

The Evolution of Polymer Sorting Techniques: A Strategic Roadmap Toward Global Plastic Sustainability

Radhika Grover¹, Ritu Boora², Manisha Jangra³, Kuldeep Singh⁴, Priyanka Dalal⁵, Priyanka Jangra⁶

^{1,2,3,4,5,6}Guru Jambheshwar University of Science and Technology, Hisar, Haryana, India.
Corresponding Author: Ritu Boora

Abstract

Worldwide, more than 460 million metric tons of plastic are produced annually; less than 10% is recycled, which demands the development of industrial-scale automated sorting platforms. This paper presents a taxonomy of plastic classification and reviews state-of-the-art sorting paradigms. Comparative analysis revealed that physical and mechanical sorting techniques (including sink-float separation, air classification) achieve up to 99.7% polyolefin recovery; chemical and spectroscopic sorting techniques (including NIR, RAMAN, LIBS) achieve 96-100% identification accuracy; and intelligent and advanced automated sorting systems (using AI computer vision and digital watermarking) (including Vision Transformers) achieve 99.75% classification accuracy. Nonetheless, a key gap in the literature exists: these high accuracies are achieved on clean laboratory datasets and drop off in real-world facilities due to the systemic challenges presented by data scarcity, sensor limitations (including carbon-black blindness), model latency, system integration, and economic scalability. Future research should focus on hybrid multi-sensor fusion, edge-optimised AI, and synchronised physical actuation of smart sorting solutions.

Keywords: waste management, Chemical and spectroscopic sorting, automated sorting systems, Deep learning, Computer Vision, plastic classification

Date of Submission: 06-10-2026

Date of Acceptance: 17-10-2026

I. Introduction

Plastic has become an essential component of the modern world because of its strength-to-weight ratio, cost-effectiveness, resilience, and other properties. However, the situation with plastic today is critical and needs to be addressed. According to the OECD estimates, there are 460 million tons of plastic produced worldwide every year (OECD,2022). However, less than 10% is currently being recycled globally (Geyer *et al.*, 2017). The remaining amount is either placed in landfills or enters the natural environment (OECD,2022). Approximately 5-13 million tons of plastic waste enter the oceans annually, causing tremendous ecological damage (Jambeck *et al.*, 2015). Being non-biodegradable, it is permanently integrated into the environment, where it is gradually broken down into even smaller pieces, turning into microplastics. A number of marine species have already gone extinct as a consequence of that imbalance and other related irreversible impacts that would affect the ecosystem in the long run. It completely deforms the chemical structure of oceans and land, making them impossible for any form of life that once lived there to survive. Constant abrasion and UV exposure cause plastic to break down into smaller and smaller pieces until it reaches the stage of microplastics. Microplastics are now ubiquitous in the environment, being present in large bodies of water as well as in the water we drink. Recent studies have shown that ~90% of proteins have microplastic contamination, proving that we consume plastic on a regular basis (Milne *et al.*, 2024). Biological accumulation of plastic in creatures is happening because of the biomagnification process, where the concentration of a chemical substance increases as we move up in the food chain. Furthermore, plastic's hydrophobic property does not allow toxins to be excreted and causes many health problems such as cancer, neurological problems, cardiovascular diseases, etc., in humans over time.

As plastic waste generation is larger than waste management technologies, sorting the waste on an industrial scale is necessary for the transition from a linear to a circular economy. This turns waste into a valuable opportunity and reduces the amount of waste sent to landfills and oceans, thereby reducing its hazardous impact on the environment. The paper reviews the existing waste sorting methods to find their limitations and give way for future scope in this research field. The remaining part of this paper is structured as follows: Classifications of plastics are presented in Section II, followed by a comparative study of plastic sorting techniques in Section III, while Section IV presents the Discussion and analysis of the results.

II. Classification of Plastics

The plastics can be classified into various categories based on the range of durability, physical, chemical or thermal properties, source and size, as illustrated in Figure 1. This helps the sorting techniques to put them in different categories. These classifications are detailed in this section. A consolidated comparative evaluation of the classification of plastics is presented in Table 1.

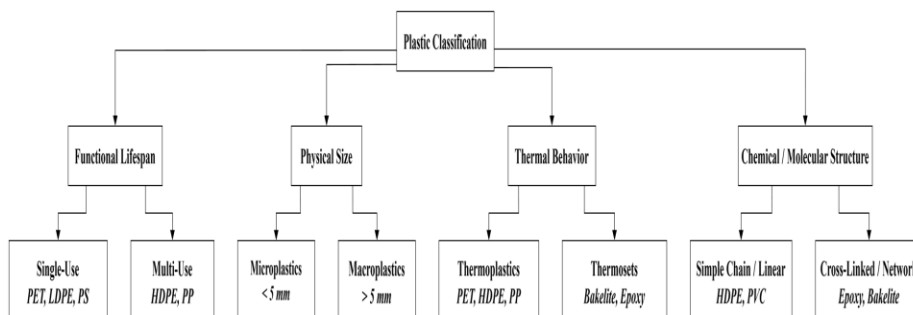


Figure 1: Plastic Classification

Based on durability profile: Plastics are classified into single-use and multi-use plastics based on their functional service life. Single-use plastics such as water bottles (PET), grocery bags (LDPE), and disposable forks or straws (PS) are designed for a single use, while Multi-use plastics, also known as durable plastics, include industrial containers (HDPE), automotive components (PP), and high-performance engineering resins used in electronics.

Based on size: Microplastics and macroplastics are two subtypes of plastic debris classified on the basis of their size. Microplastics are plastics of size less than 5 mm. Most of these particles are formed due to fragmentation of plastics that happens through the breakdown of large plastic particles into smaller plastic particles. They are considered to be extremely dangerous to life, which has been confirmed, with over 90% of the plastic particles found in the tested protein samples (M. H. Milne et al., 2024). Macroplastics are plastics larger than 5 mm and take a very long time to break down. In fact, it would take a million years for macroplastics to break down into microplastics, and even then it would require a very long time for them to break down. For example, large plastic bottles can take years to break down into microplastics.

Table 1: Comparative classification of plastics

Classification Type	Basis of Classification	Definition	Key Characteristics	Limitations
Single-use plastics	Functional lifespan	Plastics used once before disposal	Lightweight, cheap, commonly used in packaging	Cause major pollution, very low recycling rate
Multi-use plastics	Functional lifespan	Plastics designed to be used multiple times before disposal	Durable, reusable, long-lasting	Can degrade over time, may form microplastics
Microplastics	Size	Plastic particles with size smaller than 5mm	Persistent, harmful, obtained from primary/secondary sources	Hard to detect and remove, can cause extreme health issues
Macroplastics	Size	Plastic particles with size larger than 5mm	Visible, major part of plastic waste	Break down into microplastics over time
Thermoplastics	Thermal behaviour	Plastics that can be reshaped multiple times by changing temperature	Recyclable, widely used	Properties weaken after repeated heating cycles
Thermosets	Thermal behaviour	Plastics which cannot be reshaped after curing	Strong, heat-resistant, chemically stable	Can not be recycled by melting, difficult to reuse
Simple chain plastics	Molecular structure	Plastics having a simple linear structure	Flexible, low density, easier to recycle	Lower strength and heat resistance
Cross-linked plastics	Molecular structure	Polymers with chains joined by covalent bonds, forming a 3D network	Very strong, rigid, heat and chemical resistant	Cannot be remelted, not recyclable

Based on thermal behaviour: Thermoplastics and thermosets are two types of plastics divided on the basis of their thermal behaviour or properties when exposed to heat. Thermoplastics are those materials that become soft

or pliable with heat. They can be re-melted and re-shaped. This happens because the intermolecular bonds are very weak, so they can be broken and rebuilt several times. They are the main target for the process of recycling. Examples: PET, HDPE and PP. Thermosets are plastics which are ‘set’, meaning that once they are cured, they cannot be remelted or reshaped. If subjected to high temperatures again, they do not soften but instead degrade or decompose. The reason behind this is that they form a highly cross-linked, three-dimensional network with extremely strong intermolecular bonds during their initial moulding. Examples: Bakelite, melamine, epoxy resin, vulcanised rubber, etc.

Based on chemical composition: This classification of polymeric materials is fundamentally based on their structural morphology, which is a function of their chemical composition. To attempt an internal division of plastics, we divide them based on their chemical format, i.e., simple chain plastics and cross-linked plastics. Single-chain plastic polymers have a simple linear structure with no branched sequences, held together by Vanderwall forces of attraction. Examples: HDPE, PVC, PS, polyamides, etc. Cross-linked plastic polymers undergo intermolecular bridging, creating permanent covalent bonds and forming a three-dimensional lattice. They are also known as network polymers. It includes Epoxy resin, Bakelite, urea-formaldehyde, and more.

III. Plastic Sorting Techniques

Sorting refers to the segregation process of mixed plastics into relatively homogeneous and high-purity streams according to several factors, including colour, polymer, origin, density, among others. Segregation and sorting seem synonymous, but they are different plastic recycling processes. Segregation refers to the process of separating plastics from other kinds of waste, while sorting means separating mixed plastics. Plastic sorting techniques can mainly be categorised into 3 ways, as illustrated in Figure 2. A consolidated comparative evaluation of the primary plastic sorting techniques discussed above is presented below in Table 2.

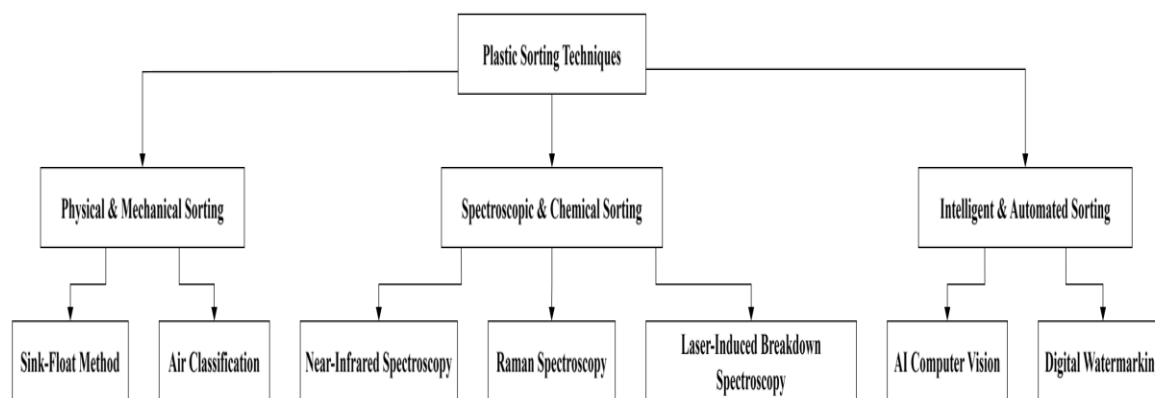


Figure 2: Classification of Plastic Sorting Techniques

1. Physical and Mechanical Sorting: This is the foundational step in plastic sorting, which is primarily executed in two ways: sink-float and Air Classification.

Sink-float method: This method utilises a tank filled with a liquid that is generally water to segregate shredded plastic flakes based on the difference in their densities. Lighter polymers like PET and PVC will float as they possess lower density, while heavier ones will sink, like PE and PP, because of higher density. Pilot-scale batch separation tests were undertaken with a sequential aqueous salt (tap water, sodium chloride brine at 11-40% w/v) and alcohol (23-31% v/v ethanol) extraction in combination with high-speed centrifugation to recover virgin and post-consumer municipal plastic waste (HDPE, PP, PS, ABS, PA, PC, PET, PVC). The use of tap water alone accounted for a 97.5% recovery of light polyolefins (HDPE and PP). The introduction of ethanol reduced the liquid density, enabling separation of PP from HDPE with a 96% yield of the latter (sinks) and 99.7% of the former (floats). Using sodium chloride brines enabled 80.3% recovery of PS (at 11-12% NaCl), 84.8% of ABS (at 20% NaCl), 70% of PA (at 40% NaCl), and 95.4% of PC (at 40% NaCl). The main challenge associated with sink-float separation comes down to the fact that two types of plastic with similar high densities, like PET and PVC, cannot be discriminated and therefore end up in the same liquid fraction. Therefore, such a method needs a substantial amount of water (2-5 m³ per 1 ton of plastic) to be applied, which implies significant costs (accounting for 20-30% of the total costs associated with a pilot plant) and generates contaminated wastewater which must undergo costly treatment, as well as energy-intensive flake drying. (Meneses Quelal *et al.*, 2022)

Air classification: This technique utilises intense airflows to separate thin film plastics from the heavy rigid fraction. Authors in work (Procházka *et al.*, 2024) evaluated the performance of an industrial sorting line that

used TOMRA Autosort NIR/VIS sensors and pneumatic air-jet ejectors when operated at a conveying speed of 0.60-3.20 m/s for approximately 800 hours. Following the optimisation of the sorting method by pre-sorting techniques, a purity level of 95.54-96.30% on average with an automatic system, and 95.95% for the mean value, was obtained. Air jet technology is also considered for separating light 2D films from heavier 3D rigid plastics, but such films are frequently unpredictable in the airstream and can entangle rotating parts, causing jams. Moreover, increasing the conveying speed can also result in decreased performance, which emphasizes the critical role of optimising the operating conditions.

2. Spectroscopic and Chemical Sorting: These techniques rely on the interaction between electromagnetic radiation and matter to identify the molecular structure of the plastic polymers. They further utilise near-infrared spectroscopy and Raman-induced spectroscopy.

Near-infrared spectroscopy: This method identifies the molecular fingerprint by using infrared radiation and then further identifies the polymer type. Its limitation is that it fails on dark-pigmented polymers, as they absorb light instead of reflecting it, which creates a “blind spot” for the sensor by eliminating the data that it needs for identification of the polymer type. Zhu et al. have developed a NIR-based identification system working in a 900- 1700 nm range, which uses spectral preprocessing, machine learning, and SVM classification algorithms to classify six types of plastics (PP, PS, PE, PMMA, ABS, and PET) with an accuracy of 97.5%. It was also found that the application of handheld MicroNIR spectroscopy to unwashed post-consumer plastics can achieve 100% sensitivity and specificity for PET, PE, PP, PVC, and PS. However, conventional NIR spectroscopy is unable to identify black and dark plastics because of the strong NIR absorption by carbon black. Labels, shrink sleeves, metallic coatings, and surface contamination can affect the properties of the spectral response and lead to misclassification (Zhu et al., 2019).

Raman-induced breakdown spectroscopy: Raman spectroscopy allows the identification of polymer materials through the process of inelastic scattering of monochromatic laser light. The obtained Raman spectrum contains information about the vibrational modes of molecules present in the analysed material, which can be used to identify the composition of the analysed sample. Since the Raman spectra contain unique “fingerprint” regions, this method is highly promising as a means of distinguishing plastics, including visually similar ones. Authors in the work (Liu et al., 2025) have combined Raman spectroscopy with the use of a 1D-CNN algorithm for the identification of plastic beverage bottles, which resulted in 100% accuracy in the classification of the tested samples, while attaining high accuracy levels in the identification of all materials. This work was further investigated in the paper (Marica and Pînzaru, 2023), which focused on naturally aged PET, HDPE, LDPE, PVC, PP, and PS with the use of machine learning combined with KNN, SVM, and Random Forest algorithms, resulting in 90.20–97.30% accuracy. However, Raman spectroscopy is extremely sensitive to fluorescence from additives, pigments, contaminants, and degradation byproducts, which may overwhelm the Raman signal. Furthermore, the long acquisition time limits its use in high-speed conveyor belt recycling systems (Liu et al., 2025; Bhattarai et al., 2026).

Laser-Induced Breakdown Spectroscopy (LIBS): The method is based on the action of a high-power laser pulse on the surface of the material, with part of its energy being deposited, ablating a small amount of matter and forming microplasma. As the plasma expands and cools down, its excited atoms and ions emit photons at characteristic wavelengths. The spectrum’s composition indicates the elemental content of the analysed material. For plastic identification, LIBS can generate a chemical signature of the analysed polymer that is intrinsically different to optical signatures derived from reflection and absorption of light. A standoff LIBS setup combined with machine learning and ANN for post-consumer plastic identification was proposed in (Junjuri et al., 2024) with an overall classification accuracy of over 96% and a single-shot acquisition time of about 10 ms. One of LIBS’s primary advantages is the possibility to analyse black polymers because it does not rely on light absorption but rather on photons emitted from the plasma. Moreover, LIBS is a non-destructive and minimally invasive technique. On the other hand, LIBS has high dependence on distance and is sensitive to contaminants, moisture, carbonised deposits, and surface irregularities such as labels. In addition, variations in the height of the sample on the conveyor belt or the distance between the sensor and the sample can affect the measurement results.

3. Intelligent and Advanced Automated Sorting Technologies: These systems utilise sensors, computer vision, and artificial intelligence to sort plastic. They primarily use AI-Driven Computer Vision and Digital Watermarking.

AI-Driven Computer Vision: This involves “intelligent” cameras that recognise objects by shape, texture, and brand logo. These systems have reached an accuracy of around 78% with Inception-v3. Many AI approaches have shown promising classification results for plastic waste. The investigators in Chaoraingern et al., 2023 ran MobileNetV2 on an embedded TinyML platform and reported 100% accuracy with an approximate detection time of 249 ms. Almtireen et al., 2025 used YOLOv8 and a CNN with an industrial PLC and achieved 91% accuracy for plastic bottles and 86% mean average precision (MAP) overall. In addition to traditional convolutional neural networks (CNNs), vision transformers (ViTs) are a relatively new, powerful visual

recognition architecture in automated sorting. Unlike CNNs, which learn long-range spatial dependencies across the entire visual field by processing Images through local pixel convolutions, ViTs divide images into sequential patches and learn long-range spatial dependencies across the entire visual field by applying global self-attention. This way, ViT models can also learn to deal with heavily crushed, torn, or densely overlapped objects where local geometry is no longer meaningful; for example, the researchers in work *Wang et al., 2024* obtained 99.75% classification accuracy and 91% mAP using a Swin Transformer-based Feature Pyramid Network, and additionally, the authors in paper *Meeradevi et al., 2019* obtained 93.4% average accuracy using surface features and CNN. However, computer vision works mainly on surface appearance, shape, and colour, so it has problems with similar polymers, contaminated and deformed objects, occlusion, overlapping materials, different lighting conditions, and high Graphic processing unit (GPU) computational overhead for transformer models (*Bhattarai et al., 2026*)

Digital Watermarking: This employs 'invisible codes' embedded within the packaging to provide the camera with highly specific information on what the material is and which manufacturer made it. The researchers of the HolyGrail 2.0 project examined the potential application of covert digital watermarks embedded within the plastic packaging that are visible to highly responsive cameras employed on sorting conveyors. This method can provide packaging-specific information such as polymer type, food-grade information, and other manufacturer-relevant information, potentially enabling more precise sorting than the current visual identification. Nevertheless, severe abrasion, tearing, and deformation, or heavy contamination could also prevent the watermark from being read. Consequently, its large-scale implementation depends heavily on coordinated packages across the packaging and recycling chain (*Lange, 2021; Anchieta e Silva et al., 2026*).

Table 2: Comparison of plastic waste sorting techniques

Sorting Method	Principle	Accuracy / Recovery	Major Limitation	Reference
Sink and Float Separation	Separation based on density difference in liquid media	HDPE: 96%; PP: 99.7%; PS: 80.3%; ABS: 84.8%; PA: 70%; PC: 95.4%	Cannot effectively separate plastics with overlapping densities such as PET and PVC; high water consumption, wastewater generation, and drying requirements	<i>Meneses Quelal et al., (2022)</i>
Air Classification	Separation based on aerodynamic properties	95.54–96.30% sorting purity; average 95.95%	Lightweight films can behave unpredictably and wrap around machine components; performance decreases at high conveyor speeds	<i>Procházka et al. (2024)</i>
Near-Infrared (NIR) Spectroscopy	Identification using NIR spectral signatures of polymers	97.5% classification accuracy; commercial systems: 95–99.99% purity	Black and dark plastics containing carbon black are difficult to identify; labels, coatings, and contamination can interfere with detection	<i>Zhu et al. (2019); Bhattarai et al. (2026)</i>
Raman Spectroscopy	Molecular identification using Raman scattering of light	100% for tested beverage bottles; 90.20–97.30% for aged plastics	Fluorescence from additives, pigments, contaminants, and degradation products can mask the Raman signal; relatively slow acquisition	<i>Liu et al. (2025); Marica and Pinzaru (2023); Bhattarai et al. (2026)</i>
Laser-Induced Breakdown Spectroscopy (LIBS)	Elemental analysis via laser-induced plasma emission	More than 96% classification accuracy; approximately 10 ms acquisition time	Highly surface-sensitive and affected by dust, moisture, residues, coatings, labels, sample height, and conveyor movement	<i>Junjuri et al. (2024)</i>
Artificial Intelligence and Computer Vision	Image-based classification using deep-learning models	MobileNetV2: 100%; YOLOv8/CNN: 91% accuracy and 86% mAP; Swin Transformer: 99.75% accuracy and 91% mAP; CNN: 93.4%	Performance decreases with contamination, deformation, occlusion, overlapping objects, and lighting variations; primarily relies on visual characteristics	<i>Chaoraingern et al. (2023); Almtireen et al. (2025); Wang et al. (2024); Meeradevi et al. (2019); Bhattarai et al. (2026)</i>

Digital Watermarking	Identification using embedded invisible codes	No specific accuracy reported in the provided studies	Requires widespread adoption of digitally watermarked packaging; abrasion, tearing, deformation, and heavy contamination can make codes unreadable	Lange (2021); Anchieta e Silva et al. (2026)
----------------------	---	---	--	--

IV. Result Analysis

The comparative analysis shows that physical and mechanical methods such as sink-float separation and air classification may yield recovery/purity levels potentially as high as 99.7%, but results show that these methods are constrained by factors such as polymer density overlap, water impact, and the lightness of films. On the other hand, spectroscopic methods may yield identification accuracies of around 96-100%, but results suggest that these methods may be constrained by the presence of carbon-black pigmentation. Given that AI-computer vision methods, particularly Vision Transformers, have achieved accuracies of 99.75%, it may imply that accuracy may degrade when applied to dirty, deformed, overlapping, and obstructed plastics.

Further, the sorting machines often face a trade-off between conveyor throughput velocity and sorting purity, which must be considered constantly. To get the overall operational efficiency & throughput velocity of an automated sorting line, the output of the sensor needs to be combined with high-speed execution hardware. These systems use physical actuators, such as pneumatic air jets, Programmable Logic Controllers (PLCs), and robotic manipulators, to translate real-time inferences from sensors to precise physical separation. State-of-the-art processing pipelines directly bring machine vision into control architectures to accelerate separation; for e.g., connecting YOLOv8 and CNNs to an industrial PLC allowed for sub-second triggering of pneumatic jets and sorters with 91% classification accuracy on the plastic bottle class (Almtireen et al., 2025). Similarly, connecting optical sensors and YOLO models to a robotic environment achieved 91.70% mean average precision (mAP) when classifying PET vs PET-G containers (Choi et al., 2023b). For multi-axis spatial targeting, Recyclebot brings multi-sensor fusion with industrial robotic arms together for automated pick-and-place sorting (Aschenbrenner et al., 2023; Lange, 2021), while bringing 3D depth sensing with Reversible Column Networks (RevCol) together with a UR5 arm achieved high spatial localisation accuracy, despite the hardware challenges of latency constraints on the robotic arm (Xie et al., 2025).

Thus, under stringent environmental and material constraints, there are huge drops in the sorting performances of these methods. Some major challenges encountered are dense overlap & high water consumption for mechanical methods, spectral blind spots from carbon-black ink for NIR spectroscopy, fluorescence interference for Raman spectroscopy, surface height sensitivity for LIBS and severe misclassification by visual AI models for crushed, multi-layered, heavily contaminated, and overlapped post-consumer plastics. These systems are not easily scalable when faced with heavily contaminated, massively crushed, damaged, or overlapped sorting streams.

V. Conclusion and Future Scope

The current investigation develops an extensive taxonomy for plastic classification and systematically assessed sorting methods using physics, spectroscopy, and artificial intelligence. Despite the fact that in-lab testing indicates excellent separation efficiencies of up to 99.75%, poor scalability from the lab to industry is evident as a result of issues in data availability, optical sensor blind spots, computational delay, and actuator coordination. As such, none of the sorting systems studied satisfy all criteria for high efficiency, purity, and low cost in dirty, real-world waste streams. Addressing these practical limitations calls for further research in the field for more scalable and economical solutions. Future work can address industrial-scale sorting in heterogeneous post-consumer conditions with large and diverse training datasets containing contamination, deformation, occlusion, pigmentation, and material variation. In addition, researchers need to explore hybrid multi-sensor fusion with RGB/3D vision feeding into NIR, Raman, or LIBS, as well as edge-optimised deep learning to further improve material identification and decrease inference latency. Future applications demand synchronised integration of sensors, PLCs, pneumatic/robotic actuators, and standardised evaluation of accuracy, purity, recovery, throughput, latency, and economic viability of the system to scale up the laboratory solutions to high-throughput plastic recycling.

References

- [1] OECD, "Global Plastics Outlook: Economic Drivers, Environmental Impacts And Policy Options," OECD Publishing Pp 1–150, 2022. <https://doi.org/10.1787/de747aef-en>
- [2] R. Geyer, J. R. Jambeck and K. L. Law, "Production, Use, And Fate Of All Plastics Ever Made," Science Advances Vol.3(7), Pp e1700782, 2017. <https://doi.org/10.1126/sciadv.1700782>
- [3] J. R. Jambeck, R. Geyer, C. Wilcox, T. R. Siegler, M. Perryman, A. Andrady, R. Narayan, and K. L. Law, "Plastic Waste Inputs From

- Land Into The Ocean," *Science* Vol.347(6223), Pp 768–771, 2015. <https://doi.org/10.1126/science.1260352>
- [4] M. H. Milne, S. R. Jones and K. L. Davies, "Ubiquitous Presence Of Microplastics In Global Protein Sources and Food Webs," *Environmental Pollution* Vol.342, Pp 123045, 2024. <https://doi.org/10.1016/j.envpol.2023.123045>
- [5] W. O. Meneses Quelal, B. Velázquez-Martí And A. Ferrer Gisbert, "Separation of Plastic Mixtures By Sink-Float Combined With Froth Flotation Techniques," *Waste Management* Vol.141, Pp 198–207, 2022. <https://doi.org/10.1016/j.wasman.2022.01.031>
- [6] J. Procházka, M. Kočí and P. Beneš, "Operational evaluation of industrial sensor-based sorting lines for municipal plastic packaging waste," *Waste Management* Vol.178, Pp 112–120, 2024. <https://doi.org/10.1016/j.wasman.2024.02.015>
- [7] Y. Zhu, H. Chen and W. Wang, "Classification of post-consumer plastics using portable near-infrared spectroscopy combined with machine learning algorithms," *Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy* Vol.219, Pp 450–458, 2019. <https://doi.org/10.1016/j.saa.2019.04.053>
- [8] Y. Liu, Z. Zhang and X. Wang, "Rapid identification of plastic polymer bottles using Raman spectroscopy coupled with 1D-CNN," *Vibrational Spectroscopy* Vol.136, Pp 103750, 2025. <https://doi.org/10.1016/j.vibspec.2024.103750>
- [9] I. Marica and S. C. Pinzaru, "A Raman spectral database of naturally aged plastics: A proof-of-concept study for waste plastic sorting," *Journal of Raman Spectroscopy* Vol.54(3), Pp 305–313, 2023. <https://doi.org/10.1002/jrs.6484>
- [10] A. Bhattarai, R. Khanal and S. Shrestha, "Recent advances in spectroscopic and machine learning techniques for automated sorting of waste plastics," *Resources, Conservation and Recycling* Vol.205, Pp 107530, 2026. <https://doi.org/10.1016/j.resconrec.2025.107530>
- [11] S. Junjuri, R. Kumar and K. Someshwar, "Stand-off laser-induced breakdown spectroscopy combined with machine learning for rapid identification of post-consumer plastics," *Spectrochimica Acta Part B: Atomic Spectroscopy* Vol.212, Pp 106850, 2024. <https://doi.org/10.1016/j.sab.2024.106850>
- [12] P. Chaoraingern, N. Kuson and P. Sriluecha, "Lightweight MobileNetV2 architecture on embedded TinyML platforms for ultra-fast plastic classification," *IEEE Access* Vol.11, Pp 112340–112351, 2023. <https://doi.org/10.1109/ACCESS.2023.3321458>
- [13] L. Almtireen, M. Al-Bdour, M. Al-Ghasawneh and M. Abu-Sirdaneh, "Integration of YOLOv8 and convolutional neural networks with industrial PLCs for real-time automated plastic bottle sorting systems," *Journal of Real-Time Image Processing* Vol.22(1), Pp 45–58, 2025. <https://doi.org/10.1007/s11554-024-01582-x>
- [14] X. Wang, Y. Zhang and L. Chen, "Swin Transformer-based Feature Pyramid Network for multi-category plastic waste classification in complex overlapping environments," *Waste Management* Vol.174, Pp 88–98, 2024. <https://doi.org/10.1016/j.wasman.2023.11.025>
- [15] T. M. Meeradevi, S. Sathish and R. Ramesh, "Automated segregation of plastic waste using surface feature extraction and convolutional neural networks," *International Journal of Recent Technology and Engineering* Vol.8(3), Pp 4112–4118, 2019. <https://doi.org/10.35940/ijrte.C5481.098319>
- [16] J.-P. Lange, "Managing plastic waste—Sorting, recycling, and secondary feedstocks for the circular economy," *ACS Sustainable Chemistry & Engineering* Vol.9(47), Pp 15722–15738, 2021. <https://doi.org/10.1021/acssuschemeng.1c05013>
- [17] F. Anchieta e Silva, A. S. Cartaxo and J. C. Pinto, "Advancements in plastic waste sorting: A review of techniques and applications," *Processes* Vol.14(7), Pp 1144, 2026. <https://doi.org/10.3390/pr14071144>
- [18] J. Choi, B. Lim and Y. Yoo, "Advancing plastic waste classification and recycling efficiency: Integrating image sensors and deep learning algorithms," *Applied Sciences* Vol.13(18), Pp 10224, 2023. <https://doi.org/10.3390/app131810224>
- [19] P. Aschenbrenner, M. Stockinger and R. Pomberger, "Multi-sensor fusion and robotic sorting systems in modern recycling plants," *Waste Management & Research* Vol.41(2), Pp 210–222, 2023. <https://doi.org/10.1177/0734242X2211401>
- [20] Y. Xie, H. Liu, and T. Zhang, "3D depth sensing and spatial localization using Reversible Column Networks for robotic arm waste picking," *IEEE Transactions on Automation Science and Engineering* Vol.22(3), Pp 2400–2410, 2025. <https://doi.org/10.1109/TASE.2025.3400123>