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Challenges and prospects in the identification of micro and nano plastics using Raman spectroscopy: a comprehensive review

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Raman spectroscopy (RS) is a widely employed technique for analyzing emerging environmental pollutants, microplastics and nanoplastics (MNPs), detection of biomolecules, identification of cells and pathogens. Detecting, identifying, and quantifying these particles in environmental samples and living organisms poses significant challenges due to their minute size, irregular shapes, diverse polymer compositions, surface coatings, and large surface areas that readily attract chemical and microbial contaminants. Raman Spectroscopy is a reliable, specific, fast, more sensitive method for the characterization of small sized particles. Moreover, the handheld Raman device is easily deployable in the field. This review addresses the key analytical strengths and the challenges that limit precise characterization of MNPs and provide recommendations to improve data reliability, that further include strategies to mitigate common quality control issues, particularly the challenge of distinguishing between plastic particles present in the sample and those introduced through contamination during sampling, processing, or analysis. Recently, the use of artificial intelligence (AI) and machine learning has been incorporated with Raman spectroscopy to facilitate the detection of MNPs and provide automation.

KEYWORDS

artificial intelligence, machine learning, microplastics, nanoplastics, Raman spectroscopy

Introduction

Plastics have become an integral part of everyday life due to their wide applicability in almost every field, ranging from construction, textile industry, packaging, consumer goods, transportation, electronics sector, healthcare, and the industrial sector. It has become a revolutionary material which gradually replaced metal usage in a variety of applications due to its affordability and resilience to harsh environmental conditions. The widespread use of plastics is evident in daily use items like manufacturing of bags, bottles, pipes, buckets, furniture, nets, and clothing. Therefore, the production of plastic has increased considerably

in recent decades (Fadare et al., 2020; Thompson et al., 2009a; Thompson et al., 2009b). Different plastic materials such as polyethylene (PE), polypropylene (PP), polystyrene (PS), polyvinyl chloride (PVC), and polyethylene terephthalate (PET), each have distinct chemical structures that give them specific properties. These plastics are widely used across sectors, from packaging and consumer goods (PE, PP, PET) to construction materials (PVC) and disposable products or insulation (PS). Despite the numerous benefits associated with using plastics, their extensive use is leading to elevated environmental issues (Kiran et al., 2022).

The Technical Report CEN ISO/TR 21960 provided a definition of “microplastic” as “any solid plastic particle insoluble in water with any dimension between 1 and 1,000 μm ” and categorized “large microplastics” as particles of size ranging from 1 to 5 mm (ISO/TR 21960: 2020, 2020). Microplastics (MPs) can further break, leading to the formation of nanoplastics (NPs) (Bergmann et al., 2015; Laurent et al., 2017; Schwaferts et al., 2019; Ivleva, 2021). NPs are the particles of size between 1 and 1,000 nm [EFSA Panel on Contaminants in the Food Chain (CONTAM), 2016]. Primary microplastics and nanoplastics (MNPs) are the small plastic particles that are added to various products for specific functions, such as abrasives in toothpaste, cosmetics, and exfoliating agents. In contrast, secondary MNPs are formed through the breakdown of larger plastic items into smaller fragments due to environmental influences like ultraviolet (UV) radiation, physical and chemical weathering, mechanical stress, and biological activity (Kumar R. et al., 2021). This also includes MNPs resulting from abrasion of bottles and caps during use. Microfibres are tiny filament shaped particles typically less than 5 mm in length that originate from fibrous materials such as textiles and ropes. Their small size and filamentous shape allow them to travel long distances in water and air, spreading pollution broadly. Microfibers are the most dominant MP type in the environment, with nearly 75% of the analyzed fibers identified as natural (Horton et al., 2017; Ross et al., 2021; Genchi et al., 2023). Recent studies further indicate that a substantial proportion of environmental microfibers are of natural or semi-synthetic origin, underscoring the importance of accurate chemical identification using spectroscopic techniques such as FTIR and Raman microscopy (Remy et al., 2015). The challenges in MNPs research include lack of standardized sampling procedures (Hermsen et al., 2018; Ivleva, 2021), analytical difficulties and the limited use of common quality control measures (Hermsen et al., 2018; Brander et al., 2020).

A typical gold standard pipeline for MNPs detection involves sample collection, visualization or pre-screening using light microscopy, removal of organic matter, identification using Fourier transform infrared spectroscopy (FTIR) or Raman spectroscopy (RS) and AI or machine learning for automation.

Spectroscopic techniques are among the most reliable methods for identifying MNPs (Kedzierski et al., 2019; Morgado et al., 2021; Kumar B. V. et al., 2021; Li et al., 2018; Hermsen et al., 2018; Renner et al., 2018; Primpke et al., 2020). Now optical detection techniques using various probes and sensors are increasingly used in the detection of MNPs, which are based on principles of fluorescence, localized surface plasmon resonance, surface-enhanced RS, and calorimetry (Praveena et al., 2024).

Due to their small size, the identification of MNPs is quite difficult. Extensive knowledge of methods related to MNPs identification, characterization, and quantification is needed to understand their properties and implications for human health. Researchers have highlighted the presence of MNPs in various types of products meant for human use and consumption (Bouwmeester et al.,

2015; Kwon et al., 2020). MNPs are able to traverse the biological barriers inside the human body and produce strong toxicological effects (Lehner et al., 2019; US Environmental Protection Agency (EPA), 2020; Xu M. et al., 2019). It has been found that exposure to nanopolystyrene particles in the maternal lungs results in their transfer into placental and fetal tissues (Fournier et al., 2020). Studies have indicated that over the course of a lifetime, an individual may accumulate thousands of MNPs within their body (Mohamed Nor et al., 2021). MPs have also been detected in human feces with an average of 2 MP particles per gram of fecal sample (Schwabl et al., 2019).

RS is an analytical method that identifies molecular vibrations, producing distinct spectral patterns, often referred to as chemical fingerprints, that allows for precise identification of materials. This capability makes RS useful in determining the potential origin of various types of plastics. The technique offers several advantages, including being fast, non-destructive, requiring minimal sample amounts, and providing high-resolution molecular analysis at sub-micron scales. Notably, water does not interfere with RS measurements, making it especially suitable for analyzing samples in aqueous environments (Ribeiro-Claro et al., 2017).

RS has been widely recognized as an effective tool for determining the chemical composition of MNPs and plays a crucial role in examining very small MNPs. The growing number of studies utilizing RS for detecting MNPs in aquatic environments reflects its increasing importance in plastic research.

Using RS, for the first time, Ragusa and his coworkers detected multiple fragments of MPs in the human placenta (Ragusa et al., 2021). Plastic particles in the human blood have been detected in a recent study (Leslie et al., 2022). Majority of MNPs consist of PE, PS, and PP resulting from the degradation of products of their synthetic polymers. In this review, we will highlight the prospects and challenges associated with detection of MNPs using RS. Also, precautions related to sample handling, avoiding contamination, methods of measurement, data processing, analysis and method validation will be discussed.

Historical development in MNPs detection

Reporting of MPs (1970s–1980s): MPs were first reported in the North Atlantic Ocean (Carpenter and Smith, 1972). Plastic pellets and fragments in plankton tows were observed, but the term microplastics was not used at that time. Detection was visual, light microscopy was employed to identify small plastic particles.

Basic Methods for detection (1990s): Density Separation and Visual Sorting, Saline solution (e.g., NaCl) was used to float plastics from sediments or water, research into pellet pollution and plastic debris ingestion by marine organisms was in progress (Gregory, 1996; Shiber, 1979).

Development of Spectroscopy (2000s): FTIR, RS, and Py-GC/MS were introduced for polymer identification (Ng and Obbard, 2006; Sofra et al., 2010). FTIR identifies polymers based on IR absorbance. Raman works similarly but detects scattered light signals, effective for smaller particles.

Enhancement and Standardization (2010s): Adoption of standard protocols for sampling, digestion (e.g., H_2O_2), and analysis was carried

out. Micro-FTIR (μ -FTIR) and micro-Raman (μ -Raman) allowed automatic identification of particles $>10\ \mu$ (Masura et al., 2015).

Automation and NPs detection (2020s–Present): Focus expands to NPs ($<1\ \mu\text{m}$). Emergence of: Nano-FTIR, ToF-SIMS (Time-of-Flight Secondary Ion Mass Spectrometry) (Meyns et al., 2023).

Historical developments related to MNPs detection is depicted in Figure 1.

The diagram summarizes major developments from the 1970s to the 2020s. Initial observations of microplastics in marine environments during the 1970s relied primarily on visual identification. The 1990s marked the introduction and formal use of the term microplastics. Significant methodological advances occurred in the 2000s with the application of spectroscopic techniques along with initial efforts to detect nanoplastics. The 2010s saw rapid improvements in analytical sensitivity and the emergence of high-resolution and real-time detection approaches. By the 2020s, automation and artificial intelligence became integrated into detection pipelines, accelerating throughput and enhancing accuracy in microplastic and nanoplastic analysis (Figure 2).

The figure illustrates the major sources through which humans are exposed to microplastics and nanoplastics. These include consumables such as bottled water, personal care products; food items such as seafood and biological samples including, urine, blood, and kidney tissue along with their representative Raman spectra and graphs from literature.

MNs have been identified in fecal samples collected from the community of fishermen in the coastal region of Indonesia. Over half of the analyzed fecal samples were found to contain MNPs. High-density polyethylene (HDPE) was the most prevalent among various types of MNPs detected (Luqman et al., 2021).

A study in Mexico focused on common beverages such as energy drinks, soft drinks, cold tea, and beer was conducted to detect the occurrence of MNPs using RS. The research also focused on the shape, size, morphology, and polymer composition of MNPs. Among the different samples tested, surprisingly MNPs were found in 48 out of 57 samples. Various forms of MNPs (fibers and fragments) and sizes (0.1–3 mm) of colors (blue, brown, red, black and green) were detected. Particles were identified as poly(ester-amide), polyamide, polyethyleneterephthalate (PET) and acrylonitrile-butadiene-styrene emphasizing MNPs contamination in beverage products originated from synthetic textiles and their packaging (Shruti et al., 2020).

Aquatic organisms including fish, crustaceans, and shellfish reportedly contain high level of plastic debris. Around species of commercial importance have been found to accumulate MNPs in their bodies which include organisms such as mussels, common shrimps, clams, oysters, etc. (FAO, 2017; Neto et al., 2020). It is particularly concerning baby feeding bottles are made of PP, which release large amounts of MNPs as a consequence of frequent sterilization at high-temperature (Li et al., 2020). The exposure could be higher in case of NPs because their small size allows them to pass through the intestinal epithelium (Toussaint et al., 2019), thus entering the body tissues and result in toxicity. MNPs in human food, beverages (ACS Meeting, 2020) and human tissues have been detected.

Schymanski et al. (2018) investigated the MNP content in various packaged water samples and their analysis revealed the presence of both small (50–500 μm) and very small (1–50 μm) MNP particles in all tested samples. Remarkably, approximately 80% of the detected particles ranged in size from 5 to 20 μm . Most MNP particles identified in returnable bottles were polyester, PET and PP, consistent with the materials used in the bottles and their caps (Schymanski et al., 2018). In contrast, only a few PET particles were found in water from single-use bottles. Water samples from beverage cartons and glass bottles contained PE or polyolefins, likely due to PE-based coatings and lubricated caps. These findings suggest that the packaging material itself is a potential source of MNPs contamination.

Collectively, these findings highlight the growing significance of MNP contamination as a critical issue for food safety research and raise an urgent question about the potential health impacts of MNP ingestion.

Sample preparation, handling and processing for analysis with RS

Sample preparation strategy for RS for various samples are described, which depend on type of sample used.

Seafood/biological samples

Researchers are exploring MNPs in a variety of environmental and food samples. Leung et al. (2021) developed an improvised

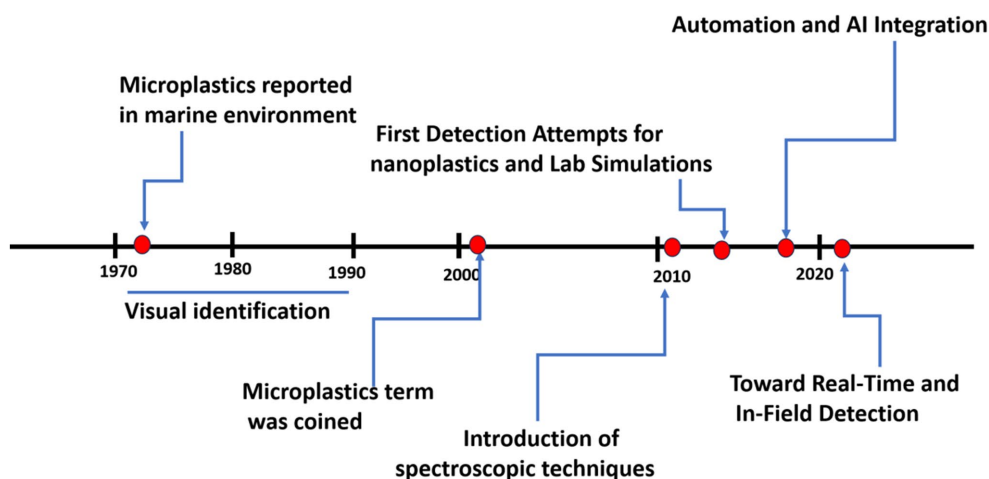


FIGURE 1
Historical developments related to MNPs detection.

In earlier studies, characterization of MNPs was primarily based on visual inspection, which, although capable of achieving around 70% accuracy, often led to overestimations (Verlaan et al., 2019). With advancements in analytical technologies, techniques such as Raman and FTIR spectroscopy have greatly enhanced the precision and reliability of MNPs identification. Despite these improvements, visual pre-screening remains a necessary step to isolate potential MNP particles for individual analysis. This process is not only time-consuming but also subject to human error and bias. To overcome these limitations, newer models of Raman and FTIR spectrometers now feature automated mapping capabilities. These systems can scan predefined areas on filter membranes and accurately determine the polymer composition, size, and shape of MNPs, thereby reducing the dependence on manual sorting and improving consistency in results (Sobhani et al., 2019; Sobhani et al., 2020; Xu J. et al., 2019).

Water samples

RS is one of the few analytical methods that can be effectively used with liquid samples, including those from aquatic environments (Wang and Song, 2024; Kniggendorf and Meinhardt-Wollweber, 2011). This approach helps overcome many of the difficulties associated with examining the dried samples on delicate filter membranes. It is especially useful for analyzing the drinking and the tap water, where the relatively low presence of biological material allows for the direct detection of MPs. Kniggendorf and his coworkers successfully employed RS for the detection of MPs having size of 0.1 mm in the tap water. They developed an innovative and portable setup that can directly monitor the water by directly attaching it to a tap without the requirement of any sampling or sample processing (Kniggendorf et al., 2019).

To analyze MNPs content in water, the process typically begins with sampling and initial sample preparation prior to identification and quantification. For waterborne MNPs in small volumes or controlled environments, sampling is commonly carried out using filters or sieves. In these cases, the smallest detectable particle size is limited by the mesh size of the filtering device. Following collection, the sample undergoes further treatment, usually involving the removal of organic matter to isolate MNP particles. These isolated particles are then examined to determine their polymer composition (Kniggendorf et al., 2019).

Sediment samples

For the identification of MNPs, a simplified process has been developed to pretreat the MNPs obtained from marine sediments, omitting digestion procedures, and then coupling it with μ -RS. Characteristic peaks are analyzed and a spectral reference library is created (Liu et al., 2020). Predominantly, components of the particles are PP (42%) and PE (20%), highlighting the effectiveness of Raman spectroscopy in the detection of MNP particles in the environment and its high applicability for identifying MNPs in marine sediments (Liu et al., 2020).

In order to separate MNP samples, density flotation is to be done via static sedimentation. To collect MNPs with variable densities, saturated NaCl and NaI solutions can be employed (Thompson et al., 2004; Hidalgo-Ruz et al., 2012). The acid–base digestion step can be excluded while dealing with sediment samples.

Soft drinks/energy drinks

The collected beverage samples should be filtered under laboratory conditions using Whatman Grade 1 filter paper, which has a pore size of 11 μ m, connected to a vacuum pump (Sridhar et al., 2022). Prior to filtration, all components of the filtration setup must be thoroughly rinsed with Milli-Q water to minimize the risk of contamination. New filters should be used adequately for the remaining volume if the existing filter unit becomes choked or clogged. Each sample of beverage from the same batch should be in triplicate. After filtration, all filters should be carefully transferred to the petri-dishes and the whole filter is visually analyzed for MNP particles using microscopy. SEM can be used for morphological characterization of the particles. Material composition of MNPs can be done using μ -RS (Shruti et al., 2020).

Food samples

A study conducted in Indonesia investigated MPs contamination in the food by collecting various commonly consumed items, such as drinking water, staple foods, seafood, table salt, and toothpaste based on dietary data provided by participants (Luqman et al., 2021). For the sample preparation, all the collected items have to be completely dried, mixed with Fenton reagent and allowed to react at room temperature. The resulting mixtures need to be filtered using a cellulose nitrate-cellulose acetate membrane, which are subsequently digested with nitric acid (HNO₃), followed by an additional 10-min incubation at 70 °C. The digested solutions have to be diluted with distilled water before MPs analysis via RS. Notably, the drinking water samples required no prior treatment and can be analyzed directly using RS (Luqman et al., 2021).

Comprehensive summarized table presenting the key points for each sample type analyzed for using Raman Spectroscopy (RS) is demonstrated in Table 1.

Advantages of MNPs detection using RS (improved Raman spectra)

Detection of MNPs of small size

Some of the common advantages associated with RS and FTIR when compared to other techniques used in MNPs characterization are their non-destructiveness, requirement of low amounts of sample, and potential for high-throughput screening (Ribeiro-Claro et al., 2017). Raman techniques show better spatial resolution down to 1 mm when compared to FTIR which is 10–20 mm, broader spectral coverage, lower water interference (Ivleva et al., 2017).

Environmental stressors gradually break down into smaller fragments, leading to a significant increase in the number of small-sized MPs (Andrady, 2017). For instance, Conkle et al. (2018) conducted a review of 41 studies investigating MPs in the aquatic environments, where samples were primarily harvested by employing neuston nets. Most of these studies employed nets with mesh sizes of around 300 μ m, which failed to capture smaller MP particles. As a result, the actual MPs burden in these samples was likely underestimated. Similarly, a long-term study spanning three decades was conducted by Beer et al. (2018) on MPs concentration in the Baltic Sea using a bongo net with mesh

TABLE 1 Summary of MNPs detection using Raman spectroscopy in various sample types.

Sample type	Key methods	Challenges/Solutions	References
Seafood/ biological samples	<ul style="list-style-type: none"> • Digestion of biomass using KOH • Density separation with dense salt solutions • Use of stainlesssteel filter membranes 	<ul style="list-style-type: none"> • Filter membrane interference resolved using stainless steel filters. • Incomplete digestion causes autofluorescence, ensure full digestion. • EDTA can be used as decalcifying agent to remove inorganic residues. 	Leung et al. (2021) , Xiong et al. (2018) , Karbalaie et al. (2019) , James et al. (2020) , Dehaut et al. (2016) , Karami et al. (2017a) , Teng et al. (2019) , Gündoğdu et al. (2020) , Garnier et al. (2019) , Hossain et al. (2020) , Dehaut et al. (2016) , Nie et al. (2019) , Verlaan et al. (2019) , Sobhani et al. (2019) , Sobhani et al. (2020) , Xu J. et al. (2019) , and Khuyen et al. (2021)
Water samples	<ul style="list-style-type: none"> • Liquid samples can undergo direct analysis using RS. • Portable RS setups can monitor tap water directly. • Sampling through filters or sieves based on mesh size. 	<ul style="list-style-type: none"> • Low biomass simplifies detection. • Smallest detectable size limited by filter mesh. 	Kniggendorf and Meinhardt-Wollweber (2011) and Kniggendorf et al. (2019)
Sediment samples	<ul style="list-style-type: none"> • μ-RS used to identify polymer type; spectral reference library built. • Density flotation via NaCl or NaI solutions for MNP separation. 	<ul style="list-style-type: none"> • Acid–base digestion can be omitted. 	Liu et al. (2020) , Thompson et al. (2004) , and Hidalgo-Ruz et al. (2012)
Soft drinks/ energy drinks	<ul style="list-style-type: none"> • Filtered using Whatman Grade 1 paper under vacuum. • Setup rinsed with Milli-Q water to avoid contamination. 	<ul style="list-style-type: none"> • Replace filters as needed due to clogging. • Ensuring contamination-free environment is critical. 	Sridhar et al. (2022) and Shruti et al. (2020)
Food samples	<ul style="list-style-type: none"> • Sample dried and treated with Fenton reagent. • Filtered through cellulose nitrate-acetate membranes. • Further digested with HNO₃, incubated at 70 °C. 	<ul style="list-style-type: none"> • Ensuring full digestion and proper filtration critical. • Avoid over-digestion that may alter MNP structure. 	Luqman et al. (2021) .

size 150 nm. They did not find a significant increase in the abundance of MPs because they might have missed the MPs fraction below 150 nm. Therefore, it is important to properly measure the abundance of MPs smaller than 40 nm when estimating the total MP load in the sample. Micro-Raman analysis is able to detect MPs in the edible fish tissues ([Collard et al., 2017](#); [Karami et al., 2017b, 2018](#)), bottled water ([Schymanski et al., 2018](#)), and table salt ([Gündoğdu, 2018](#); [Karami et al., 2017c](#)). A study was conducted by [Käppler et al. \(2015\)](#), which was based on a comparison of FTIR and Raman techniques for the identification of MPs demonstrates the superior performance of RS for detection of small MPs. Both of the techniques were found to be equally capable for the detection of particles of size more than 20 nm, for smaller particles the detection success rate of FTIR was lagging behind.

Despite its many advantages, RS has not achieved the same level of widespread adoption for MP identification as FTIR spectroscopy, although the interest in its application is steadily growing, as reflected by the increasing number of publications. RS is particularly valuable for analyzing very small MPs, particles below the detection limits of FTIR, highlighting its importance in the studies where conventional FTIR techniques has been proven to be ineffective.

Enhancement in signal quality

RS has a major drawback in having a typically weak intensity, thereby requiring longer acquisition times in order to achieve a decent signal. One potential solution for the enhancement of signal quality in RS arises from the advancement in the development of advanced detectors. Relative to conventional CCD detectors, electron-multiplying charged coupled device (EM-CCD) detectors feature a multiplication register that operates before readout, thus amplifying the gain up to 1,000 times ([Tripathi, 2007](#); [Griffiths and Miseo, 2014](#)). Consequently, EM-CCD detectors offer faster data acquisition compared to the conventional CCD detectors, achieving the same signal-to-noise ratio in significantly less time.

Spectral libraries and matches

MPs in the environment undergo continuous exposure to a large number of environmental stressors that result in weathering ([Lenz et al., 2015](#); [Andrady, 2017](#)). Photo-oxidation of the most of the common polymers like PE, PP results in the formation of oxygenated species,

which exhibit strong intensities in the infrared spectrum (Andrady, 2017; Cai et al., 2018; Da Costa et al., 2018; Rodrigues et al., 2018). However, it is important to note that photooxidation poses less issue for MP identification using RS as compared to FTIR spectroscopy. This aspect of RS is advantageous when the aim is solely to identify the type of plastic or a disadvantage when the study is focused on the assessment of the extent of polymer degradation.

Moreover, advancements in automated Raman mapping routines have facilitated the rapid detection of plastic particles without much involvement of operator. By integrating particle detection software and techniques such as fluorescent tagging of MPs these systems streamline the pre-selection process. As a result, the number of data points required for analysis is significantly reduced, while still maintaining the accuracy of the measurements (Araujo et al., 2018).

Recent advancements and challenges

Despite the various advantages offered by RS, it suffers from some serious drawbacks. One notable downside is vulnerability to fluorescence interference. Use of a laser as a light source might result in sample heating, which results in background emission and often polymer degradation.

Another critical issue during the MNPs analysis is sample contamination, thus the sampling protocol requires extensive preparation which includes precision filtering of all the chemicals used during spectroscopy, blank controls for each step, and handling of the samples only under sterile conditions (Mintenig et al., 2019). More emphasis is needed on studies related to sample collection and pre-treatment techniques for MNPs. Establishing detailed guidelines for technologies used in MNP separation, such as membrane filtration and the techniques for breaking MNPs down into smaller particles, like enzyme digestion, is crucial. These guidelines would improve clarity and efficiency, ultimately saving time in future research. Additionally, factors including the particle size, shape, density, temperature, and chemical composition must be thoroughly evaluated, taking into account the specific type of plastic being analyzed.

Microfibers have been demonstrated to contribute to MNP pollution recently and highlighted as major environmental pollutants, affecting both terrestrial and marine ecosystems (Cai et al., 2022; Ronda et al., 2023; Das et al., 2025). Microfibers generated by anthropogenic actions (majorly domestic washing) are often under-reported due to methodological limitations in their collection. Although, RS provides a robust approach for the chemical characterization of plastic debris but there are specific challenges associated with microfiber detection using RS. These challenges include control of background noise, proper sample digestion, interference caused by dyes/pigments/fillers within the microfibers and overlapping spectra between natural (e.g., cellulose) and semi-synthetic fibers interfere with spectroscopic fingerprints that complicate polymer classification (Silva et al., 2024; Tripathy et al., 2024).

A major analytical challenge associated with RS of environmental MNPs and microfibers is spectral overlap between the polymer vibrational bands and signals arising from non-target components present in samples which significantly lower the signal-to-noise ratio and obscure characteristic peaks needed for polymer identification (Umurhan et al., 2025). Under controlled laboratory conditions, these diagnostic peaks are well-resolved and can be easily matched to their

reference libraries. However, environmental samples rarely present pristine polymer spectra. Organic matter such as humic substances, biofilms, or decaying biological material, and inorganic particulates like clay minerals, sediment particles often remains partially attached to MNPs even after the separation procedures. They produce broad spectral features or fluorescence that overlap with polymer bands (Anić-Vučinić et al., 2025). Because such spectral overlaps can distort peak positions and relative intensities, researchers need careful substrate control, optimized laser wavelength selection and very high spatial resolution to isolate true polymer spectra from confounding signals (Silva et al., 2024). Also, H₂O₂ is used widely to remove organic matter can cause the degradation of certain MPs, affecting the identification and quantification of microfibers in environmental samples (Stanton et al., 2019).

One key source of spectral overlap arises from additives and fillers incorporated during plastic manufacturing. Pigments, stabilizers, flame retardants, and mineral fillers possess strong Raman signatures that can coincide with, distort, or dominate polymer peaks in the fingerprint region (Christie, 1994; Zweifel et al., 2009; Fremout and Saverwyns, 2012; Liu et al., 2023). Because these additive bands may overlap with characteristic polymer vibrations, the resulting composite spectrum can shift diagnostic features, leading to ambiguous spectral matching. Dye/pigment molecules possess conjugated systems and strong Raman activity that can dominate SERS spectra because they absorb onto SERS substrates preferentially. Azari et al. (2024) provided empirical evidence that colorants, including dyes can distort polymer Raman signatures and noted that red pigments in particular can obscure characteristic polymer bands, complicating spectral interpretation.

To overcome these challenges, Silva et al. (2024) have demonstrated the experimental setup for microfiber detection using RS which include a simple stepwise process starting from acquisition of Raman spectra using a Renishaw in-Via reflex system with 785 nm diode laser. Choice of laser affects the spectra of colored samples, for example, in many blue or green polymeric materials, excitation with a red laser can coincide with the absorption band of the dye, leading to resonance effects and Raman spectra dominated by dye-related signals. Access to both green and near-infrared (NIR) laser lines offers clear advantages for the analysis of colored polymers. Sample needs to be immobilized using double sided tape with proper handling techniques which facilitates sample analysis and reduce the chances of sample contamination associated with use of filters, where choice of tape affects background contributions. Removal of organic matter can be done using oxidative agents. Using a green laser, which lies farther from the dye absorption region, can reduce this interference and improve polymer identification (Silva et al., 2024). Beyond sample constituents themselves, instrumental factors also influence the degree to which spectral overlap confounds analysis. Relatively weak scattering signal associated with RS makes it sensitive to underlying fluorescence and noise; strong background signals from matrix materials or additives can easily overshadow the weak polymer peaks. Techniques for mitigating fluorescence can reduce overlap but often fail to eliminate it entirely, particularly in heterogeneous environmental samples (Liu et al., 2023; Umurhan et al., 2025). Weathering processes (e.g., UV irradiation, oxidation) introduce new functional groups or broad absorptive features that shift or broaden polymer bands, making them less distinct and more prone to overlap with background signals (Dong et al., 2020; Phan et al., 2022). These intrinsic limitations and complex backgrounds require careful interpretation and often

advanced analytical strategies beyond automated spectral libraries (Silva et al., 2024). Integration of Raman imaging and hyperspectral techniques for higher sensitivity and spatial resolution with use of machine learning is necessary to facilitate environmental monitoring frameworks for microfiber pollution.

One of the most common drawbacks of classical Raman scattering for MNPs detection and analysis is the inherent weakness of the Raman signal, where only about 1 in 10^8 photons interacting with the sample generate a Raman response (Borman, 1982). Additionally, the technique is highly susceptible to fluorescence interference, which may originate from the main constituents of MNPs or from impurities such as coloring agents, biological material, and degradation products. The weak signal often requires longer integration times, increasing the risk of laser-induced sample degradation. In severe cases, fluorescence can elevate the baseline to the point of obscuring the Raman signal entirely. To address these limitations, various strategies have been explored. One significant approach involves replacing the spontaneous Raman scattering with nonlinear Raman techniques, which inherently offer higher signal-to-noise ratios and are largely free from fluorescence interference (Borman, 1982). However, the adoption of nonlinear Raman methods is restricted by the need for costly equipment, advanced technical skills, and expert operation, limiting their widespread application in MNP analysis (Zada et al., 2018). Despite these challenges, ultrafast nonlinear Raman techniques such as stimulated Raman scattering, especially when combined with flow cytometry, hold promise for real-time, high-throughput monitoring of plastic microbeads, addressing a critical need in MNP identification (Araujo et al., 2018).

The upcoming decade promises significant advancements in RS for MNP analysis. Coherent anti-Stokes Raman scattering (CARS) and stimulated Raman scattering (SRS) are the Nonlinear Raman techniques, that offer enhanced signal strength and open up new possibilities for real-time MNP detection. These methods generate strong signals specifically from the molecular vibrations of interest, effectively eliminating fluorescence interference even in the presence of strongly fluorescing contaminants. As a result, high-quality signals can be acquired rapidly, and the need for extensive sample preparation is reduced, making these techniques particularly advantageous for real-time MNP analysis. When traditional methods like infrared and spontaneous RS are insufficient, advanced spectroscopic approaches like SRS are important for accurate assessment of microfiber pollution in environmental monitoring (Laptenok et al., 2020; Genchi et al., 2023).

CARS has been successfully applied to study the uptake, distribution, and accumulation of MNPs in a variety of aquatic organisms. Cole et al. (2013) provided one of the first experimental evidences that MPs are ingested by a wide range of marine zooplanktons, highlighting an important pathway for plastics into marine food webs. Fluorescence microscopy and coherent anti-Stokes Raman scattering (CARS) imaging were used to observe interactions between polystyrene bead and zooplankton and it was reported that MPs contamination not only enters lower trophic levels, but also has the potential to affect zooplankton feeding efficiency and ecological function (Cole et al., 2013). Similarly, Watts et al. (2014, 2016) used CARS based imaging detect MPs within the digestive system to examine effect of MPs exposure in crabs. Further applications of CARS include studies on fairy shrimp and zebrafish embryos, where CARS microscopy has been utilized to track the uptake and distribution of MNPs during early developmental stages. The high spatial resolution of CARS enabled visualization of particles at subcellular scales, highlighting its

suitability for studying nanoscale particles that are difficult to detect using conventional vibrational or imaging techniques (Galloway et al., 2017).

Stimulated Raman scattering (SRS) microscopy has emerged as a promising tool for rapid MNP detection, gaining attention for its efficiency (Zada et al., 2018). Zhang and his colleagues demonstrated the effectiveness of combining SRS with flow cytometry (FC-SRS) to quickly identify plastic microspheres, highlighting the potential of such integrated systems for broader applications in the near future (Zhang et al., 2017). More recently, Liao et al. (2017) introduced a handheld SRS microscope that merges real-time Raman analysis and imaging with optical fiber laser delivery, enabling *in situ* and *in vivo* chemical identification. This portable device offers speed, stability, and accuracy, making it a compelling option for real-time monitoring of MNPs in consumer products such as food and cosmetics. Floess et al. (2024) evaluated the applicability and limitations of SRS microscopy for detecting MPs in fish tissues, addressing a key challenge in plastic pollution research, that is chemical identification in complex biological matrices without extensive sample pre-processing. Polystyrene (PS) and polymethyl methacrylate (PMMA), were used as model polymer particles, the study demonstrated that SRS provides label-free, chemically specific imaging based on characteristic vibrational signatures of polymers (Floess et al., 2024). Beyond tissue-based detection, SRS also enables the quantification of accumulated MPs with size less than 10 μm in protozoa (Wang et al., 2024). Ao et al. (2023) demonstrated SRS based 3D imaging of MNPs at single-particle resolution and label-free detection of NPs below the size of 100 nm, well below the practical limits of standard Raman methods. Qian et al. (2024) designed hyperspectral SRS microscopy platform with data driven spectral matching algorithm enabling rapid identification of NPs of size even less than 100 nm. The first application of hyperspectral SRS imaging was performed to quantitatively track the uptake, distribution, and toxicity of MNPs in live zebrafish embryos during early development to study liver inflammation and lipid metabolism changes induced by MNPs exposure (Xin et al., 2024). Collectively, these studies underscore the unique advantages of SRS-based techniques for high-resolution, label-free detection and quantification of MNPs in complex environmental and biological samples.

Surface-Enhanced Raman Spectroscopy (SERS) is a technique that improves sensitivity of conventional Raman analysis by enhancing inherently weak Raman signals, thus enabling the detection of plastic particles at extremely low concentrations or at trace levels and potentially down to the nanoscale that are otherwise extremely difficult to detect using standard vibrational spectroscopic techniques, thus at the nanoscale, SERS can provide molecular-level chemical information while maintaining high spatial resolution, allowing researchers to probe surface chemistry, polymer composition, and presence of additives in extremely small particles (Lv et al., 2020; Lenz et al., 2015; Mogha and Shin, 2023; Qi et al., 2024). Using a novel combined SERS/SRS detection strategy, NPs in commercial sea salt were identified and multiple polymer types (PS, PE, PP) in salt were detected, demonstrating widespread contamination in salt samples (Ruan et al., 2024). The enhancement in signal arises from localized surface plasmon resonance generated on nanostructured metallic surfaces, which can amplify Raman scattering by several orders of magnitude (Creighton et al., 1979; Laor and Schatz, 1981; Yi et al., 2025). However, the effective application of SERS relies critically on the use of carefully engineered metallic substrates, typically composed of silver, gold, or copper which are required to achieve sufficient signal

amplification (Le Ru and Etchegoin, 2009; Pérez-Jiménez et al., 2020). At the nanoscale, this creates strong substrate dependence, thus spectral intensity and peak ratios vary depending on where and how the analyte adsorbs onto the SERS surface. Minor variations in substrate preparation can produce significant spectral variability, reducing reproducibility across laboratories. In environmental NPs studies, it is difficult to distinguish whether spectral differences arise from true chemical variation or substrate-induced enhancement artifacts (Le Ru and Etchegoin, 2009). Only molecules within nanometers of this surface experience significant signal amplification (Le Ru and Etchegoin, 2009) which creates inherent chemical selectivity and surface bias, wherein surface chemistry largely determines what is detected depending upon adsorption affinity of the substrate with the sample. Environmental MNPs often carry surface contaminants which may adsorb preferentially and dominate the SERS spectrum, masking signals from the polymer itself. The orientation and conformation of adsorbed molecules relative to the metal surface influence which vibrational modes are enhanced, meaning that spectra can be biased representations of surface functional groups rather than complete polymer signatures (Le Ru and Etchegoin, 2009; Sharma et al., 2013; Ouyang et al., 2017).

Another persistent methodological concern for SERS is validation and quantification. Unlike conventional RS, where spectral intensity has a more direct relationship with concentration and composition, SERS lacks standardized calibration protocols. SERS enhancement varies with hotspot formation, analyte placement, and substrate aging, making it difficult to define and compare enhancement factors reliably (Le Ru and Etchegoin, 2009). Because SERS signals originate from surface-enhanced interactions, there is a substantive risk of false positives, particularly in complex environmental samples where many species may adsorb onto the plasmonic substrate. Natural organic matter, dyes, surfactants, or other environmental contaminants may bind strongly to the substrate and generate enhanced spectra that are misinterpreted as polymer signatures (Kneipp et al., 1999; Chung et al., 2017; Pilot et al., 2019). SERS studies of NPs indicate that some plasmonic substrates preferentially enhance polymer types that have better surface interaction with the substrate, while other materials show weak or absent signals. In studies using Au nanoparticle colloids, PS gave well-defined SERS peaks at low concentrations, whereas PE signals were weak or absent without optimized conditions (Mikac et al., 2023). This implicates that differences in surface affinity lead to biased spectra, where strongly interacting polymers dominate the SERS response, potentially misrepresenting the true composition of environmental samples. A recent study used SERS to detect nanoplastics together with adsorbed pesticides on PS nanoparticle surfaces and found that this type of spectrum inherently contains multiple sets of vibrational bands (polymer + adsorbate) that overlap and require careful deconvolution which shows that overlapping spectra from plastic polymers and sorbed contaminants can easily be misattributed if they not analyzed with multivariate or complementary methods (Rani-Borges et al., 2025). Therefore, SERS has undeniably expanded the analytical sensitivity enabling detection of nanoscale analytes, however its indirect detection nature derived from plasmonic substrate-sample interactions introduces methodological implications.

Also, commercially available SERS substrates often exhibit heterogeneous enhancement factors across their surfaces which results in inconsistent signal intensities that complicate quantitative comparison and reduce analytical reliability in real nanoparticle sized samples (Shi et al., 2017). The need for such specialized substrates, along with

challenges associated with substrate reproducibility and sample-substrate interactions limits the routine use of SERS for large-scale environmental monitoring of plastic debris. Future developments are expected to focus on improving substrate reproducibility and scalability, as current variability in enhancement factors remains a major limitation.

These combined challenges highlight the need for careful method optimization, complementary analytical techniques, and standardized protocols to fully exploit the capabilities of Raman spectroscopy.

Challenges associated with traditional RS along-with latest developments are illustrated in Figure 3.

The figure outlines the disadvantages of conventional RS along-with recent developments to overcome these challenges. Techniques like SERS, SRS and CARS which improve overall sensitivity, saves time and eliminates the risk of fluorescence interference are demonstrated with representative data from literature.

Precautions to be followed during sample analysis via RS are highlighted in Table 2.

Application of AI and deep learning

Using Artificial Intelligence (AI) into MNPs research is gaining momentum, offering promising enhancements in detection capabilities. AI is particularly valuable for automating and accelerating the identification process, while also improving the accuracy of MNPs recognition. By incorporating AI into environmental science workflows, researchers can significantly streamline MNPs detection across various matrices. One of the key strengths of AI lies in its application to image processing, where it enables the rapid and automated identification of MNPs in diverse environments, including aquatic systems, soil, and even atmospheric samples.

Microplastics and nanoplastics with distinct shapes can be detected through visual inspection or using a microscope. However, this approach is labor-intensive, dependent on the observer's expertise, and often prone to errors in identification (Dekiff et al., 2014). Electron microscopes provide significantly a greater magnification than optical microscopes, which helps offset their relatively lower resolution. SEM is a valuable tool for examining the surface morphology of MNPs, enabling researchers to analyze their shape, size, and surface characteristics in detail (Van Cauwenberghé et al., 2013). SEM's high magnification allows distinguishing various types of MNPs by analyzing their specific surface textures, supporting precise identification. However, the process is time-intensive and involves intricate sample preparation (Primpke et al., 2020). This approach offers broader wavelength coverage, better resistance to water interference, and higher spatial resolution, down to around 100 nm (Sobhani et al., 2020). However, the presence of materials like organic matter and additives in the sample can lead to substantial inaccuracies in detection, and the analysis process is still time-consuming.

While machine-learning and rule-based algorithms can efficiently process large spectral datasets, their performance is intrinsically dependent on how well the reference spectra capture the true chemical diversity of the target materials. In complex environmental samples, this requirement is rarely met, leading to systematic classification uncertainties. Factors such as biofouling, weathering, additives, dyes, pigments, and degradation products in polymers from environmental samples can substantially alter Raman spectral features by reducing band intensities and fluorescence interference, resulting in mismatches with the reference spectra, thus

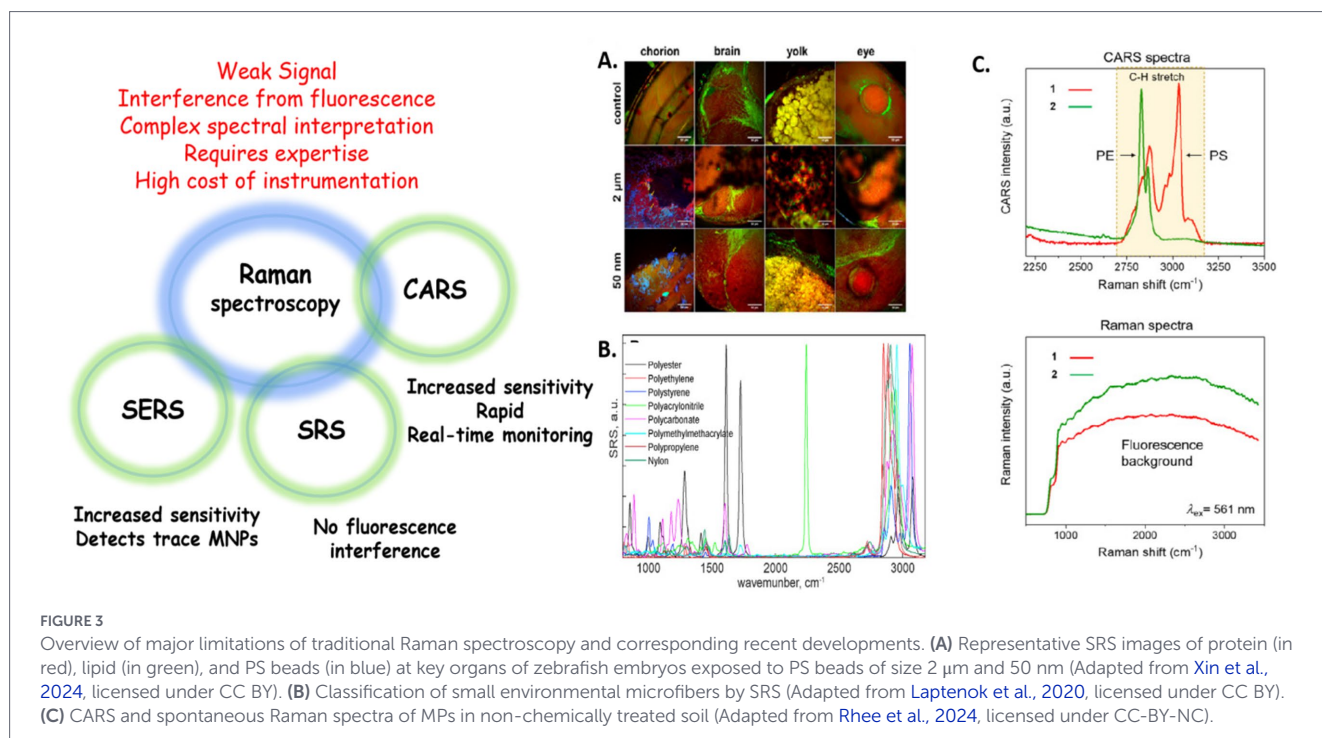


TABLE 2 Measures to minimize sample contamination in MNPs analysis using spectroscopy.

Aspect	Description/Recommendation
Main challenge	Sample contamination during MNP analysis using spectroscopy (Wiesheu et al., 2016).
Contamination control environment	All filtration steps should be performed within a laminar flow workbench to minimize airborne contamination (Brander et al., 2020).
Personnel precautions	Laboratory staff should wear 100% cotton lab coats, particle-free nitrile gloves, and arm sleeves to reduce particle shedding (Hermesen et al., 2018 ; Witzig et al., 2020).
Water quality	Use ultrapure deionized water filtered through a 0.22 μm membrane to eliminate particulates and bacteria (Zhang et al., 2020).
Filter pre-analysis	Each membrane filter must be pre-analyzed using Raman spectroscopy (RS) to identify and pre-count any polymer particles already present. This pre-count is subtracted from the total particle count after filtration.
Cleaning protocol	Follow a rigorous cleaning process for all glassware (funnels, petri dishes, beakers): <ul style="list-style-type: none"> Wash thoroughly with deionized water and detergent. Wipe using lint-free wipes. Inspect for cracks or scratches, as they may harbor particles (Dris et al., 2018; Koelmans et al., 2020; Brander et al., 2020).
Work area recommendation	Conduct all sample processing within a clean bench to prevent new particle contamination.
Goal	Maintain sample integrity and ensure accurate and reliable MNP analysis.

increased rates of wrong polymer identification and classification ([Dong et al., 2020](#); [Azari et al., 2024](#)). Existing spectral libraries lack data for environmentally aged, weathered, or dyed polymers, limiting the ability of automated systems to correctly match and classify real-world spectra ([Käppler et al., 2016](#); [Primpke et al., 2018](#); [Cowger et al., 2020](#)). Machine learning models trained on limited or homogeneous datasets may also perform poorly on spectra from heterogeneous environmental matrices, underscoring the need for diverse, high-quality spectral databases that encompass representative variations in polymer composition, aging states, and contamination. These constraints impede the development of generalized, high-throughput automated workflows for environmental monitoring and motivate ongoing efforts to create standardized, open-access Raman spectral libraries enriched with environmentally relevant spectra ([Cowger et al., 2024](#)).

Automated classification of Raman spectra has become widespread in analytical chemistry due to its capacity to rapidly assign chemical entities to unknown spectra using spectral libraries or ML models by comparing unknown spectra against reference spectra and provide a match based on similarity metrics. However, the reliability of automated classification is fundamentally dependent on chemical representativeness, diversity of spectral libraries and the compatibility of the spectral data used for matching. These dependencies become especially problematic in complex environmental samples, where sample chemistry and spectral characteristics often diverge significantly from pristine laboratory references. [Jin et al. \(2022\)](#) demonstrated effectiveness of RS coupled with multivariate analysis in achieving nearly 96.8% accuracy when applied to real MP samples aged by environmental stress. [Dong et al. \(2020\)](#) found that weathered plastics collected from real environments exhibited weakened or even absent

characteristic peaks compared to reference spectra, and new bands associated with oxidation appeared in weathered materials. Araujo et al. (2018) demonstrated that many environmental MPs produce spectra that do not align cleanly with existing library entries due to weathering and additive interference; thus there is a need for the development of expanded libraries including aged and chemically modified polymer spectra. Similarly, Xu J. et al. (2019) highlighted that conventional libraries lack sufficient coverage of environmental polymer variants, leading to frequent misclassification or unrecognized spectra. In some cases, automated matches may produce false positives, assigning a strong match to a polymer that is not actually present because the classifier has no mechanism to recognize “unknown” classes or the presence of mixed signals. This is a well-recognized limitation in spectral library approaches; unless explicit thresholds for acceptance are used, the algorithm will always return a best match, even if the match is poor. Studies applying ML to Raman data have shown higher classification accuracy compared to simple spectral library matching, but performance dropped significantly when tested on external environmental datasets that were not part of the training set, demonstrating the need for diverse and representative training libraries (Weber et al., 2023).

As a result, conventional detection techniques are often slow, require substantial manual effort, and have a limited range of application (Lin et al., 2022). Consequently, incorporating AI technology offers a promising approach to enhance the efficiency and accuracy of MNPs detection, potentially playing a vital role in addressing the global issue of MNPs pollution.

Deep convolutional neural networks (CNNs) and U-Net architectures can be employed to process and classify microscopic images of MNPs. These models automatically segment and count MNPs in complex images, minimizing the need for manual intervention and enabling batch image recognition (Lee et al., 2022). Deep learning classifiers trained on expanded Raman datasets spanning multiple polymer types show strong performance, but with notable differences depending on data quality. A 1D-CNN model achieved up to 97% accuracy on a set of eight plastic types under varied acquisition conditions (Qin et al., 2024). ResNet based neural

networks designed to handle inferior quality spectra achieved approximately 97.8% accuracy even under low signal-to-noise conditions, highlighting robustness but also the need for sophisticated architectures to handle real-world noise (Huang et al., 2025). Over 97% accuracy has been observed in spiked environmental water samples, demonstrating that automated models can work even with environmental complexity when the data capture both classes and conditions in training (Xie et al., 2023). This shows strong classifier performance when spectral libraries and datasets include environmental variability, but such results depend on comprehensive training data, which is not yet standard for many environmental Raman databases.

These models distinguish MNPs from natural particles based on the features like shape, color, transparency, and surface texture. Currently, several deep learning models like VGG16, U-Net, and MultiResUNet have been employed to support the recognition of MNPs from SEM images demonstrating enhanced predictive performance and accuracy (Hu et al., 2024).

Modern ML programs, incorporated with RS in multiple hidden layers, enable them to automatically learn complex patterns and representations from data, an advancement that surpasses the limited capabilities of traditional machine learning methods (Sunil et al., 2024). Integration of ML and RS, when combined with conventional techniques has the potential to provide benefits by reducing manpower requirements, dependency on high end equipment that cuts down the time and cost, but enhances the accuracy, thereby positively impacting a wide range of industries. A flow chart showing the steps for the integration of AI with RS for the detection of MNPs is demonstrated in Figure 4.

The figure illustrates a workflow for Raman spectroscopy-based microplastic analysis enhanced by AI/ML. It begins with sample preparation and Raman spectral acquisition, followed by pre-processing steps such as baseline correction and noise filtration. The cleaned spectra are then subjected to AI- and ML-driven spectral fingerprinting for classification and identification. Finally, the processed information is used for result interpretation and data visualization.

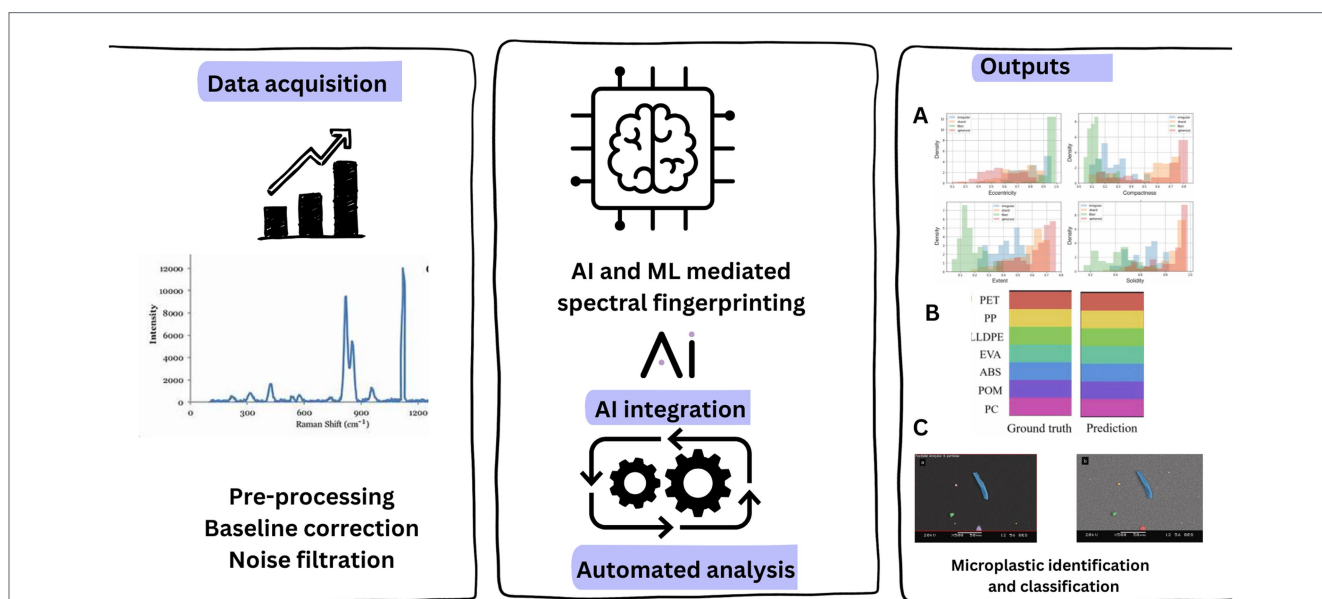


FIGURE 4

(A) Histograms of eccentricity, compactness, extent and solidity of MP samples using approaches based on weakly-supervised segmentation without the use of pixel-wise human-labeled data (Reproduced from Phan et al., 2023, licensed under CC-BY-NC-ND). (B) Visual representation of the ground truth versus the predictions from ML model for MPs classification (Adapted from Jiao et al., 2024, licensed under CC BY). (C) Micrograph showing FastSAM (AI enhanced automatic annotation tool) detected and annotated 6 PE particles (a) and the human expert verified the FastSAM segmentation and annotated remaining 4 PE particles (b) (Reproduced from Rezvani et al., 2025, licensed under CC-BY-NC-ND).

From detection to decision-making: Raman-based techniques in MNPs risk evaluation and mitigation

Raman-based techniques play an increasingly important role in MNPs risk evaluation and mitigation, because accurate risk evaluation requires reliable data on polymer type, particle size, abundance, and spatial distribution. RS provides unambiguous polymer identification through characteristic vibrational fingerprints (Käppler et al., 2016; Primpke et al., 2018; Balan et al., 2019). Advanced Raman-based techniques such as SRS and SERS extend detection capacity to submicron and nanoscale levels, which are often underestimated but considered potentially more hazardous due to higher bioavailability (Cowger et al., 2020; Ao et al., 2023).

By correlating size and chemistry of the plastic particle with biological responses, Raman techniques help move risk assessment of MNPs from studies based on occurrence towards mechanistic hazard evaluation. SRS and CARS microscopy allow label-free imaging of MNPs alongside endogenous biomolecules such as lipids and proteins, revealing bioaccumulation patterns, tissue localization, and metabolic disruption (Floess et al., 2024; Qian et al., 2024). RS can also identify dyes, additives, pigments, and degradation products, which may drive toxicity independent of the polymer backbone (Madariaga, 2012; Casadio et al., 2010; Lin and Chang, 2022).

Strategies for mitigation of MNPs depend on identifying dominant sources of pollution. The polymer-specific information obtained from RS allows MNPs to be traced back to their source, including synthetic textiles (polyester, polyamide), plastic packaging (PE, PP), and tyre-based particles (Akyildiz et al., 2022; Hager et al., 2018; Schymanski et al., 2018; Worek et al., 2022). Analysis of MNPs content of wastewater, drinking water, and filtration systems allows assessment of treatment efficacy, thereby allowing technological improvements and evidence-based regulatory measures (Mintenig et al., 2017; Fortin et al., 2019; Becucci et al., 2022). Recently, Shiwani et al. (2025) developed a high-throughput Raman screening technique demonstrates improved speed and scalability compared to conventional Raman microscopy, potentially facilitating large-scale monitoring of MNPs pollution in environmental and industrial contexts. Advancement in automated Raman imaging, ML assisted spectral analysis, and standardized spectral libraries have made Raman-based techniques increasingly suitable for large-scale monitoring of MNPs long-term evaluation of the effectiveness of mitigation and regulatory strategies.

Future perspectives

RS used for MNP detection typically involves a mapping approach, where spectra are collected point-by-point across the sample. These individual spectra are then compiled to form a Raman map or image. However, this method does not represent true imaging. Raman imaging can be performed using spontaneous or nonlinear techniques in which a broad area or entire section of a sample is illuminated by defocusing the laser, enabling the acquisition of a complete image in a single measurement. Despite its potential for rapid, label-free chemical mapping, this method has not yet been applied to the analysis of MNPs in environmental samples. A significant challenge in MNP characterization is the real-time analysis of particles in flow. Conventional Raman methods,

which rely on spontaneous Raman scattering, are generally unsuitable for this application because the Raman signal is inherently weak, necessitating relatively long acquisition times, ranging from milliseconds to seconds to achieve an adequate signal-to-noise ratio.

An innovative technique, standoff RS, has been developed to detect samples that are difficult to access or hazardous to handle (Gares et al., 2016; Stewart et al., 2012). For example, Östmark et al. (2011) utilized hyper spectral spontaneous Raman imaging to distinguish explosives from inorganic particles approximately 5 mm in size from a distance of 10 meters. The same method was later applied successfully to detect sulfur microparticles (around 20 µm) scattered on a brick surface (Östmark et al., 2011). Additionally, standoff coherent anti-Stokes Raman scattering (CARS) has been employed to identify trace amounts of explosives within a complex chemical background of polymer solutions such as PS and polymethyl methacrylate (PMMA) in toluene (Bremer et al., 2011).

Looking ahead, standoff Raman techniques hold great promise for monitoring MNPs on ocean surfaces from passing ships or aerial platforms like drones and helicopters. Such advancements could represent a significant breakthrough in MNPs research and environmental monitoring.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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