

Article

Towards Scalable Ecological Monitoring: Assessing AI-Based Annotation of Benthic Images

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Abstract

Mediterranean rocky reef habitats are ecologically valuable yet increasingly degraded due to cumulative human pressures, necessitating efficient, large-scale ecological status assessments to inform management. Macroalgal communities are widely used as indicators of rocky reef conditions and are typically assessed via photoquadrat sampling. However, the manual annotation of benthic images remains time-consuming and costly. This study evaluates the performance of CoralNet (version 1.0), an AI-assisted image annotation platform, using a pre-annotated dataset of 2537 photoquadrat images from 89 rocky reef sites in the Aegean Sea, Greece, classified into 23 taxonomic and morphofunctional groups. Half of the dataset was used to iteratively train CoralNet classifiers, while the remainder was used to compute the reef-EBQI index and compare ecological status estimates with those derived from manual annotations. The classifier accuracy improved with training volume, reaching 67% using the entire dataset. Reef-EBQI scores derived from CoralNet showed 87% agreement with the manual classifications. Despite challenges and limitations, AI-assisted annotation proved effective in regional-scale ecological assessments based on broad taxonomic and morphofunctional categories. Automated tools like CoralNet can reduce post-processing bottlenecks and enable scalable, cost-effective monitoring, especially when integrated with standardized protocols and citizen science initiatives.

Keywords: CoralNet; reef-EBQI; benthic monitoring; artificial intelligence; automated image analysis; rocky reefs; photoQuad



Academic Editors: Ernesto Weil and Weicheng Cui

Received: 1 August 2025

Revised: 28 August 2025

Accepted: 3 September 2025

Published: 5 September 2025

Citation: Zotou, M.; Sini, M.; Trygonis, V.; Greggio, N.; Mazaris, A.D.; Katsanevakis, S. Towards Scalable Ecological Monitoring: Assessing AI-Based Annotation of Benthic Images. *J. Mar. Sci. Eng.* **2025**, *13*, 1721. <https://doi.org/10.3390/jmse13091721>

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1. Introduction

Rocky reefs are among the most diverse, widespread, and biologically productive coastal ecosystems, providing a broad range of ecosystem services [1,2]. Understanding their structure and function under natural and anthropogenic pressures is essential for assessing ecological status. In the infralittoral zones of temperate regions, rocky reefs are typically dominated by photophilous macroalgal communities, whose distribution and abundance are shaped by complex interactions with abiotic (e.g., light and nutrient availability) [3,4] and biotic (e.g., herbivory) [5] factors. In the Mediterranean, well-preserved rocky reefs of the upper infralittoral zone are characterized by canopy-forming perennial macroalgae, forming forest-like structures, primarily from the genera *Cystoseira* sensu

lato (s.l.) [2,6] and *Sargassum* [7,8]. These canopy algae function as autogenic ecosystem engineers, hosting diverse assemblages of other macroalgae, invertebrates, and fish [6,9,10].

However, the Mediterranean Sea is one of the most heavily impacted marine regions globally [11–13], subject to the cumulative impacts of numerous human-induced stressors. Major threats to rocky reef ecosystems include overfishing and associated trophic cascades [14], pollution [15], invasive non-native species [16,17], coastal development [18], destructive fishing practices [19], and climate change [20–22], with marine heatwaves driving mass mortalities of reef biota [23]. The intensification of cumulative impacts over time has triggered regime shifts, transforming structurally complex, canopy-dominated macroalgal assemblages into degraded states with reduced biodiversity and a simplified community structure [24–26]. Canopy-forming macroalgae across the Mediterranean have suffered marked declines in species richness, area cover, and biomass [2,26,27]. These shifts, resulting in barren substrates dominated by turf and encrusting algae, entail severe losses of biodiversity, ecosystem functioning, and services [2,8,14]. Consequently, photophilous rocky reef communities with canopy-forming algae have been classified as an endangered habitat type in the European Red List of Habitats [28].

Assessing the composition and health of rocky reefs and macroalgal communities is critical in detecting early signs of ecological change and defining measurable thresholds and management objectives [29,30]. A major challenge in marine biodiversity assessment and conservation lies in the lack of robust, comparable, quantitative data on the historical and current distribution of species and habitats, as well as on their spatial and temporal dynamics. In regions lacking a long time-series of biodiversity, such as the Greek seas, biotic indicators have traditionally been employed as practical tools for evaluating ecosystem health. Macroalgae, in particular, are widely used due to their structural role in benthic communities, their sedentary nature, and their differential sensitivity to various stressors. These characteristics make them reliable indicators for assessing and monitoring ecological status in line with regional objectives and the EU Marine Strategy Framework Directive [8,31–35]. As such, reef-EBQI is an ecosystem-based indicator [8] to assess the ecological status of reef biodiversity by monitoring macroalgal communities, developed to support the Marine Strategy Framework Directive [32].

Macroalgal assemblages can be studied using a variety of field methods, from destructive techniques, such as scraping, to non-destructive approaches, such as in situ visual assessments or the analysis of photoquadrats (i.e., photographic samples obtained using a quadrat frame to define the sampling area) [35]. Photoquadrat sampling is widely preferred for its low cost and minimal environmental impact, enabling rapid data collection without harming organisms or habitats [36–38]. It also facilitates the creation of a visual image archive, which is useful for communication, future comparisons, and hypothesis testing. Although it limits species-level identification [39], it is often employed with surrogate classifications, such as morphofunctional groupings based on shared morphological and ecological traits [40,41], which are widely applied in ecological status assessments [35].

Over the past three decades, many benthic monitoring programs have transitioned from traditional in situ measurements to image-based survey methods, such as photoquadrats and video recordings. These approaches offer key advantages, including reduced underwater survey time—an important limitation of SCUBA-based assessments—thereby enhancing monitoring efficiency [37,38,42]. However, a major challenge remains in the post-processing phase, particularly regarding the extraction of quantitative data from the collected images. This typically involves manual annotation using software platforms, such as BIIGLE, CPCe, PhotoGrid, photoQuad, or pointCount99 [43,44]. Manual annotation is labor-intensive and time-consuming, increasing costs, limiting throughput, and delaying results [45]. Additionally, taxonomic uncertainty and inconsistency among analysts intro-

duce observer bias, which is further compounded when multiple annotators or annotation methods are used [46,47].

To address the limitations of manual annotation, recent advances in computer vision and machine learning have enabled the development of automated and semi-automated tools for analyzing benthic images [44,46,48–50]. These approaches aim to reduce the annotation time and cost while enhancing consistency and scalability. A cost–benefit analysis by González-Rivero et al. [51] estimated that expert manual annotation costs of US\$5.41 per image, compared with US\$0.07 using machine learning (1.3% of the manual cost), with machine learning annotating 1200 images in 1 h versus 16 h manually by a very experienced benthic ecologist. Similarly, Hermanto et al. [52] found that automated tools can complete in two days what would otherwise require two months of manual effort. By training classifiers on annotated datasets, these systems can label new images, often with confidence scores, guiding user verification. Some platforms also employ active learning or iterative training strategies, improving the classifier performance as annotated data accumulates. Tools like BIIGLE, CoralNet, TagLab, Squidle+, VIAME, and custom deep learning pipelines have shown promising results in benthic cover estimation and species identification across diverse marine environments [44,46,50,53–55]. Although full automation remains difficult for complex assemblages or rare taxa, these technologies offer a major advance in high-throughput, standardized biodiversity assessments. Annotation accuracy, however, still depends on image quality, organism density, and the performance of the trained model.

In this study, photoquadrat images from multiple rocky reef sites across the Aegean Sea were used to evaluate the performance of CoralNet (Version 1.0) in estimating benthic cover and assessing the ecological status of macroalgal communities. All the images were manually annotated by marine biology experts at the Marine Biodiversity and Ecosystem Management Lab, University of the Aegean, using photoQuad (Version 1.4) [56,57]. A subset of these annotations (train subset) was used to train CoralNet’s classifiers, while a separate evaluation subset was used to automatically estimate benthic cover across morphofunctional groups. The ecological status in the test subset was then assessed using the reef-EBQI index [8] and compared with the manually derived results reported by Savin et al. [57].

2. Materials and Methods

2.1. Study Area and Image Collection

The study area comprises 89 sampling sites scattered across the Aegean Sea (Figure 1/Supplementary Table S1), which can be divided into two broader subregions: the North (N) Aegean and the South (S) Aegean [58], based on their contrasting oceanographic regimes—shaped by Black Sea inflow in the north and Levantine water in the south—creating distinct ecological conditions across its basin [59,60]. The image collection took place in 2016 and 2020, covering the Aegean Sea in a representative manner. Of the 89 sampling sites, 44 were located in the N Aegean Sea and 45 in the S Aegean Sea.

Benthic image sampling was conducted using a 25 × 25 cm quadrat at three depths (0–1 m, 5 m, and 15 m) within upper sublittoral rocky reef habitats. We included the 0–1 m zone to ensure comparability with Savin et al. [57], who analyzed the same dataset, and to maximize the number of available images. While some authors (e.g., [8]) exclude this zone due to its environmental variability, others (e.g., [34,61,62]) consider it central to ecological status assessments, and it is explicitly targeted by the EEI index. Including this depth range, therefore, allows broader applicability and consistency with multiple assessment frameworks.

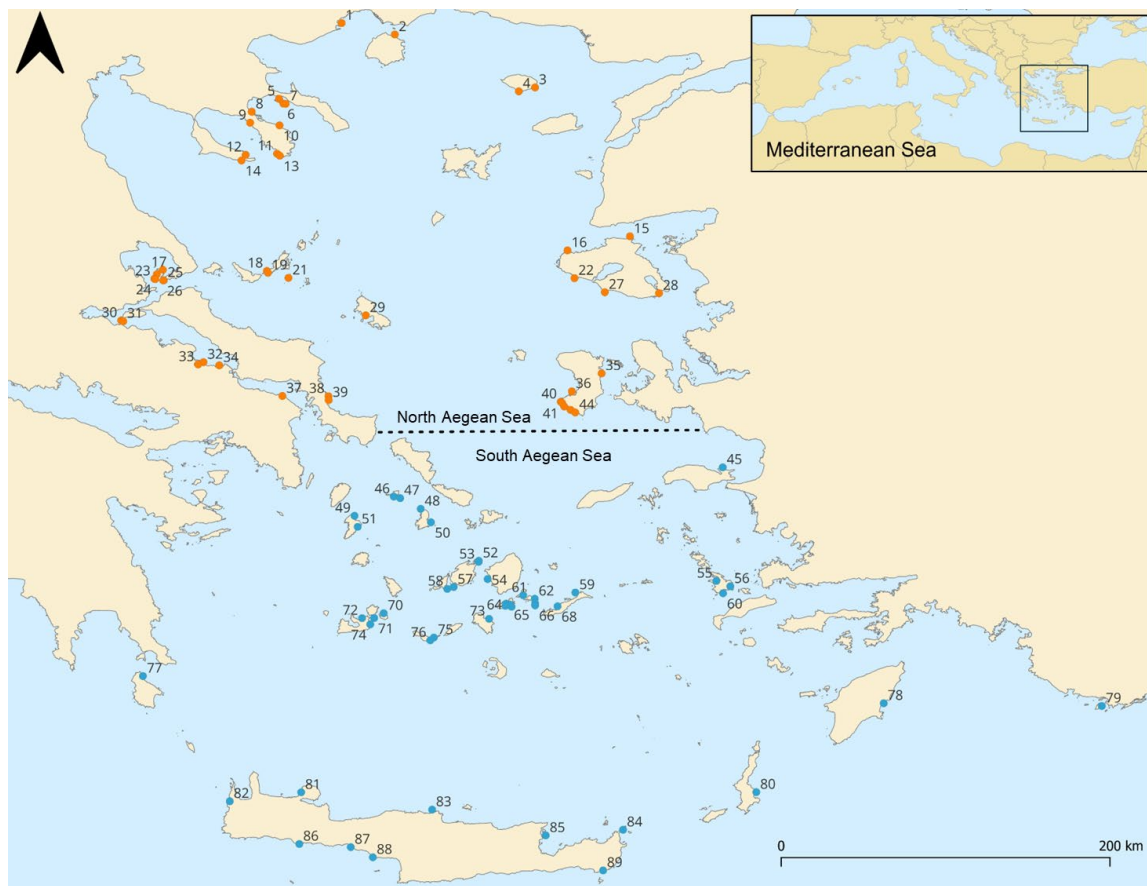


Figure 1. Map of the Aegean Sea showing the distribution of the sampling sites. The dashed line indicates the boundary between the North and South Aegean subregions. Site numbers are ordered from the highest to the lowest latitude. North Aegean sites are colored orange, while South Aegean sites are colored blue.

At each site, eight images were collected at 0–1 m and eighteen at both 5 m and 15 m, when applicable, using a systematic random design [57]. A total of 2537 images were collected, with 17% from 0–1 m, 63% from 5 m, and 20% from 15 m. Among the 89 stations surveyed, the 0–1 m depth was sampled at 52 stations, 15 m at 29 stations, and 5 m at all stations. Photographic samples were nearly evenly distributed between the North and South Aegean, comprising 53% and 47% of the dataset, respectively (Supplementary Table S2).

2.2. Annotation Workflow

2.2.1. Manual Annotation

All the images were initially annotated manually by Savin et al. [57] using the software photoQuad [40] to estimate the percentage cover of benthic components. Each image was overlaid with 60–100 stratified or uniformly distributed points, which were classified into twelve macroalgal categories, seven sessile benthic invertebrate categories, and four substrate types (Table 1; Supplementary Figure S1 [57]). Biotic elements were categorized based on their taxonomic and morphofunctional characteristics. The resulting percentage cover data, derived from the photoQuad analysis, were published by Savin et al. [57]. A subset of this annotated dataset was subsequently used to train CoralNet’s semi-automated annotation tool in the present study.

Table 1. CoralNet labels (labelset), morphofunctional group, taxonomic group, description, and exemplar species of CoralNet labels used to annotate points, adopted from Savin et al. [57].

CoralNet Labels	Morphofunctional Group	Taxonomic Group	Description	Example Species
Algal turf	Turf/Encrusting	Algae	Low-lying species of macroalgae	<i>Cladophora</i> sp., <i>Pseudochlorodesmis furcellata</i>
Encrusting calcareous algae	Turf/Encrusting	Algae	Heavily calcified thalli with stone-like texture and prostrate growth, forming flat, but sometimes multi-layered epilithic crusts	<i>Lithophyllum</i> spp., <i>Mesophyllum</i> spp., <i>Peyssonnelia squamaria</i> , <i>Peyssonnelia rosa-marina</i>
Non-calcareous encrusting algae	Turf/Encrusting	Algae	Thin, soft-textured thalli lacking calcium carbonate, typically forming smooth or slightly uneven crusts, with a flexible, often gelatinous or membranous consistency	<i>Palmophyllum</i> spp.
Articulated calcareous algae 1	Shrubby	Algae	Heavily calcified branched/multilayered/articulated algae	<i>Liagora</i> spp., <i>Jania</i> spp., <i>Corallina</i> spp., Multilayered forms of <i>Peyssonnelia</i>
Articulated calcareous algae 2	Shrubby	Algae	Semi-calcified erect	<i>Halimeda tuna</i> , <i>Flabellia petiolata</i> , <i>Peyssonnelia rubra</i>
Shrubby algae 1	Shrubby	Algae	Foliose macroalgae with large thalli forming pseudo-canopies	<i>Padina pavonica</i> , <i>Zonaria tournefortii</i> , <i>Stypopodium schimperi</i>
Shrubby algae 2	Shrubby	Algae	Foliose macroalgae with thin thalli forming pseudo-canopies	<i>Dictyota</i> spp., <i>Dictyopteris</i> spp.
Shrubby algae 3	Shrubby	Algae	Upright, well-developed thalli of moderate height, forming bushy aggregations	<i>Laurencia</i> spp., <i>Halopteris</i> spp.
Canopy-forming macrophytes 1	Arborescent perennial	Algae	Perennial stems, upright, tree-like thalli with thick blades and branches, forming dense canopies found primarily in pristine environments	<i>Cystoseira</i> spp., <i>Gongolaria</i> spp.
Canopy-forming macrophytes 2	Arborescent perennial	Algae	Perennial stems, upright, tree-like thalli with thick blades and branches, forming dense canopies. Present high-adaptive plasticity and can survive in adverse conditions; found in pristine and moderately degraded environments	<i>Cystoseira compressa</i> , <i>Sargassum</i> spp.

Table 1. Cont.

CoralNet Labels	Morphofunctional Group	Taxonomic Group	Description	Example Species
Massive algae	Shrubby	Algae	Wide cauloid	<i>Codium bursa</i>
Mucilaginous	Turf/Encrusting	Algae	Mucus-like phenotype	<i>Chrysophyceae</i>
Animal turf		Animals	Low-lying, turf-like growth form, typically not higher than 2–3 cm	<i>Aglaophenia</i> sp.
Perennial animal boring		Animals	Species that bore into the substrate	<i>Rocellaria dubia</i> , <i>Lithophaga lithophaga</i> , <i>Cliona</i> spp.
Perennial animal cup		Animals	Cup-like or tooth-like animals	<i>Balanophyllia europaea</i> , <i>Caryophyllia inornata</i>
Perennial animal encrusting		Animals	Species growing as crusts over hard substrate, typically not higher than 2–3 cm	<i>Crambe crambe</i> , <i>Phorbas</i> spp., <i>Reptadeonella violacea</i>
Perennial animal massive		Animals	Large invertebrates with an upright growth form	<i>Sarcotragus foetidus</i> , <i>Ircinia</i> spp.
Perennial animal tree		Animals	Branching or tree-like invertebrates	<i>Axinella</i> spp., <i>Adeonella</i> spp., <i>Myriapora truncata</i>
Perennial tube forming animals		Animals	Organisms creating calcareous tubes	<i>Polychaeta</i>
Bare rock		Substrate	Bare rock areas	
Substrate pebbles/sand		Substrate	Soft motile sediment: pebbles, sand, biogenic substrate	
Substrate holes		Substrate	Holes in the substrate	
Unidentified substrate		Substrate	Unclear parts of the image	

2.2.2. AI-Assisted Tool Selection

An extensive review was undertaken to identify existing artificial intelligence (AI) tools employing machine learning and deep neural networks for the automatic or semi-automatic annotation and quantification of benthic images. A comprehensive market analysis was performed to capture a broad spectrum of potentially relevant AI-based solutions. Adopting a snowball sampling strategy—combining a systematic literature review, backward and forward citation tracking, and targeted web-based searches (including the use of ChatGPT [GPT-4, accessed via the ChatGPT Plus subscription in July 2024])—over 30 distinct tools were identified and assessed based on predefined criteria (Supplementary Table S3). These criteria aimed to select a platform capable of: (a) performing automated or semi-automated annotation of benthic images using AI; (b) AI-assisted calculation of species cover; (c) handling the annotation of multiple habitat types and taxa within a single image; (d) enabling AI training with pre-annotated image datasets; (e) operating without the need for specialized hardware or proprietary software; and (f) being freely accessible. Based on this evaluation, CoralNet (<https://coralnet.ucsd.edu/>; Version 1.0) [46] was selected as the most suitable tool for this study.

2.2.3. AI-Assisted Tool Description

CoralNet is a free, open-source, web-based repository and collaboration platform for benthic image analysis, developed at the University of California, San Diego [46] (<https://coralnet.ucsd.edu/>; Version 1.0; accessed on 5 May 2025). It employs AI for fully or semi-automated point-based annotation of benthic images.

After manually annotating a subset of images, an initial classifier—a supervised learning model based on a convolutional neural network, trained iteratively on confirmed point annotations to classify benthic substrate categories—is trained and used to automatically generate annotations for the remaining images, which are then marked as “unconfirmed.” In the annotation interface, suggested labels appear for each point, accompanied by posterior probability values indicating the classifier’s confidence in each prediction. As more images are confirmed, the classifiers are iteratively retrained.

Administrators (CoralNet users authorized to edit the source or project) can set a confidence threshold, above which point annotations are automatically accepted. By default, this threshold is set to 100%, essentially turning off auto-confirmation since posterior probabilities never reach this level. To activate auto-confirmation, administrators can consult built-in diagnostic tools that help to determine an optimal threshold balancing manual workload and performance. For classifier validation, the confirmed dataset is split into eight subsets, with seven used for training and one for testing. The accuracy is calculated by comparing manual annotations with automated annotations generated using CoralNet for the test subset.

In this study, a CoralNet source (project) was created using a uniform grid (10×10) point sampling scheme (mirroring photoQuad’s 100-point layout) and a label set comprising the 23 predefined categories (algae, invertebrates, substrate; Table 1). The confidence threshold was set to 100% to retain complete control over annotation verification.

2.2.4. Data Import Bridge

To enable data transfer from photoQuad to CoralNet, a custom MATLAB (Version 2012a, access date is not applicable) script was developed. Since photoQuad does not export point coordinates in pixel units, the script batch-parses the photoQuad layer files and automatically generates a CoralNet-ready CSV file per image, including each point’s pixel coordinates and assigned label (Figure 2).

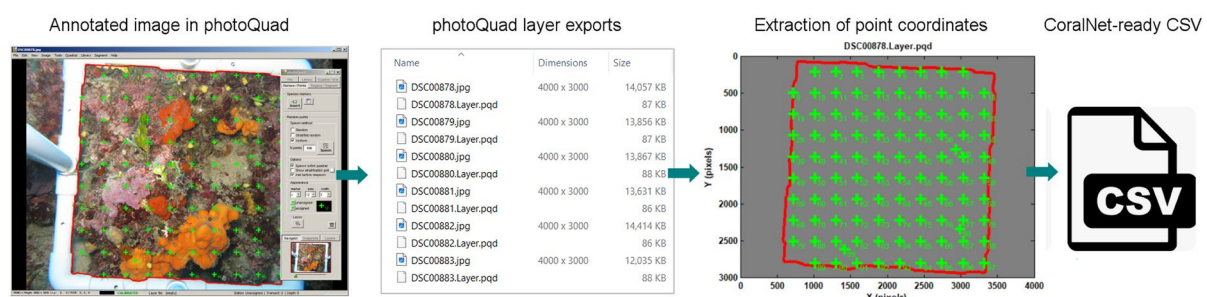


Figure 2. Processing pipeline of the automatic conversion of the photoQuad layer files to CoralNet-ready CSVs.

2.3. Training Dataset Preparation

2.3.1. Annotation Process

The image dataset, organized by depth zone per station (i.e., depth station), was randomly split into two subsets: a training subset, used to train CoralNet’s classifier with manual annotations from photoQuad [57]; and an evaluation subset, used to validate CoralNet’s automated annotations by comparing them with the manually annotated images. The training subset included 26 stations at 0 m (12 from the North Aegean,

14 from the South Aegean), 44 stations at 5 m (21 North, 23 South), and 15 stations at 15 m (8 North, 7 South). The evaluation subset comprised 26 stations at 0 m (15 North, 11 South), 45 stations at 5 m (23 North, 22 South), and 14 stations at 15 m (10 North, 4 South) (Supplementary Table S4). Depth zones and geographic regions were balanced across subsets, while random station assignment was used to reduce selection bias.

2.3.2. Number of Images Used in Training Sets

CSV files containing manual photoQuad annotations were progressively imported into CoralNet in 11 systematic iterations, increasing the number of confirmed images by 122–128 per iteration (Table 2) to trigger 10 sequential classifier updates. As the model accuracy improved, CoralNet automatically retrained the source's predictive model during this iterative learning process. The final classifier (using the entire training subset), which achieved the highest accuracy, was used to annotate the evaluation subset, and its outputs were compared with manual annotations to assess performance.

Table 2. List of classifiers triggered per iteration, number of confirmed images used to train the classifiers, number of images added in every iteration, classifier ID, and accuracy (confidence threshold 0%).

Iteration	Classifier Number	Number of Confirmed Images the Classifiers Were Trained On	Number of Confirmed Images Added to Trigger the Next Classifier	Classifier ID	Classifier's Accuracy
1	-	36	122	54,712	-
2	1	158	123	54,735	55%
3	2	281	126	54,737	58%
4	3	407	126	54,741	60%
5	4	533	126	54,759	61%
6	*	659	126	-	-
7	5	785	126	54,863	63%
8	**	911	128	-	-
9	6	1039	124	54,890	64%
10	7	1163	122	54,905	65%
11	8	1285	-	54,922	66%

* Not accepted as the source's new classifier. Highest accuracy among previous classifiers on the latest dataset: 0.67; threshold to accept new: 0.68; accuracy from this training: 0.67. ** Not accepted as the source's new classifier. Highest accuracy among previous classifiers on the latest dataset: 0.67; threshold to accept new: 0.67; accuracy from this training: 0.66.

2.4. Reef-EBQI Index Calculations

Reef-EBQI [8] is an ecosystem-based index designed to provide a comprehensive indication of the health status of Mediterranean phytophilous rocky reef communities using key trophic and functional groups (i.e., from macroalgae to invertebrates and fish of different trophic status, and birds). It has been implemented in several Mediterranean regions, including the Aegean Sea [8,57,63]. In this study, the reef-EBQI was used to compare health status assessments derived from CoralNet annotations with those obtained through manual annotations at the level of depth station. Its application here focuses solely on the vegetative elements of the upper sublittoral zone.

To meet the reef-EBQI requirements, macroalgal categories were grouped into three morphofunctional types (arborescent perennial, shrubby, and turf/encrusting algae), representing different vertical layers of multicellular photosynthetic life. The percent cover of each type was recalculated per image, excluding sessile invertebrates. Following Thibaut et al. [8], only the topmost visible layer in each image was considered, assuming that lower layers grow beneath it. Based on the dominant cover type, each image received a reef-EBQI score from 4 (highest condition) to 0 (lowest) (Supplementary Table S5). These

scores were normalized to a 0–10 scale and averaged per depth and station to assign one of five ecological quality classes: Bad, Poor, Moderate, High, and Very High, following the classification system used by Thibaut et al. [8] (Supplementary Table S6). Maps visualizing the station-level ecological status were produced using QGIS (version 3.40.1—Bratislava).

To compare the manual and automated approaches, reef-EBQI index values were examined at the depth station level. The training subset (consisting of 1285 images), used to train CoralNet’s classifiers with photoQuad annotations, overlaps with Savin et al. [57] and was therefore excluded from a direct comparison. The methodological comparison focused on the evaluation subset (consisting of 1252 images), where annotations were generated solely using CoralNet’s classifier. Spearman’s ρ and Pearson’s r correlation coefficients were calculated to quantify the strength of the relationship between the two sets of results. A confusion matrix was generated to visualize the magnitude of the differences between reef-EBQI values derived from photoQuad and CoralNet per depth station within the evaluation subset.

2.5. Additional CoralNet Training for Accuracy Improvement

Following the calculation of the reef-EBQI index, additional iterations were conducted using the full pre-annotated dataset (including the subset previously used for evaluation) to assess the effect of extended training on the classifier performance.

All the images (2537) were confirmed within the CoralNet platform by uploading the corresponding annotation CSV files. As per CoralNet’s retraining logic, seven additional classifier updates were automatically triggered at each 10% increment in confirmed images. After each retraining event, the classifier performance was evaluated using CoralNet’s internal threshold sweep and validation framework. The objective was to quantify changes in classification accuracy and the proportion of high-confidence predictions across successive training stages.

3. Results

3.1. Automated Annotation Classifier Training

Following 11 iterations and the progressive import of 1285 manually annotated images into CoralNet (representing half of the total dataset), eight classifiers were successfully trained, while two were discarded due to lower accuracy compared with earlier versions. The classifier accuracy improved with the number of confirmed images: the initial classifier, trained on 158 images, achieved 55% accuracy, whereas the final classifier, trained on 1285 images, reached 66% accuracy (Table 2; Figure 3).

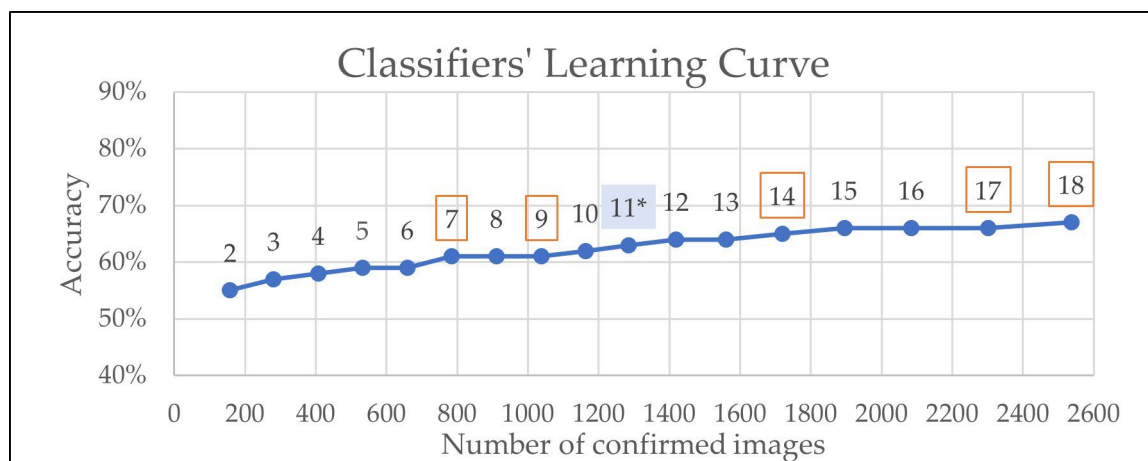


Figure 3. Learning curve of all the triggered classifiers and the number of images that each classifier was trained on (0% confidence threshold). Reef-EBQI values were estimated with annotations from

iteration 11 (marked with an asterisk and a light blue colored box on the plot). Red colored boxes indicate iterations whose classifiers were not accepted as the source's new classifier. Iterations 12–18 represent the additional training of CoralNet for accuracy improvement.

Accuracy estimates were calculated using a confidence threshold of 0%; as expected, increasing this threshold improves the overall accuracy while decreasing the number of high-confidence automatically confirmed point annotations (Figure 4). This trade-off directly influences the time required for manual verification during annotation. In this study, the confidence threshold was kept at 100% to retain complete control and avoid the automatic confirmation of points. However, lowering the threshold to 65% would yield 77.4% accuracy, with 10,263 points automatically confirmed, equivalent to approximately 100 fully annotated images (at 100 points per image).

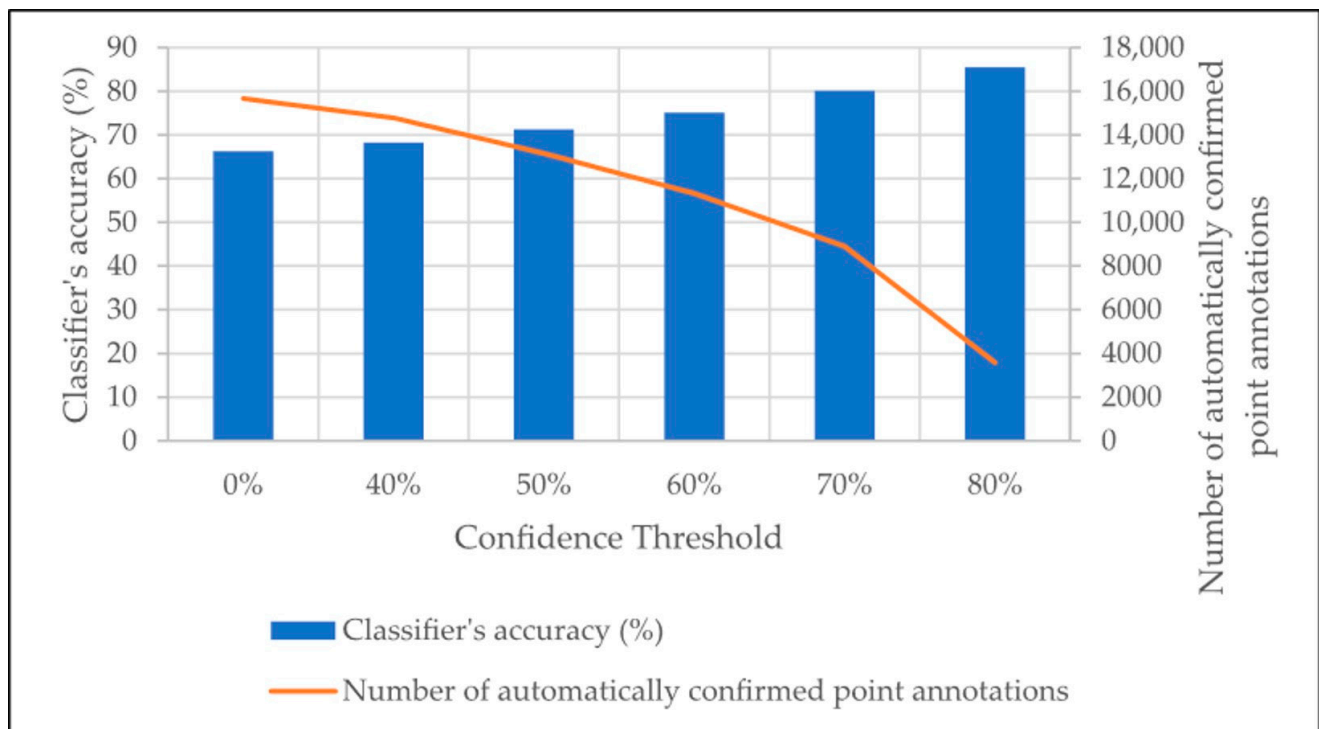


Figure 4. Accuracy (blue bars) and number of automatically confirmed annotation points (orange line) in different confidence thresholds of classifier number 8 (iteration 11), which was used to annotate the evaluation subset for the comparison of reef-EBQI values.

3.2. Comparison of Ecosystem Health Index Outputs

Reef-EBQI values were estimated per depth station in both subsets (training and evaluation), and the ecological status characterization was assigned using those values (Figures 5, S2 and S3).

Among the 85 depth stations in the evaluation subset, the ecological status classifications showed a relatively high consistency between methods (Supplementary Table S7): 10 cases were rated higher using manual annotation, 1 using the CoralNet approach, and 74 received identical ratings, yielding 87% agreement overall (Table 3). Discrepancies largely reflected lower reef-EBQI scores in the AI approach (up to four status classes difference).

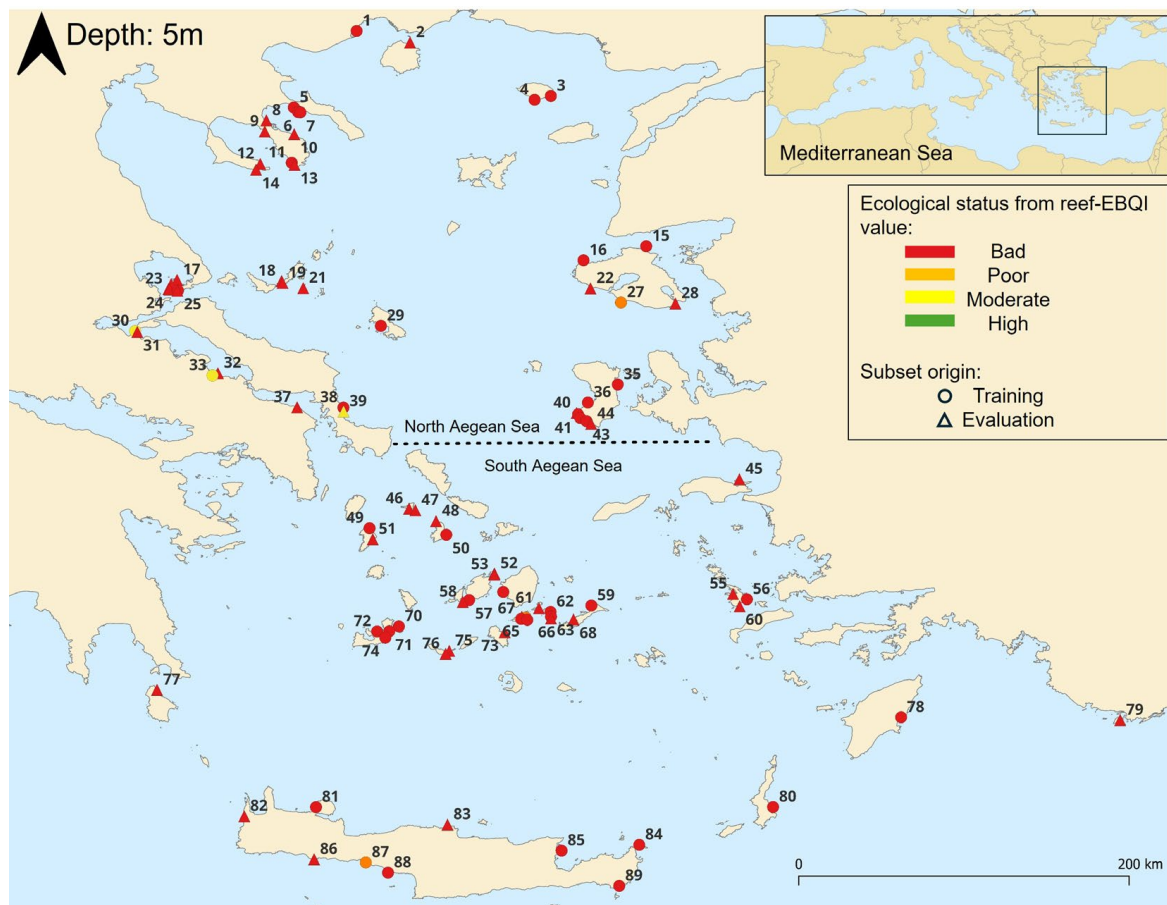


Figure 5. Map depicting the ecological status according to the reef-EBQI index for each station at the 5 m depth zone. Stations with red color represent “Bad”, orange color represents “Poor”, yellow represents “Moderate”, and green represents “High” ecological status. Triangles represent stations from the evaluation subset (CoralNet’s automated annotations), while circles represent stations from the training subset (manual annotations).

Table 3. Confusion matrix depicting the number of depth stations from the evaluation subset that were annotated both manually (X-axis) and automatically in CoralNet (Y-axis), and their ecosystem status ranking according to each approach. Stations assessed as higher by the manual approach are depicted in shades of orange, stations ranked similarly by both approaches are shown in shades of green, and stations assessed as higher by the AI approach are displayed in shades of blue.

	Ecological Status	Manually Annotated			
		Bad	Poor	Moderate	High
AI Annotated	Bad	64	1		2
	Poor		5	4	1
	Moderate			3	
	High				2
	Very High			1	

The correlation analysis between reef-EBQI values derived from CoralNet annotations and those from manual photoQuad annotations [57] revealed a strong concordance, with Spearman’s $\rho = 0.91$ and Pearson’s $r = 0.84$.

A confusion matrix was created showing which labels the classifier performs better or worse on, and which labels it frequently confuses with other labels (Table 4). The diagonal elements indicate the number of correctly classified points for each label, while

the off-diagonal values represent misidentifications. High values along the diagonal suggest that the classifier performs well for several dominant labels. For instance, the first classes (namely, ‘Turf algae’, ‘Bare rock’, and ‘Shrubby algae 2’) show notably high true positive counts (respectively: 5385, 775, 718), indicating a strong predictive accuracy. However, a degree of misidentification is evident, particularly among visually or morphologically similar classes, as seen in the off-diagonal dispersion in the upper rows (e.g., other labels being misclassified as ‘Turf’). Some classes, especially those with fewer samples, exhibit higher rates of confusion (e.g., Animal turf, Canopy-forming macrophytes 2) (Supplementary Table S8). This suggests a class imbalance and possibly overlapping features that affect the classifier performance. Overall, while the model performs well on abundant and distinct classes, there is room for improvement in distinguishing less-represented or more similar categories.

Table 4. Confusion matrix illustrating the classification performance across multiple classes, with true labels represented on the horizontal axis and predicted labels on the vertical axis. The color range is representative of the number of point annotations for each label.

Turf algae	5385	406	122	102	77	102	30	32	25	25	4	1	1	3	0	1	0
Encrusting calcareous algae	962	1148	119	37	30	11	12	3	12	2	3	0	2	0	0	0	0
Substrate: bare rock	653	187	775	13	6	75	3	0	11	1	7	0	1	0	0	0	0
Shrubby algae 2	291	20	2	718	20	4	6	19	0	14	1	5	2	0	0	5	0
Articulated calcareous algae 1	223	19	11	17	524	7	0	16	1	4	1	1	0	0	0	1	0
Substrate: pebbles/sand	339	22	75	13	1	326	5	1	2	0	1	0	0	2	0	0	0
Perennial animal massive	57	9	0	5	1	1	596	0	10	2	12	0	0	0	0	0	0
Canopy-forming macrophytes 1	181	19	0	4	6	0	0	361	0	1	0	0	0	0	0	0	0
Perennial animal encrusting	215	43	17	4	1	4	55	0	214	0	7	1	0	1	0	0	0
Shrubby algae 1	68	5	1	15	6	1	1	0	0	261	0	0	0	0	0	0	0
Perennial animal boring	92	8	18	1	1	6	4	1	20	0	37	0	0	0	0	0	0
Articulated calcareous algae 2	28	1	0	5	0	0	0	0	0	8	0	23	0	0	0	0	0
Shrubby algae 3	40	5	1	1	0	1	0	0	0	0	0	0	3	0	0	0	0
Mucilaginous	15	0	1	10	0	1	0	0	0	0	0	0	0	14	0	0	0
Unidentified	12	0	0	1	0	0	2	0	0	0	0	0	0	0	0	0	0
Animal turf	5	0	0	1	2	0	0	0	0	0	0	0	0	0	0	0	0
Canopy forming macrophytes 2	0	0	0	2	0	0	0	4	0	0	0	0	0	0	0	0	0
	Turf algae	Encrusting calcareous algae	Substrate: bare rock	Shrubby algae 2	Articulated calcareous algae 1	Substrate: pebbles/sand	Perennial animal massive	Canopy forming macrophytes 1	Perennial animal encrusting	Shrubby algae 1	Perennial animal boring	Articulated calcareous algae 2	Shrubby algae 3	Mucilaginous	Unidentified	Animal turf	Canopy-forming macrophytes 2

3.3. Additional CoralNet Training for Accuracy Improvement

Successive retraining with the full dataset led to improvements in classifier accuracy. The initial classifier (number 8), trained on 1285 confirmed images, yielded an initial accuracy of 66% (confidence threshold 0%). As more annotated images were added, the

accuracy of classifier number 8 dropped to 63%, while after the full confirmation of all 2537 images, the accuracy of classifier number 12 (iteration 18) reached 67% (confidence threshold 0%) (Table 5).

Table 5. Complete list of classifiers triggered per iteration (including the additional training), number of confirmed images used to train the classifiers, and accuracy (confidence threshold 0%). Reef-EBQI values were estimated with annotations from iteration 11 (marked with an asterisk).

Iteration	Classifier Number	Number of Confirmed Images the Classifiers Were Trained on	Classifier's Accuracy
1	NA	36	-
2	1	158	55%
3	2	281	57%
4	3	407	58%
5	4	533	59%
6	NA	659	59%
7	5	785	61%
8	NA	911	61%
9	6	1039	61%
10	7	1163	62%
11 *	8	1285	63%
12	9	1419	64%
13	NA	1561	64%
14	10	1720	65%
15	11	1895	66%
16	NA	2085	66%
17	NA	2302	66%
18	12	2537	67%

NA: Not accepted as the source's new classifier.

Correspondingly, the proportion of point annotations exceeding the 70% confidence threshold increased from 8903 (classifier 8) to 17,130 (classifier 12), allowing for more automated confirmations during annotation. These findings demonstrate the effectiveness of iterative training using a complete, high-quality annotated dataset to enhance classifier reliability in large-scale benthic monitoring workflows.

4. Discussion

Despite the relatively low accuracy of CoralNet's classifier (66%), the application of the reef-EBQI index and the ecological status classification on the automatically annotated images showed an 87% agreement with those estimated using manual annotations. This indicates that ecological indices can integrate functional information in a way that reduces the impact of misclassifications in individual categories. Our findings suggest that ecological indices, such as reef-EBQI, can buffer against moderate classification errors, highlighting their robustness as tools for AI-assisted monitoring and the importance of further testing their sensitivity to temporal ecological changes.

The image dataset spanned a broad geographic area, with a balanced representation of North and South Aegean sites, covering distinct depth zones across both islands and mainland coasts. Although the habitat types and environmental conditions (such as turbidity, light availability, and nutrient levels) varied considerably, the CoralNet classifier generated macroalgal cover estimates with sufficient accuracy compared with the manual annotations, thereby enabling the subsequent calculation of reef-EBQI scores with a certain confidence. This demonstrates the feasibility of deploying regional-scale, AI-assisted image analysis to meet monitoring and research demands more efficiently.

Achieving higher classification accuracy requires addressing several technical and ecological limitations that are inherent to AI-assisted annotation. Image quality is a critical factor, as issues such as illumination conditions, color aberration, turbidity, blurred spots, and lens distortion can hinder both human and machine interpretation [46,64–66]. Because CoralNet learns from image features, such as color, shape, and texture, poor image quality compromises the classifier performance [52]. Environmental variability, e.g., due to wave exposure in shallow zones or changing light regimes, can further affect the image clarity and morphology of sessile organisms, increasing the annotation uncertainty [51]. However, our dataset consisted of images taken with the same camera and artificial light conditions, resulting in consistent image quality throughout the dataset. Environmental conditions varied among the sampling stations, but no station was characterized by significant turbidity. Future projects should incorporate explicit image quality metadata and stratified training/evaluation designs to allow a quantitative assessment of how factors such as turbidity or illumination conditions influence the classifier performance and the robustness of derived ecological indices.

Complex benthic structures also pose challenges, especially in habitats with dense or branched macroalgae that obscure underlying layers, or substrates with crevices and topographic variation. The limitations of photoquadrat methods in capturing three-dimensional habitat complexity constrain the accuracy of cover estimates in macroalgae-dominated reefs [52]. Additional complications arise from patchiness, indistinct boundaries, complex and varying growth forms, and taxonomic ambiguity [51].

Label design plays an important role in the classifier performance [67]. In this study, each label corresponded to a morphofunctional group, encompassing multiple morphologically diverse genera or species, which introduced variability and reduced classification accuracy. These issues have been documented in other studies using functional group labels, especially for algae [46,51–53,68]. The “turf” category proved particularly problematic, as it spans a broad range of visual characteristics, from nearly bare, cropped substrates to thick, multi-layered mats, with substantial differences in color, texture, and shape, making both manual and automated classification error-prone [52,68]. Refining label definitions could reduce variability and improve classifier accuracy [46]. Nevertheless, morphofunctional level annotations overall simplify the classification procedure compared with species level labels, which is essential, especially in the manual annotation process.

Class imbalance in training datasets is another challenge, as models tend to prioritize dominant labels while underrepresenting or misclassifying rarer ones [66]. In our case, canopy-forming macroalgae—key indicators of healthy reefs—were underrepresented (1.7% cover), reflecting their rarity in the Aegean (Supplementary Table S8). This likely led to the misclassification and underestimation of ecological conditions in specific cases where manual annotations indicated “Very High” or “High” reef-EBQI scores but CoralNet produced much lower values (i.e., at certain depths in stations 5, 9, 30, 38, and 63; Supplementary Table S7). As values above 7.5 require >50% cover of arborescent perennial macroalgae, their omission by CoralNet highlights the classifier’s difficulty in identifying canopy-forming macroalgae, a very important group affecting ecological status. Future monitoring projects should therefore prioritize targeted sampling or dataset enrichment for rare but ecologically important functional groups, such as canopy-forming macroalgae, to improve classifier training and reduce the underestimation of high ecological status. In parallel, future research should also test how the accuracy changes depending on the level of aggregation of morphofunctional categories versus lower taxonomic classifications, and explore AI platforms that allow weighted training strategies to mitigate class imbalance.

While human annotations serve as the current benchmark for AI performance, they are not free from error. Misidentifications by experts and inconsistencies among multiple

annotators can introduce variability that is comparable with that seen between human and machine outputs [47,66]. Indeed, variability among expert annotators is often comparable in magnitude with the differences observed between the CoralNet and aggregated manual results under consistent classification schemes [68]. To reduce these sources of error, standardized annotation protocols are essential in improving the quality of training datasets and the reliability of AI outputs [66].

Developing effective automated tools also requires careful planning of the training strategy. The model must be exposed to a sufficiently large and diverse dataset to generalize well without overfitting. Too little training data reduces the predictive accuracy [66]. In this study, the available dataset was divided between the training and evaluation subsets to allow method comparison, which constrained the total number of images available for classifier training. However, expanding the dataset by also including annotations from the evaluation subset slightly enhanced the performance.

AI-assisted annotation cannot currently completely replace expert-led analyses of benthic imagery; it complements them by accelerating processing and enabling broader spatial coverage. CoralNet-derived outputs should be treated as screening-level assessments that guide targeted expert checks, particularly near ecological-status class boundaries, for under-represented functional groups, and where image conditions are suboptimal. For deployment, we recommend documenting image-quality metadata, adopting stratified designs that explicitly test robustness across conditions, and pre-defining quality-control procedures (e.g., verification rules, confidence thresholds), so that accuracy–throughput trade-offs are transparent and reproducible.

5. Conclusions

This study demonstrates that reef-EBQI index assessments derived from automated image analysis using CoralNet are comparable with those obtained through manual annotation. Leveraging a pre-existing annotated dataset enabled efficient classifier training and facilitated direct methodological comparison. The adequate estimation of benthic cover across varied shallow-water rocky habitats highlights the potential of automated tools to enhance the scale and efficiency of benthic monitoring. Even when integrated into human-based workflows, such tools can alleviate the bottlenecks of manual image analysis, lower the associated costs, and enable the analysis of more extensive datasets. Moreover, integrating automated image analysis with citizen science initiatives under a standardized protocol presents a valuable opportunity to expand participation, generate large-scale consistent datasets, and support conservation, management, and research efforts. However, automated tools, such as CoralNet, should be deployed as cost-efficient, scalable complements to expert workflows, paired with standardized protocols and targeted quality control to ensure reliable ecological status assessments across variable conditions.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/jmse13091721/s1>, Table S1: List of sampling stations, with coordinates in Decimal Degrees, subregion (North or South Aegean Sea and the use of data per depth zone. The purple-colored cells display data used for training CoralNet, and the yellow-colored cells correspond to data used for evaluating the classifier; Table S2: Number of image samples taken per depth zone and subregion; Table S3: The 30 tools and software identified using the snowball approach, along with their characteristics. Among these, CoralNet was chosen for the present study; Table S4: Number of stations per depth zone used for training and evaluation of CoralNet's classifier; Table S5: Reef-EBQI strata of multicellular photosynthetic organisms (MPOs), their corresponding macroalgal/substrate categories of the current study, MPOs percentage area cover categories, their respective reef-EBQI grades and rescaled scores [8,57]; Table S6: Ecological status characterization and range values of the reef-EBQI index [8]; Table S7: Comparison of reef-EBQI values and correspond-

ing ecological status of the evaluation subset estimated in the present study with those published by [57]; Table S8: Number of annotated points per label category in the entire dataset and the training dataset; Figure S1: Indicative example images of label categories used for annotations: (i) Algal turf, (ii) Encrusting calcareous algae, (iii) Non-calcareous encrusting algae, (iv) Articulated calcareous algae 1, (v) Articulated calcareous algae 2, (vi) Shrubby algae 1, (vii) Shrubby algae 2, (viii) Shrubby algae 3, (ix) Canopy forming macrophytes 1, (x) Canopy forming macrophytes 2, (xi) Massive algae, (xii) Mucilaginous, (xiii) Animal turf, (xiv) Perennial animal boring, (xv) Perennial animal cup, (xvi) Perennial animal encrusting, (xvii) Perennial animal massive, (xviii) Perennial animal tree, (xix) Perennial tube forming animal, (xx) Bare rock, (xxi) Substrate: pebbles/sand, (xxii) Substrate holes. If a point does not fall into the categories above, then it is characterized as “un-identified”; Figure S2: Map depicting the Ecological Status equivalent of the reef-EBQI index of each station at the 0 m depth zone. Stations with red color represent “Bad”, orange color represents “Poor”, yellow represents “Moderate”, and green represents “High” ecological status. Triangles represent stations from the evaluation subset (CoralNet’s automated annotations), while circles represent stations from the training subset (manual annotations).; Figure S3: Map depicting the Ecological Status equivalent of the reef-EBQI index of each station at the 15 m depth zone. Stations with red color represent “Bad”, orange color represents “Poor”, yellow represents “Moderate”, and green represents “High” ecological status. Triangles represent stations from the evaluation subset (CoralNet’s automated annotations), while circles represent stations from the training subset (manual annotations).

Author Contributions: Conceptualization, M.Z., S.K. and A.D.M.; methodology, M.S. and V.T.; software, V.T.; validation, M.Z., M.S., V.T. and S.K.; formal analysis, M.Z.; data curation, M.Z. and N.G.; writing—original draft preparation, M.Z.; writing—review and editing, M.Z., M.S., V.T. and S.K.; visualization, M.Z.; supervision, M.S., V.T. and S.K.; project administration, A.D.M. and S.K.; funding acquisition, M.Z., M.S., V.T., A.D.M. and S.K. All authors have read and agreed to the published version of the manuscript.

Funding: This study was supported by the project NEMO-Tools (next-generation monitoring and mapping tools to assess marine ecosystems and biodiversity) and carried out within the framework of the National Recovery and Resilience Plan Greece 2.0, funded by the European Union—NextGenerationEU (implementation body: HFRI)—project number: 16035. The views and opinions expressed are, however, those of the beneficiaries only and do not necessarily reflect those of the European Union. Neither the European Union nor the granting authority can be held responsible for them.

Data Availability Statement: The data presented in this study are available upon request from the corresponding author due to the large image dataset used in the study and the numerous Supplementary Files that accompany the image dataset.

Conflicts of Interest: The authors declare no conflicts of interest.

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