Detecting Underwater Macroplastic Pollution: A Review on AI-Based Computer Vision Methods and Their Relevance to Sri Lanka's Marine Ecosystem

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***Abstract*— The escalating crisis of marine plastic pollution, particularly macroplastic debris, poses severe threats to marine biodiversity, coastal ecosystems, and human livelihoods. Sri Lanka, ranked among the top global contributors to marine plastic waste, suffers from a lack of systematic and scalable monitoring mechanisms, especially for underwater macroplastic detection. Traditional survey methods are often manual, labour-intensive, and limited in coverage. Recent advancements in artificial intelligence, specifically computer vision, present promising alternatives for automating detection and analysis of marine debris. This review critically examines the current landscape of AI-based approaches for underwater macroplastic detection, highlighting their methodologies, datasets, performance metrics, and limitations. While global efforts have largely emphasized surface litter and microplastic detection, underwater macroplastic monitoring remains underexplored. Moreover, Sri Lanka lacks context-specific studies and affordable, software-based AI tools that can leverage existing underwater imagery to detect macroplastic waste. By synthesizing global literature and identifying region-specific research gaps, this paper advocates for the development of lightweight, AI-powered systems tailored to the Sri Lankan coastline. Such innovations could enable continuous monitoring, inform policy decisions, and strengthen marine conservation efforts in data-scarce and resource-constrained settings.**

Keywords*— Underwater Macroplastic, Microplastics, Entanglement, Plastic Ingestion, Computer Vision Technique, Preprocessing, Deep Learning

I. INTRODUCTION

Marine plastic pollution has emerged as one of the most pressing environmental challenges globally. An estimated 11 million metric tons of plastic enter the ocean each year, severely impacting marine life and ecosystems. Alarmingly, studies suggest that by 2050, the oceans could contain more plastic than fish by weight [1].

Plastic pollution poses significant risks to biodiversity, the food chain, public health, economy and the climate changes [2]. Marine fauna including seabirds, turtles, and mammals often ingests or become entangled in plastic waste, leading to injury or death [2].

Sri Lanka ranks fifth among the top 20 countries contributing waste to the ocean, with the majority of marine debris consisting of plastics [3]. Despite this, the total extent of marine litter in Sri Lankan waters remains poorly evaluated [3]. Scientific investigations into marine plastic pollution in the country lag significantly behind global research efforts [4]. While most existing studies have largely focused on microplastic pollution, there is a notable lack of attention to the distribution, fate, and impact of macroplastic (>5mm) debris [4].

This lack of comprehensive, on-ground data has resulted in overreliance on global model predictions, which may not reflect the local reality [5]. As a result, the country's pollution profile and ranking could be misrepresented, warranting re-evaluation based on localized, empirical data.

Accurate, scalable, cost-effective, and accessible monitoring solutions are urgently needed to support management decisions at appropriate spatial and temporal scales [6]. Traditional methods in Sri Lanka largely depend on manual beach surveys and surface-level observations [4][7]. These techniques are labour-intensive, time-consuming, and difficult to scale, particularly for detecting submerged macroplastic debris, which remains largely unmonitored [8]. Moreover, the absence of a centralized national marine litter monitoring system or database has led to fragmented and insufficient data, hindering effective policymaking and conservation efforts.

Underwater environments present unique challenges for visual detection due to factors such as water turbidity, complex backgrounds, and variable lighting. These conditions introduce high-intensity noise, texture distortion, uneven illumination, low contrast, and limited visibility in underwater images [9]. To overcome these limitations, several underwater object detection techniques have been developed in recent years [9].

However, their application to underwater macroplastic detection remains limited globally and is virtually unexplored in the Sri Lankan context. The lack of open-source datasets further impedes progress, underscoring the need for low-cost, software-driven approaches that utilize underwater imagery for continuous and accurate monitoring.

This paper critically reviews AI-based computer vision techniques for detecting underwater macroplastic pollution, evaluates their applicability to Sri Lanka, and identifies key research gaps. It also proposes future research directions, including the development of localized datasets, adoption of lightweight AI models for low-cost deployments, and integration of AI monitoring into national marine policies.

II. METHODOLOGY

This review was conducted using a structured and systematic approach to identify, evaluate, and synthesize relevant literature on underwater macroplastic detection using AI-based computer vision techniques. The methodology consisted of the following steps:

A. *Literature Search*

A comprehensive literature search was performed using major scientific databases, including IEEE Xplore, ScienceDirect, SpringerLink, and Google Scholar. Keywords such as “underwater macroplastic detection,” “marine plastic pollution,” “AI and computer vision,” “deep learning in ocean monitoring,” and “Sri Lanka marine litter” were used. Only peer-reviewed articles, technical reports, and policy briefs published between 2015 and 2025 were considered. Studies focusing on surface plastics or microplastics were excluded unless they offered insights applicable to underwater macroplastic detection.

B. *Inclusion and Exclusion Criteria*

Inclusion: Studies implementing AI or computer vision techniques for underwater macroplastic detection; studies providing dataset descriptions, performance metrics (accuracy, precision, recall, F1-score), or methodological insights; regional studies relevant to Sri Lanka’s coastal plastic pollution.

Exclusion: Studies limited to surface plastic detection or microplastic studies without applicable methods; non-English publications; non-peer-reviewed articles. Figure 1 shows preferred reporting items for systematic review and meta analyses.

C. *Structured Evaluation Criteria*

To ensure a consistent assessment of the selected studies, each paper was evaluated based on the following criteria:

- AI Technique Used: Type of model (e.g., CNN, YOLO, Faster R-CNN, SVM).
- Dataset: Type, source, size, and applicability to underwater environments.
- Performance Metrics: Accuracy, precision, recall, F1-score, and other relevant metrics reported.
- Applicability to Sri Lanka: Potential relevance to local coastal environments, feasibility for replication, and availability of region-specific datasets.

D. *Comparative Synthesis*

The selected studies were summarized in a comparative table to facilitate synthesis of findings. The table includes the AI techniques, datasets used, reported performance metrics, and potential applicability to underwater macroplastic detection in Sri Lanka. This approach allows identification of methodological trends, research gaps, and areas for future investigation.

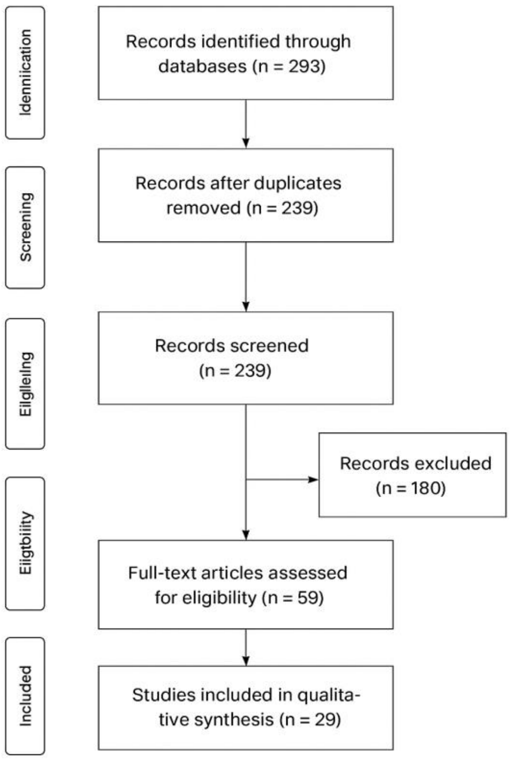

Figure 1. Prisma Diagram for The Review.

III. Marine Plastic Pollution and Its Impact

Plastic debris can persist in the environment for hundreds of years, acting as a continuous source of pollution. Plastics are broadly categorized by size into four groups: mega plastic, macroplastic, mesoplastic, and microplastic [2]. Marine plastics are typically divided into macroplastics (>5 mm) and microplastics (<5 mm). Macroplastics primarily originate from improperly discarded fishing gear, packaging materials, and consumer waste, whereas microplastics mostly result from industrial byproducts or the breakdown of larger plastic items.

Plastics pose physical hazards to marine organisms if ingested. These effects include blockage of the intestinal tract, inhibition of gastric enzyme secretion, reduced feeding stimuli, decreased steroid hormone levels, delayed ovulation, and reproductive failure. Ingestion of both macroplastics and microplastics can lead to reduced food consumption and subsequent nutritional deficiencies. Species such as seabirds, tuna, and sea turtles are notably affected by plastic ingestion. For example, plastic ingestion by green turtles increased by nearly 20% from 1985 to 2012 [10], as turtles mistake white plastic debris for jellyfish. Additionally, at least 48 cetacean species, including whales and dolphins, suffered from plastic ingestion between 2000 and 2010 [10].

Marine animals including sea turtles, mammals, seabirds, and crustaceans are also vulnerable to entanglement in plastic debris, which can result in mortality. Young sea lions and seals, due to their smaller size, are particularly susceptible as their necks or legs can easily pass through plastic materials, leading to entrapment [10].

Plastic debris such as bags and ropes physically damage coral reefs by dragging across and breaking coral branches during water movement. A 2018 study published in *science* showed that corals in contact with plastic are 89% more likely to develop diseases such as skeletal eroding band disease [11]. Furthermore, floating debris blocks sunlight essential for coral photosynthesis by their symbiotic algae (zooxanthellae). Large plastic debris covering coral surfaces can cause tissue death and bleaching. Stressed corals expel these colourful algae, turning white ("bleached") and risking death if the stress persists [11].

Scuba divers have severe health risks in trapping and entangling in the discarded plastic gear such as "ghost nets". There is a high risk of loss of lives by accidents due to the accumulation of mega-size marine plastic debris in the ocean. Further, polluted coastal and marine zones are associated with negative health issues on tourists and coastal residents [12].

Macroplastics degrade into microplastics, which are ingested by zooplankton and subsequently by fish, shellfish, and ultimately humans. Toxins associated with microplastics bioaccumulate in fatty tissues and biomagnify at higher trophic levels, increasing exposure risks for top predators, including humans [13][14]. Human consumption of contaminated seafood has been linked to liver toxicity, endocrine disruption, reproductive problems, and neurological disorders [15].

In some small island nations and developing countries such as Bangladesh, Cambodia, Ghana, Indonesia, Sierra Leone, and Sri Lanka, fish contribute to approximately 50% or more of total animal protein intake. The depletion of fishery resources caused by plastic pollution directly impacts the economies of these countries and leads to socio-economic crises and health problems [12].

Plastic pollution in beaches and marine environment triggers a negative effect on aesthetic value, natural beauty, and health of ecosystems. As a result, the lowered aesthetic and recreational value in coastal shore areas and marine systems lead to a significant reduction in the total number of tourists. Offshore ocean basin and sensitive coastal ecosystems (e.g., healthy coral reef ecosystems) are associated with tourism-related activities such as coral watching, snorkelling, whale watching, turtle watching, sport fishing, and scuba diving. Death of a coral cover by plastic debris implies the loss of such kind of tourism activities and reducing the number of tourists visiting a specific region [12].

Marine plastics significantly contribute to climate change by emitting greenhouse gases (GHGs) throughout their entire life cycle, from fossil fuel extraction, production, and transportation to disposal and degradation. Marine plastic pollution adds to climate change in several ways. Making plastic uses fossil fuels and releases greenhouse gases. When plastic is burned or breaks down in the ocean, it releases gases like methane and ethylene that warm the planet. Plastics also harm coral reefs and seagrass, which normally help absorb carbon dioxide from the air [14]. When these ecosystems are damaged, they can't fight climate change as well. So, plastic pollution not only harms the ocean, but it also makes climate change worse. Having established the impacts of plastic pollution, we now focus on the Sri Lankan context of marine plastic pollution.

IV. Marine Plastic Pollution in Sri Lanka

Sri Lanka is situated in the Indian Ocean. The land area of the island is approximately 65,610 sq. km, and its coastal stretch is approximately 1620 km [3]. As a coastal island nation, Sri Lanka is highly vulnerable to the impacts of marine plastic pollution. It has been ranked among the top five countries globally for mismanaged plastic waste entering the ocean. In the western coastal water of Sri Lanka, the mean density of total plastic was recorded as 140.34+-13.99 items per cubic meter, during August–November 2017 (end of south-west monsoon), mainly by the sources of tourism and fishing activities [12].

Marine litter has become a major concern of the island in the past few decades because five out of nine provinces of Sri Lanka are bordered by a coastal belt. Nearly 80% of the tourism industry is based on coastal habitation. Marine litter in Sri Lanka can be derived from either land-based or sea-based sources. Studies show that more than 90% of the litter found along Sri Lankan coasts originates from the land-based mainly occurs in river mouths and urban beach areas [3]. Apart from the inland-based sources, there are sea-based sources that also include transboundary pollution. Thus, it is inclined to debris accumulation including foreign debris floating on the sea [3].

The situation is exacerbated by inadequate waste management systems, growing plastic consumption, and high coastal population density [3]. A significant portion of the pollution originates from urban runoff, illegal dumping, poor waste collection infrastructure, fishing gear disposal, and inadequate recycling mechanisms [2]. Indeed, in Sri Lanka according to [18], many Sri Lankans hold negative perceptions toward single-use plastics and demonstrate relatively high awareness of their environmental consequences.

Sri Lanka's rich marine biodiversity is particularly at risk. Its coral reefs, seagrass beds, and mangrove ecosystems support thousands of marine species and play a key role in carbon sequestration, shoreline protection, and the livelihoods of coastal fishing communities [16] [17]. Under the Fauna and Flora Protection (Amendment) Act No. 22 of 2009, several marine mammals, reptiles, fishes, corals and invertebrates are legally protected in Sri Lanka. However, these sensitive habitats are increasingly threatened by plastic debris accumulation, especially macroplastics that entangle corals, damage reef structures, and alter benthic habitats [11]. Figure 2. shows that stack net can be damaged by reefs and seagrass.

Numerous varieties of plastic debris do not float on the surface and are lost to the depths of the ocean. Such debris collects in large patches called ocean gyres [1]. While much attention has been placed on surface-level and shoreline plastic debris, macroplastics in the underwater zone remain underexplored [3] [4]. These submerged items often go unnoticed due to visibility challenges and limited surveillance technology, yet they pose serious threats to bottom-dwelling.

Species and benthic ecosystems [9], Sri Lanka's scuba diving tourism and small-scale fishing sectors are particularly vulnerable, from ghost nets, submerged plastic bags, and packaging waste can disrupt both ecological function and economic activity.

The interaction between climate change and marine plastic pollution creates a compound threat to Sri Lanka's marine ecosystems. Rising sea temperatures, coral bleaching events, and ocean acidification already stress marine life. When combined with plastic debris, which introduces toxins, microplastic fragmentation, and physical smothering, the overall resilience of the marine environment declines [11][14].

Figure 2. This shows how reefs and seagrass meadows can be damaged [16].

Moreover, human health and food security are at stake. With 70% of protein intake in coastal communities coming from seafood, the risk of plastic ingestion by fish and transfer up the food chain poses direct threats to public health [15]. Additionally, marine litter negatively impacts tourism revenue (which is a key source of national income) by polluting scenic coastlines and dive sites, reducing Sri Lanka's global appeal as an eco-tourism destination [3].

Despite these challenges, there is a vast need to evaluate the severity of plastic pollution in marine environments [3]. Given these risks, there is an urgent need for national-level policy interventions targeting marine plastic pollution, especially the detection and monitoring of underwater macroplastics. Enhanced detection would support evidence-based marine spatial planning, pollution hotspots mapping, and enforcement of plastic bans or recycling policies.

To better understand how existing global research relates to Sri Lanka's marine plastic crisis, In this context, Table 1 summarizes global and local literature with relevance to AI-assisted detection of marine plastics, especially concerning Sri Lanka's underwater macroplastic pollution scenario. Table 1 presents a summary of key literature and their applicability to the Sri Lankan context.

While the previous section highlighted the extent of marine plastic pollution in Sri Lanka and the relevance of AI-assisted detection methods based on global literature, addressing this issue effectively requires a clear understanding of the challenges involved in detecting underwater macroplastics. The complex and dynamic nature of the marine environment poses significant obstacles to both manual and automated monitoring. The following section outlines these key challenges, which must be addressed to develop scalable and accurate detection systems suited to Sri Lanka's coastal waters.

V. Challenges in Underwater Macroplastic Detection

The detection of underwater macroplastic pollution poses significant scientific, technological, and logistical challenges that limit effective detecting and response strategies. Methodologies for the quantification of seafloor litter can be divided into those involving (i) the collection of litter and those relying on (ii) in situ observations, either directly by humans or by using cameras mounted on a variety of platforms [19].

A. *Shallow-water surveys*

In shallow waters, SCUBA divers or snorkelers can make direct observations. These surveys can cover small areas of seafloor in great detail, potentially focusing on accumulations of macroplastic litter in hydro dynamic traps associated with seafloor unevenness, such as rocky outcrops or coral reefs [19]. They enable direct observation of litter, biota interactions, collection of physical samples for inspection, manipulation experiments and spontaneous adaptation of surveys if interesting processes or features are observed as well as the involvement of citizen scientists. However, the depth and area that can be covered by such surveys are limited by air supply, field conditions (water turbidity, temperature) and safety considerations [19].

B. *Trawl surveys*

Scientists collect and study fish, benthic organisms, and marine debris (including plastics) from the seafloor or water column using a trawl net, a large fishing net towed behind a research vessel. For instance, macroplastic, which is low-density could easily be transported from one location to another by the action of bottom currents or bottom fishing gear, leading to highly dynamic scenarios [19]. In addition, bottom trawls are not always in constant contact with the seabed and can get temporarily stuck on bottom features and also stay on the seafloor for some time prior to recovery [19].

C. *Visual surveys and Imaging*

Sea floor imagery is increasingly being used to study the abundance and distribution of debris on the sea floor as well as its interactions with marine organisms.

One of the primary obstacles is low visibility in underwater marine environments, with high turbidity [9]. Underwater images are frequently affected by several factors, such as water flow, lighting variations, limited visibility, and substantial changes in pose and spatial position information, resulting in high noise and low contrast [9].

Two significant potential challenges of the image-based approach to sea floor macroplastic litter quantification are, first, that the minimum size of litter that can be identified depends on the resolution achievable by the cameras and, second, that only seabed-exposed litter can be observed [19]. Underwater plastics often become entangled in seaweed, embedded in sediments, or bio fouled with algae and organisms, making them harder to distinguish visually from natural marine elements [19] [20].

TABLE I. SUMMARY OF KEY LITERATURE ON MARINE PLASTIC POLLUTION AND RELEVANCE TO AI-BASED DETECTION IN SRI LANKA

Study	**Region / Context**	**Research Question / Focus**	**Key Findings**	**AI/Computer Vision Relevance**
[2]	Global	Impact of plastic on marine life.	Plastic causes ingestion, entanglement, and ecological harm.	Highlights ecological harm but lacks AI solution.
[10]	Global	Sources and effects of marine plastic pollution	Macroplastics are a major issue; calls for regulatory responses.	Identifies monitoring gaps; supports argument for automated solutions.
[12]	Global & Sri Lanka	Sources, impacts, and policy responses	Sri Lanka suffers ecological and socio-economic damage from plastics.	Validates the urgency of detecting macroplastics underwater in Sri Lanka; supports the need for AI-driven visual monitoring to fill this gap.
[14]	Global	How marine plastic pollution and climate change intersect.	Climate change worsens plastic impact on ecosystems.	Highlights broader environmental context; supports urgency for improved plastic tracking systems like AI-based detection; underscores need for ecosystem-level solutions relevant to Sri Lanka.
[15]	Global	Policy frameworks, recycling, and environmental impact.	Promotes EPR and circular economy, warns of health risks	Helps inform the importance of policy enforcement and circular economy models in Sri Lanka; supports using EPR and plastic tracking for more effective marine litter management.
[3]	Sri Lanka	Research and policy gaps on marine litter.	90% marine litter land-based; major monitoring/policy deficits. Highlight the absence of scientific surveys and national level statistics.	Strongly supports national need for AI monitoring infrastructure.
[5]	Sri Lanka	Validity of model-based plastic waste rankings.	Global models overestimate SL waste; need for local data.	Reinforces field-based, AI-assisted detection for accuracy and actual contribution to marine litter by Sri Lanka.
[4]	Jaffna, Sri Lanka	Baseline on macroplastic density & composition.	High plastic presence: sources include fisheries and tourism.	Provides ground-truth data for training AI detection models.
[7]	Sri Lanka	Microplastic composition and sources in sediments.	Identifies polymer types and surface weathering.	Useful for identifying land-sea plastic links; less direct AI use.
[18]	Sri Lanka (coastal)	Community awareness and attitudes.	High concern over marine plastics; calls for policy change.	Public support justifies cost-effective AI monitoring systems.

Additionally, deep-sea pressure, currents, and mobility of plastic waste across tidal zones further complicate precise detection and localization [20], especially when plastic debris is suspended or partially buried on the ocean floor or blended within accumulations of litter formed by mixtures [19].

D. *Dataset Scarcity and Quality Issues*

Furthermore, the construction of underwater datasets for underwater macroplastic detection has proven to be a challenging task-one that has affected the progress of underwater macroplastic detection work and severely limited the practical applications of underwater macroplastic detection and recognition [9].

Another core challenge is the lack of large, diverse, and labelled datasets needed to train robust AI-based detection models [9]. Unlike terrestrial plastic detection, which has benefited from vast publicly available datasets, underwater plastic imagery is scarce, often inconsistent in format, and limited in geographic or depth coverage. This bottleneck significantly hinders the accuracy and generalizability of deep learning models.

E. *Limitations of Manual Detection Methods*

Conventional detection techniques, such as underwater video inspection or net-based sampling, are time-consuming, labor-intensive, and expensive [8] [21]. These methods offer limited spatial coverage and poor scalability, especially in deeper waters or vast coastal regions. Furthermore, manual methods lack repeatability and standardization, making them unsuitable for long-term, large-scale monitoring programs [9].

F. *Technical and Infrastructural Barriers to AI/Automation*

The implementation of AI-driven detection systems in underwater environments faces both technical and infrastructural constraints. Underwater imaging systems are subject to distortions in light and signal propagation, requiring sophisticated hardware setups that are often expensive and complex to maintain [22].

There is a growing consensus on the need for automated, repeatable, and scalable solutions to detect underwater plastic pollution. However, the integration of AI and computer vision in underwater applications is still in its early stages and faces hurdles related to cost, technical complexity, and data limitations.

VI. POTENTIAL OF AI AND COMPUTER VISION IN UNDERWATER MACROPLASTIC DETECTION

With increasing recognition of the limitations of manual monitoring and the complex environmental challenges of underwater detection, Artificial Intelligence (AI), particularly computer vision, has emerged as a promising tool to automate and scale the identification of underwater marine macroplastics. Computer vision is a branch of AI that studies how computers can 'see' [23]. It is a field that provides significant value for advancements in academia and artificial intelligence by processing images captured with a camera. In other words, the purpose of computer vision is to impart computers with the functions of human eyes and realise 'vision' among computers [23].

AI-based approaches offer significant potential to improve accuracy, reduce human effort, and enable real-time, wide-area monitoring in marine environments, even in turbid or low-light conditions. AI can process large amounts of data in a short time, while being able to provide conclusions which, at times, are difficult for humans to even imagine [1]. AI also makes possible better coordination between researchers in sharing and analysing data [1]. These trends and variations may be missed out by humans, as small changes in the environment may go unnoticed and, with time, may cause serious changes in the environment [1]. Such changes would invariably be noticed and flagged by AI.

AI, and specifically deep learning (DL), has demonstrated notable success in image classification, object detection, and segmentation tasks in terrestrial and aerial domains. Deep learning is a method of realising computer vision using image recognition and object detection technologies [23].

AI systems trained for inspection tasks can often outperform human observers by analysing thousands of images or real-time frames rapidly, detecting imperfections or items that are not easily visible to the naked eye [23].

One of the core strengths of using Artificial Intelligence is that it is very suitable for monitoring large areas involving many variables [24]. These various variables can be processed quickly and accurately by utilizing Artificial Intelligence [24]. In addition, Artificial Intelligence can provide useful outputs for researchers to take appropriate strategies to reduce marine pollution [24].

When deployed underwater, AI-based systems can process imagery collected from various platforms such as Remotely Operated Vehicles (ROVs), Autonomous Underwater Vehicles (AUVs), or diver-mounted cameras [1]. These systems can automatically detect plastic debris by analysing shape, texture, and colour patterns, even distinguishing between biofouled plastic items and natural marine features such as rocks, corals, or algae-covered objects [19].

Core Technologies and Workflow in AI-Based Underwater Macroplastic Detection

AI-based detection systems for underwater macroplastics generally follow a structured pipeline that integrates several computer vision and deep learning components.

A. *Image Acquisition*

Image acquisition is the first and most critical stage in any AI-based underwater macroplastic detection pipeline. This phase involves the collection of raw sensory data, primarily in the form of visual imagery or acoustic signals, from underwater environments. The quality and reliability of the acquired data significantly affects the performance of all downstream processes, such as enhancement, segmentation, classification, and detection [9].

Due to the complex nature of the underwater environment, characterized by factors such as turbidity, light absorption, and scattering, specialized and robust acquisition techniques are essential [9][23]. Modern underwater image acquisition relies on a combination of advanced imaging technologies and deployment platforms that work together to gather high-resolution data under challenging aquatic conditions.

Imaging Technologies

Underwater image acquisition systems utilize various sensing technologies, including:

- **Sonar-Based Acoustic Sensing**: Historically dominant in underwater exploration, sonar imaging, especially 3D sonar, uses multi-frequency acoustic pulses and sonar array cameras to visualize underwater scenes even in turbid or dark conditions [22]. Although robust, sonar often lacks the fine-grained resolution needed for accurate macroplastic classification.

- **Underwater Laser Scanners**: These offer highly detailed 3D reconstructions and are suitable for precise mapping. However, they are costly and susceptible to scattering artifacts caused by suspended particles in the water [22].

- **Optical Cameras**: Increasingly adopted in AI-based systems, underwater cameras are cost-effective, easy to deploy, and compatible with machine learning models [22]. They are capable of capturing high-resolution still images and videos, which are well-suited for macroplastic identification, image mosaicking, object tracking, and underwater SLAM (Simultaneous Localization and Mapping) [22]. Nevertheless, their performance is degraded in turbid water due to colour distortion and low contrast [9].

- **Stereo Vision Systems**: These use two synchronized cameras to generate depth information and 3D models by calculating disparity maps [22]. While stereo vision enhances spatial awareness and object localization, its effectiveness underwater is limited by calibration complexity and real-time computational demands.

To overcome optical limitations, preprocessing methods such as color segmentation, contrast enhancement, and feature extraction are employed to improve image clarity and highlight plastic objects [22].

Deployment Platforms

The choice of platform significantly influences data coverage, accessibility, and image quality. Common platforms include:

- **Remotely Operated Vehicles (ROVs)**: Tethered robots controlled from surface vessels, ROVs are equipped with cameras, sonar, lighting, and sensors for depth, temperature, and turbidity [25]. They offer real-time feedback and are ideal for capturing high-resolution footage in deep or complex marine environments [19]. However, they require specialized equipment and a large operating crew [19].

- **Autonomous Underwater Vehicles (AUVs)**: These untethered, programmable systems autonomously survey large seafloor areas and collect thousands of images during extended missions [19][25]. AUVs are ideal for generating large training datasets for AI models, especially in wide-area plastic litter surveys.

- **Human-Occupied Vehicles (HOVs)**: Though now less common due to high costs and safety concerns [19], HOVs allow human observers to capture close-up footage and validate AI models through direct visual inspection and ground-truthing.

- **Towed Underwater Cameras (TUCs)**: These are camera systems mounted on sleds or platforms dragged behind research vessels [25]. TUCs are a cost-effective option for covering large seabed areas, though they lack maneuverability and real-time monitoring. Their output is often processed later using AI-based classification algorithms.

- **Unmanned Aerial Vehicles (UAVs)**: While not used underwater, drones are occasionally employed to detect floating macroplastics on the water’s surface, complementing subsurface acquisition methods [25].

B. *Preprocessing*

Preprocessing is the second critical stage in the underwater macroplastic detection workflow, following image acquisition. Given the challenging and often degraded nature of underwater imagery, affected by turbidity, color attenuation, backscatter, and low contrast, this step plays a vital role in preparing data for accurate and efficient AI-based analysis. Without appropriate preprocessing, the performance of segmentation, classification, and object detection models can be significantly compromised [22].

Effective preprocessing typically involves several image enhancement techniques tailored to underwater scenes. These include:

- **Color Correction**: Algorithms such as histogram equalization and white balancing adjust for the selective absorption of light wavelengths underwater, helping restore natural color tones and improve visual clarity [22].

- **Dehazing and Contrast Enhancement**: Techniques like CLAHE (Contrast Limited Adaptive Histogram Equalization) are used to improve visibility in murky water by enhancing local contrast [9].

- **Denoising**: Filtering methods such as median or bilateral filters help remove speckle noise and artifacts introduced by suspended particles [22].

- **Geometric Corrections**: Camera lens distortions and refraction effects caused by the water-glass-air interface are corrected through calibration models [22].

- **Super-Resolution**: Some AI-based systems use deep learning techniques to enhance image resolution before feeding them into detection models [21].

These preprocessing steps are typically implemented as part of a real-time pipeline, ensuring that incoming imagery is optimized for downstream AI analysis.

C. *Object Detection and Classification*

Following preprocessing, the core stage in AI-based macroplastic monitoring is object detection and classification. This is where AI, particularly deep learning models such as Convolutional Neural Networks (CNNs) and transformer-based architectures, are employed to automatically recognize, localize, and classify plastic debris in images. Table 2 presents the comparative analysis of AI-Based underwater microplastic detection.

Key approaches include:

- **YOLO (You Only Look Once)** and **Faster R-CNN**: Widely used object detection frameworks capable of real-time inference, suitable for identifying various marine litter categories [24][25].

- **Semantic Segmentation** (e.g., U-Net, DeepLab): These models assign class labels to every pixel in an image, enabling precise delineation of macroplastic shapes and sizes [21][22].

- **Instance Segmentation** (e.g., Mask R-CNN): Extends object detection by identifying distinct instances of macroplastic items, even when overlapping or clustered [21].

- **Custom CNN Architectures**: Several researchers have proposed domain-specific neural networks optimized for underwater plastic detection tasks using curated datasets [24][25].

Training these models requires extensive, annotated datasets of underwater litter. Open datasets are limited, prompting researchers to compile domain-specific image collections using AUVs, ROVs, or TUCs [19]. Some studies also use synthetic data generation or transfer learning to overcome dataset scarcity [22]. Table 3 provides overview of available underwater litter datasets.

Once trained, these models can generalize across different underwater environments, detect partially occluded objects, and even distinguish between plastic debris and biological elements such as coral or seagrass using texture and spectral cues [9][25].

D. *Post-Processing and Output Interpretation*

The final stage involves post-processing the model outputs to refine detection accuracy, remove false positives, and support ecological interpretation. Outputs may be visualized using:

- **Bounding Boxes or Segmentation Masks**: Indicating detected plastic debris.

- **Heat Maps or Probability Maps**: Showing confidence scores or object density.

- **Spatial Mapping Tools**: Integrating geolocation metadata (e.g., GPS or SLAM coordinates) to map plastic distributions across surveyed regions [25].

These results can then be incorporated into marine monitoring dashboards, support policy decision-making, or contribute to long-term environmental datasets. Recent works also integrate AI detection results with oceanographic models to predict plastic accumulation zones [24].

TABLE II. COMPARATIVE ANALYSIS OF AI-BASED UNDERWATER MACROPLASTIC APPROACHES

AI Technique / Model	**Dataset(s) Used**	**Performance Metrics**	**Strengths**	**Limitations / Challenges**	**Applicability to Sri Lanka**	**Methodological Notes**
YOLOv5 / YOLOv8 **[25] [26] [27]**	TrashCan, Portofino	mAP:~96% (YOLOv5s), Precision: ~96%, Recall: ~93%	Real-time detection; lightweight	Needs annotated datasets; struggles with occlusions	Suitable for shallow-water, diver-mounted cameras and Raspberry Pi edge devices	Problem Definition: Real-time plastic detection; Method Selection: YOLO for speed; Data Use: Pre-trained + transfer learning; Analysis: Precision/recall;

						Validation: Cross-dataset testing
Faster R-CNN **[25] [28]**	CleanSea, DeepTrash	Accuracy: ~85–90%	High detection accuracy; robust in complex scenes	Computationally heavy; slower inference	Better for national research labs/universities with GPU clusters	Problem Definition: Accurate detection in complex underwater environments; Method Selection: Faster R-CNN for robustness; Analysis: Accuracy, confusion matrix; Validation: Benchmark on diverse scenes
U-Net (Semantic Segmentation) **[25]**	Custom underwater litter datasets	IoU: ~70–80%	Pixel-level segmentation; detects partially buried plastics	Requires high-quality annotated masks; limited transferability	Useful for coral reef & seagrass zones (Hikkaduwa, Batticaloa)	Problem Definition: Identify exact plastic locations; Method Selection: U-Net for segmentation; Data Use: Annotated masks; Validation: IoU metric; Analysis: Pixel-wise evaluation
Mask R-CNN (Instance Segmentation) **[26] [28]**	TrashCan, Synthetic data	mAP: ~82%	Separates overlapping plastics; strong generalization	Needs large training data; high compute	Suitable for Sri Lankan ports where nets & bags overlap in clusters	Problem Definition: Detect and separate clustered debris; Method Selection: Mask R-CNN for instance-level segmentation; Analysis: mAP; Validation: Synthetic + real data comparison
Custom CNN Architectures **[29]**	Region-specific small datasets	Varies (60–75%)	Tuned for local debris types	Poor generalization; limited scalability	Could work if Sri Lanka develops LankaTrashNet dataset	Problem Definition: Local debris recognition; Method Selection: CNN design; Analysis: Model evaluation on small dataset; Validation: Hold-out test set

TABLE III. OVERVIEW OF UNDERWATER LITTER DATASETS [25]

Dataset Name	**Year**	**Collection Method**	**Size**	**Number of Classes**	**Annotations**	**License**
TrashCan 1.0	2020	ROV	7,212 images	TrashCan-Material: 16, TrashCan-Instance: 22	Segmentation masks, bounding boxes	Academic use only
Japan Agency for Marine-Earth Science and Technology (JAMSTEC) Deep-Sea Debris	1984–today	ROV	Large-scale	9	Bounding boxes, metadata	Open access
SeaClear Dataset	2024	ROV	8,610 images	40	Segmentation masks, bounding boxes	Open access
Underwater Trash Detection (Walia et al.)	2023/24	ROV + Diver	9,625	3	Bounding boxes	Open access
Trash - ICRA19	2020	Unknown	6,148 images	3	Bounding boxes	Open access
Deep Plastic Dataset	2021	Field-collected / publicly available images	3,174 images	1	Bounding boxes	Open access
Underwater Plastic Pollution Detection	2024	Manual	4,770 images	15	Bounding boxes	Open access

CleanSea Dataset	2022	ROV	1,223 images	19	Segmentation masks / bounding boxes	Free for research

E. *End-to-End Workflow Representation*

The full underwater macroplastic detection pipeline, from image acquisition to final output visualization, is illustrated in Figure 3. This end-to-end representation highlights the integration of classical image processing techniques with advanced AI models such as YOLOv8, as well as real-time feedback through heatmaps and bounding boxes.

F. *Decision Flow: Mono vs. Stereo Vision Input*

In scenarios where 3D spatial awareness or depth estimation is necessary, such as tracking plastic debris drift or mapping seafloor litter volumes, a stereo vision system may be more appropriate. Figure 4. presents a decision flowchart for choosing between mono and stereo input configurations based on application requirements.

AI-powered computer vision systems hold immense potential for revolutionizing the monitoring of underwater macroplastic pollution. Through a structured pipeline involving high-quality image acquisition, preprocessing, detection, and post-processing, such systems can deliver accurate, scalable, and cost-effective solutions for marine debris surveillance. While challenges remain, such as the lack of annotated underwater datasets and the complexity of biofouled plastic detection, ongoing advancements in imaging, deep learning, and autonomous vehicles are rapidly addressing these limitations [19][21][24][25].

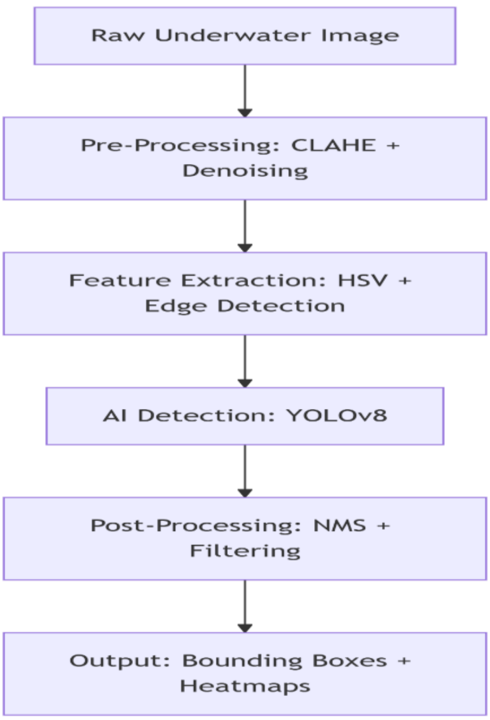

Figure 3. End-to-end ai-based computer vision workflow for underwater macroplastic detection.

The integration of AI in this field does not merely augment traditional methods but redefines what is possible in terms of detection scope, efficiency, and objectivity. As highlighted by current literature, the combination of robust computer vision techniques and adaptive learning algorithms paves the way toward a more intelligent, responsive, and data-driven approach to marine environmental protection.

VII. Opportunities for Sri Lanka

Sri Lanka, as an island nation with a vast exclusive economic zone and a rich biodiversity in its coastal waters, has both an urgent need and a valuable opportunity to leverage emerging AI-based underwater plastic detection technologies. By aligning with global trends and adapting solutions to local contexts, Sri Lanka can take meaningful steps toward mitigating marine plastic pollution.

A. *Cost-Effective Detection Using Low-Cost Tools*

While high-end underwater robots and sensors remain expensive, Sri Lanka can adopt low-cost underwater cameras, drones, and mobile AI solutions for macroplastic detection in shallow waters. Open-source computer vision tools and edge computing devices, such as Raspberry Pi-based camera systems, can make real-time detection feasible even on a limited budget. Leveraging freely available AI models fine-tuned for underwater environments can further reduce development costs.

B. *Building a National Plastic Debris Dataset*

Internationally, datasets such as TrashCan, Garda, and Portofino have enabled the training and benchmarking of AI models for marine litter detection, especially in the Mediterranean and Atlantic regions. However, Sri Lanka currently lacks a standardized, annotated dataset that reflects the unique characteristics of its marine ecosystem, such as coral reef zones, estuaries, and fishing harbors.

Creating a localized dataset, potentially named *LankaTrashNet* or *SL-MarineLitter-DB*, would allow

AI researchers to fine-tune models to detect region-specific debris like fishing nets, sachet packets, and polythene bags commonly found in South Asian waters. Such a dataset could be developed collaboratively by marine biologists, computer scientists, and volunteers, using both diver footage and drone imagery from hotspots like Hikkaduwa, Negombo, and Trincomalee.

C. Informing Policy and Action Plans

Insights derived from AI-powered detection systems can be directly used to inform Sri Lanka's National Marine Litter Action Plan, as well as help track progress toward Sustainable Development Goal 14.1 (which aims to reduce marine pollution by 2025). Automated, visual data collection reduces the reliance on manual surveys, offering a scalable approach for continuous marine litter monitoring.

D. Collaboration with Universities, NGOs, and Researchers

Sri Lanka has a strong academic base in both marine biology and computer science. Universities such as the University of Colombo, University of Ruhuna, and The Open University of Sri Lanka can lead pilot projects in collaboration with NGOs (e.g., the Pearl Protectors, MEPA) and international researchers in AI. Such collaborations can follow global models like the TrashCan dataset initiative but adapted to local conditions.

In addition, student-led AI hackathons and citizen science projects could involve the public in tagging plastic debris in images, further accelerating the creation of a national dataset while promoting awareness.

E. Pilot Projects in Critical Zones

Pilot deployments can begin in high-risk coastal areas, such as:

- Negombo Lagoon - impacted by urban runoff and tourism
- Hikkaduwa Reef - a major tourist attraction threatened by litter
- Batticaloa and Trincomalee - areas with growing marine activity

These pilots can use AI tools to detect and quantify litter patterns over time, evaluate intervention strategies (e.g., floating barriers or cleanup campaigns), and feed data into policy-making and community initiatives.

As summarized in Table 4, Sri Lanka lags behind in datasets, technical readiness, and policy integration compared to global best practices. These gaps, however, present unique opportunities to build cost effective, context-specific solutions. The following subsections outline key pathways for Sri Lanka to advance in AI-based underwater macroplastic detection.

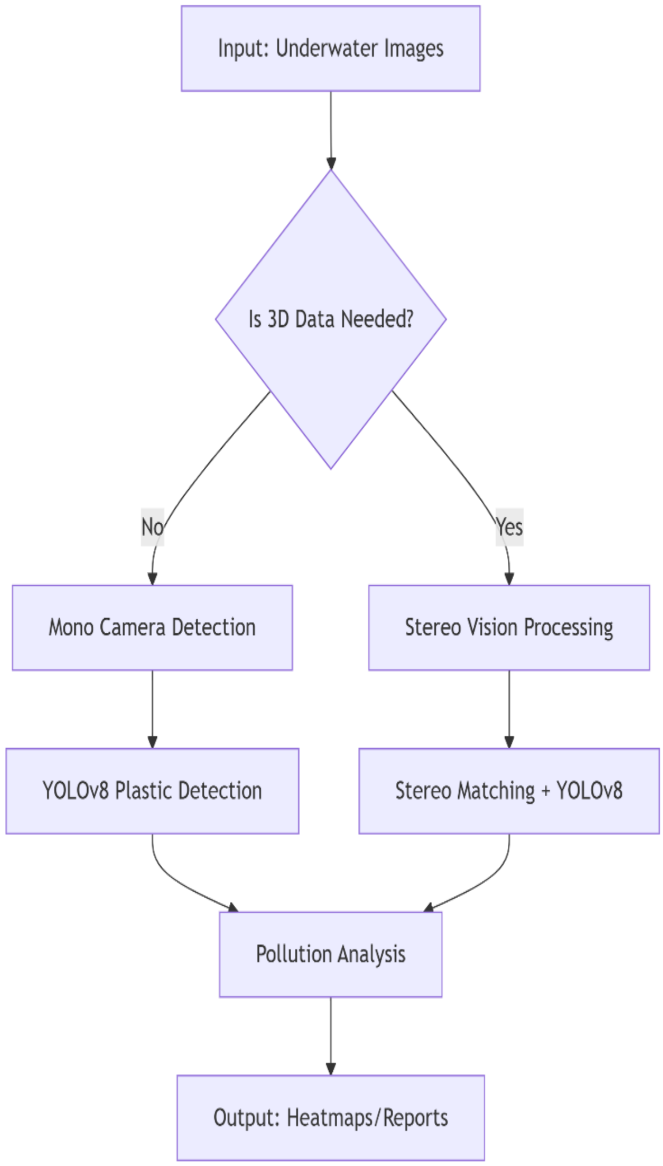

Figure 4. Decision-making flow for mono vs. stereo vision systems in underwater plastic detection.

TABLE IV. COMPARATIVE GAP ANALYSIS OF GLOBAL BEST PRACTICES AND SRI LANKAN READINESS FOR AI-DRIVEN UNDERWATER PLASTIC DETECTION

Research Aspect	Global Best Practice	Current Status in Sri Lanka	Gap Identified	Actionable Recommendation
Datasets	Public datasets (TrashCan, Garda, Portofino) with 10k+ annotated images	Lack standardized dataset; fragmented surveys only	Lack of localized annotated underwater imagery	Develop LankaTrashNet with 5k+ labeled images from Negombo, Hikkaduwa, Trincomalee
AI Techniques	Deep learning models (YOLO, Faster R-CNN, U-Net, Mask R-CNN)	No Sri Lanka-specific studies	No benchmarking against local conditions	Benchmark top 3 models on Lankan dataset
Hardware	ROVs, AUVs, stereo vision, edge AI	Reliant on manual SCUBA surveys	Lack of affordable hardware deployments	Start with low-cost underwater cameras + Raspberry Pi
Policy Integration	AI-driven monitoring informs EU, Mediterranean, and Japanese marine policies	Fragmented marine litter policies, no AI integration	Weak data-policy linkage	Feed AI outputs into National Marine Litter Action Plan
Regional Readiness	Maldives, Mauritius exploring AI pilots	Sri Lanka has awareness but no pilots	Readiness gap	Launch pilot AI detection projects in 2 coastal hotspots

VIII. CONCLUSION

The escalating threat of underwater macroplastic pollution demands targeted, evidence-based solutions. This review synthesized global advances in AI-based underwater detection, compared leading approaches, and identified critical gaps in their applicability to Sri Lanka. While techniques such as YOLO, Faster R-CNN, and U-Net have achieved accuracies of 75–90% in international studies, their transferability remains limited without localized datasets and cost-effective deployment strategies.

A structured gap analysis revealed four priority areas for Sri Lanka: (i) development of a national underwater macroplastic dataset (targeting at least 5,000–10,000 annotated images across key hotspots), (ii) benchmarking of three core AI models (YOLOv8, Faster R-CNN, and U-Net) on local data within the next 2–3 years, (iii) pilot deployment of low-cost underwater camera + edge AI systems in critical zones such as Negombo Lagoon and Hikkaduwa Reef, and (iv) integration of AI-derived outputs into the National Marine Litter Action Plan and SDG 14.1 monitoring framework.

By prioritizing these actions, Sri Lanka can realistically achieve a baseline AI-powered monitoring network by 2027, enabling scalable, continuous, and low-cost detection of macroplastic pollution. Beyond academic value, these outcomes will strengthen policymaking, guide conservation strategies, and safeguard livelihoods dependent on healthy marine ecosystems. In doing so, Sri Lanka can position itself as a regional leader in leveraging artificial intelligence for sustainable ocean management.

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