Ecological Informatics 89 (2025) 103170

Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf

Deep learning for automated coral reef monitoring a novel system based on YOLOv8 detection and DeepSORT tracking

Younes Ouassine [a,*], Noël Conruyt [b], Mohsen Kayal [c,e], Philippe A. Martin [b], Lionel Bigot [b], Vignes Lebbe Regine [d], Hajar Moussanif [a], Jihad Zahir [f]

[a] Computer Science Department, LISI, Cadi Ayyad University, Morocco
[b] EA2525 LIM, (I.T. Department), University of La Réunion, 97400 Saint-Denis, France
[c] ENTROPIE, IRD, IFREMER, CNRS, University of La Reunion, University of New Caledonia, Noumea, New Caledonia
[d] Institut de Systématique, Evolution, Biodiversité (ISYEB), SU, MNHN, CNRS, EPHE, UA - CP 48, 57 rue Cuvier, 75005 Paris, France
[e] Station Marine d'Endoume, Marseille, France
[f] UMMISCO, IRD, Computer Science Department, LISI, CADI Ayyad University, Morocco

ARTICLE INFO

Keywords:
Coral reefs ecosystems
Deep learning
Methodology
YOLOv8
DeepSORT

ABSTRACT

Coral reefs are vital for biodiversity, coastal protection, food security, and tourism, yet they face severe threats from anthropogenic activities and climate change, which are leading to their decline. Effective coral reef monitoring is essential for ecological understanding and conservation, but traditional methods are resource-intensive and rely on experts. To address these challenges, we present an automated, deep learning-based monitoring system that integrates YOLOv8, a state-of-the-art object detection algorithm, with DeepSORT, a robust multi-object tracking method, to identify and track coral formations in underwater video footage. Our system was fine-tuned using two curated and annotated datasets: AIMECORAL1 (580 images from the Southwest Indian Ocean) and AIMECORAL2 (282 images from New Caledonia, Pacific Ocean), encompassing diverse coral species and environmental conditions. The system's performance was evaluated using established metrics: object detection precision, Multiple Object Tracking Accuracy (MOTA), Multiple Object Tracking Precision (MOTP), and Identity F1 Score (IDF1). Precision improved from 59.9 % (after fine-tuning on AIMECORAL1) to 84.7 % on the combined datasets. The tracking system achieved a MOTA of 82.63 %, MOTP of 83.28 %, and IDF1 of 70.76 %, demonstrating reliable multi-object tracking in complex underwater environments. We applied our framework to a case study involving video transects from an outer reef site in New Caledonia, comparing data from 2021 and 2022. This automated solution offers a scalable, cost-effective alternative to traditional monitoring methods, supporting seamless, large-scale reef assessment. By leveraging deep learning, our approach enables more efficient data collection, contributing to the protection of these vulnerable ecosystems in the face of increasing environmental pressures.

1. Introduction

Coral reefs are among the most diverse and productive ecosystems on Earth, often referred to as the "rainforests of the sea" due to their exceptional biodiversity (Apprill et al., 2023). These vibrant ecosystems serve as crucial habitats for numerous fish species and invertebrates, many of which are economically valuable to both local and global fisheries. Beyond their ecological significance, coral reefs provide essential services to coastal communities by acting as natural barriers that protect shorelines from storm surges and erosion, mitigating the impact of natural disasters (Carlot et al., 2023). Additionally, they contribute substantially to local economies through tourism and recreation, attracting millions of visitors each year (Eddy et al., 2021; Obura et al., 2019).

Despite their immense social and ecological importance, coral reefs face severe threats from human activities and environmental changes. Climate change, marked by rising sea temperatures and ocean acidification (Baag and Mandal, 2022), is driving widespread coral bleaching and weakening coral skeletons, leading to increased mortality rates (Sill and Dawson, 2021; Staley et al., 2017; Walker et al., 2023). Pollution from agricultural runoff, sewage discharge, and marine debris further degrades reef ecosystems by introducing harmful nutrients and

* Corresponding author.
E-mail address: y.ouassine.ced@uca.ac.ma (Y. Ouassine).

https://doi.org/10.1016/j.ecoinf.2025.103170
Received 15 February 2025; Received in revised form 21 April 2025; Accepted 27 April 2025
Available online 28 April 2025
1574-9541/

chemicals that promote the overgrowth of fleshy algae, turf algae, and pathogens (Nalley et al., 2023). Overfishing disrupts the trophic balance of reef ecosystems, making them even more vulnerable to these stressors. Additionally, coastal development and other destructive practices have accelerated the rapid decline of coral reefs (Good and Bahr, 2021). Given these escalating threats, effective and expanded coral reef monitoring initiatives are essential for assessing reef health and guiding conservation strategies. Timely and data-driven interventions are crucial to preserving these vital ecosystems and mitigating further degradation.

Traditional coral reef monitoring methods, such as diver surveys and the manual analysis of still photographs or video footage, are labor-intensive and time-consuming for experts, limiting their large-scale applications and the number of sampling stations. Diver surveys require trained personnel to physically assess reef sites within restricted immersion times, which constrains spatial coverage and is further limited by safety considerations. While photographs and videos can help expand monitoring coverage (Kayal et al., 2023), their manual analysis demands significant observer effort and is prone to inconsistencies and subjectivity. Additionally, these methods cannot process continuous, real-time data, making frequent or large-scale monitoring challenging and costly, particularly in remote locations.

To address these challenges, this research introduces a novel deep learning-based system for the first global approach to coral reef assessment. Our system leverages advanced object detection and tracking algorithms—YOLOv8 (Redmon et al., 2016) and DeepSORT (Bewley et al., 2016) —to automatically detect and track hard corals in underwater video footage. YOLOv8 (You Only Look Once, version 8) is a state-of-the-art object detection model known for its high speed and accuracy, making it well-suited for complex underwater environments. Compared to Faster R-CNN, YOLOv8 is significantly more efficient, featuring a smaller model size (e.g., YOLOv5: 14.9 MiB vs. Faster R-CNN: 166 MiB) and a faster inference time (9 ms vs. 42 ms per frame) (El Ghmary et al., 2023). Importantly, we chose YOLOv8 over YOLOv5 because YOLOv8 is more powerful: it introduces a more advanced backbone and head architecture, improved feature extraction, better handling of small and overlapping objects, and enhanced training strategies, all these components improve the accuracy of detection and robustness in challenging scenarios such as underwater coral detection. This efficiency is critical for real-time processing and deployment in resource-constrained marine monitoring applications. DeepSORT (Simple Online and Realtime Tracking with a Deep Association Metric) enhances YOLOv8 by providing robust object tracking across video frames, enabling continuous and reliable monitoring of coral reef colonies over time.

DeepSORT offers several advantages that make it particularly suited for underwater tracking. It effectively handles occlusions, maintaining object tracking even when corals are temporarily obscured or out of view. The algorithm accurately distinguishes between multiple corals in complex underwater scenes, ensuring reliable identification. Additionally, DeepSORT enables real-time performance, which is essential for continuous video analysis. Its modular architecture further enhances its adaptability, allowing seamless integration with various object detection models and providing flexibility for different applications.

We have enhanced our coral reef monitoring system by leveraging a meticulously curated dataset of underwater videos, manually annotated to encompass the diverse coral reef environments of the Southwest Indian Ocean (Eparses Islands) and the Pacific (New Caledonia). This high-quality dataset enables the training of our deep learning model to accurately classify a wide range of coral species and capture the intricate structures of reef ecosystems. By ensuring precise species identification and morphological analysis, our approach strengthens ecological assessments with unprecedented accuracy. We integrated state-of-the-art deep learning and computer vision techniques to build a robust, automated monitoring system. We fine-tuned the YOLOv8 object detection model to achieve high-precision coral identification and incorporated DeepSORT, an advanced tracking algorithm, to enable continuous tracking of individual coral colonies across video sequences. This fusion of deep learning and multi-object tracking facilitates the detection of spatial and temporal changes in coral populations, supporting long-term reef health assessments. Our system is designed to be scalable, efficient, and adaptable, offering ecologists a powerful tool for monitoring coral dynamics while minimizing manual effort. By analyzing multiple videos transects recorded at different time points, our framework quantifies coral abundance and size variations over time, providing actionable insights for conservation efforts. The synergy between ecological expertise and cutting-edge AI solutions empowers researchers to make data-driven decisions, optimize marine conservation strategies, and enhance the resilience of vulnerable reef ecosystems.

The key contributions of this paper are as follows:

- High-Precision Coral Detection: We optimized YOLOv8 using a richly annotated dataset to improve the accuracy of coral species identification.
- Advanced Tracking Mechanism: By integrating YOLOv8 for detection and DeepSORT for real-time tracking, we developed a reliable system for monitoring coral colonies over time.
- Automated Monitoring Framework: Our system processes sequential video transects of the same reef, recorded in different years, to assess temporal changes in coral population structure, growth, and degradation.

By combining ecological domain knowledge with AI-driven automation, our approach enhances the efficiency, consistency, and scalability of coral reef assessments, contributing to global marine conservation efforts.

2. Literature review

2.1. Coral reef monitoring

Recent advancements in coral reef monitoring have introduced innovative methods and technologies to address the various challenges in enhancing our understanding of these vulnerable ecosystems and their conservation. Non-invasive monitoring techniques, complementing satellite, aerial, and underwater cameras, such as photogrammetry and low-cost hyperspectral imagery, have been explored to enable detailed mapping of coral health, composition, and structural complexity without causing harm to the reefs (Ceccarelli et al., 2020). These methods provide valuable tools for conducting comprehensive surveys. Comparative studies have highlighted the importance of understanding the comparability and complementarity of different monitoring approaches. For instance, underwater visual censuses and baited remote underwater video stations have been compared to offer a more comprehensive view of reef health and biodiversity (Cheal et al., 2021).

Further innovations have focused on integrating ecosystem monitoring with the enhancement of habitats conducive to coral growth and biodiversity. The concept of artificial coral reefs—structures designed to provide optimal conditions for coral growth and serve as in situ mesocosms for assembling healthy reef communities—has been introduced (Baer et al., 2023). These artificial coral reef structures function as long-term research platforms for studying coral reef ecosystems under controlled conditions. In addition, various survey methods, such as environmental DNA (eDNA), have been highlighted for assessing fish and invertebrate taxonomic and functional diversity along mangrove-seagrass-coral reef continua (Qiu et al., 2023). Technological advancements, including Google Earth Engine-based applications for managing shallow coral reefs using drone imagery (Zapata-Ramírez et al., 2023) and scalable semantic 3D mapping of coral reefs using deep learning (Sauder et al., 2023), have further enhanced monitoring capabilities. These tools enable efficient and accurate large-scale data collection and analysis, supporting ongoing conservation and management efforts by providing high-resolution, actionable data.

2.2. YOLO and deep learning in marine biology

Recent advancements in deep learning techniques, particularly the integration of You Only Look Once (YOLO) models, have shown promising results in various marine biology applications. For example, a hybrid solution combining optical flow and Gaussian mixture models with YOLO deep neural networks has been introduced for fish detection and species classification in underwater environments (Jalal et al., 2020). This approach has proven effective in detecting and classifying fish in unconstrained underwater videos. In a related development, YOLO Nano Underwater has been proposed as a fast and compact object detector tailored for marine species such as scallops, starfish, echinus, and holothurians. This model aimed to reduce inference time while maintaining accuracy (Wang et al., 2020).

Real-time recognition and tracking methods for deep-sea organisms have been developed using YOLO, emphasizing its speed and accuracy in multi-object tracking underwater (Lu et al., 2020). Building on this foundation, real-time marine animal detection in coral reef ecosystems has also been demonstrated using YOLO-based deep learning networks, showcasing its versatility in marine biology research (Zhong et al., 2022). Further advancements include a lightweight underwater object detection method based on YOLOv4 and MobileNet v2, which strikes a balance between accuracy and speed for target detection in marine environments (Zhang et al., 2021). Similarly, SCoralDet, a YOLO-based framework, introduces innovations such as the Multi-Path Fusion Block and adaptive label assignment to enhance real-time soft coral detection in underwater environments, achieving superior accuracy and computational efficiency (Lu et al., 2025).

In other domains, a YOLOv3-based deep learning algorithm has been proposed for ship recognition under complex weather conditions, incorporating an improved dark channel defogging algorithm to enhance recognition accuracy (Chen et al., 2020). Similarly, the YOLO-CASS framework, integrated with a Coordinate Attention (CA) mechanism, has been introduced for SAR ship detection tasks, highlighting the use of lightweight models for improved performance (Xie et al., 2022). Additionally, a few-shot multi-class ship detection algorithm, utilizing attention feature maps and a multi-relation detector based on the YOLO framework, has been developed to enhance target features in remote sensing images (Zhang et al., 2021).

However, evaluations of deep learning architectures for autonomous inspection systems in marine vessels have highlighted the limitations of regular object localization architectures like YOLO, particularly in accurately detecting corroded areas in ballast tanks (Andersen et al., 2020).

2.3. Tracking algorithms

The application of deep learning technology in object-tracking algorithms has gained significant attention in recent years. A tracking system developed using YOLOv4 and DeepSORT has effectively tracked athletes in NBA and World Cup scenes, showcasing advanced technology in sports tracking(Zhang et al., 2020). Additionally, a comparative study of various object detection and tracking algorithms for vehicle counting has highlighted the effectiveness of combinations such as CenterNet and DeepSORT, Detectron2 and DeepSORT, and YOLOv4 and DeepSORT (Mandal and Adu-Gyamfi, 2020).

Improvements in ship detection and tracking have been achieved through enhanced YOLOv3 and DeepSORT algorithms, demonstrating advancements in target detection capabilities (Jie et al., 2021). Evaluations of SORT and DeepSORT algorithms for multi-object tracking in mobile robotics have highlighted the importance of data association metrics in navigation tasks (Pereira et al., 2022).

Further developments include a deep learning-based method for citrus fruit detection and tracking, which outperforms existing standard SORT and DeepSORT algorithms in terms of accuracy (Zhang et al., 2022). A comparison of DeepSORT, Strong-SORT, and customized tracking algorithms for the automated detection and tracking of black cattle introduced an enhanced re-identification approach for improved accuracy (Myat Noe et al., 2023). Additionally, the exploration of computer vision solutions for handball player action recognition, utilizing custom datasets and deep neural networks, demonstrated accurate tracking and localization (Host et al., 2023).

Additionally, the tracking of parking time violations in Thailand using YOLOv8 and tracking algorithms has demonstrated the application of state-of-the-art detection techniques in real-world scenarios (Sharma et al., 2023). An innovative Ego-motion Aware Target Prediction (EMAP) module has been introduced for robust multi-object tracking, integrating camera motion and depth information with object motion models, alongside various base multi-object tracking (MOT) algorithms (Mahdian et al., 2024).

Moreover, recent advancements in marine monitoring have employed CNN-based tracking methods to enhance fish detection and classification by leveraging both image and temporal video data (Zouin et al., 2024). This approach, combining a fine-tuned Faster R-CNN model with a tracking module, improved detection accuracy by 12 % and significantly benefited rare species detection through a bidirectional tracking strategy. The method is cost-effective, adaptable for real-time use, and holds promise for large-scale marine ecosystem monitoring and biodiversity assessments.

3. Methodology

3.1. System overview

Our work is divided into three main parts: the first focuses on the fine-tuning process for coral detection, the second details the coral tracking process, and the third addresses the monitoring process:

3.1.1. Coral reef fine-tuning process

As shown in Fig. 1, the process begins with a YOLOv8 model pre-trained on ImageNet (Singh et al., 2023), which serves as the foundational backbone. Leveraging transfer learning, the model undergoes a two-stage fine-tuning process. Initially, it is fine-tuned on the AIMECORAL1 dataset collected from the SWIO-Eparses Islands region. This stage enables the model to learn regional-specific features such as species morphology and local environmental characteristics. Subsequently, the model—now specialized in AIMECORAL1 data—is further fine-tuned using the AIMECORAL2 dataset, sourced from the Pacific-New Caledonia region. This sequential transfer learning approach facilitates knowledge accumulation across geographies, enabling the model to generalize across diverse coral reef environments. The final model benefits from this cumulative adaptation, enhancing its ability to detect and differentiate between hard (reef-building) and soft (non-calcifying) corals. This methodology complements recent coral detection models, including those proposed by (Ouassine et al., 2024) and SCoralDet (Lu et al., 2025). by emphasizing cross-regional robustness and domain-specific fine-tuning.

3.1.2. Coral reef tracking process

As illustrated in Fig. 2, the process involves analyzing sequential underwater video frames (F1, F2, F3, etc.) captured at site x in year y. Initially, the video is divided into individual frames, which are simultaneously processed using the YOLOv8 model, fine-tuned specifically for the two coral datasets (AIMECORAL1 + AIMECORAL2). The detected coral objects are then passed to the DeepSORT tracking algorithm, which assigns unique identifiers to each detection and ensures consistent tracking across consecutive frames. This integrated pipeline combines object detection and tracking technologies, generating comprehensive tracking outputs for station x in year y and facilitating the production of comparable ecological metrics of coral reef dynamics (e.g., coral abundance and size) over time.

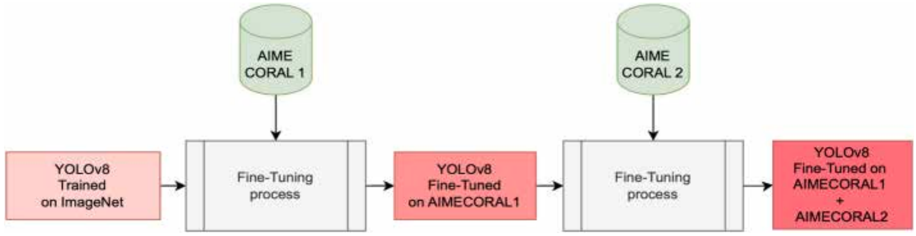

Fig. 1. Coral reef Fine-Tuning process.

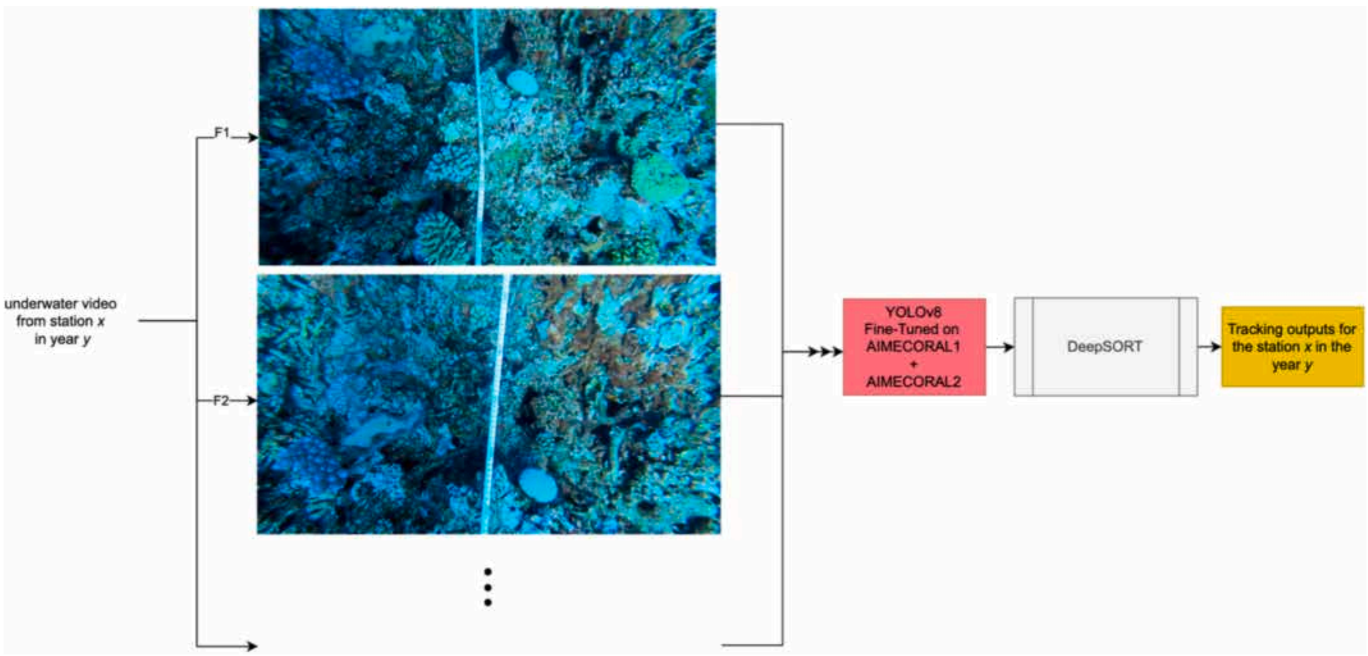

Fig. 2. Coral reef Tracking process.

3.1.3. Coral reef monitoring system

Our coral reef monitoring system is designed to assess reef conditions in terms of coral abundance and size using automated video-based analysis, enabling the characterization of changes in reef health over time and space. As shown in Fig. 3, the system can process underwater videos from a given site x at distinct time periods, year y and year $y + i$, to estimate changes in coral colony abundance and size over time. The video inputs are divided into sequential frames (Frame 1 through Frame z), which are processed through the tracking system (Fig. 2). The outputs from this system feed into a centralized metadata component, recording ecological metrics of coral abundance and size for each site and year.

We applied this methodology to a case study involving video transects recorded one year apart (2021 and 2022) at the same reef location (i.e., permanent transect) at an outer-reef site in New Caledonia. A 3-m-long portion of the transect was used for this demonstration. The metadata functions included a function to record the number of distinct corals identified in each video transect, and an additional function to compute the mean diameter of each coral as: meanDiameter = (Length + Width) / 2. The mean diameter was chosen because corals are rarely rectangular, and the area of the bounding box drawn around the length and width of the coral would otherwise overestimate coral size.

3.2. Data sources

The data used in this study was obtained by extracting frames from recorded video transects of coral reef surveys. The Artificial Intelligence for Marine Ecosystems (AIME)[1] project, which focuses on leveraging AI to monitor and protect marine ecosystems, and Track Changes, which develops tools and analyses to support ecosystem management, provided the datasets. Two datasets were compiled to train and evaluate the tracking system:

AIMECORAL1[2]: The first dataset (Fig. 4), derived from previous research on coral detection using YOLOv5 (Ouassine et al., 2024), consists of 580 underwater images. Of these, 400 images were originally captured during research expeditions to various coral reef locations around La Reunion and other scattered islands in the Indian Ocean. These images represent a wide range of coral reef conditions, including variations in coral health, reef habitats, depths, and lighting. To enrich the dataset, the 400 original images were enhanced through resizing, rotation, and blurring, resulting in an augmented dataset of 580 images. This expanded version includes diverse coral species, colony sizes, and orientations, providing a comprehensive representation of the underwater environment.

AIMECORAL2[3]: The second dataset (Fig. 5), consists of 282 images,

[1] AIME: https://umr-entropie.ird.nc/index.php/portfolio/projets-en-cours/aime

[2] AIMECORAL1: https://github.com/Youassin/AIMECORAL.git

[3] AIMECORAL2: https://github.com/Youassin/AIMECORAL.git

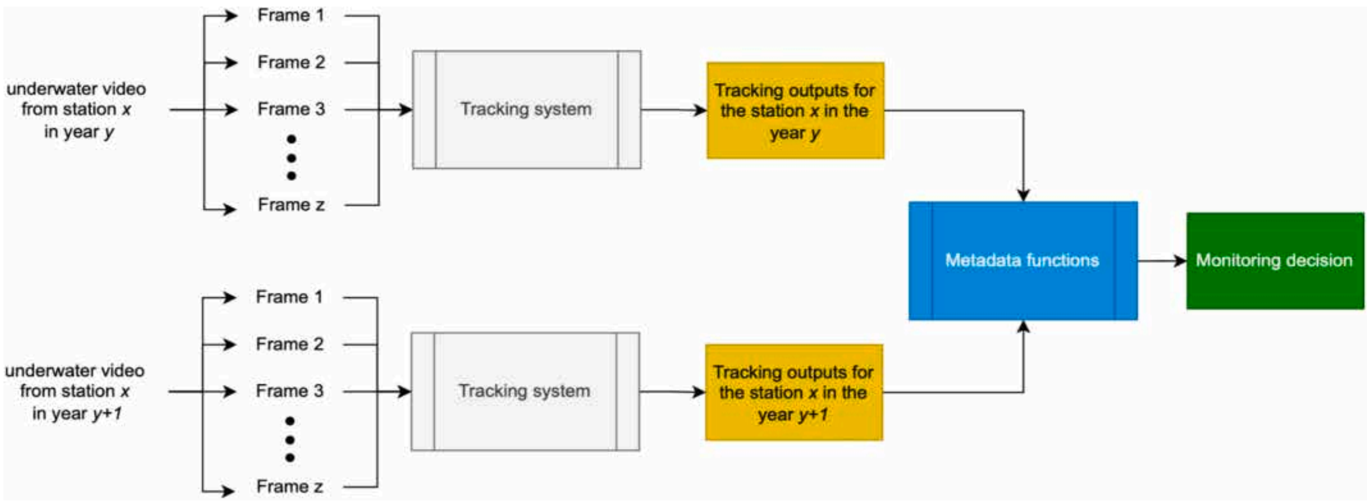

Fig. 3. Monitoring process.

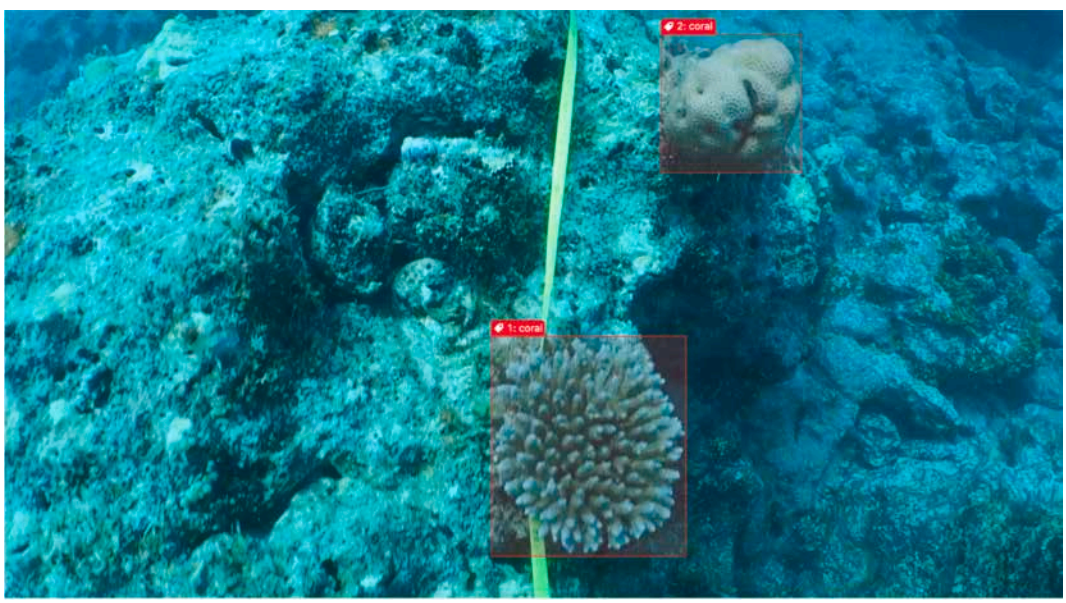

Fig. 4. Example of an image frame from the original dataset used in previous research (Ouassine et al., 2024).

including 200 newly captured images from video transects recorded at another coral reef monitoring site in New Caledonia, Pacific Ocean (Kayal et al., 2023), annotated using Label Studio framework.[4] Of these, 222 are original image frames, while the remaining images are augmented through data augmentation techniques (resizing, rotation, blurring), enhancing the dataset's ability to address the challenges of underwater image analysis. This dataset complements AIMECORAL1 by contributing recent observations and expanding the diversity of the training data, together providing a robust foundation for evaluating the tracking system under diverse conditions. (See Figs. 6 and 7)

As part of our data preprocessing, all images from both datasets were resized to 640 × 640 pixels using bilinear interpolation to ensure compatibility with the input requirements of YOLOv8. Bilinear interpolation was chosen because it provides a good balance between computational efficiency and image quality, preserving important features and minimizing distortion or artifacts that could negatively impact the performance of the detection model.

[4] LABELSTUDIO: https://labelstud.io

3.3. *YOLOv8 for object detection*

YOLOv8 (You Only Look Once version 8) represents a significant advancement in real-time object detection, building on the strengths of its predecessors. It features an enhanced backbone network for improved feature extraction, where convolutional operations refine the model's ability to detect fine-grained details and small objects, which is crucial for identifying different coral species and colony sizes. Mathematically, feature extraction can be thought of as a series of convolutional operations:

$$F_l = \sigma(K * F_{l-1} + b) \tag{1}$$

- F_l is the feature map at layer l,
- K is the convolutional kernel,
- F_{l-1} is the feature map from the previous layer,
- b is the bias term,
- σ is the activation function (e.g., ReLU or Sigmoid).

The updated neck and head architecture refines the feature maps,

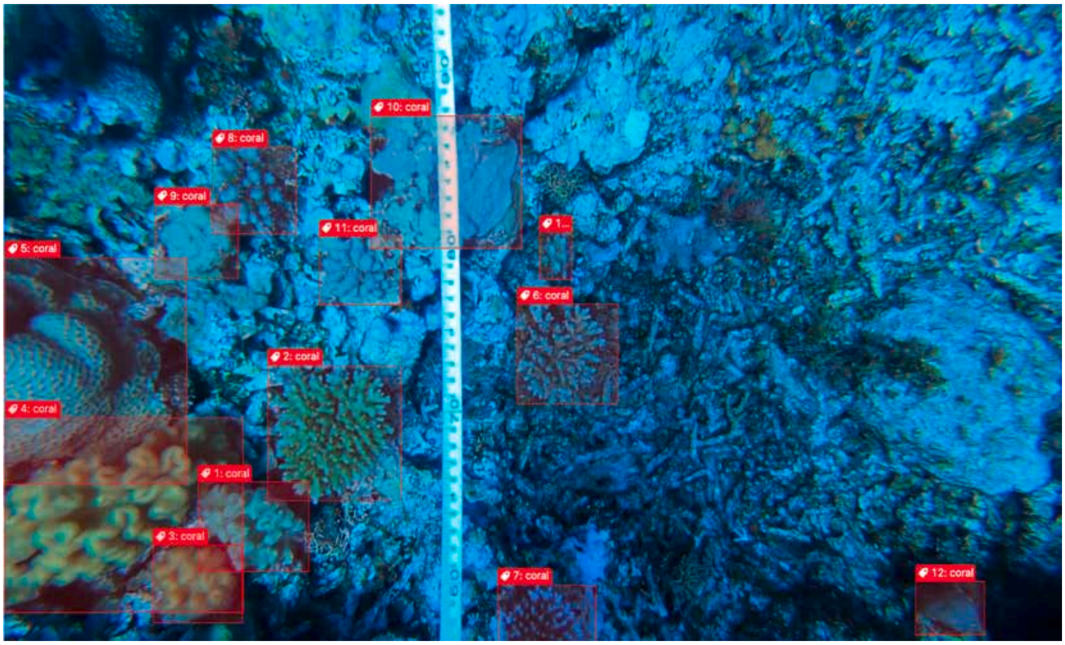

Fig. 5. Sample images from the newly captured dataset, highlighting their diversity and quality, including examples of soft (#1, #3, and #4) and hard corals.

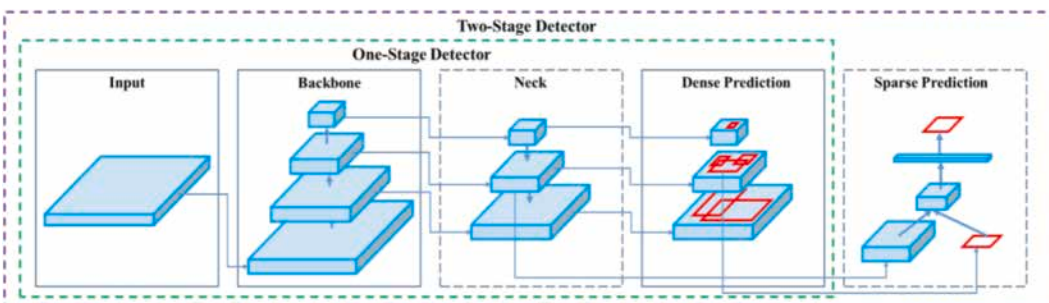

Fig. 6. YOLOv8 architecture, showcasing the key components.

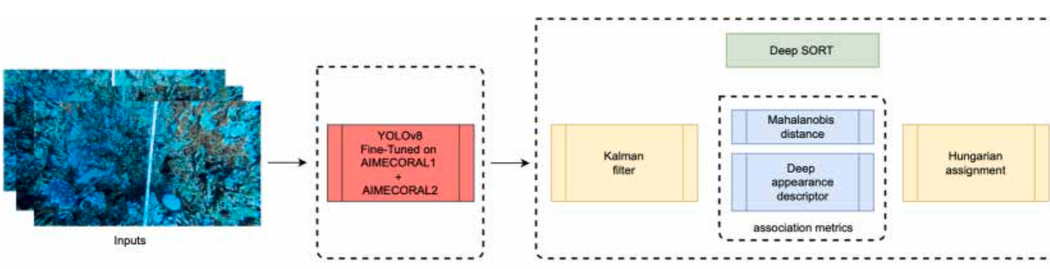

Fig. 7. DeepSORT architecture for object tracking and illustrating the system's components.

with the head responsible for object classification and bounding box prediction, helping to distinguish various coral types and subtle variations in the reef environment. The head of the network can be described by the following:

$$p = \sigma\left(W^{T}F_{\text{final}} + b\right) \quad (2)$$

- p represents the class probability output,
- W is the weight matrix for classification,
- F_{final} is the final extracted feature map,
- b is the bias term,
- σ is the activation function (e.g., SoftMax or Sigmoid).

$$B = W'_{box}F_{\text{final}} + b'_{box} \quad (3)$$

- B represents the predicted bounding box parameters,
- W'_{box} is the weight matrix for bounding box regression,
- F_{final} is the final feature map,
- b'_{box} is the bias term for bounding box prediction.

YOLOv8 also incorporates techniques to reduce computational complexity and increase processing speed, such as depth wise separable convolutions, which decrease the number of floating-point operations

(FLOPs), enabling real-time detection with high accuracy. These techniques are represented by the following equation:

$$FLOPs = D_K^2 \cdot M \cdot N \cdot D_F^2 \tag{4}$$

- D is the depth multiplier,
- K is the kernel size,
- M and N are the input and output channels,
- D_F is the spatial dimension of the feature map.

3.4. DeepSORT for object tracking

DeepSORT is an extension of a simpler tracker called SORT (Simple Online and Realtime Tracking), which incorporates more advanced features like deep learning for improved object re-identification. The tracking process can be broken down into several mathematical components:

➔ Kalman Filtering: This is a recursive state estimation process that involves two main steps—predict and update. The Kalman filter assumes the object state is represented by a Gaussian distribution in terms of its position and velocity.

➔ Predict: The state of the object (e.g., position, velocity) at time $t+1$ is predicted based on the state at time t. The prediction is obtained using the following equations:

$$\widehat{x}_{(t+1|t)} = F_t * \widehat{x}_{(t|t)} + B_t * u_t + w_t \tag{5}$$

- $\widehat{x}_{(t+1|t)}$: The predicted state at time $t+1$ given information up to time t.
- F_t: State transition matrix that models how the state evolves over time.
- B_t: Control matrix that relates control input to the state.
- u_t: Control input vector (optional, if external control inputs exist).
- w_t: Process noise, assumed to be Gaussian.

$$P_{(t+1|t)} = F_t * P_{(t|t)} * F_t^T + Q_t \tag{6}$$

- $P_{(t+1|t)}$: The predicted error covariance at time $t+1$ given information up to time t.
- Q_t: Process noise covariance matrix that accounts for uncertainties in the model.

➔ Update: When a new measurement (detection) z_{t+1} is available, the prediction is updated using the following equations:

$$K_{t+1} = P_{(t+1|t)} * H_{t+1}^T * \left(H_{t+1} * P_{(t+1|t)} * H_{t+1}^T + R_{t+1}\right)^{-1} \tag{7}$$

- K_{t+1}: Kalman gain, which determines the weight given to the new measurement.
- H_{t+1}: Measurement matrix that maps the state space to the measurement space.
- R_{t+1} :Measurement noise covariance matrix.

$$\widehat{x}_{(t+1|t+1)} = \widehat{x}_{(t+1|t)} + K_{t+1} * \left(z_{t+1} - H_{t+1} * \widehat{x}_{(t+1|t)}\right) \tag{8}$$

- z_{t+1} New measurement vector (e.g., detected object location).

$$P_{(t+1|t+1)} = (I - K_{t+1} * H_{t+1}) * P_{(t+1|t)} \tag{9}$$

- I: Identity matrix.

➔ Object *Re*-Identification: The appearance features of detected objects are extracted through a deep convolutional neural network. These features form a high-dimensional vector space where the Euclidean distance can be calculated between feature vectors. The closer the feature vectors are in this space, the more likely they are to belong to the same object.

➔ Data Association: The Hungarian algorithm is employed to solve the assignment problem, which optimally matches detections to existing tracks. The problem is formulated as a cost matrix, C, where C_{ji} represents the cost of assigning detection i to track j. The cost is a weighted sum of the Mahalanobis distance (for motion compatibility) and the cosine distance (for appearance similarity). The Hungarian algorithm finds the assignment with the lowest overall cost.

3.5. Evaluation metrics

The evaluation of our tracking system is based on several established metrics that assess both object detection and object tracking performance.

➔ Precision: The precision is used to evaluate the accuracy of the YOLOv8 object detection model in identifying coral structures within video frames. It is defined as the ratio of true positive detections to the total number of detections, indicating the proportion of correctly identified objects among all predictions and reflecting the model's reliability in avoiding false positives.

$$\text{Precision} = \frac{\text{True Positives (TP)}}{\text{True Positives (TP)} + \text{False Positives (FP)}} \tag{10}$$

➔ Multiple Object Tracking Accuracy (MOTA): MOTA evaluates the overall accuracy of the tracking process, incorporating the effects of false positives (FP), false negatives (FN), and identity switches (IDSW). It is defined as:

$$\text{MOTA} = 1 - \left(\frac{\Sigma_t\,(FN_t + FP_t + IDSW_t)}{\Sigma_t\, GT_t}\right) \tag{11}$$

where FN_t is the number of false negatives (missed detections) at time t, FP_t is the number of false positives (incorrect detections) at time t, $IDSW_t$ is the number of identity switches at time t, and GT_t is the number of ground truth objects at time t. MOTA provides a single score that summarizes how well the system tracks objects without errors.

➔ Multiple Object Tracking Precision (MOTP): MOTP measures the precision of the tracker in estimating the positions of objects. It calculates the average distance between the predicted positions of tracked objects and the actual positions. This metric focuses on the spatial accuracy of the tracking:

$$\text{MOTP} = \frac{\Sigma_{t,i} d_{t,i}}{\Sigma_t\, c_t} \tag{12}$$

where $d_{t,i}$ is the Euclidean distance between the ground truth position and the predicted position for object i at time t, and ct is the number of correctly matched object detections at time t.

➔ Identity F1 Score (IDF1): The IDF1 score measures the balance between the precision and recall of correctly identified objects over all frames. It is particularly useful in assessing how consistently the tracking system maintains the correct identity of objects across consecutive frames. It is defined as:

$$\text{IDF1} = \frac{2*\text{IDTP}}{(2*\text{IDTP} + \text{IDFP} + \text{IDFN})} \tag{13}$$

where IDTP is the number of true positive identities, IDFP is the number of false positive identities, and IDFN is the number of false negative identities.

➔ Track Continuity (TC): Track continuity measures the duration for which an object is consistently tracked without interruptions or identity switches. This metric is essential for evaluating the system's ability to maintain continuous observations of coral structures in consecutive image frames, which is crucial to avoid the resampling of individual corals in the video-transects used for ecological studies and monitoring.

4. Results

4.1. Object detection performance

As shown in Fig. 8, YOLOv8l pre-trained on ImageNet, achieved a precision of 5.2 % on the AIMECORAL1 image dataset from the Indian Ocean before fine-tuning. After fine-tuning, it achieved a precision of 59.9 % on the AIMECORAL1 dataset and 84.7 % on the combined AIMECORAL1 and AIMECORAL2 datasets from the Indian and Pacific Oceans.

4.2. Tracking performance

The performance of the tracking system, which integrates YOLOv8 and DeepSORT, was evaluated using four metrics: Multiple Object Tracking Accuracy, Multiple Object Tracking Precision, Identity F1 Score, and Track Continuity. Fig. 9 summarizes these results.

4.3. Application to coral reef monitoring

Applied to coral reef video-transects recorded at the same monitoring site in consecutive years, the model outputs effectively characterize year-to-year changes in coral populations. While the system does not track individual coral colonies across different years (e.g., between 2021 and 2022), it enables robust population-level comparisons by analyzing consistent spatial areas across time. The outputs show that overall coral abundance increased from 114 colonies in 2021 to 117 in 2022. Additionally, the average coral mean-diameter rose from 99.22 pixels in 2021 to 108.11 pixels in 2022, with the median mean-diameter increasing from 98.04 pixels to 110.14 pixels, as illustrated in Fig. 10. These changes suggest a general trend of coral growth and recovery at the site over the one-year interval.

4.4. Visual analysis

In this section, we present the visual results of our system, which is divided into two key parts: detection results and tracking results.

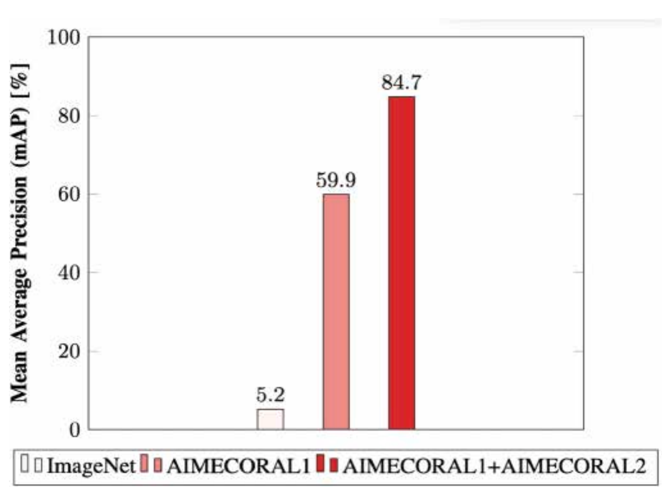

Fig. 8. Object detection performance of YOLOv8 on the two coral image datasets.

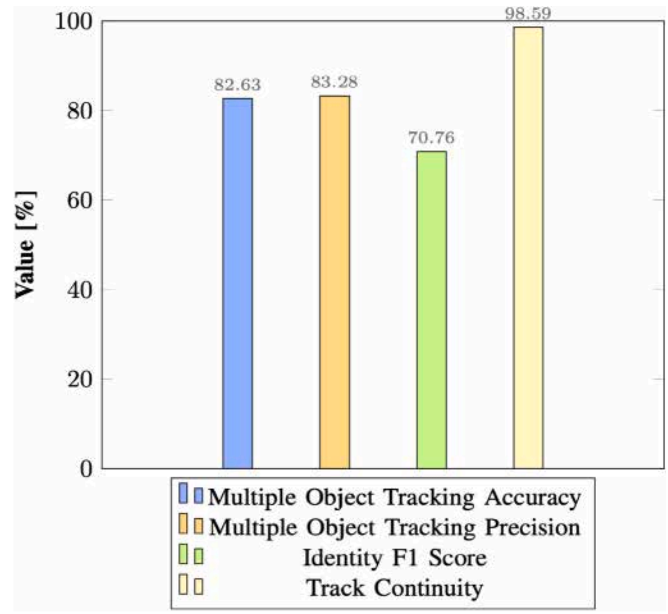

Fig. 9. Tracking performance metrics using YOLOv8 fine-tuned on AIMECORALL1 + AIMECORAL2 and DeepSORT.

4.4.1. Detection results

The detection results demonstrate the performance of YOLOv8, with bounding boxes superimposed on the images to visualize the outcomes, as shown in Fig. 11.

4.4.2. Tracking results

The tracking results showcase the performance of the DeepSORT algorithm in re-identifying the same individual corals over consecutive frames. The visualizations feature trajectories overlaid on the sequences, illustrating the algorithm's effectiveness in reliably tracking coral entities, as demonstrated in Fig. 12.

5. Discussion

The integration of YOLOv8 for object detection and DeepSORT for object tracking allows effective monitoring of coral size and abundance, key indicators of reef ecosystem health. Changes in these factors such as increases in coral abundance or size may reflect positive ecological trends like recovery or reduced stress. However, it's crucial to assess if these changes are statistically significant and ecologically meaningful, as small increases might indicate early recovery, while larger shifts could signal long-term improvements or stability in reef health.

5.1. Object detection analysis

The performance of the YOLOv8 model in detecting coral structures across different datasets reveals a high level of precision, particularly with the AIMECORAL2 dataset. The model achieved a precision of 59.9 % when applied to the AIMECORAL1 dataset from the Indian Ocean, which is a promising result considering the complex underwater environment and the challenge of detecting small, occluded, or damaged coral colonies. However, the model showed a marked improvement when tested on the combined AIMECORAL1 and AIMECORAL2 datasets, achieving a precision of 84.7 %. This increase can be attributed to several factors:

- Image Quality and Consistency: The higher quality and more consistent images in the AIMECORAL2 dataset played a significant role. The use of a camera stands during data collection (Kayal et al., 2023, p. 202) (Fig. 11). helped maintain a steady camera distance

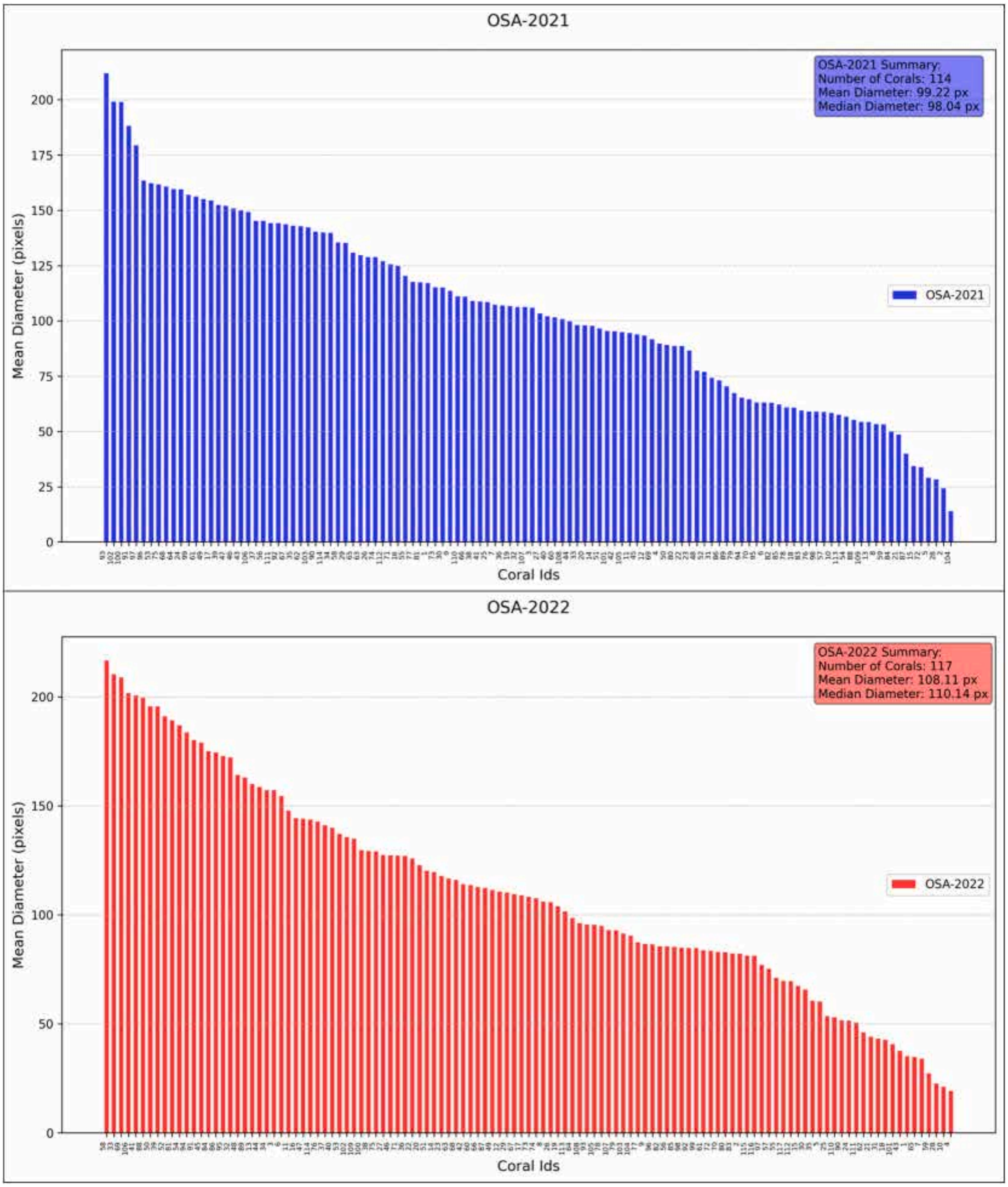

Fig. 10. Ecological monitoring results for outer-reef site in New Caledonia in 2021 and 2022.

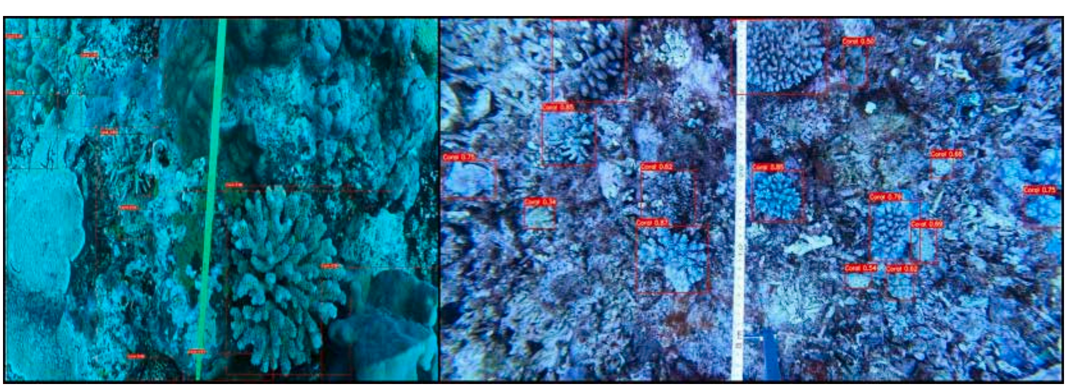

Fig. 11. Detection examples with bounding boxes from images set from the Indian Ocean (left) and Pacific Ocean (right). In the video-transects from New Caledonia, the stand attached to the camera, ensuring a fixed distance of 50 cm from the substrate.

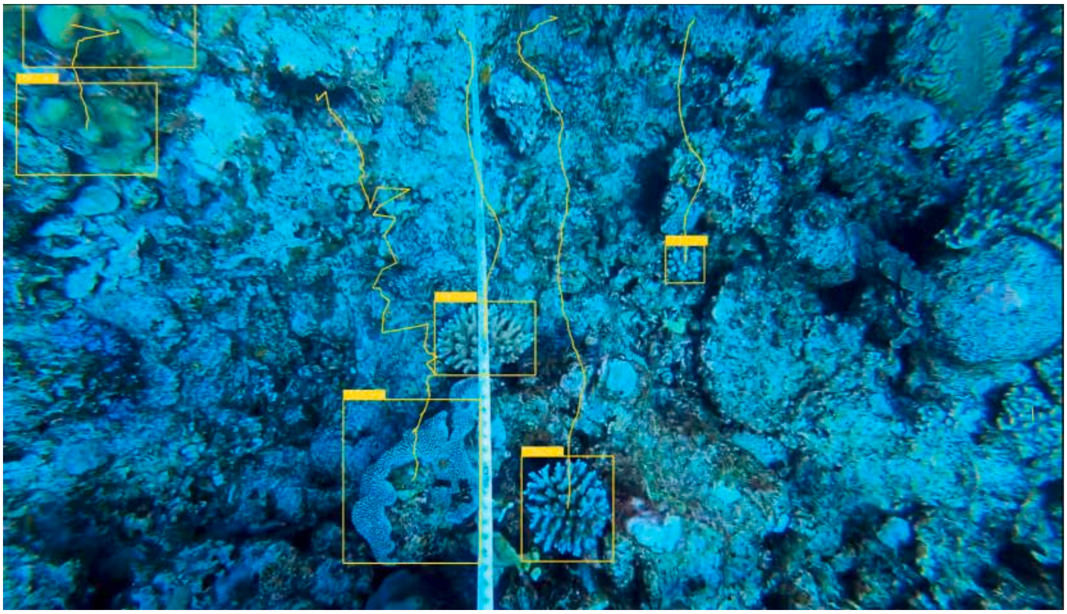

Fig. 12. Tracking result with trajectory overlays illustrated as yellow trajectory lines tracing the positions of the corals through consecutive image frames in the video-transects. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

from the transect tape, leading to clearer, more usable images for detection. This improved camera positioning likely reduced the impact of factors such as image blur, distortion, or changes in light conditions.

- Richer Training Data: The AIMECORAL2 dataset also featured more comprehensive annotations per site and a greater variety of coral species and environmental conditions. This added diversity in the dataset allowed YOLOv8 to learn from a wider range of coral morphologies and environmental variables, enhancing the model's ability to generalize and detect coral across different reef habitats. This reflects the robustness of YOLOv8's advanced feature extraction capabilities, such as its enhanced backbone and neck architectures, which are specifically designed to handle complex and varied visual inputs.

The ability of YOLOv8 to detect various coral types, from branching corals to encrusting species, across both Indian and Pacific Ocean datasets demonstrates its adaptability and efficiency in a challenging underwater context. These results underscore YOLOv8's potential as a reliable tool for continuous reef monitoring, offering a scalable approach for large-scale coral ecosystem assessments.

The Table 1 summarizes the performance of various coral detection models, including YOLOv8's results, along with the results of other prominent models:

Table 1
Comparison of coral detection models' accuracy across different datasets, highlighting the performance of our model on the combined AIMECORAL1 and AIMECORAL2 datasets.

Model Name	Dataset Used	Accuracy (%)
YOLOv5-based Coral Detection System (Ouassine et al., 2024)	AIMECORAL1	59.9
UTD-Yolov5 (Wang and Yu, 2022)	CSIRO Dataset	78.54
Our Model	AIMECORAL1 & AIMECORAL2	**84.7**

5.2. Tracking performance analysis

The integration of DeepSORT for object tracking further enhances the monitoring system's capabilities. The system achieved an impressive Multiple Object Tracking Accuracy (MOTA) of 82.63 %, indicating its effectiveness in tracking multiple coral colonies simultaneously with minimal errors. This is particularly important for ecological studies, where accurately tracking individual coral colonies over time can provide crucial insights into growth patterns, mortality, and environmental stressors. The high Multiple Object Tracking Precision (MOTP) of 83.28 % also highlights the model's strong ability to consistently assign detections to the correct objects in each frame.

The Identity F1 Score of 70.76 % indicates that while the system effectively minimizes identity switches, there is still room for improvement in terms of maintaining stable identity over long sequences. In underwater video, issues such as occlusion, movement blur, and changes in coral appearance due to environmental factors (e.g., water movement, lighting) can contribute to occasional tracking errors or identity misassignments. Despite these challenges, the results show that the system can reliably track corals over extended periods, providing a powerful tool for temporal monitoring.

Our system's ability to accurately track coral colonies and their movements represents a significant step forward in the field of reef monitoring. This is the first known coral tracking system to employ AI-driven methods for such analysis, and the results suggest that AI-based tracking can be used effectively to monitor long-term trends in coral populations and health.

The Table 2 summarizes the performance of various underwater object tracking systems, including UMOTMA and FSTA, along with the

Table 2
Comparison of coral detection models' accuracy across different datasets.

System	Application Context	MOTA (%)
UMOTMA (Underwater Multiple Object Tracking with Memory Aggregation)(Hao et al., 2022)	Underwater multiple object tracking	81.1
FSTA (Fish-School Tracking Algorithm) (Liu et al., 2022)	Underwater multiclass fish-school tracking	79.1
Our system (Coral Reefs Tracking)	**coral reefs tracking**	**82.63**

results of our proposed coral reefs tracking system:

5.3. Implications for temporal coral reef monitoring

The application of our system to video transects recorded in 2021 and 2022 at the same reef site revealed interesting insights into temporal changes in coral abundance and size distribution. The detection of a slight increase in coral abundance, from 114 colonies in 2021 to 117 colonies in 2022, indicates a modest but positive trend in coral population dynamics at this site. This result is consistent with the broader ecological expectation that coral populations can show signs of replenishment through recruitment and growth under favorable environmental conditions (Kayal et al., 2015; Kayal et al., 2018).

Furthermore, the model's assessment of coral size distribution demonstrated an increase in both the mean and median colony size. Specifically, the mean coral size (diameter) increased from 99.22 pixels in 2021 to 108.11 pixels in 2022, while the median coral size shifted from 98.04 pixels to 110.14 pixels over the same period. These changes in size metrics suggest that corals at this site are experiencing healthy growth, which is an encouraging indicator of ecosystem vitality. Larger colony sizes may also be associated with higher reproductive potential, suggesting that the reef could be on a positive trajectory in terms of ecosystem regeneration.

While these findings are based on a limited set of transects for demonstration purposes, they highlight the utility of our system in detecting and quantifying ecological changes over time. By automating the detection and tracking of corals in video transects, our system opens up new possibilities for continuous, high-frequency monitoring of reef health. This approach is particularly valuable for assessing long-term trends and the impacts of environmental stressors, such as ocean warming, bleaching events, or changes in local water quality.

Moreover, the use of computer vision techniques for coral monitoring holds significant promise for large-scale reef assessments, especially in remote or difficult-to-reach areas. As the system becomes more refined and applied to broader reef areas, it could provide critical insights into coral mortality processes, the effects of conservation interventions, and the overall resilience of coral reef ecosystems in the face of climate change and other threats.

5.4. Limitations and future work

While our automated system performs effectively, several limitations can be addressed in future work to further enhance its contribution to ecological monitoring of coral reefs. First, the coral detection system currently identifies coral structures broadly without distinguishing between specific coral genera or ecological functions (e.g., hard versus soft corals, different morphotypes), which remains a key area of research. Second, while the tracking capacity of the model was demonstrated on individual corals in consecutive frames from the same video survey, preventing the recounting of the same corals across different frames in population abundance assessments, the model was not tested for tracking individual corals across separate videos taken at the same site in different years. Such an application would provide valuable insights into annual coral dynamics (e.g., survival, growth, recruitment) (Kayal et al., 2023). Currently, the system focuses on characterizing changes in coral abundance and size at the population level, and further development is required to enable tracking of individual corals over time. Addressing these limitations will enhance the system's accuracy and provide deeper insights into coral reef dynamics.

Future work will focus on several key areas to enhance coral reef analysis. First, data augmentation and expansion will involve incorporating more diverse datasets, including various types of coral reef habitats such as reef flats, reef slopes, and patch reefs, as well as additional environmental variables, to improve the model's generalizability. Efforts will also be directed toward enhanced coral classification, aiming to discriminate between hard and soft corals, identify different coral morphologies (such as branching, massive, and tabular forms), and enable taxonomic classification at the genus level. Model optimization will be pursued by investigating advanced deep learning architectures and incorporating attention mechanisms to better distinguish visually similar coral genera through the detection of subtle differences in corallite structures. Additionally, integration with other sensors such as x-ray, sonar, or environmental sensors will be explored to gain a more comprehensive understanding of coral reef functioning. Finally, optimizing the system for real-time video analysis will be prioritized, as this capability could be crucial for rapidly assessing coral health following disturbances like bleaching, hurricane effects, or anthropogenic destruction, thereby supporting conservation and adaptive management efforts.

6. Conclusion

This study presents a novel deep learning-based system that integrates YOLOv8 for object detection and DeepSORT for multi-object tracking to automate coral reef monitoring. The proposed approach achieves significant advancements over traditional methods, demonstrating high accuracy in coral detection (84.7 %) and robust tracking performance (Multiple Object Tracking Accuracy: 82.63 %) across diverse datasets. By leveraging deep learning, the system effectively addresses critical challenges encountered in manual monitoring, such as the labor-intensive nature of coral observations, which often result in limited spatial coverage in traditional surveys.

The ability to automatically analyze a large number of underwater videos for coral identification and tracking between consecutive frames enables the assessment of coral population abundance and sizes, providing valuable insights into reef ecological health, structure, and resilience. As demonstrated with our video transects recorded in 2021 and 2022 at the same reef location, our automated system offers data-driven insights into coral population dynamics.

This innovation represents a scalable, cost-effective solution for large-scale coral reef monitoring, aiding researchers and marine protected area managers in protecting these vital ecosystems. Future efforts will focus on enhancing the system's generalizability by incorporating more diverse datasets, enabling real-time processing on larger datasets, and expanding its functionality through the integration of additional sensors and advanced deep-learning architectures aimed at coral genus-level identification. These enhancements are designed to advance the field of marine ecosystem monitoring, ensuring timely and informed decision-making for effective coral reef conservation.

Declaration of competing interest

The authors declare that there is no conflict of interest regarding the publication of this paper. All authors have contributed equally to the research and writing of this manuscript, and no financial, personal, or professional relationships have influenced the research. The authors have no competing interests to disclose.

CRediT authorship contribution statement

Younes Ouassine: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Formal analysis, Data curation, Conceptualization. **Noël Conruyt:** Writing – review & editing, Supervision, Methodology. **Mohsen Kayal:** Writing – review & editing, Validation, Supervision, Methodology, Data curation. **Philippe A. Martin:** Writing – review & editing, Validation. **Lionel Bigot:** Writing – review & editing, Validation, Data curation. **Vignes Lebbe Regine:** Writing – review & editing, Validation, Supervision. **Hajar Moussanif:** Writing – review & editing, Supervision. **Jihad Zahir:** Writing – review & editing, Validation, Supervision, Conceptualization.

Acknowledgments

This research was funded by the Artificial Intelligence for Marine

Ecosystems (AIME) initiative, whose financial support made this work possible. We also extend our thanks to the developers and community behind Label Studio for their excellent annotation tool, which significantly streamlined our data preparation process. Coral reef monitoring in New Caledonia was performed as part of the Track Changes project supported by the French Laboratory of Excellency CORAIL and the French Ministry for Europe and Foreign Affairs through the regional cooperation grant Fonds Pacifique. Finally, we are grateful to our colleagues for their constructive feedback and guidance, which greatly enhanced the quality of this manuscript.

Data availability

The datasets used during this study are available at the following link: https://github.com/Youassin/AIMECORAL.git

References

Andersen, R., Nalpantidis, L., Ravn, O., Boukas, E., 2020. Investigating deep learning architectures towards autonomous inspection for marine classification. In: 2020 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR). Presented at the 2020 IEEE International Symposium on Safety, Security, and Rescue Robotics (SSRR), pp. 197–204. https://doi.org/10.1109/SSRR50563.2020.9292621.

Apprill, A., Girdhar, Y., Mooney, T.A., Hansel, C.M., Long, M.H., Liu, Y., Zhang, W.G., Kapit, J., Hughen, K., Coogan, J., Greene, A., 2023. Toward a new era of coral reef monitoring. Environ. Sci. Technol. 57, 5117–5124. https://doi.org/10.1021/acs.est.2c05369.

Baag, S., Mandal, S., 2022. Combined effects of ocean warming and acidification on marine fish and shellfish: a molecule to ecosystem perspective. Sci. Total Environ. 802, 149807. https://doi.org/10.1016/j.scitotenv.2021.149807.

Baer, J.L., Carilli, J., Chadwick, B., Hatay, M., van der Geer, A., Scholten, Y., Barnes, W., Aquino, J., Ballard, A., Little, M., Brzenski, J., Liu, X., Rosen, G., Wang, P.-F., Castillo, J., Haas, A.F., Hartmann, A.C., Rohwer, F., 2023. Coral reef arks: an in situ Mesocosm and toolkit for assembling reef communities. J. Vis. Exp. JoVE. https://doi.org/10.3791/64778.

Bewley, A., Ge, Z., Ott, L., Ramos, F., Upcroft, B., 2016. Simple online and realtime tracking, in: 2016 IEEE international conference on image processing (ICIP). In: Presented at the 2016 IEEE International Conference on Image Processing (ICIP), pp. 3464–3468. https://doi.org/10.1109/ICIP.2016.7533003.

Carlot, J., Vousdoukas, M., Rovere, A., Karambas, T., Lenihan, H.S., Kayal, M., Adjeroud, M., Pérez-Rosales, G., Hedouin, L., Parravicini, V., 2023. Coral reef structural complexity loss exposes coastlines to waves. Sci. Rep. 13, 1683. https://doi.org/10.1038/s41598-023-28945-x.

Ceccarelli, D.M., McLeod, I.M., Boström-Einarsson, L., Bryan, S.E., Chartrand, K.M., Emslie, M.J., Gibbs, M.T., Rivero, M.G., Hein, M.Y., Heyward, A., Kenyon, T.M., Lewis, B.M., Mattocks, N., Newlands, M., Schläppy, M.-L., Suggett, D.J., Bay, L.K., 2020. Substrate stabilisation and small structures in coral restoration: state of knowledge, and considerations for management and implementation. PLoS One 15, e0240846. https://doi.org/10.1371/journal.pone.0240846.

Cheal, A.J., Emslie, M.J., Currey-Randall, L.M., Heupel, M.R., 2021. Comparability and complementarity of reef fish measures from underwater visual census (UVC) and baited remote underwater video stations (BRUVS). J. Environ. Manag. 289, 112375. https://doi.org/10.1016/j.jenvman.2021.112375.

Chen, Y., Yang, S., Suo, Y., Chen, W., 2020. Research on recognition of marine ships under complex conditions. In: 2020 Chinese Automation Congress (CAC). Presented at the 2020 Chinese Automation Congress (CAC), pp. 5748–5753. https://doi.org/10.1109/CAC51589.2020.9327607.

Eddy, T.D., Lam, V.W.Y., Reygondeau, G., Cisneros-Montemayor, A.M., Greer, K., Palomares, M.L.D., Bruno, J.F., Ota, Y., Cheung, W.W.L., 2021. Global decline in capacity of coral reefs to provide ecosystem services. One Earth 4, 1278–1285. https://doi.org/10.1016/j.oneear.2021.08.016.

El Ghmary, M., Ouassine, Y., Ouacha, A., 2023. Automatic license plate recognition with YOLOv5 and faster-RCNN. In: Lazaar, M., En-Naimi, E.M., Zouhair, A., Al Achhab, M., Mahboub, O. (Eds.), Proceedings of the 6th International Conference on Big Data and Internet of Things. Springer International Publishing, Cham, pp. 351–361. https://doi.org/10.1007/978-3-031-28387-1_30.

Good, A.M., Bahr, K.D., 2021. The coral conservation crisis: interacting local and global stressors reduce reef resiliency and create challenges for conservation solutions. SN Appl. Sci. 3, 312. https://doi.org/10.1007/s42452-021-04319-8.

Hao, Z., Qiu, J., Zhang, H., Ren, G., Liu, C., 2022. UMOTMA: underwater multiple object tracking with memory aggregation. Front. Mar. Sci. 9. https://doi.org/10.3389/fmars.2022.1071618.

Host, K., Pobar, M., Ivasic-Kos, M., 2023. Analysis of movement and activities of handball players using deep neural networks. J. Imag. 9, 80. https://doi.org/10.3390/jimaging9040080.

Jalal, A., Salman, A., Mian, A., Shortis, M., Shafait, F., 2020. Fish detection and species classification in underwater environments using deep learning with temporal information. Ecol. Inform. 57, 101088. https://doi.org/10.1016/j.ecoinf.2020.101088.

Jie, Y., Leonidas, L., Mumtaz, F., Ali, M., 2021. Ship detection and tracking in inland waterways using improved YOLOv3 and deep SORT. Symmetry 13, 308. https://doi.org/10.3390/sym13020308.

Kayal, M., Vercelloni, J., Wand, M.P., Adjeroud, M., 2015. Searching for the best bet in life-strategy: a quantitative approach to individual performance and population dynamics in reef-building corals. Ecol. Complex. 23, 73–84. https://doi.org/10.1016/j.ecocom.2015.07.003.

Kayal, M., Lenihan, H.S., Brooks, A.J., Holbrook, S.J., Schmitt, R.J., Kendall, B.E., 2018. Predicting coral community recovery using multi-species population dynamics models. Ecol. Lett. 21, 1790–1799. https://doi.org/10.1111/ele.13153.

Kayal, M., Mevrel, E., Ballard, J., 2023. Video transect-based coral demographic investigation. Coasts 3, 370–382. https://doi.org/10.3390/coasts3040022.

Liu, T., He, S., Liu, H., Gu, Y., Li, P., 2022. A robust underwater multiclass fish-school tracking algorithm. Remote Sens. 14, 4106. https://doi.org/10.3390/rs14164106.

Lu, H., Uemura, T., Wang, D., Zhu, J., Huang, Z., Kim, H., 2020. Deep-Sea organisms tracking using Dehazing and deep learning. Mob. Netw. Appl. 25, 1008–1015. https://doi.org/10.1007/s11036-018-1117-9.

Lu, Z., Liao, L., Xie, X., Yuan, H., 2025. SCoralDet: efficient real-time underwater soft coral detection with YOLO. Ecol. Inform. 85, 102937. https://doi.org/10.1016/j.ecoinf.2024.102937.

Mahdian, N., Jani, M., Enayati, A.M.S., Najjaran, H., 2024. Ego-Motion Aware Target Prediction Module for Robust Multi-Object Tracking. https://doi.org/10.48550/arXiv.2404.03110.

Mandal, V., Adu-Gyamfi, Y., 2020. Object Detection and Tracking Algorithms for Vehicle Counting: A Comparative Analysis. https://doi.org/10.48550/arXiv.2007.16198.

Myat Noe, S., Zin, T.T., Tin, P., Kobayashi, I., 2023. Comparing state-of-the-art deep learning algorithms for the automated detection and tracking of black cattle. Sensors 23, 532. https://doi.org/10.3390/s23010532.

Nalley, E.M., Tuttle, L.J., Conklin, E.E., Barkman, A.L., Wulstein, D.M., Schmidbauer, M. C., Donahue, M.J., 2023. A systematic review and meta-analysis of the direct effects of nutrients on corals. Sci. Total Environ. 856, 159093. https://doi.org/10.1016/j.scitotenv.2022.159093.

Obura, D.O., Aeby, G., Amornthammarong, N., Appeltans, W., Bax, N., Bishop, J., Brainard, R.E., Chan, S., Fletcher, P., Gordon, T.A.C., Gramer, L., Gudka, M., Halas, J., Hendee, J., Hodgson, G., Huang, D., Jankulak, M., Jones, A., Kimura, T., Levy, J., Miloslavich, P., Chou, L.M., Muller-Karger, F., Osuka, K., Samoilys, M., Simpson, S.D., Tun, K., Wongbusarakum, S., 2019. Coral reef monitoring, reef assessment technologies, and ecosystem-based management. Front. Mar. Sci. 6. https://doi.org/10.3389/fmars.2019.00580.

Ouassine, Y., Zahir, J., Conruy, N., Kayal, M., Martin, P.A., Chenin, E., Lionel, B., Lebbe Regine, V., 2024. Automatic Coral Detection with YOLO: A Deep Learning Approach for Efficient and Accurate Coral Reef Monitoring, pp. 170–177. https://doi.org/10.1007/978-3-031-50485-3_16.

Pereira, R., Carvalho, G., Garrote, L., Nunes, U.J., 2022. Sort and deep-SORT based multi-object tracking for Mobile robotics: evaluation with new data association metrics. Appl. Sci. 12, 1319. https://doi.org/10.3390/app12031319.

Qiu, S., Ooi, J.L.S., Chen, W., Poong, S.-W., Zhang, H., He, W., Su, S., Luo, H., Hu, W., Affendi, Y.A., Du, J., Loh, K.-H., 2023. Heterogeneity of fish taxonomic and functional diversity evaluated by eDNA and gillnet along a mangrove–seagrass–coral reef continuum. Animals 13, 1777. https://doi.org/10.3390/ani13111777.

Redmon, J., Divvala, S., Girshick, R., Farhadi, A., 2016. You only look once: unified, real-time object detection. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). Presented at the 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 779–788. https://doi.org/10.1109/CVPR.2016.91.

Sauder, J., Banc-Prandi, G., Meibom, A., Tuia, D., 2023. Scalable Semantic 3D Mapping of Coral Reefs with Deep Learning. https://doi.org/10.48550/arXiv.2309.12804.

Sharma, N., Baral, S., Paing, M.P., Chawuthai, R., 2023. Parking time violation tracking using YOLOv8 and tracking algorithms. Sensors 23, 5843. https://doi.org/10.3390/s23135843.

Sill, S.R., Dawson, T.P., 2021. Climate change impacts on the ecological dynamics of two coral reef species, the humphead wrasse (*Cheilinus undulatus*) and crown-of-thorns starfish (*Ancanthaster planci*). Ecol. Inform. 65, 101399. https://doi.org/10.1016/j.ecoinf.2021.101399.

Singh, N.D., Croce, F., Hein, M., 2023. Revisiting Adversarial Training for ImageNet: Architectures, Training and Generalization across Threat Models. https://doi.org/10.48550/arXiv.2303.01870.

Staley, C., Kaiser, T., Gidley, M.L., Enochs, I.C., Jones, P.R., Goodwin, K.D., Sinigalliano, C.D., Sadowsky, M.J., Chun, C.L., 2017. Differential impacts of land-based sources of pollution on the microbiota of Southeast Florida Coral reefs. Appl. Environ. Microbiol. 83, e03378-16. https://doi.org/10.1128/AEM.03378-16.

Walker, N.S., Nestor, V., Golbuu, Y., Palumbi, S.R., 2023. Coral bleaching resistance variation is linked to differential mortality and skeletal growth during recovery. Evol. Appl. 16, 504–517. https://doi.org/10.1111/eva.13500.

Wang, J., Yu, N., 2022. UTD-Yolov5: A Real-time Underwater Targets Detection Method based on Attention Improved YOLOv5. https://doi.org/10.48550/arXiv.2207.00837.

Wang, L., Ye, X., Xing, H., Wang, Z., Li, P., 2020. YOLO Nano underwater: A fast and compact object detector for embedded device. In: Global Oceans 2020: Singapore – U.S. Gulf Coast. Presented at the Global Oceans 2020: Singapore – U.S. Gulf Coast, pp. 1–4. https://doi.org/10.1109/IEEECONF38699.2020.9389213.

Xie, F., Lin, B., Liu, Y., 2022. Research on the coordinate attention mechanism fuse in a YOLOv5 deep learning detector for the SAR ship detection task. Sensors 22, 3370. https://doi.org/10.3390/s22093370.

Zapata-Ramírez, P.A., Hernández-Hamón, H., Fitzsimmons, C., Cano, M., García, J., Zuluaga, C.A., Vásquez, R.E., 2023. Development of a Google Earth Engine-based application for the management of shallow coral reefs using drone imagery. Remote Sens. 15, 3504. https://doi.org/10.3390/rs15143504.

Zhang, Y., Chen, Z., Wei, B., 2020. A sport athlete object tracking based on deep Sort and Yolo V4 in case of camera movement. In: 2020 IEEE 6th International Conference on Computer and Communications (ICCC). Presented at the 2020 IEEE 6th International Conference on Computer and Communications (ICCC), pp. 1312–1316. https://doi.org/10.1109/ICCC51575.2020.9345010.

Zhang, M., Xu, S., Song, W., He, Q., Wei, Q., 2021. Lightweight underwater object detection based on YOLO v4 and multi-scale attentional feature fusion. Remote Sens. 13, 4706. https://doi.org/10.3390/rs13224706.

Zhang, W., Wang, J., Liu, Y., Chen, K., Li, H., Duan, Y., Wu, W., Shi, Y., Guo, W., 2022. Deep-learning-based in-field citrus fruit detection and tracking. Hortic. Res. 9, uhac003. https://doi.org/10.1093/hr/uhac003.

Zhong, J., Li, M., Qin, J., Cui, Y., Yang, K., Zhang, H., 2022. Real-time marine animal detection using Yolo-based deep learning networks in the coral reef ecosystem. ISPRS - Int. Arch. Photogramm. Remote Sens. Spat. Inform. Sci. 46W1, 301–306. https://doi.org/10.5194/isprs-archives-XLVI-3-W1-2022-301-2022.

Zouin, B., Zahir, J., Baletaud, F., Vigliola, L., Villon, S., 2024. Improving CNN fish detection and classification with tracking. Appl. Sci. 14, 10122. https://doi.org/10.3390/app142210122.