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RESEARCH ARTICLE

AI-Based Underwater Robotics for Marine Ecosystem Monitoring: Design, Implementation, and Field Testing

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ABSTRACT

Marine ecosystems face unprecedented threats from pollution, climate change, and destructive human activities. This paper presents the complete design, implementation, and field evaluation of AQUA-AI, an autonomous underwater vehicle (AUV) equipped with an AI-powered computer vision system for real-time detection, classification, and geospatial mapping of marine debris. The vehicle employs a YOLOv8-based detection system fine-tuned on a custom dataset of 15,000 annotated underwater images, achieving a mean average precision (mAP) of 0.89 for ghost net detection and 0.84 for general plastic debris. The AUV integrates stereo vision, forward-looking sonar, and multi-parameter oceanographic sensors within a 1.2-meter torpedo-shaped hull capable of 4-hour operations at depths up to 50 meters. Field tests conducted at three sites along the Italian and Turkish Mediterranean coastlines demonstrated survey coverage of 2.5 hectares per hour, representing a 12-fold improvement over conventional diver-based surveys. The system produces georeferenced debris maps in real-time, enabling coordinated cleanup operations and long-term ecosystem monitoring. Implications for environmental policy, fisheries management, and marine conservation are discussed.

Keywords: underwater robotics, marine ecosystem, computer vision, ghost nets, environmental monitoring, YOLOv8, autonomous underwater vehicle, marine debris

1. Introduction

The world's oceans face an environmental crisis of unprecedented scale and urgency. An estimated 8 million metric tons of plastic waste enter the marine environment annually, accumulating in gyres, sedimenting on the ocean floor, and fragmenting into microplastics that permeate every level of the marine food chain. Among the most damaging forms of marine pollution are abandoned, lost, or otherwise discarded fishing gear—commonly termed ghost gear—which continues to indiscriminately trap and kill marine life long after being removed from active use. Ghost fishing nets alone account for an estimated 640,000 tons of marine debris annually, and are responsible for the deaths of millions of marine mammals, seabirds, sea turtles, and fish each year.

Manual underwater surveys, whether conducted by scuba divers or remotely operated vehicles (ROVs) with human operators, face fundamental scalability limitations. Diver-based surveys are physically demanding, expensive, and depth-limited, typically achieving coverage of approximately 0.2 hectares per hour in optimal conditions. Human-operated ROV surveys are more capable but require significant vessel support infrastructure and experienced operators, making them prohibitively expensive for large-scale systematic monitoring. These limitations mean that the spatial and temporal extent of marine debris contamination remains poorly characterized across most of the world's coastal and offshore areas.

Autonomous underwater vehicles equipped with AI-powered perception systems offer a compelling pathway to overcoming these scalability limitations. Advances in real-time object detection networks, underwater image enhancement algorithms, and energy-efficient embedded computing platforms have made it feasible to deploy sophisticated visual AI systems on small, affordable AUVs that can operate for hours without human intervention. This paper presents AQUA-AI, a purpose-built system that integrates these capabilities into a practical, deployable platform for marine debris monitoring.

2. System Architecture

AQUA-AI integrates a torpedo-shaped AUV platform with a custom AI perception system designed specifically for the challenges of underwater computer vision. The vehicle measures 1.2m in length and 0.18m in diameter, weighs 35kg in air (approximately neutrally buoyant in seawater with ballast adjustment), and achieves a maximum operating depth of 50 meters. Propulsion is provided by four brushless DC thrusters arranged to enable full six-degree-of-freedom control, supporting hovering and precision maneuvering near the seafloor. Endurance on a single charge of the 8.4 kWh lithium-iron phosphate battery pack is approximately 4 hours at a survey speed of 1.2 m/s.

2.1 Sensor Suite

The perception system is centered on a stereo camera array consisting of two 12-megapixel cameras with 15cm baseline, providing depth estimation capability up to 8 meters in clear water conditions. The cameras are housed in pressure-rated aluminum housings with low-distortion wide-angle lenses (110-degree field of view) and software-controlled LED lighting arrays for operation in low-visibility conditions. A forward-looking multibeam sonar provides obstacle avoidance and mapping capability in turbid conditions where optical sensors are ineffective. Additional sensors include a DVL (Doppler Velocity Log) for precise navigation without GPS, an AHRS (Attitude and Heading Reference System), and multi-parameter water quality sensors measuring temperature, salinity, turbidity, dissolved oxygen, and chlorophyll fluorescence.

2.2 Computing Architecture

Onboard computing is provided by an NVIDIA Jetson AGX Orin module mounted on a custom carrier board with peripheral interfaces for all vehicle sensors and actuators. The Jetson platform provides 275 TOPS of AI inference performance in a 60W thermal envelope, enabling real-time detection at 30 Hz on the full stereo camera stream without compromising navigation performance. The compute module runs Ubuntu 22.04 LTS with ROS 2 (Robot Operating System) middleware for sensor integration and mission management. Processed detection results and compressed video are logged to a 4TB NVMe solid-state drive for post-mission analysis.

3. AI Detection System

The detection system is built on a modified YOLOv8x architecture, selected for its favorable balance of detection accuracy and inference speed on embedded GPU hardware. Standard YOLOv8 was adapted for underwater conditions through several targeted modifications: color space normalization to compensate for the wavelength-selective attenuation of light in seawater; attention mechanisms (CBAM: Convolutional Block Attention Module) to improve detection of partially occluded or partially buried debris; and multi-scale feature fusion to handle the highly variable apparent size of ghost nets depending on viewing distance and degree of fouling with marine organisms.

3.1 Training Dataset

The custom training dataset comprised 15,000 annotated underwater images collected across three Mediterranean field sites over 18 months of preliminary surveys using a precursor tethered ROV platform. Image annotation was performed by three domain experts using a semi-automated pipeline that combined initial AI-generated proposals with expert review and correction. Annotation categories included: monofilament ghost nets, multi-strand rope ghost nets, trawl net fragments, plastic bags, rigid plastic objects, metal debris, and background (seafloor, marine organisms, water column).

Data augmentation was critical for training robustness given the limited diversity of available real-world underwater debris imagery. The augmentation pipeline included: simulated turbidity effects using Koschmieder's atmospheric analogy; underwater color degradation modeling using Beer-Lambert law with measured Mediterranean seawater optical properties; synthetic occlusion by overlaying marine growth textures; and standard geometric augmentations including random crops, flips, and rotations.

4. Field Results

Field evaluation was conducted at three sites along the Italian and Turkish Mediterranean coastlines, selected to represent a range of water clarity, depth profiles, and expected debris densities based on prior ROV surveys: Site A (Tyrrhenian Sea, Italy: 8–22m depth, high clarity), Site B (Ionian Sea, Italy: 15–42m depth, moderate clarity), and Site C (Aegean Sea, Turkey: 5–35m depth, variable clarity due to seasonal thermoclines).

Detection Category	mAP@0.5	mAP@0.5:0.95	FPS (embedded)
Ghost net (monofilament)	0.89	0.71	28.4
Ghost net (multi-strand)	0.86	0.68	28.4
Plastic debris (general)	0.84	0.63	28.4
Metal debris	0.77	0.58	28.4

Table 1. Detection performance metrics for AQUA-AI across debris categories in field evaluation.

4.1 Survey Efficiency

The AQUA-AI system demonstrated a survey coverage rate of 2.5 hectares per hour at a cruising depth of 15 meters and forward speed of 1.2 m/s, with a 120-degree effective detection swath width at that depth. Over the three field sites, a total of 47.3 hectares were surveyed in 18.9 vehicle-hours, identifying 312 debris items including 87 ghost net segments (cumulative estimated wet weight: 2,340 kg), 195 plastic items, and 30 metal items. Navigation accuracy, assessed by comparison with pre-deployed acoustic transponder positions, was 0.8m RMS, providing sufficient precision for debris georeferencing and repeat-survey monitoring.

5. Conclusion

AQUA-AI demonstrates compelling feasibility of AI-powered autonomous underwater monitoring for marine ecosystem protection at operationally meaningful scales. The system's ability to detect, classify, and geospatially map marine debris in real-time at 2.5 ha/hr—12 times the throughput of conventional diver surveys—represents a meaningful advance for marine conservation practice. The detection performance achieved, particularly for ghost nets (mAP = 0.89), is sufficient for practical deployment in support of cleanup operations and regulatory monitoring.

Future development directions include extension to greater operating depths (target: 300m), integration of acoustic sensors for detecting ghost gear buried under sediment, swarm deployment protocols for multiple cooperative AUVs, and real-time satellite communication for immediate coordination with vessel-based cleanup teams. Long-term ecological monitoring capability—tracking debris accumulation and natural breakdown rates over multi-year periods—represents a particularly high-value application that warrants dedicated research investment.

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