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Original Research Paper

Development of Sensors for Microplastic Detection Using Artificial Intelligence

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Abstract: The increasing spread of microplastics throughout the world aquatic ecosystems is a significant ecological and health risk, which highlights an immediate need to develop sophisticated strategies of detection and characterization. The existing analytical approaches to microplastic quantification and identification are commonly not only labor-intensive but also time-consuming and restricted in terms of throughput especially in complicated matrices like soil, river water as well as biosolid fertilizers. Therefore, high-speed, dependable and affordable detection systems are the key to successful environmental surveillance and control measures. To break those limitations, this paper examines the means of integrating artificial intelligence with sophisticated sensor technologies and provides a detailed analysis of the current solutions and suggests new ones to detect microplastic better. In particular, this paper explores the usage of machine learning algorithms to process sensor data, thus making it possible to more efficiently and timely identify, quantify, and even classify microplastic particles. This research paper will seek to give a comprehensive history of some of the sensor modalities, including spectroscopies, optical, and electrochemical techniques, as well as a critical analysis of the AI models, such as deep learning and machine learning, that can be used together to create strong microplastic detection systems. The challenges that this integration tackles include high detection limit, and inability to operate in a portable mode, which is characteristic of the traditional approaches, leading to higher-end, real-time monitoring.

Keywords: Artificial Intelligence, Deep Learning, Environmental Monitoring, Machine Learning, Microplastics.

1. Introduction

The issue of plastic pollution around the world has reached the point of proliferation of tiny debris. Microplastics (MPs) are commonly referred to as those that are smaller than 5 mm in diameter, and nanoplastics (NPs) as the ultra-fine fraction, which is normally less than 1 mm in diameter [1]. There are two major ways these particles are produced and they are referred to as; primary types, which are produced with a specific purpose of use as a commercial product (e.g., cosmetics), and the secondary types, which are the products of the mechanical and chemical breakdown of large pieces of the plastic waste under the influence of various factors (e.g., UV exposure, physical abrasion) [2].

The proliferation of MPs and NPs is terrifying ecologically and to human health. These particles settle at the ecological levels and create physical injuries and physiological stress. More importantly, they are dynamic vectors of toxins, which makes the transport and bioaccumulation of heavy metals and co-contaminants possible, thus leading to an increase in the overall toxicological risk to the ecosystems [3]. In humans, the contact is rampant in terms of food, water, and air contamination. This exposure is linked to cellular and molecular damage, such as oxidative stress, inflammatory reactions, and probably, epigenetic changes [4].

Correct monitoring of micro- and nanoplastics presents a very challenging analytical task because particles with high heterogeneity in size, shape, and polymer chemistry are very small. Existing ways of detecting have various limitations:

- High Cost and Labor
  The older methods of analysis like Fourier-transform infrared (mFTIR) spectroscopy and Raman spectroscopy, although necessary in identifying polymers, are time-consuming, resource-intensive, and confined to concentrated laboratory conditions [5].
- Low Throughput and Matrix Interference
  These are because in analysis, there is usually excessive sample preparation e.g., chemical digestion and sequential filtration which restricts throughput. Moreover, it is difficult to detect it because of the severe interference of the natural organic matter in the matrix or because of the high ionic strength of marine samples [6].
- Lack of Standardization
  The second main barrier is the poor standardization of protocols to be used in collection and analysis, as this obstructs universal data comparison between different teams in the world conducting research [1].

Such an analytical bottleneck allows replicating the paradigm shift to smart sensor systems with augmented Artificial Intelligence. AI has become critical in this change, allowing it to be automated and smart in the way it interprets data:

- Automation and Speed
  AI, as a field of application of Machine Learning (ML) and Computer Vision (CV), automates work-intensive processes like counting particles manually, estimating their size, and classifying them [5]. This transformation speeds up throughput by an amazing speed and makes it possible to do analysis in real-time or nearly real-time.
- Enhanced Specificity
  ML algorithms detect fine spectral or visual features, and this increases the specificity of sensors. This enables the classification of any polymer fast (e.g., polystyrene vs natural organic debris) and raise detection accuracy on a complicated background [7].
- Field-Deployable Solutions
  AI models can be deployed straight onto small devices, including microfluidic chips, electrochemical sensors, or bespoke optical cameras, to help in high-sensitivity, real-time sensing in severe environmental conditions [8].

2. Literature Review

2.1. Sensor Technologies for Microplastic Detection

The identification and designation of microplastics (MPs) have received increasing interest because of the impact of microplastics on the environment and health. A number of sensor devices have been invented to enhance the detection accuracy, sensitivity, and reliability [9]. Microwave-microfluidic sensors, Raman spectroscopy, UV laser induced fluorescence technique and optical and

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electrochemical sensors are some of the most frequently studied. Both of them have their working principle, strengths, and weaknesses [10].

1) Microwave-Microfluidic Sensors
Microwave-microfluidic sensors integrate electromagnetic resonators with microfluidic channels to detect dielectric changes when microplastics pass through a flowing medium. As the particles alter the local permittivity, a measurable shift in resonance frequency or signal amplitude occurs. [9] This change helps determine particle concentration and size distribution in water samples [10].

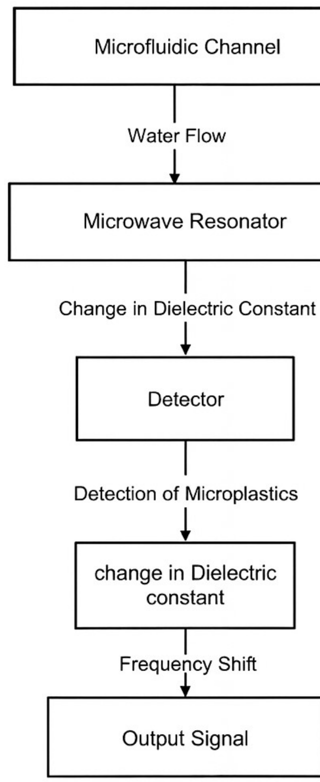

Figure 1. Microwave-Microfluidic Sensors

Advantages:
- Label-free and non-destructive detection.
- Real-time, continuous monitoring through microfluidic integration.
- Sensitive to differences in dielectric properties between plastics and water.
- Sensitive to changes in physical properties, allowing quantitative estimation of particle size and concentration.
- Low power consumption and miniaturization potential make them suitable for lab-on-chip devices.

Drawbacks:
- Cannot identify polymer type; only detects dielectric contrast.
- Accuracy is affected by temperature, salinity, and background particles.
- Limited sensitivity for nano-scale particles.
- High fabrication complexity of microfluidic channels and microwave circuits.
- Performance can be influenced by temperature and viscosity variations.

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2) Raman Spectroscopy

Raman spectroscopy measures inelastic scattering of monochromatic laser light, revealing unique vibrational fingerprints of molecules. Each polymer type, such as polyethylene (PE), polypropylene (PP), or polyethylene terephthalate (PET), produces a distinct Raman spectrum, enabling direct polymer identification even at microscopic scales [11].

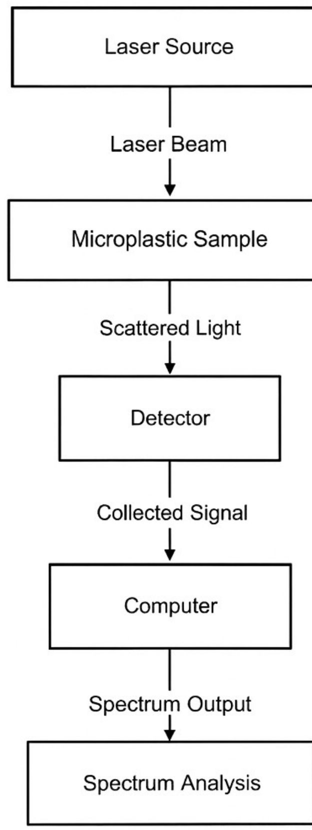

Figure 2. Raman Spectroscopy

Advantages:

- High chemical specificity for polymer identification.
- Non-destructive and capable of analyzing individual particles.
- Compatible with imaging techniques for combined visual and chemical data.
- Works on both dry and aqueous samples.
- Can be integrated with automated imaging and mapping for high-throughput screening.

Drawbacks:

- Fluorescent interference from organic matter may mask Raman signals.
- Time-consuming for large-scale environmental analyses.
- Instruments are expensive and require laboratory conditions.
- Requires skilled operators and spectral libraries for accurate identification.
- Difficult to detect dark or carbon-filled plastics, as they absorb laser light.

3) UV Laser-Induced Fluorescence (LIF)

Many LIF techniques rely on UV-laser excitation to induce fluorescence in polymers. When exposed to UV light, plastics emit fluorescence with intensities and spectral shapes characteristic of their composition. This emission is analyzed spectrally to detect and differentiate plastics within environmental samples [12].

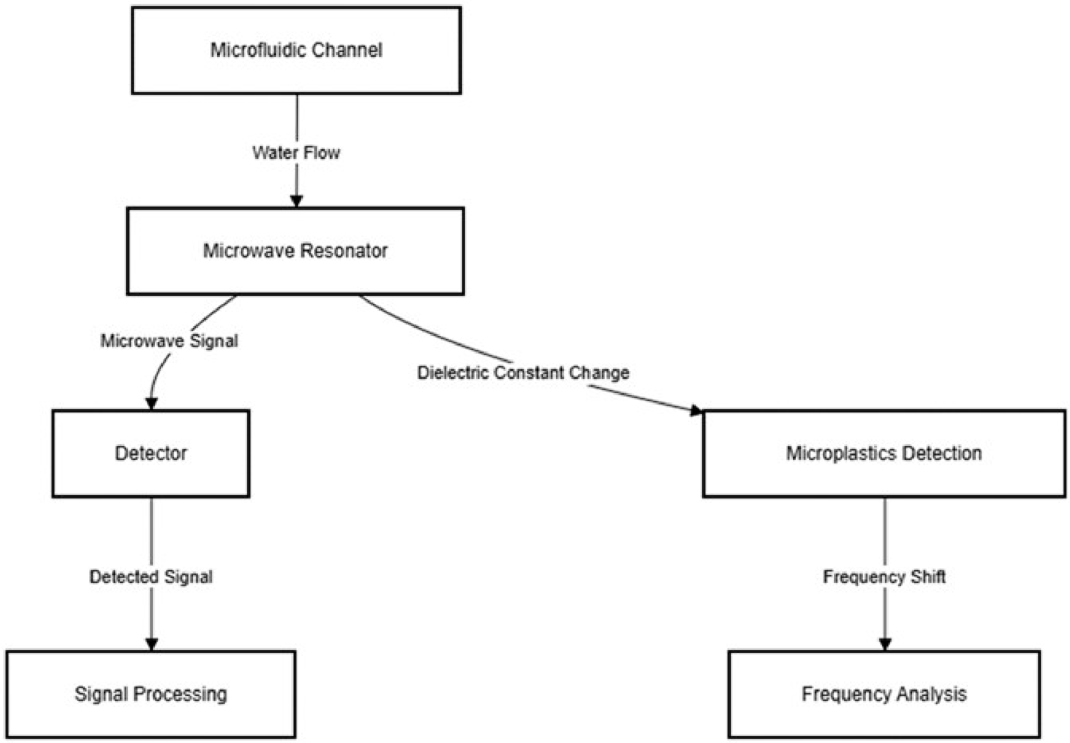

Figure 3. UV Laser-Induced Fluorescence (LIF)

Advantages:
- Rapid and suitable for real-time or large-area screening.
- Portable and adaptable for field use.
- Detects plastics with fluorescent additives or surface coatings.
- Can be combined with machine learning algorithms for real-time polymer classification.
- LIBS provides elemental composition, offering additional information about additives or contaminants.

Drawbacks:
- Not all polymers exhibit strong fluorescence signals.
- Background organic matter can cause false positives.
- Aged or biofouled plastics may show altered fluorescence patterns.
- Potential sample damage or fragmentation from intense laser pulses.
- Requires controlled environmental conditions to maintain signal stability.

4) Optical and Electrochemical Sensors
Optical sensors detect microplastics based on light absorption, reflection, or scattering. Techniques such as hyperspectral imaging or surface plasmon resonance (SPR) measure how microplastics interact with incident light, helping identify their presence and approximate size or concentration [11].

Advantages:
- Quick, non-invasive, and capable of high-throughput imaging.
- Minimal sample preparation required.
- Enables automated image-based particle counting.
- Non-contact and non-destructive technique.
- Easily integrated with imaging systems for automated counting and sizing.

Drawbacks:
- Limited polymer identification capability without spectroscopy.
- Accuracy decreases in turbid or complex matrices.
- Sensitive to ambient light and sample color variations.
- Requires frequent calibration to maintain consistency.

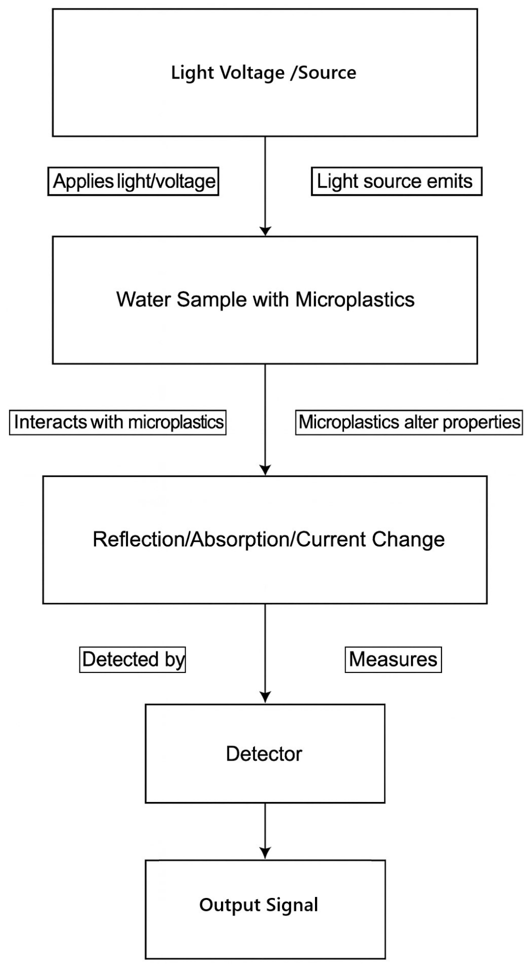

Figure 4. Optical and Electrochemical Sensors

2.2. Artificial Intelligence Techniques in Microplastic Analysis

Artificial Intelligence (AI) is a new significant apparatus of environmental monitoring, particularly content detection of microplastics in water bodies. Conventional techniques (microscopy, FTIR, Raman spectroscopy, etc.) are correct, but are somewhat time-consuming, very expensive, and inapplicable in the field. AI models are simpler and more automated, can scale, and they transform classification into a scalable and can enhance detection accuracy. In this section, important AI methods applied in the detection of micro plastics are examined with references to their advantages, disadvantages, and emerging technologies.

1) Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are typically utilized in image detection of microplastics. They can identify spatial characteristics such as shape, texture, and edges in camera or microscopic images. CNNs can also be trained on well-labeled datasets at classification rates above 90% [13]. Nonetheless, they require enormous quantities of data and they are also influenced by the lighting conditions and background noise, which could affect its performance in the real-world environment.

2) Support Vector Machines
The Support Vector Machines (SVMs) are useful in spectral and morphological data classification. They are also good at separating microplastics and non-plastic material when combined with dimensionality reduction algorithms such as Principal Component Analysis (PCA). Raman and FTIR data have shown relevance in the classification of polymers with the use of SVMs. They are very precise and have quite low data requirements [14].

3) You Only Look Once
Support Vector Machines (YOLO) models, and in particular YOLOv5 and YOLOv7, are designed to be used in real-time object detection. On edge devices such as the Jetson Nano, they are able to drive up to 42 frames per second, and are very popular in the field. YOLO works effectively when particles are overlapping, and the water flow is at varied rates, it might not be able to criticize the environments with low contrast and when the surroundings change [15].

4) Ensemble and Hybrid Models
Better generalization and classification accuracy Hybrid architectures implementing CNNs dominated by SVMs or decision trees are better. Random Forests and Gradient Boosting are also used as ensemble models in analyzing spectral and morphological data. The models are more resistant to overfitting and offer greater robustness; however, they require larger computing power and adjustment of the model parameters [16].

5) Deep Learning with Spectral Analysis
Deep learning information can now be used with hyperspectral imaging to identify microplastics with their individual spectral fingerprints. Such models as 1D-CNN and LSTM are able to process spectral sequences and have achieved polymer discrimination accuracies as high as 89.7% [17]. They are applicable in a controlled setting where they offer a lot of efficiency but when applied to the field, they demand a great amount of computational resource and uniform datasets.

6) Lightweight and federated Learning Models
Researchers have proposed federated learning systems and minimal AI to address the problem of energy consumption and scale. Such procedures allow decentralized training of different sensor nodes and maintain the privacy of the information. CNNs with weights under 5W and quantized have been demonstrated to be suitable for real-time environmental monitoring in remote settings [17].

7) Transfer Learning and Pretrained Models
Transfer learning allows models which are trained on large datasets to be adapted essentially without retraining to find microplastics. Ready-made networks like ResNet and MobileNet are optimised for the classification of microplastics. This reduces the time of training as well as increases the performance on small datasets. This is a useful technique, especially when the labels are difficult to locate or the labels are very expensive to obtain [18].

8) AI-Driven Image Segmentation and Object Tracking
In addition to classification, image segmentation and monitoring of moving microplastic particles in complex conditions can be performed with the help of AI. U-Net networks and semantic segmentation networks are able to distinguish microplastics and complex backgrounds. Object tracking algorithms are algorithms that track the movement of the particles with time. These applications enhance the level of detection and real-time analysis in running water systems [19].

2.3. Challenges and Limitations
Despite the significant advancements in sensor technologies in sensing microplastics (MPs), it is observed that the technology encounters various challenges with adverse implications on the efficiency, precision, and the general use of the technology. The complex nature of MPs and the changing nature of the environment pose a great challenge in identifying the correct detection and total classification in the real-world environment.

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1) Limitation of Sensitivity and Detection

Microplastics are available in various sizes, where some are large enough to be visible with the naked eyes, others are small in diameter, in nanometers. This diversity makes it a very challenging task to identify them. The majority of detection devices work well in a controlled laboratory scenario, but not in the analysis of the real-life samples of water due to low concentration of the microplastics and the high density of the environmental interference. These fragments are small and, thus, it is their weak signals are difficult to distinguish against the noise of the environment, hence affecting the accuracy of detecting them.

2) Polymer Selectivity and Chemical Differentiation

Several types of various microplastics exist, including polyethylene (PE), polypropylene (PP), polystyrene (PS), and polyvinyl chloride (PVC), among others, possessing varying optical and electrical characteristics. Nevertheless, most detectors are capable of identifying the presence of such microplastics but not the type of polymers that they are composed of [20]. This deficiency of selective identification will make the proper determination of the level of danger and the origins of the pollution very difficult.

3) Complexity of Samples, Environmental Interference

The presence of organic elements, salts, and fine particles in the natural sources of water may distort data being captured through sensors. These disruptive properties interfere with the visual, electric, or microwave characteristics of the test samples. This can lead to falsely positive outcomes or outcomes of the magnitude [21]. A second large technological issue would be to make sure that sensors work reliably and consistently, even when there is variability in temperature, acidity, and cloudiness.

4) Absence of Standard Calibration Processes

There are no standardization procedures and reference materials of MP sensors at this stage. The ways of preparing the samples and testing of each group of research are dissimilar. It creates a lack of poor comparability of results [22], Lack of reproducibility and reliability between studies in MP detection is caused by the inconsistency of standards.

5) AI and Data Processing Artificial Intelligence Use

The AI approaches of detection that presuppose the recognition of images and the interpretation of the patterns are more automated. They require the massive usage of large datasets, strongly labeled to be effective in training [23]. The variation in light, the state of flow, and the position of the photo might influence the holistic performance of the AI models. The outcome of this can be false identifications or false classifications as to the things in certain groups. The future of AI algorithms is a key issue that is of interest to be examined as it has the potential to be flexible and able to endure over time.

6) Complexity and Cost Limitations Fabrication

The modern sensing technologies, including plasmonics-based sensing technologies, micro-fluidics and microwave technologies, are highly sensitive to changes in the movements of minute variations. Nonetheless, the design of the devices is not a simple process since it entails not only multi-faceted manufacturing processes, but also needs specific materials and machines [20]. These sensors are not very affordable and accessible, as it is expensive to produce and maintain them, taking into account situations, that require the continuous observation process of the environment.

7) Field Deployment Requirements and Durability

Even though sensors are generally good in the controlled settings of the laboratories, there is still concern about whether they would be strong when applied in real-life settings and daily environments. The duration of sensor life and their accuracy are all decreased by physical stress or biological accumulation, and the temperature variability [24]. They need to be waterproof and use little energy in case continuous operation of sensors is required in the real world, which most prototypes still fail to meet.

8) Human Reliability and Data validation
Although the automation has been improved, in some instances, an individual is required to scroll through the data to verify how different items of data are classified. The step of such involvement can present subjective perspectives and the chances of injustice. It is in this reason that the creation of detection measures that do not demand so much support of people and can rectify their errors automatically are of significant value [23].

3. Methodology

This review adopts a systematic methodology designed to synthesize recent developments in AI-enhanced sensing of microplastics and nanoplastics within environmental science. The study involves a structured search and selection of peer-reviewed literature from major scientific databases, followed by a critical evaluation of the synergistic integration between artificial intelligence and modern sensing technologies, including microfluidic, electrochemical, and emerging optical methods. The selected studies are analyzed to map current applications of AI in classification, quantification, and predictive modeling of plastic pollutants, while identifying persistent technical limitations and knowledge gaps. Comparative assessment techniques are used to examine the performance, scalability, and reliability of different AI-sensor frameworks.

The findings are then synthesized to formulate a research roadmap aimed at advancing interdisciplinary innovation and supporting the development of internationally standardized, scalable, and highly accurate monitoring tools for effective global plastic pollution management.

4. Finding and Discussion

4.1. Gaps in the Present Research

Microplastic (MP) and nanoplastic (NP) pollution is a widespread issue that is a growing threat to the environment and human health [25]. Although this is a pressing problem, once again, we cannot see the pollutants easily and conveniently, especially in real-time (in situ) and online. Traditional detection tools are also, however, informative, but they are several times faulty [26]. These are spectroscopic, microscopic, and visual inspection detection devices that are largely confined to the laboratory. They are time consuming, labor consuming, and capital-consuming, and they require trained staff and specialized expertise. Therefore, they do not perform excellently in both massive-environmental monitoring and in establishing effective measures of minimizing pollution on the basis of data [27]. The already available state-of-the-art detection tools are also capable of destroying samples such that the same samples cannot be used in analysis. Specifically, there exists a special challenge when it comes to detecting nanoplastics (NPs) as the existing technologies cannot cope with the plastic particles smaller than the 1 um mark, and the field is still comparatively recent.

Our proposed project will overcome such challenges by developing a completely new AI-based sensor system that can be easily scaled and is cost-effective. We develop a design that combines an optical camera-based portable device and an AI processing chain to provide an opportunity to detect, count, measure the size, and calculate the velocity of microplastics in real time. The aspect of deep learning-based models is able to identify visual information with reasonable accuracy. The system also significantly reduces the need to use a manual and cumbersome method and leaves an analytical instrument in the hands of the environmental scientists and policy strategists. To achieve these, we have tried to make the technology easy to use to access and replicate off-the-shelf supplies, accelerating research and building, to create an open global monitoring device network.

Although the research in the field of the identification of microplastic (MP) and nanoplastic (NP) are progressing, there are essential gaps that prevent the effectiveness and overall applicability of the detection. The loopholes should be closed to introduce sound, scalable solutions.

1) Low-Cost, Small-Sized and Portability Sensor Requirement
Large-scale or real-time field monitoring is expensive because of the existing exploitation of expensive, laborious, and large-scale laboratory equipment, e.g. FTIR and Raman spectroscopy [28]. Differences between the high cost of specialized equipment and the need to employ highly trained operators render them unreachable by most researchers and citizen science projects [29]. This is strongly needed in low cost and small-format sensors that can be transferred to remote locations to make on site measurements without the need for very elaborate sample sampling and transportation. Minimization of these sensors remains yet to be finished, though, since some of the current prototype

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still have size issues, power consumption problems that make them difficult to be used in autonomous platforms.

2) Perception Models Based on Advanced Deep Learning Models Under Noisy Real-World Conditions
Although it is possible to visualize microplastics with the assistance of the AI, the most important issue is the initial realization of the model that would operate under the conditions of constant change and the real world [30]. This is due to the fact that most current models of deep learning are trained on clean samples of microplastics in the laboratory environment, which do not apply to real-world aquatic environments [31]. Natural samples consist of a variety of non-plastic particles, organic material, and sediment which seem to display visual features similar to microplastics. This opens up the chances of false values or fake values. Such models have their accuracy reduced significantly when put under the soiled or weathered particles of the environment. The creation of better deep learning models capable of effectively distinguishing micro plastics among non plastic materials in simulated and noisy backgrounds need to be developed.

3) Standard Datasets for Training AI
There are no diverse, quality-confirmed, publicly opened datasets that hamper the development and testing of good-performing AI models. The existing datasets are fragmented most of the time, and focus on specific types of plastics or controlled laboratory environments, which limits the model's performance to entirely different settings [32]. Standardity is also lacking, which affects the overall process of analysis, sampling process, and separation procedures. This impedes the comparison of the data between the studies, along with the global understanding of the problem [33]. The need also exists to have a comprehensive data sharing and data collection integrating model to drive change in this field of research.

4) Simultaneous Detection of Multipollutants
Microplastics also have the capacity to transport other toxic chemicals like heavy metals and organic toxins. The majority of the sensor technologies that are currently available can only monitor a single type of pollutants, making the total estimation of the degree of pollution a challenge [34]. Multi-modal technologies that can concurrently track microplastics and their co-contaminants are urgently required so that the characteristics of the latter can be identified [35]. There is the highest demand of multivalent environments in which various pollutants can interfere with the detecting signal.

5) Real-time Continuous Monitoring Systems
Manual sampling and lab tests pose obstacles to the quick reaction to pollution cases or real-time evaluation of microplastics circulation in the field. Absence of incessant surveillance devices means the impossibility of describing the pollution hotspots in detail and the effectiveness of pollution mitigation efforts [36]. There exists a necessity of technologies that can deliver continuous, informative data to support the environmental policy and inform management decisions in a prompt manner. This is most acute in the case of remote areas where the cost-based and logistically inaccessible traditional sampling cannot be made economical [37].

4.2. Proposed AI-Enabled Sensor System

Our project addresses this empty spot by proposing a new technology of identifying microplastics. The device combines an intelligent optical camera and artificial intelligence processing to come up with a completely autonomous, continuous observation device.

1) System Components
The machine has an optical and high-quality camera to capture images of water samples that flow into a fluidic channel [38]. A processing unit is supported with the latest AI models, such as Convolutional Neural Networks (CNNs), to process the images online in real-time [39]. The entire system is mobile and housed in an IP67protected case to be used in the field under marine conditions in the field.

2) AI Methodology
One object detection model (You Only Look Once (YOLOv5)) is used to detect MPs in an image in the system architecture. A deep SORT tracking algorithm is used to track the movement of MPs through the successive image frames. This has rendered the system in a position to measure the sizes of the particles, the velocities, and even track the movements of the moving microplastics. It is also in the classification that the remaining machine learning techniques, like the K-nearest neighbor (KNN), are used [40].

3) Real-time and Cost-Effective Design
It is based on an open-source and commercially available platform (Raspberry Pi), low-quality cameras, and LED lights to create a low-priced and reproducible design. The device is used to monitor in real time, by looking at a continuous flow of water and transmitting the data to a cloud database in real time. This offers a good substitute to the lab-based methods that are static [41].

4) Validation
The instrument has been tested in real time both in the laboratory and in the immediate river, where it performs well in terms of the number of MPs. Training of the models is presented on a mixed dataset of experimentally weathered or experimentally humic acid treated microplastics to mimic the field conditions in order to achieve improved performance [42]. The work also suggests developing an annotated dataset of underwater microplastics to aid in doing the subsequent work.

5. Conclusion

This paper has conducted a review of existing sensor technologies and AI-based microplastic detection methods and suggested a low-cost and portable AI-based optical sensing system to monitor in real-time. Although spectroscopic and microfluidic systems are very specific to chemical analysis in the laboratory, they are costly and cannot be used widely due to their cost and portability. On the other hand, image-based methods based on AI (e.g., CNNs, YOLOv5) can be used to provide automated classification and detection in real-time, but standardized and varied datasets and durable models are needed under conditions of a noisy field. To address the above gaps, we propose a framework consisting of an optical imaging sensor, on-the-board, YOLOv5-based detection, and Deep -SORT tracking to allow us to have a continuous, in-situ monitoring with off-the-shelf hardware. The current situation will be addressed, and future efforts will center on developing an annotated and open dataset of microplastics, conducting field validation in mixed water chemistries, and streamlining the lightweight models in order to deploy them on the edges. When effectively completed, this work will facilitate scaling microplastic monitoring and give useful data that can be used to implement remediation and policy changes.

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