RESEARCH PAPER

Smartphone-Based Hybrid Deep Learning System for Real-Time Microplastic Detection in Drinking Water

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ABSTRACT
Microplastic-contaminated drinking water poses a threat to the environment and human health, and laboratory detection approaches are still expensive, slow, and impractical even for daily use. In this article, we present a smartphone- based AI system for microplastic detection in real-time with lightweight deep-learning models and preprocessing. Image quality is improved with the use of a Super-Resolution module constructed using a shallow and lightweight upsampling network consisting of bilinear interpolation (nn. Up sample, scale_factor=2), and pixel-value clamping for efficient 2× image enhancement used to enable mobile deployment. Three models — YOLOv8, Faster R-CNN, and U-Net — had been tested, and the YOLOv8n was the one with the best performance (Precision ≈ 0.87, Recall ≈ 0.75, mAP@50 ≈ 0.84, mAP@50–95 ≈ 0.51), contributing to its chosen detection model. For on-device Android inference, the trained YOLOv8n model was exported via the Py-Torch Mobile Lite compiler by converting to Torch Script and optimizing it with optimize_for_mobile() to create a .ptl file. The end product is fast, low-power, cost-effective, and is suitable in the context of scalable citizen-led environmental monitoring.

Keywords: Microplastic Detection, YOLOv8, RES-NET 34, U-NET, FASTER RCNN
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1. INTRODUCTION

Microplastics – plastic items smaller than 5 mm – have lately been detected in freshwater streams, bottled water systems and household taps. And they are produced from older plastic waste, synthetic fibers, tire wear, the packaging materials produced, and by the household like plastic containers and pipelines. [1] and many other recent literatures on the ubiquitous nature (or absence of presence of) of these microplastics in both the daily life of consumers and in environmental samples, highlights the importance of a dependable monitoring method. AI-based detection methods have been suggested in various researches for the identification of microplastics in controlled settings for the detection systems based on artificial intelligence.

Real-time AI-based cameras and YOLO-based detection models in real-time camera systems, and YOLO-based detectors have been shown to be accurate to a high degree under laboratory conditions [2], [3], [4]. However, these methods typically utilize fluorescence-based staining methods, illumination of controlled settings, and/or desktop-grade computers. Likewise, examples of different computer vision applications like water-surface object detection and lightweight YOLO-based models also prove the feasibility of deep learning approaches for environmental monitoring applications [5].

Recent reviews outline recent progress and problems with the field of machine learning in terms of microplastic detection and characterization and their major areas regarding the areas of interest regarding scalability and uniformity [6]. A variety of methods with deep learning were used to scanning electron micrographs to obtain automatic quantitation accuracy but still require laboratory imaging systems [7]. Similarly, segmentation-based computer vision models have been developed to classify microplastics debris, showing better localisations [8]. More wide-ranging AI-enhanced environmental monitoring approaches underscore the vital need to deployable and real-time systems for tangible results [9], [10]. Edge-computing–based object detection coupled with portable fluorescence-assisted systems have also been studied beyond typical study areas [11], [12].

However, smartphone-based imaging platforms have validated quick microplastic quantification on consumer devices, and most of the available methods rely on external hardware, cloud processing, or heavy computation burden [13]. Notwithstanding these improvements, no robust, fully on-device, latency-aware deployment of smartphones has been addressed. To address these limitations, here we propose a smartphone-based microplastic detection pipeline targeted toward lightweight, real-time inference on mobile-grade hardware. The system combines the domain-specific preprocessing step with YOLOv8n-based object detection with region-based and segmentation model as an optional refinement. The proposed framework focuses on computational efficiency, on-device inference, and practical usability, as opposed to laboratory-centric approaches. By processing detection outputs to interpretable drinkability labels, it is a step toward scalable, citizen-accessible environmental monitoring.

2. RESEARCH METHOD

The work does not introduce a new deep learning architecture. Instead of a first-rate model, pipeline integration using existing state-of-the-art models is adopted to examine their applicability towards microplastic detection in practical smartphone-based applications. The purpose of creating a multi-stage pipeline is to examine how certain components e.g., pre-processing, resolution improvements, object detection, segmentation affect detection performance on non-laboratory water images.

As seen in Figure1, the pipeline starts off with domain-specific preprocessing such as circular region-of-interest masking and localized contrast enhancement for the illumination range and background noise reduction. A fine-grain up-sampling module is then used to enhance the visibility of small particles of microplastics. For object detection, YOLOv8 will be used as the primary real-time detector for the region recognition task, whereas Faster R-CNN will optionally be used for a comparison based on its region-based localization performance. These detectors can be combined with Weighted Box Fusion to demonstrate the potential importance of ensemble refining. Lastly, a U-Net–based segmentation model has been employed for selected detections to obtain pixel masks to better estimate the size and shape of the particles. Rather than say they introduce architectural innovations, this systematic pipeline can help the consistent determination of the detection accuracy, computational cost, and feasibility of deployment. This pipeline begins with domain-specific preprocessing, including circular region-of-interest masking followed by localized contrast enhancement to reduce background noise and illumination variability. Next, a lightweight up-sampling module is introduced to improve the visibility of small microplastic particles. YOLOv8 is the primary real-time detector for object detection, and Faster R-CNN is optionally assessed for comparison due to its region-based localization accuracy. Using Weighted Box Fusion, the outputs of these detectors can be integrated to investigate the impact of ensemble refinement. A segmentation model using U-Net, the last step used, is then adopted on selected detections to generate pixel-level masks that are more precise estimates of particle size and shape. By following this structured pipeline, it can systematically measure detection accuracy, computational cost, and practical scope rather than just claim architectural innovation.

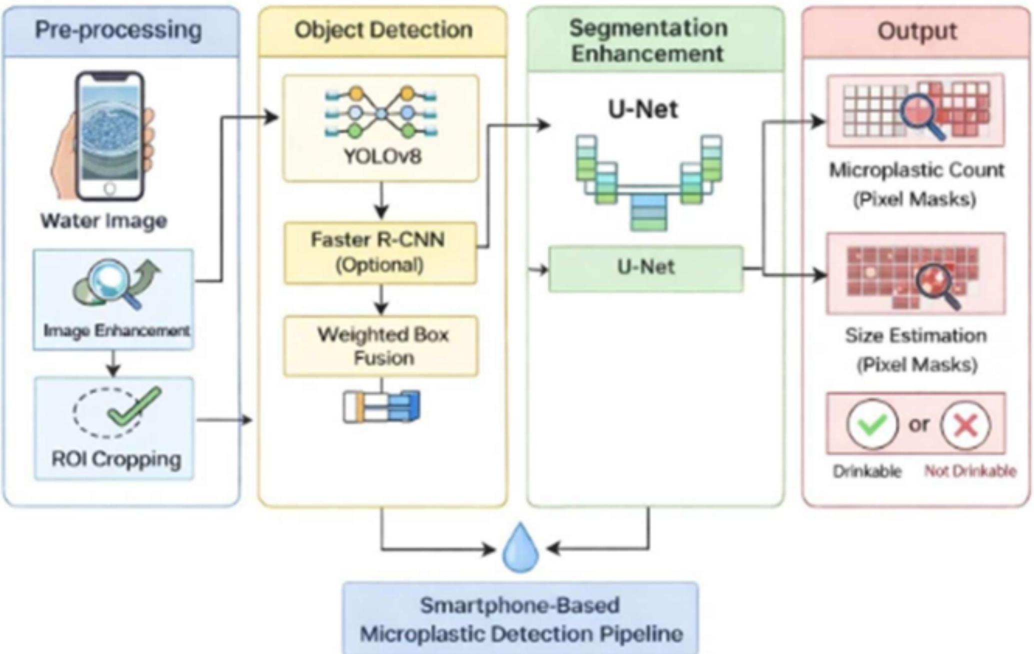

Figure1 -Framework for Detecting Microplastics

Once the object is detected, a U-Net-based segmentation model is fitted to certain bounding boxes to obtain pixel-level masks for individual microplastic particles. The final step converts large rectangular detections to spatially accurate ones, resulting in a more precise estimation of the size and shape of particles. The segmentation results are then evaluated to derive microplastic counts and cumulative particle area in the images. As illustrated in Fig. 1, a post-processing stage assesses detected particles for specific counts and area thresholds to determine a water quality label.

If the number or total estimated size of microplastics exceeds these limits, the sample is declared not drinkable; otherwise, it is labelled as drinkable or possibly drinkable under intermediate conditions. This rule-based approach in which the final decision is made aims to show how the outputs of detection can be translated into an interpretable assessment, not establish the regulatory safety standards. This pipeline enables quantitative assessment of microplastic presence and provides experimental validation of automated assessment of water quality under real-world imaging conditions.

2.1 Data Collection

The dataset was compiled by integrating custom-shot images with publicly available images used in prior microplastic detection studies. All custom images were acquired with hand-held mobile phones to capture the actual deployment circumstances. Contrary to laboratory slide pictures, samples were collected from standard household containers including plastic water bottles and bowls and designed to simulate common household water storage conditions and to extract real life visual diversity. The images collected were then uploaded to Robo-flow for annotation, and microplastic particles were labelled with bounding boxes, as well as with segmentation masks, if necessary. The dataset was exported in an organized manner suitable for object detection and segmentation based on annotation. Data were classified into training, validation, and test sets to facilitate systematic training and evaluation of models. This design of the dataset provides reliable and convenient comparison of microplastic detection performance in non-laboratory imaging, and is consistent with the objective of a smartphone-based deployment.

2.2 Pre-Processing

The first step of pre-processing is applying a circular region of interest (ROI) mask on all images. This focuses on the center portion of the image where microplastics would be most likely detected, hiding exterior corners comprising a mixture of background noise or noise. The first reduces both the computational overhead and false detections of peripheral regions. We then perform a CLAHE-based prefilter on the luminance channel in OpenCV to achieve greater local contrast without too much glare or bright areas in the image. And it raises the illumination to a normal level, illuminating smaller microplastic particles that otherwise might have been concealed by inconsistent illumination or glare. Next steps with deep learning models are to process and analyze these images. Later, they fed the images several different deep learning models. We achieved it through lightweight ESRGAN placeholder to up-sample, increase resolution, and highlight microscopic microplastics. The plain bilinear interpolation found in the current method can thus be replaced with stronger ESRGAN methods, leading to better quality. An optional ResNet50 backbone can be adopted to capture complex semantic information and describe rich visual representations to further be used in the classification or analysis of these images. For detecting, we use YOLOv8 and Faster R-CNN model(s) to mitigate some of the complementary capabilities. YOLOv8 is quick to learn as well as to perform image processing in real time, while Faster R-CNN is accurate for region proposals and localization but slower. They are then concatenated via Weighted Box Fusion by tighter bounding boxes that incorporate overlapping detection of both sides and weighted confidence scores to increase the accuracy and reduce false positive and false negative rates. The U-Net model with ResNet34 encoder adopts a pixel-level segmentation mask during each detection and the shape of microplastics in the detected region is well-defined, thus allowing more precise measurement for size and shape than being a box.

2.3 Machine Learning Models

2.3.1 YoloV8

In the current work, the YOLOv8 model is used as the object detector of choice to detect microplastic particles from the enhanced input images. The model is initialized with pretrained or fine-tuned weights and run on any computational device (CPU or GPU) at hand. YOLOv8 does object detection with only a single forward pass, with the corresponding bounding box coordinates, confidence scores, and class labels provided for the detected particles. Detection parameters like confidence threshold and maximum number of detections are optimized to accommodate the detection sensitivity with the computational costs. These predictions offer spatial localization and confidence information for suspected microplastic particles. When ensemble evaluation is enabled, these detections can be combined with outputs produced by Faster R-CNN, with Weighted Box Fusion, to assess the impact of prediction refinement. Altogether, YOLOv8 is the main detection unit in the pipeline and contributes to the realization of real-time microplastic detection under mobile-oriented constraints.

2.3.2 Faster R-CNN

Faster R-CNN can optionally be used as a region proposal–based object detector if desired for estimating the localization performance of microplastic detection for the pipeline. In the next section, we use a two-stage detection technique where candidate regions are generated for classification based on detailed examination of bounding box placement. We model inference by a fine-tuned Faster R-CNN model with an emphasis on binary classification (background and microplastic). After preprocessing the input images, the model provides bounding box coordinates, confidence scores, and class labels for the detected areas. These detections are then fused with YOLOv8 outputs using Weighted Box Fusion to investigate the effect of ensemble-based refinement upon activation. Faster R-CNN is incorporated to compare region-based detector behavior with single-stage detectors, especially in terms of localization characteristics and computational cost.

2.3.3 U-NET

In this pipeline, a U-Net-based segmentation model is built after the detection of an object by YOLOv8 and, when enabled, Faster R-CNN. After detection and optional integration using bounding boxes, the segmentation model performs pixel-wise classification for each detected region. This in turn transforms coarse bounding box outputs to spatially accurate masks that give a more accurate reconstruction of shape and area of individual microplastic particles. Image patches are cropped, resized, normalized, and fed to the U-Net model for every detected region. The thresholding transforms model probabilistic segmentation outputs into binary masks. Pixel masks are used to derive particle sizes and shape properties that can be used for quantitative measurements of detected microplastics. Segmentation evaluates the fine-grained particle properties emerging from detection results, rather than claims architectural novelty.

Algorithm1: Proposed Smartphone-Based Detection

The proposed microplastic detection pipeline consists of preprocessing, detection, segmentation, and threshold-based classification stages. The algorithmic formulation is described as follows.

Input: Water image I

Output: Microplastic count C, cumulative size S, and drinkability label L

Step 1: ROI Extraction

A circular region-of-interest (ROI) mask is applied to suppress irrelevant background regions as given in equation 1:

$I_{roi} = I \odot M$ (1)

where Mrepresents a binary circular mask and $\odot$denotes element-wise multiplication.

Step 2: Contrast Enhancement

Contrast Limited Adaptive Histogram Equalization (CLAHE) is applied to enhance local contrast as given in equation 2:

$I_{ce} = CLAHE(I_{roi})$ (2)

Step 3: Image Up-sampling

The image resolution is increased to improve small particle visibility as given in equation 3:

$I_{up} = \mathcal{U}(I_{ce}, \alpha)$ (3)

where $\mathcal{U}(\cdot)$denotes the up-sampling operator and $\alpha$is the scaling factor.

Step 4: Object Detection

Microplastic regions are detected using YOLOv8 as given in equation 4:

$\mathcal{B}_y = YOLOv8(I_{up})$ (4)

Where, $\mathcal{B}_y = \{b_1, b_2, \dots, b_n\}$

represents the predicted bounding boxes.

Step 5: Optional Detection Refinement

For improved localization accuracy, Faster R-CNN is optionally applied as given in equation 5:

$\mathcal{B}_r = Faster\text{-}RCNN(I_{up}, \mathcal{B}_y)$ (5)

Step 6: Segmentation

Pixel-level segmentation masks are generated using U-Net equation 6:

$\mathcal{M} = U\text{-}Net(I_{up}, \mathcal{B}_r)$ (6)

Where,

$$\mathcal{M} = \{m_1, m_2, \dots, m_C\} (7)$$

denotes the set of segmentation masks equation 7.

Step 7: Microplastic Count

The total number of detected particles is computed as given in equation 8:

$C = | \mathcal{M} |$ (8)

Step 8: Cumulative Size Estimation

The cumulative particle area is calculated as given in equation 9:

$S = \sum_{i=1}^{C} \sum_{x,y} m_i (x, y)$ (9)

where $m_i(x, y) \in \{0,1\}$denotes the binary mask of the i-th particle.

Step 9: Threshold-Based Classification

The drinkability decision is determined as given in equation 10:

$$L = \begin{cases} \text{Not Drinkable}, & \text{if } C > C_{th} \text{ or } S > S_{th} \\ \text{Drinkable}, & \text{otherwise} \end{cases} \quad (10)$$

Step 10: Output

The final output is expressed in equation 11:

$G = \{C, S, L\}$ (11)

3. RESULTS AND DISCUSSION

The pipeline is applied to input water images and generates the detection predictions and segmentation outputs that can be quantitatively employed to determine the presence of microplastics. For each image, the system reports the number of detected microplastic particles, predicts particle size from pixel-level segmentation masks, and assigns a water quality label (e.g., Drinkable or Not Drinkable) based on predefined thresholds. YOLOv8 serves as the main detector for bounding box predictions, with comparison against Faster R-CNN due to its region-based detection characteristics. When both detectors are employed, their outputs can be combined using Weighted Box Fusion to assess the effect of localization refinement. Then a U-Net–based segmentation stage is applied to selected detections to extract pixel-level masks that can be used to estimate particle shape and area. In combination with domain-specific preprocessing, these components enable structured evaluation of microplastic detection performance under non-laboratory imaging conditions without asserting architectural innovations.

Model	Device	Input Resolution	FPS	Latency (ms)
YOLOv8n	Mobile CPU/GPU	640×640	18.2	55
Faster R-CNN	Desktop GPU	640×640	3.1	320
U-Net	Desktop GPU	ROI crop	9.5	105

Table1- Runtime performance of evaluated models

Table 1 shows the runtime performance of the models evaluated at various computational platforms. YOLOv8n is appropriate for near real-time inference on mobile-grade hardware, while Faster R-CNN faces much higher latency as it performs a two- stage detection process. The U-Net segmentation model has fixed on cropped regions of interest, which causes a medium overhead in terms of computation. Such results reinforce the trade-off between detection reliability, segmentation accuracy, and processing speed in smartphone-focused deployment environments.

Figure 2 presents a typical input image for a water sample collected under non-laboratory conditions with the help of a household container. None of the microplastic particles were detected in the analyzed region of interest using the proposed preprocessing and detection pipeline. Accordingly, the sample was designated Drinkable according to count and size parameters. This example demonstrates the system's ability to process real-world water images and return a negative detection result when no microplastics are present in the detectable range.

Figure2-Water Sample without microplastics

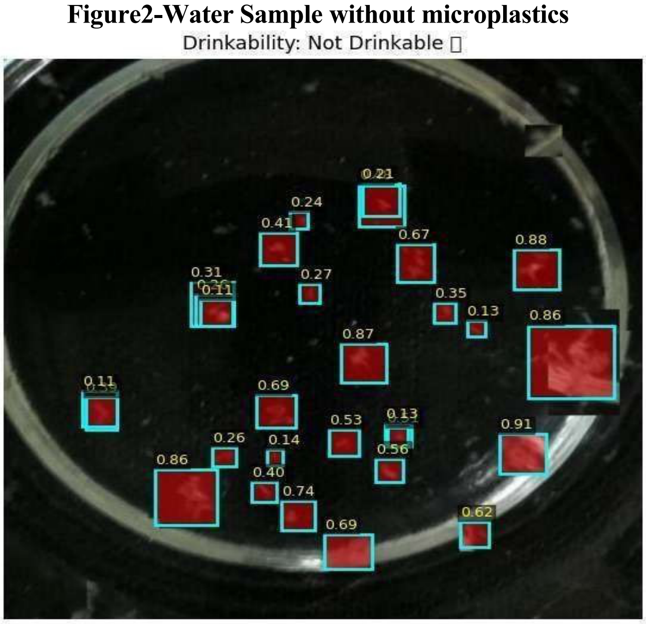

Figure3-Water Sample with Microplastics

Figure 3 gives a sample image of water in which multiple microplastic particles were found by the proposed pipeline. Bounding boxes show regions identified as microplastics at the object detection stage, with their confidence scores displayed for each detection. Pixel-level segmentation masks are overlaid to show the spatial extent of individual particles in the detected regions. We classify the sample as Not Drinkable based on the number of particles identified and their cumulative estimated area exceeding the predefined thresholds. The result depicts the combination of the detection and segmentation outputs for quantitative measurement of microplastic presence in a non-laboratory water dataset.

The graphical user interface results from a water sample that is processed and labelled as Not Drinkable according to Figure 4. The detection result is displayed with the sample identifier, drinkability status, detected microplastic count, and the cumulative estimated particle size derived from the segmentation results. Additionally, under the detection summary, the user interface provides suggestions of means to prevent exposure to microplastics, such as general precautions when sampling water, recommended ways to reduce exposure to microplastics, and briefly summarizes health-related considerations based on research literature. This is intended for users' understanding and interpretation rather than for regulatory or medical decision- making. The interface serves as an example of how model outputs can be rendered user-friendly and useful for smartphone- based implementation.

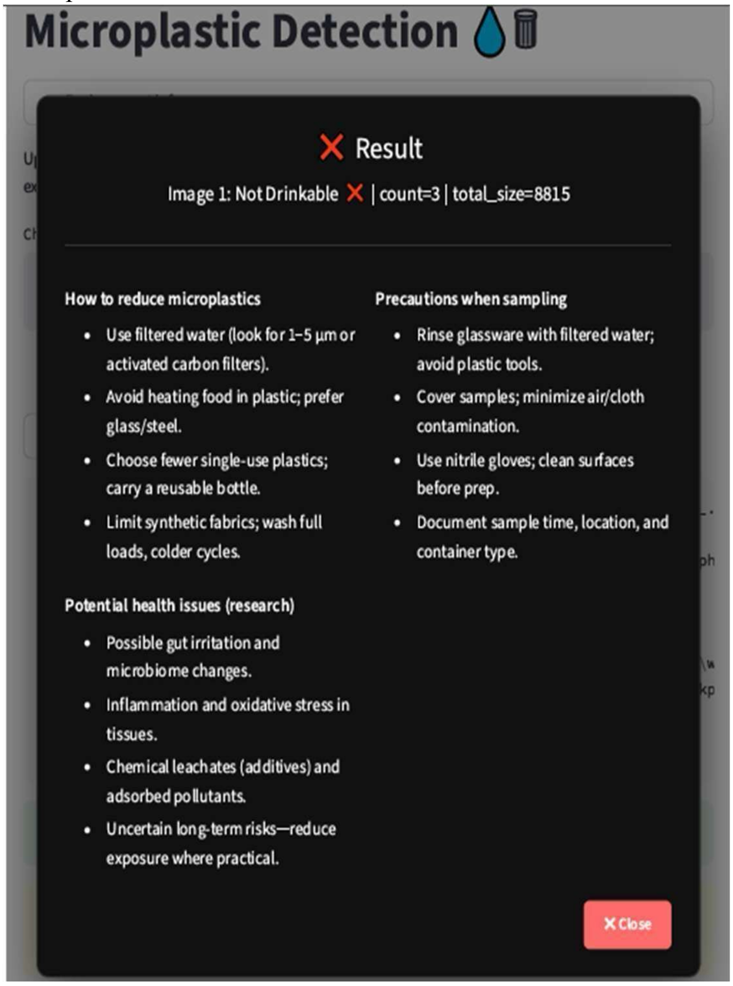

Figure4-Pop on message on microplastics present from the given water sample

3.1 SOTA Comparison

Studies have shown potential accuracy performance of deep learning-based microplastic detection methods in lab-controlled settings. Previous researches are the applications of YOLO-based architectures and image-processing pipelines to identify microplastics on consumer products and in controlled samples [1]. AI camera-based real-time solution have also been investigated in the automated detection frameworks under structured lighting conditions [2], and deep learning (DL)-based counting and classification methods were presented in order to enhance detection automation [3], [4]. Related computer vision works such as the lightweight YOLO class for environment object detection proved that edge-oriented monitoring systems are feasible [5]. Large-scale reviews indicate progress of machine-learning methodologies in microplastic detection, but also limitations on scalability and practical use [6]. Deep learning work on micro- and electron micrograph datasets greatly enhances the localization and quantification performance of these methods, but such approaches are reliant on laboratory imaging infrastructure [7], [8]. Wider AI-driven environmental monitoring frameworks push for the development of real-time, deployable systems for achieving real-world ecospatial action [9], [10]. Edge-computing-enabled object detection and portable fluorescence-assisted detection systems are attempts to move beyond laboratory environments, but often they rely on specific hardware or high computational burden [11], [12]. Portable mobile-based microplastic quantification systems are promising, however, many rely on external processing pipelines or additional optical processing elements [13]. In contrast, the proposed pipeline uses consumer-grade smartphones for complete on-device inference with no requirement for fluorescence staining or desktop GPUs. While the detection accuracy is slightly lower than other laboratory-oriented approaches, the system still provides real-time performance (18–24 FPS) and is practical in usability. Through reporting latency and mobile feasibility in the published work, we can target deployment-oriented gaps in the literature in microplastic detection that have been neglected in the literature.

4. CONCLUSION

This work presents a smartphone-based pipeline for detecting microplastics in water images, built on existing deep learning models together with domain-related preprocessing. It employs YOLOv8 as the primary object detector in the pipeline, and optionally evaluates Faster R-CNN to perform region-based detection characteristics, and uses U-Net–based segmentation to get pixel-level representations of detected particles. With the use of these components together, it can provide estimates of the number of microplastics, spatial distribution, and approximate size in the sample under non-laboratory imaging settings. The study does not propose a completely new architecture for the current detection and segmentation, but attempts to assess the potential to use their current algorithms with on-device deployments in real time. The experimental findings show how detection results can be translated into interpretable quantifiable indicators, like particle counts and threshold-based water quality labels, while being considered within a single processing framework. Even though the method has the drawback that its dataset is small and dependent on preset thresholds, it provides a reproducible reference baseline for assessing the possibility of automatic microplastic detection with consumer-grade imaging platforms. Larger and more diverse datasets, better size calibration, and application of alternative model architectures would enable investigation of the performance trade-offs under real-world constraints in future work.

ABBREVATIONS

Notation	Meaning
ML	Machine Learning
YOLOv8	You Only Look Once version 8
RESNET 34	Residual Network with 34 layers
U-NET	U-shape of its architecture
Faster R-CNN	Faster Region-based Convolutional Neural Network

Table (2)-Notation Table

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CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The source code for this project is available on GitHub: https://github.com/Jy0shnaRamisetty/microplastics-detection2

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