in underwater images where conditions change constantly and cannot be controlled. We list computer vision tools and algorithms available for analyses of underwater images, including enhanced tracking algorithms that recognise objects and treat images as a time series.
3. Although AI and computer vision methods offer ample and robust analytical solutions for (semi-) automated image processing, their uptake by marine ecologists has

been slow. Collaboration among ecologists, modellers, statisticians, engineers and computer scientists is needed to integrate ecological questions, data selection and computational methodology. We propose a four-phase framework for image data processing and analysis (video checking and manipulation, image processing, image labelling and model development) accompanied by detailed python code. We also outline the additional complications in aligning the diverse scalar movement metrics from bio-loggers along with image-based data, such as acceleration, depth and location, which typically are collected at different resolutions. Building analytical frameworks for on-board image data collection (e.g. lightweight models) is also explored.

4. We advocate for a collaborative research community at the Ecology-AI interface, emphasising sharing and exchange of both data and tools to drive cross-disciplinary innovation. Beyond the Ecology-AI interface, we pave the path for the application of insights from image-based bio-logging technology enabling collaboration among scientists, conservation managers, and policymakers. Systematic applications of computer vision tools to image-based bio-logging technology will enhance the power these data hold, informing about the status of marine ecosystems, testing and developing ecological theory and aiding conservation.

KEYWORDS

artificial intelligence, bio-logging, computer vision, conservation, marine ecosystems, underwater image

1 | INTRODUCTION

1.1 | The need for animal-borne underwater images in marine conservation

Earth's oceans have undergone major physical, biological and chemical changes during the Anthropocene, resulting in shifts in environmental baselines and in marine ecosystem functioning. Therefore, the need to effectively manage and preserve the health of our oceans has become a priority in environmental sciences and policy alike. However, conservation of marine biodiversity and ecosystems often faces the added challenge of being remote and difficult to access, whether geographically (e.g. polar regions) or within the deep oceans. While significant progress has been made in sampling physical and biogeochemical data in the oceans at increasingly finer spatiotemporal scales, a major deficit of in situ biological data at scales relevant to ecosystem management persists (Hoegh-Guldberg & Bruno, 2010; Xavier et al., 2016). Information on cryptic underwater behaviours of marine animals and their interaction with each other, with prey fields and with local environmental variability is still lacking. Yet, such information is vital if we are to understand, manage and preserve ecosystem processes. In recent decades, data obtained from bio-logging devices have begun to fill these knowledge gaps (Harcourt et al., 2019; Sequeira et al., 2021).

Bio-logging science refers to the deployment of electronic devices containing various types of sensors onto animals to collect information from the equipped animals (e.g. their movements, behaviour or physiology) or the environment they encounter (Boyd et al., 2004; Ropert-Coudert & Wilson, 2005). Through bio-logging, free-ranging marine predators can sample their immediate environment at very fine spatiotemporal scales, even in the most inaccessible parts of the oceans, while providing insights into their behaviour (Fedak, 2013). Various environmental sensors incorporated in bio-logging devices have provided new opportunities to collect data on the physical and chemical components of oceans (e.g. salinity, temperature, light, fluorescence, dissolved oxygen or sound levels) (Charrassin et al., 2010; Roquet et al., 2014). Similarly, high-resolution sensors such as triaxial accelerometers and magnetometers allow estimation of energetic expenditure or prey encounters from fine-scale movements of predators (Chung et al., 2021; Watanabe & Papastamatiou, 2023). Despite these considerable advances, scientists continue to make assumptions about what these remotely collected scalar data indicate (Carter et al., 2016). Underwater images collected by bio-logging devices may provide real observational data that could be used to validate inferences made from other sensors.

The collection of underwater images from animal-borne sensors has lagged behind other types of sensor data, mainly because technological constraints resulted in relatively large device sizes. As such, most of the early image-based data were collected from large marine mammals (Davis et al., 1992). However, advances in consumer electronics technology are currently driving significant progress in image-based bio-logging science, enabling the collection of diverse underwater images (Marshall, 1998; Rutz &

Troscianko, 2013). Increasingly, bio-logging devices offer small cameras or innovative sonar sensors (Figure 1) that enable the collection of still images, videos and echograms, which are directly relevant to the ecology of the animals carrying the devices. These devices can be an invaluable source of new knowledge about marine ecosystem function, leading to the testing and development of ecological theory. For example, micro-sonar devices have increased our understanding of predator–prey relationships of seals at sea, both from the perspective of predator-hunting strategies and prey escape behaviour (Chevallay et al., 2024; Goulet et al., 2019; Tournier et al., 2021). Video recordings from multiple predator species have similarly allowed us to gain new insights into (i) underwater prey-capture and foraging behaviour (Handley & Pistorius, 2016; Thiebot et al., 2017; Watanuki et al., 2008), (ii) flight characteristics (Kempton et al., 2022; Schoombie et al., 2019), (iii) social behaviour (Hinke et al., 2021; McInnes & Pistorius, 2019; Papastamatiou et al., 2022; Pearson et al., 2019; Tremblay et al., 2014) and (iv) characteristics of the surrounding environment (e.g. seafloor mapping, type of benthic cover) (Chapple et al., 2021; Gallagher et al., 2021). Image-based data can also improve measurements of physical oceanographic features, such as sea-ice concentration, at spatial scales relevant to marine predators (Linsky et al., 2020) (Figure 2).

1.2 | Integrating image-based bio-logging in underwater data acquisition: Commonalities and challenges

Beyond the field of bio-logging, underwater images mainly originate from research in benthic ecosystems, wreckage exploration, inspection of underwater cables and pipelines, as well as underwater search and rescue operations. In these fields, data are typically collected using baited remote underwater video systems (BRUVs), autonomous underwater vehicles (AUVs), remotely operated vehicles (ROVs) or side-scan sonars (Bagnitsky et al., 2011; Li et al., 2022; Phillips et al., 2019; Rasmussen et al., 2017). While these instruments are often equipped with high-resolution image-sensors, the underwater environment poses several challenges to image data collection. Specifically, underwater images are inherently affected by the non-homogenous effects of light absorption and scattering by biotic and abiotic particles in the water (Li et al., 2020; Sun et al., 2023). The scattering effect by suspended particles reflecting light rays in various directions can render underwater images blurry. Additionally, the absorption caused by the degradation of light rays in water according to their wavelength can create low-contrast images or reduce visible ranges. Not all colours (wavelengths) are absorbed equally in water; shorter wavelengths (e.g. red, orange and yellow) are absorbed more quickly than longer ones (e.g. blue and green). This leads to the differential and successive disappearance of image colours with depth and water type (coastal vs. open ocean) (Akkaynak & Treibitz, 2018; Pedersen et al., 2019), which would make objects appear uniform and lead to misinterpretation of features.

In bio-logging, the aforementioned challenges are made more complex given that images are collected from animals moving freely within the water column. Thus, despite capturing invaluable visual data, images collected by marine animals can suffer from loss of quality due to ever-changing backgrounds as the animal moves through the water column, causing shifts in focus and rapid changes in illumination, colour, water turbidity and noise (Figure 3). Collecting images that are representative of an individual's environment is therefore problematic since image quality is dependent on specific situations (e.g. time, location, behaviours) that are optimal for camera or sonar sensors. This makes it difficult to build datasets that adequately account for behavioural and environmental variability. Consequently, underwater image datasets are prone to uneven sample sizes with considerable differences in data available for different underwater objects (Jin & Liang, 2017). The bias toward one type of identifiable object over another is a real challenge when trying to make inferences on an animal's environment or behaviour.

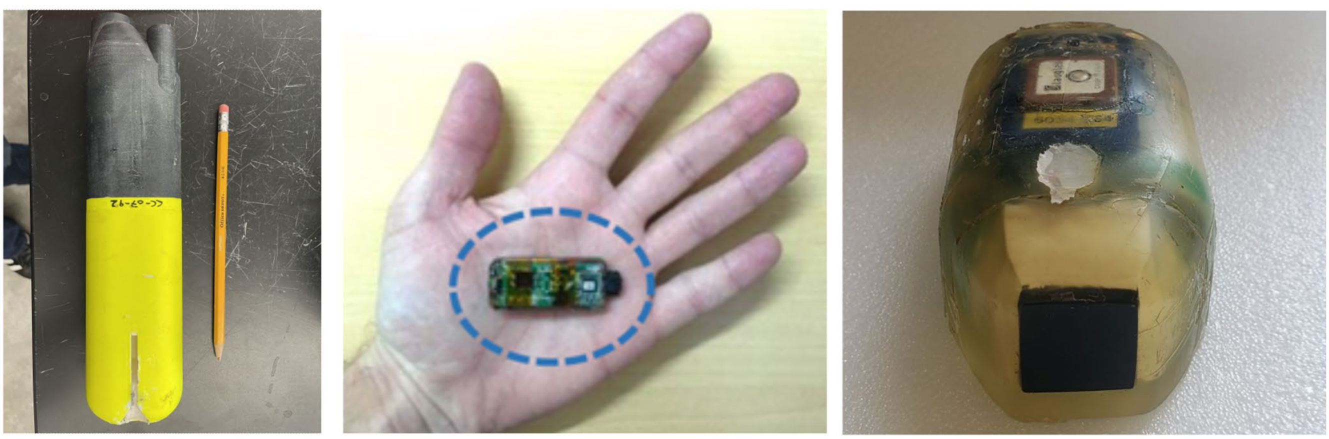

FIGURE 1 Examples of image-based bio-logging technology (left to right: Two types of cameras and a microsonar). Typically, cameras record video for only a few hours (with the recording duration dependent on battery capacity, acquisition settings, and environmental conditions). Microsonars provide a series of acoustic images and are usually triggered by other sensors, such as pressure (depth) and the time of day (dimensions: 85 × 45 × 20 mm).

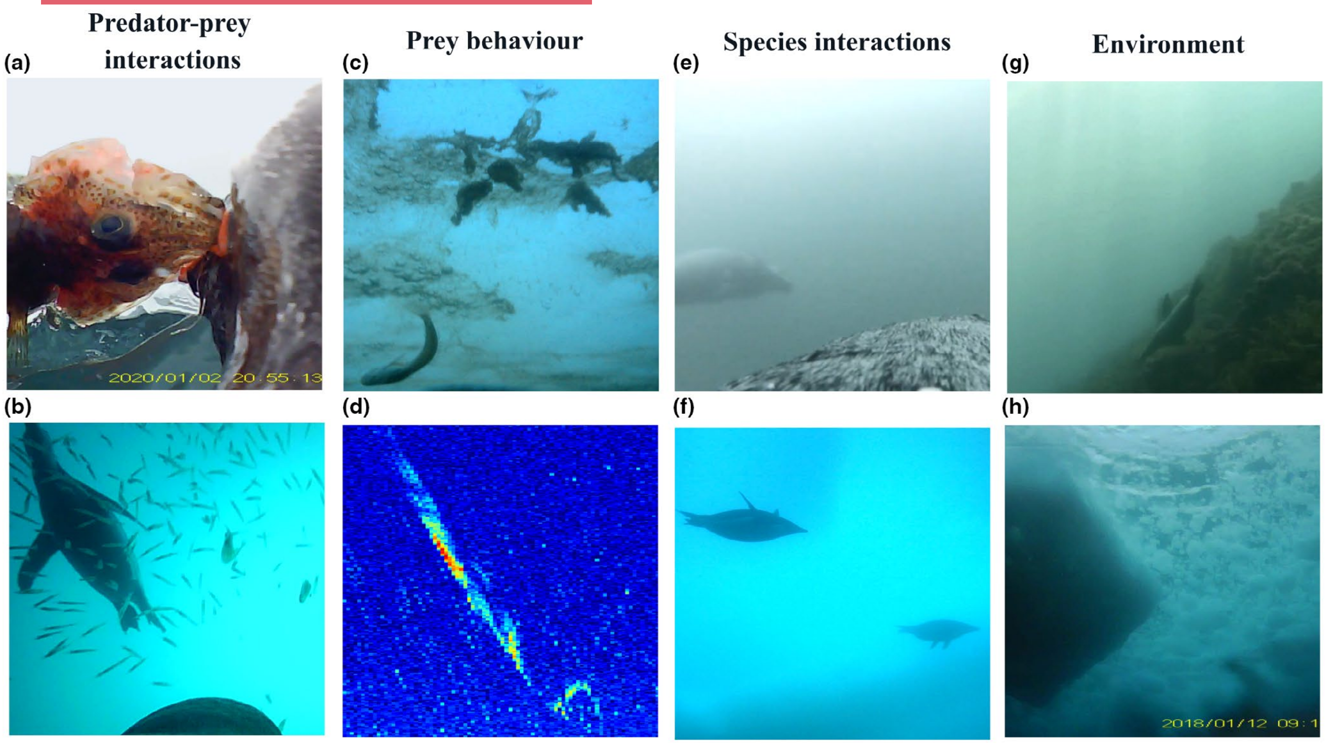

FIGURE 2 Examples of images collected using image-based bio-logging technology in marine ecosystems and the ecological information they provide. Predator–prey interactions: Penguins foraging (a) on a single prey item and (b) in krill swarms. Prey behaviour: (c) fish underneath sea ice, (d) echogram showing a prey escaping from the predator. Species interactions: (e) seals and (f) penguins travelling in groups. Environment: (g) view of the barrier reef and (h) sea ice.

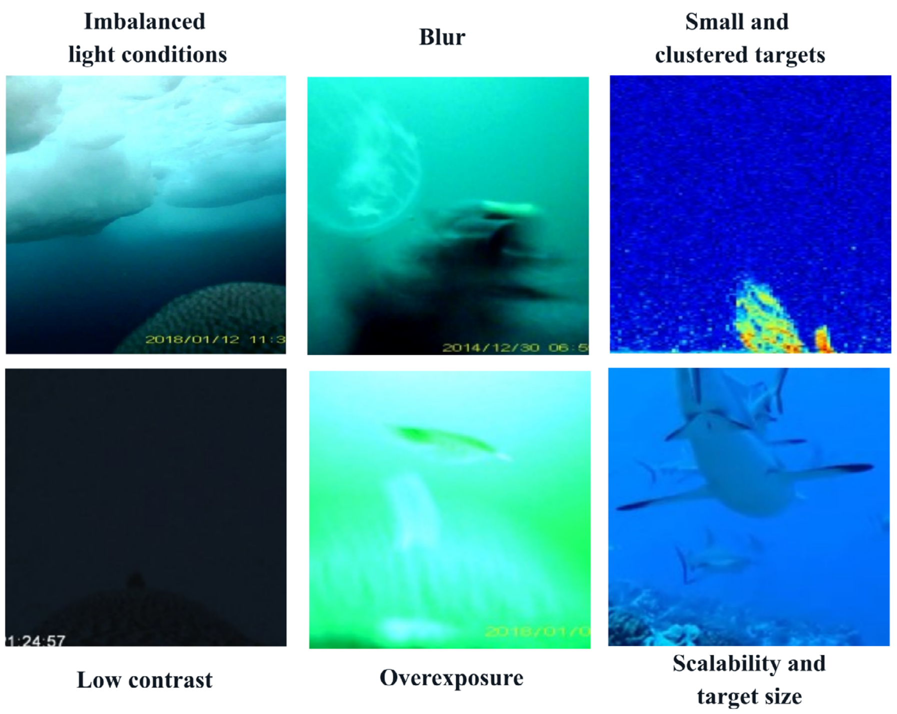

FIGURE 3 Examples of challenges encountered in image-based bio-logging (both camera and microsonar tags).

1.3 | Common AI tools for the analysis of image data

Computer vision-based methods can address some of the difficulties associated with collecting image data in underwater environments, including those obtained from animal-borne imagery (Belcher et al., 2023; Khurana & Tirpude, 2020; Li et al., 2023; Li & Du, 2022). These approaches, which include image enhancement, segmentation, and object detection and recognition, can be developed and applied together or independently.

Image enhancement approaches help restore visibility, colour, and natural appearance of underwater images (Figure 4). They are also used to extract additional information and variables (called 'features') for display, object detection and classification purposes. Within the field of computer vision, image enhancement may include white balance and colour correction, histogram equalisation for contrast adjustment, and a mix of them named 'fusion-based methods'. More advanced tools were recently developed using generative AI to enhance images such as the General Adversarial Networks (GANs) and Retinex-based algorithms (the latter aiming at eliminating the effects of diverse environmental illumination) (Abirami & Vincent, 2021; Li & Du, 2022). Convolutional Neural Networks (CNNs) are also highly effective for image enhancement tasks such as denoising and contrast adjustment, leveraging their ability to learn complex feature representations (Han et al., 2020; Jiang et al., 2020). Through working on large datasets and also aided by transfer learning (machine learning [ML]) technique where a model could learn from a wide range of images (Yang et al., 2024), CNNs can automatically correct and improve image quality.

Image segmentation can be used to segregate a digital image into multiple regions according to the different properties of pixels, for example for categorising seabed characteristics (Diesing et al., 2016). Segmentation can be used to extract meaningful information for easier object detection tasks but, because it partitions an image into non-overlapping regions, it can find it difficult to define object boundaries and complex shapes (Chuang et al., 2015). Image segmentation approaches can range from low-level or pixel-level vision tasks (Figure 4) to complex models intertwined with classification and object detection algorithms (being a single model or multiple stages). High-performance approaches to segmentation can be embedded in a model performing object detection and classification, so segmentation and detection/classification are not always distinct processes (Fan et al., 2021).

The last step, generally known as object detection, classification and recognition, aims at developing computational approaches that provide information on the identity of objects within each image and their location (Zou et al., 2023) (Figure 4). The ideal underwater object detector and/or classifier should have good recognition abilities across various underwater targets without

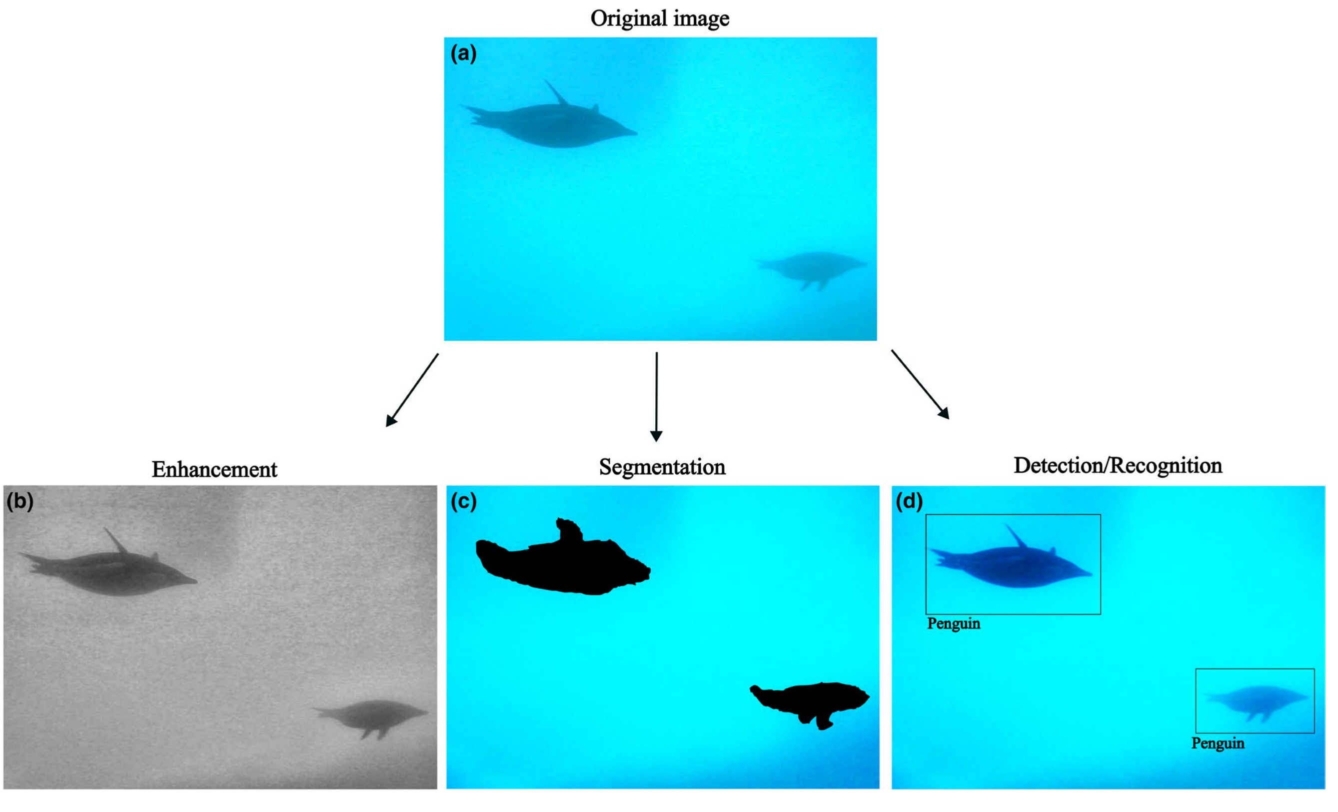

FIGURE 4 Example of common AI tools for the analysis of image data applied to an image obtained with image-based bio-logging technology. (a) Original image, (b) example of enhancement: Contrast Limited Adaptive Histogram Equalisation (CLAHE) (Khurana & Tirpude, 2020) enhancing local contrast and bringing out details in darker or lighter areas, (c) example of segmentation and (d) of object detection/recognition (presence of bounding boxes) on the sharpened original image.

false or missed detections, should exhibit high accuracy, precision and recall, to provide accurate target location, and should have low inference time and memory usage (Xu et al., 2023). In addition to challenges common to other computer vision tasks, such as recognition of objects from different viewpoints, illumination and intraclass variations, additional challenges in object detection in underwater images also include object rotation and scale changes (e.g. small objects), object density, and possible object occlusion. Detection tasks such as simple object identification, species recognition, overlapping object detection and detection of the same object at various sizes each present unique challenges and may require distinct approaches.

1.4 | A roadmap to leveraging image-based bio-logging data for ecological research and conservation

Image-based bio-logging data are becoming increasingly common in ecology, and yet AI-based methods remain underused for their analysis despite advancements in computer vision and their advantages in terms of analysis time gain. There is thus a timely relevance to review these AI-based methods currently lacking in this branch of bio-logging. We consequently provide an original and comprehensive review to streamline image-based bio-logging data analyses for ecological purposes. We first review literature related to (i) underwater image manipulation and analysis using AI and (ii) image-based bio-logging in the marine environment. The aim of the literature review is to explore the application and potential of computer vision approaches in these two fields, as well as highlight and discuss challenges, current gaps and opportunities for the integration of AI-based computer vision and image-based bio-logging. We then propose a framework to promote collaborations across computer vision and image-based bio-logging fields, outlining steps to take when processing and analysing image data (along with a practical example in a jupyter notebook to follow through). We pay particular attention to the knowledge exchange required between the fields of ecology and computer science. Finally, we provide best-practice recommendations to enhance the accessibility and utility of bio-logging images for conservation. While image-based bio-logging data undoubtedly advance our understanding of marine ecosystem dynamics, their application to conservation efforts remains underdeveloped. We promote a comprehensive approach, drawing insights from environmental monitoring and computer vision to unlock the full potential of image-based bio-logging for conservation.

2 | OVERVIEW OF LITERATURE SEARCH, KEYWORDS USED AND DATASET PROCESSING

We conducted three independent searches in both Scopus and Web of Science to capture research topics related to (i) underwater image manipulation and analysis using AI, (ii) bio-logging in the marine environment and (iii) image-based bio-logging in the marine environment. The following keywords were searched within the 'abstract' section of publications:

- Underwater image manipulation and analysis using AI. Keywords: '*image*', '*imaging*', '*detection*', '*recognition*', '*segmentation*', '*classification*', '*enhancement*', '*marine*', '*underwater*'.
- Bio-logging in the marine environment. Keywords: '*biotelemetry*', '*bio-telemetry*', '*biologging*', '*bio-logging*', '*animal-borne*', '*marine*', '*underwater*', '*sea*'. We also searched for publications specifying the main marine taxa within abstracts, using the keywords '*seabird*', '*seal*', '*shark*', '*pinniped*', '*cetacean*', '*whale*', '*dolphin*', '*penguin*', '*fish*', '*ray*', '*turtle*'; and the mode of underwater locomotion, with the keywords '*diving*', '*swimming*', as well as the specific bio-logging tag used, with keywords '*TDR*', '*argos*', '*accelerometer*', '*GPS*', '*GLS*', '*pop-up*', '*archival*'. This ensured that we were capturing publications that inconsistently used these words.
- Image-based bio-logging in the marine environment. Keywords: '*biotelemetry*', '*bio-telemetry*', '*biologging*', '*bio-logging*', '*animal-borne*', '*marine*', '*underwater*', '*sea*', '*image*', '*video*', '*camera*', '*CritterCam*', '*video-recorder*'.

The lists of peer-reviewed papers obtained from the two databases (hereafter 'records') were loaded in R (version 4.4.1; R Core Team, 2024). Results from the same research topic were merged and duplicates, retractions, and irrelevant records were removed. To illustrate trends in the number of relevant publications by year, we included research published between 1977 and 2023. For records on underwater image manipulation and analysis using AI, we calculated the average number of citations per year. All records with an average of two or more citations per year (i.e. between the median (1) and mean (2.9)) were selected for further screening. From this subset (2072 records), we extracted 100 records: 91 randomly selected records and nine records that are selected as three top-cited papers (excluding big reviews) within each of the three main AI problem areas: image enhancement, segmentation, and detection/recognition. With this selection, we aimed at extracting (i) most used basic solutions as well as (ii) successful custom solutions that could be transferred to the field of ecology. Additionally, we used latent Dirichlet allocation (LDA) to calculate the similarity of paper titles and obtained their respective distributions over AI problems presented (Jelodar et al., 2019).

Records related to image-based bio-logging technology identified from the broader search on bio-logging in the marine environment were added to the list of records belonging to the image-based bio-logging dataset, if they were not already included. This was done to ensure that we were capturing publications, which inconsistently reported the use of image-based bio-logging technology. It is possible that our searches might have omitted some relevant records that do not possess the specified words within their abstracts, but we should nonetheless have captured a representative sample of the literature.

3 | OVERVIEW OF RECORDS COLLECTED AND EMERGING TRENDS

3.1 | Trends in underwater image manipulation and analysis using AI

The literature search within the field of underwater image manipulation and analysis using AI produced 6079 records. The publication trend from 1977 to 2023 showed exponential growth, with most papers published after 2010 (Figure 5).

The applications of computer vision techniques reviewed from the subset dataset (containing 100 records) were developed across various types of underwater data, including acoustic, camera, spectrometer, stereo and ortho-projection data. These records were fully reviewed and further divided into subcategories according to the AI problem they were addressing: image enhancement, image segmentation, object detection and/or recognition. See Table 1 and the following paragraphs for an overview of model types.

Image enhancement was performed using both simple approaches such as hue intensity saturation (HIS), background elimination, histogram equalisation methods (CLAHE, HE), fusion and gamma correction, as well as more complex deep learning structures such as Generative Adversarial Networks (GANs). Both image segmentation and object detection and/or recognition categories included a wide variety of Convolutional Neural Networks (CNNs) such as VGG, ResNet, FasterCNN, YOLO (across versions). These models aimed at, for example, general sonar image segmentation, phytoplankton classification, marine species recognition, solving the problem of distinguishing overlapping objects within images and detecting objects of different sizes (Lee et al., 2022; Lyu et al., 2022; Muniraj & Dhandapani, 2023; Tang et al., 2021; Yeh et al., 2022). These problems, and proposed solutions, are applicable to the data collected via image-based bio-logging technology (see Figure 2 for examples) where there is the need to count, detect and identify overlapping objects, for example prey items and/or conspecifics encountered.

The metric used to assess model accuracy was not consistently reported across records, varying from accuracy, mean model accuracy (mAP), F1 score, genuine acceptance rate (GAR) and Intersection over Union (IoU). Reported values across all metrics also showed large variation, from 0.3 (being very bad) to over 0.9 (very good model accuracy). These results were related to the type of the problem that needed to be addressed (e.g. define classes boundaries, detection of species), type of training used (underwater images collected from the marine environment, synthetic images, images generated in laboratory experiments, online sourced images) as well as modelling approach used (Lee et al., 2022; Liu et al., 2019; Lopez-Vazquez et al., 2020; Shin et al., 2022).

Models with highest performances (>0.95, sourced from the pool of the 100 records) were developed for underwater acoustic target classification (UATC-DenseNet), a scalable lightweight live crab detector (EfficientNet-Det0), detection of debris using VGG16, MaskR-CNN for segmentation of images containing fish and detecting overlapping objects (Cao et al., 2021; Doan et al., 2022; Fan et al., 2021; Garcia et al., 2020; Moorton et al., 2022). Light-weight models also emerged from the top records across both image enhancement and object detection/recognition. The lightweight design of a particular model reduces the network parameters, but without reducing the network performance, and is aimed at a more efficient 'network calculation method' (Zhou et al., 2020). These models are used to deliver real-time transmission of enhanced or corrected images, as well as to detect objects of interest (Cao et al., 2021; Muksit et al., 2022; Yeh et al., 2022).

The LDA analysis (which looked only at the paper titles) confirmed the results obtained from the in-depth review (summarised in Table 1), by also identifying three distinct AI problems (Figure 6): underwater image enhancement (57.3%, Figure 5a), application of neural networks for image recognition (22.2%, Figure 5b) and

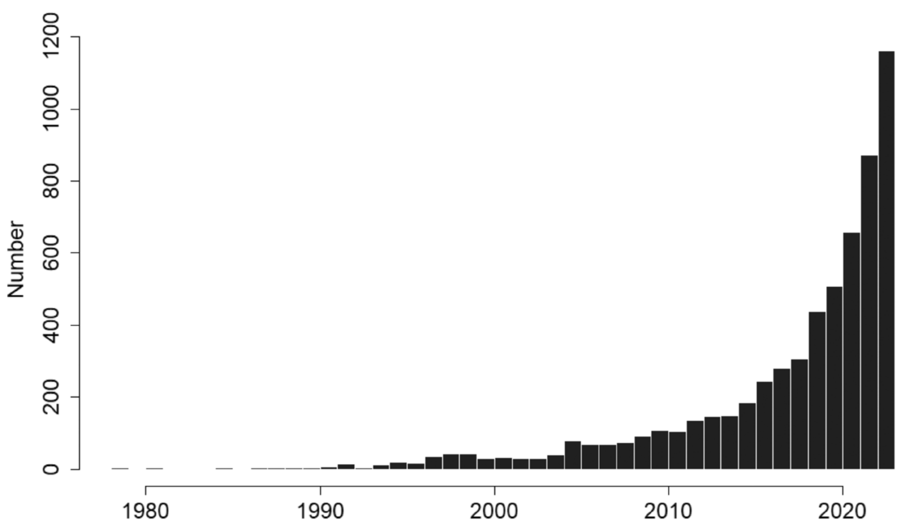

FIGURE 5 Temporal trend of the number of publications in the field of underwater image manipulation and analysis using Artificial Intelligence (AI) approaches.

TABLE 1 Overview of computer vision problems tackled and associated methodologies across underwater data types: Acoustic, camera, spectrometer, stereo and ortho-projections.

Problem	Example method
Enhancement (low contrast, colour distortion, low light, edge preserving, blurriness, polarisation in highly turbid waters, suspended particles)	• **Water-Net (*)** • **UWCNN (*)** • **Retinex with optimisation for low-light conditions (*)** • Retinex • Conversion from Red Green Blue (RGB) to Hue Intensity Saturation (HIS) • Multi-scale fusion (CCMF) • Contrast Limited Adaptive Histogram Equalization (CLAHE) • Sharpening and adapting gamma correction • Adaptive Look-UP-Table based on probability threshold. • Fast local Laplacian Filter (FLLF) • Histogram-equalization (HE) approximation using physics-based dichromatic modelling (PDM) • Point spread function (PSF) model • Image fusion • Improved Segmentation Dark Channel Prior (ISDCP) defogging method • Backscatter removal and colour compensation • Hierarchical attention aggregation with multi-resolution feature learning for Generative Adversarial Networks (GANs) • Degradation-aware and Colour-Corrected Network (DCN) • WaterGAN • Learning-based low-illumination image enhancer (LigED) • Colour space conversion • Background separation with binarization • Noise removal with image filters • Image morphology • MBFFNet • Transformer
Segmentation	• **Segmentation of Underwater IMagery (SUIM)-Net (*)** • **Mask R-CNN (*)** • **ResNet, Region Proposal Network (RPN), dynamic instance segmentation (*)** • ResNet50 • Feature pyramid network (FPN) • SparseConvNet (SCN) • ESANet
Detection/recognition	• **Infrared Shape Network (ISNet) (*)** • **YOLO with improvements using FPN and PANet (*)** • **Improved CNN with FPN (*)** • Support Vector Machine • K-Nearest Neighbours • Random Forest • Faster R-CNN • Underwater acoustic target classification DenseNet (UATC-DenseNet) • MobileNet (across versions) • EfficientDetD7 • VGG16 • Curvature scale space (CSS) • Fuzzy Overclustering (FOC) using ResNet50 • EfficientNet-Det0 • Fuzzy logic controller (FLC) with extended Kalman filter (EKF)

Note: This overview was sourced from 100 selected peer-reviewed papers related to underwater image manipulation and analysis using AI. Computer vision approaches developed and/or adopted in the top three most cited papers for addressing the problems of enhancement, segmentation and detection/recognition are marked in bold with (*). References for these papers can be found in Section 3.1.

classification and feature detection in marine environments (20.5%, Figure 5c). Here, we report the top five most relevant terms.

The first problem was strongly focused on improving the quality of images captured underwater. The presence of terms such as 'segmentation' and 'underwater' suggests that this topic is not only concerned with general image enhancement techniques but also with specific applications such as the identification and analysis of underwater objects and marine life. This aligns with current trends in computer vision, where deep learning techniques are increasingly applied to solve complex problems in image processing.

The second problem highlighted the role of neural networks and image recognition in the analysis of underwater images, particularly

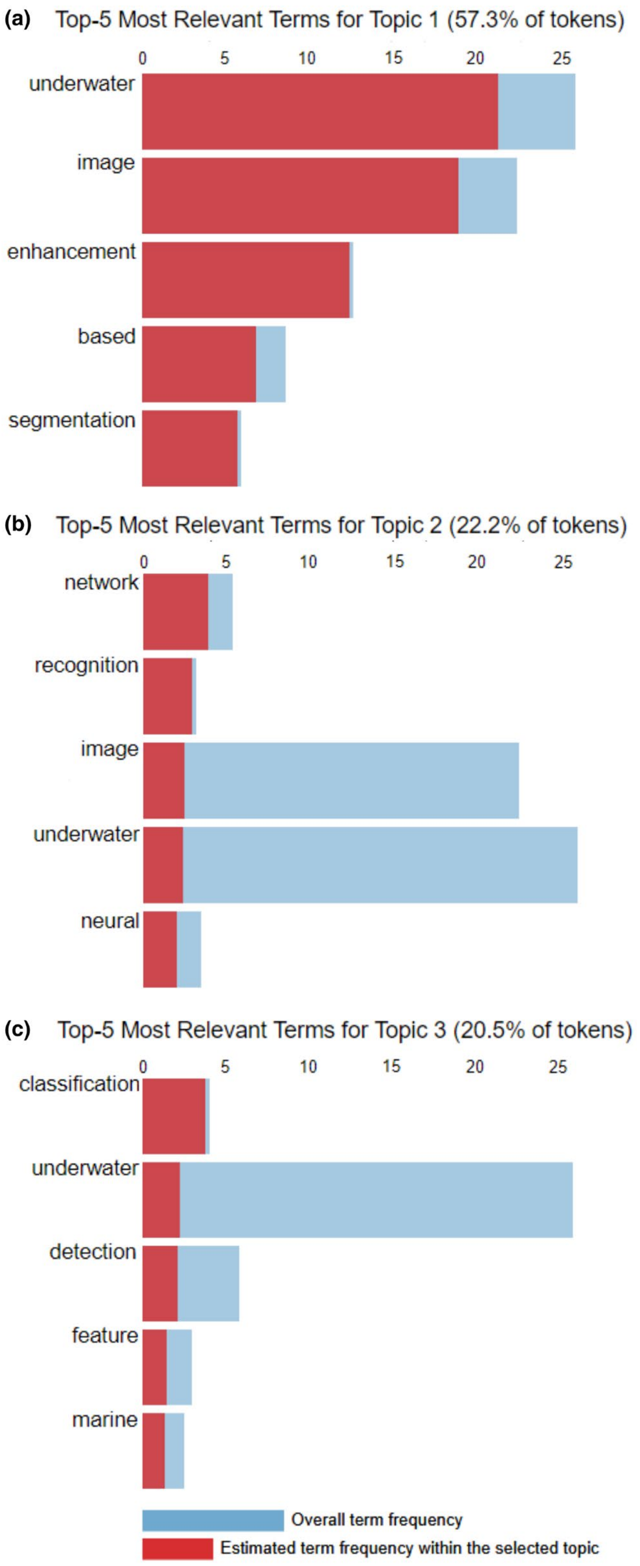

FIGURE 6 Latent Dirichlet allocation topic modelling results. (a) Problem 1: Underwater image enhancement. (b) Problem 2: Neural networks and image recognition. (c) Problem 3: Classification and feature detection.

in underwater settings. Terms such as 'network' and 'neural' indicate a significant focus on deep learning architectures, specifically Convolutional Neural Networks (CNNs), which are widely used for image recognition tasks. The inclusion of 'recognition' suggests that this topic is concerned with the development and application of algorithms for recognition, which encompasses both object detection—identifying what objects are present in an image—and object localization, determining the position of these detected objects within the image. The repeated mention of 'underwater' indicates that these neural network techniques are being specifically tailored for underwater environments, where unique challenges such as poor visibility and colour distortion need to be addressed.

The third problem centred around classification and feature detection, with a particular emphasis on marine applications. Key terms like 'classification' indicate that tasks in this category involve determining which category a given image belongs to. Another task covered in this topic is 'detection', which focuses on identifying the species present within an image of underwater environments.

3.2 | Bio-logging in the marine environment and image-based bio-logging trends

The literature search within the field of bio-logging in the marine environment produced 2542 records. The number of publications per year has increased steadily during the last two decades to ~150 per year (Figure 7) (Ropert-Coudert et al., 2009). By contrast, the literature search within the field of image-based bio-logging research in the marine environment produced only 171 records. The trend data (Figure 8) indicated that image-based bio-logging technology is relatively new compared to the wider bio-logging field, with the number of publications increasing after 2010 with most years having 10–35 records. Across these records, all marine taxa were represented: seabirds including penguins (35%), marine mammals (21%), sea turtles (20%), cartilaginous fish, for example sharks and rays (16%), bony fish (7%) and invertebrates (1%).

While AI tools were applied to time series data collected with bio-logging technology (e.g., GPS, accelerometers, time-depth recorders; for example Del Caño et al., 2021; Jeantet et al., 2020; Sutton et al., 2021) in most of these studies, image data were annotated (either manually or using pre-existing tools) and the content either described or matched with the relevant ancillary scalar data (e.g. Michel et al., 2022; Mori et al., 2005; Weber et al., 2023). We only found two records (~1.2% of the total) that directly applied computer vision tools to underwater images collected by marine species. In the first instance, Okuyama et al. (2015) used a template-matching technique to extract the head movements of sea turtles to understand their visual assessment of surroundings. In another study, Conway et al. (2021) used CNN-based approaches (VGG16, ResNet50, Inception v3 and Inception-ResNet v2) and recurrent neural network approaches (RNN-CNN) on single frames as well as on video sequences to classify types of behaviours of two marine top predators. Additionally, a search of literature published in 2024 revealed the use of open-source Video and Image Analytics for a Marine Environment (VIAME) and the neural network EfficientNet

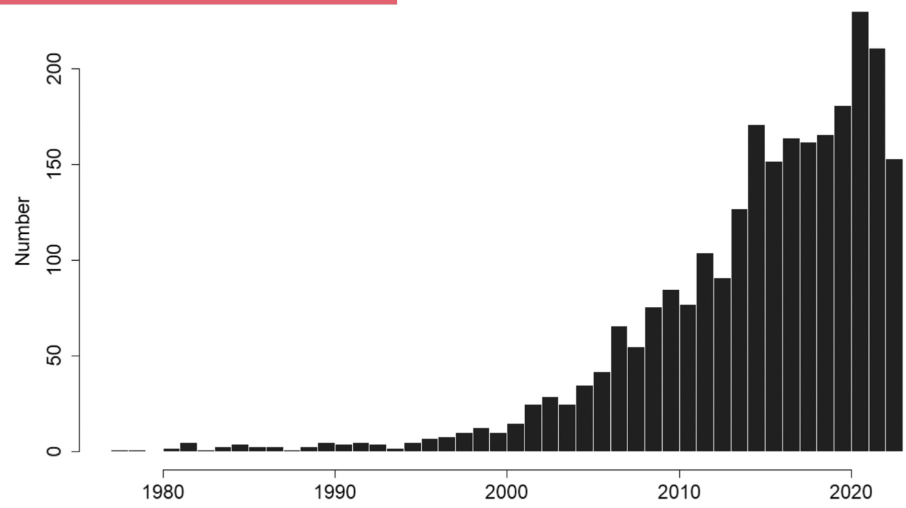

FIGURE 7 Temporal trend of the number of publications in the field of bio-logging research in the marine environment.

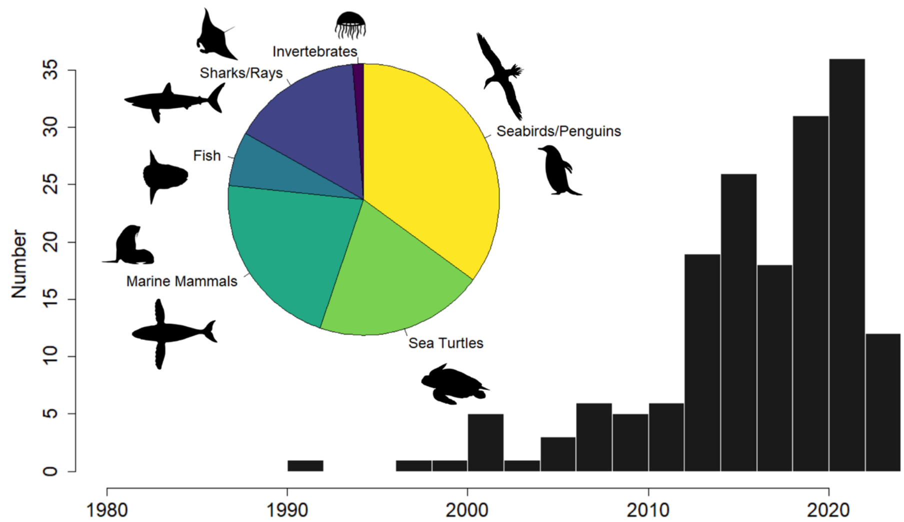

FIGURE 8 Trends in the number of publication records published in the field of bio-logging research using image-based technology in the marine environment. Left: By taxa. Right: By year.

to estimate prey density from single-camera images (Hermanson et al., 2024).

4 | A FRAMEWORK TO ENHANCE THE USE OF IMAGE-BASED BIO-LOGGING DATA FOR MARINE ECOLOGY

The bio-logging community has yet to fully embrace computer vision approaches for fast and accurate analyses of underwater image datasets. Indeed, while machine learning holds significant potential to contribute to the fields of marine ecology and conservation, large and complex image datasets are still predominantly processed and analysed manually (e.g. Barry et al., 2023; Wilson et al., 2017). These slow, labour-intensive manual tasks may discourage further collection of invaluable underwater images across broader spatial and temporal scales. They can also delay the application of information embedded within the datasets, slowing knowledge transfer. Conversely, the wide range of model architectures developed and implemented within the field of computer vision that can be applied to underwater images can be daunting for non-specialists, and difficult and time-consuming to apply. Moreover, the challenges that ecologists might face in using AI in image-based bio-logging are likely species-dependent. For example, a fast-moving penguin equipped with a lower-quality camera (due to size constraints) will collect lower-resolution images compared to slower and larger moving species equipped with a large (better) camera.

4.1 | How to: A path for starting image-based bio-logging data manipulation and analysis

To provide information and solutions to aid conservation in a timely manner, image-based bio-logging datasets need to be manipulated and analysed with appropriate, fast and accurate tools drawn from and developed within other disciplines dealing with similar data, for example robotics, engineering, automated ecosystem monitoring systems and Artificial Intelligence. This leads to interdisciplinary collaborations between ecologists and computer scientists. We have outlined the fundamental steps that ecologists, ecological modellers, statisticians and computer scientists should consider when approaching these types of analysis (Figure 9). The framework we propose here assumes an open science approach, with collaborative work and information exchange among scientists. Understanding the functioning of ecological systems and the modelling requirements and capabilities, as well as mathematical skills for the development of novel algorithms, are necessary to analyse these complex datasets.

The 'how to' path we propose serves as a starting point. Our jupyter notebook (see Supporting Information; Kato Ropert & Ropert-Coudert, 2025) provides functional steps along with code examples for each phase [(1) video checking and manipulation, (2) image processing, (3) image labelling, and (4) model development]. We have opted for Python libraries because of their efficiency and open source resources well suited for image processing and analysis. 'OpenCV' (a C++, Python and Java library) is one of the most popular computer vision libraries available in Python, while 'TensorFlow' and 'PyTorch' (https://pytorch.org/) are widely used for the implementation of object detection, image segmentation and classification algorithms. A search within the Comprehensive R Archive Network (CRAN), the programming language most ecologists use, returned three main packages for performing computer vision tasks: 'AzureVision', 'autovi' and 'opencv' (Li, 2024; Ooi, 2020; Ooms & Wijffels, 2023), while the 'reticulate', 'shiny' and 'Rcpp' R packages help bridge the gap between R and Python languages (Chang et al., 2024; Eddelbuettel & François, 2011; Ushey et al., 2024).

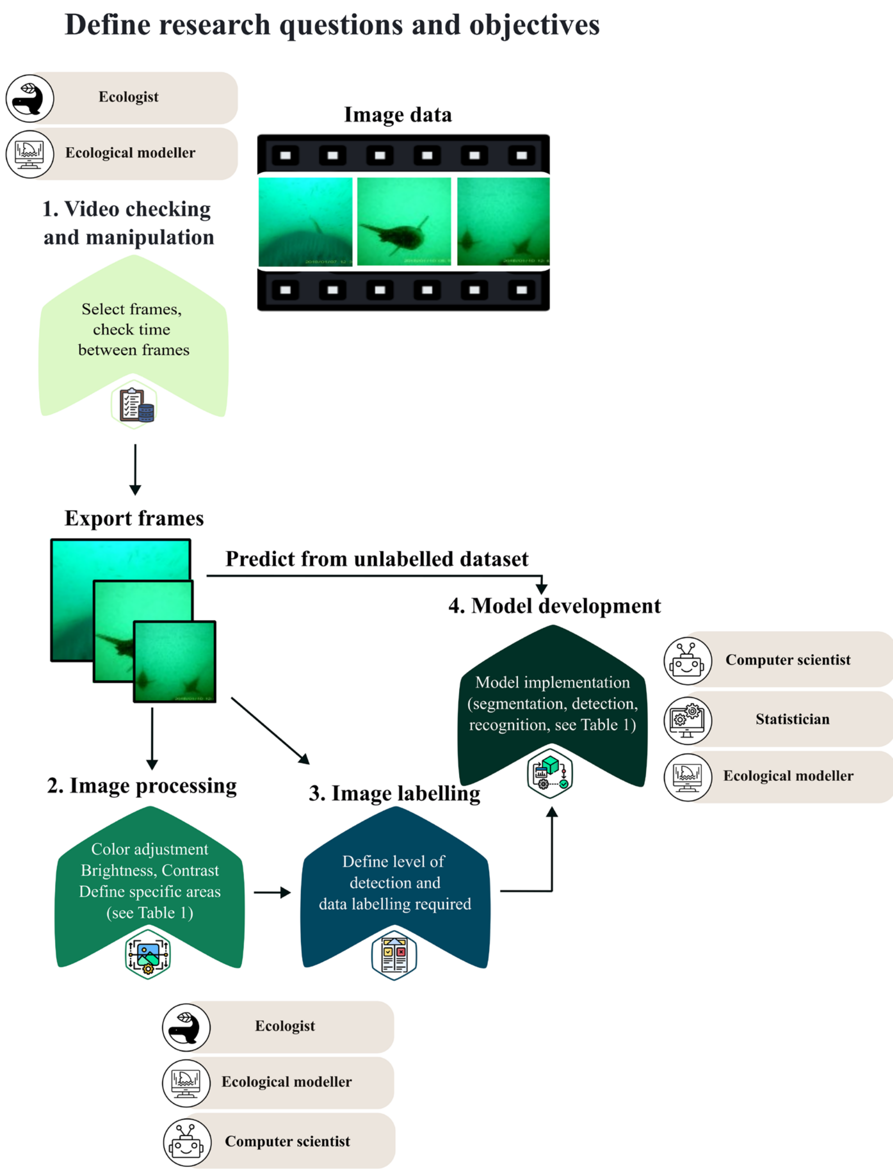

FIGURE 9 Overview of analytical phases for the manipulation and analysis of image-based bio-logging data, from data collection to training and running a model. Sample codes for detailed steps are available from the jupyter notebook in Supporting Information.

Once datasets have been collected, we suggest getting the basic properties of the loaded videos such as the frame rate and total number of frames, processing frames and handling the missing ones, and finally saving the processed data and extracting specific frames as images (Phase 1 in Figure 9, steps 1–7 in jupyter notebook). Depending on the video formatting from specific bio-logging devices, time between frames might not always be constant. Regular time stamps for image data are essential if researchers wish to match other data streams by date and time (see Section 4.4), and for further analyses requiring time series data (see Section 5). Additionally to checking the time between frames, calculating the red value of each individual image can help detect overexposure or darkness of each frame (see Step 2–4 in jupyter notebook). This step facilitates future data screening and can potentially reduce the number of frames needing processing. Individual frames can be processed with image enhancement if required (Phase 2, Figure 9, see steps 8–11 in jupyter notebook for sample code). Conversion to grayscale and work on saturation can help with images with low exposure, while image edge sharpening helps define boundaries of the objects within each image. We suggest that phases 1 and 2 be performed by or under the supervision of ecologists and ecological modellers, since knowledge of data collection and species biology and ecology is required.

Defining 'objects of interest' within images should be discussed prior to analyses (Phase 3 in Figure 9, step 12 in jupyter notebook). Decisions on the appropriate modelling tools will then depend on the research focus, for example image segmentation or object detection. The steps needed to prepare the dataset for computer vision analysis are interlinked with the level of detection required, for example simple binary classification (presence/absence of an animal or object within a frame), object classification (species recognition, recognition of environmental features) or tracking objects across frames (prey items being chased by marine predators often disappear and reappear across images). We emphasise the importance of these steps since the way the datasets are labelled will affect the number and/or type of classes to be detected, as well as the number of observations in each class and, as a consequence, the model performance (Belcher et al., 2023). Labelling objects within images can be achieved by using common open access labelling tools, such as LabelImg (python package on https://pypi.org/), Label Studio (https://labelstud.io/), BIIGLE (Langenkämper et al., 2017) and VIAME (Richards et al., 2019). Phase 3 requires collaborative work across disciplines, as ecologists would know what to label, while computer scientists would advise on analytical tools and methods.

At this point, an object detection model can be implemented and trained (phase 4 Figure 9, steps 13 and 14 in jupyter notebook), potentially starting with a pre-trained deep learning model (e.g. YOLOv5) that would need to be fine-tuned. We suggest splitting the dataset in to 'train' and 'test' subsamples (usually between 70% and 80% of the total dataset available to train the model and 20%–30% to test it) (Piechaud et al., 2019). The trained model runs inferences on an image, and returns predicted bounding boxes. In the provided example, the model predicted two boxes, stating a label and the confidence around the classification (see step 14 in our jupyter notebook), with a clear case of object mislabeling (both label and location of predicted boxes are incorrect). The training loss curves—both training and validation box losses—show how well the model learns from the data and how well it can generalise to unseen data. If both decrease, the model is learning well. If validation loss stops decreasing or increases while training loss keeps dropping, the model is overfitting (memorising training data but not generalising). If both losses stay high, the model is underfitting (not learning patterns well).

To develop and implement new models (Phase 4, Figure 9), we recommend starting with the PyTorch library since it contains the structures of the models mentioned in Table 1. Decisions regarding model architecture and implementation as well as interpretation of model performances would benefit from inputs from computer scientists, statisticians, and ecological modellers, while ecological interpretation of results would rely more on ecologists and ecological modellers. Model evaluation should include precision, recall, F1 scores, intersect over union (IoU), mean average precision (mAP) and confusion matrices (Belcher et al., 2023). The appropriate score index depends on the research question and the impact that object classification—or misclassification (or object detection/misdetection)—has on the ecological meaning of the results. For example, if an object is correctly classified 50% of the time, the model might not be learning correctly, that is similar objects are associated with different classes or there might not be enough images across classes. The confusion matrix provides an estimate of this misclassification error that can be used to improve the model, as well as information that can be used to fine-tune other models.

Biases should be expected in the training datasets. This often arises from imbalanced or underrepresented samples, which can lead to models that favour groups over others or yield inaccurate predictions in real-world applications (see also 'Common caveats and bugs' in our jupyter notebook). Class weighting and transfer learning (e.g. use of a model trained on another dataset) can for example help dealing with such issues (Siddiqui et al., 2018). Overfitting occurs when a machine learning model learns the training data too well, capturing noise and specific patterns that don't generalise to new data, leading to poor performance on unseen examples. To check for overfitting, we suggest monitoring, for example, the model's performance on a separate validation set: if it performs well on training data but poorly on validation data, overfitting is likely to occur (train the model from image data collected from one study site and validate the predictions on image data collected from a different study site for example).

4.2 | Standardising image data to promote collaboration across disciplines

Preparing datasets for subsequent analysis across research disciplines (e.g. ecology and computer science) is a challenge. Ecologists might tend to pre-select 'frames of interest' depending on the research question(s) (e.g. the detection of prey capture events by marine predators), and manually sort and label images with the behaviour of interest (Aoki et al., 2013; Del Caño et al., 2021; Dodge et al., 2018). Decisions are thus made on a case-by-case basis and are rarely transferable across case studies. On the other hand, computer scientists tend to label all objects within each frame, yet these label formats are rarely standardised (Belcher et al., 2023). Moving toward a standardised way of labelling and processing images will generate datasets that could be used across fields. YOLO text files, Pascal VOC XML files, and COCO ('common objects in context', https://cocodataset.org/) Java Script Object Notation (JSON) are currently the preferred formats for metadata storage (Belcher et al., 2023). It is therefore critical that collaborators are in agreement with the approach to image processing before proceeding with the analytical steps.

4.3 | Open access, reproducibility, transferability of data and software

Robust, innovative, interdisciplinary projects benefit from access to analytical tools and large and comprehensive repositories for data as well as analytical processes and pipelines. A wide variety of source codes across analytical processes is freely accessible from GitHub, a code hosting platform popular with developers worldwide. The GitHub platform offers a free version for individual developers and open-source projects. As the ecological community continues to embrace open science, it is imperative to create a culture that not only values data sharing but also supports the infrastructure necessary for effective collaboration and communication. Stakeholders, researchers, educators, policymakers and community members are and should continue to be involved in the conversation about open science. Examples of open-access data repository within the bio-logging community include Movebank (https://www.movebank.org), the Expert Group on Antarctic Biodiversity Informatics of SCAR (https://scar.org/science/life/egabi), Biologging Intelligent Platform (https://www.bip-earth.com/), Ocean Biodiversity Information System (OBIS) (https://obis.org), and Global Biodiversity Information Facility (GBIF) (https://www.gbif.org/) (Hindell et al., 2020; Kays et al., 2022).

Gathering robust and diverse image datasets to train and build computer vision models is challenging (Chen et al., 2024). Large image repositories on marine invertebrates and fish are becoming available, for example CoralNet (https://coralnet.ucsd.edu), Woods Hole Plankton Dataset (https://darchive.mblwhoilibrary.org/home) and Wildfish (Zhuang et al., 2018). Image repositories currently allow for both png and jpeg image formats. Choosing the appropriate image compression is also being evaluated in computer vision. JPEG XR format is suggested for low resolution and high definition (HD) image compressions, while formats such as JPEG 2000 and JPEG XT are suggested for greyscale and 4K image compressions respectively (Naveen Kumar et al., 2021).

Thus far, government and institutional grants typically provide significant resources for supporting repositories, especially for initiatives aligned with public interest, scientific advancement, and conservation. Changing political priorities, economic fluctuations, and grant cycles put the continuity of these platforms at risk. Long-term government commitments are a more sustainable approach (e.g. the European based repository Zenodo, https://zenodo.org/, the French government-based repository https://recherche.data.gouv.fr/en, American scientific agency https://data.noaa.gov/onestop/, Biologging Intelligent Platform, https://www.bip-earth.com/).

4.4 | Data standardisation across sensors

It is important to note that animal-borne underwater images are merely a small fraction of the complex datasets collected by bio-logging devices. Bio-loggers are often multi-sensor devices with at least a pressure sensor to record depth and a geolocation sensor, whether GPS or Argos, to record location. Tri-dimensional accelerometers and magnetometers that record both fine-scale movements and the position of the animal's body in space have also become common sensors in bio-loggers. These ancillary data provide complementary information to the images to help decipher the behaviour of marine animals.

The temporal synchronisation of data collected from these multi-sensor devices is an area in need of standardisation. Video and ancillary data are often sampled by separate devices that are not temporally synchronised, leaving the user to manually synchronise these data streams prior to analysis. Synchronisation is often done manually through visual inspection, but without a clear definition of the process that was followed (although some tag manufacturers have started to provide help on data handling and synchronisation). Such synchronisation may be difficult to maintain over longer periods, as image-based sensors are often subject to temporal drift (Del Caño et al., 2021), and synchronisation on a single point in time may not be sufficient. This may be further complicated by the way that video loggers from different manufacturers save individual video files. Low-cost, miniature video loggers mostly record with a variable frame rate, that is the number of frames per second varies with time, but files are saved at a higher, fixed frame rate by duplicating missing frames. While some manufacturers produce bio-logger devices that sample video and ancillary data on a single processor with a common clock, this is not the norm. Wider availability of single processor devices would greatly reduce the complexities of synchronising various data streams in the future.

Further steps in data standardisation are required before incorporating them all into a single global analytical framework (e.g. Cade et al., 2021; Conway et al., 2021). Understanding the complexity of marine ecosystems and aiding conservation requires multifactorial data collection, as well as tools to handle and process large, complex and mismatched datasets.

5 | FROM DISCRETE OBJECT DETECTION TO DYNAMIC TRACKING

Oceans are dynamic three-dimensional environments in which animals continuously move at different speeds. Most underwater images collected by bio-logging devices are videos or time series images that directly show the movements and activities of marine animals, and their interactions with each other and their environment. Yet, most of the methods for image analysis developed to date reduce videos to discrete as they inherently do not process data as a time series. To capture the complex and dynamic nature of videos and time series images, tracking-based methods accounting for the temporal aspect of the collected images need to be implemented.

Within the image-based bio-logging literature, long short-term memory (LSTM), SimpleRNN, and gated recurrent units (GRU) have been proposed as valuable options (Conway et al., 2021). These models, however, cannot be trained in parallel. Given a sequence of images, the computed hidden states/objects of the first image need to be computed first in order to encode the second image. This is a first-order information retention process, which means that the information obtained from the first image will not affect the detection of hidden states or objects in the third image. On the other hand, transformer attention-based models are sequence-to-sequence deep learning models that process the image sequence as a whole. They can learn both local and global features of an image and treat information extracted from image-based bio-logging devices as a time series (Bi et al., 2021; Guo et al., 2022). Overall, these models can follow relevant data in space and time at a much finer scale to better understand a complex and fluid ecosystem. Ultimately, this information can be used to predict future trends, such as future behaviours or interactions displayed by an animal given a specific environment or change thereof. However, the structure of these models remains complex, and interdisciplinary collaborations between ecologists and computing scientists will undoubtedly help to fully explore, develop, and democratise these dynamic models for marine ecological purposes.

6 | DATA PROCESSING ON-BOARD BIO-LOGGERS

To date, all bio-loggers that collect underwater images have to be physically recovered to access the data. Thus, for most marine species whose individual movements are unpredictable, underwater imagery from bio-loggers is currently not available. This creates a considerable taxonomic and geographical bias in current research and our understanding of the most inaccessible environments (Treasure et al., 2017). Transmitting bio-logging data to receivers such as Argos satellites, GSM or Mote systems can help to circumvent this hurdle (Jeanniard-du-Dot et al., 2017; Jessopp et al., 2013; Vacquié-Garcia et al., 2024; Vincent et al., 2010). However, efficiently synthesising raw imagery data on-board bio-loggers for near real-time transmission faces the simultaneous constraints of limited processors and battery capacities as well as device size.

Given the ongoing developments of lightweight underwater sampling platforms in the fields of computer vision, robotics, engineering and more recently bio-logging, we recommend that future development of on-board image processing for near real-time transmission be based on these types of models (Cao et al., 2021; Li et al., 2017; Lyu et al., 2022; Muksit et al., 2022; Tanigaki et al., 2023). Lightweight models have a simpler architecture with fewer networks than those currently available, and thus are less computer intensive. As such, they maximise battery life while maintaining the same level of performance as more complex models. For example, Yeh et al. (2022) proposed a lightweight underwater object detection network for joint image enhancement and object detection ('Improved CNN with FPN'; Table 1). The effectiveness of this model was tested on a Raspberry Pi platform and its performance was superior to Faster R-CNN, YOLOv2 and YOLOv3 (Yeh et al., 2022). To our knowledge, manipulation and analysis of underwater images have not yet been implemented on board bio-logging devices. Overcoming this hurdle should be a research priority as it will open a new avenue of understanding of poorly sampled areas of the oceans.

7 | HOW IMAGE-BASED BIO-LOGGING RESEARCH PROVIDES EFFECTIVE CONSERVATION TOOLS

Image-based learning approaches similar to those used in bio-logging applications are increasingly applied in underwater conservation. By leveraging advanced machine-learning algorithms, underwater videos at fixed stations or on gliders have been used to catalogue marine species, map coral reefs or monitor environmental change (Magneville et al., 2023; Sauder et al., 2024; Schmid et al., 2020). AI-powered image systems can detect signs of coral bleaching or disease, enabling timely intervention (Kopecky et al., 2023; Sauder et al., 2024). AI has also been widely used to monitor marine systems using both active and passive acoustics, to assist in interpreting sound backscatter into images or echograms for example (Gugele et al., 2021). Echograms from active acoustics enhance the ability to characterise and map habitats and species occurrence. In passive acoustics, AI-based models applied to spectrogram images can identify species and interpret their behaviours (e.g. tail slaps warning of predators, or whale songs near a breeding range) (Dudzinski et al., 2009). AI detection classification models operating on real-time data streams can lead to management of commercial ship slowdown and fisheries closures to protect vulnerable marine life (e.g. detection of North Atlantic right whales (*Eubalaena glacialis*) in the shipping lanes of the Gulf of St. Lawrence, or of Southern Resident killer whales (*Orcinus orca*) in the shipping lanes of the Salish Sea, Canada). In short, AI-based methods provide powerful new tools for ecologists (Pichler & Hartig, 2023).

For image-based bio-logging to become an effective conservation tool, long-term, consistent data collation is essential, particularly when integrated with AI-driven solutions and open science practices. This initial step creates a broader community for cross-disciplinary collaboration, beginning with scientists directly involved in the collection, collation, and analysis of image-based bio-logging data. Predictions emerging from AI-based analytical models (see also Figure 9) provide insights into marine ecosystem dynamics, such as predator–prey interactions, prey behaviour, interspecies relationships, mid-trophic layer dynamics, conditions in environments like sea ice and coral reefs, and many others. These insights inform ecological models further supporting environmental monitoring and conservation efforts. We anticipate that image-based bio-logging datasets will soon contribute to existing remote sensing and environmental monitoring databases, such as EMODnet (https://emodnet.ec.europa.eu/en) and NOAA's Ocean Explorer (https://oceanexplorer.noaa.gov). Large-scale democratisation of AI-based image processing and analysis within the ecological community, enabled by ongoing collaboration with the computer vision community, is essential for unlocking the full potential of recent advances in bio-logging data acquisition, producing timely, actionable outputs for conservation. At this stage, open science practices are crucial for sharing results, summary outputs, and associated metadata. These shared resources then flow to conservation professionals, ecosystem managers and policymakers. Only by implementing close collaborations between all these professionals, along with open science practices, will we be able to take full advantage of the wealth of new and invaluable knowledge that direct observation through bio-logging based underwater images provides. This will then be translated into informed and effective conservation actions in a timely manner.

AUTHOR CONTRIBUTIONS

Marianna Chimienti, Akiko Kato, Muriel Visani, Mickael Coustaty, Tiphaine Jeanniard-du-Dot conceived the idea; Marianna Chimienti, Akiko Kato and Vahid Seydi designed the methodology. All authors improved the idea and provided underwater images used for the figures of the manuscript. Marianna Chimienti and Tiphaine Jeanniard-du-Dot led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

This manuscript has sourced and reviewed publicly available information from Scopus and Web of Science. Sample image-based bio-logging data and python codes used for the 'how to guide' are available at: https://doi.org/10.48579/PRO/GU2JCY (Kato Ropert & Ropert-Coudert, 2025).

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SUPPORTING INFORMATION

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

Data S1: How_To_Image_Based_bio-logging providing the python code for manipulating and analysing image-based bio-logging data.

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