Luz *et al.*
Intelligent Marine Technology and Systems (2025) 3:2
https://doi.org/10.1007/s44295-024-00052-1

Intelligent Marine Technology and Systems

RESEARCH PAPER Open Access

Early detection of marine bioinvasion by sun corals using YOLOv8

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Abstract

Sun coral (*Tubastraea* spp.) is an invasive species that poses a considerable threat to coastal ecosystems. Therefore, early detection is essential for effective monitoring and mitigation of its negative impacts on marine biodiversity. This study presents a novel computer vision approach for automated early detection of invasive *Tubastraea* species in underwater images. We used the YOLOv8 object detection model, which was trained and validated on a manually annotated dataset augmented with synthetic images. The data augmentation addressed the challenge of limited training data that is prevalent in underwater environments. The model achieved performance metrics (in terms of precision accuracy, recall, mAP50, and F1 score) of over 90% and detected both open and closed coral stage classes. Test phase results were compared with expert validation, demonstrating the model's effectiveness in rapid detection (16 ms) and its limitations in areas highly covered by *Tubastraea*. This study demonstrates the potential of deep learning with data augmentation to facilitate the rapid assessment of large image datasets in monitoring sun coral bioinvasion. This approach has the potential to assist managers, taxonomists, and other professionals in the control of invasive alien species.

Keywords Invasive species, Deep learning, Object detection, Convolutional neural network, YOLO, Conservation ecology

1 Introduction

Bioinvasion by sun corals refers to the introduction and establishment of *Tubastraea* species in non-native marine environments (Creed et al. 2017a; Dutra et al. 2023). Originally native to the Indian and western Pacific Ocean, sun coral species have spread over time to large areas of the Atlantic Ocean, including the Caribbean Sea (1943), the Gulf of Mexico (1977), the southwestern Atlantic (late 1980s) and the Canary Islands (2017) (Vaughan and Wells 1943; Fenner 1999, 2001; Fenner and Banks 2004; de Paula and Creed 2004; López et al. 2019). This expansion has raised concerns about their negative impacts on coastal ecosystems (de Oliveira et al. 2016; Miranda et al. 2018). The invasion of sun corals can have detrimental impacts on marine ecosystems, including competition with native species, predation on local organisms, changes in the structure of marine communities, increased environmental risks, and negative economic consequences for offshore industries (de Paula et al. 2014; Hoeksema and ten Hove 2017; Mizrahi et al. 2017; Silva et al. 2019; Braga et al. 2021; Silva et al. 2022).

Addressing the challenges of bioinvasion effectively requires a comprehensive approach that combines prevention, control, and restoration strategies (Savio et al. 2021). Although control measures can be used to limit *Tubastraea* population growth, their effectiveness varies

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depending on ecosystem dynamics and the specific management techniques employed (Creed et al. 2017b; Brancaccio et al. 2023). Early detection, where an invasive species is identified in a new area before it spreads widely, is crucial for successful management. By allowing for timely intervention, early detection can reduce the costs and difficulties associated with eradication or control significantly, as this allows for targeted management actions to control or eradicate the organism before it becomes established (Reaser et al. 2019).

Studies using techniques such as remote sensing, a geographic information system combined with predictive models of environmental vulnerability, environmental DNA (eDNA), and underwater visual census from diver surveys have been used to prevent and mitigate the impacts of invasive species (Lazzaro et al. 2017; Bastos et al. 2022; Chong et al. 2023). Despite their utility, these techniques have limitations, including the time required to obtain results, high implementation costs, and human physiological constraints such as a lack of workforce and the decline in taxonomic experience (Cook and Coutts 2017; Lopez-Marcano et al. 2020).

The incorporation of computer vision and deep learning models in bioinvasion studies is a promising solution due to their speed and accuracy in detecting species from underwater images (Pedersen et al. 2019; Lopez-Marcano et al. 2021; Yang et al. 2021; Saleh et al. 2022). Examples such as the You Only Look Once (YOLO) object detection model can automate the identification of invasive coral species in underwater images, enhancing the efficiency and accuracy of monitoring efforts significantly. This allows for rapid identification of new infestations and thereby facilitates timely intervention (Alshahrani et al. 2024; Wang et al. 2024). Early detection enables deep learning models to help prevent the further spread of invasive species and protect marine habitats. Additionally, the development and application of these models can help in advancing the field of computer vision and its application to ecological conservation (Raphael et al. 2020b; Oraño et al. 2023).

Computer-vision-based object detector models can be trained using large datasets of one or more species to identify species automatically using annotated bounding boxes (Pathak et al. 2018; Schneider et al. 2019). Data augmentation techniques increase the robustness of datasets and model performance by increasing both the number and diversity of images (Gómez-Ríos et al. 2019b). Some examples of computer vision models already implemented in the biological context include AlgaeNet (Gao et al. 2022), WilDect-YOLO (Roy et al. 2023), YOLO-Fish (Muksit et al. 2022), specifically for coral detection (Mahmood et al. 2017; Jiang et al. 2023). However, studies using computer vision models for invasive corals are rare (Tait et al. 2023).

Over the past decade, the International Maritime Organization (IMO) has emphasized the importance of early detection and rapid response (EDRR) as a key strategy for mitigating the impacts of invasive aquatic species (IMO 2011, 2012). While the specific guidelines and recommendations do not mention deep learning models explicitly, the underlying principles of early detection and prevention align well with the capabilities of these technologies. In response to the growing need for technologies capable of supporting EDRR efforts (Martinez et al. 2020), this study evaluates the use of a state-of-the-art object detection model called YOLO for the early detection of invasive sun corals in an underwater environment. While other deep learning models such as Faster region-based convolutional neural networks (R-CNN), single-shot detector (SSD), and RetinaNet are also capable of object detection, YOLO often outperforms them in terms of speed, accuracy, and ease of use, making it the preferred choice for many applications, including coral and fish monitoring (Gayá-Vilar et al. 2024; Santoso et al. 2024). Techniques such as manual annotation and data augmentation were used for preprocessing. Model performance was compared with coral species identification by a taxonomist to assess its effectiveness for monitoring tasks, and accuracy was calculated by considering whether at least one coral was detected correctly in each test image.

2 Materials and methods

2.1 Data acquisition and preprocessing

A set of 550 images was obtained from the online citizen science platform iNaturalist (https://www.inaturalist.org/), which allows for the recording of biodiversity observations. Images of organisms classified as '*Tubastraea* spp.' and records made from various locations in the Atlantic and Pacific Oceans were included. Additionally, unpublished records of *Tubastraea* spp. (personal communication) were provided by researchers from the Instituto de Estudos do Mar Almirante Paulo Moreira and used in the testing stage of the identification model. The limited availability of image resources specifically for *Tubastraea* species justifies the relatively small sample size used in this study. Nonetheless, the original dataset size is comparable to those used in similar deep-learning research efforts focused on coral detection (Younes et al. 2024).

All images were adjusted to a threshold resolution of 640 pixels, as specified in Ultralytics' YOLOv8 documentation (Jocher et al. 2023). The YOLO was chosen for this study because it offers a balance between speed and accuracy, making it a practical option for rapid assessment in monitoring invasive species. As a single-stage detector, YOLO predicts both bounding boxes and class probabilities in a single pass, improving efficiency compared to two-stage detectors like Faster R-CNN (Gayá-Vilar et al. 2024). In this context, YOLOv8 is well-suited for species detection in underwater images and outperforms real-time object detection (Terven et al. 2023).

The image set was subjected to manual annotation of the bounding boxes using the web application 'Computer Vision Annotation Tool' (https://www.cvat.ai), where two classes were created: 'tubastraea open' and 'tubastraea closed. These two classes represent the sun coral in two distinct morphological aspects: open polyps and closed polyps, respectively. For each image, files with annotated labels and values were exported in the YOLO format.

2.2 Data augmentation

To ensure the best performance of the CNN model, a large amount of data is required, so the initial set of images was augmented using the Augmentor (Bloice et al. 2017) and the Albumentations (Buslaev et al. 2020) libraries, both developed in the Python language (https://www.python.org/doc/). The adjustments made were: flip, which consists of rotating the images; blur; Contrast Limited Adaptive Histogram Equalization (CLAHE), which is a contrast enhancement function; elastic distortion, which applies a distortion filter; skew, which tilts the image toward one of its ends; Gaussian noise; brightness; and contrast. Underwater images often exhibit non-uniform lighting, blur, haze, low contrast, and color distortion, resulting in less information than normal atmospheric optical images (Schettini and Corchs 2010; Xu et al. 2023). Therefore, the adjustments made were chosen specifically to simulate variations in seawater turbidity and visibility, which can alter the accuracy of object detection in the marine environment. The final image set consisted of 7150 images (Fig. 1), which were later used in the training and validation steps of the model. The intention was to expand the dataset to more than 1000 images, in line with the average size of public coral datasets like EILAT and MLC (Gómez-Ríos et al. 2019b). This approach has been used in similar deep-learning studies for object detection to increase model robustness (Aota et al. 2021; Li et al. 2021; Gorro et al. 2023; Rusli and Mohtar 2023; Wang et al. 2024). The text files containing the annotation values were also augmented and standardized across the set.

2.3 Training, evaluation and model implementation

The total dataset was divided into 70% (5005 images) for the training phase and 30% (2145 images) for the validation phase. By allocating most of the data for training, the model benefits from a substantial number of examples, which improves its ability to generalize to new data. Meanwhile, reserving a portion for validation allows for the evaluation of unseen data, thereby mitigating overfitting and providing a more accurate assessment of model performance (Goodfellow et al. 2016). The nano version of YOLOv8 was implemented using the Ultralytics library in Python. Model performance results were then exported for further statistical analysis and evaluation. Metrics such as mAP50, recall, F1 score, loss, and detection speed per object instance were then considered to evaluate the model performance. Additionally, a test was performed with a new random set of 100 sun coral images. Detection accuracy during testing was determined by checking whether the model made at least one correct detection in each image, and the total number of detections made by the model was compared to that made by a sun coral specialist.

The model was implemented through a graphical interface developed using the open-access library Streamlit

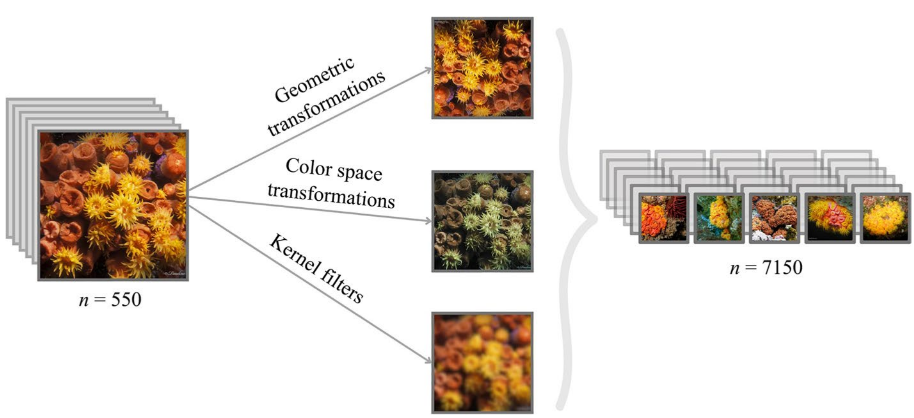

Fig. 1 Image set augmentation step with the transformations performed. Geometric transformations include flip, skew, and elastic distortion. Color and spatial transformations include CLAHE, brightness, and contrast. Kernel filters include blur and Gaussian noise

(Khorasani et al. 2022) for Python, following the reference documentation (https://docs.streamlit.io/get-started). The process adopted in this study is described in Fig. 2.

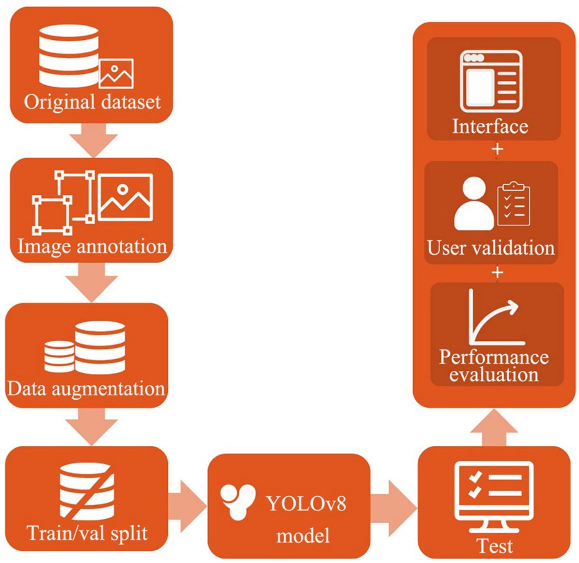

Fig. 2 Development process of the sun coral detector model. Preprocessing includes the original dataset, image annotation, data augmentation, and dataset split for the training and validation process. The YOLO model is run and tested for performance evaluation, including expert validation and interface development

The initial model training and validation stage was conducted on a local machine with an Intel Core i5 processor, 8 GB RAM, and Windows 11 operating system. To speed up the training process and benefit from the increased computational power of the Google Colaboratory's NVIDIA T4 GPU, the model was then trained on this platform. This transition reduced the training time significantly from 8 h and 27 min to 3 h and 24 min for 100 epochs.

3 Results

The performance metrics for the model demonstrated its effectiveness in detecting sun corals. Precision reached 0.906, indicating a low false positive rate. A recall of 1.0 confirmed that the model identified all sun corals accurately and achieved mAP50 and F1 score values of 0.994 and 0.998, respectively, which further solidified the overall performance of the model. Figure 3 visually illustrates the model's ability to detect sun corals in both open and closed states.

The loss values, represented by box_loss, cls_loss and dfl_loss, decreased as the number of epochs increased. Performance metrics, such as precision, recall, and mAP, showed an increasing trend, eventually reaching values above 90% (Fig. 4).

The normalized detection values, comparing the model predictions with the true values, were organized into a confusion matrix (Fig. 5). This matrix shows that the model detected some false positives, 0.56 for open corals and 0.44 for closed corals, which were background, and a false negative rate of 0.04, where closed corals were mistakenly identified as background.

The number of instances identified as closed corals was greater than that identified as open corals. In the model generated, corals were mostly present in the central position of the bounding boxes. In addition, the smaller the size of each bounding box, the greater its detection capacity (Fig. 6).

The model was tested on a new set of sun coral images ($n = 100$), resulting in a total of 261 true positives and 27 false positives, as shown in Fig. 7. The average speed of detection values per image was 2.5 ms in preprocessing, 16.0 ms in inference and 30.3 ms in post-processing. The accuracy of the model was 93% for the test dataset and was related to the task of detecting at least one coral in each image. This ensured the ability of the model to identify the presence of corals quickly and accurately, which is deemed essential for effective monitoring and conservation efforts. Meanwhile, the detection task performed by a specialist resulted in a total of 786 identifications for the same images, which means that the model was able to correctly predict 33% of the total detections made by the user, with a confidence level of 60%.

4 Discussion

This work evaluated the use of the YOLOv8 model for the early detection of sun corals (*Tubastraea)* from images, aiming to assist in the monitoring, prevention, and response to their bioinvasion. The model exhibited excellent detection performance for both classes of objects, with precision, mAP, recall, and F1 score all exceeding 90%. Although the application of deep learning models for coral detection has been documented previously (Shihavuddin et al. 2013; Raphael et al. 2020a; Lumini et al. 2023), this study represents one of the first specific initiatives to focus on an invasive coral genus. While there are publicly available coral image repositories–such as EILAT, RSMAS, MLC, and Red Sea–that have been used to train CNN models (Shihavuddin et al. 2013; Gómez-Ríos et al. 2019b), they lack annotations for the genus *Tubastraea*. Furtado et al. (2023) recently incorporated sun corals in their image dataset and compared three alternative machine learning models, achieving an 86% accuracy using a semantic segmentation approach. Although this study used a different method from our

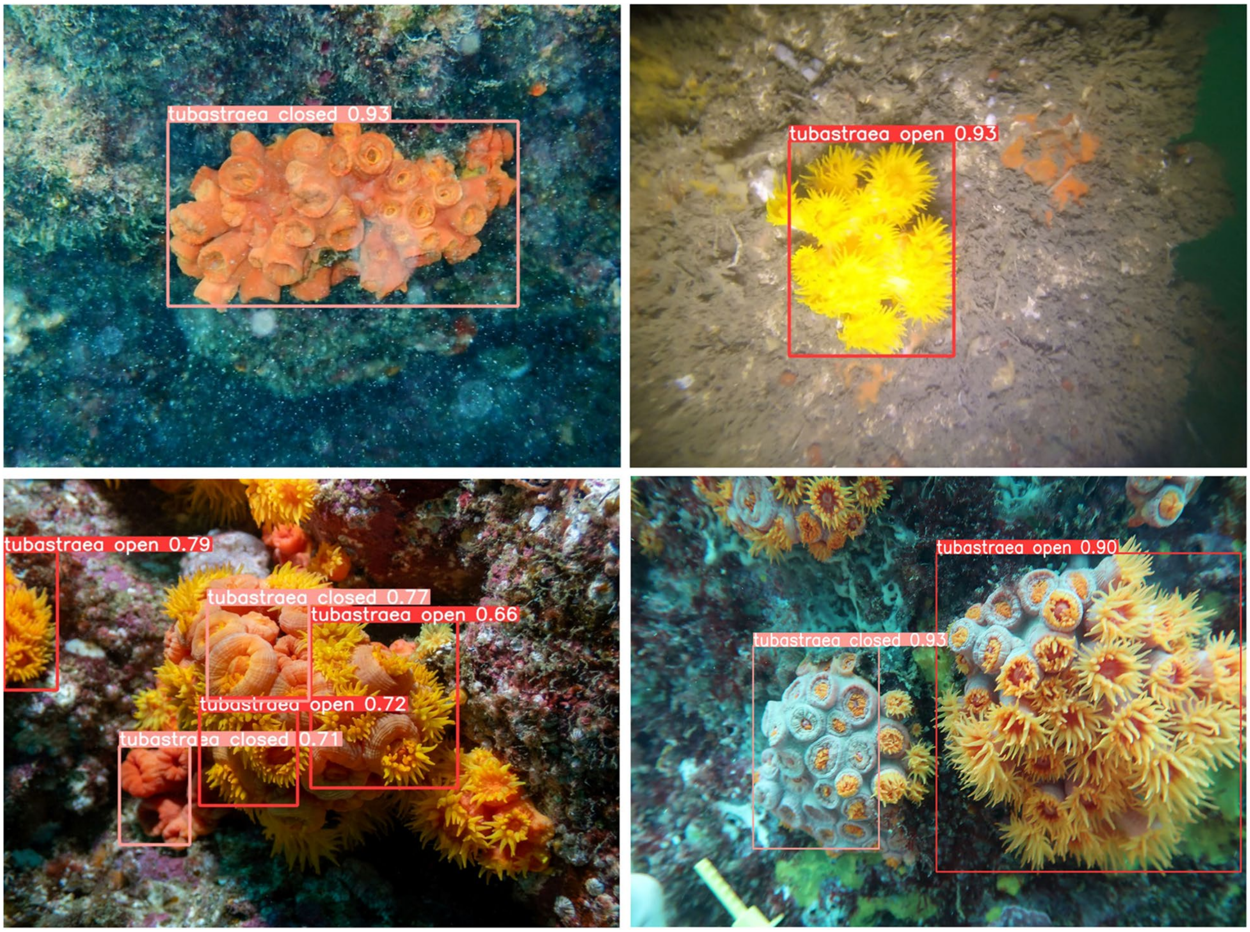

Fig. 3 Examples of some detections made by the model. The differently colored bounding boxes indicate closed (pink) and open (red) coral

approach, it demonstrates the general potential of deep learning for coral detection tasks.

The results of the study by Raphael et al. (2020a) are consistent with the findings of this study, as they report a high level of precision (>90%) using a classification model for 11 classes of corals (excluding *Tubastraea* spp.) from a dataset of 5500 images. The authors argue that only a deep learning approach can manage large quantities of images effectively, whether in real time or not, obtained through monitoring activities. In contrast, Lumini et al. (2023) attributed the high performance of their model (F1 score>90%) to their classification method, which utilized image sets of two groups of organisms (plankton and corals) and a combined system of several CNN models, while our study focused only on the detection of a single coral genus.

Regarding data augmentation, Abayomi-Alli et al. (2021) emphasize the importance of applying data augmentation techniques that intentionally reduce image quality, such as blurring and Gaussian noise. These transformations helped their model to better detect regions of interest (in their case, diseases of plant leaves even in low-quality images). For YOLOv8, a resolution of 640 pixels or fewer is recommended, as higher resolutions may affect model performance negatively (Jocher et al. 2023). These findings have been incorporated into the model presented in this paper, improving its ability to detect sun corals under various image quality conditions.

The identifications not made by the model suggest that its performance is better for images with few or just one sun coral colony, as areas with a higher density of colonies compromise identification (Fig. 7). When testing the model and comparing its detections with those of a taxonomist, we observed instances of false negatives, indicating that the model fails to detect all the target organisms present in some images. González-Rivero et al. (2020) showed similar results regarding the precision of a deep learning model trained to identify benthic organisms in coral reefs compared to expert identifications.

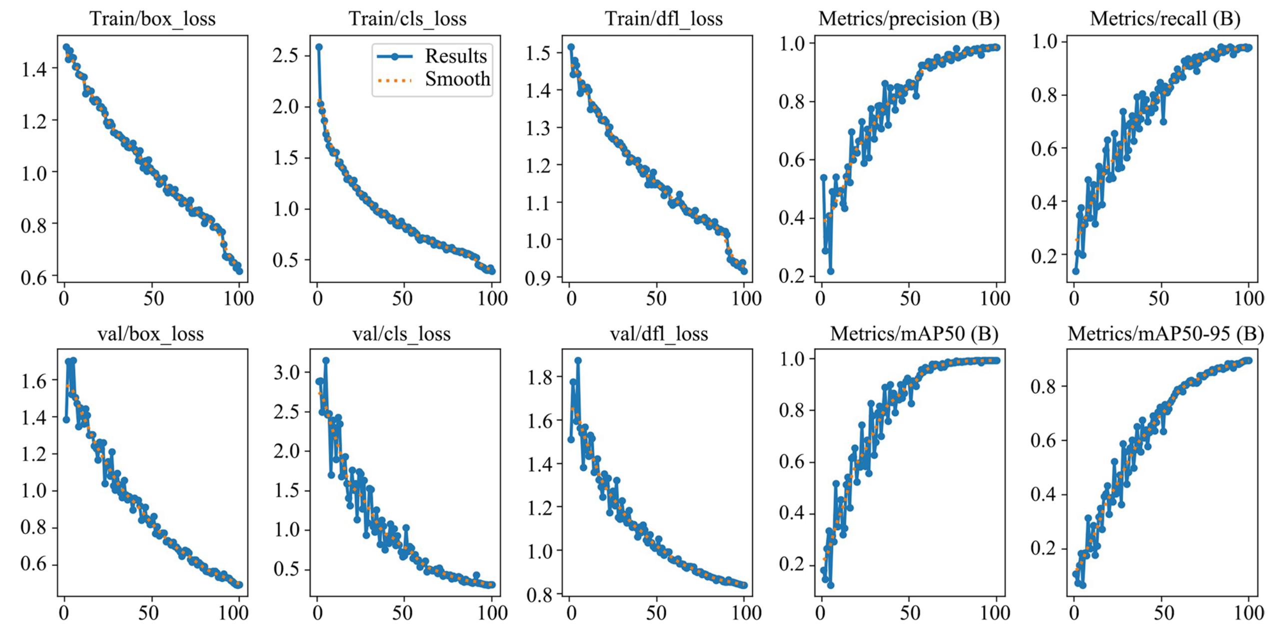

Fig. 4 Loss, precision, recall, mAP50 and mAP50-95 curves. The horizontal axis represents the number of epochs. On the left, the loss plots–box_loss, cls_loss and dfl_loss–are shown for both the training and validation stages. Additional performance metrics are shown on the right. The mAP50-95 indicates the average accuracy value when the confidence level is set at 95%

However, in contrast to the present study, some classes of organisms were not defined at the genus or species level. In both studies, we can conclude that automatic image analysis will not replace expert observation but will serve as a complementary tool for monitoring tasks, considering the high speed of detection in large volumes of images.

While it is acknowledged that the model has limitations in detecting corals within high-density populations, it is important to note that this is a common challenge in

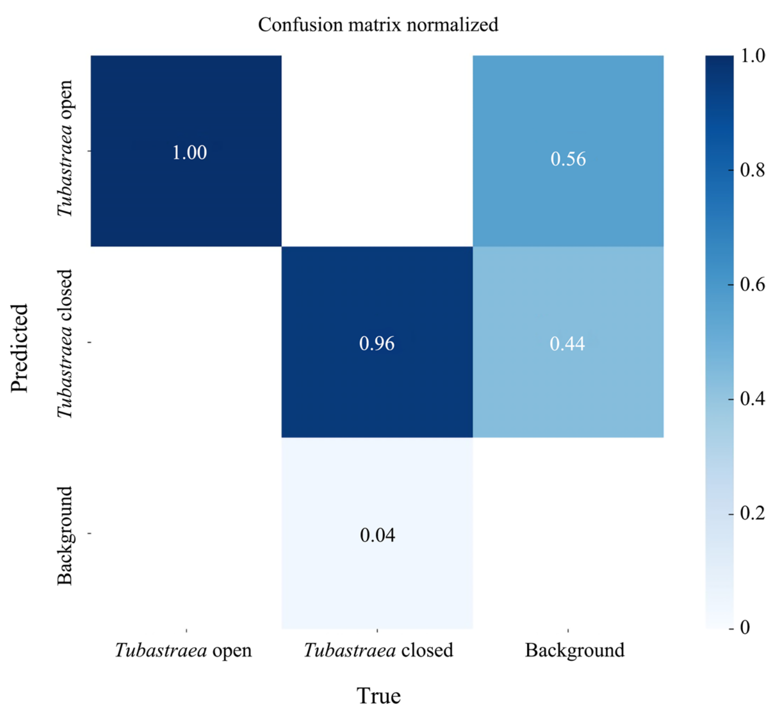

Fig. 5 Confusion matrix (normalized values) showing the ground truth and model predicted classes. In addition to the open and closed coral classes (*Tubastraea* open and *Tubastraea* closed), the model generated a third class defined as background

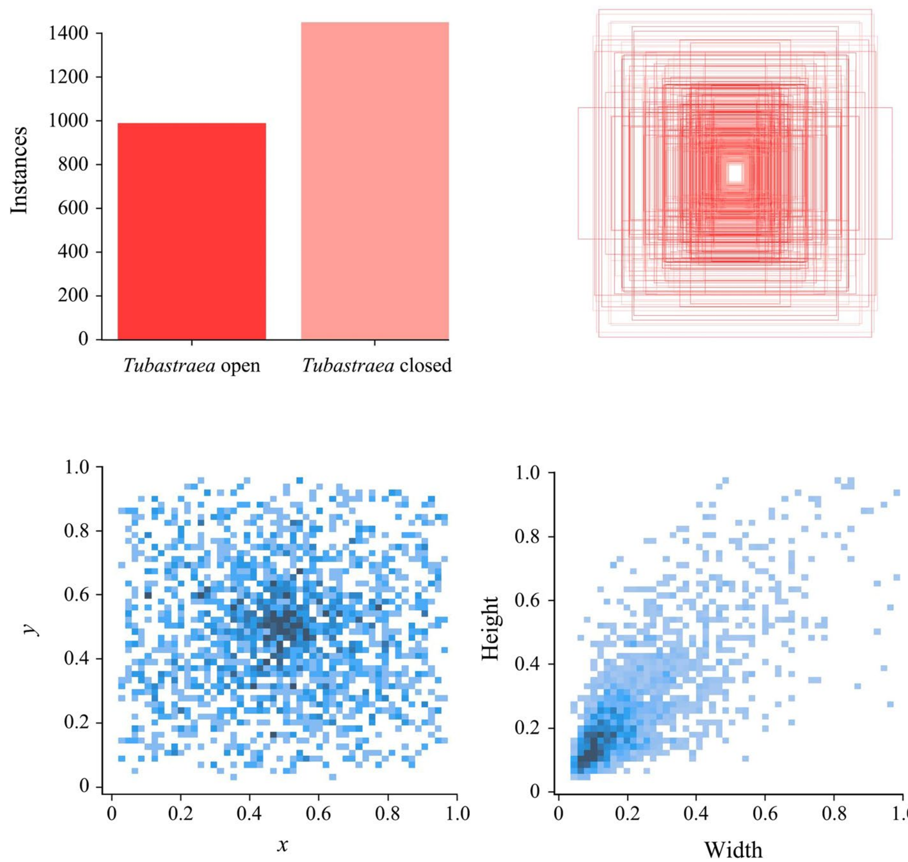

Fig. 6 Behavior of classes and overall representation of bounding boxes in the model, taking into account the instances, format, position (*x*, *y*), and size (height, width)

object detection tasks, especially in complex and crowded scenes (Elias 2023; Xu et al. 2023). The performance of the model could be further evaluated using datasets with a higher proportion of densely populated coral scenes to assess its limitations comprehensively. The model is not intended to replace human expertise but rather to serve as a valuable tool for coral identification and monitoring. By providing a preliminary assessment of large datasets, the model can help to prioritize areas for further expert investigation.

To optimize the model's detection capabilities, tasks such as diversifying the image set and including additional object classes could improve its ability to distinguish sun corals from the background. The sharpness factor of underwater images has likely influenced the detection process, as noted by other studies (Gómez-Ríos et al. 2019a; González-Rivero et al. 2020; Lumini et al. 2023). This highlights the inherent challenges of working with underwater images, which often involve issues such as brightness, particulate matter, high diversity of organisms in the same frame, and proximity of organisms (aggregations) (Gómez-Ríos et al. 2019a).

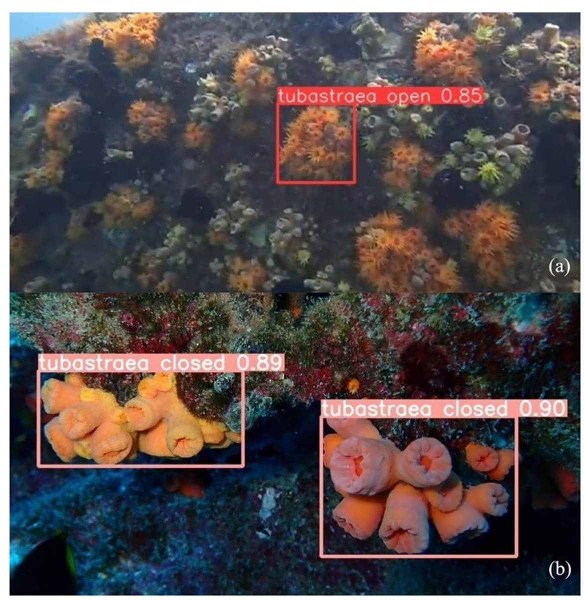

Fig. 7 Example of detections in the test dataset. Images include the class name and confidence level. **a**, the model shows false negatives by detecting only one colony; **b**, the model was able to detect all the colonies present

Considering the DAFOR scale (Sutherland 2006), which has been applied in studies related to sun coral (Silva et al. 2011; Mondal et al. 2018; Machado et al. 2023), the most suitable categories for applying this model, based on the results of the test phase are: rare (1%–10% coverage), occasional (11%–25% coverage), and frequent (26%–50% coverage). Despite its estimated and subjective nature, this scale can be used effectively alongside the current model for early detection and monitoring of sun corals.

Piechaud and Howell (2022) used a YOLO model to map a deep-water xenophyophore species at a depth of 1200 m. Their results confirm that this detection method, when combined with technologies such as autonomous underwater vehicles (AUVs), offers an effective alternative for monitoring marine biodiversity in scenarios where traditional techniques, such as a visual census by divers, are risky or unfeasible. Similarly, the present model could be incorporated into inspection routines using remotely operated vehicles (ROVs) for various applications, including the monitoring of ship hulls, coral reefs, and seabeds based on local bioinvasion inspection and control needs.

5 Conclusions

This study demonstrates the feasibility and potential of computer vision for the automated early detection of invasive sun coral (*Tubastraea* spp.) in underwater imagery. Using a CNN, we achieved a high accuracy of over 90% in detecting sun corals and a rapid object identification per instance (16 ms), demonstrating the model's ability to assist experts in rapid and efficient monitoring. The application of computer vision in this study suggests its potential in the field of marine ecology and conservation and could be used to monitor areas susceptible to bioinvasion, such as port regions, offshore activity zones, and marine protected areas.

While the proposed YOLOv8 showed promising results, comparisons with other deep learning models and investigations into standardized image acquisition protocols can help refine this technology. Comparison with detections of taxonomists suggests that the model, although still in need of improvement to reduce false negatives in the images, can be implemented as a supporting tool for monitoring activities and early detection of sun corals. Future research directions may include investigating other invasive species, leveraging annotated image datasets from scientific collections to train more versatile models, and exploring techniques such as ensemble methods or data augmentation specifically designed for dense object detection.

Acknowledgements
We sincerely appreciate the contribution of Nathália Bastos and Fernanda Azevedo for providing some of the photos that composed this study. We extend our gratitude to the users and contributors of the iNaturalist platform. We also would like to thank the reviewers. We sincerely appreciate the constructive feedback, which contributed to improving the manuscript. This work was funded in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior-Brasil (CAPES)-Finance Code 001.

Additional information
Edited by: Lin Gao.

Author's contributions
All authors contributed to the study conception and design. Material preparation, data collection and formal analysis were performed by Ana Carolina N. Luz, Viviane R. Barroso, Aléxia A. Lessa and Fábio C. Xavier. Daniela Batista contributed by reviewing and editing the drafts and was the taxonomist validator for the *Tubastraea* spp. images. Ricardo Coutinho also contributed by reviewing and editing the drafts. The first draft of the manuscript was written by Ana Carolina N. Luz, and all authors commented on previous versions of the manuscript. All authors read and approved the final manuscript.

Data availability
Data supporting this study will be available upon formal request to the corresponding author (Ana Carolina N. Luz).

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors have no relevant financial or non-financial interests to disclose.

Received: 23 August 2024 Revised: 5 December 2024 Accepted: 24 December 2024
Published online: 06 January 2025

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