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Advances in machine learning for the detection and characterization of microplastics in the environment

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Microplastics are increasingly recognized as a pervasive pollutant in both aquatic and terrestrial environments, raising pressing concerns about their ecological impacts and implications for human health. Traditional detection and quantification methods—including manual microscopy and standalone spectroscopic techniques—offer reliable accuracy but are limited by labor-intensive procedures and low throughput. Recent advances in machine learning (ML) have revolutionized the field of microplastic research by automating and enhancing detection processes. In particular, algorithms such as support vector machines, random forests, and convolutional neural networks have demonstrated considerable success in classifying microplastics based on chemical signatures and visual characteristics. This review offers a comprehensive overview of ML approaches utilized for monitoring microplastic contamination across diverse aquatic settings. Spectral techniques, including infrared and Raman spectroscopy, leverage molecular vibrations to facilitate highly specific identification of polymer types, even within heterogeneous matrices. Image-based methods make use of sophisticated computer vision techniques to classify microplastics by shape, size, and color, reducing the subjectivity inherent in manual counting. Extending these capabilities further, hyperspectral imaging combines spatial and spectral data to generate comprehensive chemical maps, enabling the simultaneous assessment of polymer composition and distribution. Integrating ML algorithms into these various approaches has improved sensitivity, speed, and scalability, thereby addressing critical challenges in high-throughput and real-time monitoring. Despite these advances, key obstacles remain, including the need for larger, higher-quality datasets and the development of robust models capable of handling complex environmental conditions. Nevertheless, ongoing improvements in imaging hardware and ML methodologies hold significant promise for establishing more effective, automated, and accurate strategies for microplastic detection. By providing a comprehensive overview of current technologies and future opportunities, this review aims to guide researchers and stakeholders in developing science-based solutions for mitigating the global threat of microplastic pollution.

KEYWORDS

spectral imaging, deep learning, artificial intelligence, microplastic contamination, environmental monitoring, big data analytics

Introduction

The emergence of microplastics in aquatic environments has become a significant environmental challenge, posing substantial risks to marine life and human health. Microplastics are plastic particles typically smaller than 5 mm in diameter (Moore, 2008; Zarfl et al., 2011). They originate from a wide array of sources—including the fragmentation of larger plastic debris, cosmetics, synthetic textiles, and industrial activities—and have been detected in aquatic ecosystems across the globe (Andrady, 2011; Cole et al., 2011; Eriksen et al., 2014; Mao et al., 2020; Xu S. et al., 2020). These contaminants include primary microplastics (manufactured particles used in product) and secondary microplastics (fragments generated by the breakdown of large plastics) (Browne et al., 2011; Cole et al., 2011). Due to their durability and small size, these contaminants spread extensively and infiltrate diverse habitats and ecosystems, rendering microplastics persistent, pervasive pollutants (Barnes et al., 2009).

Microplastic pollution exerts adverse impacts not only on the environment but also on public health (Barnes et al., 2009; Rochman et al., 2013). Because these particles are ubiquitous in both marine and terrestrial ecosystems, they are ingested by a broad spectrum of organisms—from plankton to larger marine fauna (Barboza and Gimenez, 2015; Lusher et al., 2015; Bhatt and Chauhan, 2023). Such ingestion can cause physical damage, hinder feeding, and expose organisms to adsorbed toxins or pathogens (Rochman et al., 2013; Wright et al., 2013; Curto et al., 2021). The risks intensify as microplastics accumulate and biomagnify up the food chain. Beyond ingestion, microplastics can disrupt natural habitats, contribute to biodiversity loss, and serve as vectors for other pollutants. Human health implications are also evident: microplastics may enter our bodies through contaminated water and seafood, raising concerns about food safety and public wellbeing (Wright et al., 2013). These multifaceted ecological and health repercussions underscore the urgent need for enhanced research and robust management strategies (Barboza and Gimenez, 2015).

Effective monitoring of microplastic pollution is imperative for mitigating its ecosystem-level and public health impacts (GESAMP, 2015). As these particles disperse widely through different environments, documenting their concentrations and movements is essential for understanding their ecological footprint. Advanced predictive models are particularly valuable, as they forecast the dispersion and identify likely accumulation zones of microplastics (Löder and Gerdts, 2015). Such models play a crucial role in pinpointing high-risk areas and informing the creation of targeted environmental policies and cleanup initiatives. In tandem, monitoring programs offer real-time data on pollution levels, providing key metrics to assess the efficacy of enacted measures and to raise public awareness (Napper and Thompson, 2020). Collectively, rigorous monitoring and modeling efforts form a holistic approach to addressing the escalating challenges of microplastic pollution.

Despite progress in understanding microplastic contamination, the detection and quantification of these particles remain technically demanding. The small size and diverse chemical composition of microplastics complicate analyses, particularly in complex environmental matrices like seawater, sediments, and biota, each often requiring extensive sample preparation to isolate microplastics. Traditional approaches—such as visual sorting and manual counting—are time-intensive and prone to errors, especially when particles measure less than 1 mm. Advanced spectroscopic techniques like Fourier-transform infrared spectroscopy (FTIR) and Raman spectroscopy yield more accurate identifications but can be both expensive and time-consuming (Hidalgo-Ruz et al., 2012). Additionally, the absence of standardized protocols hampers data comparability across different investigations (Shim et al., 2016). Together, these challenges underscore the need for more efficient, reliable methods to detect and quantify microplastics, steps that are essential for accurately gauging pollution levels and guiding impactful mitigation efforts.

In light of these complexities, adopting innovative monitoring and predictive strategies is essential (Blettler et al., 2018). Machine learning (ML)—a domain of artificial intelligence—has begun to revolutionize environmental science by offering advanced tools for complex data analytics and forecasting (Koelmans et al., 2019). Owing to its capacity to handle large, complex datasets, ML is particularly well-suited to revealing patterns and anomalies that might remain hidden using conventional methods (Thompson et al., 2009; Löder and Gerdts, 2015).

The utility of ML in environmental research extends beyond microplastics, encompassing applications such as climate change modeling, biodiversity conservation, pollution assessment, and waste management (Zhang et al., 2017; Reichstein et al., 2019). These diverse case studies highlight ML's versatility and demonstrate its transformative potential to address the most pressing environmental challenges (Olden et al., 2008; Tuia et al., 2022; Kazi, 2025). In microplastic research specifically, ML algorithms excel at uncovering correlations in large environmental datasets, enabling more accurate predictions of microplastic dispersion, concentration hotspots, and movement trajectories (Su et al., 2023). By integrating diverse data sources—from satellite imagery and water samples to chemical composition analyses—ML-based methods can significantly enhance the detection and quantification processes (Koelmans et al., 2019; Prata et al., 2020). Taken together, these capabilities offer a more comprehensive view of microplastic pollution, paving the way for stronger, evidence-based mitigation strategies.

In this review, we examine the evolving role of ML in microplastic research. We discuss a range of applications that deepen our understanding of the distribution, concentration, and biological impacts of microplastics and illustrate how data-driven insights can inform policy and management. By harnessing the power of ML, researchers can detect previously hidden patterns, develop more precise models of microplastic spread, and craft more effective interventions. We conclude by highlighting emerging directions for future work, aiming to inspire further integration of ML techniques into the study and remediation of microplastic pollution.

Machine learning methodologies in microplastic prediction

ML methodologies have become integral to predicting and understanding microplastic pollution in aquatic environments. By leveraging their capacity to process large, complex datasets, ML

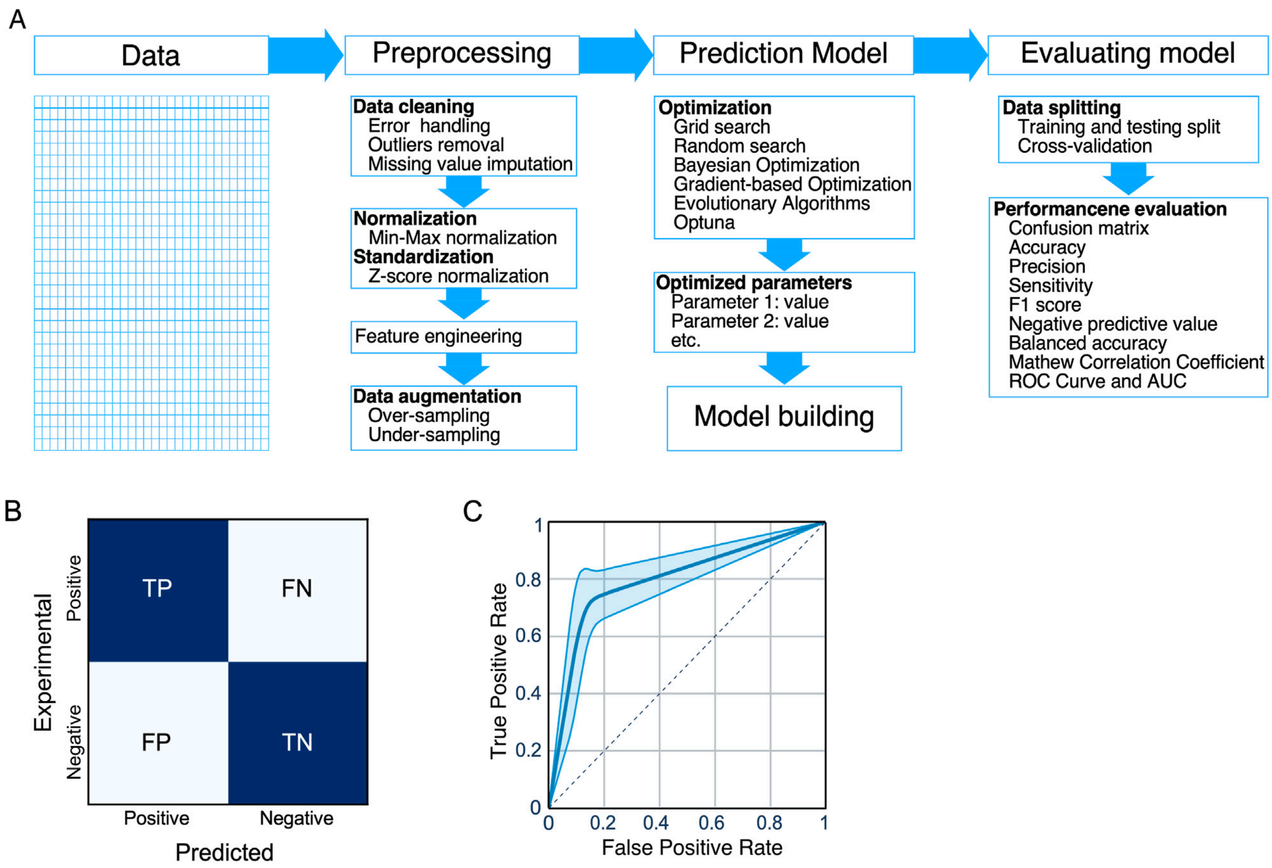

FIGURE 1
Optimization and Evaluation of Predictive Models. **(A)** Illustrates the comprehensive methodology for data preprocessing, including cleaning, normalization, feature engineering, and augmentation, followed by model optimization through techniques such as grid search, random search, and Bayesian optimization. This panel emphasizes the significance of preparing data and selecting optimal parameters to enhance model performance. Evaluation metrics, including accuracy, precision, sensitivity, and the ROC curve, are detailed, highlighting the rigorous assessment of model efficacy. **(B)** The confusion matrix depicted provides a visual comparison of experimental versus predicted values, offering insights into the model's predictive accuracy by displaying the number of true positives, false positives, true negatives, and false negatives. This visualization aids in understanding the model's performance in classifying data accurately. **(C)** Features the Receiver Operating Characteristic (ROC) curve, plotting the True Positive Rate (Sensitivity) against the False Positive Rate (1-Specificity) at various threshold settings. The area above the dashed line represents the model's performance exceeding random chance, with points further away from the line indicating higher predictive accuracy. This curve is crucial for evaluating the trade-offs between sensitivity and specificity in model predictions.

approaches often surpass traditional statistical methods in environmental studies (Su et al., 2023). Within the scope of microplastic research, such algorithms integrate diverse data sources—ranging from satellite imagery and oceanographic measurements to *in situ* field samples—to construct accurate models of microplastic distribution, concentration, and movement. In particular, supervised learning methods (e.g., random forests, support vector machines) and unsupervised techniques (e.g., clustering algorithms), along with deep learning approaches (e.g., convolutional neural networks), have been applied to identify, measure, and predict microplastic contamination across various aquatic ecosystems (Nesterovschi et al., 2023).

The incorporation of ML tools signifies a critical advancement in environmental research, equipping scientists with more powerful and nuanced analytical capabilities than conventional methods. These innovations are widely regarded as essential for robust monitoring and effective management of microplastic pollution, thereby fostering more proactive environmental stewardship (Chantry et al., 2021). For instance, real-time data from remote sensing platforms—when coupled with ML-based predictive models—can pinpoint high-risk accumulation areas, guide policy interventions, and streamline targeted cleanup efforts. However, ML approaches are used to augment, not fully replace, conventional methods. Traditional microscopy and spectroscopy without ML maintain proven accuracy but are extremely labor-intensive and time-consuming (Song et al., 2021), whereas ML-driven methods offer high-throughput automation at the expense of requiring significant data and computing resources (Sarker, 2021a).

A comprehensive evaluation of ML models typically employs a suite of performance metrics and techniques (Figures 1A–C). Metrics such as accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic (ROC) curve each illuminate different strengths and limitations of a given model. Cross-validation strategies, confusion matrices, and sensitivity analyses further refine these insights by indicating how well the model generalizes to new datasets or conditions. Using multiple assessment approaches in concert not only affords a fuller understanding of each model's capabilities but also directs

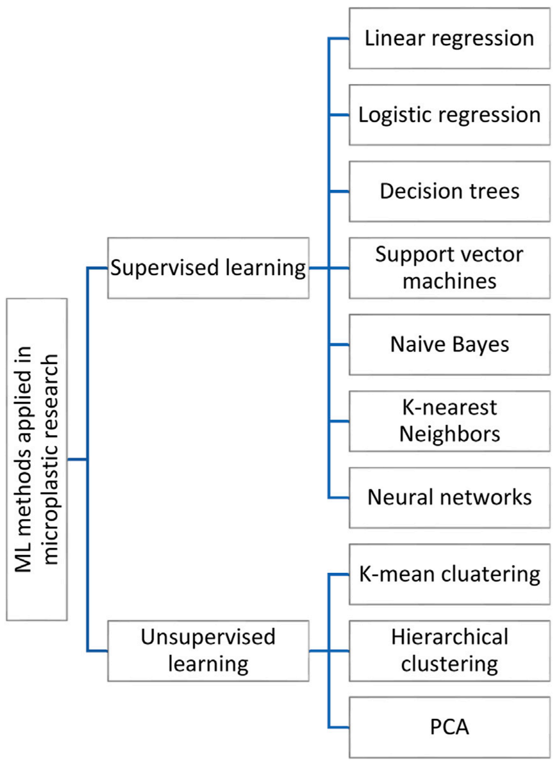

FIGURE 2
Schematic overview of ML methods commonly employed in microplastic research. Methods are categorized under supervised learning (linear regression, logistic regression, decision trees, support vector machines, naïve Bayes, k-nearest neighbors, and neural networks) and unsupervised learning (k-means clustering, hierarchical clustering, and principal component analysis). The figure highlights how supervised learning algorithms are used to predict or classify microplastic-related phenomena based on labeled data, while unsupervised methods are instrumental in uncovering hidden patterns and structures in unlabeled datasets.

researchers toward more informed decisions concerning model refinement and deployment. These rigorous evaluative practices ensure that ML-driven solutions for microplastic prediction remain both robust and adaptable to the inherent variability of natural systems. In practice, many studies apply k-fold cross-validation to ensure models perform well on unseen data and to avoid overfitting (Lee and Jhang, 2021). Additionally, hyperparameter tuning and regularization during model training are employed to optimize performance without overtraining.

Supervised and unsupervised learning

Supervised and unsupervised learning are two essential ML classes widely used in microplastic research (Figure 2), each distinguished by their specific methodologies and applications (Sarker, 2021b). Supervised learning algorithms are applied for tasks involving prediction or classification based on already-known output data (Rafique et al., 2021; Kazi, 2023). This application is evident in scenarios like distinguishing between different types of microplastics or predicting contamination levels based on previously analyzed samples. Unsupervised learning is highly effective in exploring data patterns where there are no pre-established categories. This approach is invaluable for uncovering unknown patterns or groupings in microplastic data, such as identifying areas with high levels of contamination or discovering new classes of microplastic pollutants based on their properties (Zhang Y. et al., 2023).

Supervised learning algorithms are a diverse set of tools designed to infer a function from labeled training data, allowing for predictions or classifications on new, unseen data. Application of some prominent supervised learning algorithms in the field of microplastic including linear regression, logistic regression, decision trees, support vector machines, Naive Bayes, k-Nearest Neighbors (k-NN), and neural networks have been discussed below.

Unsupervised learning techniques, such as clustering and dimensionality reduction, have emerged as valuable tools in microplastic research because they reveal hidden patterns in large, unlabeled datasets. By using methods like k-means, hierarchical clustering, and principal component analysis (PCA), researchers can group microplastic particles based on physical features (size, shape) and chemical signatures (FTIR or Raman spectral profiles) without the need for extensive manual labeling. This is particularly advantageous given the high variability of microplastic properties and the challenge of analyzing massive sample collections. In practice, clustering allows automatic segregation of polymer types, while dimensionality reduction methods make it easier to visualize and interpret complex spectral data.

Despite these benefits, several obstacles remain. Heterogeneous data collection methods, differences in sample preparation, and the complexity of spectral measurements can limit both reproducibility and interpretability. Addressing missing values adds another layer of complexity (Younus et al., 2024; Mousafi Alasal et al., 2025). Additionally, large-scale adoption of unsupervised methods necessitates robust infrastructure capable of managing high-throughput spectral or imaging data. Future directions are likely to focus on integrating domain knowledge into algorithm design, standardizing data processing protocols, and advancing automated systems that streamline end-to-end analysis.

Data for microplastic contamination research

Research on microplastic contamination has gained prominence in environmental science due to growing evidence that microplastics represent a pervasive pollutant with potential threats to both wildlife and human health (Larue et al., 2021; Blackburn and Green, 2022). These minute plastic particles occur in a wide range of environments—from oceans and freshwater systems to terrestrial habitats—prompting extensive efforts to determine their prevalence, distribution, and ecological impacts. A cornerstone of these endeavors is the availability of diverse databases and resources that collectively advance our understanding of microplastic pollution (Kunz et al., 2023; Zhen et al., 2023).

Among the most influential global resources is the Global Microplastics Initiative, which relies on citizen science to compile and analyze data on microplastic contamination. This grassroots effort is complemented by the NOAA Microplastics Database,

TABLE 1 The various resources used in microplastic research.

Resource/ initiatives	Scope and focus	Data type	Notable features and significance	Reference
Global microplastics initiative	Global citizen-science platform for microplastic pollution	Geographic coordinates, contamination levels, volunteer observations	- Leverages crowdsourced data - Broad geographic coverage - Raises public awareness	Barrows et al. (2018)
NOAA microplastics database	Marine-focused data on microplastic occurrence and effects	Oceanic measurements, ecological impact data, lab analyses	- Concentrates on marine environments - Provides insights into oceanic ecosystem health	Nyadjro et al. (2023)
UNEP and GRID-Arendal's marine litter database	Comprehensive repository on marine litter, including microplastics	Global surveys, remote sensing data, literature records	- Covers broad aspects of marine pollution - Facilitates cross-comparison of litter types	UNEP (2025)
ML datasets for microplastic research	Structured data used to train and validate ML models	Tabular data (e.g., shape, size), spectral properties, pollutant adsorption characteristics, images	- Enables predictive and classification modeling - Data quality directly affects ML accuracy	Lin et al. (2022), Yu and Hu (2022), Su et al. (2023)
Multidisciplinary research inputs	Contributions from environmental science, chemistry, marine biology, public health	Varies: e.g., chemical analyses, biological assays, monitoring records	- Provides holistic understanding of microplastic impacts - Facilitates comprehensive mitigation strategies	Gray et al. (2018), Lusher et al. (2021)

primarily focused on marine environments and providing insights into the impacts of microplastics on oceanic ecosystems (Jenkins et al., 2022; Nyadjro et al., 2023). Likewise, the United Nations Environment Programme (UNEP) and GRID-Arendal's Marine Litter Database constitutes a vital repository for information on marine debris, including microplastics, enabling in-depth investigations into the complexities of marine pollution.

A significant advancement in this area is the application of ML models, which depend on robust datasets to drive the development of predictive and classification tools (Su et al., 2023). These datasets must be carefully structured—often in tabular form—and encompass a variety of data types, ranging from high-resolution imagery to categorical and numeric attributes (Coleman, 2025). Capturing the physical, chemical, and biological characteristics of microplastics is crucial, particularly features such as shape, spectral signatures, and potential pollutant adsorption (Lin et al., 2022). Reliable and high-quality datasets, typically derived from experimental research and monitoring programs, play a critical role in validating ML-based predictions. Although resource and sampling constraints can limit the size and quality of these datasets, proper selection of data sources is key to realizing the full potential of ML in microplastic research (Yu and Hu, 2022).

Microplastic contamination research inherently spans multiple scientific disciplines, drawing on expertise in environmental science, analytical chemistry, marine biology, and public health (Gray et al., 2018; Lusher et al., 2021). The databases described above thus serve as invaluable repositories of data and relevant literature, laying the groundwork for assessing the extent, origins, and ecological consequences of microplastics. They also inform the design of mitigation strategies and remediation plans. Looking ahead, the field is poised for further growth through the development of specialized databases dedicated solely to microplastic studies. These evolving resources will enable more holistic and data-driven examinations of microplastic pollution, supporting efforts to address one of the most pressing environmental challenges of our time (Table 1).

Machine learning in microplastic contamination prediction

Traditional methods for detecting microplastics—including visual identification, pyrolysis gas chromatography–mass spectrometry (Py-GC-MS), Fourier-transform infrared spectroscopy (FTIR), and Raman spectroscopy—remain highly accurate but are increasingly constrained by the demand for high-throughput, real-time, and extended environmental monitoring (Phan et al., 2023). Such techniques often require intensive labor, substantial time, and considerable data processing resources. For example, visual identification can be subjective and prone to human error, while advanced approaches like FTIR and Raman spectroscopy, though capable of providing molecular-level information, necessitate extensive sample preprocessing and meticulous data analysis, making them less optimal for large-scale or continuous field assessments. Py-GC-MS, which offers detailed chemical profiles, can be destructive to samples, further complicating efforts aimed at sustained observation (Primpke et al., 2020).

Against this backdrop, ML has emerged as a transformative solution, offering automated, efficient, and scalable methods for the detection and classification of microplastic particles. By leveraging high-dimensional data, ML-based approaches can expedite and refine the identification process without compromising detection thresholds. Indeed, ML can significantly enhance monitoring systems by automating classification tasks, uncovering intricate relationships in complex datasets, and minimizing human intervention (Kida et al., 2024). Moving forward, research integrating ML with advanced sensing technologies stands to

TABLE 2 A comparative analysis of traditional methods and ML approaches.

Criteria	Traditional methods	ML-based methods	References
Methodology	Visual identification, pyrolysis gas chromatography-mass spectrometry (Py-GC-MS), Fourier-transform infrared spectroscopy (FTIR), Raman spectroscopy	Automatic classification using complex datasets with high-dimensional features	Mariano et al. (2021), Coleman (2025), Zhang et al. (2025)
Accuracy	High accuracy, molecular-level insights	High accuracy without compromising sensitivity	
Processing time	Limited by capacity to process large volumes	Capable of handling large, complex datasets	
Data handling capacity	Subjective (visual identification), prone to human error	Reduces subjectivity by automating classification tasks	
Subjectivity	Subjective (visual identification), prone to human error	Reduces subjectivity by automating classification tasks	
Preprocessing requirements	Extensive for FTIR and Raman; destructive for Py-GC-MS	Minimal compared to traditional methods	
Suitability for continuous monitoring	Not suitable (especially Py-GC-MS)	More suitable due to non-destructive nature	
Potential for scale-up	Limited due to manual and labor-intensive processes	Highly scalable, suitable for large-scale assessments	

TABLE 3 Methods for microplastic detection.

Method	Key principle	Advantages	Limitations	Suitability for high-throughput	Reference
Visual Identification	Manual examination of samples (e.g., under a microscope)	- Straightforward, low-cost setup - Requires minimal equipment	- Subjective, prone to human error - Time-intensive	Low	Mariano et al. (2021), Lim et al. (2025)
Pyrolysis GC–MS (Py-GC–MS)	Thermal degradation of samples followed by GC–MS to identify polymers	- High chemical specificity - Capable of identifying polymer composition	- Destructive to samples - Involves extensive sample prep - Not ideal for real-time	Moderate to Low	Bouzid et al. (2022), Santos et al. (2023), Ccanccapa-Cartagena et al. (2025)
FTIR spectroscopy	Infrared absorption spectra used to identify molecular fingerprints	- Accurate molecular characterization - Nondestructive analysis possible	- Requires preprocessing - Limited throughput (analysis of one sample at a time)	Moderate	Chen et al. (2020), Campanale et al. (2023), Bin Zahir Arju et al. (2025)
Raman spectroscopy	Inelastic scattering of monochromatic light to determine composition	- Detailed chemical/ molecular info - Minimal sample prep (in many cases)	- Sensitive to fluorescence - Time-consuming for large datasets	Moderate	Araujo et al. (2018), Chakraborty et al. (2023), Jung et al. (2024)
ML approaches	Automated classification and pattern recognition using large, high-dimensional datasets	- High scalability - Rapid classification and analysis - Reduced human bias	- Model performance depends on quality/ quantity of training data - Requires computational resources	High	Lin et al. (2022), Campanale et al. (2023), Weber et al. (2023)

narrow the gap between the laboratory-grade precision of traditional techniques and the real-world requirement for swift, large-scale monitoring.

Moreover, ML is particularly suitable for boosting the efficiency of spectral, imaging, and hybrid spectral-imaging techniques. Emerging tools can be grouped according to the types of datasets they process—for instance, purely spectral data, purely image-based data, or a fusion of both. This categorization helps researchers select the most appropriate ML framework for their specific applications, whether they seek to identify microplastics in near-real time or analyze large, retrospective datasets to map pollution trends. We summarize a comparisons between traditional and ML methods (Table 2) and provide method-wise summaries (Table 3).

Spectral identification of microplastics

Microplastics possess distinct molecular structures and functional groups that interact with electromagnetic radiation, giving rise to characteristic spectral signatures. These spectral features emerge when microplastics are exposed to ultraviolet (UV), visible (Vis), or infrared (IR) light via mechanisms such as electron transitions and molecular vibrations. For example, polyethylene (PE) and polystyrene (PS) exhibit unique absorption profiles in UV-Vis spectroscopy due to differences in their electronic configurations, thus allowing for preliminary differentiation based on absorption and scattering behaviors. However, more precise polymer identification often relies on vibrational spectroscopy techniques—namely IR and Raman—which measure specific molecular vibrations unique to each polymer (Xu J-L. et al., 2020). In IR spectroscopy, polymers like PE display pronounced C–H stretching vibrations, whereas PS exhibits distinct aromatic C=C vibrations. Raman spectroscopy complements IR by detecting inelastic scattering associated with molecular vibrations, making it especially valuable for discriminating microplastics in complex matrices. Although these techniques can achieve high levels of accuracy, manual interpretation of the resulting spectra is frequently labor-intensive and time-consuming.

ML is transforming the way spectral data are analyzed and interpreted, particularly by automating the detection and classification of microplastics. Rather than relying on manual comparisons, ML models are trained on extensive spectral datasets to discern features that distinguish different polymer types. Traditional ML algorithms—such as support vector machines (SVMs) and random forests—have been used effectively to classify microplastics based on their FTIR or Raman signatures. For instance, SVMs have demonstrated strong performance in differentiating PE, polypropylene (PP), and polyethylene terephthalate (PET) by leveraging their unique vibrational modes in FTIR data (Enyoh et al., 2024). Likewise, random forests have proven resilient against overfitting when classifying microplastic spectra obtained from Raman measurements.

Deep learning approaches, especially convolutional neural networks (CNNs), further streamline microplastic identification by automatically extracting salient features from raw spectral data. CNNs have been employed to classify microplastics using either direct spectral inputs or image-based representations of those spectra (Zhang W. et al., 2023). One-dimensional CNNs (1D-CNNs) show particular promise for analyzing Raman spectra (Ng et al., 2020), reliably capturing nuanced patterns and delivering high classification accuracy for multiple polymer types. These advantages become especially clear when real-time analysis of environmental samples is required—for instance, in soil or water monitoring applications. Recent studies indicate that 1D-CNN models can achieve classification accuracies exceeding 95% for polymers such as PE, PP, and polyvinyl chloride (PVC) in soil samples, surpassing many traditional ML methods (Xu et al., 2023).

In scenarios where labeled spectral data are scarce, transfer learning has emerged as a powerful strategy (Qiu et al., 2020). This technique utilizes models pre-trained on related tasks—for example, hyperspectral imaging—then adapts them to novel but similar tasks, such as near-infrared sensor data. Studies have shown that transfer learning significantly reduces both the amount of labeled data required and the computational overhead, thereby speeding up real-time detection (Zhao et al., 2021). When applied to portable NIRS systems, transfer learning not only cuts down on data collection efforts but also enhances detection accuracy. Despite the notable potential of transfer learning, more traditional ML models remain viable whenever sufficient labeled data are available, striking a balance between interpretability and performance.

The incorporation of ML—particularly deep learning and transfer learning—into existing spectral workflows is revolutionizing microplastic detection. While classic ML algorithms continue to offer a strong combination of simplicity and accuracy, deep learning approaches excel at deciphering large, intricate datasets. As these techniques advance, they will increasingly surmount the limitations of conventional spectral methods, delivering faster, more accurate, and scalable solutions for monitoring microplastic pollution across a broad range of environmental contexts (Table 4).

Image identification

Advances in image processing and deep learning have significantly improved the accuracy and reliability of microplastic detection, leveraging fine-grained visual attributes such as shape, size, color, and texture (Han et al., 2023). Historically, identifying and enumerating microplastics relied on visual microscopy—an approach that is both labor-intensive and subject to human bias, particularly when examining large volumes of environmental samples. These challenges often result in discrepancies between actual and recorded microplastic counts, underscoring the need for more robust and scalable methodologies. To address this gap, researchers have developed various semi-automatic and fully automated techniques that harness ML and sophisticated image processing algorithms, substantially enhancing the speed, consistency, and throughput of microplastic identification (Rodriguez Chialanza et al., 2018; El Hayany et al., 2020; Huang et al., 2023; Liu et al., 2023; Valente et al., 2023; Dacewicz et al., 2024; Grand et al., 2024; Tang et al., 2024; Vitali et al., 2024).

One notable development is the application of the Canny edge detection algorithm, a widely used method for delineating object boundaries in digital images (Mogale, 2017; Giardino et al., 2023). By focusing on the edges of particles, this approach accurately isolates microplastics based on geometric criteria. For instance, a semi-automatic protocol integrating Canny edge detection demonstrated both high accuracy and rapid analysis for detecting microplastics (Phan et al., 2023; Fritz et al., 2024). The effectiveness of this algorithm can be further boosted through Nile Red staining, a fluorescent dye that selectively binds hydrophobic particles—such as microplastics—thereby improving detection rates in complex environmental matrices (Maes et al., 2017).

Beyond semi-automated systems, deep learning architectures have exhibited strong potential for automatically identifying and classifying microplastics (Lorenzo-Navarro et al., 2020). Convolutional neural networks (CNNs), in particular, excel at extracting and learning intricate visual signatures from labeled image datasets, resulting in high classification accuracy (Lorenzo-Navarro et al., 2021; Meyers et al., 2022). Utilizing images captured by digital cameras or mobile devices, these CNN-based approaches can both expedite analyses and remove much of the subjectivity encountered in manual counting. As a result, they offer a consistent and repeatable framework that is well-suited for large-scale or remote monitoring programs.

TABLE 4 Key spectral techniques and associated ML approaches for microplastic identification.

Technique	Key principle	Advantages	Challenges	Example ML approaches	Reference
UV-vis spectroscopy	Measures absorption/scattering of UV-Vis light due to electron transitions	- Rapid preliminary screening - Can differentiate polymers with distinct electronic configurations	- Limited specificity (better for initial differentiation) - Susceptible to overlapping peaks	- Logistic regression or SVM for classification based on absorption data	Tsuchida et al. (2024)
IR Spectroscopy	Detects absorption of IR light, causing molecular vibrations	- High chemical specificity - Non-destructive in many applications	- Requires sample preparation and sometimes complex preprocessing - Slower throughput	- SVM for polymer classification - Random forest models leveraging vibrational signatures	Morgado et al. (2021), Tan et al. (2023)
Raman Spectroscopy	Measures inelastic scattering of monochromatic light	- Detailed chemical information - Capable of handling complex matrices (soil, water)	- Fluorescence interference - Time-consuming for large datasets	- Random forest for noise-resistant classification - 1D-CNN for feature extraction	Weber et al. (2023), Sunil et al. (2024)
Machine Learning	Uses labeled spectra to learn decision boundaries or ensemble-based rules	- Good performance with moderate data sizes - Often more interpretable than deep learning	- Limited for highly complex datasets - May require feature engineering	- SVM for IR spectra classification - Random forest for Raman spectra	Weber et al. (2023), Sunil et al. (2024)
Deep Learning	Learns features from raw spectral data via convolutional filters	- Excels with large, complex spectral datasets - Reduces need for hand-crafted features	- Computationally intensive - Requires large labeled training sets	- 1D-CNN for Raman, NIR, or FTIR data classification	Akkajit et al. (2023), Weber et al. (2023)
Transfer Learning	Adapts models trained on one task/domain to a related task/domain	- Reduces need for extensive labeled data - Faster model convergence for real-time detection	- Effectiveness depends on similarity between source and target domains - Model interpretability can be lower	- Pre-trained CNNs adapted for NIR or Raman - Transfer from hyperspectral to NIRS data	Akkajit et al. (2023)

The ability of automated image-based techniques to rapidly evaluate large datasets also expands the geographical scope of microplastic assessment. Portable systems—ranging from smartphone-enabled imaging to field-deployable devices—make it feasible to gather reliable data from diverse environments without requiring specialized equipment or trained personnel. Additionally, new research explores multi-scale image processing combined with deep learning to enhance detection accuracy in varied conditions, demonstrating improved robustness and generalizability of microplastic detection (Yang et al., 2024). Likewise, hybrid methods that integrate classic image processing algorithms (e.g., Canny edge detection) with advanced ML models (e.g., CNNs) show promise for boosting accuracy across multiple sample types (Dacewicz et al., 2024; Fritz et al., 2024; Grand et al., 2024; Tang et al., 2024; Vitali et al., 2024; Yang et al., 2024).

These continuous innovations in automated image identification methods are poised to transform the global monitoring of microplastic pollution (Table 5). By delivering superior precision, scalability, and accessibility compared to manual counting, they enable more comprehensive evaluations of contamination patterns and ecological impacts. As these technologies continue to evolve, they will play an increasingly pivotal role in understanding, managing, and ultimately mitigating the environmental risks posed by microplastics.

Spectral imaging identification

Microplastics are pervasive pollutants in aquatic and terrestrial environments, posing potentially severe ecological and public health risks. By leveraging ML to analyze unique spectral signatures and spatial morphologies, spectral imaging represents a powerful approach for accurately identifying and characterizing microplastics across diverse ecosystems (Ai et al., 2022; Su et al., 2023). This integration of hyperspectral imaging with ML signifies a major stride in environmental monitoring, offering more efficient detection and robust analysis of microplastic contamination (Xu et al., 2023).

Hyperspectral imaging has shown exceptional promise for detecting microplastics in settings like farmland soils (Valls-Conesa et al., 2023). Because it collects spectral data over a broad wavelength range, hyperspectral imaging supports rapid, non-destructive screening, enabling timely remediation measures (Ai et al., 2022; Xu et al., 2023). By providing detailed chemical information and spatial distribution patterns of microplastics, this technique facilitates swift responses to emerging pollution concerns and helps protect soil integrity.

Recent studies have illustrated the effectiveness of combining FT-IR hyperspectral imaging with random forest algorithms to classify microplastics (Valls-Conesa et al., 2023). This approach not only boosts the efficiency and accuracy of microplastic identification but also offers a fine-grained chemical breakdown of samples, making it well-suited for environmental assessments. Furthermore, the application of laser direct infrared (LDIR) imaging in conjunction with ML methods has shown promise in overcoming traditional limitations, such as matching errors and reduced accuracy in complex samples (Cheng et al., 2022). By incorporating ML algorithms into LDIR workflows, researchers

TABLE 5 Summary of image-based approaches for microplastic detection.

Method	Techniques	Advantages	Challenges	Applications	Reference
Manual counting	Visual microscopy	Traditional method, provides basic estimates	Labor-intensive, subjective, prone to error	Basic environmental sample analysis	Mariano et al. (2021), Lim et al. (2025)
Semi-automatic image processing	Canny edge detection, Nile Red staining	Enhances detection accuracy, reduces error, fast detection speeds	Still requires some manual oversight	Improved accuracy and speed in environmental monitoring	Phan et al. (2023), Fritz et al. (2024)
Deep learning (CNNs)	CNNs trained on labeled image datasets	High accuracy, automatic classification, scalable, removes subjectivity	Requires large labeled datasets, high computational resources	Extensive environmental monitoring, high-resolution analysis	Akkajit et al. (2023)
Mobile-based detection	Image capture via digital cameras or mobile phones	Accessible, scalable, suitable for field settings	Depends on the quality of mobile imaging and network connectivity	Real-time, large-scale environmental monitoring	Leonard et al. (2022)

TABLE 6 Overview of spectral imaging techniques and ML methods for microplastic detection.

Technology	Description	Benefits	Applications	Reference
Hyperspectral imaging	Captures spectral data across a wide range of wavelengths, offering a non-destructive, rapid means of assessing microplastic pollution	Timely remediation measures; crucial for mitigating pollution and protecting soil health	Effective in environments like farmland soil	Ai et al. (2022), Valls-Conesa et al. (2023), Xu et al. (2023)
Random Forest + FT-IR hyperspectral	Captures extensive spectral data, classifying microplastics by providing a detailed chemical breakdown of samples	Improves efficiency and accuracy of microplastic identification; powerful for environmental monitoring	Suitable for classifying complex environmental samples	Valls-Conesa et al. (2023)
Laser Direct Infrared (LDIR) Imaging + ML	Enhances microplastic identification, traditionally faced with matching errors and reduced accuracy, by improving precision with ML algorithms	Reduces errors in identifying microplastics, offering insights into their characteristics and distribution	Promising for complex samples, including improvement over traditional LDIR challenges	Cheng et al. (2022b)
Hyperspectral imaging + SVM	Utilizes hyperspectral data and SVM to handle high-dimensional, nonlinear data; effective in classifying microplastics in marine environments	High accuracy and robustness in detecting microplastics despite environmental challenges	Valuable in marine environments, particularly with variations in polymer types and sizes	Shan et al. (2019)

can enhance precision, minimize errors, and gain deeper insights into the distribution and properties of microplastics.

ML is particularly valuable in settings where interference from organic matter or other substances complicates microplastic detection. By learning to recognize distinct spectral profiles, ML models substantially reduce the labor and time involved in microplastic extraction (e.g., sampling, filtration, chemical digestion). In aquatic environments, factors like turbidity, refractive variability, and high attenuation rates can degrade hyperspectral data, introducing noise that obscures microplastic signatures. However, advancements in both imaging technology and ML-based analysis have shown potential for direct identification of microplastics in environmental samples without extensive preprocessing. Specifically, SVMs trained on hyperspectral data have demonstrated high accuracy in detecting microplastics in seawater and associated filtrates, even in the face of polymer variability and organic material (Shan et al., 2019).

Looking ahead, spectral imaging for microplastic detection is poised for noteworthy advances in both spatial and spectral resolution. High-resolution imaging systems will further refine the differentiation between microplastics and natural particles, improving overall detection accuracy (Table 6). Additionally, the advent of real-time or near-real-time spectral imaging promises to revolutionize environmental monitoring by enabling on-site detection and timely intervention when pollution events arise. Realizing these improvements will entail progress in algorithmic development—such as faster data processing and more sophisticated ML models—and in hardware engineering, which must support rapid data capture and analysis.

Limitation of usage of ML techniques

While ML offers significant advantages in microplastic research, there are notable limitations that must be carefully considered. A major challenge is the significant computational power required by many ML algorithms, particularly deep learning models. Although deep learning has achieved remarkable success in diverse applications, it necessitates extensive computational resources, including specialized hardware and substantial processing time, making it infeasible for all research environments, particularly those with limited funding or infrastructure. Training deep neural networks typically involves considerable processing capabilities, often requiring specialized hardware such as Graphics Processing Units (GPUs) or Tensor Processing Units (TPUs) (Schmidhuber, 2015; Song et al., 2021). Additionally, the extensive datasets and numerous training iterations needed can result in prolonged processing periods and heightened energy consumption, posing substantial barriers for smaller research teams or institutions constrained by budget or limited computing facilities (Talaei Khoei et al., 2023). Moreover, microplastic research faces specific challenges regarding data availability, as microplastics are unevenly distributed across aquatic ecosystems and exhibit chemically diverse compositions, complicating dataset creation and training. The high energy demands associated with training large-scale models have further sparked concerns about environmental impacts, prompting calls for the development of more energy-efficient algorithms (Strubell et al., 2019). As the complexity of models grows, so too does the demand for computational resources for both training and inference, potentially limiting accessibility to these advanced tools for a broader range of researchers and industries.

Technical and practical considerations extend beyond computing resources. The requirement for high computational power and specialized hardware makes real-time or *in situ* analysis challenging, as portable devices must navigate trade-offs between processing capabilities and power efficiency. Another critical limitation is interpretability. Advanced deep learning models often function as "black boxes," complicating efforts by researchers and regulatory bodies to comprehend the underlying reasons behind classification outcomes (Ali et al., 2023; Nasimian et al., 2024). This reduced transparency may impede the trust and widespread adoption of AI-driven methodologies. Thus, enhancing the explainability, interpretability, and user-friendliness of ML algorithms will be essential for validating outcomes and ensuring broader acceptance within the research community and among regulatory authorities.

Influence of polymer types and environmental conditions on accuracy of ML models

The accuracy of ML models in predicting microplastic pollution can be influenced by polymer types and environmental conditions. Different polymers, such as PE and PP, possess distinct physical and chemical properties—including density, degradation rates, and chemical composition—that affect their environmental behavior and accumulation patterns. Buoyant polymers like PE typically float, whereas denser polymers like PS are prone to sinking, leading to varied distribution patterns in aquatic environments (Thompson et al., 2009). Moreover, polymers such as PET degrade more slowly than PE, resulting in prolonged environmental persistence and varied ecological impacts (Andrady, 2011). Environmental conditions, such as temperature, UV radiation, water currents, and microbial activity, further influence the degradation dynamics and transport of microplastics. Elevated temperatures and increased UV radiation accelerate plastic degradation, altering particle size and shape, which affects mobility, detectability, and environmental persistence. Additionally, microbial activity in marine ecosystems can alter microplastic buoyancy and biodegradability, further complicating predictions of their behavior (Zettler et al., 2013). Consequently, ML models trained under specific polymer compositions or environmental settings may encounter significant accuracy limitations when generalized to diverse ecological scenarios, unless these variables are comprehensively integrated into the modeling process.

Practical detection limits further compound these challenges. Advanced spectroscopic methods commonly struggle to identify microplastic particles below approximately 10–20 μm, leaving the smallest particles largely undetected and potentially underestimated in current assessments (Cunsolo et al., 2021). Recent advances, such as ML-assisted hyperspectral imaging, have begun addressing these limitations, extending microplastic detection capabilities to soil and sediment samples following necessary preprocessing steps (Ai et al., 2022; Valls-Conesa et al., 2023; Xu et al., 2023). However, these techniques are still emerging and require further refinement. Real-time analysis and monitoring capabilities are also essential for effective response to pollution events. The complexity and variability of environmental samples pose additional obstacles; for example, factors such as water turbidity or high organic content in sediments can degrade spectral data quality, necessitating more sophisticated algorithms and enhanced preprocessing strategies to maintain robust model accuracy under challenging environmental conditions.

Conclusion

The integration of advanced ML techniques with spectral, image, and spectral imaging methods marks a transformative leap in the detection, classification, and analysis of microplastics (Shan et al., 2019; Primpke et al., 2020; Ai et al., 2022; Su et al., 2023; Valente et al., 2023; Valls-Conesa et al., 2023; Xu et al., 2023; Zhang Y. et al., 2023; Dacewicz et al., 2024; Fritz et al., 2024; Grand et al., 2024; Tang et al., 2024; Vitali et al., 2024). Traditional methods like visual microscopy and spectroscopy, while reliable in terms of accuracy, are hindered by their labor-intensive nature and limitations in processing large volumes of environmental data efficiently (Hidalgo-Ruz et al., 2012). These conventional approaches, though foundational, struggle to meet the demands of high-throughput and real-time environmental monitoring. The application of ML algorithms—such as SVM, random forests, and deep learning models like CNNs—has enabled us to overcome these limitations by automating and significantly improving the precision, speed, and scalability of microplastic identification tasks (Valls-Conesa et al., 2023; Yang et al., 2024). Spectral identification, a powerful tool for identifying microplastics, uses molecular vibration data from techniques such as IR and Raman spectroscopy to discern microplastics based on their unique chemical signatures (Liu et al., 2023; Zhang W. et al., 2023; Grand et al., 2024). This method is particularly valuable for its ability to differentiate polymers by their functional groups and molecular bonds, offering high accuracy in complex environmental matrices. Image identification, on the other hand, uses deep learning models to automate the classification of microplastics based on visual characteristics like shape, size, and color, thus reducing the human subjectivity and labor required in manual identification. These models, trained on large image datasets, can rapidly process high-resolution images, providing a more reliable and scalable solution for environmental monitoring. Spectral imaging, which combines the advantages of both spectral and spatial data acquisition, represents a comprehensive approach to microplastic

TABLE 7 Several developments in spectral identification of microplastics in aquatic environments.

Year	Spectral techniques	ML algorithms	Microplastic types identified	Key developments	References
2010	FT-IR, GC-MS	NA	PE, PP	Samples collected from beaches were analyzed	Frias et al. (2010)
2013	Pyrolysis-GC-MS	N/A	PE, PP, PS	Early stages of using Pyrolysis-GC-MS for microplastic identification, but no significant ML integration yet.	Fries et al. (2013)
2014	Raman Spectroscopy	N/A	PE, PS	Introduction of Raman Spectroscopy for more detailed molecular characterization of microplastics	Cozar et al. (2014), Lusher et al. (2014), Yonkos et al. (2014)
2015	FPA-FT-IR	NA	PE, PP, PVC, PS	Multiple microplastic types were analyzed using spectral analysis	Tagg et al. (2015)
2018	Stimulated, Raman Spectroscopy	NA	PE, PS, PET, PP	Accelarated identification of several microplastic types	Zada et al. (2018)
2019	NIR hyperspectral Imaging FT-IR	SVM Random Forest	PE, PP, PS	SVM and FT-IR were used for classification of microplastic types based on spectral data	Hufnagl et al. (2019), Shan et al. (2019)
2020	FT-IR	PCA, UMAP, Clustering	PE, PP, PVC	PCA, UMAP and clustering were used on FT-IR spectrum	Wander et al. (2020)
2021	FT-IR	Bootstrap method	PE, PP	Identification microplastics from river sediments	Morgado et al. (2021)
2022	Raman Spectroscopy	PCA, dual PCA, MCR-ALS	PP, PE, PS	Several methods were developed to classify data from Raman spectroscopy	Cheng et al. (2022a), Luo et al. (2022), Tian et al. (2022)
2023	Multispectral Imaging, FT-IR	Neural Networks, Random Forest	PP, PE, PET, PVC	Advancements in multispectral imaging combined with ML for better identification accuracy	He et al. (2023), Valls-Conesa et al. (2023)
2024	FT-IR	Deep Learning	PE, PP, PA, PS	Quantification of microplastic using FT-IR with deep learning	Guo et al. (2024)

detection. Hyperspectral imaging, paired with ML algorithms, allows us to simultaneously capture chemical composition and spatial distribution, enabling detailed characterization of microplastics in diverse environments (Valls-Conesa et al., 2023; Xu et al., 2023). This method not only enhances the identification accuracy of microplastics but also provides valuable insights into their ecological impact and distribution patterns, making it a critical tool for environmental monitoring programs. The Table 7 offers a comprehensive look at the evolution of ML techniques and spectral imaging identification methods for microplastics in recent years. Over the past decade, microplastic detection techniques have increasingly incorporated ML components. In the early 2010s, it was relied on traditional spectroscopy with minimal ML involvement. By the mid-2010s, initial ML techniques such as PCA were introduced to assist in interpreting spectral data. The late 2010s saw the adoption of dedicated classification algorithms like SVM and random forests, which improved the automation and accuracy of microplastic identification. In the early 2020s, deep learning models emerged, further boosting classification performance and enabling more complex analyses such as segmenting microplastics in images. This timeline highlights a clear trend: the integration of ML has evolved from simple data processing tools to advanced neural networks, significantly enhancing the speed, accuracy, and scalability of microplastic detection in recent years.

Despite the significant progress in leveraging ML for microplastic detection, several challenges remain. A major limitation is the need for larger, more diverse, and high-quality datasets to train ML models comprehensively. Data scarcity currently hampers the ability of models to recognize less common polymer types or environmental scenarios. Ensuring that models generalize across various environmental conditions, polymer types, and interference from organic or other particulate matter is crucial. Furthermore, the development of real-time analysis capabilities will be essential for enabling on-site monitoring and immediate responses to pollution events. The complexity of environmental samples, particularly in water matrices where factors like turbidity and light attenuation can degrade the quality of spectral data, poses additional hurdles that require more sophisticated algorithms capable of compensating for such variances.

Standardized datasets ensure consistency in data collection, facilitating comparisons across studies and enhancing the reliability of predictions across diverse environmental contexts. Several global initiatives and organizations are actively working toward standardizing microplastic monitoring methods. For example, the International Pellet Watch provides a standardized global database for microplastic data collection and sharing (Ogata et al., 2009). Similarly, the Global Partnership on Plastic Pollution and Marine Litter (GPML) is developing unified protocols for microplastic sampling and analysis in various ecosystems. Open data platforms such as Marine Litter Watch, and NOAA's global microplastics data portal further facilitate standardized data sharing and harmonization across the research community (Bergmann et al., 2017; Nyadjro et al., 2023). Furthermore, recent international guidelines have been proposed to unify microplastic data reporting practices, aiming to address variations in environmental conditions and polymer types that complicate data consistency (Jenkins et al., 2022). Despite these ongoing challenges, global collaboration and open-access data sharing are critical to creating robust standardized datasets, ultimately enhancing predictive accuracy and generalizability of machine learning models in microplastic pollution studies.

Integration with other approaches offers a promising path to overcome some of these limitations. One emerging direction is the combination of ML with Internet of Things (IoT) sensor networks and robotics for environmental monitoring. For instance, compact optical sensors or AI-enabled cameras deployed on drones and buoys have been tested for real-time microplastic detection (Zhao et al., 2024). Such systems feed data continuously to ML models, potentially enabling near real-time tracking of microplastics over large areas. Another approach is to couple ML models with physics-based oceanographic and transport models. By incorporating known hydrodynamic processes (e.g., currents, settling behavior) into the prediction pipeline, data-driven models can produce more physically informed forecasts of microplastic dispersion (Zhang and Choi, 2025).

Policy and implementation considerations also present challenges. Environmental regulatory frameworks have only begun to grapple with the adoption of AI-driven monitoring tools. Agencies will require validated protocols to accept ML-based methods as part of official pollution assessment, for example, verification that an ML identification of microplastics is as reliable as a human or traditional analytical method. Developing standardized validation procedures and certification for AI tools will be essential at national and international levels. Moreover, global cooperation in data sharing will be necessary to fully exploit ML capabilities, since microplastic pollution transcends borders. Initiatives like NOAA's data portal and international working groups are steps toward this direction (Jenkins et al., 2022; Nyadjro et al., 2023). Policymakers may need to provide funding and infrastructure to deploy these advanced systems, especially in regions where technical resources are limited. In summary, addressing the policy-level challenges—through updated regulations, investment in technology, and education of stakeholders—will be key to moving AI-based microplastic detection from research into practical, widespread use (Pauna et al., 2022).

Nevertheless, ongoing advancements in ML and imaging technologies show great promise in addressing these challenges. As ML models become more robust, and imaging hardware evolves to support higher resolution and faster processing speeds, the future of microplastic monitoring will become increasingly automated, accurate, and scalable. These innovations are poised to revolutionize how we detect, classify, and monitor microplastics, ultimately contributing to better environmental management and more effective strategies for mitigating microplastic pollution. By enhancing the precision and efficiency of microplastic detection, these technologies will play a critical role in safeguarding ecosystems and addressing one of the most pressing environmental challenges of our time.

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