



## AI-Based Aquatic Plastic Waste Detection Using Underwater Image Processing and Deep Learning Algorithms

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### Abstract

Aquatic plastic waste has become a major environmental threat because plastic debris affects marine organisms, degrades water ecosystems, and reduces the ecological and economic value of aquatic environments. Conventional monitoring of underwater plastic pollution depends on manual visual inspection, diver surveys, net sampling, and image-based field observation, which are time-consuming, labor-intensive, and limited by water turbidity, illumination variation, occlusion, and large spatial coverage requirements. To address these limitations, this paper proposes an AI-based aquatic plastic waste detection framework using underwater image processing and deep learning algorithms. The proposed system combines underwater image acquisition, image enhancement, plastic object detection, semantic segmentation, and pollution severity assessment. Underwater images are first preprocessed using color correction, denoising, contrast enhancement, and normalization. A YOLO-based detection module identifies plastic objects such as bottles, bags, wrappers, fishing nets, and mixed debris. A U-Net segmentation module extracts pixel-level plastic regions for area estimation, while CNN-based feature learning supports classification of plastic and non-plastic objects. K-means clustering and Random Forest-based decision analysis are used to group monitoring zones and estimate pollution severity. The performance is evaluated using precision, recall, F1-score, intersection over union, mean average precision, and pollution severity classification. The proposed framework provides an efficient decision-support method for aquatic plastic pollution monitoring, underwater robotic surveys, environmental assessment, and sustainable cleanup planning.

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## 1. Introduction and Related Work

Plastic pollution has become one of the most serious threats to aquatic and marine ecosystems. Large quantities of mismanaged plastic waste enter rivers, lakes, coastal zones, and oceans through human activity, urban runoff, fishing operations, tourism, and poor waste management practices. Jambeck et al. reported that land-based plastic waste is a major contributor to ocean pollution, emphasizing the need for improved monitoring and management strategies [1]. The continuous production and disposal of plastics have further increased environmental concern because plastics persist for long periods and fragment into smaller particles that can affect aquatic life and food chains [2].

Plastic debris in aquatic environments creates ecological, economic, and social impacts. It can entangle aquatic organisms, be ingested by fish and marine animals, transport invasive species, reduce tourism value, and affect fisheries. Law discussed the persistence and distribution of plastics in the marine environment, highlighting the complexity of plastic transport, degradation, and ecological interaction [3]. In addition to direct removal, policy-based control of single-use plastics and microplastics has been identified as an important strategy to reduce marine pollution [4]. However, policy implementation must be supported by reliable detection, quantification, and mapping of plastic waste in aquatic environments.

Traditional aquatic plastic monitoring methods include manual shoreline surveys, diver-based observation, trawl sampling, visual inspection from boats, and remote sensing. These methods provide useful information, but they are limited by human effort, survey cost, low temporal resolution, and environmental conditions. Underwater visual monitoring is especially difficult because underwater images suffer from color distortion, scattering, light attenuation, turbidity, shadows, and object occlusion. Therefore, automated underwater image processing methods are required to support continuous and scalable plastic waste detection.

Recent advances in artificial intelligence and deep learning have improved object detection and image segmentation performance. Fulton et al. demonstrated that deep visual detection models can be used for robotic detection of marine litter in underwater environments [5]. The TrashCan dataset further supported underwater marine debris research by providing images with bounding box and segmentation annotations for object detection and semantic segmentation [6]. Such datasets are important for training AI models that can distinguish plastic objects from rocks, plants, sand, animals, and other underwater background structures.

Object detection algorithms such as YOLO are suitable for real-time plastic waste detection because they predict object locations and class probabilities in a single forward pass [7]. Segmentation architectures such as U-Net are useful for identifying pixel-level plastic regions and estimating polluted area [8]. Region-based detectors such as Faster R-CNN provide strong localization performance but may require higher computational effort compared with single-stage detectors [9]. Deep residual networks support feature extraction in complex image recognition tasks and can be used as backbones in aquatic plastic detection models [10]. In addition, Random Forest and K-means clustering can support pollution severity classification and monitoring-zone grouping [11], [12].

The proposed work develops a complete AI-based aquatic plastic waste detection framework using underwater image processing and deep learning algorithms. The framework integrates preprocessing, object detection, semantic segmentation, classification, severity estimation, and decision support. The objective is to provide an automated system that can detect visible plastic debris in underwater images, classify plastic type, estimate affected area, and support cleanup prioritization for aquatic environmental studies.

## 2. Methodology

The methodology of the proposed system consists of six major stages: underwater image acquisition, image preprocessing, plastic object detection, semantic segmentation, pollution severity assessment, and decision support. The proposed architecture is shown in Fig. 1.

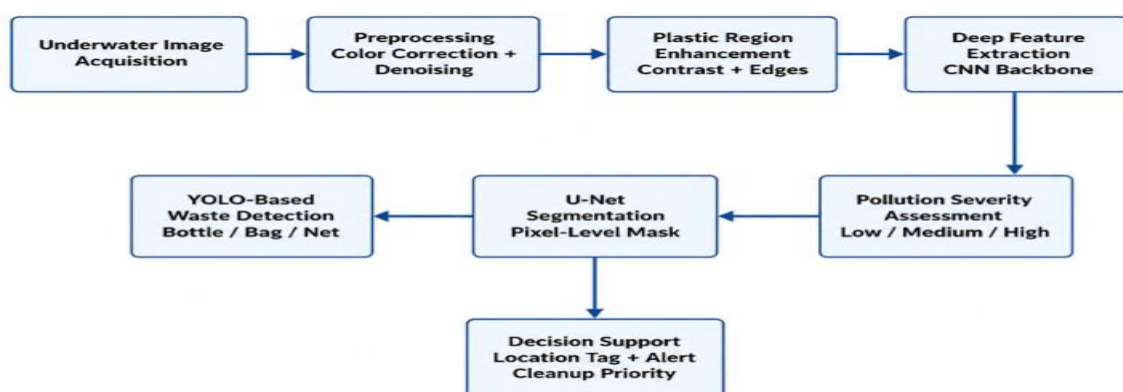


Fig. 1. Proposed AI-based aquatic plastic waste detection architecture.

## 2.1 Underwater Image Acquisition

The first stage of the system is underwater image acquisition. Images or video frames can be obtained from underwater cameras, remotely operated vehicles, autonomous underwater vehicles, diver-mounted cameras, or fixed monitoring stations. The acquired images may contain plastic bottles, bags, nets, wrappers, ropes, cans, and mixed debris. In aquatic environments, visual quality may be affected by turbidity, uneven illumination, marine growth, low contrast, and object overlap. Therefore, image enhancement is required before detection.

## 2.2 Image Preprocessing and Enhancement

The preprocessing stage improves underwater image quality and prepares the data for deep learning analysis. The main operations include resizing, denoising, color correction, white balancing, contrast enhancement, and normalization. Since underwater images often appear bluish or greenish due to wavelength-dependent absorption, color correction improves object visibility. Normalization scales pixel values into a common range and reduces intensity variation across different images.

$$I_n(x, y) = \frac{I(x, y) - I_{\min}}{I_{\max} - I_{\min}} \quad (1)$$

## 2.3 Plastic Object Detection Using YOLO

After preprocessing, plastic objects are detected using a YOLO-based deep learning model. YOLO is selected because it provides high-speed object detection and is suitable for real-time environmental monitoring. The model predicts bounding boxes, objectness confidence, and class labels for visible plastic objects. The detected classes may include plastic bottle, plastic bag, wrapper, fishing net, rope, container, and mixed debris. Object localization performance is measured using intersection over union between the predicted bounding box and ground-truth bounding box.

$$IoU = \frac{\text{Area}(B_p \cap B_g)}{\text{Area}(B_p \cup B_g)} \quad (2)$$

## 2.4 Plastic Region Segmentation Using U-Net

Object detection gives the location of plastic waste, while segmentation provides pixel-level plastic region extraction. In the proposed system, U-Net is used to generate segmentation masks for plastic regions. The encoder part extracts deep features, while the decoder part restores spatial resolution and generates a binary or multiclass mask. Segmentation is useful for estimating the area covered by plastic waste and for separating plastic objects from background regions such as sand, rocks, plants, and water.

## 2.5 Pollution Severity Assessment

The detected objects and segmented plastic masks are used to estimate aquatic pollution severity. Object count, plastic-covered area, confidence score, and monitoring-zone location are considered for severity calculation. The system categorizes aquatic zones into low, medium, high, and critical pollution levels. A confidence score combines detection probability and class probability to represent reliability of the detected object.

$$C_d = P(\text{object}) \times P(\text{class} | \text{object}) \quad (3)$$

## 2.6 AI Algorithms Used in the Proposed System

The proposed framework uses multiple AI algorithms to address different stages of aquatic plastic waste monitoring. CNN-based feature extraction learns spatial patterns from underwater images. YOLO detects plastic objects, U-Net performs plastic region segmentation, Random Forest classifies pollution severity using extracted features, and K-means clustering groups monitoring zones based on waste density and environmental similarity.

**Table 1.** Underwater Imaging Challenges and Preprocessing Responses.

Challenge	Effect on detection	Preprocessing response
Color distortion	Plastic objects may appear similar to background	White balancing and color correction
Turbidity	Object boundaries become unclear	Denoising and contrast enhancement
Low illumination	Small plastic debris may be missed	Brightness correction and CLAHE
Occlusion	Waste may be partially hidden	Multi-scale detection and segmentation
Background similarity	False detections may increase	CNN feature learning and object confidence filtering

**Table 2.** AI Algorithms Used in the Proposed Aquatic Plastic Waste Detection System.

Algorithm	Purpose in proposed system	Output
CNN	Automatic feature extraction from underwater images	Deep visual feature maps

YOLO detector	Real-time plastic waste localization	Bounding boxes and class labels
U-Net	Pixel-level segmentation of plastic regions	Plastic mask and affected area
Random Forest	Pollution severity classification	Low, medium, high, or critical class
K-means clustering	Grouping of monitoring zones	Waste-density clusters

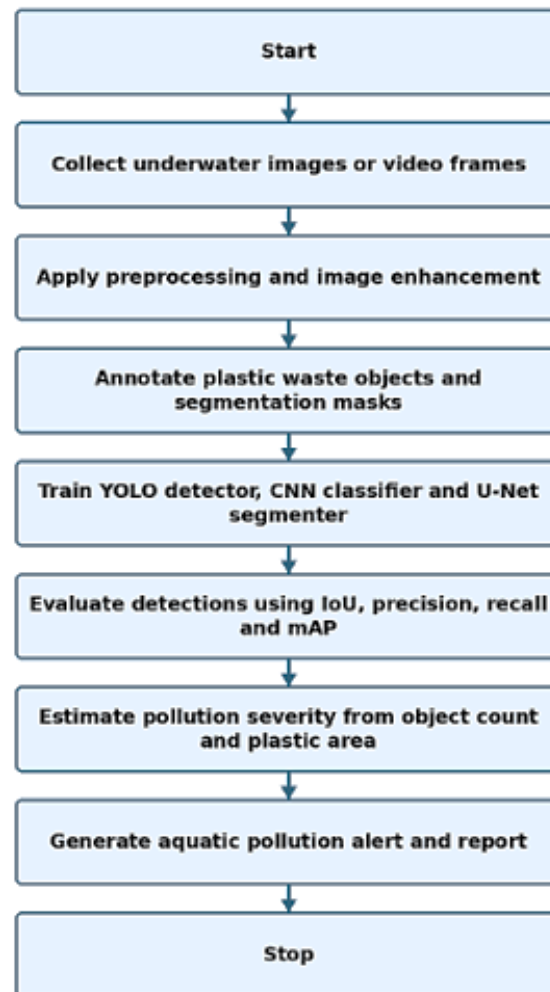


Fig. 2. Methodological flow of the proposed aquatic plastic waste detection system.

### 2.7 Algorithm

Input: Underwater image or video frame.

Output: Plastic object class, segmentation mask, confidence score, and pollution severity level.

1. Acquire underwater image from camera, robot, or monitoring dataset.
2. Resize image and apply color correction, denoising, and normalization.
3. Enhance plastic object visibility using contrast and edge information.
4. Apply YOLO-based detector to locate plastic waste objects.
5. Apply U-Net to generate pixel-level plastic region masks.
6. Calculate IoU, confidence score, object count, and plastic area.
7. Use Random Forest to classify pollution severity.
8. Use K-means clustering to group monitoring zones by waste density.
9. Generate alert, cleanup priority, and aquatic pollution report.

### 3. Results and Discussion

The proposed AI-based aquatic plastic waste detection system is evaluated using underwater image-based pollution monitoring conditions. The evaluation focuses on object detection performance, segmentation capability, pollution severity classification, and environmental decision support. The dataset configuration and evaluation parameters are summarized in Table 3. The visual representation of the detection and segmentation output is shown in Fig. 3.

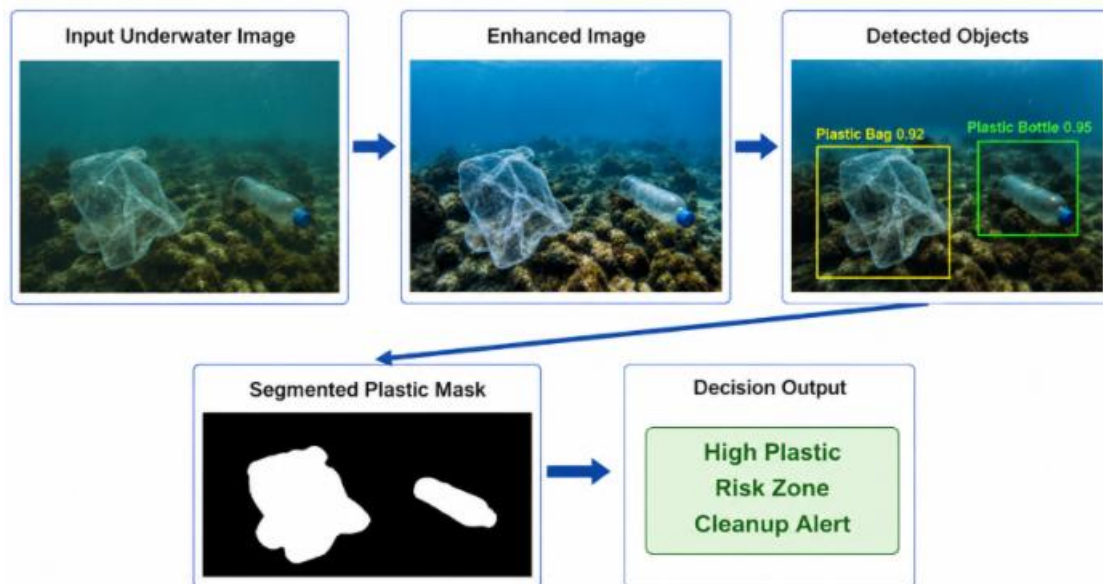


Fig. 3. Underwater plastic waste detection and output representation.

Table 3. Dataset and Experimental Configuration.

Parameter	Configuration
Input data	Underwater images and video frames
Image size	640 x 640 pixels for detection model
Object classes	Plastic bottle, bag, wrapper, fishing net, rope, container, mixed debris
Detection model	YOLO-based object detector
Segmentation model	U-Net-based plastic mask generator
Severity classifier	Random Forest using object count, area, and confidence features
Evaluation metrics	Precision, recall, F1-score, IoU, mAP@0.5, severity accuracy

### 3.1 Evaluation Metrics

Detection performance is evaluated using precision, recall, F1-score, IoU, and mean average precision. Precision indicates how many detected plastic objects are correct, while recall indicates how many actual plastic objects are detected. The F1-score provides a balanced measure between precision and recall.

$$F1\text{-score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \quad (4)$$

### 3.2 Detection and Classification Performance

Table 4 presents the performance comparison of different AI models used for aquatic plastic waste detection. The hybrid AI model combines YOLO detection, U-Net segmentation, and Random Forest-based severity classification. The results show that the hybrid AI model achieves higher detection reliability because it combines object-level and pixel-level information.

Table 4. Performance Comparison of AI Models for Aquatic Plastic Waste Detection.

Model	Precision (%)	Recall (%)	F1-score (%)	mAP@0.5 (%)	Processing role
CNN classifier	88.60	87.90	88.25	86.80	Plastic / non-plastic classification
Faster R-CNN	90.90	89.70	90.30	89.40	Accurate object localization
U-Net segmentation	91.40	90.80	91.10	90.10	Pixel-level plastic mask extraction
YOLO detector	94.30	93.80	94.05	94.70	Real-time plastic waste detection
Hybrid AI model	96.20	95.60	95.90	96.50	Detection, segmentation, and severity assessment

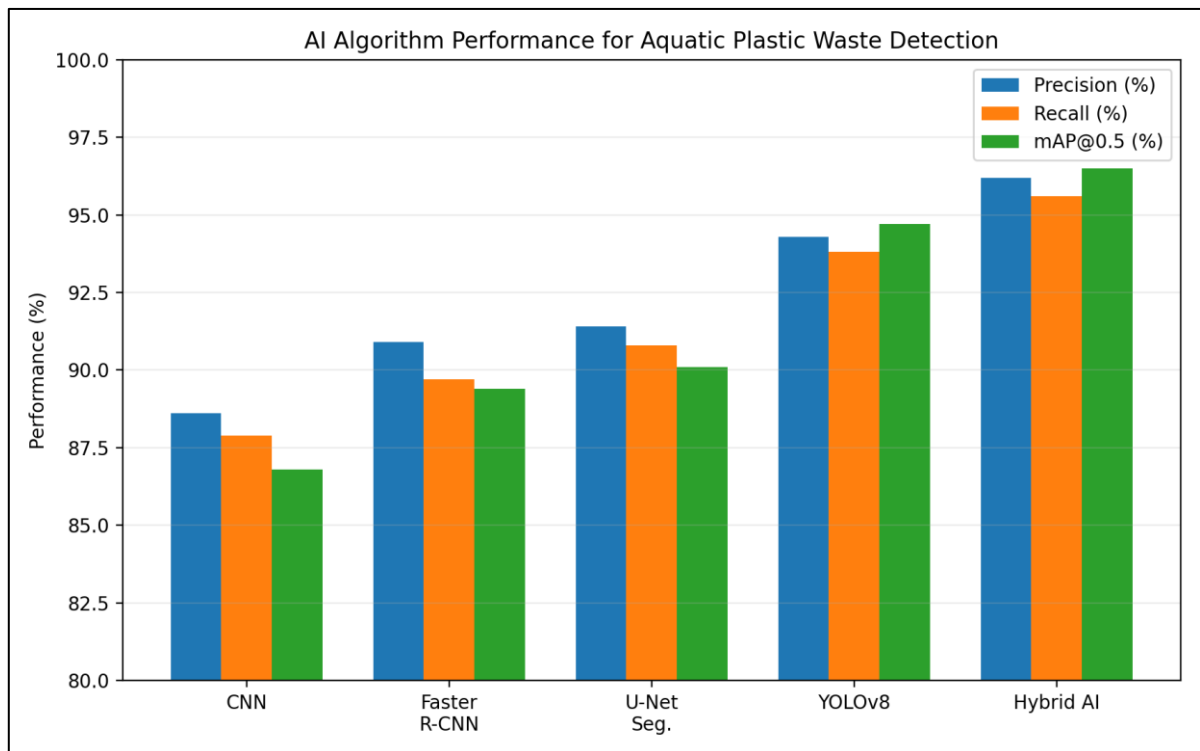


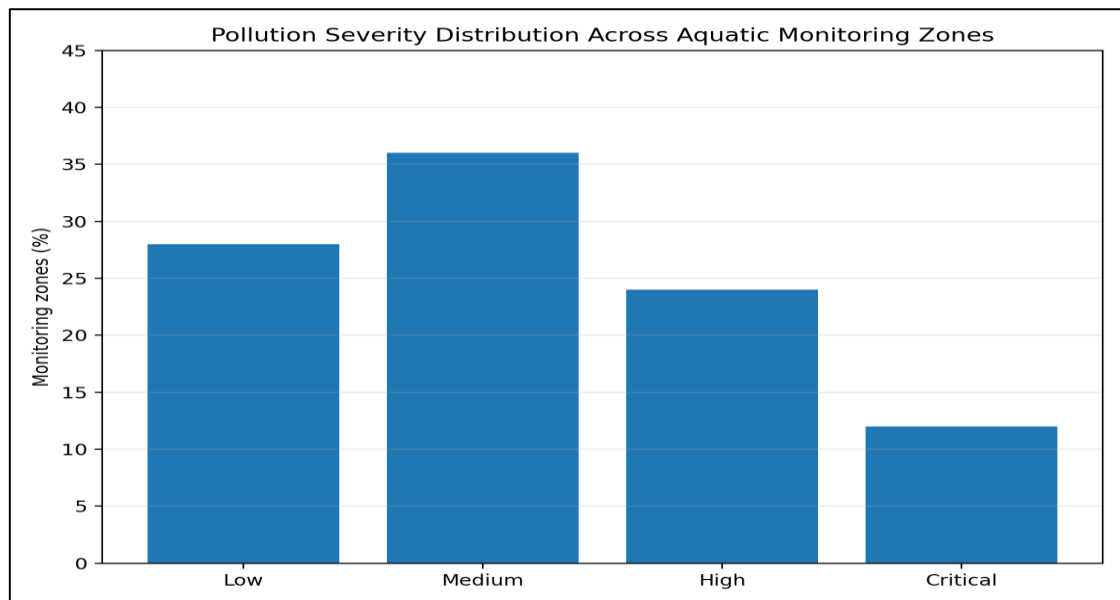
Fig. 4. AI algorithm performance for aquatic plastic waste detection.

### 3.3 Pollution Severity Interpretation

The pollution severity level is determined using detected plastic object count, segmented plastic area, and detection confidence. This classification helps environmental authorities prioritize cleanup zones. Table 5 provides the interpretation used in the proposed system, while Fig. 5 shows the distribution of monitoring zones according to severity level.

Table 5. Pollution Severity Interpretation Based on Plastic Waste Detection.

Severity level	Detection condition	Aquatic interpretation
Low	Few objects and small segmented plastic area	Minor local debris presence
Medium	Moderate object count or medium plastic area	Monitoring and periodic cleanup required
High	Large object count or wide plastic coverage	High pollution stress and cleanup priority
Critical	Dense plastic accumulation with repeated detections	Severe aquatic pollution condition requiring immediate action



**Fig. 5.** Pollution severity distribution across aquatic monitoring zones.

### 3.4 Discussion

The results indicate that deep learning-based detection can support efficient monitoring of plastic waste in aquatic environments. YOLO provides fast object localization and is useful for real-time underwater monitoring. U-Net improves the estimation of plastic-covered area by generating segmentation masks. Random Forest and K-means provide additional decision-support capability by classifying pollution severity and grouping monitoring zones. The hybrid AI model performs better than individual models because it combines detection, segmentation, and environmental interpretation.

The proposed system is useful for environmental researchers, aquatic monitoring agencies, underwater robotic platforms, and cleanup planning teams. It can reduce manual inspection effort and provide repeatable pollution assessment. However, practical deployment requires diverse training images collected under different water conditions, lighting levels, depths, camera angles, and plastic object states. Future implementation can integrate GPS-tagged underwater video, autonomous vehicle navigation, and real-time edge-AI processing for continuous aquatic pollution monitoring.

### 4. Conclusion

This paper presented an AI-based aquatic plastic waste detection framework using underwater image processing and deep learning algorithms. The proposed system integrates underwater image acquisition, preprocessing, YOLO-based object detection, U-Net-based segmentation, Random Forest-based pollution severity classification, and K-means-based monitoring-zone grouping. Image preprocessing improves visual quality under challenging underwater conditions, while deep learning models detect and segment plastic debris from complex aquatic backgrounds.

The proposed framework provides object labels, bounding boxes, segmentation masks, confidence scores, and pollution severity levels. The hybrid AI approach improves detection reliability by combining object-level and pixel-level analysis. The system supports aquatic pollution monitoring, marine debris mapping, cleanup prioritization, and environmental decision-making. Future work can focus on real-time deployment on underwater robots, larger annotated datasets, multimodal sensing, satellite-aerial-underwater data fusion, and field validation in rivers, lakes, reservoirs, and coastal environments.

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