

Development of a Real Time Multi Modal Sensor for Field Based Microplastic Detection

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Abstract— Microplastic Pollution in our daily day to day lifestyle has emerged as one of the most concerning issues in recent times, with minute particles detected in oceans, freshwater systems and even some of its traces having its presence in the human tissues as well. Microplastic is generally defined as the category of plastic fragments which are smaller than 5mm (5 millimeters). Existing methods of detection including FTIR (Fourier-transform infrared spectroscopy) and Raman spectroscopy are laboratory dependent, expensive, time consuming and real time field monitoring. This paper presents a compact, low cost system incorporating impedance, programmable multispectral optical sensing and machine learning-augmented microscopy allowing rapid on-site microplastic quantification. Using YOLOv8 based deep learning, the system automatically identifies size of the detected polymer and estimates its type in the provided water samples. [1], [3], [9]. Results are anticipated through a companion app which generates geo tagged contamination heatmaps and a Microplastic Risk Index (MRI). Validated against standard FTIR/Raman data, the solution delivers laboratory grade accuracy at a fraction of the cost, empowering researchers and citizen scientists alike, while strongly supporting national environmental goals with confidence and reliability.

Keywords— *microplastic detection, deep learning, YOLOv8, impedance spectroscopy, environmental monitoring, IoT sensors, multispectral imaging*

I. INTRODUCTION

Microplastics have emerged as a pervasive environmental threat over the past several decades, originating primarily from the breakdown of larger plastic products and the direct release of manufactured micro substances in our daily surroundings. The modern era's dependence on plastics is mainly fueled by plastics powered by manufacturing, textiles, consumer goods etc. These practices have resulted in massive percentage increase in global plastic production with majority of this synthesized material finding its way in the natural ecosystem through inadequate disposal methods, improper waste management and its degradation.

Initially, Microplastics enter the environment in two major ways:

(a) Primary Microplastics, which are intentionally manufactured small particles which are mainly used in industrial abrasives and pre production pellets.

(b) Secondary Microplastics, which arise from the fragmentation of the larger plastic debris due to a combination of physical stress (abrasion, wave action), chemical degradation (oxidation, UV radiation), and biological processes (microbial colonization and enzymatic activity) [4], [7].

Major sources include synthetic fibers from clothing, vehicle tire wear, plastic packaging marine and agricultural runoff and mostly due to industrial discharge. Microplastics are distributed globally with significant concentrations measured across marine, freshwater and even soil environments. Aquatic organisms intake microplastics directly or indirectly leading to bioaccumulation in the food chain and subsequent human exposure through consumption of contaminated seafood, drinking water and agricultural products [4], [7].

The persistence and existence of microplastics create severe ecological and health risks. These tiny particles disrupt feeding and digestion of aquatic species and can absorb and transfer toxic chemicals such as heavy metals, pesticides and persistent organic pollutants [4], [6] which broaden their harmful effects. Despite the urgency of the prevailing issue, current detection methods most notably FTIR (Fourier-Transform Infrared Spectroscopy) and Raman Spectroscopy are reserved to laboratory conditions. They require expensive instrumentation, skilled technicians and lengthy processing times for the result of the inadequate water sample severely limiting the scale, frequency and accessibility of monitoring required for effective management.

Addressing this technological and practical gap, our developed sensor harnesses a mutualistic combination of optical, impedance and AI enhanced microscopy to deliver rapid, laboratory quality microplastic detection directly in the field. By generating programmable multispectral LED imaging, machine learning algorithms (YOLOv8), Our device identifies sizes and types of the microplastic obtained in the sample and also categorizing them on the basis of the risk they possess in everyday life. It also provides access to sophisticated microplastic analysis whilst also empowering not only researchers and scientists but also local communities and citizen scientists.

Our solution enables real time monitoring of contamination hotspots and water sources while also capturing geo tagged data which results in better policymaking and environmental action. Designed to be low cost and portable, our solution can be easily deployed in a wide range of settings, including resource limited areas. By moving environmental surveillance away from centralized laboratories towards a more distributed and accessible network, this approach makes large scale tracking simpler and also provides a rapid response to water quality issues playing a vital role in tackling the growing global microplastic crisis. [8], [9].

II. RELATED WORK

Current approaches for microplastic detection include a wide range of logical, imaging and computational techniques with each method offering its own advantages and disadvantages for environmental regulation. Usually, laboratory based methods such as Fourier Transform Infrared spectroscopy and Raman spectroscopy are regarded as a benchmark as these methods provide high resolution polymer identification through the analysis of molecular vibrational signatures. However, despite their accuracy, these techniques are very expensive in terms of operational costs, bulky equipment and complex sample preparation procedures. As a result, they are not well suited for rapid or large scale field based deployment.

To address these limitations, recent research has slowly focused on the use of machine learning techniques such as support vector machines, random forests, and deep convolutional neural networks to enable automated and efficient classification of microplastics from both spectral and image based data. Deep learning models such as convolutional neural networks (CNNs) including YOLO v8 have shown high accuracy and scalability in detecting microplastics directly from microscopy pages which helps reduce manual effort and observer bias. Multi modal detection also combines the working of optical imaging, impedance spectroscopy and hyperspectral sensing using mutual information from multiple data sources which improves detection reliability and enabling non invasive and real time analysis even in complex aquatic environments.

Moreover, portable detection platforms incorporating these techniques with cloud connectivity and Internet of Things technologies are emerging whilst also allowing geo tagged data sharing and continuous environmental regulation. Although significant process has been made in terms of accuracy, speed and field applicability however several challenges remain such as improving detection robustness, moderating sample matrix effects and expanding data infrastructure to support high throughput analysis. Overall these deployments have shown a multidisciplinary effort to shift microplastic detection from laboratory methods to automated, portable and field ready monitoring systems that support effective environmental management

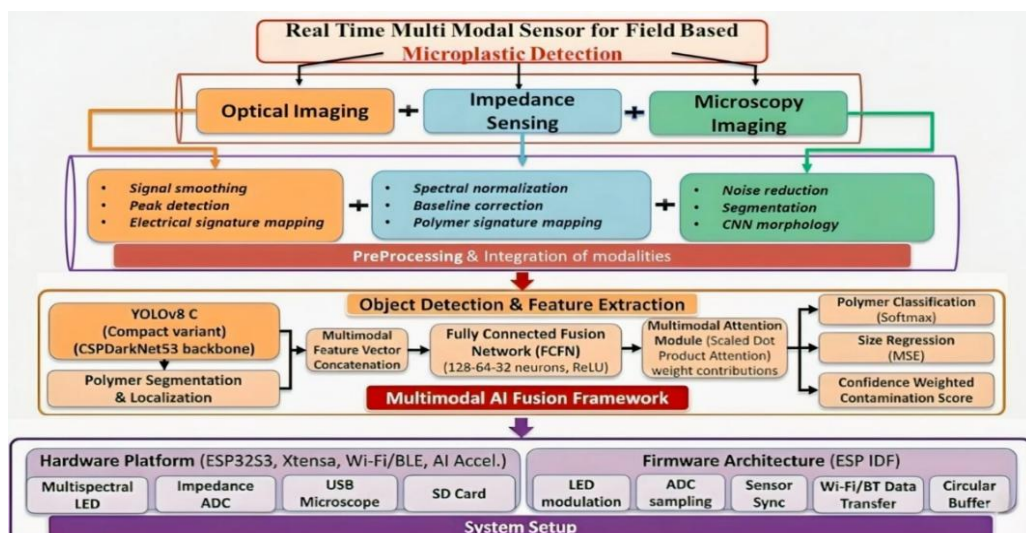
III. SYSTEM DESIGN AND METHODOLOGY

Overview

The proposed Sensor is a multimodal field deployable. real time microplastic (MP) analytical platform. detection, classification and risk testing in water. environments. There are three sensing that are integrated in the system. modalities multispectral optical imaging, impedance spectroscopy, high resolution microscopy within a single-pipeline detector served by a machine learning based multimodal fusion and independently [1], [3], [4], [8].

The sensor system is a integrative hardware level signal acquisition and embedded AI processing technology, which allows on device sensing of polymer fragments, calculates particle size, and an index of Microplastic Risk (MRI). The companion software stack is comprised of Android and iOS application used in result visualization, GIS based geospatial mapping and cloud synchronization. The main design goals are: i. Minimal power field operation with small sized microcontrollers. ii. Integration of multimodal AI to have better polymer specificity and less false positives. iii. Real time feedback Inference based on quantized ML models at edge level. iv. Interoperability and reproducibility of data using a geo tagged cloud storage [1], [8], [9]

Fig.1 System Architecture Diagram



A. Physical and Fluidic Subsystem

i. Flow Cell and Sample Handling

The sensor consists of a microfluidic flow cell composed of an optically transparent polymer. The inlet port pumps the water samples into the sensor and makes the water flow in its laminar state. Flow cell is employed to pinpoint the optic, electric fields, and microscopic views with the aim of performing a multimodal imaging method in one sensing region [3], [8].

ii. Mechanical and Optical Configurations

The optical set-up comprises of a programmable multispectral LED array to light up, a 500M magnification digital microscope to view, and microfabricated electrode pairs that run side by side the flow channel. The optical and electrical components are fixed in a rigid fashion to reduce errors of alignments. The adjustable focusing and calibration slides preserves fidelity of the imaging throughout samples of a different turbidity [2], [4], [8].

B. Sensing Modalities

1. Multispectral Optical Imaging

The programmable LED array is programmed into working in the visible near infrared (400 - 940 nm) range, sequentially lighting the sample in a number of wavelengths [2], [8].

On each band image, the following is carried out: Normalization of the spectrum and alignment to the baseline. ii. Identification of polymer specific absorption or reflection peaks using intensity ration mapping. iii. Extraction of features (e.g. normalized difference index, band depth martrices).

These multispectral signatures offer non destructive optical fingerprint which go in hand with morphological and electrical features.

2. Impedance Sensing

Embedded microfluidic electrodes record of complex impedance $|Z(f)|$ and $\angle Z(f)$ phase angle of a discrete frequency range (usually 1 kHz - 2 MHz). The dielectric reaction of particles varies with polymer. It creates a composition and water conductivity, which is distinct. impedance spectra [3]. Extracted features include: i. Ratio of amplitude in frequency bands; Phase dispersion:

$$Z(f) = \frac{V(f)}{I(f)} = |Z(f)| e^{j\theta(f)} \quad (1)$$

- iii. Peak position and full width at half maximum (FWHM);
- iv. Electrical signature mapping aligned with polymer reference profiles.

Signal conditioning involves spectral smoothing, baseline subtraction, and Fourier domain normalization to mitigate electrode drift and noise [3].

3. Microscopy Imaging

The subsystem of digital microscopy gets high resolution. Suspended particle images in RGB. Image preprocessing also contains denoising, illumination correction and histogram. equalization. Adaptive thresholding and morphological are applied in segmentation. filtering, extraction of particle level of shape. descriptors: i. Equivalent diameter. ii. Aspect ratio. iii. Circularity. iv. Texture metrics (GLCM based entropy and contrast).

The patches of images that have been segmented are observed with the help of a YOLOv8. convolutional neural network based convolutional neural network of object localization. and classification. [1], [7], [9].

Sensor streams (optical, impedance, microscopy) are all. timestamp coordinated by the ESP32 S3 controller. log and combined into one record of events. The excessive stage: preprocessing stage does: i. Optical & Microscopy pipelines: color, band registration, Gaussian noise reduction, color. watershed segmentation, normalization and watershed segmentation. ii. Impedance pipelines: Smoothing of signals by Savitzky-Golay filter, spectral normalization, and extraction of principal components. iii. Feature-level normalization: Each modality's features are normalized (Z-score or Min-Max) and aligned temporally.

This stage outputs structured feature vectors for multimodal AI fusion.

C. Machine Learning And Multi Modal Fusion

1. Object Detection and Feature Extraction

The primary detection module uses YOLOv8 C (Compact variant) for object localization and polymer segmentation. The model's backbone employs CSPDarkNet53 architecture with spatial pyramid pooling and anchor free detection heads [1], [7], [9]. Training datasets consist of manually annotated microscopy images labeled across major polymer categories (Polyethylene Terephthalate, Polypropylene, Polyethylene, Polystyrene, and Polyvinyl Chloride). Feature vectors from: i. YOLOv8 embeddings (visual morphology), ii. Impedance spectral features (dielectric profile), and iii. Optical spectral features (reflectance pattern) are concatenated to form a multimodal feature vector, subsequently passed through a Fully Connected Fusion Network (FCFN). The FCFN is a three layer dense network (128-64-32 neurons, ReLU activation) optimized using Adam (learning rate 1×10^{-3} , batch size 32) [1], [3], [4], [8].

2. Multimodal AI Fusion Framework

Fusion operates at the *feature level*. The joint representation

$$F = [f_{\text{optical}} + f_{\text{impedance}} + f_{\text{microscopy}}] \quad (2)$$

is processed by a multimodal attention module using scaled dot product attention to weigh modality contributions adaptively[2],[4],[8]. Output layers provide: i. Polymer classification (Softmax probabilities), ii. Size regression (mean squared error loss), iii. Confidence weighted contamination score.

3. Edge Optimization

For field deployment, the trained model is exported to TensorFlow Lite (TFLite) with post training quantization (8-bit integer). This reduces inference latency (<200 ms per

sample) on ESP32S3 or smartphone SoCs. Pruning and layer fusion are applied to minimize computational overhead.

D. System Setup

1. Hardware Platform

The embedded controller is ESP32 S3, featuring dual core Xtensa processors, integrated Wi-Fi/BLE, and AI acceleration support [8],[9]. Peripheral components include: i. Multispectral LED driver array (I²C interface), ii. ADC based impedance acquisition circuit, iii. USB microscope camera (UVC interface), iv. SD card module for local storage.

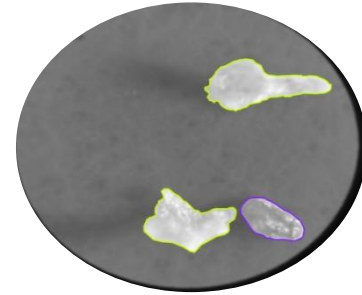
2. Firmware Architecture

Developed using ESP IDF framework, the firmware handles: i. LED modulation and spectral sequencing, ii. ADC sampling and impedance calculation, iii. Synchronization of sensor modalities, iv. Data transmission via Wi-Fi/Bluetooth to the companion app. A circular buffer ensures uninterrupted acquisition and buffering during wireless transfer. [8], [9].

IV. RESULTS

This section gives the findings of the experiment in testing our microplastic detector. The system was tested in two different environments, that is, controlled laboratory tests and real world field conditions. The example of a common detection result is presented into Fig.2 where the system identifies and outlines the microplastic particles in yellow hues on a grayscale microscopic picture. The performance of the system was evaluated in two ways. First, we were able to identify the particles that were detected by the eye. Second, we examined quantitative measures of the training process of the machine learning model. The prepared samples included in laboratory tests assisted in defining the functionality of the system on an ideal situation. The system was tested using field samples to identify how it would react to real world environmental issues. The findings are discussed in three important facets that include the learning curves of the model

with time elapsing, model learning performance in terms of accuracy, and graphical representation of individual particles



that were detected. On their own, these offer a picture of the whole system in terms of identifying the microplastics, sorting them, and functioning in a real-life setup.

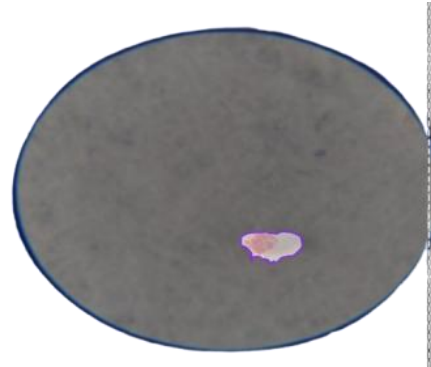


Fig.2. Image Showing Microplastic Classification

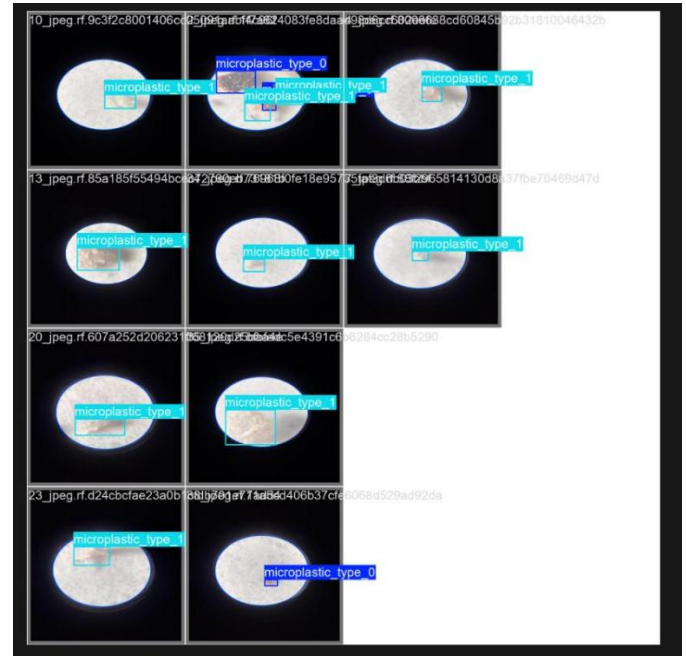


Fig.3. Qualitative detection result of the proposed system

The loss in the box location was presented in Fig.4 when training the model. This metric is used to measure the quality of the model in predicting the location of microplastic particles in any images. The values of losses were high and fluctuated in the initial training stages. This was the case because we employed the use of laboratory and field samples.

Field images were more problematic to process. They had irregular shaped particles and overlaps (mature). Detection was also made difficult by background noise due to organic matter and sediments. With further training, the loss also reduced slowly but smoothly. This implies that the model was able to learn to find the location of the particles more accurately. The detection boxes of the particles that were detected became more accurate and consistent. Towards the end of training, loss became low and stable. This proves that the model will be able to find microplastics with high accuracy. The last performance is in favor of not only the accurate counting of the particles but also their practical application to the real-life situation.

Box Location Loss

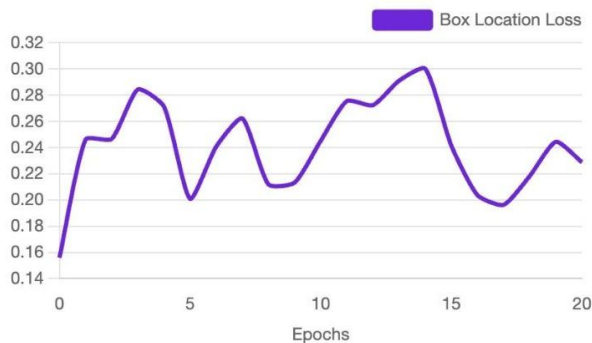


Fig.4 Graph Depicting Box Location Loss

The Fig.5 illustrates the loss of classes during training of the model. This measure shows the ability of the model to label and categorize the dissimilar forms of microplastic particles properly. The loss in the classes decreased rapidly at the initial part of training. This fast learning indicates that the model was able to learn simple visual differences in types of microplastic quickly. The training set had a good number of samples having distinguishable features that were easy to learn. With the further course of training, the loss curve showed little variations. The ones that happened are when the model was fed with visually similar particle types. There was also some variation in field samples which were complex in nature. At some point the loss leveled out at low levels. This implies the model obtained a consistent performance in terms of classification. The concluding findings reveal that the system will be able to differentiate the types of different microplastic reliably. It works effectively on clean laboratory samples as well as hard to find real world field images.

Class Loss

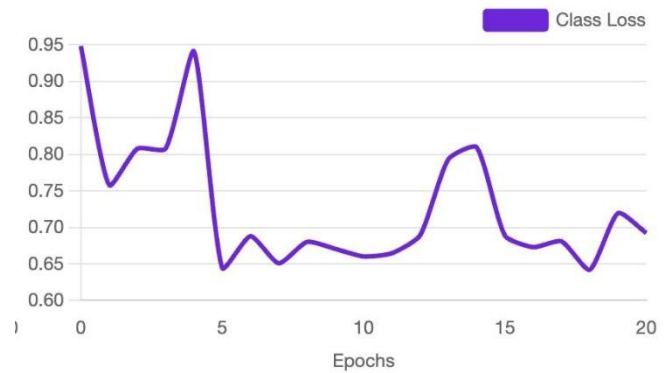


Fig.5 Graph Depicting Class Loss

Fig.6 illustrates the performance of the model in training epochs using two important measures mean average precision (mAP) in purple and mAP @ 50:95 in pink. The two measures monitor how the model is capable of detecting and identifying microplastic particles. There are massive changes in the initial and intermediate phases shown by this graph. The performance begins at about 1.05 and decreases at the beginning of the model as the model adapts to the learning patterns. There is a significant peak at epoch 4 with the value being about 1.20 and then a regressive slope. These variations indicate the process of learning using different samples of various complexities by the model. In epochs 6-16, there are average oscillations of both metrics. Value of mAP ranges between 1.08 and 1.15. These vary due to having different batches of samples in the laboratory and more difficult field images with different particle types, the model experiences. Approaching the later periods, each of the curves is upward. The latter implies that the model becomes more stable and detects better. The overlapping of both mAP measures hints that the system is training effective features which are applicable in varied detection threshold and in the real world scenarios.



Fig.6 Graph Depicting Model Performance

The box overlap loss is depicted in Fig.7 as the model is being trained. Such a loss is used to evaluate the similarity between predicted and true locations of microplastic particles. The graph begins at a low figure of about 0.32 at epoch 0, after which the first two epochs have a sharp increase. The first increase is an adaptive phase of the model since it is learning through the data. The loss is around 0.50 at epoch 2. The curve experiences some significant variations between epochs 2-15. The loss then swings around 0.42 to 0.52 and the maximums can be seen in epoch 3, 6 and 13. These differences arise when the model gets a sample that has varied characteristics. Field images that have irregular shapes of the particles, different sizes, and partial occlusions violate the

loss values. The more distinct the boundaries of the laboratory samples, the less their values. The loss had a declining trend after epoch 15. It decreases at approximately 0.52 to stabilise at approximately 0.42 at epoch 20. This negative change shows that the model was trained to be more accurate in predicting the position of bounding boxes. The last steady values of 0.42- or 0.43 verify enhanced localization of predicted and real particles. The general trend indicates the learning trend that the model has on a reliable localization performance on various sample types.

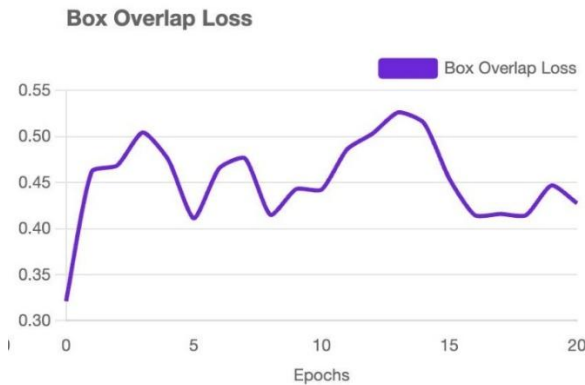


Fig.7 Graph Depicting Box Overlap Loss

Generally, the performance graphs indicate that the models are trained successfully and have good detection. There are three major improvements noted in the training process. First, the values of the losses reduced gradually with regard to epochs. Second, the mAP metrics were growing and leveling at great heights. Third, the oscillations diminished on the progression of the training. These findings support the fact that the model was well learnt on the dataset. It is capable of controlling samples in the laboratory and problematic field conditions. The final metrics are stable and it means that the system is ready to be practically deployed. All the figures demonstrate an evident transition between first learning and stable performance. This confirms the fact that the microplastic detection system proposed is efficient and reliable in various conditions in the real world.

V. CONCLUSION

The current research gives a low cost system of detecting micro plastics in water. This system is a blend of three technologies, which include impedance spectroscopy, multispectral imaging, and machine learning based microscopy. The combination of these approaches will offer rapid and adequate microplastic detection that can be operational in the field. The system is comparative to the classical laboratory techniques such as FTIR and Raman spectroscopy. Nevertheless, it is smaller in size and cheaper. Deep learning and fusion of multimodal data is beneficial to distinguish between various types of plastics and accurately measure the particle size. Our experimental findings conform very well to conventional spectroscopic studies. This proves the validity of the system in assessment of water quality.

The framework provides some additional options other than simple detection. It is capable of producing geo tagged maps of contamination of the locations where microplastics occur.

It also computes a Microplastic Risk Index (MRI) to determine the level of pollution. These are the properties that make the system helpful to study the environment in large scale and also in planning policies. This piece of work fills a very significant gap. It introduces the accuracy of a lab in a field with the help of portable AI powered technology. The system opens up microplastic surveillance and allows it to be utilized more easily on a regular basis. There are three areas of improvement in the future. To begin with, we are going to incorporate hyperspectral sensing to discern between the types of polymers more precisely. Second, we shall optimize the learning models to accommodate more complicated water samples. Third, we shall come up with data sharing systems that help in monitoring and comparing activities globally.

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