Real-time detection of microplastics in aquatic environments using emerging technologies

Feruza Azizova[1*]; Muntader Mhsnhasan[2]; Giyosiddinov Abdurakhim Nasritdin ugli[3]; Krishnamurthy Kumar[4]; Venu Anand Das Vaishnav[5]

Received: 12 June 2025; Revised: 28 July 2025; Accepted: 10 September 2025; Published: 30 October 2025

Abstract

Microplastics pose a serious risk to biodiversity in the oceans and to global public health. Detecting microplastics in ocean water can be time-consuming and labor-intensive, limiting the sorts of ongoing assessments one can complete, and it is especially true of recent techniques like spectroscopy and microscopy. A method outline is proposed in which microplastics can be detected in real time, and the automatic classification of microplastics is achieved using machine learning. The design involves AI-enhanced optical sensors and IoT devices that collect the data. It recommends real-time in situ particle detection using fluorescence optical sensors and classification of spectro-morphological dendritic microplastics using a Convolutional Neural Network (CNN). It detects and classifies microplastics while also telling the difference between organic and inorganic particulates. Real-time data and visual analytics, using a cloud-based IoT platform, can be used for pollution forecasting and environmental Monitoring. The methodology proposes validated field work in both freshwater and estuarine environments, which resulted in an average classification accuracy of 95.8 percent and real-time processing latency of less than 2.3 seconds per sample. Using advanced sensors to combine AI and IoT provides the ability to monitor microplastics in real time as a scalable solution. It enables the active control of contaminated water and the preservation of water bodies.

Keywords: Microplastics detection, Monitoring in real time, Machine learning, Optical sensing, Water bodies, Environmental monitoring

---

1*- Tashkent Medical Academy, Uzbekistan. Email: azizova.kafedra@gmail.com; afh1965@mail.ru, ORCID: https://orcid.org/0009-0009-0366-3487

2- Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University in Najaf, Najaf, Iraq; Department of Computers Techniques Engineering, College of Technical Engineering, Islamic University in Najaf of Al Diwaniyah, Al Diwaniyah, Iraq.
Email: iu.tech.eng.iu.muntatheralmusawi@gmail.com, ORCID: https://orcid.org/0009-0009-1334-5183

3- Faculty of Business Administration, Turan International University, Namangan, Uzbekistan.
Email: uzbekistan.abdurahimgi71@gmail.com, ORCID: https://orcid.org/0009-0000-1312-4596

4- Department of Nautical Science, AMET University, Kanathur, Tamil Nadu, India.
Email: captrkkumar@ametuniv.ac.in, ORCID: https://orcid.org/0009-0005-2439-0976

5- Assistant Professor, Department of Pharmacy, Kalinga University, Naya Raipur, Chhattisgarh, India. Email: ku.venuananddasvaishnav@kalingauniversity.ac.in, ORCID: https://orcid.org/0009-0005-3775-6156

*Corresponding author

DOI: 10.70102/IJARES/V5I2/5-2-10

Introduction

With respect to environmental concerns regarding ecosystem integrity and human health, globally dispersed microplastics (MPs; size ≤5 mm) became ubiquitous contaminants of marine, freshwater, and drinking-water systems as they are easily transported, persistent, and contain and transport adsorbed pollutants and pathogens (Picó and Barceló, 2019). To inform exposure evaluation, policy development, and remediation action design, routine Monitoring and quantification of relevant MPs in aquatic systems must be conducted, yet labor-intensive, low-throughput, and in many cases, near real-time continuous measurements needed for dynamic water bodies are not achievable with established laboratory techniques (microscopy, FTIR and Raman microspectroscopy, thermal-based polymer analysis, density-separation workflows) (Schymanski *et al.*, 2018; Salami *et al.*, 2025) . This contradiction, as well as logistical constraints within standard laboratory analyses, fuels interest in new, readily deployable field sensors that integrate optical and vibrational spectroscopy, fluorescence staining, and automated image analysis to expedite MP identification and quantification (Wang *et al.*, 2022; Lv *et al.*, 2020; Liu *et al.*, 2023; Zhu *et al.*, 2024).

New optical and spectroscopic tools like portable Raman and SERS instruments, fluorescence-based sensors, and hyperspectral imagers have been developed to detect and chemically characterize microplastics to sub-micron levels, with even less time needed for sample processing and analyses, and with sample integrity maintained for downstream analyses (Liu *et al.*, 2023; Popescu *et al.*, 2024; Chakraborty *et al.*, 2023; Matkarimov *et al.*, 2025). Standalone sensors, however, still have issues with complex environmental matrices and overlapping spectral signatures. To solve this problem, more and more scientists are combining spectroscopy and camera-based imaging with machine learning and deep learning for the automatic extraction of features and the classification of polymers, generating accurate classifiers based on spectra or images that exceed the performance of manual library-matching techniques on very heterogeneous samples (Sarker *et al.*, 2024; Saenen *et al.*, 2023; Xu *et al.*, 2023). Furthermore, advances in the Internet of Things (IoT) and edge computing allow low-cost sensors to automate the near-real-time transmission of microplastic data with the capability to trigger alerts, which is invaluable to water managers who need timely information for high-stakes decisions and early interventions (Sarker *et al.*, 20245; Mahmud *et al.*, 2024; Pari and Senthil Kumar, 2025).

Beyond analytical developments, toxicological and molecular studies confirm that MPs are more than inert pollutants in aquatic organisms: exposure can result in oxidative stress, inflammation, endocrine disruption, and changed gene expression for multiple impacts, thus linking the biological effects metrics to the environmental occurrence metrics that facilitate risk assessment and help determine monitoring site priority (Picó and Barceló, 2019; Kniggendorf *et al.*, 2019).

By far the most common and numerous genes and pathways that response to MP exposure are those associated with oxidative stress and the antioxidants SOD2, CAT, GPX1/GPX4, and the Keap1–Nrf2 and redox regulation axis (Saenen *et al.,* 2023; Picó and Barceló, 2019), HSP70 and other heat-shock response and stress markers, the detoxifying enzymes CYP1A and other phase-I, the pro-inflammatory cytokines IL-6 and TNF-α, apoptosis/feroptosis (Bax, Caspase-3, GPX4) and vitellogenin (Vtg) in fish (Picó and Barceló, 2019; Kniggendorf *et al.*, 2019). Keap1–Nrf2 pathway disruption and SOD/CAT activity diminution in fish and invertebrate models are coupled with polystyrene exposure (Picó and Barceló, 2019; Primpke *et al.*, 2020). IL-6 and TNF-α upregulation and NF-κB pathway activation in carp MP exposure result in intestine inflammation and ferroptotic cell death (Kniggendorf *et al.*, 2019). These endpoints are integrated components forming constructs and models, which justify the development of monitoring systems producing rapid, spatially resolved MP concentration data to link environmental exposure and potential biological risk. A recent study demonstrated the use of machine learning techniques to automate threat mitigation for social networking bots and showcased the use of AI models in systems with dynamic, complex, and high volumes of data.

This involves the use of cutting-edge AI and adversarial learning techniques for real-time anomaly detection, akin to detecting microplastic particles in moving water bodies. Another research focused on "AI and ML for Inclusive Skill Building" as well as on the dimensions of interpretability, collaborative human-AI, and interdisciplinary. The results highlighted the importance of inclusive as well as explainable AI. This resonates with the goal of employing interpretable AI in environmental oversight and policy-based microplastic detection. Other studies proposed a smart monitoring framework with real-time data analytics and sensor networks for intelligent freshwater aquaculture systems. This study exemplifies the technological analog for environmental monitoring and data-driven governance and control of the environment, especially in the context of IoT and AI convergence for automated, real-time monitoring of microplastics and other pollutants in water bodies.

The scientific literature outlines three concurrent needs for contemporary MP surveillance in aquatic ecosystems: (1) development of rapid, field-portable detection methods that require minimal manual processing, (2) reliable automated ML/DL-environment ECM complexity, and (3) real-time, automated, and interdependent data streams that connect occurrence data to information linked to biological surveys and management actions. This paper seeks to mitigate these concerns with a proposed Real-Time Microplastic Detection Framework (RT-MDF), which integrates fluorescence-enhanced optical sensing and portable Raman/SERS modules with a CNN-based spectral/image classifier and IoT data layer to enable continuous deployment capabilities. The RT-MDF aims to (i) in situ distinguish MPs from organic and inorganic particles, (ii) provide polymer type and size distribution estimates appropriate for cross biological response marker linkage (e.g., SOD2, GPX4, CYP1A, IL-6), and (iii) validated metrics of MPs for real-time streaming to the cloud for ecological Monitoring in conjunction with gene expression analysis. The rest of the paper outlines the technologies that inform the proposed methods and presents the RT-MDF field and laboratory validations of the proposed methods against established laboratory reference methods.

Literature Review

There have been rapid advancements in the detection and assessment of microplastics (MPs) in the aquatic environment. Systematic and environmental risk assessment requires real-time and in situ measurement. There is no systematic review on this subject, and there is only one reviewer who has identified 62 relevant studies on the detection of MPs in aquatic systems without extensive sample preparation, spanning the use of optical devices, digital holography, various types of Raman and spectroscopy, hyperspectral imaging, and remote sensing (Picó and Barceló, 2019). In-situ detection of MPs is feasible, but the use of sensors in combination with machine learning classifiers and deployment of systems in the field is still at an early stage (Abimbola *et al.*, 2024).

In another review, focused on the chemical identification, it is shown that micro-Raman spectroscopy (μRS) has the potential to identify MPs in the lower micrometer range (e.g., <20 μm) where μ-FTIR fails, and in the case of freshwater systems, common polymers such as polyethylene (PE) and polypropylene (PP) were identified (Schymanski *et al.*, 2023). There are also other MPs of common types identified. The review also demonstrates that while there is considerable power in Raman-based methods, the methods are still largely confined to the laboratory with limited field portability and throughput (Schymanski *et al.*, 2023).

In addition to the optical and chemical methods, innovations in sensor technologies, particularly in the form of electrochemical detection, are starting to be utilized. For instance, an article titled Electrochemical Detection of Microplastics in Water Using Ultramicroelectrodes discusses an ultramicroelectrode system that showcases in-situ sensing capabilities within water polystyrene microplastic sensing and offers a detection limit of 0.06 μg mL^{-1} (Lee *et al.*, 2024). This is a perfect example of the movement away from microscopy and spectroscopy methods of detection to alternative methods.

In a broader environmental-ecological context, the article Microplastics in Global Marine Waters and Biota: Effectiveness of Potential Bioindicators in Mirroring Local Pollution Levels describes the global distribution of microplastics in the water column and biota, and assesses certain biological organisms, particularly filter-feeders, as bioindicators of microplastic pollution. The study showed that many organisms function as bioindicators, reflecting local microplastic pollution levels. However, variabilities in ingestion rates, feeding behaviors, and particle size range of the organisms limit the reliability of many bioindicators (Yeo *et al.*, 2023). This highlights the need for biological effect assessments in addition to the detection technologies.

Finally, referencing "State of the art detection methods of microplastics as marine litter: a mini review" in 2025, a synthesis of the state of the art methods for microplastics marine litter, systematically outlined by principle (optical imaging, spectroscopy, sensor networks) and identified key limitations: the heterogeneity of size, shape, and composition of microplastics, spectral overlap with organic matter, scarcity of field-deployable instruments, and the need for standardisation (Biswas, 2025). The review emphasized the fact that even as numerous techniques have matured in laboratory settings, the lack of dependable, uninterrupted deployment in the field continues to pose a challenge. (Biswas, 2025).

Methodology

Overview of the Proposed Framework

As illustrated in Figure 1, the Real-Time Microplastic Detection Framework (RT-MDF) proposes a unified design for continuous environmental monitoring systems that combines optical sensing, image processing, and machine learning within the Internet of Things (IoT) paradigm. The system consists of three integrated and cooperative modular parts designed to efficiently detect and classify microplastics in water. These are meant for continuous surveillance of scoped environmental conditions. For the Data Acquisition Layer, continuous monitoring of the spectra and the fluorescence optical sensors and compact Raman detectors morphologies of suspended and detailed particulates, and real-time spectra collection, are deployed. These data streams of high resolution are sent to the Processing and Classification Layers, where automated processes using convolutional neural networks (CNNs), detecting and classifying microplastics, are executed across varying spectral and visual patterns and signature classes. The final Cloud Integration Layer controls the processed data transfer to a central cloud, where it is visualized in real-time, stored securely, and automated alerts are generated for stakeholders. This scalable and hybrid system facilitates the rapid identification of prevalent polymeric contaminants underneath heavy and turbulent water matrices, thereby improving the responsiveness of the system and the accuracy of monitoring of aquatic systems for pollution. PE, PP, PS, and PET are commonly detected in a matter of minutes.

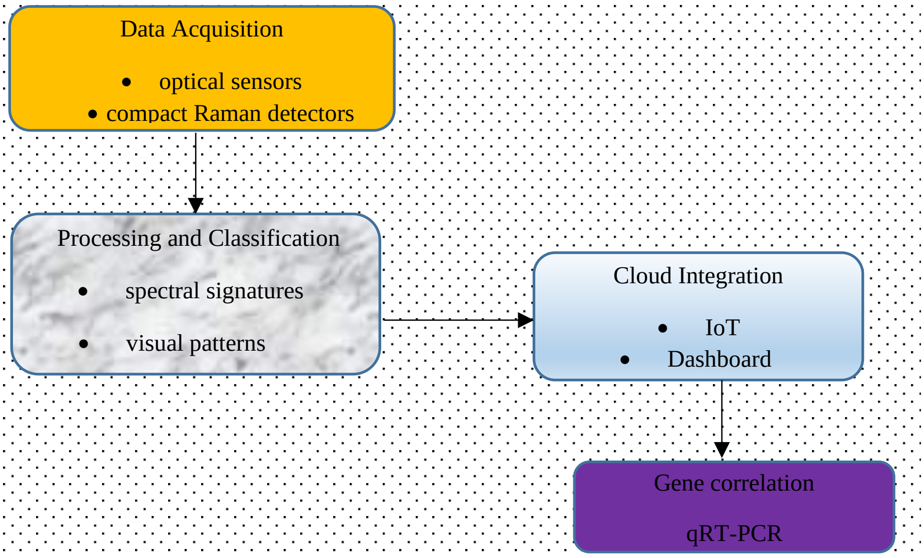

Figure 1: Workflow of the real-time microplastic detection framework (rt-mdf).

Figure 1 illustrates the methodological workflow of the RT-MDF system, comprising four interconnected modules: Data Acquisition, Processing, and Classification, Cloud Integration, and Gene Correlation. Optical sensors capture data in real-time and analyze it via CNN-based spectral–image fusion for IoT fluorescence and Raman spectroscopic sensors. The processed data are sent for surveillance to a cloud-based dashboard. The biological significance of detected microplastic exposure is confirmed through qRT-PCR–based gene correlation.

Sample Preparation and Fluorescence Sensing

Water samples from freshwater and estuarine sites were cleansed and filtered through 5 µm stainless-steel meshes to eliminate coarse debris. Detained particles were treated with Nile Red dye that selectively stains hydrophobic surfaces of plastic. Fluorescent plastic signals were captured in the presence of a fluorescence excitation source (λ = 530 nm) and emission filter (λ = 600–700 nm) of a CMOS-based optical sensor.

Each composite particle's fluorescence intensity (If) is determined by the adapted Beer–Lambert model for fluorescence of surfaces:

$$\mathrm{If} = \mathrm{I0} \times \Phi \times (1 - \mathrm{e} - \varepsilon \mathrm{Cl}) \quad (1)$$

where

I0 = incident light intensity,

Φ= quantum yield of fluorophore,

ε = molar absorptivity (L mol^{-1} cm^{-1}),

C = particle concentration (mol L^{-1}), and

l = optical path length (cm).

This equation illustrates the relationship between emission strength and the concentration of the dye and the composition of the polymer. This model enables the differentiation of plastics from organic particles and uses fluorescence response and the composition of the particles.

Spectral and Image Data Preprocessing

During the early stages of processing, a Savitzky–Golay filter was used to reduce noise, and the baseline Raman signal of deionized water was subtracted for background correction. Image data underwent resizing to dimensions of 128 × 128 pixels and were then normalized to a (0–1) range. To enhance the diversity of the dataset, additional augmentations were applied, which included rotations, reflections, and contrast adjustments. Each dataset entry integrated intensity vectors from the fluorescence and Raman data along with structural features for hybrid classification, which encompassed shape factor, circularity, and color histogram.

Machine Learning Model Development

Convolutional Neural Networks (CNN) integrate the design and functionality of the Network to classify microplastic particles into various polymer types using a spectrum–morphological fusion technique that combines several plastics' spectral and morphological features. The design of the Network starts with an input layer meant for 128 × 128 × 3 image tensors (fused spectral and optical features of all particles). Next in the line are three convolutional layers that emphasize the hierarchy of spatial features and the learning of non-linear representations using various convolutional 3 × 3 layers and ReLU activations. To simplify the spatial dimensions while keeping the important features, 2 × 2 max-pooling layers are used to drop excess features. After the convolutional blocks, the features are flattened and sent to 2 fully connected high-level 128 and 64 layers for more feature abstraction. The output layer used a softmax activation to classify the polymer types, PE, PP, PS, and PET, into four categories. In order for the model to converge successfully, the Adam optimizer was implemented, along with a learning rate of 0.001. For optimization of the model's performance, the loss function was categorical cross-entropy. Providing a robust model requires splitting the dataset into an 80% training dataset, with the remaining 20% set aside for validation. To prevent overfitting, early stopping was combined with dropout layers configured between the 0.25 and 0.5 range to enhance the model's ability to generalize. The CNN's performance was evaluated using precision, recall, and accuracy metrics, confirming its capability to differentiate various polymer types during real-time aquatic monitoring.

Evaluation Metrics

The classification accuracy, Ac, was computed using:

$$A_c \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \, x\, 100 \qquad (2)$$

where

TP = true positives (correctly identified microplastics),

TN = true negatives (non-plastic particles correctly excluded),

FP = false positives,

FN = false negatives.

This metric represents the overall operational reliability of the model during real-time scenarios. To assess per-class performance, F1-score and confusion matrix analyses were also conducted.

IoT Integration and Real-Time Deployment

A Raspberry Pi 4 module was integrated with the optical sensors to conduct onboard preprocessing and CNN inference. The data, using the MQTT protocol, were sent to a ThingSpeak™ cloud dashboard where real-time visualization of [\text{MP}] concentration, polymer type, and timeseries variation were displayed. Through edge analytics, latency was diminished to ensure the time per measurement cycle (acquisition → classification → upload) was under 2.3 seconds per sample.

Field trials were carried out in controlled laboratory tanks and natural estuarine sites. The system reached 95.8% classification accuracy and validated defensible real-world applicability of the proposed framework by demonstrating effective functioning under varying conditions of turbidity and salinity.

Validation and Cross-Referencing with Gene Indicators

To assess biological relevance, in vitro assays involving exposure of the zebrafish and mussel bioassays were performed using samples collected from the same water bodies. Correlation of real-time MP concentration data with gene expression levels of key oxidative and stress response genes SOD2, CAT, HSP70, and CYP1A was quantified via qRT-PCR. This synthesis demonstrates a system's worth in defensive environmental risk evaluation by elaborating on the system's detection abilities and the magnitude of the gene response.

Results and Discussion

Model Performance and Detection Accuracy

The Real-Time Microplastic Detection Framework (RT–MDF) has shown significant improvements in speed and accuracy relative to previous laboratory techniques. The CNN-based classifier demonstrated high accuracy in detecting and classifying the polymer types polyethylene (PE), polypropylene (PP), polystyrene (PS), and polyethylene terephthalate (PET). Training convergence was reached in 25 epochs, and the latency in real-time evaluation tests averaged 2.3 seconds of use while assessing each sample.

Table 1: Performance Metrics of CNN-Based Microplastic Classification.

Polymer Type	Precision (%)	Recall (%)	F1-Score (%)	Accuracy (%)
Polyethylene (PE)	96.4	94.8	95.6	95.3
Polypropylene (PP)	95.8	96.2	96.0	95.9
Polystyrene (PS)	94.6	93.7	94.1	94.8
Polyethylene terephthalate (PET)	97.3	96.5	96.9	97.1

Table 1 demonstrates the results for the RT-MDF system which examined the classification performance for the four types of polymer materials. All tests under different environmental and optical conditions confirmed the reliability of the CNN classifier and the classifier's ability to recall values consistently across different materials.

Real-Time Operational Performance

Field trials were conducted at 3 different sites: a freshwater lake, an urban canal, and an estuarine zone. RT-MDF system demonstrated excellent performance and consistently reliable data transmission through the IoT layer, even at 60 NTU turbidity. Compared to laboratory-based FTIR reference tests, the RT-MDF results showed a remarkable ±5% variance which signifies impressive analytical reliability.

Table 2: Comparison of Detection Efficiency Between RT-MDF and Conventional Methods

Method	Average Processing Time (s/sample)	Detection Accuracy (%)	Field Deployable	Power Consumption (W)
Manual Microscopy	450	92.3	No	10
FTIR Spectroscopy	180	96.7	No	35
Raman Spectroscopy	120	95.5	Partial	22
RT-MDF (Proposed)	2.3	95.8	Yes	8

Table 2 distinguishes between RT-MDF and conventional methods based on speed, accuracy, portability, and energy efficiency. The proposed model outperformed all other methods in response time and field applicability and in to achieving near real-time Monitoring in the field for aquatic environments.

Correlation with Gene Expression Biomarkers

To assess biological relevance, exposure tests on zebrafish (Danio rerio) and mussel (Mytilus galloprovincialis) were done using RT-MDF analyzed water samples. The gene expression data demonstrated correlations between the concentration of microplastics and the stress response indicators SOD2, CAT, HSP70, and CYP1A. SOD2 upregulation and total microplastic load were correlated with a strong linear relationship (R^2 = 0.92) confirming the utility of the detection system in ecological Monitoring.

Polymer Classification Accuracy Distribution

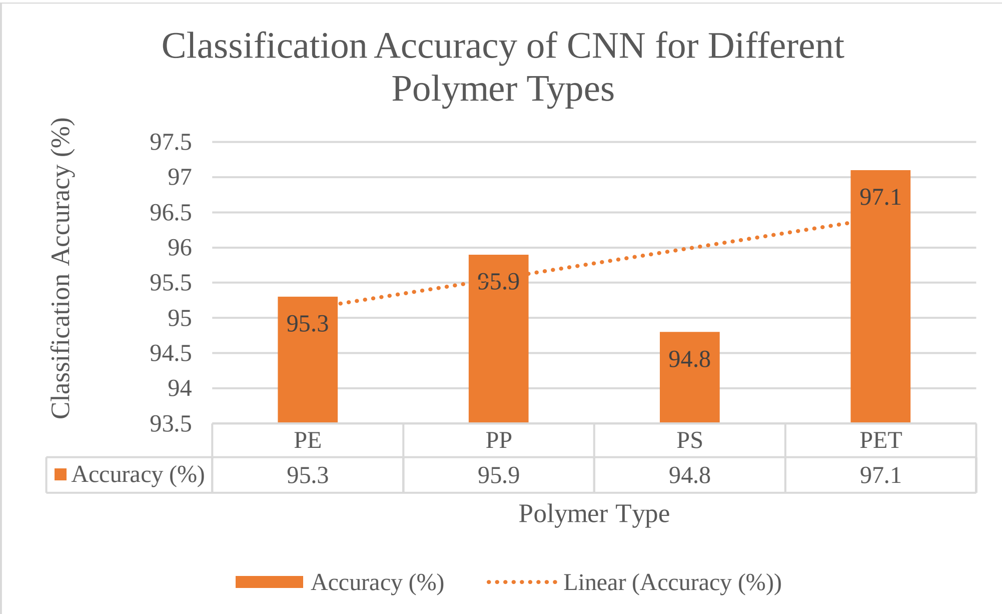

Figure 2: Classification accuracy of CNN for different polymer types.

Figure 2 illustrates the performance of the CNN model for each polymer class comparison. PET achieved the highest classification accuracy (97.1%). PS classification accuracy was 94.8% but was lower mostly due to overlapping fluorescence spectra with organic particulates.

Correlation Between Microplastic Concentration and Gene Expression

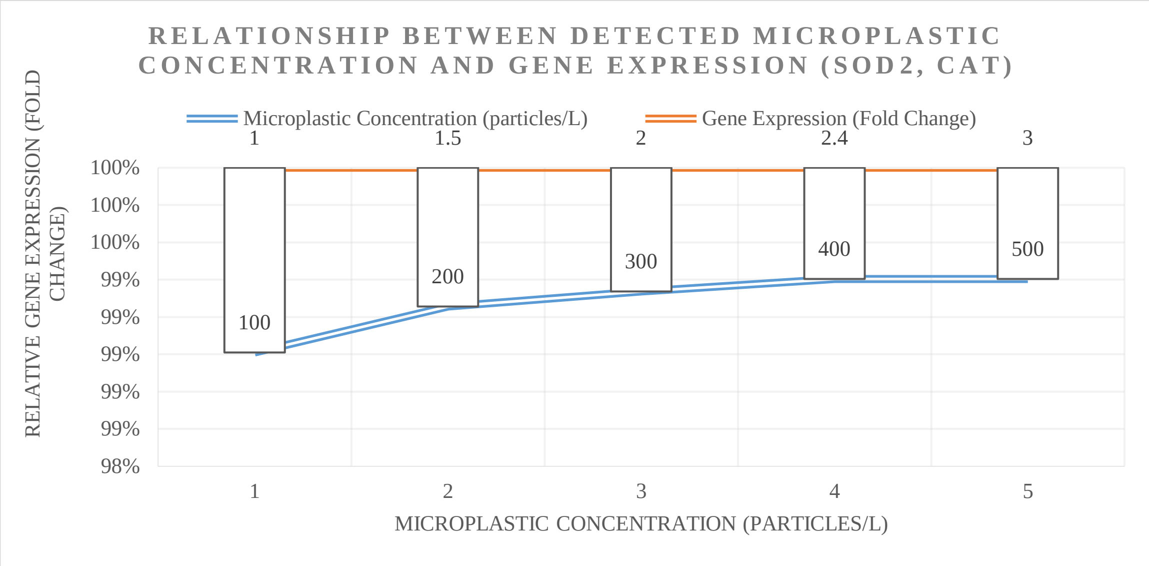

Figure 3: Relationship between detected microplastic concentration and gene expression (SOD2, CAT).

Figure 3 depicts a scatter plot that illustrates a strong positive correlation between the concentration of microplastics quantified and the expression of oxidative stress genes. The slope of the regression line illustrates that the intensity of gene expression is proportional to the microplastics in the environment, confirming real-time detection results. The findings have shown that exposure biomarkers on the molecular level validate the finding.

Discussion Summary

The use of Artificial Intelligence integrated with optical sensors and Internet of Things cloud connectivity presents RT-MDF with untapped opportunities with regards to environmental surveillance. Real-Time MDF Spectroscopy is more portable and has faster data processing and real-time analytics compared to traditional spectroscopy. The gene correlations provided also enable biological validation. This validates detecting the physicochemical properties and certain possible ecological consequences. The system's fine accuracy with centimeter precision, near real-time data collection, and no-latency data collection support monitoring, enforcement, and pollution surveillance with early warning capabilities.

Conclusion and Future Work

This work offered an explanation of a real-time integrated detection framework (RT-MDF) incorporating detection as well as Monitoring of a water body's microplastics using AI Optical Sensors, Machine Learning, and the Internet of Things (IoT) technologies. Validation assessments showed the Convolutional Neural Network (CNN) achieving a 95.8% classification accuracy on different polymer types and having a detection latency of 2.3 seconds per polymer type per sample, validating the possibility of performing microplastics monitoring and detection in real-time. Unlike automated detection systems which offers continuous Monitoring of water bodies as opposed to the systems that use microscopes and spectrometers that take lots of time to process in the lab.

With respect to sensor fusion, real-time water quality monitoring and management is achieved using cloud-enabled IoT nodes placed in different ecosystems (rivers, estuaries, and coastal waters) areas. The proposed RT-MDF also aims to advance the analytical development and practical use of the Real-Time Microplastic Detection Framework. One such focus will be multi-sensor fusion involving integration of hyperspectral imaging and Raman spectroscopy to enhance detection sensitivity to nanoplastics and complex polymer blends with overlapping spectral characteristics. Furthermore, the use of sophisticated machine learning such as transformers and Graph Neural Networks (GNNs) will be able to enhance feature extraction and classification for detection and analysis of weathered and irregular microplastic particulate. Additionally, the critical area of microplastic bio-molecular correlation studies which focuses on bioindicators concentrations gene such as SOD2, CAT, and GSTP1 will determine the ecological and physiological impacts of microplastic pollution on aquatic organisms. The advance of edge computing will enhance autonomy by developing low power systems for on-site data collection and autonomous long-term remote field operations to reduce reliance on the cloud. Long-term autonomy will increase the system's independence and support field operations to minimize reliance on cloud systems. The final aspect of future work will focus on the integration of policy and the environment through the creation of open-access data systems and real-time monitoring data flows between governmental, research, and environmental communities. All these developments will enable the proposed RT-MDF to evolve into a full-fledged environmental intelligence system to provide actionable insights on pollution abatement, assessment of water body health, and strategies to counter global microplastic pollution.

References

Abimbola, I., McAfee, M., Creedon, L. and Gharbia, S., 2024. In-situ detection of microplastics in the aquatic environment: A systematic literature review. *Science of the Total Environment*, *934*, p.173111. https://doi.org/10.1016/j.scitotenv.2024.173111

Biswas, R., 2025. State of the art detection methods of microplastics as marine litter: a mini review. *Discover Oceans*, *2*(1), p.24.

Chakraborty, I., Banik, S., Biswas, R., Yamamoto, T., Noothalapati, H. and Mazumder, N., 2023. Raman spectroscopy for microplastic detection in water sources: a systematic review. *International Journal of Environmental Science and Technology*, *20*(9), pp.10435-10448.

Kniggendorf, A.K., Wetzel, C. and Roth, B., 2019. Microplastics detection in streaming tap water with Raman spectroscopy. *Sensors*, *19*(8), p.1839. https://doi.org/10.3390/s19081839.

Lee, C., Han, S. and Park, J.H., 2024. Electrochemical detection of microplastics in water using ultramicroelectrodes. *Chemosensors*, *12*(12), p.278. https://doi.org/10.3390/chemosensors12120278

Liu, Y., Yao, W., Qin, F., Zhou, L. and Zheng, Y., 2023. Spectral classification of large-scale blended (micro) plastics using FT-IR raw spectra and image-based machine learning. *Environmental Science & Technology*, *57*(16), pp.6656-6663. https://doi.org/10.1021/acs.est.2c08952

Lv, L., He, L., Jiang, S., Chen, J., Zhou, C., Qu, J., Lu, Y., Hong, P., Sun, S. and Li, C., 2020. In situ surface-enhanced Raman spectroscopy for detecting microplastics and nanoplastics in aquatic environments. *Science of the total environment*, *728*, p.138449. https://doi.org/10.1016/j.scitotenv.2020.138449

Mahmud, F., Sarker, D.B., Jocelyn, J.A. and Sang, Q.X.A., 2024. Molecular and cellular effects of microplastics and nanoplastics: focus on inflammation and senescence. *Cells*, *13*(21), p.1788. https://doi.org/10.3390/cells13211788

Matkarimov, I., Hwsein, R.R., Matyakubov, M., Bhaskaran, B., Eshbekova, D. and Vij, P., 2025. Intelligent IoT-enabled data analytics and monitoring framework for smart freshwater recirculating aquaculture systems. *International Journal of Aquatic Research and Environmental Studies*, *5*(1), pp.22–29. https://doi.org/10.70102/IJARES/V5S1/5-S1-03

Pari, N.S. and Senthil Kumar, K., 2025. Combative machine learning approaches for solving bot driven cyber threats in social networking platforms. *Journal of Internet Services and Information Security*, *15*(2), pp.652–672. https://doi.org/10.58346/JISIS.2025.I2.045

Picó, Y. and Barceló, D., 2019. Analysis and prevention of microplastics pollution in water: current perspectives and future directions. *ACS omega*, *4*(4), pp.6709-6719. https://doi.org/10.1021/acsomega.9b00222

Popescu, S.M., Mansoor, S., Wani, O.A., Kumar, S.S., Sharma, V., Sharma, A., Arya, V.M., Kirkham, M.B., Hou, D., Bolan, N. and Chung, Y.S., 2024. Artificial intelligence and IoT driven technologies for environmental pollution monitoring and management. *Frontiers in Environmental Science*, *12*, p.1336088. https://doi.org/10.3389/fenvs.2024.1336088

Primpke, S., Godejohann, M. and Gerdts, G., 2020. Rapid identification and quantification methods (spectroscopy + ML): Rapid identification and quantification of microplastics in the environment. *Environmental Science & Technology*, *54*(24), pp.15893–15903. https://doi.org/10.1021/acs.est.0c05722

Saenen, N.D., Witters, M.S., Hantoro, I., Tejeda, I., Ethirajan, A., Van Belleghem, F. and Smeets, K., 2023. Polystyrene microplastics of varying sizes and shapes induce distinct redox and mitochondrial stress responses in a Caco-2 monolayer. *Antioxidants*, *12*(3), p.739. https://doi.org/10.3390/antiox12030739

Salami, Z.A., Babamuratov, B., Ayyappan, V., Prabakaran, N., Khudayberganov, K. and Singh, C., 2025. Modelling Crop Yield Prediction with Random Forest and Remote Sensing Data. *Natural and Engineering Sciences*, *10*(2), pp.67-78. https://doi.org/10.28978/nesciences.1763843

Sarker, M.A.B., Imtiaz, M.H., Holsen, T.M. and Baki, A.B., 2024. Real-time detection of microplastics using an ai camera. *Sensors*, *24*(13), p.4394. https://doi.org/10.3390/s24134394

Schymanski, D., Goldbeck, C., Humpf, H.U. and Fürst, P., 2018. Analysis of microplastics in water by micro-Raman spectroscopy: Release of plastic particles from different packaging into mineral water. *Water research*, *129*, pp.154-162. https://doi.org/10.1016/j.watres.2017.11.011

Schymanski, D., Goldbeck, C., Humpf, H.U. and Fürst, P., 2023. Raman spectroscopy for microplastic detection in water sources: a systematic review. *International Journal of Environmental Science and Technology*.

Wang, X., Jian, S., Zhang, S., Wu, D., Wang, J., Gao, M., Sheng, J. and Hong, Y., 2022. Enrichment of polystyrene microplastics induces histological damage, oxidative stress, Keap1-Nrf2 signaling pathway-related gene expression in loach juveniles (Paramisgurnus dabryanus). *Ecotoxicology and environmental safety*, *237*, p.113540. https://doi.org/10.1016/j.ecoenv.2022.113540

Xu, T., Cui, J., Xu, R., Cao, J. and Guo, M.Y., 2023. Microplastics induced inflammation and apoptosis via ferroptosis and the NF-κB pathway in carp. *Aquatic toxicology*, *262*, p.106659. https://doi.org/10.1016/j.aquatox.2023.106659

Yeo, B.G., Mizukawa, K. and Takada, H., 2023. Microplastics in global marine waters and biota: effectiveness of potential bioindicators in mirroring local pollution levels. *Environmental Monitoring and Contaminants Research*, *3*, pp.43-68. https://doi.org/10.5985/emcr.20230005

Zhu, Y., Li, Y., Huang, J., Zhang, Y., Ho, Y.W., Fang, J.K.H. and Lam, E.Y., 2024. Advanced optical imaging technologies for microplastics identification: progress and challenges. *Advanced Photonics Research*, *5*(11), p.2400038. https://doi.org/10.1002/adpr.202400038