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Review

Artificial intelligence-empowered collection and characterization of microplastics: A review

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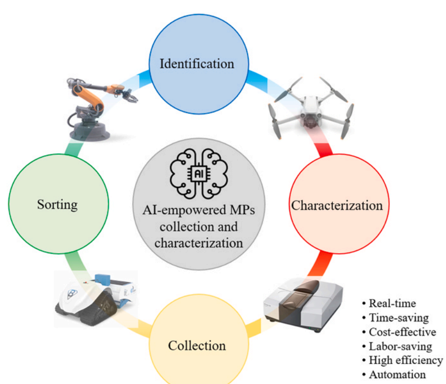
HIGHLIGHTS

- Artificial intelligence-empowered collection and characterization of microplastics are reviewed.
- A framework is created to unify efforts for collecting, processing, and characterizing microplastics.
- Robots and machine learning methods are integrated in the detection and collection of microplastics.
- The limitations and technology readiness levels of artificial intelligence technologies are discussed.
- Future opportunities for autonomous collection and characterization of microplastics are discussed.

GRAPHICAL ABSTRACT



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ABSTRACT

Microplastics have been detected from water and soil systems extensively, with increasing evidence indicating their detrimental impacts on human and animal health. Concerns surrounding microplastic pollution have spurred the development of advanced collection and characterization methods for studying the size, abundance, distribution, chemical composition, and environmental impacts. This paper offers a comprehensive review of artificial intelligence (AI)-empowered technologies for the collection and characterization of microplastics. A framework is presented to streamline efforts in utilizing emerging robotics and machine learning technologies for collecting, processing, and characterizing microplastics. The review encompasses a range of AI technologies, delineating their principles, strengths, limitations, representative applications, and technology readiness levels, facilitating the selection of suitable AI technologies for mitigating microplastic pollution. New opportunities for future research and development on integrating robots and machine learning technologies are discussed to facilitate future efforts for mitigating microplastic pollution and advancing AI technologies.

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1. Introduction

The global production of plastics exceeds 400 million tons annually, while roughly 14 million tons of waste plastics infiltrate water systems [1]. Waste plastics then undergo fragmentation into microplastics (MPs) through physical, photochemical, and biodegradation processes [2,3]. MPs are typically defined as plastic particles with a size smaller than 5 mm in length [4]. These tiny plastic particles can come from a variety of sources, including the breakdown of larger plastic items, microbeads used in personal care products, and fibers shed from synthetic clothing, among others [5]. The presence of MPs is widespread, extending across diverse ecosystems including oceans, rivers, lakes, soils, and even the atmosphere. Due to the small particle size of MPs, it causes serious environmental problems and social impacts.

Various environmental, ecological, and health problems are associated with MPs. Marine organisms, including fish and turtles, are vulnerable to mistaking MPs for food. [6]. These particles have the potential to disrupt ecosystems by affecting nutrient cycles and aquatic communities, as well as adsorb and transport pollutants, leading to the accumulation of toxins and exacerbation of water pollution [7]. Increasing evidences suggest that MPs can infiltrate the food chain through seafood consumption and drinking water [8], posing risks such as abrasion, inflammation, reproductive issues, developmental problems, and immune responses upon ingestion [9]. In addition, MPs may clog filters and pipes within water treatment plants, reducing their efficiency and increasing operation and maintenance (O&M) costs [10]. Overall, addressing the increasing distribution and accumulation of MPs is an urgent task globally.

The substantial volume, widespread distribution, and profound impacts of MPs emphasize the urgent need for their collection and characterization. Traditional methods for collecting and characterizing MPs usually involve manual processes that are time-consuming and labor-intensive. The challenges originate from the small size, wide distribution, and large variations of MPs in terms of sizes, shapes, and sources [4]. Under natural conditions, the mixture of different types of MPs further complicates the process of manual identification.

Recently, applications of artificial intelligence (AI) technologies have extended to the domain of waste management. Intelligent robots have been developed to autonomously collect and classify MPs [11–13], and machine learning models have been developed to analyze and interpret data for microplastic characterization efficiently [14–16]. These breakthroughs have created new avenues in the study, utilization, and management of MPs. The advances in AI technologies for MPs is aligned with the Internet of Things (IoT) in the era of Industry 4.0 [17].

The use of machine learning technology has been reviewed in references [18,19]. Reference [18] primarily focused on reviewing machine learning methods for detecting plastic debris, and reference [19] primarily focused on remote sensing and machine learning methods for detecting plastic debris, as shown in Table 1. Both references highlight the advantages of machine learning methods for detecting litter or other large debris theoretically, while it is still unclear whether machine learning methods are practical for collecting and characterizing MPs. Moreover, these references did not consider integrating hardware (robots) and software (machine learning models) for the collection and characterization of MPs. It remains unclear how robots and machine learning techniques can be integrated to collect, sort, classify, detect, and quantify MPs.

Table 1
Comparison of this study with existing review papers.

Investigated contents		This study	Reference [18]	Reference [19]
Focused object		MPs	Litter	Litter
Automatic collection		√	×	×
Automatic sorting		√	×	×
Automatic characterization	AI-assisted spectral analysis	√	×	×
	AI-assisted detection	√	√	√
	AI-assisted quantification	√	√	×
Technology readiness level		√	×	×
Economic and environmental assessment		√	×	×
Regulatory, ethical, and social implications		√	×	×

To solve these problems, this paper reviews the state-of-the-art robots and machine learning technologies for the collection and characterization of MPs, aiming to facilitate the application of AI technologies for mitigating MP problems. The contributions of this research are summarized as follows: (1) This paper proposes an AI framework for automatic management of MPs, covering the collection, sorting, detection, quantification, and characterization tasks for MPs. (2) This paper discusses the benefits and limitations of each technology for the detection and characterization of MPs while identifying future research and development opportunities. (3) The paper discusses the technology readiness level (TRL) of various devices and methods, along with their performance metrics, to aid in the selection of appropriate technologies for practical applications (4) The paper presents an overview of the types, distribution, and magnitude of MPs to elucidate the motivations and challenges. (5) Traditional collection and characterization methods are outlined to highlight the advantages offered by AI technologies. By conducting a comprehensive comparison, suitable methods can be identified for different scenarios.

2. Methodology

2.1. Keywords and databases

The keywords include “microplastics (MPs)”, “collection”, “characterization”, “robots”, “sensors”, “machine learning (ML)”, “artificial intelligence (AI)”, “laboratory”, and “field”. These keywords were combined in different ways to search relevant publications from multiple databases. The investigated databases include “ScienceDirect”, “Scopus”, “Web of Science”, “Google Scholar”, “Nature”, “Science”, “Optica Publishing Group”, “IOPscience”, and “IEEE Xplore”. Advanced settings for searching include: (1) Years: between 2010 and 2023. (2) Article types: review articles, research articles, book chapters, and short communications. (3) Language: English.

2.2. Statistics of relevant publications

The increase in the number of publications related to MPs from 2010 to 2023 is shown in Fig. 1. An exponential surge is observed from Fig. 1 (a), indicating increasing concern. The number of publications from different countries (publications over 200) is shown in Fig. 1(b), indicating that this environmental challenge has attracted worldwide attention.

2.3. Selection of publications

The scope of this review includes: (1) The types, sources, sizes, and spatial distributions of MPs. (2) Traditional collection and characterization technologies for MPs. (3) AI-empowered approaches such as robots and machine learning technologies. Based on this scope, a systematic approach was used to collect relevant publications, as shown in Fig. 2. The general process includes: First, relevant publications were collected from databases using keywords (see Section 2.1). The search and selection tasks follow the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) method [20]. The initial search found a total of 74,648 relevant publications. After removing duplicates, the remaining publications were sorted by relevance, and 144 journal articles were selected. During the review process, some necessary references were added. Finally, this method selects a total of 177

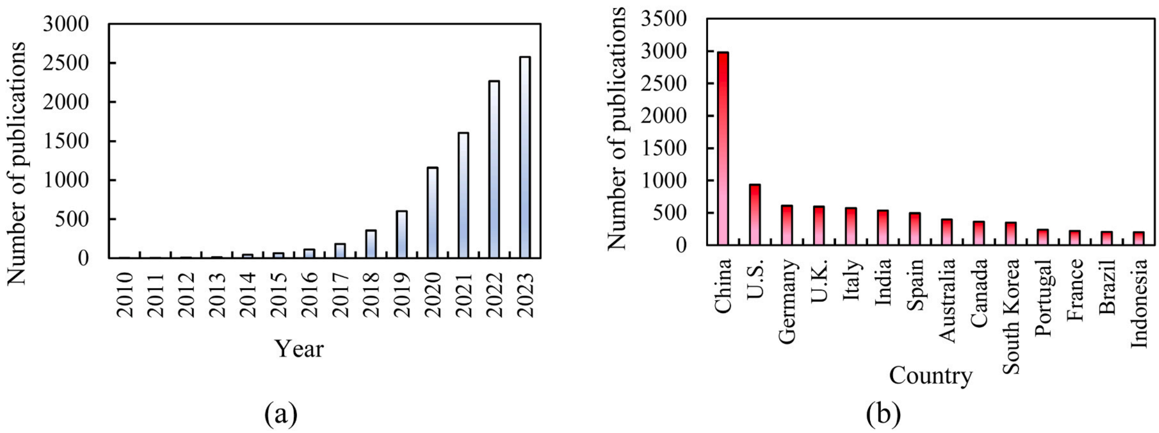

Fig. 1. Number of publications from 2010 to 2023: (a) in each year, and (b) from different countries.

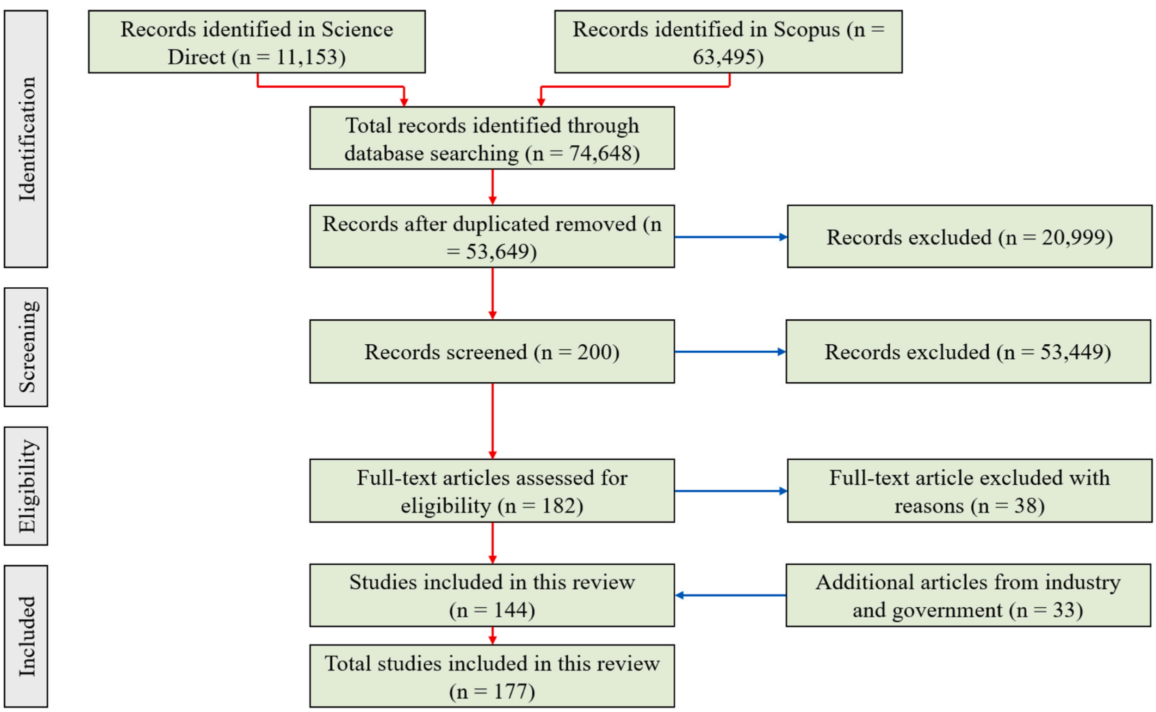

Fig. 2. Flowchart for the method used to search and select the references in this review paper.

publications satisfying the specified criteria.

3. Categorization and distribution

3.1. Categories and sources

MPs can be classified into primary and secondary categories, as shown in Fig. 3(a). Primary MPs are intentionally produced, and secondary MPs are generated via ultraviolet light degradation or biodegradation degradation of coarse debris [21]. MPs have different morphological properties and chemical compositions. The morphology of MPs includes fragments, fibers, pellets, films, and foams, as shown in Fig. 3(b) [22]. Fibers and fragments are the dominant types, accounting for 28% and 31%, respectively [22]. Fig. 3(c) shows the statistical results of the chemical composition of MPs [23]. MPs can be made from a variety of polymers with different chemical compositions, such as polypropylene (PP), polyethylene (PE), polystyrene (PS), polyethylene terephthalate (PET), polyamides (PA), polyvinyl chloride (PVC), and polyurethanes (PU). The main sources of MPs are PE and PP polymers, accounting for 29% and 17%, respectively [23].

The types and primary applications of MPs are shown in Table 2 according to the chemical composition. PE is one of the most widely used type, commonly found in products such as bags, bottles, and containers [24]. PE is further categorized into high-density polyethylene (HDPE) and low-density polyethylene (LDPE), which can persist for over 500 years [24]. HDPE and LDPE are commonly found as pellets (beads) and films, respectively [25,26]. PP appears as fragments and textiles, known for its high chemical resistance, toughness, and heat resistance [27]. PET, utilized widely in textiles, possesses notable strength, moisture resistance, and chemical resistance [27]. PS is typically found in foam packaging [28].

3.2. Spatial distributions

Despite the different sources, oceans are often the destinations of MPs through water flows. The spatial distributions of MPs in aquatic and

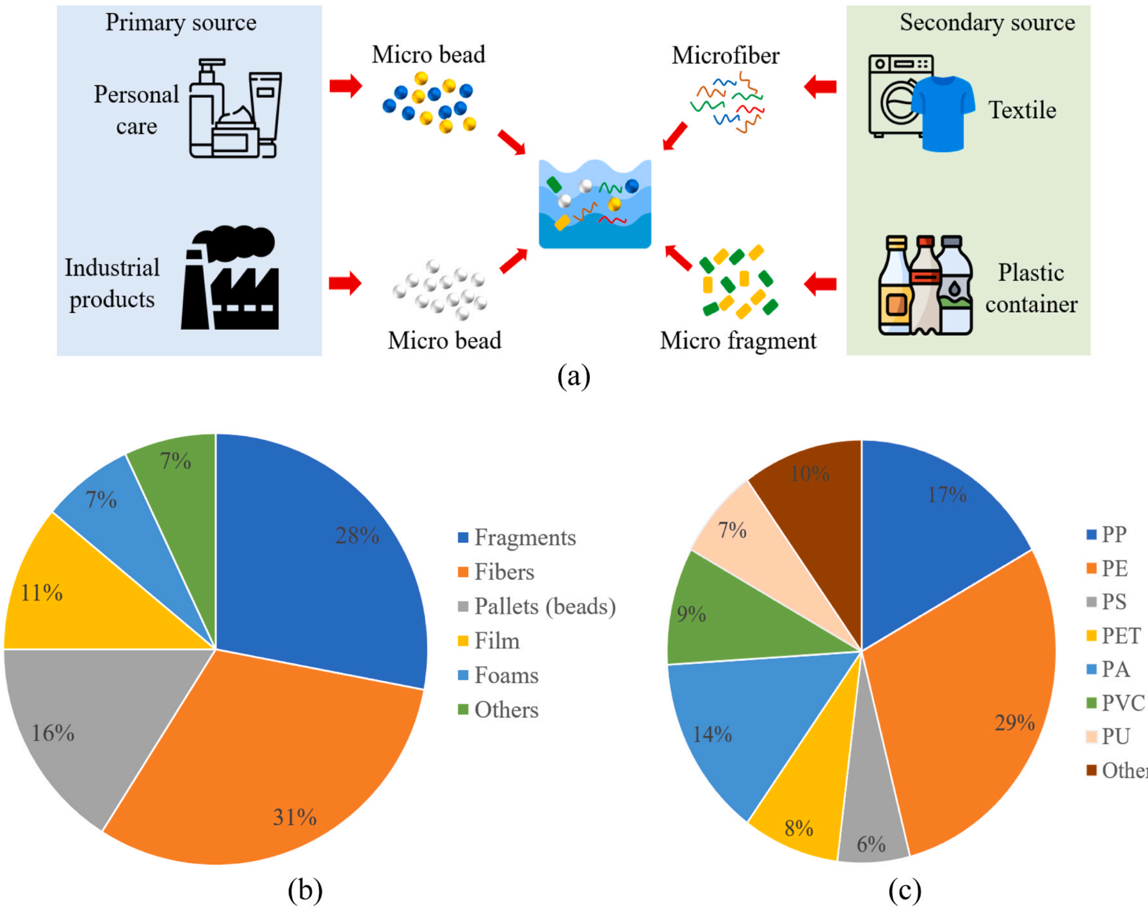

Fig. 3. Categories and sources of MPs: (a) categories, (b) statistics of morphology [22], and (c) statistics of chemical compositions [23].

Table 2
Properties of typical polymers in MPs.

Type	Density (g/cm^3)	Lifespan (years)	Applications
LDPE	0.91-0.94 [29]	500-1000 [24]	Plastic bags, packaging, agricultural films [24]
HDPE	0.94-0.97 [29]	< 100 [24]	Bottles, containers, pipes [24]
PP	0.89-0.92 [29]	< 20 [30]	Packaging, textiles, automotive parts [24]
PS	1.04-1.07 [31]	< 50 [24]	Disposable cups, packaging, insulation [24]
PET	1.34-1.39 [32]	5-10 [24]	Soda bottles, textile fibers, packaging [24]
PVC	1.38 [32]	> 100 [33]	Pipes, vinyl flooring, cables [33]
PA	1.13-1.15 [23]	30-40 [34]	Textiles, automotive parts [35]
ABS	0.99-1.10 [31]	< 50 [36]	Automotive parts, pipe, electrical enclosures [37]
POM	1.41 [38]	-	Gear, bearings, automotive components [39]
PMMA	1.17-1.20 [40]	< 20 [41]	Acrylic glass, signage, medical devices [41]
PU	0.03-0.19 [42]	20-30 [43]	Insulation, coating, mattresses, sportswear [44]
PC	1.20 [45]	-	Compact discs, electronic components, automotive components [46]

Note: PMMA- polymethyl methacrylate; ABS-acrylonitrile butadiene styrene; POM- polyoxymethylene; PC- polycarbonate.

terrestrial systems are discussed in this section.

3.2.1. Aquatic environment

Approximately 11 million tons of MPs enter aquatic systems annually [47], with high abundance found in lakes, rivers, and oceans [48]. The ubiquity of MPs and their abilities to carry heavy metals and microbial communities generate major concerns. Statistical data of MPs in aquatic systems are shown in Table 3. The overall quantity of MPs in oceans across both hemispheres exhibits comparable orders of magnitude [49]. High abundance was observed in densely inhabited areas such as the South China Sea coast with 243–349 items/m^3. Conversely, low abundance is reported in remote areas such as the Southern Ocean with 0.008 items/m^3 [50]. MPs in the ocean are dominated by fragments, fibers, and films composed of PP, PE, and PET. Transparent, white, blue, and black are the most common colors. Statistical findings indicate significant differences in the abundance, morphology, chemical composition, and color of MPs across various aquatic systems.

3.2.2. Terrestrial environment

The accumulation of MPs in soils poses a threat to ecosystems [64]. MPs can infiltrate the topsoil by various means such as tillage, earthworms activities, water penetration from digging, or physical degradation [65]. The primary sources of MPs in terrestrial environments include cosmetics, clothing fibers, and the breakdown of larger plastic debris [66]. MPs have been detected in soils across different countries, including farmlands in German [67], agricultural sites in Spain [68], and central valley of Chile [69]. Report indicates that 90% of Swiss floodplain soils contain MPs [70]. Representative data for distribution of MPs is listed in Table 4. Statistical results indicate significant differences in the abundance, morphology, chemical composition, color, and size of

Table 3
Statistical information about the distribution of MPs in aquatic systems.

Sampling location	Abundance (items/m^3)	Morphology	Polymer	Colors	Size (mm)	Methods	Ref
Southern Ocean (Antarctic Peninsula)	0.008	Fragment, pellet, fiber	PS, PVC, PE	Transparent	< 5	FTIR	[50]
Southern Ocean (Ross sea)	0.17	Fragment, fiber	PE, PP	Red, blue	< 5	FTIR	[51]
Arctic Ocean (Central Basin)	0.7	Fragment, fiber	PS, PA, PVC	Transparent, blue, red	0.25-5	FTIR	[52]
Arctic Ocean (Bering and Chukchi Seas)	0.23	Fiber, film	PP, PET	White, black	0.1–5	Microscope, FTIR	[53]
Atlantic Ocean (Western)	25-29	Fragment, fiber,	PP, PE, PET, PA, PVC	Blue, translucent	< 5	FTIR	[54, 55]
Pacific Ocean (South China Sea)	243–349	Fragment, fiber	PE, PP, PET, PS, PVC	Transparent, white, black	< 5	FTIR	[55, 56]
Indian Ocean	0.05-4.4	Fragments, fiber	PU, PET, PP, PVC	Green, red, blue	< 5	FTIR	[57]
Mediterranean Sea	0.15	Fragments, fiber, film, pellet, foam	PE, PP, PVC	Yellow, green, blue, red	< 5	FTIR	[58, 59]
Great Lakes	0.05-32	Fragments, fiber, film, pellet, foam	-	Transparent, white, black, blue	< 5	Digital camera	[60]
Yangtze River	0.9	Fragments, fiber,	PP, PS, PE	Transparent, blue, white, black, red,	0.3-5	Microscope, FTIR	[61, 62]
Amazon river	5-152	Fragments, fiber,	Acrylic, PET, PP, PS, PE, PVC	Black, brown, yellow	0.55-5	Microscope, FTIR	[63]

Table 4
Statistical analysis of the distribution of MPs in soil.

Area	Soil type	Abundance (items/kg)	Shape	Polymer types	Size (mm)	Depth (cm)	Color	Methods	Ref.
Shandong, China	Agricultural soil	310–5698	Fiber, fragments, films, pellet	PE, PP, PET, PVC, PS	< 5	0–5, 10–25	Transparent, white, blue	FTIR	[71]
Yunnan, China	Agricultural soil	900–4080	Fragments, fiber	-	< 5	0-30	Transparent, black, blue	Microscope	[72]
Tibetan Plateau, China	Grassland soil	910.9	Fiber, fragment, pellet	PE, PP, PS, PVC	< 5	0-10	Transparent, white, black	FTIR	[73]
Chile	Agricultural soil	540	Fibers, films, fragments	PS, PE, PP	< 2	-	-	Microscope, FTIR	[69]
Germany	Agricultural soil	0-217.8	Fragment, fiber, pellet	PE, PP, PA	1–5	0–10, 10–20	Black, white	FTIR	[67]
Southeast, Spain	Agricultural soil	50-3500	Fragments, fiber	PS, PE, PVC	< 5	0–10	-	FTIR	[68]
Ontario, Canada	Agricultural soil	14,000	Fiber, fragment	PE, PP, PS, PMMA	< 5	0–15	-	FTIR	[74]
Melbourne, Australia	Urban soil	529.3	Fiber, film, fragment, pellet	PS, PE, PP	< 5	-	-	FTIR	[75]
Zhejiang, China	Coastal soil	313.9	Fragments, film, fiber, foams	PP, PE, PET	< 5	0–20	White, black, yellow	FTIR	[76]
Switzerland	Floodplain soil	593	Fragments	PE, PS, PVC	0.125–0.5	0–5	-	FTIR	[70]

MPs across different regions, and PP and PE are the most common types of MPs in soils, primarily in the form of fragments and fibers. Transparent MPs are the most prevalent color, followed by white and black colors.

4. Collection and characterization

This section reviews innovative technologies leveraging AI and robots for collecting and characterizing MPs. In Section 4.1, a framework is presented to integrate the efforts for collecting, processing, and characterizing MPs using various devices and data analysis methods. Section 4.2 discusses traditional and automated methods for collecting MPs. Section 4.3 delves into techniques for sorting and separation of MPs. Section 4.4 presents characterization methods employing robots and machine learning, aiming to enhance the efficiency of efforts for characterizing MPs.

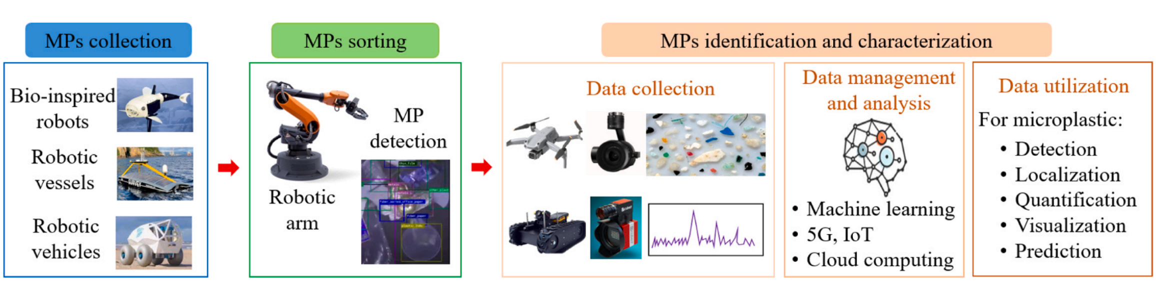

Fig. 4. Framework for AI-empowered collection, processing, and characterization of MPs.

4.1. Framework

A framework is presented to integrate the efforts for collecting, processing, and characterizing MPs (Fig. 4). The framework consists of three primary tasks:

(1) Collection. The collected samples usually contain impurities such as soil. Robotic systems have been developed to collect MPs from diverse environments [77].
(2) Processing of samples. The primary purpose of this task is to obtain clean MPs. Robotic arms have been developed to automatically sort and pick waste plastics [78–80].
(3) Characterization. Various methods have been developed to collect data for characterizing MPs. Some methods can be integrated with robots such as drones to automate the data collection process. The data collected from robots can be analyzed using machine learning models which can be trained to characterize MPs automatically [81–83].

4.2. Collection

Representative tools for collecting MPs from aquatic environments are shown in Fig. 5. MPs in the near surface of water can be collected using net-like tools such as manta trawl [84], Bongo net [85], and plankton net [86]. These tools are manually operated or attached to a boat to collect MPs. Manta trawl and Bongo net can cover a large area, achieving high efficiency in collecting a substantial quantity of MPs from surface water [87]. These instruments are capable of collecting various sizes of MPs, ranging from 0.3 mm to 5 mm [87]. The specific size of collected MPs is dependent on the mesh size. In contrast, plankton net is smaller in size and inefficient for large-scale collection. However, plankton net is relatively simple to operate and inexpensive compared with manta trawl and Bongo net [86]. These sampling methods necessitate support from a ship, and increased collection efforts result in more ship time, making the process both time-consuming and resource-intensive. Despite these challenges, the use of such tools is essential for assessing the prevalence and distribution of MPs in marine environments. Each tool offers different advantages that can be tailored to specific research or monitoring goals. For instance, while manta trawl and Bongo net are ideal for quantitative assessment over wide areas, plankton net is more suitable for qualitative studies in localized regions.

Low-density MPs may initially float on water surface and then gradually sink into sediment as biofilm and mineral deposits accumulate on the surfaces of MPs [88]. The accumulation of MPs in sediments is concerned since it can lead to long-term contamination of aquatic ecosystems, affecting both the organisms and water quality. MPs in sediment can be sampled using multi-corer [89], box corer [90], and gravity corer [91]. The multi-corer device has a unique design to collect multiple samples simultaneously, significantly improving sampling efficiency [92]. However, it can only collect samples from the top layer of sediment, making it less suitable for studies requiring deeper sediment profiles. In addition, the complexity of the device also makes it more expensive. Box corer has higher collection efficiency because it samples a large volume of sediment [93]. Gravity corer is designed to penetrate deeper into sediment layers. In general, the gravity corer has advantages such as simple operation and high cost-effectiveness. However, it can only collect a limited number of samples at a time [91]. The traditional method for collecting MPs from terrestrial environments involves manually picking MPs from the ground or using coring devices to extract soil samples [94]. Soil samples are usually extracted from different locations, and at each location, samples are extracted from different depths to investigate the spatial distribution of MPs. The above methods have been used to sample MPs in sediments, while large-scale cleanup of MPs in sediments remains a challenge.

Various robots, such as robotic fish, drones, and smart cars, have been developed to collect MPs from water and beaches [77,95–102]. A 3D printed bio-inspired robotic fish called Gillbert, shown in Fig. 6(a), was invented to collect MPs from water [77]. Gillbert is a salmon-sized robot equipped with a filtration system and remoted control module. The gills of robotic fish act as a filter, trapping MPs up to 2 mm while allowing water to pass. The collected MPs are stored in an internal container, which can be retrieved for recycling or proper disposal. At this moment, the machine is small and can be only used for MPs sampling. In future research, scaling up the robot to enable large-scale collection of MPs in water needs to be considered. In reference [96], a multi-vehicle system was designed to clean MPs from seafloors. A remotely operated vehicle (ROV) was used to scan seafloors using multibeam echosounder, providing a bathymetric map of the seabed. Large litters were detected and marked on the bathymetric map. When the water was transparent, a drone was operated to identify areas with

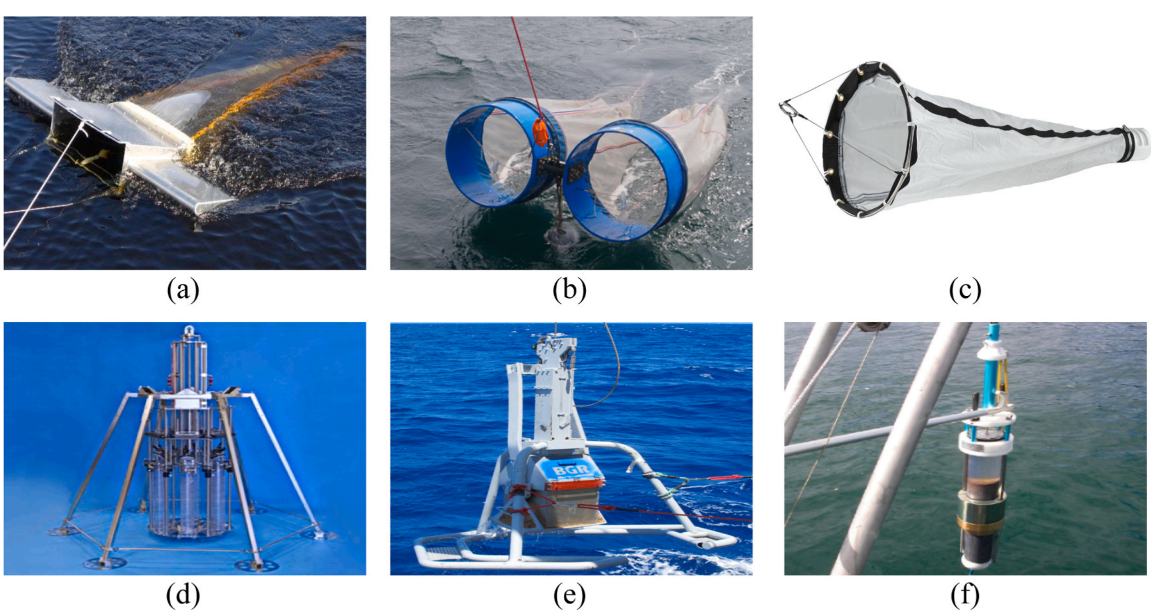

Fig. 5. Representative tools used for collecting MPs: (a) manta trawl [84]; (b) Bongo net [85]; (c) plankton net [86]; (4) multi-corer [89]; (5) box corer [90]; and (6) gravity corer [91].

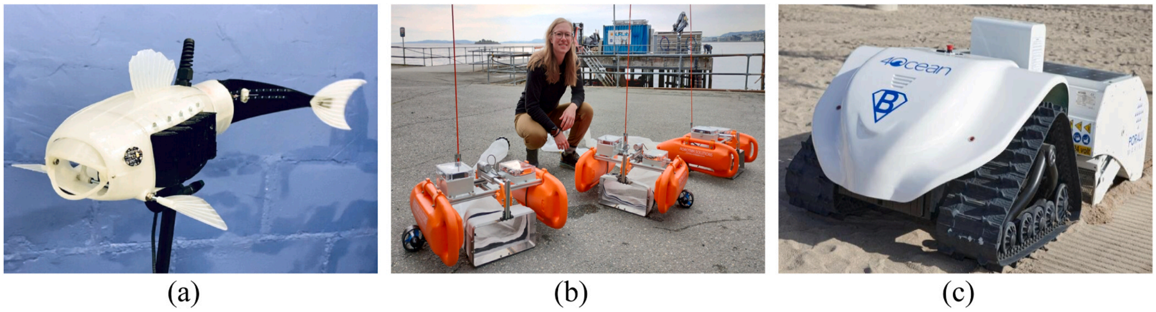

Fig. 6. Representative robots used for collecting MPs: (a) robotic fish [77]; (b) portable Catamaran drones [97]; and (c) robotic vehicle [98].

abundant MPs. A small ROV was used to targeted scans of the sea bottom to find MPs using deep learning-based object detection technology. The targets of detection can be MPs and other marine debris, depending on the dataset used to train the deep learning models. An unmanned surface vehicle served as a central hub for deploying and managing the ROVs and drone. Reinforcement learning was applied for path planning and controlling the movement of observing and collecting ROVs.

Portable drones have been designed to collect MPs from the water surface, as shown in Fig. 6(b) [97]. Drones equipped with an automatic pilot system collected MPs from areas inaccessible to boats. The end of the drone was connected to the plankton net for collecting MPs. The model of plankton nets varied depending on the application, with mesh sizes ranging from 0.053 mm to 3 mm. The average moving speed of drones reached 0.58 m/s, which greatly mitigates the difficulty of collecting MPs from water surface. Up to 14,000 samples were collected within 9 min. This tool can be scaled up in the future to automate large-scale water surface cleanup of MPs. A robot vehicle was developed to collect plastic waste from beaches with an efficiency of 3000 m^2/hour, as shown in Fig. 6(c) [98]. The robot was powered by a combination of solar energy and battery and remotely operated from distances of up to 300 m, effectively collecting waste plastics and preventing them from seeping into soils. Representative studies on robotic systems for collecting MPs are listed in Table 5. The use of robots significantly improved the efficiency of collecting MPs from aquatic environments and beaches.

4.3. Processing

The primary purpose of processing tasks is to obtain clean MPs from collected samples which usually contain contaminations such as sand. Robotic systems have been developed to sort waste objects (Fig. 7). A robot is equipped with a digital camera to identify plastic objects based on deep learning. The digital camera captures images, which are then analyzed using deep learning models, enabling the models to accurately identify, locate, and classify plastic objects for intelligent control of robots to efficiently sort plastics.

Table 6 shows representative studies on sorting plastics using robots [78,80,103–108]. These robots utilize cameras and machine learning algorithms to automate sorting tasks. For example, an innovative robot was developed to detect and grasp plastic objects based on a depth (RGB-D) camera [80]. A YOLACT model was trained using 1500 images of plastic objects such as bottle caps, drinking bottles, and foam food containers. The images had complex backgrounds such as tiles, sidewalks, grass, and roads. Therefore, a model trained using such images achieved a reliable object detection capability in real-world scenarios. The RGB images from depth cameras were utilized to detect and locate plastic objects using the trained YOLACT model. Upon testing, the trained YOLACT model achieved real-time target detection based on video streams. The depth information from depth cameras helped generate point clouds to simulate the surface condition of plastic objects and aided in devising the grasp strategy. The grasp success rate exceeded 90% [80].

In reference [104], a real time waste sorting system was designed to pick up plastic objects. Various deep learning models including YOLOR, YOLOv6, and YOLOv7 were trained to detect plastic objects. The dataset used to train the deep learning models comprised 3217 images. The YOLOv6 model demonstrated the highest prediction accuracy (95.5%) in detecting plastic objects. After detecting and locating plastic objects, SolidWorks was utilized to simulate the architecture of a real robotic arm. This simulation adopted a simple geometric method to calculate the angles of the arm's joints, enabling it to pick up plastic objects quickly.

In reference [78], a robot and Mask-RCNN model was integrated to pick bottles, achieving a remarkable accuracy of 96.4%. A robot was developed employing YOLOX to detect and classify various plastic objects, such as supply bottles, beverage bottles, and tableware boxes [103]. The highest detection accuracy (90.8%) was achieved in picking express packages, whereas beverage bottles had the lowest detection accuracy (68.5%).

Current robotic arms were not designed to sort MPs, and there is a lack of research on using robots for sorting MPs. However, with the escalating pollution caused by MPs, there is a pressing need to develop robots for sorting MPs. These robots are crucial in addressing the growing concern surrounding microplastic contamination.

Table 5
Summary of robotic systems for automatic collection tasks.

Reference	Robots	Location	Automation	Year
[77]	Robotic fish	Water body	Yes	2022
[97]	Catamaran drone	Water surface	Yes	2022
[98]	Robotic vehicle	Beach	Yes	2022
[99]	Aquatic drone	Water surface	Yes	2023
[12]	Robotic vehicle	Beach	Yes	2022
[102]	Aquatic surface robot	Water surface	Yes	2020
[100]	Amphibious robot	Water surface	Yes	2023
[95]	Robotic fish	Water body	Yes	2022
[101]	Robotic vehicle	Beach	Yes	2021
[96]	Robotic vessel	Water body	Yes	2023

4.4. Characterization

Advanced technologies have been developed to character MPs regarding morphology and chemical composition. Representative technologies for data collection (Section 4.4.1) and data analysis (Section 4.4.2) are reviewed.

4.5. Data collection

(1) Microscopy.

Various microscopes, such as optical microscopes [5109], fluorescence microscopes [110,111], scanning electron microscopes (SEM) [112,113], and atomic force microscopes (AFM) [114,115] have been used to collect data for characterizing the morphology and size of MPs (Fig. 8). These microscopes differ in resolution and function.

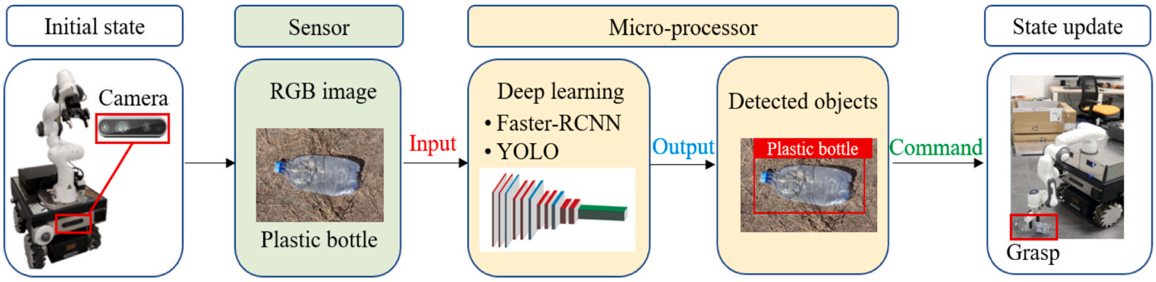

Fig. 7. Sorting plastics using a smart robot system composed of robotic arms and AI models.

Table 6
Summary of robotic systems for sorting MPs.

Reference	Robots	Data source	Algorithm	Accuracy	Year
[80]	Robotic arm	Digital camera	YOLACT	97.4%	2021
[78]	Robotic arm	Digital camera	Mask-RCNN	89.4%	2022
[103]	Robotic arm	Digital camera	YOLOX	68.5-90.8%	2023
[104]	Robotic arm	Digital camera	YOLOv7	96.5%	2023
[104]	Robotic arm	Digital camera	YOLOv6	95.6%	2023
[104]	Robotic arm	Digital camera	YOLOR	95.7%	2023
[104]	Robotic arm	Digital camera	YOLOv4	98.4%	2023
[105]	Robotic arm	Digital camera	SSD	87%	2022
[106]	Robotic arm	Depth camera	Mask-RCNN	86.5%	2022
[107]	Robotic arm	Digital camera	Mask-RCNN	97%	2023
[108]	Robotic arm	Digital camera	MobileNet_V2	99%	2023

(2) Digital camera.

Digital camera is the most used imaging system, due to the advantages such as ease of use, portability, and cost-effectiveness, making them suitable for various field projects. The drawbacks include limited magnification and certain sensitivity to lighting conditions. Digital cameras can be mounted on robots, such as drones and crawlers, to efficiently detect MPs [116]. Digital photos can be analyzed using deep learning-based computer vision methods for efficient detection of MPs, as shown in Fig. 9. More details about methodologies are available in Section 4.4.2.

(3) Fourier transform infrared spectroscopy, Raman spectroscopy, and hyperspectral imaging.

Fourier transform infrared spectroscopy (FTIR) based on the electromagnetic wave absorption has been used to evaluate chemical bonds and compositions of MPs [117]. The measured data are presented in the frequency domain to evaluate the chemical composition, as shown in Fig. 10. FTIR software generates Hit Quality Index (HQI) to measure the similarity between two spectra [117]. HQI values range from 0 to 100, with higher values indicating greater similarity between the test material and the library-stored material. Raman spectroscopy based on Raman scattering was also used to analyze the chemical compositions of MPs [118]. This involves frequency shifts of incident light waves correlated with the chemical bonds of samples. The Raman spectrum

Fig. 8. Representative types of microscopes: (a) optical microscope, (b) fluorescence microscope, (c) scanning electron microscope, and (d) atomic force microscope.

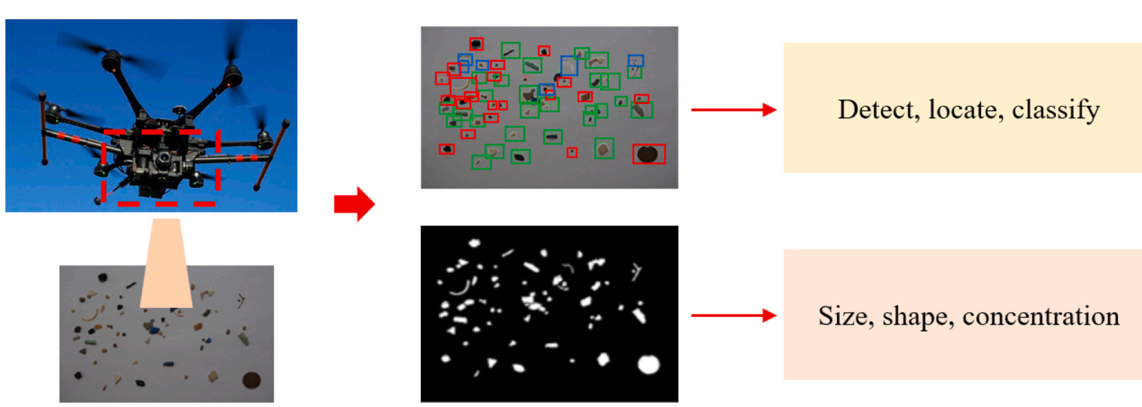

Fig. 9. Detection and quantification of MPs using digital cameras installed on a drone [116].

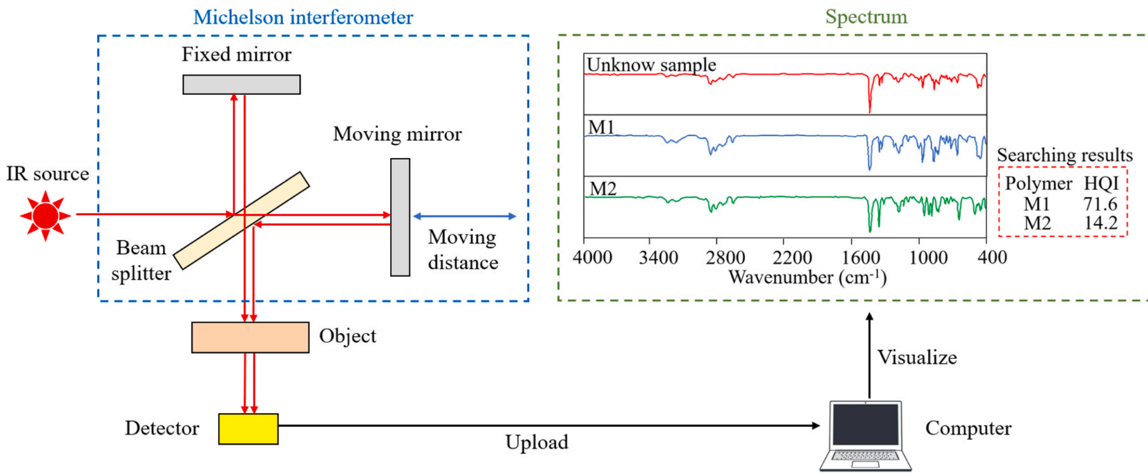

Fig. 10. Machine learning-empowered identification of polymer types via analyzing FTIR data.

represents the intensity of the inelastically scattered light as a function of its frequency shift. Each molecule has a unique Raman spectrum, acting as a molecular signature, following a concept that is similar to using FTIR fingerprints to identify polymer types.

Hyperspectral imaging techniques employ a hyperspectral camera to capture images of a sample across three dimensions (width, height, and spectrum). In contrast to FTIR devices, which provide spectral information, hyperspectral cameras provide both spectral and spatial information, as shown in Fig. 11 [119]. The spectrum of the sample is measured at each pixel to determine the polymer type, and the different polymers distributed in the image can be visualized. This is useful for characterizing samples with mixed MPs. A hyperspectral imaging technique was successfully applied to analyze MPs larger than 250 μm [119], exhibiting significantly shorter time than FTIR and Raman spectroscopy. Moreover, small-size and lightweight hyperspectral cameras (0.7 to 2.0 kg) have been developed, making them suitable for deployment on robots such as drones, as shown in Fig. 11 [120].

(4) Other techniques.

Other popular techniques for characterizing MPs include pyrolysis-gas chromatography-mass spectrometry (Py-GC-MS) [5], X-ray diffraction (XRD) [121], and thermogravimetric analysis (TGA) [122]. These techniques can effectively characterize the chemical composition of polymers in MPs. However, these techniques have not been combined with machine learning or robots.

The comparison of different methods for data collection is shown in Table 7. The collected data can be analyzed using machine learning algorithms to improve the efficiency and accuracy of detecting and characterizing MPs.

4.6. *Machine learning-assisted data analysis*

Machine learning-based methods have been developed to enable automatic identification, classification, and quantification of MPs based on the data collected using technologies reviewed in Section 4.4.1. The capabilities of machine learning methods are reviewed as follows:

(1) Identification.

Deep learning models have been developed to identify MPs from images obtained from digital cameras [123] and microscopes [81]. The concept is to train deep learning models using images labelled with MPs. The labelled pictures are the "source of knowledge" for the models to extract key features (e.g., shape, size, color, and texture) related to MPs [124]. The primary function of the trained models is to recognize key features of MPs and add bounding boxes around the detected MPs in new images unseen in the training process [125]. The images can be either photos or frames of videos [126]. A Faster-RCNN model for detecting MPs is shown in Fig. 12.

Representative applications of deep learning methods were presented in references [81,127–131]. For example, a YOLOv5 model was used to detect MPs with dimensions of 1–7 mm [127]. A digital camera was used to take photos of MPs immersed in water, each with a resolution of 3264 × 2448 pixels. These images were annotated with bounding boxes to mark MPs. The dataset used to train the YOLOv5 model had 300 images of MPs with annotations. After 200 iterations of training, the detection accuracy of MPs achieved 94%. In the results,

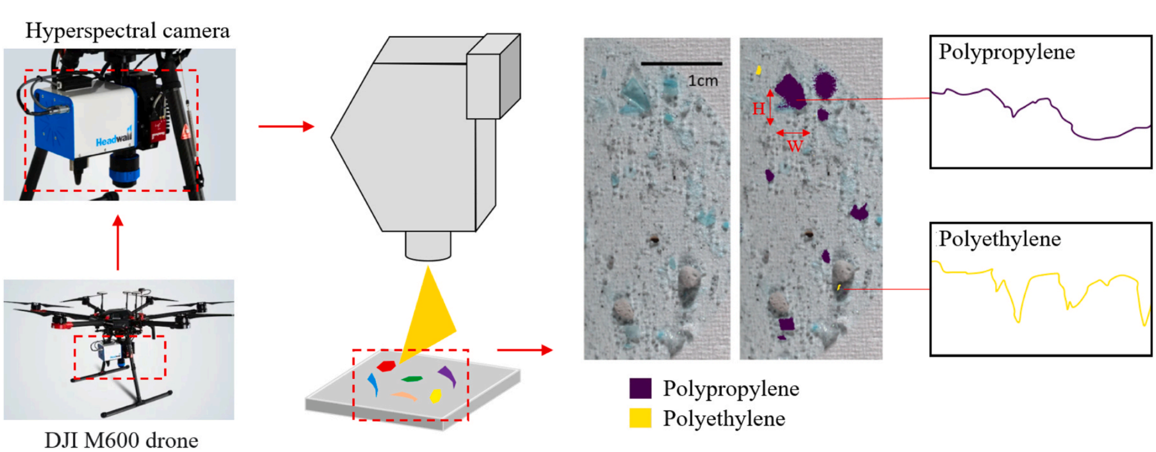

Fig. 11. Drone-based hyperspectral imaging system for identification of polymer type [119,120].

Table 7
Comparison of data collection methods.

Methods	Strengths	Limitations
Optical microscope	• Visualization • Cost-effectiveness • User friendly • Non-destructive analysis	• No chemical information • Time consuming • Limited resolution for portable device
Florence microscope	• Enhanced contrast • Specific staining techniques • Composition analysis	• Preparation and staining time • Higher price than normal optical microscope • Selective staining: not detect all polymer types
Digital camera	• Cost-effective • Portability • Ease of Use • Assembled on different platforms	• Lower magnification • Light sensitivity • Calibration requirements
SEM	• Size and shape characterization • Elemental analysis • High-resolution imaging	• Sample preparation • Costly SEM device • Destructive evaluation
AFM	• Three-dimensional imaging • High-resolution surface imaging • Non-destructive analysis	• Sample preparation • Complex operation and analysis • Slow imaging speed
FTIR	• Non-destructive evaluation • High efficiency • Minimal sample preparation • Automated data analysis • Versatility: solids, liquids, and gases	• Water vapor and CO_2 interference • Limited uses of homonuclear diatomic molecules • Complexity of data interpretation • Overlapping peaks • Costly FTIR instruments
Raman spectroscopy	• Non-destructive evaluation • High efficiency • Minimal sample preparation • Automated data analysis • Versatility: solids, liquids, and gases • Available for fine particles (~1 μm)	• Subjected to fluorescence influence • Weak signal (low signal-to-noise ratio) • Complexity of data interpretation • High-power laser, long acquisition time • Costly Raman instruments
Hyperspectral imaging	• Non-destructive evaluation • Minimal sample preparation • Automated data analysis • Assembled on different platforms	• Subjected to lighting conditions • Large amount of data • Complexity of data interpretation • Sophisticated algorithms for software • Costly hyperspectral cameras
Py-GC-MS	• Quantitative and qualitative results • Minimal sample preparation	• Destructive evaluation • Need more samples • Complexity of data interpretation • Need specialists for the operation and analysis Costly equipment and maintenance
TGA	• Thermal stability assessment • Decomposition assessment	• Costly device • Complexity of data interpretation
XRD	• Crystallinity analysis • High sensitivity and accuracy • Automated control	• Costly device • Destructive evaluation

even transparent MPs were well detected, overcoming interference from factors such as light reflection. A key advantage of the YOLOv5 model is the streamlined architecture, which enables the model to process each image within 30 ms, ensuring the effectiveness of large-scale detection of MPs. In reference [128], MPs collected from beaches were filtered through sieves (size: 0.85 mm to 4.76 mm). These MPs were mainly composed of fibers, fragments, and particles. The collected samples were spread on white paper and a total of 3000 images were taken using a digital camera with a resolution of 512 × 512 pixels. The dataset was utilized to train a Mask-RCNN model, which achieved an overall accuracy of 94% for detecting various types of MPs. The trained model showed good performance in detecting MPs on simple background. In addition, a dataset of images captured on complex backgrounds (sand, soil, and water) under different lighting conditions was used to evaluate the generalizability of the model. The accuracy of the Mask-RCNN model dropped to 80%, meaning training a model trained on simple backgrounds has reduced accuracy in complex environments. It is necessary to establish high-quality datasets to train the model, or use other methods, such as transfer learning or generative AI, to improve model accuracy for different scenarios.

Representative studies are summarized in Table 8. The results of accuracy are presented to show the advancement of these studies, rather than comparing them. It is noted that the results of accuracy are related to many factors, such as the quality and quantity of data, data processing method, and machine learning algorithm. The accuracy value of the same algorithm will change if the data and data processing method are changed. The detection model is limited to categorizing MPs based on their morphology, without the ability to identify their chemical compositions.

(2) Classification.

Machine learning models for classifying MPs have been developed to analyze data from FTIR spectrometers [14], Raman spectrometers [83], and hyperspectral cameras [133]. Machine learning models are trained using a large amount of data labelled with the type of MPs. The labelled data relate key features (e.g., shape and fingerprint information) to the type of MPs [124]. For FTIR spectrometry, the fingerprint information lies in the wavenumbers of troughs, and for Raman spectrometry data, the fingerprint information is embedded in the wavenumbers of peaks. Hyperspectral imaging data contains fingerprint information within hyperspectral cubes, encompassing both spatial (e.g., morphology) and spectral (e.g., wavenumbers) characteristics of MPs. Trained machine learning models can identify polymer types based on key features of MPs.

An example of using machine learning models for classifying MPs (PP, PVC, PET, PA, and PS) with FTIR data is shown in Fig. 13 [14,83,134]. The procedure of establishing machine learning models includes four steps: First, FTIR data are obtained and labelled for various MPs. Then, the data are processed via denoising, feature engineering, and format conversion. Next, the processed data are used to train machine learning models. Various machine learning models are trained because it is unknown which machine learning algorithm performs the best beforehand. Finally, the trained models are evaluated in terms of accuracy, generalizability, and efficiency.

Various machine learning models have been developed in literature [14–16,83,133–139]. For instance, a variety of machine learning algorithms including decision trees (DT), Gaussian Naive Bayes (GNB), k-nearest neighbors (kNN), random forest (RF), support vector machines (SVM), multilayer perceptions (MLP), and linear regression were trained to classify MPs using FTIR data, as detailed in reference [136]. The wavenumber of captured spectra ranged from 4000 cm^{-1} to 600 cm^{-1}. The dataset comprised 958 spectra that were categorized into 17 different types of polymers. A grid search was conducted to optimize the hyperparameters for each algorithm. Among these algorithms, SVM demonstrated the highest prediction accuracy, which varied between 72% and 100% across different polymer types. The highest prediction accuracy was observed for cellulose acetate, while the lowest was for "polyethylene like".

In addition to the use FTIR data, Raman spectrometry have been used in a similar way [83]. In reference [139], a database was constructed using 3675 Raman spectra from six types of MPs (i.e., PP, PE, PS, PC, PVE, and PET). Each spectrum was standardized to a consistent wavenumber range from 500 cm^{-1} to 1800 cm^{-1}, which included most

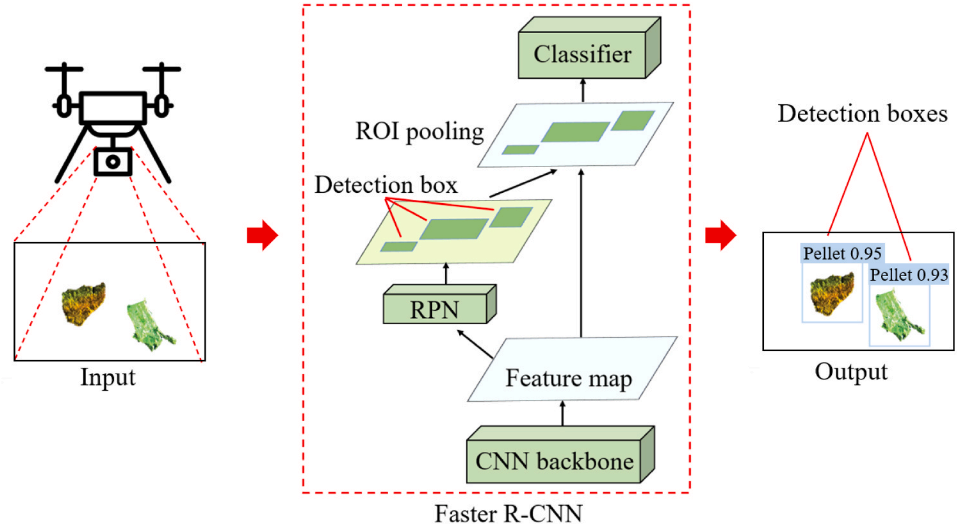

Fig. 12. Flowchart and architecture of a Faster-RCNN model developed for detecting MPs.

Table 8
Summary of deep learning methods for identifying MPs.

Ref.	MPs	Data source	Algorithm	Accuracy	Year
[130]	Pellet	Digital camera	YOLOv5	89%	2021
[123]	Fragment, fiber, film, pellet	Digital camera	Mask-RCNN	93%	2022
[123]	Fragment, fiber, film, pellet	Digital camera	SSAP	86%	2022
[81]	Pellet	Microscope	Faster-RCNN	98.5%	2023
[81]	Pellet	Microscope	SSD	96%	2023
[127]	Pellet	Digital camera	YOLOv5	94%	2023
[128]	Fragment, fiber, rod, pellet	Digital camera	Mask-RCNN	94%	2023
[129]	Pellet	Digital camera	YOLOv5	100%	2023
[132]	Plastic debris	Digital camera	YOLOv3	83.4%	2023
[131]	Fragment, fiber, pellet	Digital camera	Faster-RCNN	85.5%	2024

characteristic peaks. The dataset was divided into a training set (80%) and testing set (20%). The spectra dataset was trained using a sparse-autoencoder. After 2500 iterations of training, the model achieved an overall accuracy of 99.1%. Additionally, traditional machine learning methods such as SVM and MLP demonstrated lower accuracy on this dataset, achieving prediction accuracies of 94.0% and 74.6%, respectively. Representative results of machine learning models for classifying MPs are shown in Table 9. The results of accuracy are not used to compare the different models because accuracy is related to many factors. Currently, the primary challenge is the absence of a high-quality open-source dataset for training machine learning models used to identify MPs.

Advanced algorithms are required to process data obtained from hyperspectral cameras. In reference [133,600 hyperspectral data were collected from soil samples with a hyperspectral camera in the wavelength range of 369 nm to 988 nm. The spectra underwent denoising through smoothing techniques, and principal component analysis (PCA) was applied to compress the data. The collected data were used to train a CNN model for classifying PE, PP, and PVC. The model achieved an overall prediction accuracy higher than 93%. In reference [140], a framework used to process the hyperspectral data was proposed. The collected spectra were preprocessed to highlight the difference between various types of MPs. Hyperspectral curves were clustered using the PCA method, and partial least squares discriminant analysis was performed to calculate the differences between the unknown polymers and the clustered data, as shown in Fig. 14 [140].

(3) Quantification.

Machine learning models have been developed to quantify MPs from images via distinguish the pixels representing MPs (Fig. 15) [19]. First, the original images are converted to binary images where MPs are shown in black color and the background is shown in white color. Then, the sizes and abundance of MPs are quantitatively evaluated using a machine learning model and computer vision techniques. The pixel numbers representing MPs are quantified along the horizontal and vertical directions. With the pixel numbers, the sizes of MPs are

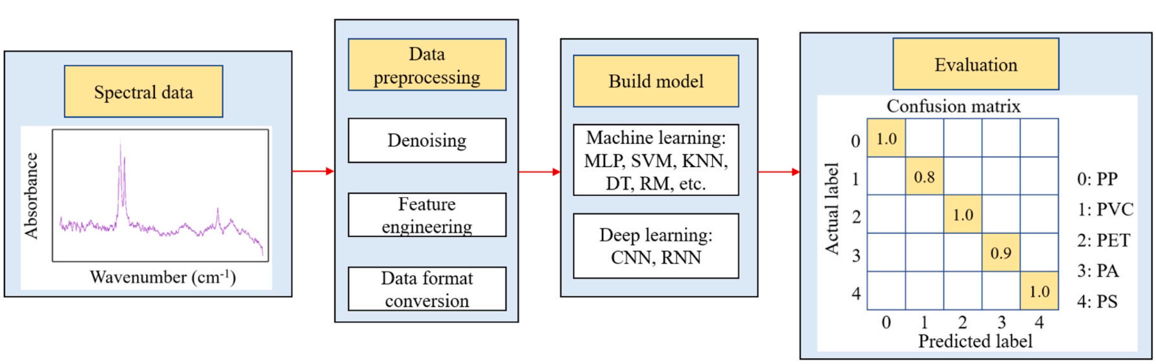

Fig. 13. Procedure of using machine learning models to classify the types of MPs with FTIR data.

Table 9
Summary of machine learning methods for classifying MPs.

Reference	Data	Machine learning method	Application	Accuracy	Year
[14]	FTIR	2-D CNN	Classification	99%	2021
[15]	FTIR	Autoencoder	Denoise	-	2021
[135]	FTIR	KNN	Classification	> 90%	2019
[16]	FTIR	PCA + SVM, KNN, LDA	Classification	99%	2020
[136]	FTIR	Naïve Bayes, MLP, KNN, SVM, DT	Classification	94%	2022
[134]	FTIR	Recurrent neural network	Classification	94.8%	2023
[137]	FTIR	1-D CNN	Classification	87%	2021
[138]	FTIR	2-D CNN	Classification	99.2%	2023
[83]	Raman	KNN, RF, MLP	Classification	> 95%	2022
[139]	Raman	Sparse-autoencoder	Classification	99.1%	2023
[133]	Hyperspectral	PCA + 2-D CNN	Classification	97%	2022

determined by a relationship, established based on computer vision techniques [126], between the pixel size and physical length. The pixel number is converted to a physical length using the ratio of the focal length to the distance between the camera and MPs. With the sizes of all MPs in each image, the abundance of MPs is evaluated by considering many images. The quantity of MPs can also be counted from the images via border analysis [126]. The above methods have been applied to quantify cracks [124,141], but there are limited applications for MPs.

Semantic segmentation models have been employed to quantify MPs as detailed in references [82,116,128,143–145]. In reference [82], a deep learning model was trained using a dataset of 1498 images of fragments, pellets, and fibers. These images were labeled and reformatted into binary data to train a Mask-RCNN model, which achieved an average segmentation accuracy of over 75% with a processing time of 0.2 s per image. The low quality of the training dataset explains the limited accuracy. In reference [143], deep learning architectures such as U-Net and MultiResUNet were employed to analyze fragments, pellets, and fibers from SEM images. A dataset comprising 237 images was used to train these models. Upon comparison, MultiResUNet exhibited superior accuracy. The highest classification accuracy was achieved for pellets at 93.6%, while the lowest accuracy was observed for fibers at 74.3%. In reference [128], both Mask-RCNN and U-Net were trained to assess MPs using a dataset of 2100 images with a resolution of 512 × 512 pixels. The Mask-RCNN model demonstrated an accuracy of 93.4% on a white background and 80% on complex backgrounds involving soil, sand, and water.

Representative results of deep learning models are summarized in Table 10. The accuracy results are presented to show the performance of these models, rather than comparing different models or recommending certain models. While instance segmentation techniques have been used in the analysis of MPs, further research should focus on using these methods to accurately measure the size and determine the abundance of MPs.

5. Challenges and opportunities

5.1. Technology readiness level

The technology readiness levels (TRLs) of the methods for the collection and characterization of MPs reflect the maturity of different methods and are important metrics in selecting appropriate methods according to the recommendation of the United States Department of Energy [146]. The value of TRL is from 1 to 9, with 9 for mature technologies, as shown in Fig. 16, consistent with reference [147].

The TRLs and other key features of the reviewed methods are summarized in Table 11. The cost column refers to the price of the required instruments. The data format column refers to the format of data used for collecting and characterizing MPs. The polymer type and particle size columns refer to the types and the sizes of polymers that can be handled by the methods. The field use column refers to the readiness of the methods for field applications. The TRL values of conventional methods are 9, indicating mature commercial devices. Prototype robots, such as robotic fish and drones, have been developed for collection tasks, but the prototype robots still require significant improvement and validation in relevant environments, resulting in a TRL level of 7. Robots

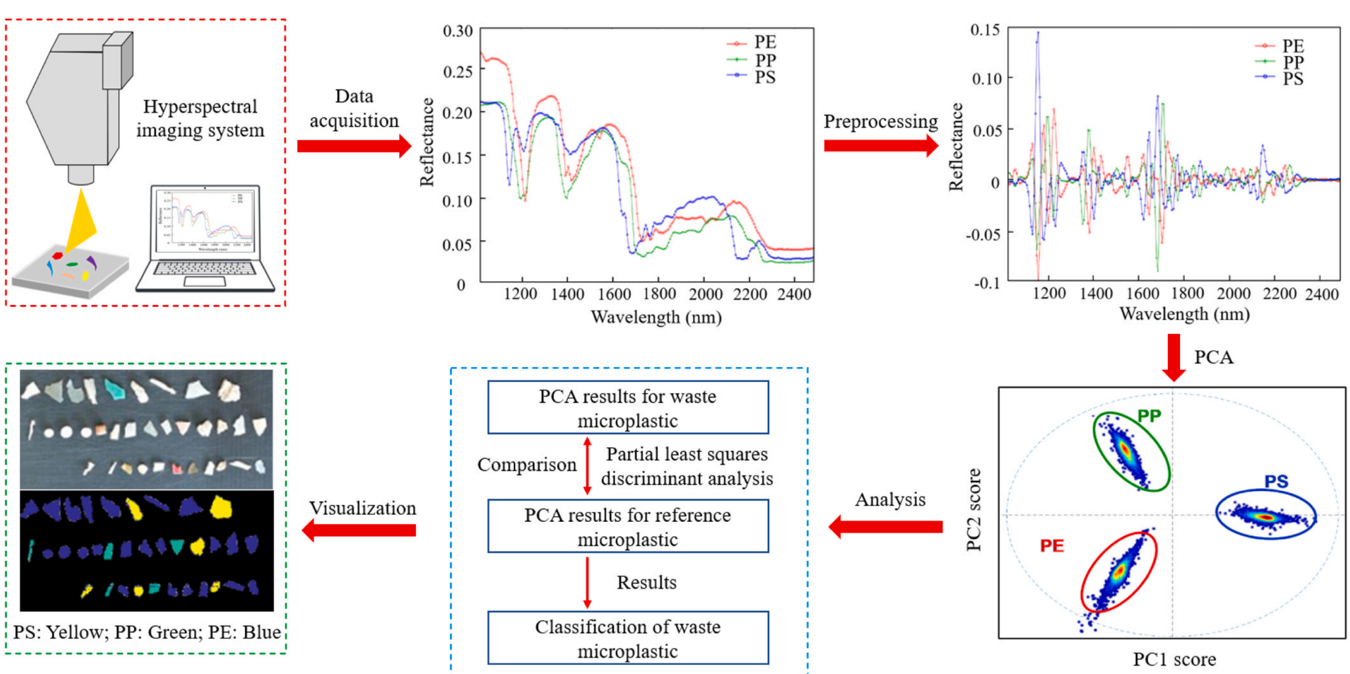

Fig. 14. Deep learning-based classification of MPs based on hyperspectral imaging data [140].

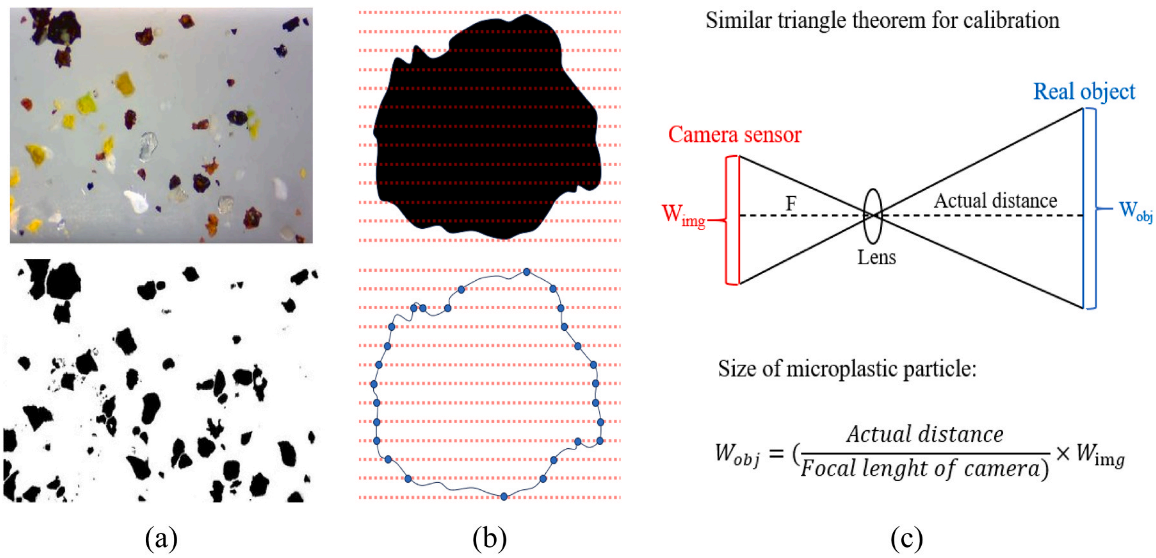

Fig. 15. Deep learning and computer vision techniques for: (a) segmentation of MPs [142], (b) quantification of pixels for MPs, and (c) calibration of the length ratio.

Table 10
Summary of deep learning methods for segmentation of MPs.

Reference	Data	Machine learning	Application	Accuracy	Year
[143]	SEM images	U-Net	Segmentation	93.1%	2022
[116]	SEM images	MultiResUNet	Segmentation	93.6%	2022
[116]	Digital images	U-Net	Counting	98.8%	2021
[82]	Digital images	Mask-RCNN	Segmentation	> 75%	2023
[128]	Digital images	U-Net	Segmentation-white background	93.2%	2023
[128]	Digital images	Mask-RCNN	Segmentation-white background	93.4%	2023
[128]	Digital images	U-Net	Segmentation-complex background	37.5%	2023
[128]	Digital images	Mask-RCNN	Segmentation-complex background	80%	2023
[144]	Digital images	U-Net	Segmentation	98.5%	2023
[144]	Digital images	UNet3plus	Segmentation	92.1%	2023
[145]	Fluorescent microscope images	U-Net	Segmentation	73.6%	2022

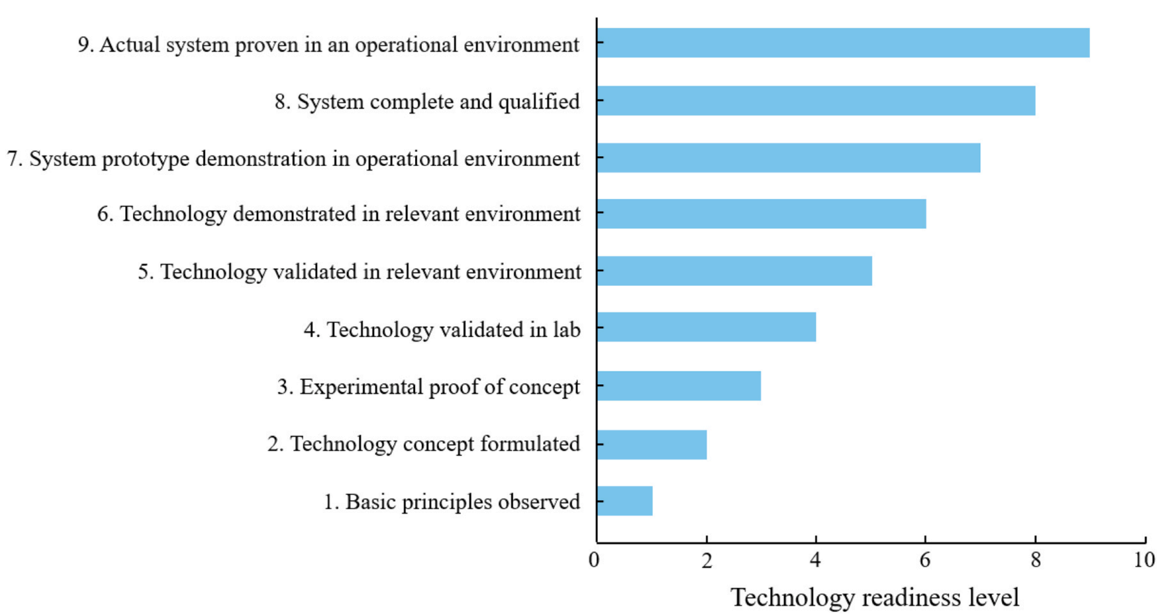

Fig. 16. Technology readiness levels according to the United States Department of Energy [146].

Table 11
Summary of the reviewed technologies.

Methods	TRL	Cost	Data format	Polymer type	Particle size	Field use	Automation
Optical microscope	9	Low	2D image	No limitation	No limitation	Yes	No
Fluorescence microscope	9	Low	2D image	Compatible with fluorescent dyes	No limitation	No	No
SEM	9	High	2D image	No limitation	Size limitation	No	No
AFM	9	High	2D/3D image	No limitation	Size limitation	No	No
FTIR	9	High	1D spectra, 2D image	No limitation	No limitation	No	No
Raman	9	High	1D spectra, 2D image	No limitation	No limitation	No	No
Portable FTIR/Raman	9	Low	1D spectra	No limitation	No limitation	Yes	No
Hyperspectral imaging	9	High	1D spectra /2D image	No limitation	No limitation	Yes	No
Digital holography	9	High	3D image	No limitation	No limitation	Yes	No
Py-GC-MS	9	High	1D spectra	No limitation	Size limitation	No	No
XRD	9	High	1D spectra	No limitation	Size limitation	No	No
TGA	9	High	1D spectra	No limitation	Size limitation	No	No
Robots-collection	7	Low	-	No limitation	No limitation	Yes	Yes
Robots-sorting	2	Low	-	No limitation	No limitation	Yes	Yes
AI-classification	4	Low	1D spectra, 2D image	No limitation	No limitation	Yes	Yes
AI-detection	4	Low	2D image	No limitation	No limitation	Yes	Yes
AI-quantification	4	Low	2D image	No limitation	No limitation	Yes	Yes

for sorting tasks are still in an infant stage, and prototypes have not been developed, thus having a TRL level of 2. Machine learning models for the detection, classification, and quantification tasks have been developed in the laboratory and validated using various images, exhibiting adequate performance for real applications. However, those models have not been fully validated in relevant environments with the consideration of various lighting conditions and complex environments, thereby resulting in a TRL of 4.

5.2. Economic and environmental assessment

An economic analysis has been performed to assess the economic viability of deploying robots and machine learning models – AI-empowered robot approach, for collecting and characterizing MPs [148]. The total cost is the sum of capital and operating costs. The capital cost encompasses one-time investments like equipment purchase, and the operating cost encompasses ongoing costs such as materials, labor, and energy. The AI-empowered robot approach is compared with the traditional manual approach, as listed in Table 12.

The costs are analyzed based on a task for characterizing MPs in an area of 1 hectare (10,000 m^2). In this task, two primary assumptions have been adopted: (1) There are 10 pieces of plastic debris per square meter on average. (2) The average times for collecting and sorting plastic debris are respectively 3 s and 2 s per piece of plastic debris. Due to the large number of debris (100,000), only a hundredth of them (1000 samples) are characterized for the comparison. This is conservative because the traditional manual approach has lower efficiency in characterizing plastic debris compared with the AI-empowered robot approach. Reducing the number of samples reduces the operation cost of the traditional manual approach.

Table 12
Comparison of the costs of lab-based and AI-empowered approaches.

Method	Task	Capital cost		Operation cost	
		Type	Cost (USD)	Time	Rate (USD/h)*
Manual	Collection	Manual operation	-	83.3 h	15
	Sorting	Manual operation	-	55.5 h	15
	Characterization	FTIR	22,000 [149]	8.3 h	60
Robot	Collection	UAV	7000	-	-
	Sorting	Robot arms	1400 [150]	-	-
	Characterization	UAV-SWIR camera	23,000 [151]	10 min	-

* Note: The wage rates listed are based on prevailing wage report of New Jersey, United States [152].

As shown in Fig. 17, the economic analysis results reveal that the capital cost of the AI-powered robot approach is 9400 USD higher than that of the traditional manual approach. However, the operation cost of the AI-empowered robot approach is significantly lower than that of the traditional manual approach. The difference of operation cost per hectare is 2441 USD, meaning that the total cost of AI-empowered robot approach is lower than that of the traditional manual approach when the approach is used for 4 ha.

The environmental benefits of using AI-empowered robots for collecting and characterizing plastic wastes include reducing the environmental footprint by optimizing operations, minimizing fuel consumption and emissions, and preserving marine ecosystems. These are discussed in the three primary aspects as follows:

(1) AI-empowered smart robots have higher time efficiency and precision in operations, as shown in Table 12. The higher time efficiency and precision reduce the time required to search for plastic debris and minimize unnecessary travels, thereby reducing fuel consumption and emissions associated with travels. The use of AI technology enables remote monitoring and control of robots, allowing operators to optimize operations without having to send humans to the job site, further reducing energy usage and emissions related to transportation.

(2) Advanced machine learning algorithms such as reinforcement learning enable robots to autonomously navigate marine environments, optimizing routes based on real-time data such as ocean currents, wind patterns, and microplastic distribution. This reduces the travelling distance and associated fuel consumption, contributing to reducing carbon emissions. In addition, machine learning models can be trained to analyze historical data and environmental variables to develop optimized deployment strategies for robots. By strategically positioning robots in areas with rich plastic debris, the collection tasks will minimize the travelling distance and maximize efficiency, further reducing negative environmental impacts.

(3) The use of AI-empowered smart robots facilitates on-site detection and efficient inspection of plastic debris compared with traditional manual approaches, eliminating or minimizing the need for transporting samples, thereby saving energy and reducing environmental impact. This also helps preserve fragile marine ecosystems by minimizing human intervention.

5.3. Regulatory, ethical, and social implications

The utilization of robots and machine learning models in environmental monitoring prompts inquiries about regulatory oversight [153] liability for errors or accidents [154] and compliance with data

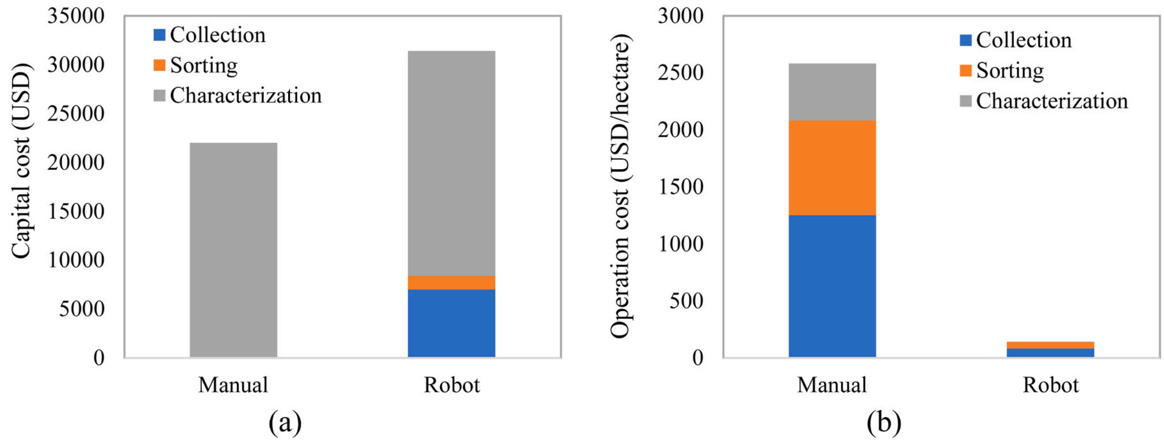

Fig. 17. Economic analysis results for the traditional manual and AI-empowered robot approaches: (a) capital cost; and (b) operation cost.

protection [155] and privacy regulations [153]. Legal frameworks and standards are imperative to govern the deployment and operation of these monitoring technologies. Establishing guidelines and standards is crucial to address concerns regarding the accuracy and reliability of monitoring results [156], potential biases introduced by AI algorithms [157], and errors in AI algorithms [158] that could lead to incorrect assessments or decisions. Moreover, it is essential to regulate the deployment of robots in sensitive areas to mitigate potential risks to ecosystems [159]. Questions also arise regarding data ownership and control [160], necessitating clear policies and regulations to govern data ownership, sharing, and use.

Ethical considerations surrounding the use of robots and machine learning in environmental monitoring include the potential displacement of workers [161], the equitable distribution of monitoring resources [162], and the unintended consequences of automated decision-making on communities and ecosystems [163]. Efforts should be made to mitigate negative economic impact on affected workers and communities. Using robots and machine learning in environmental monitoring should consider the needs and perspectives of marginalized communities, ensuring equitable access to environmental data. The deployment of robots and machine learning technologies in environmental monitoring may have unintended consequences, such as unintended environmental impacts, social disruptions, or unforeseen risks. To minimize harm, ethical considerations should guide the design, deployment, and evaluation of these technologies.

The social implications of utilizing robots and machine learning in environmental monitoring are multifaceted, necessitating careful consideration of economic, technological, and cultural factors to maximize benefits and mitigate risks for society. While robots and machine learning can significantly enhance the efficiency of environmental monitoring efforts [164–166], leading to more comprehensive and timely data collection, they also help improve public awareness about environmental issues and encourage community engagement in conservation efforts. Interactive platforms and visualizations generated by robot and machine learning technologies can help educate and empower citizens to take action to protect the environment [167]. The improved efficiency in environmental monitoring empowers communities to participate in environmental monitoring and governance processes, enabling local stakeholders to collect and analyze data relevant to their specific concerns. Participatory monitoring initiatives can foster community resilience and support bottom-up approaches to environmental management. Introducing robots and machine learning into environmental monitoring requires navigating cultural and social norms regarding technology adoption and trust [168]. Building trust and acceptance among diverse communities is critical to ensure the successful implementation of these monitoring technologies.

5.4. *Advantages and challenges*

The use of AI-empowered robot approach for identification, classification, and quantification of MPs has the following advantages compared with the conventional methods:

(1) High efficiency: The measurement data, such as FTIR and Raman spectrometry data and hyperspectral images, are analyzed and interpreted quickly by machine learning models. The computation time for each data is often shorter than 0.2 s for segmentation tasks [82] and 0.03 s for detection tasks [127], making it possible to achieve real-time or near-real-time characterization of MPs.
(2) High accuracy: Machine learning models trained using the data of MPs provide consistent characterization results and are free of human errors, thereby eliminating the uncertainties related to engineers. The trained detection models can achieve overall accuracies ranging from 83.4% to 100% (Table 8). The classification accuracy typically exceeds 90% (Table 9). The segmentation task is challenging and has lower accuracy in certain applications (Table 10). More efforts are necessary to improve segmentation accuracy.
(3) Full automation: Machine learning models can operate automatically, such as a fully automated collection device [97], robotic arms for sorting MPs [80], drones and other remote sensing technologies used for the detection and characterization of MPs [19]. These technologies can operate with no or minimal human intervention, thereby mitigating the dependence on engineers and reducing labor-related expenses.
(4) Full digitalization: Machine learning models provide digital results which are computer understandable and operatable. The digital results can be stored and utilized conveniently. For example, the results can be used to develop and update digital models [169].

The use of robots and machine learning methods for identification, classification, and quantification of MPs still has limitations:

(1) Dependance on data: Data is the source of knowledge for machine learning models. Both the quality and quantity of data play significant roles in the performance of the machine learning models trained using the data. A general challenge in the domain of MPs is the lack of high-quality databases available for developing machine learning models.
(2) Limited generalizability: In existing research, machine learning models have been trained using particular datasets that have limited number of data and lack diversity in the data. In general, a

machine learning model trained using a particular dataset has low performance when a different dataset is used. The low generalization performance has generated major concerns in real practices because real applications may involve new data that cannot be recognized by the machine learning model trained using a small dataset. For example, deep learning models trained using photos collected under laboratory conditions are not suitable for complex scenes in the real world, as reported in [128].

(3) Lack of interpretability: Machine learning models are generally black-box models. When a machine learning model is used to characterize MPs, the model outputs the result without explaining how and why the result is generated. It is difficult for engineers to trace and check the results from machine learning models. This also cause concerns about the reliability and uncertainty of machine learning models in real practice.

(4) Robot deployment: MP particles are small, requiring robots with precise sensing capabilities and maneuverability to effectively detect and characterize small microplastic particles. The limited resolution of digital cameras presents a challenge in imaging MPs, necessitating the strategic selection of appropriate cameras [170]. Digital cameras are not designed to achieve a high level of magnification required to detect tiny objects. Standard digital cameras, such as those with 720 P resolution, often cannot identify MPs [171]. Using cameras with 10 megapixel or more also presents additional challenges, such as increased cost. In addition, robots have difficulty in navigating complex environments, such as swamps and densely vegetated areas, where microplastic pollution may accumulate [172]. These terrains are not only physically challenging due to uneven ground or waterlogged soil that hinders movement but also pose significant obstacles for using sophisticated sensors to effectively detect and characterize MPs. Maintaining reliable communication and control over robots in remote or harsh environments is difficult, especially underwater or in dense vegetation where signal loss can occur [173].

5.5. Opportunities

The following opportunities have been identified for future research on further developing AI-empowered methods for collecting and characterizing MPs:

(1) The advancement in smart robots and machine learning has created new opportunities for advancing robots to streamline automatic identification, collection, and characterization of MPs. It is promising to develop smart robots with the capabilities of automated survey and path optimization for self-operation in various environmental conditions [174]. It is important to incorporate advanced sensors into robots for self-sensing and advanced machine learning algorithms such as reinforcement learning for self-navigation [175].

(2) To address the challenges of lack of data for machine learning models used to characterize MPs, with the advances in generative AI techniques [176], it is promising to develop generative AI models for producing artificial yet reasonable data that can be used to enrich the databases for training and testing machine learning models, improving their performance in terms of accuracy and generalizability.

(3) To address the challenges of interpretability of machine learning models, it is promising to develop knowledge-guided machine learning methods [177]. Domain knowledge can be incorporated into machine learning models to achieve interpretability.

(4) The development of high-quality datasets to train benchmark models for detecting and characterizing microplastics is another pressing task. For instance, creating FTIR spectral datasets for classifying MPs and developing high-definition photographic datasets for the detection and quantification of MPs.

6. Conclusions

This paper presents a comprehensive review on the categories and distribution, AI-empowered technologies, and challenges and opportunities for the collection and characterization of MPs. The following conclusions can be drawn:

- Fragments and fibers are the primary morphological types of MPs, while PE and PP are the dominant compositions found in MPs. MPs are widely distributed over the earth in the water and soil systems. The physical and chemical properties of MPs show significant differences in different regions. The differences reveal the importance of characterizing and monitoring MPs in different regions with effective and efficient methods.
- Various AI-empowered technologies have been developed and implemented to collect, process, and characterize MPs intelligently and efficiently. Representative technologies include smart robots for collecting and sorting MPs and machine learning models for analyzing and interpreting the characterization data for MPs. Various types of instruments for characterizing MPs can be integrated into robotic platforms to automate the process of collecting characterization data, and machine learning models can be trained to detect, classify, and quantify MPs without human intervention. Integrating robotic systems and machine learning models can automate the collection and characterization for MPs.
- While commercial instruments for characterizing MPs have reached a high level of maturity and application, the TRL of AI-empowered technologies remains relatively low. In particular, the development of machine learning models used for data analysis is still at its early stage, despite rapid progress in recent years. Important challenges have been identified from the literature of AI technologies, and relevant opportunities have been discussed, aimed at promoting further research and development of AI technologies.

Environmental implication

Microplastics are hazardous materials because they cause various health problems to animals and humans. Marine organisms can mistake microplastics for food. Microplastics adsorb and carry pollutants in water, accumulate toxins, and aggravate water pollution. Microplastics enter the food chain via seafood and drinking water. Microplastic ingestion causes abrasive effects, inflammation or reproductive issues, developmental problems, and immune responses. This paper reviews artificial intelligence-empowered technologies employed in the collection and characterization of microplastics. A framework is presented to integrate efforts for collecting, processing, and characterizing microplastics. Emerging robots and machine learning technologies are reviewed to promote research on mitigating microplastics pollutions.

CRediT authorship contribution statement

Yuhuan Wang: Writing – review & editing, Investigation, Data curation. **Pengwei Guo:** Writing – original draft, Visualization, Investigation, Formal analysis, Data curation. **Parastoo Moghaddamfard:** Investigation, Data curation. **Yi Bao:** Writing – review & editing, Supervision, Resources, Methodology, Funding acquisition, Conceptualization. **Shenghua Wu:** Writing – review & editing, Validation, Formal analysis, Conceptualization. **Weina Meng:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Formal analysis, Conceptualization.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yi Bao received funding from the United States National Oceanic and Atmospheric Administration.

Data availability

Data will be made available on request.

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