IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

Deep Learning Algorithms for Microplastic Detection in Water: A Review

Pooja Vidyadhar Dangat and Prof V C Maindargi
Department of E&TC
Terna College of Engineering, Dharashiv, India
dangatpooja0@gmail.com

Abstract: *The problem of contamination of freshwater and seawater systems by microplastics has become an increasing environmental and health risk. The task of quickly, precisely, and cost-effectively detecting microplastics in water has thus become a key scientific challenge. Traditional methods such as visual identification, Fourier-transform infrared (FTIR), and Raman spectroscopy are highly accurate but time-consuming and difficult to automate. Over the last ten years, the development of deep learning (DL) algorithms for automating microplastic recognition and quantification from images, spectra, and hyperspectral cubes has advanced significantly. This paper provides a structured review of DL applications for microplastic detection in water, from the perspective of CNN-based image classification, object detection algorithms such as YOLO, semantic and instance segmentation networks, hybrid Raman and FTIR spectroscopy, and a DL pipeline. This review includes over thirty works, providing a table of dataset characteristics, the metrics used by these papers, and their results. Finally, we will explore some directions for the future, including multimodal sensor fusion, self-supervised and few-shot learning, explainable AI, and edge-deployable portable detectors.*

Keywords: microplastics, deep learning, convolutional neural network, water quality monitoring, Raman spectroscopy, FTIR, object detection, image segmentation, hyperspectral imaging

I. INTRODUCTION

Microplastics (MPs) are tiny fragments of plastics less than 5 mm in size that have been found in river water, lake water, groundwater, drinking water, and oceans all around the world [1]. MPs can arise from the breakdown of larger plastics, synthetic textile fibers, tire wear, cosmetic microbeads, and industrial pellets, and these particles can stay in the water bodies for decades because they are resistant to degradation. Growing research has shown a connection between MPs in water bodies and toxicological consequences for aquatic animals, as well as potential human health concerns through food chains and drinking water [2]–[5].

Microplastic analysis requires that microplastics be detected, quantified, sized, and chemically classified (by polymer type). The classical analytical protocol, which involves manual or stereomicroscopic sorting followed by spectroscopic confirmation using FTIR or Raman, is considered the current gold standard for the chemical classification of polymers. Still, this method is time-consuming (it can take several hours or even days to analyze a single sample), highly specialized, and difficult to scale up to meet the demands of environmental monitoring [6].

The application of deep learning has revolutionized pattern recognition across various sectors, including medical imaging, remote sensing, and more. Over the past five years, it has been used to detect microplastics [7]. DL-based systems can automatically extract the discriminative features from the raw microscope images, spectra, or hyperspectral cubes, eliminating the requirement for manually designing such features, which greatly saves time. Architectures used in various papers include image classification with CNNs, object detection with the YOLO series and Faster R-CNN, semantic and instance segmentation with U-Net, 1D CNNs for spectral data, and multimodal approaches that combine imaging and spectroscopic information [8], [9].

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 6, Issue 1, August 2026 Impact Factor: 8.2

A. Contribution of this Review

In this work, we provide a survey of over thirty scholarly articles on the topic of deep learning for microplastics detection in water and related aqueous media, which were mostly published from 2018 to 2026. The contributions made in this paper are: (1) Taxonomy of DL methods by sensing technique (optical microscopy, object detection, segmentation, Raman spectroscopy, Fourier transform infrared spectroscopy, hyperspectral imaging); (2) Tabulated summary of datasets used, DL models, and achieved results; (3) Common issues faced by researchers; and (4) Future research directions.

The rest of this paper is structured as follows. Section II gives the background on microplastics and conventional techniques for their detection. Section III covers the deep learning fundamentals utilized in the reviewed papers. Section IV presents the taxonomy of microplastic detection using DL models. Section V covers the datasets and evaluation metrics. Section VI provides the comparative table with the results of our review. Sections VII and VIII cover the challenges and future directions, respectively. Section IX concludes this paper.

As illustrated in Fig. 1, the number of publications on microplastic detection using deep learning models has grown rapidly since 2022.

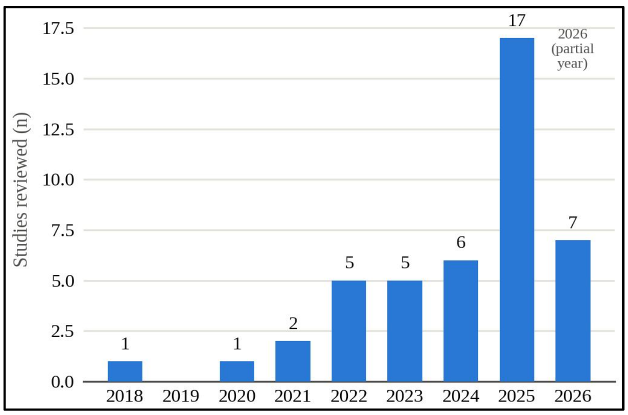

Fig. 1. Year-wise distribution of the reviewed studies (n = 44), showing rapid growth in DL-based microplastic detection research since 2022.

II. BACKGROUND

A. Microplastic Classification and Sources

Microplastics have traditionally been categorized based on their size (nanoplastics <1 µm, microplastics 1 µm-5 mm), their source (primary plastics, produced at the microscopic level, and secondary plastics, which have been fragmented from larger materials), as well as their morphology (fibers, fragments, films, foams, and beads). The polymer type from which the microplastic is made (mainly PE, PP, PS, PET, PVC) significantly affects its optical and spectroscopic properties.

B. Conventional Detection Methods

The conventional approach involves sampling (filtration, sieving, density sorting), visual identification through stereomicroscopy, and verification with spectroscopy. Fourier-transform infrared (FTIR) spectroscopy uses characteristic absorption vibrations. It is commonly employed for identifying bulk polymers, whereas micro-FTIR and focal plane array (FPA) imaging permit visualization of individual particles in filtered samples [30], [32]. Raman spectroscopy provides better spatial resolution than FTIR, especially for sub-20 µm particles, but is prone to fluorescence interference from organic substances [24]. These methods produce vast amounts of spectral data that need to be classified accurately and automatically – an area in which deep learning excels.

C. Why Deep Learning

The problems of noise in field samples, particle overlap, and interoperator variations make the manual comparison of spectral data with library spectra and image thresholding difficult. Deep learning models, especially CNNs, have learned hierarchical feature representations from raw image data or spectra and have demonstrated superior performance over traditional ML approaches such as support vector machines, random forests, and k-nearest neighbors.

III. DEEP LEARNING PRELIMINARIES

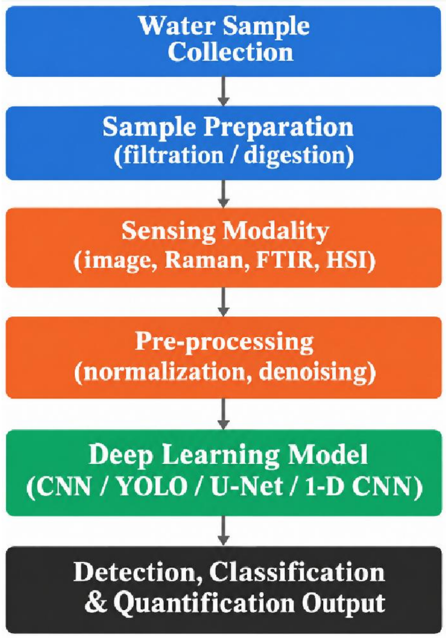

Fig. 2. Generic deep-learning-based microplastic detection pipeline, from water sampling to particle-level output.

A. Convolutional Neural Networks

CNNs use learned convolutional filters to identify spatial or positional features in the image, then apply pooling, and finally use classification layers. Transfer learning with ImageNet-pretrained backbones is the leading approach for microplastic image classification due to the limited availability of labeled MP datasets.

B. Object Detection Networks

The task of object detection involves localizing and categorizing multiple objects in a single image using bounding boxes and classification simultaneously. The YOLO algorithm is the most popular in the literature reviewed due to its favorable speed-accuracy ratio, enabling near-real-time inference even on embedded devices [21], [22].

C. Segmentation Networks

The segmentation methods that include semantic and instance segmentations (U-Net, Mask R-CNN, and further improvements of these methods) classify each pixel into some classes, making it possible to perform particle boundaries detection and calculation of its size and shape descriptors—important for determining toxicity as well as concentration estimation [18], [19].

D. One-Dimensional CNNs for Spectral Data

For Raman and FTIR spectra, the 1-D CNN treats the spectrum as a sequence and learns filters via wavenumber bins, giving it an advantage over baseline-drift- and noise-sensitive peak-matching approaches [24], [26].

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

IV. DEEP LEARNING APPROACHES FOR MICROPLASTIC DETECTION

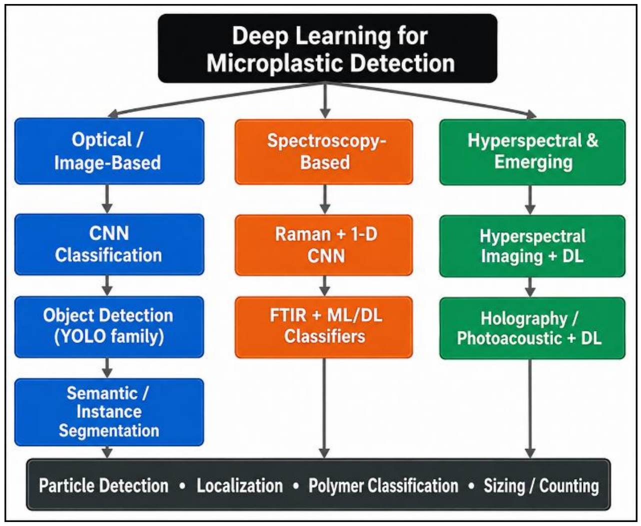

Fig. 3. Taxonomy of deep-learning-based microplastic detection approaches organized by sensing modality.

A. Image-Based Classification of Microscopy Data

Several works make direct use of CNN classifiers to analyze images from stereo or optical microscopes of isolated particles. Transfer-learning-based CNN backbones have been validated for classifying MPs by polymer type and shape, with typical accuracies ranging from 90% to 98% on laboratory-based datasets [11], [12], [14]. When comparing multiple CNN architectures (VGG16, ResNet50, InceptionV3, MobileNetV2, and EfficientNet) for classifying MPs in WTP samples, a deeper architecture with transfer learning consistently outperforms a shallow CNN trained from scratch, albeit at increased computational complexity [13]. It has also been demonstrated that fine-tuned models using particles extracted from various environmental matrices (soil, sediment, water) outperform models trained on a single matrix.

B. Object Detection for Localization and Counting

Pipeline approaches based on object detection find and count MP particles directly in unprocessed water/microscope images. Low-cost portable systems using inexpensive microscopes (such as USB microscopes connected to Raspberry Pi devices) together with YOLOv5/8 detectors have proven effective for in situ water screening, achieving mAP@50 scores in the 0.7–0.9 range [9], [21]. The fluorescent method of enhanced detection, using Nile Red dye and UV/blue illumination, has been used in conjunction with YOLOv8 to significantly increase the contrast between plastic and non-plastic particles in low-cost, portable devices [22]. Machine learning-based detection and quantification pipelines designed to detect and quantify MPs directly in aquatic environmental samples have also shown impressive accuracy, with high precision and recall in MP particle counting [10].

C. Semantic and Instance Segmentation

Pixel-wise segmentation methods are preferred when precise particle sizing and classification are required. The MP-Net method is based on U-Net and is designed for the segmentation of microplastics in fluorescence microscopy images of biological tissue (clams), demonstrating that a specialized architectural design performs better on this task than standard U-Nets [18]. The pipelines that combine YOLOv5 Detection and adaptive UNET3+ segmentation were employed to localize and separate touching microplastic particles in optical micrographs, addressing the common problem of detecting touching particles as a single object [17]. Semantic segmentation networks trained on image data from the coastal environment have been employed to distinguish MP particles from sand, shell, and organic particles

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

[19], while generic neural-network-based segmentation pipelines have been applied to enumerate particles on heterogeneous backgrounds [20].

D. Raman Spectroscopy Combined with Deep Learning

Classification of polymer types using 1-D CNNs on Raman spectra has become a de facto technique, especially for small particles smaller than the minimum practical size in FTIR. Deep 1-D CNN classifiers trained on Raman spectral libraries have demonstrated classification accuracies exceeding 95% across a variety of common polymer classes at considerably higher speed than traditional spectral database comparison techniques [24]. CNN-based classification of micro-Raman spectra has been implemented directly on sediment and freshwater samples, where the model has demonstrated its ability to address baseline fluorescence and low signal-to-noise ratios in field particles [25], [27]. There has also been an idea to build a modular CNN-based classifier with separate pre-processing, feature extraction, and classification sub-networks to make the algorithm interpretable and enable retraining of individual modules for a newly introduced polymer type [26].

E. FTIR Spectroscopy Combined with Deep Learning

FTIR spectroscopy remains the most widely used confirmatory tool, and numerous studies benchmark deep learning against traditional machine learning algorithms for classifying FTIR spectra. A comparison of various normalization/preprocessing methods, together with multiple ML and DL classifiers, has revealed that the normalization method strongly influences classification accuracy, with deep networks being the most sensitive to preprocessing [29]. Ensemble machine learning models, comprising multiple base classifiers operating on FTIR spectral descriptors, can achieve high accuracy with less training data than deep models [30]. An IEEE conference comparison study between ML and DL models on the same FTIR spectra data set has revealed that DL models generalize well to unknown spectral noise but require significantly more training data than ML models [31]. Another class of similarity learning methods, when applied to μFTIR focal-plane-array imaging spectra, has proven adaptable to changes in the reference library without requiring complete retraining, thus overcoming one of the biggest limitations of a fixed-class classifier [32]. Pipelines that automate TGA coupled with FTIR and machine-learning-based spectral analysis have been developed to simultaneously identify and quantify the MP mass fraction [33].

F. Hyperspectral Imaging Combined with Deep Learning

Hyperspectral imaging (HSI) provides a full spectral profile at each pixel in the image, thus allowing for the spatial localization and chemical identification of the sample to be determined concurrently. Near-infrared hyperspectral imaging, combined with deep learning classifiers, has been shown to rapidly screen environmental samples for microplastics down to about 100 μm [34], [35]. Hyperspectral imaging, assisted by deep learning-based classifiers in darkfield imaging, has been used to identify microplastics associated with biological cells, which is important for determining bioaccumulation [36]. In contrast, HSI-DL pipelines have also been developed for screening co-metabolic microplastic-degrading bacteria [37] and farmland soil analysis [38]. In addition, a shape-classification network on hyperspectral image cubes has shown that morphological information (fiber, fragment, film) can be identified alongside polymer identification using a single hyperspectral imaging acquisition [39]. It has also been demonstrated that classification accuracy is highly dependent on the spatial and spectral characteristics of the acquisition, which makes standardized HSI protocols necessary [40]. The HSI-DL approach has also been implemented in a shoal-simulation (sediment and water) environment [41] and for food-matrix microplastic screening [42].

G. Emerging and Hybrid Modalities

In addition to mainstream imaging and spectroscopic modalities, other sensing techniques that have emerged in recent years have also been applied using DL. The integration of holographic imaging with deep classification networks can enable lensless particle analysis without labeling and is suitable for miniaturized devices [43]. Photoacoustic imaging

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

and the application of deep learning for pre-processing have been suggested as a contactless approach for measuring MP concentration in murky water [44]. An early study that employed CNN-based classification of microbeads in urban wastewater helped establish the potential of automated MP screening at operating wastewater treatment plants, even before the prevalence of transfer-learning pipelines [16].

V. DATASETS AND EVALUATION METRICS

The studies reported the use of in-house image/spectral datasets of relatively small sizes, containing hundreds or thousands of labeled particles, which most often include PE, PP, PS, PET, and PVC classes, sometimes accompanied by non-plastic particle classes to reduce false positives. Open-source spectral databases (Raman/FTIR plastic spectra) are often used to pretrain and fine-tune classifiers on environmental datasets [30], [32]. Evaluation measures reported depend on the task under study and include accuracy, precision, recall, and F1-score for classification tasks; mAP (mean average precision) at different IoU thresholds (commonly mAP@50) for detection tasks; and IoU/Dice coefficient for segmentation tasks. Such differences in metrics and datasets across the studies significantly complicate comparison, an issue we discuss further in Section VII.

VI. SUMMARY OF REVIEWED METHODS

Fig. 4 illustrates how the 44 studies are categorized by sensing methods and method types to aid the study-by-study comparison in Table I.

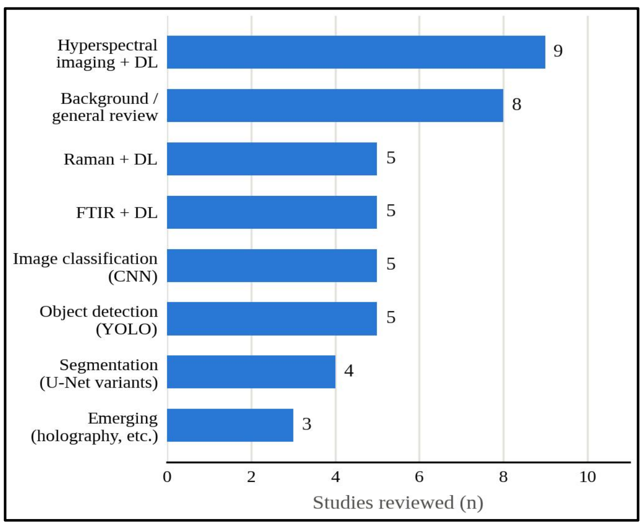

Fig. 4. Distribution of the reviewed studies (n = 44) by sensing modality/method category.

Table I presents sample research works belonging to the categories presented in section IV, detailing the sensory modality employed, the deep learning model used, the dataset size, the performance achieved, and the strengths/weaknesses of the method, respectively. (See Table I below.)

TABLE I: SUMMARY OF REPRESENTATIVE DEEP-LEARNING-BASED MICROPLASTIC DETECTION STUDIES

Ref.	Modality	DL Architecture	Dataset Scale	Reported Performance	Key Advantage / Limitation
[9]	Optical microscopy image	YOLOv5s (embedded)	Field water samples	mAP@50 ≈ 0.75	Portable, low-cost, limited to particles resolvable by a USB microscope
[21]	Optical	YOLOv8	Lab + field	High	Fast inference; sensitive to

DOI: 10.48175/IJARSCT-38032

ISSN 2581-9429 IJARSCT

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

Ref.	Modality	DL Architecture	Dataset Scale	Reported Performance	Key Advantage / Limitation
	microscopy image		images	precision/recall	lighting/background clutter
[22]	Fluorescence-stained image	YOLOv8 + Nile Red staining	Portable device dataset	Improved contrast/detection	Enhances plastic–non-plastic contrast; requires staining reagent
[11]	Optical microscopy image	Pretrained CNN (transfer learning)	Small lab dataset	Accuracy > 90%	Data-efficient via transfer learning; limited generalization to unseen polymers
[13]	Optical microscopy image	5 CNNs (VGG/ResNet/Inception/etc.)	WWTP samples	Best CNN outperforms baseline	Systematic architecture comparison; high compute cost for deeper nets
[18]	Fluorescence microscopy	MP-Net (U-Net variant)	Biological tissue images	High Dice/IoU	Precise pixel-level sizing; domain-specific, needs re-training for new tissues
[17]	Optical micrographs	YOLOv5 + UNET3+	Adherent particle images	Improved boundary accuracy	Resolves overlapping particles; two-stage pipeline adds latency
[19]	Coastal environment image	Semantic segmentation CNN	Coastal image set	High pixel accuracy	Separates MP from natural debris; the dataset is geographically limited
[24]	Raman spectrum	1-D CNN	Spectral library	Accuracy > 95%	Fast, robust to noise; needs a representative spectral library
[26]	Raman spectrum	Modular CNN	Environmental spectra	High accuracy, interpretable	Extensible to new polymers; added architectural complexity
[27]	Raman spectrum	CNN	Freshwater sediment	Robust classification	Works on field-collected particles; fluorescence interference remains a factor
[29]	FTIR spectrum	ML & DL comparison	Public FTIR spectra	DL best after normalization	Highlights preprocessing sensitivity; DL needs larger training sets
[30]	FTIR spectrum	Ensemble ML	FTIR spectral dataset	High accuracy, low data needs	Data-efficient; less flexible than end-to-end DL
[31]	FTIR spectrum	ML vs. DL comparison	FTIR dataset	DL generalizes better to noise	Useful benchmarking study; single dataset limits external validity
[32]	μFTIR (FPA imaging)	Similarity learning	FPA spectral images	Adapts to new libraries	No full retraining needed for new classes; embedding quality-dependent
[35]	NIR hyperspectral image	DL classifier	HSI cubes	High classification accuracy	Combines spatial + spectral info; costly imaging hardware
[39]	Hyperspectral image	DL shape classifier	HSI cubes	Accurate shape + polymer ID	Joint morphology/composition output; complex data pipeline
[40]	Hyperspectral image	Multiple DL/ML models	Varying resolutions	Accuracy varies by protocol	Informs optimal acquisition settings; no single best protocol
[43]	Holographic image	DL classification	Lab holograms	Good classification accuracy	Label-free, compact optics; less mature than CNN-image pipelines

IJARSCT

International Journal of Advanced Research in Science, Communication and Technology

International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal

ISSN: 2581-9429

Volume 6, Issue 1, August 2026

Impact Factor: 8.2

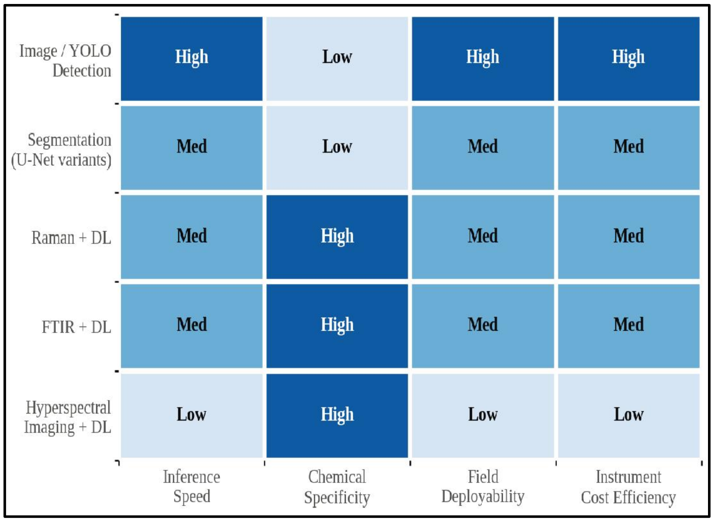

Fig. 5. Qualitative comparison of leading method categories across inference speed, chemical specificity, field deployability, and instrument cost efficiency, synthesized from the reviewed literature.

TABLE II: CATEGORY-LEVEL COMPARATIVE ANALYSIS OF MICROPLASTIC DETECTION METHODS

Method Category	n	Typical Reported Performance	Key Strengths	Key Limitations
Image classification (CNN / transfer learning)	5	Accuracy 90–98%	Mature transfer-learning ecosystem; strong on curated microscopy images	Limited generalization to unseen polymers/matrices
Object detection (YOLO family)	5	mAP@50 0.70–0.90	Fast, portable, and near-real-time capable	Sensitive to lighting/background clutter; boundary precision limited
Segmentation (U-Net variants)	4	High Dice / IoU (qualitative)	Precise particle sizing and shape extraction	Domain-specific; two-stage pipelines add latency
Raman spectroscopy + DL	5	Accuracy > 95% (1-D CNN)	High chemical specificity; effective on small (sub-20 µm) particles	Susceptible to fluorescence interference
FTIR spectroscopy + DL	5	High accuracy after normalization (qualitative)	Standard confirmatory technique; large reference spectral libraries	Preprocessing-sensitive; less effective below ~20 µm
Hyperspectral imaging + DL	9	High classification accuracy (qualitative)	Joint spatial and chemical characterization in one acquisition	Costly instrumentation; accuracy is protocol-dependent
Emerging (holography, photoacoustic)	3	Good classification accuracy (qualitative)	Label-free / non-contact sensing; compact optics	Less mature; fewer validated field deployments

Table II summarizes the results from Table I across the seven methods considered. Hyperspectral imaging was the most frequently studied method in this review (9 of 44 studies, 20%) due to ongoing research on approaches that simultaneously reconstruct both spatial and chemical information. In contrast, segmentation and novel modalities (holography and photoacoustic imaging) appear relatively unexplored (4 and 3 studies, respectively). In terms of quantitative evaluation, when available, the most accurate networks were image classification CNNs and Raman 1-D CNNs (90-98% and >95%, respectively), while object detectors sacrificed some of their accuracy in favor of mAP@50 in the range of 0.70-0.90 but with significantly lower inference time, in line with the tradeoff shown in Fig. 5.

As seen from the analysis of the works presented in Table I, the inference time and portability of the image and object detection (YOLO) systems are the fastest and most suitable, and the chemical specificity of the spectroscopy and 1D-CNN (Raman/FTIR) systems is the highest for the confirmatory analysis of polymers. The spatial and chemical characterization provided by hyperspectral imaging and deep learning systems is the best despite the complexity and cost of the equipment.

VII. CHALLENGES AND OPEN ISSUES

A. Dataset Scarcity and Class Imbalance

The majority of reviewed research is based on datasets which consist of hundreds or thousands of particles. Unusual polymer species and morphologies occur much less often in these datasets, so the training data is biased towards the most-represented classes (PE, PP, PS) [13], [15].

B. Lack of Standardized Benchmarks

As each paper captures its own set of images/spectra using varying conditions of acquisition, magnification, staining technique, and polymer database, the accuracy measures presented cannot be compared directly between studies. The lack of a common, large database for benchmarking, such as ImageNet for computer vision, remains one of the major challenges in the field [29], [40].

C. Small Particle Size and Sub-Resolution Limitations

The detection efficiency drops sharply for particles smaller than about 10-20 microns due to optical resolution limitations, low SNR, and insufficient pixel coverage, especially in inexpensive imaging systems [34].

D. Environmental Sample Complexity

Field water samples contain natural organic matter, biofilm, algae, and mineral particles that have a similar appearance and spectrum to microplastic particles, and all high-precision studies to date have used prepared samples rather than actual environmental samples [19],[33].

E. Computational Cost and Field Deployability

Although deep models tend to achieve high accuracy, they consume much more computational power, making them unsuitable for mobile devices; lightweight models (MobileNets and YOLO-nano) sacrifice some accuracy for deployability [9], [6].

F. Interpretability

For the most part, DL systems act as black boxes because they do not provide much information about which specific spectral or image characteristics are being considered for classification. This is problematic for validating the results of automated MP monitoring.

VIII. FUTURE DIRECTIONS

Several potential research directions for improving DL-based microplastic detection in water are evident from the literature review:

- Standardized, large-scale benchmark datasets. Releasing large, diverse multimodal (image and spectral) labeled datasets across varying water matrices through community collaboration will enable fair cross-study comparisons and expedite model training.

• Multimodal sensor fusion. Fusion of imaging (for morphological size) with spectroscopy/hyperspectral sensing (for chemical composition) into a single DL pipeline may yield higher sensitivity for detection and greater specificity for polymer classification than using either modality alone [39].
• Self-supervised and few-shot learning. However, given that datasets are often scarce, self-supervised pre-training on unlabeled environmental images/spectra, along with fine-tuning models using few-shot learning, may prove helpful.
• Explainable AI (XAI). The inclusion of saliency maps, attention mechanisms, or modular designs for explainability would increase trust and enable scientific evaluation of automated decisions [26].
• Edge-deployable, low-power models. Further advances in compact architecture (quantized and pruned CNNs, efficient YOLO designs) for embedded and mobile devices would prove crucial for practical implementations [6], [22].
• Real-time continuous monitoring. The integration of ML-based detection methods with in situ flow-through sensors can enable continuous monitoring of MPs in rivers and water treatment facilities without sampling.

IX. CONCLUSION

Deep learning has made significant advances in automating microplastic detection in water samples, including image classification, object detection, semantic segmentation, and spectroscopic and hyperspectral classification pipelines. This review summarizes results from more than thirty recent papers, showing that CNN- and object-detection-based image methods were the best approaches for quick, cheap, and deployable field screening, whereas spectroscopy- and hyperspectral imaging-based deep learning pipelines offered better chemical specificity for verifying the plastic type. While this technology is rapidly advancing, the following challenges remain to be addressed in this field: dataset scarcity, lack of standardized benchmark datasets, small particle-size detection limits, environmental sample complexity, and model interpretability.

REFERENCES

[1] H. G. Hoang, N. S. H. Nguyen, T. Zhang, H.-T. Tran, S. Mukherjee, and R. Naidu, “A review of microplastic pollution and human health risk assessment: current knowledge and future outlook,” Frontiers in Environmental Science, vol. 13, 2025.
[2] X. Zhang, C. Yu, P. Wang, and C. Yang, “Microplastics and human health: unraveling the toxicological pathways and implications for public health,” Frontiers in Public Health, vol. 13, 2025.
[3] “Potential health impact of microplastics: a review of environmental distribution, human exposure, and toxic effects,” Environment & Health, ACS Publications, 2024.
[4] “Microplastics: their effects on the environment, human health, and plant ecosystems,” Total Environment Research Themes, 2024.
[5] “Microplastics pollution: a comprehensive review on the sources, fates, effects, and potential remediation,” 2023.
[6] P. Akhil, B. Nagashubha, M. S. Lakshmi, V. Sowmya, G. Sonu, S. Y. Banu, C. Veeresh, C. Bandlapalli, and M. K. Sai, “AI-driven portable smartphone-based sensor for microplastic detection: a comprehensive review,” Toxicology and Environmental Health Sciences, vol. 18, no. 1, pp. 103–124, 2026.
[7] “Deep learning approaches for detection and classification of microplastics in water for clean water management,” in Proc. IEEE Conf., 2025.
[8] J. Rajeswari, B. A. Kumar, S. Senthilrani, S. Amrudha, M. A. Pushpa, and S. T. Natchiyar, “Deep learning approaches for microplastic identification in microscopic water samples,” in Proc. Int. Conf. Artificial Intelligence and Secure Data Analytics (ICAISDA), 2025, pp. 837–847.
[9] R. Kamathe, M. Deshpande, V. Hanchate, S. Borde, K. Joshi, A. Giram, S. Garad, and P. Rane, “Plastiview: deep learning based microplastic detection in water,” International Journal of Environmental Sciences, vol. 11, no. 4, pp. 1950–1968, 2025.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 1, August 2026
Impact Factor: 8.2

[10] T. Vengatesh, G. R. L. M. Tayaru, J. Nagalakshmidevi, M. B. Suthar, T. Kamaleshwar, K. T. Meena, A. J. Babu, and G. Maheswari, "A machine learning approach to microplastic detection and quantification in aquatic environments," International Journal of Environmental Sciences, vol. 11, no 23s, pp. 4006–4014, 2025.

[11] "Automated micro-plastic detection and classification using deep convolution neural network pre-trained models and transfer learning," AIP Advances, vol. 15, no. 2, art. 025207, 2025.

[12] "Deep learning based approach for automated characterization of large marine microplastic particles," Marine Pollution Bulletin, 2022.

[13] "Comparative analysis of five convolutional neural networks and transfer learning classification approach for microplastics in wastewater treatment plants," Journal of Water Process Engineering, 2023.

[14] "Automatic quantification and classification of microplastics in scanning electron micrographs via deep learning," Science of the Total Environment, 2022.

[15] "Development of fine-tuned deep learning models for physical classification of microplastics extracted from different environmental matrices," 2025.

[16] "Use of a convolutional neural network for the classification of microbeads in urban wastewater," 2018.

[17] "Automatic localization and segmentation of adherent microplastics in optical micrographs based on improved YOLOv5 and adaptive perceptual UNET3+," 2024.

[18] H.-M. Park, S. Park, M. K. de Guzman, J. Y. Baek, T. Cirkovic Velickovic, A. Van Messem, and W. De Neve, "MP-Net: deep learning-based segmentation for fluorescence microscopy images of microplastics isolated from clams," PLOS ONE, vol. 17, no. 6, e0269449, 2022.

[19] "Detection of microplastics in coastal environments based on semantic segmentation," Microplastics, vol. 5, no. 2, art. 66, 2026.

[20] "Neural network analysis for microplastic segmentation," 2021.

[21] "YOLOv8-based microplastic detection and quantification," Journal of Applied Data Sciences, 2025.

[22] "Low-cost portable microplastic detection system integrating Nile red fluorescence staining with YOLOv8-based deep learning," 2025.

[23] "Enhanced detection and classification of microplastics in marine environments using deep learning," 2024.

[24] "A deep one-dimensional convolutional neural network for microplastics classification using Raman spectroscopy," Vibrational Spectroscopy, 2022.

[25] "Identification of microplastics using a convolutional neural network based on micro-Raman spectroscopy," Talanta, 2023.

[26] "A modular convolutional neural network framework for Raman spectra-based identification of environmental microplastics," Water Research, 2026.

[27] "Detection of microplastics in freshwater sediments based on Raman spectroscopy and convolutional neural networks," Journal of Physical Chemistry B, 2025.

[28] "Machine learning-assisted Raman spectroscopy for enhanced plastic identification," Spectrochimica Acta Part A, 2026.

[29] O. Villegas-Camacho, I. Francisco-Valencia, R. Alejo-Eleuterio, E. E. Granda-Gutiérrez, S. Martínez-Gallegos, and D. Villanueva-Vásquez, "FTIR-based microplastic classification: a comprehensive study on normalization and ML techniques," Recycling, vol. 10, no. 2, art. 46, 2025.

[30] X. Yan, Z. Cao, A. Murphy, and Y. Qiao, "An ensemble machine learning method for microplastics identification with FTIR spectrum," Journal of Environmental Chemical Engineering, vol. 10, no. 4, art. 108130, 2022.

[31] "A comparative study of machine learning and deep learning models for microplastic classification using FTIR spectra," in Proc. IEEE Conf., 2023.

[32] "Adaptable microplastic classification using similarity learning on µFTIR spectra collected from µFTIR focal plane array imaging," Proceedings of the National Academy of Sciences, 2025.

[33] "Automated machine-learning-driven analysis of microplastics by TGA-FTIR for enhanced identification and quantification," Analytical Chemistry, 2025.

[34] "Optimization of a hyperspectral imaging system for rapid detection of microplastics down to 100 µm," MethodsX, 2020.

[35] "Deep-learning-assisted near-infrared hyperspectral imaging for microplastic classification," Powder Technology, 2025.

[36] "Deep learning-assisted identification and quantification of cell-associated microplastics using darkfield hyperspectral imaging," Talanta, 2026.

[37] "Deep learning-enhanced hyperspectral imaging for rapid screening of co-metabolic microplastic-degrading bacteria in environmental samples," 2025.

[38] "Application of hyperspectral and deep learning in farmland soil microplastic detection," Science of the Total Environment, 2023.

[39] "Deep learning-based shape classification for hyperspectral-imaged microplastics," Analytical Chemistry, 2025.

[40] "Efficient microplastic identification by hyperspectral imaging: a comparative study of spatial resolutions, spectral ranges and classification models to define an optimal analytical protocol," 2024.

[41] "Detection and classification of microplastics in simulated shoal environments using hyperspectral imaging technology," Marine Pollution Bulletin, 2026.

[42] S. Nayani et al., "In-situ detection of microplastic particles on food using hyperspectral imaging with one-dimensional convolutional neural network and artificial neural network," Journal of Chemometrics, 2026.

[43] "Microplastic pollution monitoring with holographic classification and deep learning," Environmental Research Communications, 2021.

[44] "Innovative methods for microplastic characterization and detection: deep learning supported by photoacoustic imaging and automated pre-processing data," 2024