

REVIEW ARTICLE

Hybrid multimodal artificial intelligence, vision sensory, and robotic cyber-physical systems for plastic inspection and sorting in digital circular remanufacturing: A review

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Abstract

Plastic inspection has emerged as an important component of industrial manufacturing processes, quality control, and recycling, driven by a growing emphasis on sustainable, circular, and efficient modes of production. This systematic narrative review focuses on three key areas: (i) a review on the imaging techniques used in the plastic industry for creating training datasets for artificial intelligence (AI) models; (ii) an evaluation of various AI approaches, including support vector machines (SVMs), deep reinforcement learning (DRL), convolutional neural networks (CNNs), and hybrid/multimodal techniques; and (iii) the integration of these techniques within robotic cyber-physical systems (CPS) for the automation of plastic defect identification, material classification, and sorting for recycling/remanufacturing, supplemented by circular business aspects. CNNs demonstrate exceptional performance in feature extraction and in detecting surface defects, such as scratches, cracks, and inconsistencies in plastic materials. SVMs, with their robustness to small, noisy datasets, provide accurate classification and quality control, making them a valuable complement to CNNs. Hybrid approaches that combine CNNs and SVMs leverage the strengths of both methods for complex tasks, thereby maximizing the advantages of each. DRL enhances the inspection and sorting capabilities of robotic CPS when integrated together. Despite these advancements, challenges remain, including high resource costs, data-intensive requirements, and constraints on real-time implementation. Potential solutions include adopting efficient architectures and lightweight frameworks. A pilot application of these AI strategies within a robotic CPS demonstrates their transformative potential to automate large-scale remanufacturing and recycling systems efficiently, accurately, and in an eco-friendly manner, supporting circular economy principles and sustainability.

Keywords: Plastic inspection and sorting; Deep reinforcement learning; Hybrid artificial intelligence models; Convolutional neural networks; Multimodal machine vision sensors; Circular remanufacturing operations; Quantum hybrid intelligence; Robot process automation

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1. Introduction

The growth of industrial plastic production plants and their associated business ecosystems, alongside rising demand for high-quality plastic products and effective recycling, has spurred the development of new and sophisticated inspection techniques, including advanced image acquisition and automated robot process analysis. Traditional systems for automated defect inspection, material classification, and quality assurance protocols are still largely manual, labor-intensive, and often lack efficiency and accuracy. To overcome such deficiencies, artificial intelligence (AI) based technologies like convolutional neural networks (CNNs)¹, support vector machines (SVMs)², deep reinforcement learning (DRL)³, as well as multimodal⁴ combinations of these techniques integrated with advanced image acquisition, are transforming the way plastic materials are examined. These technologies harness the capabilities of deep neural networks⁵ to recognize patterns in visual data for visual inspection. Integration of these AI models with robotic cyber-physical systems (CPS) enables the acceleration of tedious inspection and sorting processes in an automated, more efficient manner, while integrating humans in the loop for creative parts in a human-centric Industry 5.0 fashion. Figure 1 illustrates a generalized, circular reuse loop that integrates plastic defect inspection and sorting operations using machine

vision with DRL⁶, and the recycling of plastic materials involving human interventions assisted by generative AI algorithms⁶ for developing new plastic products/artifacts through three-dimensional (3D) additive remanufacturing. This framework encompasses both human intellect and artificial neural networks in synergetic interventions known as hybrid intelligence^{7,8} to maintain sustainable techno-economic operations in the infinite circular loop of the plastic product lifecycle management. With advances in quantum computing⁹, generative AI models, and human intelligence, one could anticipate that “quantum hybrid intelligence” will further enhance¹⁰ the synergistic capabilities for novel, techno-economic, sustainable operations in plastics.

Handcrafted features such as texture, color, and shape descriptors have traditionally been used in industrial quality inspection with machine vision systems. These methods often fail under variable lights, gloss, and rough surface textures, which are very common with plastic products, despite performing well in controlled environments. Deep learning (DL), an AI approach, addresses these gaps by automatically learning features. The shift from engineered to data-driven inspection has improved accuracy, adaptability, and dimensional real-time performance. Recent state-of-the-art research illustrates that models based on CNNs and traditional

Hybrid intelligence - Circular remanufacturing operations (CMaOps)

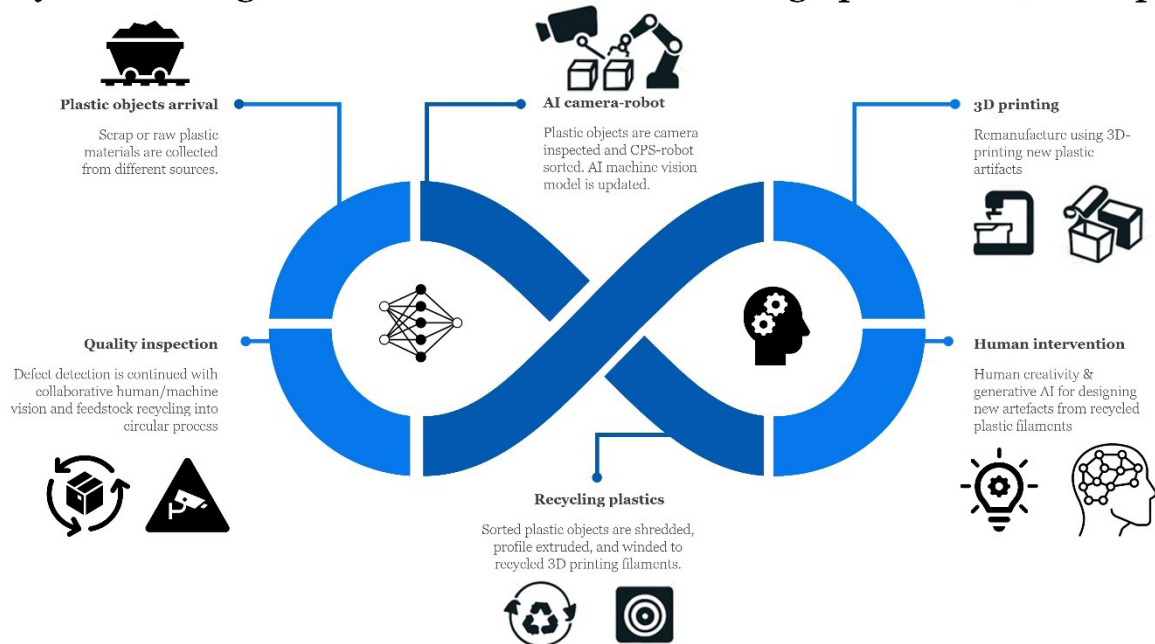


Figure 1. A generalized infinite circular loop for plastic product lifecycle management, including reuse operations, and hybrid intelligence⁷ for novel product development with three-dimensional (3D) additive remanufacturing. Image created by the authors using Microsoft PowerPoint 356. Abbreviations: AI: Artificial intelligence; CPS: Cyber-physical system.

SVMs can detect small, laser-induced defects that feature detectors often fail to identify. DRL algorithms perform control and provide robust classification, making them adaptive classifiers. AI use in plastic and composite inspection remains less mature than in metals, warranting further research to support a sustainable, circular economy in manufacturing. High-quality image acquisition for real-time processing and for large visual datasets used to train different AI models is important for the efficient operation of robotic CPS involved in automated processes for plastics quality inspection and sorting in recycling operations.

Similarly, the application of CNNs in defect detection and material classification has been significant in DL, given their ability to learn features within images at multiple levels of abstraction, enabling them to detect defects such as scratches and cracks. Their application on production lines has been shown to improve sorting and defect detection, especially for recycling processes where it is important to identify recyclable plastic from scrap plastic.¹¹ SVMs excel when data are limited, offering robust classification even in noisy or inconsistent industrial environments.¹² Their ability to identify subtle surface irregularities and classify polymer types based on texture makes them valuable for quality control and defect detection.

Defective and unsorted plastics hinder operations in recycling and industrial settings, resulting in unsatisfactory end products. Defects can be grouped into three broad categories. Surface defects, such as scratches and cracks, commonly arise during molding and extrusion processes. They directly affect the aesthetic and mechanical functionality of the end product. Structural defects include voids and inclusions occurring within the bulk of the material. These defects often remain undetected unless 3D imaging and tomographic methods are used to scan the plastic parts. Compositional defects, including uneven dispersion of industrial fillers and polymer contamination, affect the optical functionality and recyclability of the plastic. Emerging techniques such as DRL push the boundaries of automation further by enabling robotic CPS to adapt and learn autonomously, even in dynamic manufacturing environments. DRL's ability to optimize decision-making in real time presents immense potential for sorting and inspection tasks.¹³ Furthermore, hybrid approaches combining the strengths of CNNs, SVMs, transformers, and traditional image processing methods promise even greater accuracy and efficiency. For example, CNN-SVM hybrids leverage CNNs' powerful feature extraction capabilities and SVMs' robust classification to improve defect detection and sorting, even with limited training datasets.¹⁴

To provide a clear structure and logical flow, this

systematic narrative review is organized following a conceptual framework that connects imaging and AI in plastic inspection. This framework approaches the subject in four successive dimensions: imaging techniques, AI techniques, use cases with business aspects, and future directions. This structure allows the reader to follow the path from different imaging technologies to the development of various machine learning (ML) models and their application in industrial settings. It also shows how current challenges and untapped potential are shaping future research directions. The review surveys state-of-the-art techniques for AI-driven plastic artifact quality inspection, focusing on CNNs, SVMs, DRL, and hybrid AI approaches, along with various advanced industrial and laboratory image acquisition sensors/cameras and methods commonly used in the Nordic plastic industry to capture defects on plastic artifacts. Each technique is critically evaluated in terms of its applications, advantages, limitations, and integration into automated CPS, underscoring its transformative potential for improving manufacturing quality and recycling processes. The review concludes with a pilot case study of robotic CPS used to inspect and sort 3D-printed scrap artifacts within an additive remanufacturing environment farm (DIGI Microfactory Lab). In this university lab, advanced image acquisition techniques and AI machine vision models identify defects during plastics manufacturing quality control, enabling a CPS robot-assisted sorting process to operate in feasibility mode for recycling plastics in an economically viable and environmentally sustainable way.

2. Literature search

A literature search was conducted to identify relevant research on CNNs, SVMs, DRL methods, and hybrid approaches in robotic systems, particularly for plastic inspection, sorting, and manipulation tasks. The strategy employed a systematic literature review to ensure that existing knowledge is adequately covered and that this coverage can be replicated. The search was conducted across multiple scientific databases, such as Google Scholar, Scopus, IEEE Xplore, and ScienceDirect, to ensure the selection of high-quality, peer-reviewed literature, as well as state-of-the-art preprints and conference proceedings. To capture all relevant literature, the following keywords and combinations were used: "deep convolutional neural network," "support vector machines," "deep reinforcement learning," "robotic manipulation DRL," "plastic waste sorting DRL," "robotic grasping irregular objects DRL," "DRL for waste sorting and classification," "deep learning robotic," "plastic inspection," "robotic manipulation CNN," "plastic waste sorting CNN," "robotic grasping irregular objects CNN," "CNN for waste sorting and classification,"

“robotic manipulation SVM,” “plastic waste sorting SVM,” “robotic grasping irregular objects SVM,” “SVM for waste sorting and classification”, and “hybrid AI approaches for plastic inspection.” Boolean operators (AND/OR) were employed to combine terms effectively. Example combinations included: DRL AND plastic inspection AND robotic manipulation; DRL AND object grasping AND conveyor belt; Deep CNN AND plastic inspection AND robotic manipulation; CNN AND object grasping AND conveyor belt; SVMs AND plastic inspection AND robotic manipulation; and SVM AND object grasping. The first search identified approximately 520 articles. After duplicate removal, 456 articles were screened. Considering the relevance to AI-driven inspection and quality control, 228 articles were selected for full-text review. Application of the inclusion criteria-English language and relevance to industrial or laboratory plastic inspection, with an emphasis on AI or imaging techniques-yielded 218 studies for analysis in this review. Studies were excluded if they lacked methodological rigor, were purely theoretical, or involved unrelated material domains.

2.1. Inclusion and exclusion criteria

To ensure quality and relevance, the following criteria were used.

2.1.1. Inclusion criteria

Eligible studies included conference papers, peer-reviewed journal articles and review articles, and studies that implemented or analyzed imaging and spectroscopic analysis for plastics. This encompassed studies that applied DRL, CNNs, SVMs, and hybrid AI for robotic manipulation, sorting, or inspection of plastics. Imaging modalities considered included RGB or depth-resolved (DRGB), thermal, hyperspectral, and multispectral cameras; scanning electron microscopy (SEM); transmission electron microscopy (TEM); X-ray computed tomography (CT); atomic force microscopy (AFM); projected pattern photogrammetry; laser profilometry; confocal imaging; and various spectroscopic techniques. Studies focusing on industrial applications in waste management or recycling systems were also included.

2.1.2. Exclusion criteria

Studies unrelated to plastic, polymer, or waste inspection or sorting were excluded from analysis. All retrieved articles were cataloged using reference management tools such as Mendeley (version 2.142). Duplicate studies were removed during this process. In addition to database searches, manual searches for references from key papers were performed to identify any missed studies. Preprints

from platforms like arXiv and GitHub code repositories were also reviewed for recent developments.

3. Image acquisition modalities and assistive noninvasive sensors for visual dataset collection

An overview of the different types of imaging sensors used for the acquisition of plastic images and the creation of datasets is presented. This is vital for training and performing AI machine vision processing to identify the desired characteristics/features of the plastics under examination. The outcome is used to control robotic CPS for various operations, such as defect inspection or sorting based on given criteria.

3.1. RGB cameras

An RGB camera captures images by measuring the amount of light in the three primary colors. These three-color channels are then used to create a full color representation of the image. The RGB camera is extensively used in areas such as photography, computer vision, and robotics since it is inexpensive and easy to use. However, RGB cameras cannot capture object depth, limiting their application in 3D scene analysis.¹⁵ Their performance degrades in low light or under varying lighting conditions, affecting image quality and object detection.¹⁶ They struggle to differentiate between objects with similar colors but different material properties.¹⁷ Shadows and reflections can alter the perceived colors, reducing accuracy in color-critical applications.¹⁸ Detection of fiber in an RGB image using image recognition is shown in [Figure 2](#). RGB cameras offer an affordable, practical option for surface-level inspections, especially when color and texture are primary indicators of defects. Their simplicity, low cost, and seamless integration into automated inspection systems provide substantial benefits.¹⁹ However, the cameras lack depth-processing capabilities and may produce inconsistent results under different lighting conditions. This weakens the accuracy of subsurface defect detection and the differentiation of materials with similar colors. Therefore, for primary visual inspection purposes, RGB imaging systems should be used alongside depth and spectral sensors.²⁰ Most industrial RGB cameras use either a charge-coupled device or a complementary metal oxide semiconductor (CMOS) sensor to capture visible light in the 400-700 nm wavelength range. Charge-coupled device sensors generally offer higher image uniformity and lower noise, while CMOS sensors provide faster readout speeds and lower power consumption, making them suitable for real-time inspection applications.²¹



Figure 2. Detection of fiber through RGB image recognition and a convolutional neural network detection algorithm. Image created by the authors.

3.2. Depth-resolved RGB cameras

Depth-resolved RGB or RGB-D cameras combine standard RGB imaging with depth sensing. Such cameras provide depth (D) and color (RGB), which enhance the overall understanding of the captured image. Depth sensors typically work best within a limited range.²² Compared to RGB cameras, DRGB cameras are more costly due to the additional hardware required for depth sensing.²³ Adding depth data raises processing and storage needs, which could be a drawback for real-time applications.²⁴ RGB and DRGB images of the same 3D-printed plastic object acquired with an Intel RealSense D435 depth camera (Intel RealSense D435 depth camera, RealSense, Inc., US) illustrating the different camera views used in AI algorithms for detection/inspection, are shown in [Figure 3](#). In the context of CT and 3D reconstruction, the depth channel in DRGB systems can be generated using various sensor technologies. Common approaches include structured-light projection, which estimates surface depth by analyzing deformation of known light patterns; time-of-flight sensors, which measure the travel time of emitted infrared light; and stereo-vision triangulation, which derives depth from disparity between dual camera views.²⁵ Although these techniques do not achieve the same volumetric resolution as X-ray CT, they provide fast, noninvasive surface depth estimation that can complement CT scans for external geometry alignment or preliminary inspection.²⁶ Hybrid setups often use DRGB data to guide CT region of interest scanning, thereby reducing scan time and improving overall inspection efficiency.²⁷

Depth-resolved RGB cameras are among the most advanced optical sensors for inspecting plastic artifacts. By fusing the depth and color components of 3D artifacts, DRGB cameras can seamlessly perform dimensional analysis, enabling enhanced 3D inspection capabilities. Their advantages include surface irregularity detection, excessive refinement, and 3D object segmentation that accounts for multiple lighting conditions. Nevertheless, the higher computational costs and limited depth perception inhibit real-time inspection automated systems.²⁸

3.3. Thermal imaging cameras

The non-contact, real-time, and efficient temperature-monitoring capabilities of thermal cameras make them integral across industrial maintenance to biomedical imaging. These cameras measure the infrared radiation emitted by the object and visually display it using internal infrared detectors for varying temperatures. The use of thermal monitoring in additive manufacturing supports quality control by detecting flaws throughout the 3D printing process, maintaining structural integrity, and minimizing material waste.²⁹ Recent studies have begun applying AI to thermal imaging for more accurate predictive maintenance and fault detection, thereby increasing the efficiency of industrial processes.³⁰ There is also emerging interest in the application of thermal imaging in robotics for autonomous navigation and object recognition problems, where vision systems are obscured by darkness or physical barriers.^{31,32} It showcases the increasing relevance of thermal imaging across different domains, as research focuses on refining resolution, data

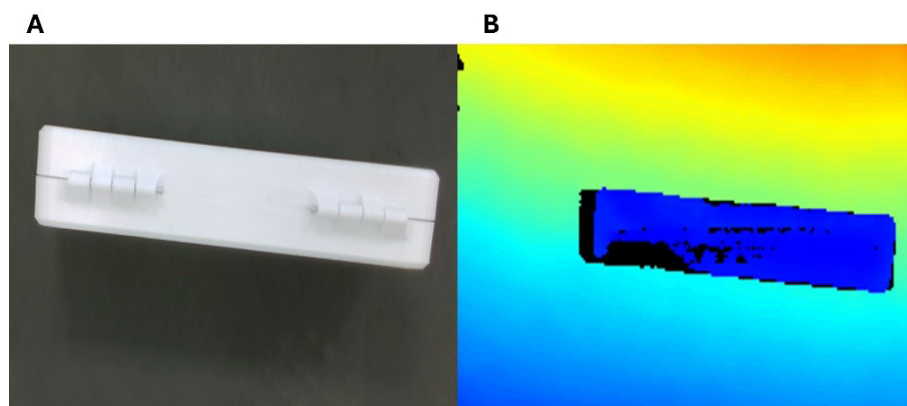


Figure 3. Images captured with a depth camera. (A) RGB and (B) depth-resolved RGB image of the same three-dimensional-printed plastic object acquired with an Intel RealSense D435 depth camera. Image created by the authors.

processing, and particular use case adjustments.³³ A case study from a continuous-feed industrial plastic profile extruder (Thermo Scientific Process 11 Twin-Screw Extruder, US) is illustrated in Figure 4. The thermal RGB camera displays, in real time, the different heated areas (thermal profile) of the extrusion system, highlighting heated regions with a color gradient ranging from blue (~20 °C) to yellow–red (~140 °C), corresponding to increasing surface temperatures. Thermal imaging serves as real-time quality inspection and monitoring for the thermal profile of the dual screw feedthrough compartment during extrusion, where the AI-enabled thermal camera control algorithm ensures an appropriate thermal profile for a smooth, continuous manufacturing process of different plastics and bio-composites commonly used in the plastics, pharmaceutical, and food industry. In summary, thermal imaging cameras are useful for detecting temperature-related defects, particularly in extrusion processes, including voids, delamination, and uneven material distribution in plastics.³⁴ Temperature-based defect detection, non-contact distance measurement, operation on opaque materials, and measurement in poor light conditions are primary advantages. However, thermal cameras are expensive, respond poorly to environmental changes, and have lower spatial resolution than other optical imaging techniques. For this reason, they are effective in situations that require thermal contrast analysis, or as part of an integration system that includes other sensors in the visible light spectrum for complete evaluation of thermal defects.³⁵ Most thermal imaging systems utilize uncooled microbolometers or short-wave infrared systems, such as indium antimonide or vanadium oxide arrays, to capture emitted infrared radiation.^{36,37} For specific high-precision applications, scientific CMOS sensors can be coupled with

infrared optics to improve temperature resolution and dynamic range, allowing for accurate detection of thermal anomalies in polymers.³⁸

3.4. Hyperspectral and multispectral cameras

Hyperspectral cameras provide images that combine the captured visible-to-near-infrared spectrum (typically 400–2,000 nm) of the object in the area of interest with spatial resolution that represents shape, texture, and compound material attributes. The resulting images contain rich information per pixel, allowing more accurate spatial classification³⁹ when combined with AI techniques.^{40–43} Similarly, multispectral cameras operate to acquire images with lower spectral resolution. The high cost of these cameras and the relatively long time to acquire images make them suitable for high-end niche projects. Collectively, hyperspectral and multispectral imaging techniques discern deeper spectral features, thereby advancing the ability to classify and distinguish various polymers. These methods are effective for distinguishing polymers due to their deeper spectral coverage and advanced compositional and chemical analysis. Thus, their ability to analyze various polymers enables their functional use in sorting, recycling plastic waste, and detecting quality or contamination in plastic waste.⁴⁴ Unfortunately, the practical application of these imaging techniques has yet to gain advancements. Their implementation in recycling plastic waste is worth pursuing, especially in integrated hybrid systems. Hyperspectral and multispectral cameras utilize diffraction gratings, prisms, and acousto-optic and liquid-crystal tunable filters to scatter light into narrow spectral bands. For visible-to-near-infrared photography, cameras typically use silicon charge-coupled devices, whereas short-wave infrared imaging uses indium

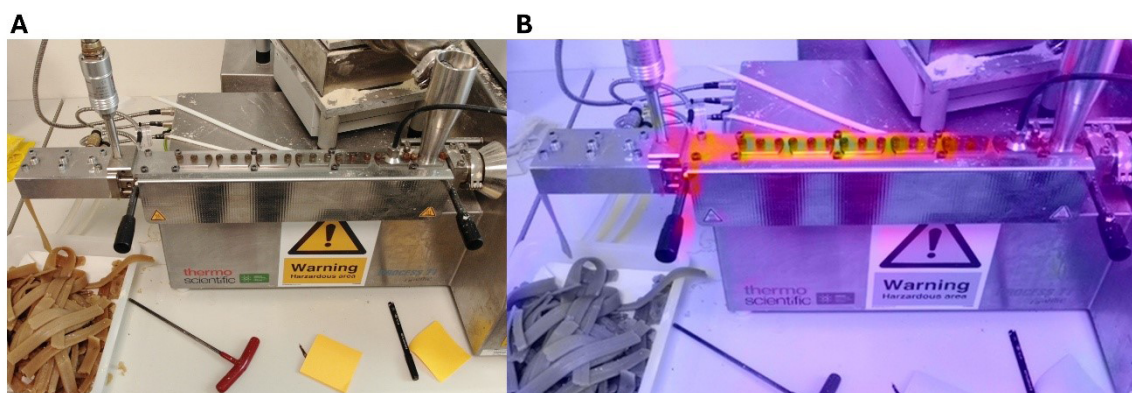


Figure 4. Images captured with a dual visible and thermal camera. (A) RGB picture of a continuous-feed plastic profile extruder during operation, and (B) the equivalent acquired with a thermal RGB camera. Image created by the authors.

gallium arsenide detectors. These arrangements can capture hundreds of hyperspectral or tens of multispectral contiguous spectral channels, allowing for thorough material analysis of plastics.⁴⁵

3.5. Scanning electron microscopy and transmission electron microscopy

The working principle of electron microscopy is based on an electron beam scanning the plastic sample in the region of interest, where the reflected electrons from the sample surface are detected to generate a clear, high-resolution image. It is a very powerful technique used to identify nanometer- to micrometer-scale structures on the sample surface, and when combined with energy-dispersive X-ray spectrometry, it can provide elemental analysis of the sample.⁴⁶ SEM is commonly used for imaging microplastics. Similarly, TEM can provide ultra-high-resolution images

down to the atomic layer.⁴⁷ Challenges include the long time required for sample preparation and image acquisition, as well as the relatively small sampling area.⁴⁸ Figure 5 shows an SEM image acquired using a Hitachi Tabletop Microscope TM3030Plus depicting nanoparticles formed on a plastic surface after ultraviolet laser irradiation. Overall, no other techniques can match the spatial resolution of SEM and TEM for examining surface morphology, microstructural defects, and filler distributions in plastic materials. These techniques enable visualization and examination at the nanometer scale, with incredible magnification and the ability to reveal subsurface details of materials that are undetectable with optical imaging.⁴⁹ Nevertheless, the need for intricate sample preparation, vacuum, and conductive coatings restricts the ability to perform in-line or real-time inspections and analyses. For this reason, these techniques are best suited for intricate analyses and examinations in

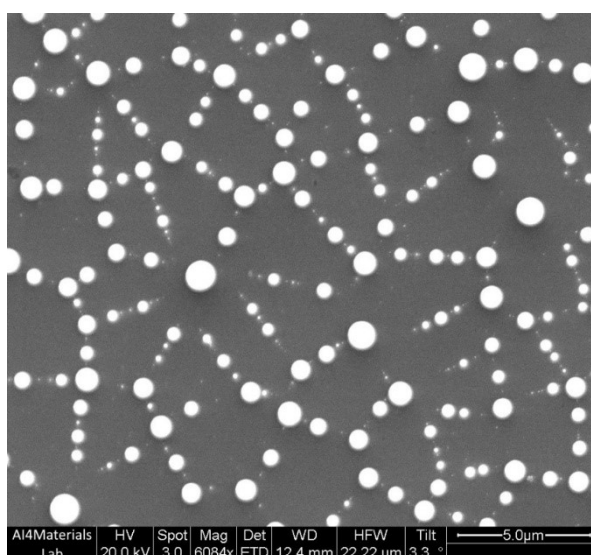


Figure 5. Scanning electron microscopy image of nanoparticle formation on a laser-treated plastic surface. Scale bar: 5 μm ; magnification: 6,084 \times . Image created by the authors.

the laboratory, and for cross-validating defects captured with less expensive imaging techniques, such as RGB, hyperspectral, or Fourier-transform infrared spectroscopy imaging.⁵⁰ Although scanning electron microscopes cannot be deployed directly in an in-line or large-scale plastic sorting system, they operate under high-vacuum conditions. In laboratory settings, it remains a crucial piece of analytical machinery. In plastic inspection, it is primarily used to validate or calibrate results from optical, X-ray, or hyperspectral imaging. For example, energy-dispersive X-ray spectrometry and SEM micrographs can verify machine vision systems' microstructural detection of surface defect micro-cracks, filler pull-outs, and delamination of microstructural origin. For this reason, it is appropriate to view SEM as a benchmark defect characterization and material verification tool, rather than an inspection tool for automated production-level defect detection.⁵¹

3.6. X-ray computed tomography imaging

X-ray CT enables 3D reconstruction of solid plastic structures by combining layered core images.⁵² It is a noninvasive imaging technique widely used in the plastic industry for quality assurance and defect analysis, including internal voids and cracks, for example, in injection-molded⁵³ and 3D-printed^{54,55} plastic parts. The imaging technique, combined with AI defect identification algorithms and CPS for automation, can speed up defect detection and improve accuracy, making it very useful for large manufacturing processes. One challenge in using conventional X-ray CT for plastics is their low X-ray attenuation coefficient. This leads to challenges with contrast for different polymer phases and between plastic and air voids. This problem complicates the identification of fine internal characteristics and defects, such as delamination, voids, and inclusions.⁵⁶ Several techniques have been developed to minimize and overcome this issue. Phase contrast CT is one example that uses a different principle for image capture and can detect phase shifts rather than only intensity differences. This results in greater edge sharpness and internal contrast for low-density substances. Even greater imaging capabilities can be achieved with micro-CT systems, which feature micro-focus X-ray sources and superior spatial resolution to capture remaining micro-scale structures and filler distribution in polymer composites. The combination of these methods with new reconstruction techniques and material-specific calibration can greatly enhance the detectability of semi-transparent plastic defects. Unfortunately, due to their increased time and cost burden, these methods are better suited for laboratory calibration of in-line imaging configurations.⁵⁷

To summarize, X-ray imaging and CT provide powerful, non-destructive insights into the internal composition of plastic materials and the identification of voids, inclusions, fractures, and internal stresses. Their main benefits include the ability to perform volumetric imaging, high spatial resolution, and the ability to work with complex shapes and opaque thermoset plastic materials.⁵⁸ On the downside, the high costs of equipment construction and maintenance, operating time, and the low contrast of low-density, low-attenuating polymers reduce the ability to visualize defects. More sophisticated systems, such as micro-CT and phase contrast, can overcome these challenges, but these systems work better in laboratories than in high-speed postproduction settings.⁵⁹

3.7. Atomic force tapping imaging

Atomic force microscopy is a powerful method for imaging polymers, polymer blends, polymer composites, plastic dispersions, and domain sizes^{60,61}, including those in plastic solar cells.⁶² Moreover, phase imaging enables the identification of variations in surface stiffness and adhesion, particularly when combined with AI-based vision techniques, such as image segmentation and deep neural networks.⁶³ AFM working principle is based on a cantilever deflection introduced by the plastic sample surface interaction with the AFM probe, where the deflection is digitally recorded with a laser beam and a position sensitive photodetector while the AFM probe scans the region of interest on the sample creating an image.⁶⁴ A limitation of AFM imaging is the relatively small scan area, typically on the order of hundreds of nanometers, as well as the slow scanning speed, with a typical probe velocity of approximately 30 $\mu\text{m/s}$.⁶⁵ In short, AFM in tapping mode is useful for studying the roughness, texture, and surface mechanical properties of plastics with nanoscale resolution. It meets the requirements for non-destructive surface characterization, quantitative surface topography, and defect and heterogeneity detection at the nanometer scale.⁶² On the downside, the limited measurable surface area, slow scanning speed, susceptibility to surface contamination, and sensitivity to environmental vibrations constitute significant practical limitations, particularly for large-scale, in-line industrial applications. Therefore, AFM should be used as a laboratory method to confirm microstructural features, which, together with optical or CT-based techniques, aid further characterization of materials.⁶⁶

3.8. Projected pattern photogrammetry

Projected pattern photogrammetry has emerged as a critical technique in robotic CPS for plastic inspection, enabling high-precision, non-contact measurement of

surface defects through structured light projection. This method enhances 3D scanning accuracy, facilitating automated defect detection and real-time quality control in manufacturing environments.⁶⁷ Recent research has shown that integrating AI algorithms with photogrammetry improves defect classification and automated feature extraction, reducing human intervention and inspection errors.⁶⁸⁻⁷⁰ A robotic CPS with projected-light pattern imaging for quality inspection of newly manufactured 3D-printed plastic products, along with its digital product passport for documentation⁷¹, is shown in Figure 6. In summary, projected pattern photogrammetry captures structured-light or fringe pattern projections from various viewpoints, enabling precise 3D reconstructions of plastic surfaces. Its main advantages for medium-sized components are non-contact gauging, rapid acquisition, and high geometric precision.⁷² The detection of surface warping, deformation, and dimensional deviation is the most challenging aspect of photogrammetric surface fitting. Deterioration in accuracy for translucent, specular, or coarse-grained patterned plastics is associated with photogrammetry pattern projection, scattering, and low-contrast patterns. Photogrammetry requires equipment calibration, patterned projection model photogrammetry, and controlled lighting to ensure gauging is consistent and dependable. In geometric inspection, photogrammetry

is quick and flexible; in this capacity, it can be used alongside other imaging modalities in hybrid inspection systems, such as CT and laser profilometry. In this way, the inspection system can be integrated seamlessly.⁷³

3.9. Laser profilometers and light beam-induced current

Laser profilometers and light beam-induced current (LBIC) systems are advanced non-contact, high-resolution techniques increasingly utilized in surface inspection and material characterization in industrial and research environments. Laser profilometers use triangulation-based laser scanning to capture precise 3D topographical data of surfaces, making them ideal for detecting micro-defects, warping, and texture inconsistencies in plastic components or films.⁷⁴ Their high-speed and non-destructive nature make them particularly suitable for integration into automated inspection lines where precision and throughput are critical. In contrast, LBIC is a photonic diagnostic technique primarily used in the semiconductor and photovoltaic industries but also applicable for inspecting conductive polymer films. It measures the current generated when a modulated laser beam scans across a material, providing spatially resolved insights into electrical uniformity and defects such as cracks, delaminations, or inhomogeneities. When applied to plastic substrates

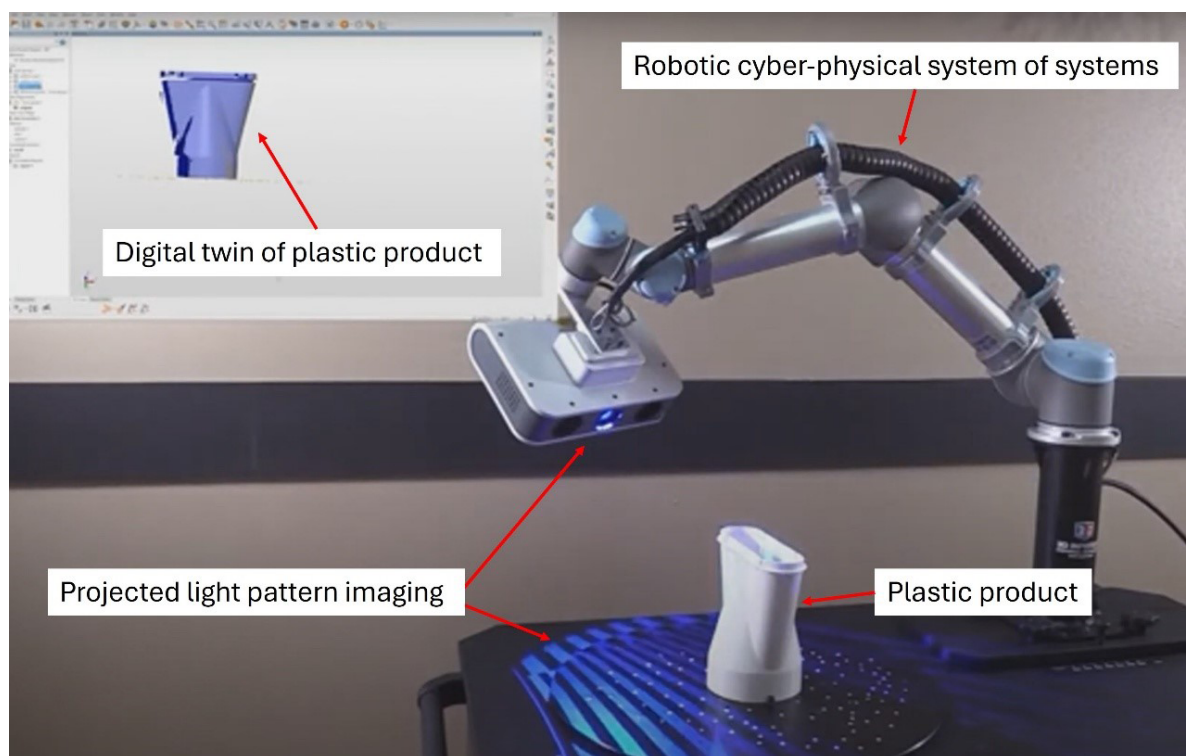


Figure 6. A robotic cyber-physical system with projected light pattern imaging for quality inspection of a plastic artefact. Image created by the authors.

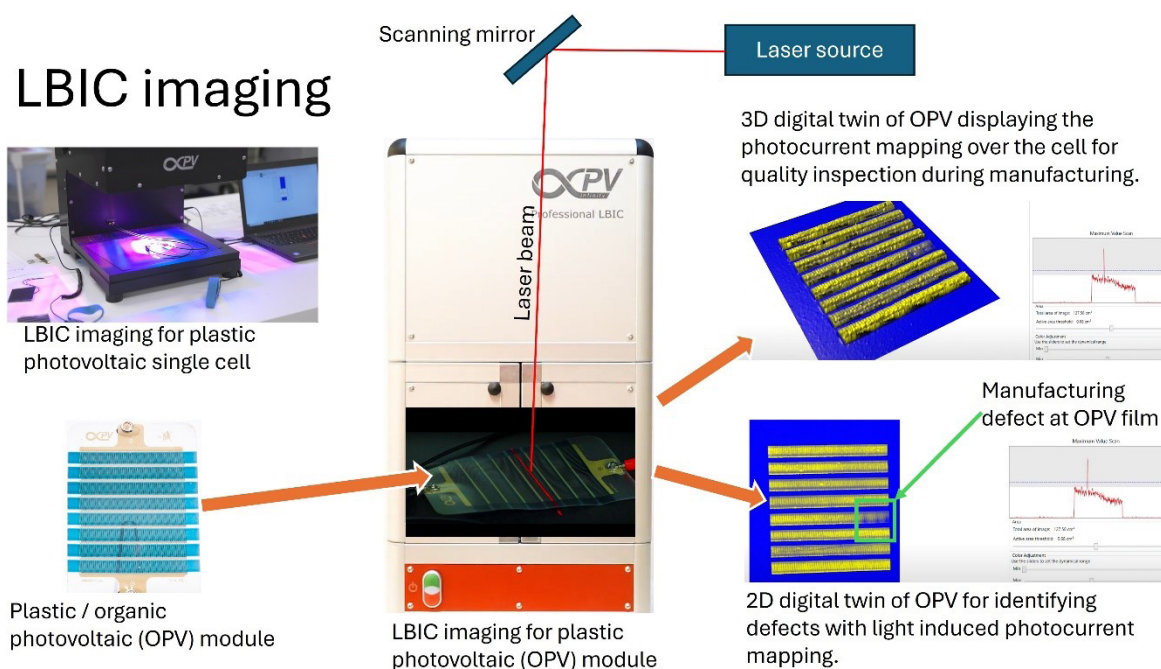


Figure 7. Light beam-induced current (LBIC) for photoactive polymers imaging, creating a digital twin of plastic photovoltaic cells/modules for quality inspection during manufacturing. Image adapted from www.infinityPV.com. Image re-created by the authors using Microsoft PowerPoint 365 with permission from infinityPV APS.

with conductive or semiconducting coatings, LBIC offers valuable real-time data on performance-affecting defects as a device digital twin, thereby supporting quality assurance in high-value applications, such as flexible electronics and organic photovoltaics.⁷⁵ The integration of these optical and electronic inspection tools into AI-driven frameworks further enhances automated defect localization and classification, aligning with Industry 4.0 quality assurance paradigms. LBIC for photoactive polymers monitoring, such as plastic/organic photovoltaics, is shown in [Figure 7](#), where a digital twin of an organic photovoltaic cell is created for quality inspection during the manufacturing process. [Figure 8](#) shows a two-dimensional/3D laser scan of a profile extruded from plastic/metal, illustrating its use for quality inspection and dimensioning profile creation during large-scale industrial profile extrusion. Overall, laser profilometers perform rapid, highly accurate 3D surface measurements to detect scratches, warping, and surface roughness in plastics, while LBIC techniques map electrical responses for conductive or coated polymer films.⁷⁶ Both methods are non-contact and highly accurate. Nevertheless, they are restricted by high equipment costs and susceptibility to alignment or surface reflectivity. These methods are best used as complementary laboratory tools for non-destructively characterizing defects in detail or for calibrating optical inspection systems.⁷⁷

3.10. Confocal imaging

Confocal imaging is a high-resolution optical technique that plays a key role in robotic CPS for plastic inspection, offering 3D surface characterization, micro-defect detection, and precision quality control. This technology leverages laser scanning and pinhole optics to eliminate out-of-focus light, making it ideal for inspecting transparent, multilayered, and micro-structured plastic materials.⁷⁸ Unlike conventional imaging techniques, confocal imaging enables macroscale scanning with high contrast, rapid acquisition of cross-sectional and longitudinal images, and minimal sample preparation, making it highly suitable for automated quality control in smart additive and traditional manufacturing.^{79,80} Additionally, it works well with transparent or semi-transparent materials.⁸¹ Nevertheless, long acquisition times, high cost, and limited field of view, along with the restricted inspection area, make confocal imaging more appropriate for laboratory studies than for industrial inspection.⁸²

3.11. Artificial intelligence-combined image and spectroscopies

When combined, the aforementioned imaging techniques, along with data acquired from various spectroscopy methods, can be integrated into supervised ML frameworks to correlate image-derived features with plastic material properties. This multimodal approach represents a

powerful data-driven decision-making strategy for robotic CPS, which are utilized in material design and synthesis⁸³, material properties identification^{84,85}, and quality control.⁸⁶ spectroscopy techniques commonly employed include Raman spectroscopy, Fourier-transform infrared spectroscopy^{87,88}, attenuated total reflection, terahertz time-domain, and time-resolved spectroscopy⁸⁹, ellipsometry⁹⁰, and nuclear magnetic resonance.⁹¹ In summary, merging imaging techniques with spectra represents a new frontier in characterizing materials by linking visual inspection with a material's molecular or chemical properties. This

approach increases the precision of defect classification and facilitates higher-order reasoning in robotic CPS for the identification and quality control of materials.⁸¹ Nevertheless, the approach's applicability in real-time scenarios might be constrained by the need for sizable, well-balanced datasets, complex data fusion algorithms, and greater computational power. Still, the fusion of AI systems with imaging techniques and spectroscopy for materials analysis and inspection of plastics shows great potential.⁹² A comparative summary of imaging methods used in plastic inspection is shown in [Table 1](#).

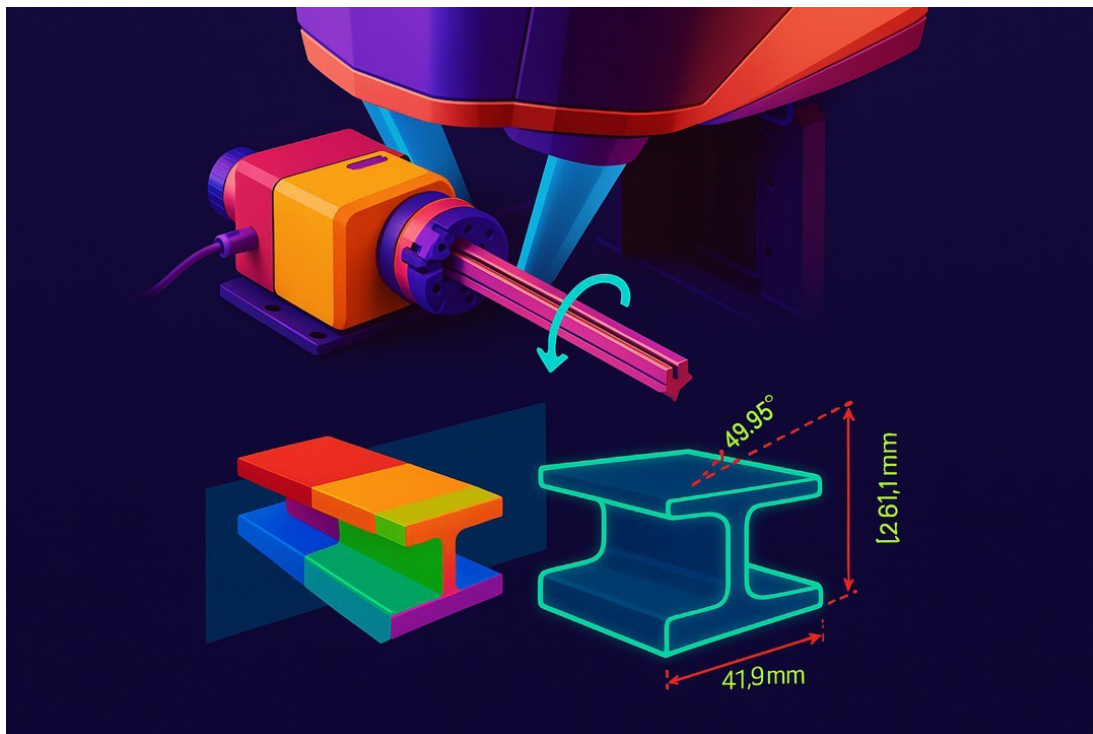


Figure 8. Laser two-dimensional/three-dimensional scanning for inspection of the dimensioning profile in a digital twin fashion. Image created by the authors using AI Microsoft co-pilot.

Table 1. Comparative summary of imaging methods

Imaging method	Primary application in plastic inspection	Advantages	Limitations	Reference
RGB cameras	Surface color and texture inspection	Low cost and simple setup	Sensitive to lighting	93
Depth-resolved RGB cameras	Three-dimensional (3D) surface geometry and defect localization	Depth with color data equals improved segmentation	Higher cost than RGB, limited range, higher processing load	94
Thermal cameras	Detecting temperature-related defects or delaminations	Works in dark environments, non-contact	Expensive, affected by ambient conditions, limited spatial detail	34
Hyperspectral and multispectral	Polymer type identification, contamination detection	Rich spectral data, accurate material discrimination	High cost; slow acquisition; complex data processing	95

(Cont'd...)

Table 1. *Continued*

Imaging method	Primary application in plastic inspection	Advantages	Limitations	Reference
X-ray	Internal defect visualization, porosity, inclusions	Non-destructive 3D imaging, high spatial resolution	Expensive, time-consuming; weak contrast for low-density plastics	96
Scanning electron microscopy/ transmission electron microscopy	Microstructural defect and filler analysis	Nanometer resolution, excellent morphology detail	Requires a vacuum, not suitable for in-line or large samples	97
Atomic force microscopy	Nanometer-scale surface roughness and microdefect mapping	Ultra-high-resolution, quantitative topography	Slow, small area, sensitive to vibration	98
Laser profilometry	Measuring warping, deformation, or roughness	High precision, non-contact, fast measurement	Sensitive to reflectivity, high equipment cost	99
Projected pattern photogrammetry	3D reconstruction and dimensional inspection	Rapid, accurate, non-contact	Poor on transparent or glossy surfaces, calibration needed	72
Confocal imaging	Surface/subsurface microdefect visualization	High depth resolution, works with transparent materials	Small field of view, slow scanning	100
Light beam-induced current	Assessing the electrical uniformity of conductive films	Quantitative defect detection, useful for coatings	Limited to conductive or doped materials, complex setup	76,101
Artificial intelligence-combined imaging and spectroscopy	Chemical visual correlation for defect classification	Multimodal insight, improved accuracy	High data volume, requires data fusion algorithms	102

4. Plastic inspection using convolutional neural networks

Artificial intelligence encompasses a broad range of definitions; at its most general level, it refers to the development of machines capable of performing tasks that typically require human intelligence, such as problem-solving, reasoning, and language understanding. AI is an umbrella term that encompasses subfields such as ML and DL. ML concentrates on learning statistical models and algorithms that enable a system to improve its performance without explicit instruction, instead relying on patterns and inference. DL, part of ML, uses advanced analytics and multi-layered neural networks to interpret large amounts of information. DL models can recognize patterns, such as edges in an image, and use learned features to formulate high-level concepts. CNN, a subset within DL, is a specialized artificial neural network, particularly effective at analyzing visual imagery. The hierarchy of ML, AI, and DL is shown in [Figure 9](#). CNNs are particularly effective for image analysis, a crucial task in plastic inspection. They can be used to analyze defects such as scratches or bubbles on surfaces by processing RGB camera data. For example, convolutional layers can detect patterns indicative of defects, and pooling layers help reduce dimensionality while retaining important features. Recent advancements

in the use of plastic inspection technologies indicate that CNN-based models achieve higher accuracy than classical image processing methods in identifying and classifying defects, including surface cracks, scratches, and color inconsistencies.¹⁰³ CNN-based segmentation networks, such as U-Net and Mask R-CNN, have also been used to accurately localize micro-defects and increase the efficiency of defect sorting in recycling lines. A considerable amount of research has fine-tuned pre-trained models such as VGG16, ResNet, and EfficientNet. Studies have reported accuracies of 95% or higher in polymer surface analysis and recyclability classification across several benchmark datasets. Domain adaptation across differing lighting conditions and plastic textures presents a considerable challenge and, in turn, a substantial opportunity for future research incorporating lightweight CNN architectures and transfer learning.¹⁰⁴ Although most transfer learning models, such as VGG16, ResNet, and EfficientNet, are pre-trained on large-scale natural image datasets like ImageNet, they can be effectively adapted for plastic defect detection through fine-tuning. The early layers of these models extract low-level features such as edges, textures, and color gradients, which are also relevant to plastic surface irregularities. Retraining only the deeper layers on smaller, domain-specific datasets allows the model to specialize in identifying plastic-specific defects while reducing training time and data requirements.

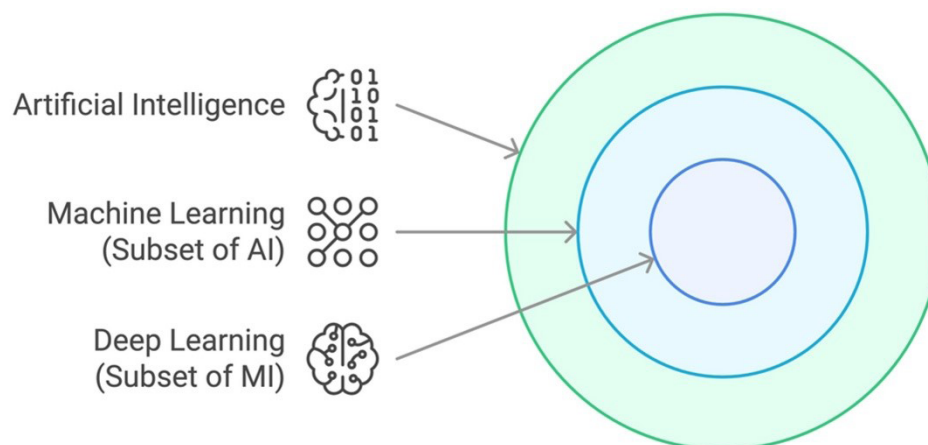


Figure 9. Hierarchy of artificial intelligence (AI), machine learning (ML), and deep learning (DL). Image created by the authors using AI online tool <https://www.napkin.ai/>.

4.1. Working mechanism of convolutional neural networks

Convolutional neural networks have frequently been employed for image recognition¹⁰⁵, object detection, and quality inspection. The fundamental aspects of CNNs¹⁰⁶, namely pooling, convolutional, and fully connected layers, allow hierarchical feature extraction from images. In the case of plastic inspection¹⁰⁷, CNNs are used to identify visual features such as defect types, material classifications, or quality assessment¹⁰⁸, as they can automatically learn the necessary features of the data without the manual overhead of feature selection.

Convolutional neural networks can distinguish between different types of defects, such as scratches¹⁰⁹, cracks, etc., by learning complex patterns through training on labeled images. These models are also effective in capturing fine surface textures in plastic materials. Their convolutional filters automatically learn local patterns such as roughness or grooves, which are critical for identifying subtle surface defects. Unlike traditional texture descriptors, CNNs extract hierarchical texture features directly from data, improving accuracy in detecting irregularities on plastic surfaces.¹¹⁰ These learned patterns are useful in quality control systems where fast, automated inspection is required, reducing reliance on manual inspections.¹¹¹

4.2. Applications in plastic inspection

Convolutional neural networks are trained to identify specific defects on plastic surfaces by analyzing textures and irregularities¹¹², and can differentiate between several types of plastics, often based on surface properties visible in images.¹¹³ These networks are increasingly used in recycling systems to sort plastics into recyclable and non-recyclable categories based on their visual properties.¹¹⁴

In manufacturing environments, these models process real-time image data from cameras integrated into production lines. These CNN-based systems enable immediate detection of quality issues, allowing rapid intervention when defects are found. Studies have shown that CNNs can achieve high accuracy in tasks like micro-crack detection, even under challenging lighting or environmental conditions, making them reliable for industrial applications.⁸⁵

Convolutional neural networks can identify complex patterns that traditional methods may miss, offering a higher level of precision.¹¹⁵ These models can be fine-tuned or retrained to detect new types of defects, which enhances their adaptability to varying quality standards.¹¹⁶ They can handle large datasets, providing detailed analysis of complex visual data, which is crucial for accurately identifying defects.¹¹⁷ These benefits have made CNNs a preferred choice for automated inspection tasks in plastic manufacturing, where accuracy, speed, and consistency are required. CNNs have shown significant enhancements over traditional image processing methods, particularly in applications involving high-resolution images and defect detection.¹¹⁸

4.3. Limitations of convolutional neural networks in plastic inspection

Training and deploying CNNs require significant computational resources, which can be a limitation for smaller manufacturing setups.¹¹⁹ CNNs generally require large, labeled datasets to perform accurately, which can be challenging and costly to obtain for niche manufacturing applications.¹²⁰ However, some tiny models are introduced that can run on low-power devices such as the Jetson Nano.¹²¹ CNNs may experience latency issues, especially

when processing high-resolution images in real time, which can delay performance in fast-paced production lines.

These challenges highlight the need for optimized architecture or hardware acceleration to implement CNNs effectively in high-speed manufacturing environments. Overall, CNN-based approaches have performed well at detecting surface- and color-based defects in plastics due to their ability to extract hierarchical features.¹¹⁰ The performance of such algorithms, however, becomes more relative to the quality and diversity of the dataset. Models trained in laboratory settings do not adapt well to the real-world conditions of factories, which vary in illumination and surface topography. Besides, without integrating data from depth or spectral domains, polymer surface defects¹¹⁸ with repetitive colors or similar patterns are misclassified. Hence, the generalization of deployed models and the integration of multiple modalities are critical issues.

4.4. Performance of convolutional neural networks in robotic cyber-physical systems

When integrated with robotic systems, CNNs enhance human-robot collaboration and automation in plastic inspection. CNNs enable robots to categorize plastics based on visual characteristics, facilitating recycling or quality control¹²², minimizing human contact with hazardous

materials during sorting operations for recycling. CNNs allow robots to identify and classify defects autonomously, reducing human inspection requirements.¹²³ In industrial manufacturing, CNNs enable robots to conduct thorough quality assessments without human intervention, thereby improving consistency. This integration of CNNs in robotic CPS is essential for enhancing productivity and precision in large-scale manufacturing operations.¹²⁴

4.5. Popular code repositories for convolutional neural networks

Developers widely use multiple repositories to implement and experiment with CNNs. TensorFlow¹²⁵ and PyTorch¹²⁶ are popular frameworks offering robust tools for CNN development and seamless graphical processing unit acceleration. Ultralytics YOLO¹²⁷, known for its speed and accuracy, is a leading repository for object detection, leveraging CNNs for tasks like real-time image and video analysis. An overview of CNN in plastic inspection is shown in Figure 10.

5. Support vector machines for plastic inspection

Support vector machines, a key machine learning classifier, excel at plastic inspection tasks such as defect detection and material sorting when datasets are limited or the

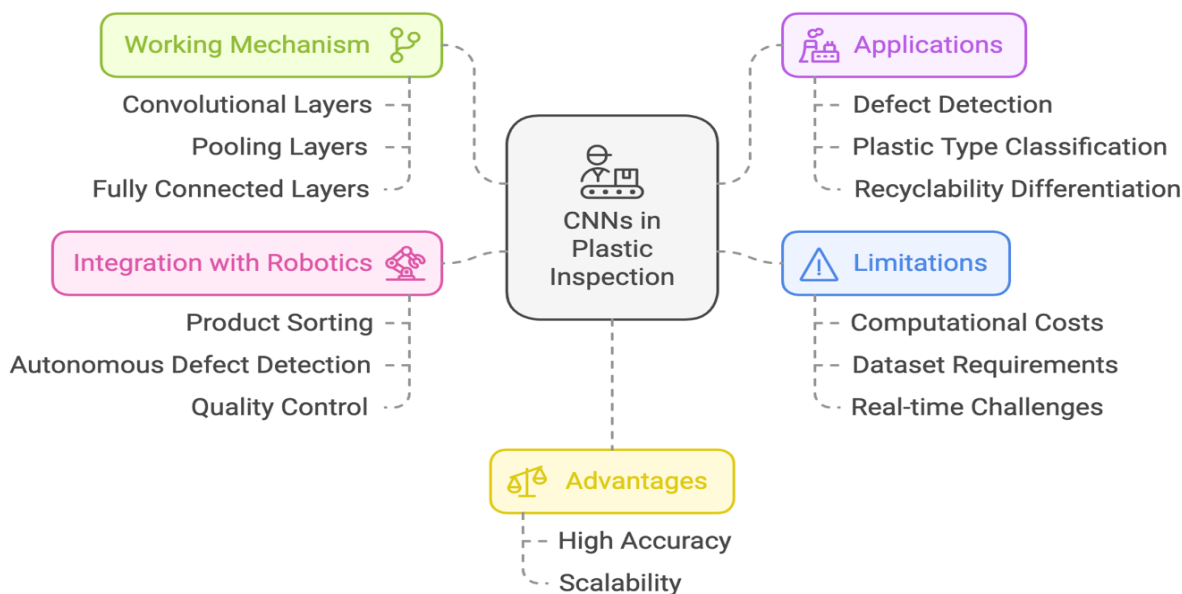


Figure 10. Overview of convolutional neural networks (CNNs) in plastic inspection. Image created by the authors using AI online tool <https://www.napkin.ai/>.

feature space is complex. They play a pivotal role in defect identification, material classification, and quality control during manufacturing.

Support vector machines were introduced by Vapnik and Cortes¹²⁸ in 1995 as a method for classifying data by finding the hyperplane that best separates the data into different classes. By increasing the margin between classes, SVMs ensure robust classification even for noisy datasets. This capability is especially important in industrial settings, such as plastic inspection, where data often contains inconsistencies due to variations in lighting, surface irregularities, or manufacturing tolerances.¹²⁸ For plastic inspection, these models can be used to classify different types of plastic or detect blemishes (e.g., cracks and bubbles) by extracting features using texture descriptors (e.g., Gabor filters or local binary patterns). SVMs can be relied upon when data collection is difficult, as they have the ability to handle small datasets.¹²⁹ They have been widely used for polymer type classification based on spectral, color, and texture features extracted from RGB, hyperspectral, and Fourier-transform infrared spectroscopy images. SVM classifiers have also been implemented for surface defect detection in injection-molded and 3D-printed plastics, achieving competitive performance compared to CNNs when training data are limited. The interpretability of SVM decision boundaries offers additional benefits for quality assurance processes, though their scalability to large-scale, real-time systems remains a limitation.^{130,131}

5.1. Application of support vector machines in plastic classification

Support vector machines have been widely used for material classification and surface defect detection. They can identify surface defects by classifying image features extracted from an RGB camera or other image sensor data.¹³² To classify industrial defects, Chittilappilly *et al.*¹³³ suggested a non-local means-based technique for denoising or restoring defect images in conjunction with SVM.¹³³ These models are used to distinguish between types of plastic based on surface patterns, textures, or spectral properties. This is particularly useful for identifying variations in polymer coatings or differentiating recycled plastics from virgin materials.¹³⁴ Inspection systems integrate SVMs to assess product quality in real time. By analyzing visual features, these systems can flag defective products or identify deviations from expected quality standards.¹³⁵

5.2. Strengths of support vector machines in plastic inspection

Support vector machines are highly effective for plastic inspection because they can handle complex, high-dimensional datasets and deliver accurate results even

with limited training samples. They excel at distinguishing subtle defects and variations in surface textures using kernel functions, such as radial basis functions, which map non-linear relationships into separable spaces.¹³⁶ These models also offer robustness against overfitting, ensuring consistent performance on noisy or small datasets, which are common in industrial settings.¹³⁷ Moreover, their relatively low computational requirements compared to DL models make them suitable for real-time applications in a small-scale manufacturing environment.¹³⁸ They deploy easily on edge/Internet-of-Things devices. For instance, SVMs have been effectively used for classifying material types and detecting surface faults in plastics, achieving adequate accuracy in fault classification tasks using image-based texture features.¹³⁶

5.3. Challenges with support vector machines

Although SVMs are strong in specific regards, they have certain limitations when implemented in a plastic inspection environment. An obvious downside is that they are prone to class overlap within the data, which may cause a loss in classification proficiency in the realm of competitive manufacturing conditions.¹³⁹ Additionally, the algorithm has hyperparameters that require manual specification, as they significantly affect the algorithm's output, causing difficulties in complex surface textures.¹⁴⁰ Scalability is another concern; as the dataset size grows, the computational time and memory requirements for training increase significantly, making SVMs less efficient for real-time inspection on large-scale production lines.^{141,142} Additionally, tuning hyperparameters such as the kernel type and regularization parameter demands expertise and can be time-consuming.¹⁴³ Finally, SVMs often struggle with multi-class classification, requiring extensions or adaptations like one-vs-one or one-vs-all approaches, which can complicate their implementation in dynamic industrial environments.^{144,145} The ability of SVMs to interpret results and their reliability with noisy data provide benefits for quality control; however, a decrease in performance as data complexity increases constrains SVMs' scalability compared to deep CNNs. Therefore, SVMs are more appropriate for simple classification tasks or as secondary classifiers in hybrid systems.

5.4. Integration of support vector machines in robotic cyber-physical systems

Support vector machines have been extensively integrated into robotic systems, enhancing automation, real-time data analysis, and precision in defect detection.¹⁴⁶ One prominent application is robotic sorting, where SVM-based systems, combined with CNN, achieve accurate classification of blood defects in cod fillets.¹⁴⁷ Another key

use is defect detection, where robots equipped with SVM-driven vision systems autonomously identify and classify defects, minimizing human intervention, and meeting strict quality standards.¹⁴⁸ Additionally, SVMs enable real-time decision-making in manufacturing lines by processing data from cameras and spectral sensors promptly, allowing robots to detect and remove objects efficiently.¹⁴⁹ These advancements showcase the transformative role of SVMs in modern robotic applications, driving efficiency and accuracy.

5.5. Popular code repositories for support vector machines

Support vector machine developers primarily rely on repositories that offer efficient implementations and integration with ML workflows. Scikit-learn¹⁵⁰ is the most popular library, providing a user-friendly interface for implementing SVMs along with various kernels and hyperparameter tuning tools. The Library for Support Vector Machines¹⁵¹ is a classic, highly efficient repository for SVMs, supporting classification, regression, and outlier detection tasks. The Library for Large Linear Classification¹⁵² is a linear SVM library optimized for large datasets. Additionally, Shogun¹⁵³ offers comprehensive support for SVMs alongside a range of ML algorithms. An overview of SVM in plastic inspection is shown in Figure 11.

6. Deep reinforcement learning for plastic inspection and sorting

6.1. Introduction to deep reinforcement learning

Deep reinforcement learning, a machine learning subset, trains agents to maximize rewards from environmental interactions using deep neural networks for policies and value functions.¹⁵⁴ In robotic applications, DRL

is increasingly used for inspection and sorting tasks, including the autonomous handling of plastic materials, by training robots to learn from experience rather than following preset guidelines.¹⁵⁵ This capability makes DRL particularly effective in environments characterized by variability and complexity, such as those encountered in waste management systems.¹⁵⁶ In the inspection and sorting of plastics, DRL enables robotic CPS for autonomous defect detection and adaptive sorting. Reinforcement learning agents learn optimal actions for manipulating or classifying defective components using visual information, enabling the robots to engage in closed-loop decision-making. Recent applications of DRL in conjunction with computer vision to enhance inspection paths, grasping techniques, and real-time sorting accuracy have been reported in recycling and additive manufacturing.¹⁵⁷

6.2. Advantages of deep reinforcement learning in robotic plastic inspection

Deep reinforcement learning offers several advantages for robotic systems engaged in inspection and sorting. DRL allows robots to adapt to dynamic environments by continuously improving their policies based on interactions with the system.¹⁵⁸ This is particularly valuable in waste sorting, where the types, shapes, and conditions of plastics can vary widely. DRL algorithms can effectively handle the constant uncertainty that characterizes most, if not all, operational environments, such as the rate of conveyor movement or the introduction of different kinds of materials.¹⁵⁹ Robots that have been trained using DRL techniques and methods are expected to operate in real time in future industrial systems, as improvements in computational efficiency are made.¹⁶⁰ These advantages position DRL as a transformative technology for enhancing the automation and efficiency of plastic inspection and sorting.

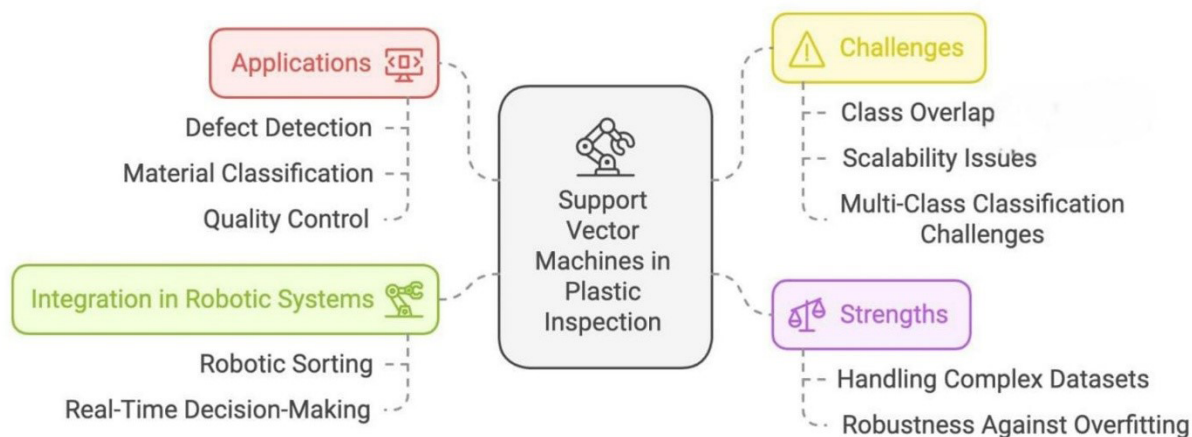


Figure 11. Overview of support vector machines in plastic inspection. Image created by the authors using AI online tool <https://www.napkin.ai/>.

6.3. Challenges and limitations of deep reinforcement learning

Despite its potential, DRL faces several challenges when applied to robotic plastic inspection. Training DRL models typically requires significant computational resources, as agents must explore vast action spaces to learn optimal policies.¹⁶¹ DRL often requires many interactions to converge, which can be impractical for real-world robotic systems without the use of simulators or efficient transfer learning techniques.¹⁶² During training, agents might take unsafe actions, which could damage robotic equipment or compromise the quality of sorting.¹⁶³ Ensuring safety during training and deployment is a critical concern. DRL models may struggle to generalize to new environments or materials not encountered during training, necessitating robust domain adaptation techniques.¹⁶⁴ The deployment of DRL on robotic platforms can be constrained by hardware limitations, such as processing power and sensory capabilities. Addressing these limitations requires advancements in DRL algorithms, training frameworks, and hardware integration.¹⁶⁵ Overall, DRL demonstrates promise for autonomous robotic inspection and sorting; its success depends heavily on the availability of high-fidelity simulated environments and on the design of reward functions. Inconsistent reward shaping or inadequate simulation-to-reality transfer often results in suboptimal policies. DRL's dynamic adaptability gives it a unique advantage for robotic CPS, but data intensity and convergence stability remain significant barriers to industrial deployment.

6.4. Deep reinforcement learning for robotic control in plastic inspection

The application of DRL to robotic control in plastic inspection involves training systems to autonomously inspect, sort, and manipulate plastic materials. DRL-trained robots can use computer vision systems to detect defects, categorize plastic types, and assess material quality.¹⁶⁶ For example, CNNs are often integrated with DRL to enhance robot autonomy during inspection.¹⁶⁷ Robots equipped with DRL algorithms can efficiently classify and separate plastic items based on characteristics such as polymer type, color, or recyclability. Reinforcement learning enables adaptive strategies that optimize sorting efficiency in real time.¹⁶⁸ DRL facilitates advanced manipulation tasks, such as grasping irregularly shaped plastic objects or reorganizing items on conveyor belts. Policies learned through DRL can accommodate diverse object geometries and achieve high precision in handling operations.^{169,170}

6.5. Popular code repositories for deep reinforcement learning

Several widely used code repositories support DRL development. Stable-Baselines3¹⁷¹ is a popular library offering robust implementations of algorithms built on PyTorch. OpenAI Baselines¹⁷² provides high-performance versions of classic RL algorithms. For TensorFlow users, TF-Agent¹⁷³ offers a flexible RL framework. Robotics-focused developers often use PyBullet¹⁷⁴ for physics simulations, while Dopamine¹⁷⁵ is preferred for lightweight, reproducible DRL research. Gymnasium¹⁷⁶ and PettingZoo¹⁷⁷ provide diverse environments for single and multi-agent RL, respectively, making these tools essential for DRL development. An overview of DRL for plastic inspection is shown in Figure 12.

7. Hybrid artificial intelligence approaches for plastic inspection

7.1. The combination of convolutional neural networks and support vector machines

Hybrid AI models that combine CNNs with SVMs can effectively leverage the strengths of both techniques. CNNs excel in extracting hierarchical features from images, offering detailed representations of texture, color, and shape, while SVMs, known for their robust classification capabilities, complement CNNs by providing accurate separations in feature space. For instance, Leng *et al.*¹⁷⁸ demonstrated a hybrid CNN-SVM model for hyperspectral image classification, highlighting its efficiency in distinguishing objects, applicable to plastic recycling scenarios.¹⁷⁸ Similarly, Meister *et al.*¹⁷⁹ reported improved accuracy in composite inspections using a parallel SVM-CNN approach, emphasizing the hybrid model's role in enhancing decision reliability.¹⁷⁹

7.2. Integration of deep learning with traditional image processing

Integrating DL with traditional image processing techniques creates a powerful synergy for defect detection and classification. Traditional methods such as edge detection, thresholding, and morphological operations play a pivotal role in image preprocessing by reducing complexity and highlighting essential features. This preprocessing enhances DL models' ability to focus on critical patterns, ultimately improving accuracy and robustness in defect analysis. This combination was effectively utilized by Fang *et al.*¹⁸⁰, where traditional crack detection methods were paired with CNNs, resulting in more precise identification

of micro-cracks in real-world applications.¹⁸⁰ In another study, Mohammed *et al.*¹⁸¹ employed a hybrid approach that combined multiple models for the detection of intracranial hemorrhages, using a dataset of CT images.¹⁸¹

7.3. Comparative analysis of hybrid approaches

Hybrid AI approaches, particularly those combining CNNs and SVMs, have consistently demonstrated superior performance compared to standalone techniques. By leveraging the strengths of each method, hybrid models can achieve enhanced accuracy, robustness, and efficiency in identifying objects.¹⁸² One notable advantage of hybrid models is their capacity to maintain high accuracy even with limited training data.¹⁸³ trained biopolymer images for medical purposes and used a CNN-SVM hybrid approach to detect hemorrhage in retinal images, outperforming

standalone CNNs or SVMs when dataset sizes were constrained.

However, these benefits come with computational trade-offs. Hybrid models generally require more resources due to the integration of multiple algorithms, which can challenge their implementation in resource-limited environments. Recent advancements, such as optimized architecture and lightweight frameworks, are addressing these limitations. For instance, Wang *et al.*¹⁸⁴ demonstrated an efficient hybrid approach for medical imaging that could potentially be adapted for polymer defect detection, achieving high accuracy with reduced computational overhead.¹⁸⁴ An overview of hybrid AI approaches for plastic inspection is shown in Figure 13, and hybrid AI models and their applications in defect detection and classification are shown in Table 2.

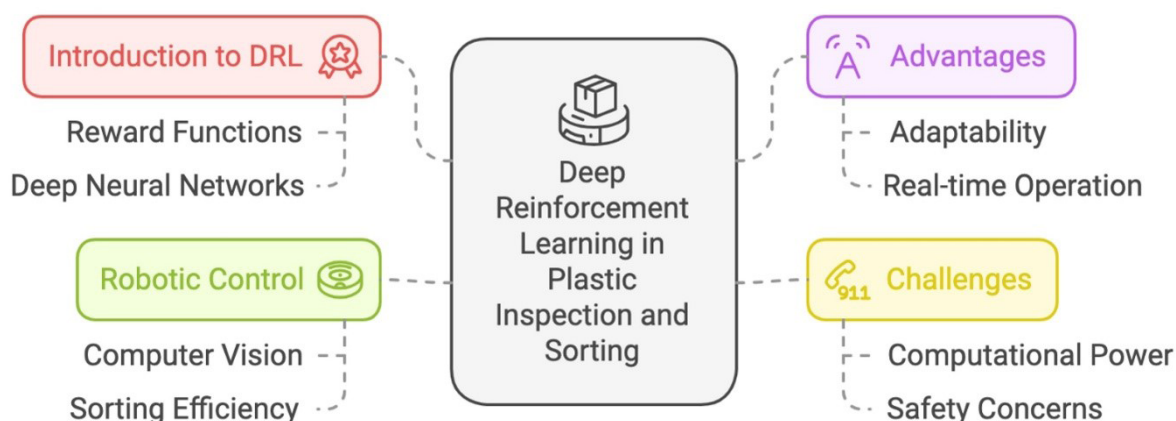


Figure 12. Overview of deep reinforcement learning (DRL) for plastic inspection. Image created by the authors using AI online tool <https://www.napkin.ai/>.

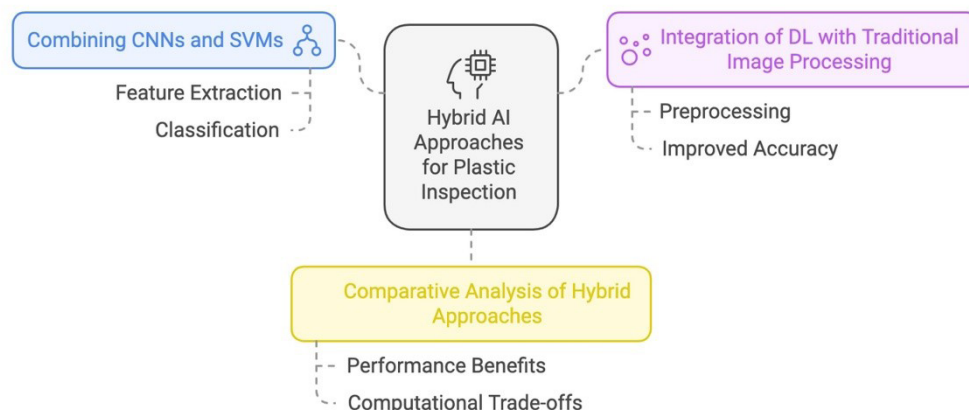


Figure 13. Overview of hybrid artificial intelligence (AI) approaches for plastic inspection. Image created by the authors using AI online tool <https://www.napkin.ai/>.

Abbreviations: CNN: Convolutional neural network; DL: Deep learning; SVM: Support vector machine.

Table 2. Hybrid artificial intelligence models and their applications in defect detection and classification

Category	Description	Case study
Hybrid CNN-SVM models	SVMs for classification and CNNs for feature extraction	Leng <i>et al.</i> ¹⁷⁸ demonstrated a hybrid CNN-SVM model for hyperspectral image classification, applicable in plastic recycling scenarios Meister <i>et al.</i> ¹⁷⁹ applied a parallel CNN-SVM approach for composite material inspection, emphasizing improved accuracy and decision reliability
DL + traditional image processing	Integrates DL with preprocessing techniques like edge detection and thresholding to enhance defect detection	Fang <i>et al.</i> ¹⁸⁰ paired traditional crack detection methods with CNNs, achieving precise micro-crack identification Mohammed <i>et al.</i> ¹⁸¹ utilized a hybrid approach by using multiple models for the detection of intracranial hemorrhages using a dataset of computed tomography images
Comparative performance	Hybrid models outperform standalone methods by combining the strengths of CNNs and SVMs, especially in limited dataset scenarios	Medical biopolymer images ¹⁸³ using CNN-SVM hybrids for hemorrhage detection achieved higher accuracy in constrained datasets Wang <i>et al.</i> ¹⁸⁴ optimized a CNN-SVM hybrid approach for medical imaging, showing potential for polymer defect detection while reducing computational demands
Advantages	Robust feature extraction and classification High accuracy with limited data	Hybrid models excel in identifying defects in materials with minimal training samples.
Challenges	Computational overhead Resource-intensive implementation in low-power environments	Lightweight architectures and frameworks are being developed to address these limitations, enabling broader applications across fields such as recycling and manufacturing

Abbreviations: CNN: Convolutional neural network; DL: Deep learning; SVM: Support vector machine.

8. Data availability and model requirements

The availability of comprehensive, meticulously annotated datasets remains integral to assessing the performance of AI models used for the inspection of plastics. Different models require different datasets, sometimes to vastly different degrees. For instance, CNN-based models require datasets of 10,000–100,000 labeled images. While transfer learning and data augmentation may alleviate this, a few thousand images on CNNs will help with general rationalization.¹⁸⁵ SVMs, on the other hand, require a few hundred to a few thousand images to perform adequately, especially with well-engineered feature extraction and noise minimization.¹⁸⁶ DRL approaches require extensive simulated or experimental interaction data, often to the tune of 10,000 episodes or more, to be able to optimize sorting and inspection strategies.¹⁸⁷

The data available depend on the imaging modality. Automated line capture of RGB and DRGB systems can be configured to construct high-throughput datasets in mere hours. CT and hyperspectral imaging systems produce lower volume datasets (hundreds of scans) due to the prolonged acquisition and processing times.¹⁸⁸ In practice, to optimize performance, it is common to augment smaller datasets with transfer learning, especially with high-quality annotated datasets from CT or spectral sensors and lower-quality large-volume RGB data. Data fusion techniques help in achieving the desired balances of performance

and robustness.¹⁸⁹ Table 3 summarizes the comparative performance, data requirements, and computational characteristics of the main AI models reviewed.

9. Business innovation aspects of digital inspection systems

The application of AI to plastic inspection systems raises multiple considerations, primarily related to costs, personnel requirements, and workforce restructuring. These factors affect the practical, scalable, and sustainable viability of implementing AI technologies in industrial settings. The expenditure is mainly focused on building, implementing, and supporting AI systems, whereas staffing for human oversight depends on the complexity of the AI's architecture and its interfacing with robotic CPS.

9.1. Cost implications of artificial intelligence-based plastic inspection systems

The integration of AI technologies in automated plastic inspection systems for defect detection and precise material classification includes many expenses, such as upfront capital expense for purchasing infrastructure equipment and software, acquiring relevant data, initial system commissioning education, and operational expenses, such as training of personnel, maintenance of the system, retirement, and energy consumption. Therefore, enterprise organizations that integrate such AI CPS systems for automated plastic inspection and sorting need to consider the total cost of ownership of such a system,

Table 3. Summary of comparative performance, data requirements, and computational characteristics of the artificial intelligence models

Models	Reported accuracy	Dataset requirements	Computational cost	Reference
CNN	90–98%	10^3 – 10^5 labeled images	High	190
SVM	85–93%	10^2 – 10^3 samples	Low	191
Hybrid	94–97%	10^3 – 10^4 samples	Moderate–high	192
DRL	80–95%	10^4 + episodes (simulated)	Very high	193

Abbreviations: CNN: Convolutional neural network; DRL: Deep reinforcement learning; SVM: Support vector machine.

consisting of capital expenses, operational expenses, and human resources costs, to ensure the return on investment is within a viable time, typically below three to five years from the initial investment.

9.1.1. Hardware infrastructure and computational costs (Back end)

Training and inference for CNNs and DRL models require the use of high-end tensor processing units or graphical processing units. Specialized equipment, such as NVIDIA RTX 4080/5090 graphics processing units, is expensive; however, these initial investments are considerable.¹⁹⁴ Furthermore, robotic CPS, including robotic arms for automated plastic sorting, comes with multiple expenses such as sensors, cameras, and actuators, which in turn drive the expenses based on intricacy.¹⁹⁵

9.1.2. Software development and integration (Front end)

Developing AI models for defect detection and plastic classification requires custom-built AI algorithms or pre-trained models.¹⁹⁶ Companies may invest in proprietary software, which is more expensive but customizable, or use open-source AI frameworks like TensorFlow, PyTorch, or OpenCV, which reduce software costs but require expertise. The integration of AI into existing manufacturing lines incurs additional costs in terms of system upgrades, cloud-based storage, and industrial Internet-of-Things infrastructure.¹⁹⁷

9.1.3. Data acquisition and model training

Artificial intelligence models for plastic inspection require extensive datasets of plastic defects, textures, and surface properties. High-quality labeled datasets are necessary, and acquiring them through manual annotation or synthetic data generation is costly, time-consuming, and laborious.¹⁹⁸ Semi-supervised learning and transfer learning strategies can reduce dataset requirements, but require investment in AI expertise.¹⁹⁹

9.1.4. Maintenance and scalability

Artificial intelligence models require continuous updates and fine-tuning to adapt to new plastic materials and defect types.²⁰⁰ Real-time AI-based inspection can incur energy costs (for graphical processing unit/tensor processing unit computations) and downtime costs due to system failures. Cloud-based AI solutions can reduce on-premises infrastructure costs but introduce subscription-based expenses.²⁰¹

9.2. Human operators: Specialization and transdisciplinary requirements

As AI automates many aspects of plastic inspection, human operators are still required for system monitoring, fine-tuning, and decision-making.²⁰² The level of specialization and interdisciplinary skills required depends on the AI model's complexity and the industry's level of automation. Operators require minimal training to interpret AI-based inspection results and handle basic troubleshooting.²⁰³

9.3. Cost-effective strategies for artificial intelligence adoption

To make plastic inspection and sorting processes financially viable, industries can implement cost-reduction measures by reducing the large dataset requirements using transfer learning.²⁰⁴ Instead of using heavy model architecture, industries can deploy lightweight models such as TinyML on edge devices to reduce computational and energy costs.²⁰⁵ They can utilize automatic labeling tools to reduce human effort²⁰⁶ and combine approaches, such as CNNs with SVMs, to achieve high accuracy and reduce dependency on a large dataset.²⁰⁷

9.4. Pilot semi-industrial use case of artificial intelligence robotic cyber-physical systems in plastics circularity

An example use case of a semi-industrial pilot line with plastic inspection and shorting capabilities for different scrap/residue 3D-printed plastic materials, utilizing a

collaborative robotic CPS and AI machine vision for plastic recycling and circular remanufacturing at DIGI Microfactory Lab, is shown in Figure 14A. The DIGI Microfactory Lab is an industry-academia open-innovation environment for demonstrating new product development, digitalization, and sustainability concepts through zero-waste manufacturing of 3D-printed plastic filaments in a circular fashion. Briefly, the circular process starts by 3D printing a plastic artifact from computer-aided design/STL files. AI machine vision is used for quality inspection,

comparing the physical 3D-printed artifact with the CAD “digital twin” artifact, and inferring a shorting decision. If quality standards are not met, a robot CPS places the 3D-printed plastic scrap artifact in the appropriate box based on the polymer used for remanufacturing. The plastic scrap is shredded/ground into small pellets (~3 × 3 mm), which are then introduced into a continuously fed polymer extruder with a 1.75 mm-diameter cylindrical extrusion profile. The extruded recycled filaments are cooled in a water chiller stage for hardening, then wound into rolls

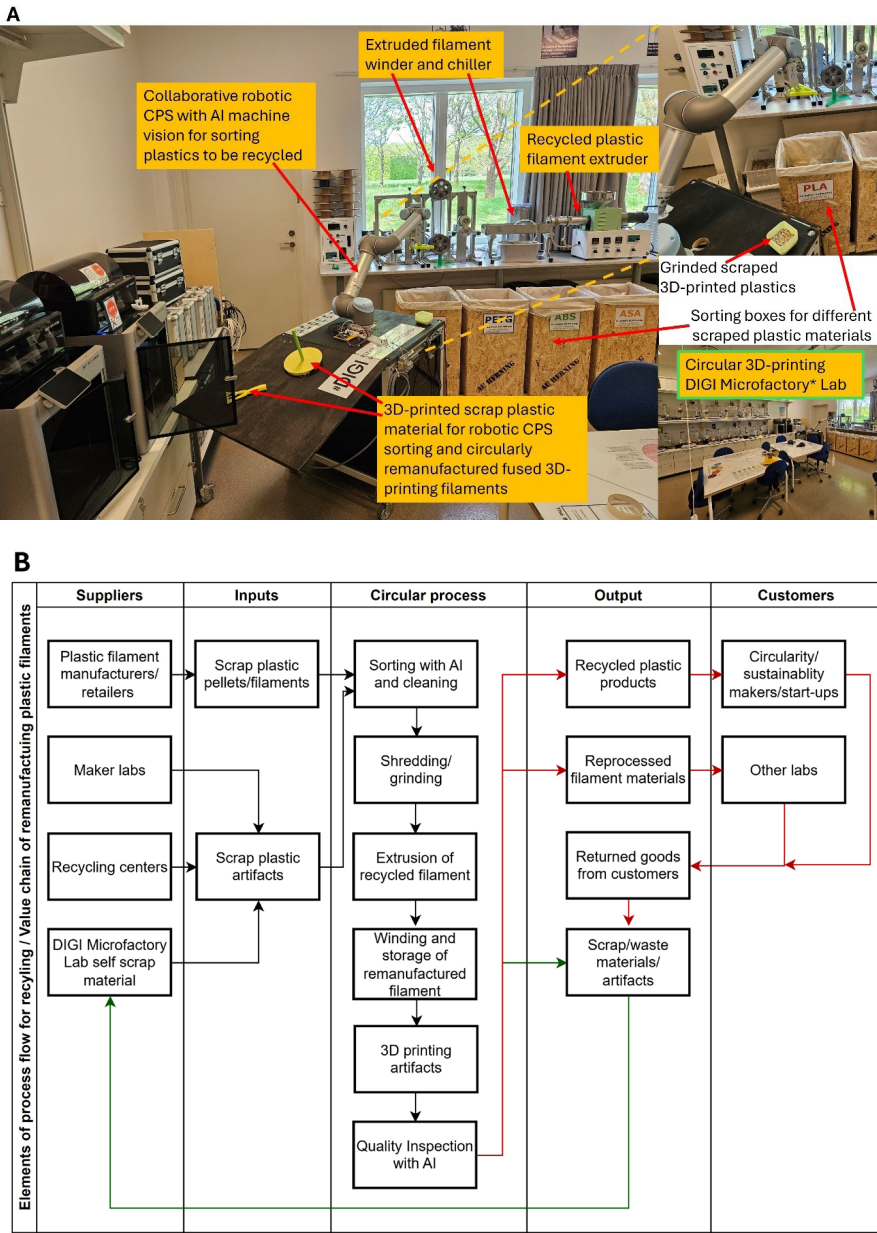


Figure 14. Image of DIGI Microfactory Lab during plastic remanufacturing operations. (A) Plastic inspection and sorting using a robotic cyber-physical system (CPS) via a semi-industrial pilot line for remanufacturing recycled filaments for three-dimensional (3D) printing. (B) Circular added value chain. Image created by the authors.

using a tension-controlled filament winder for reuse in 3D printing, in a near-zero-waste reuse and remanufacturing concept. The closed-loop process flow is displayed in Figure 14B from a business perspective, showing the circular added value chain of involved business and manufacturing process elements in the following sequence: supplier, input, circular process, output, customer.

9.5. Material cost-effectiveness and added value from adoption of circularity strategies

Considering the near-zero-waste scenario in Section 9.4, the plastic filament of material i can be 3D-printed and recycled m times before its material/mechanical properties deteriorate. One could measure empirically the created added value of recycled plastic material in the lab/enterprise operations with its material circularity added value by defining the following simplified empirical equation, as shown in Equation 1:

$$\text{Material circularity added value} = \sum_{i=1}^I Fm_i * (c_i - (Fm_i * cr_i)) \quad (1)$$

For different materials indexed $i \in \{1, 2, \dots, I\}$, the material recycling factor is explained as Fm_i , which is the sum of the times material can be recycled/ reused. c_i is the initial material cost, and cr_i is the cost of material recycling/ reuse.

10. Emerging artificial intelligence trends and future directions

Recent advances have significantly expanded the capabilities of AI-based plastic inspection and sorting. Lightweight CNN architectures, such as MobileNetV3²⁰⁸, ShuffleNetV2²⁰⁹, and EfficientNet-Lite²¹⁰, now enable real-time defect detection and efficient inference on embedded systems with reduced computation, balancing accuracy and latency for embedded machine vision applications. Lightweight models like MobileNetV3 and EfficientNet-Lite maintain low inference latency and are widely adopted in embedded and real-time vision systems, while ShuffleNet-based models offer competitive efficiency for constrained hardware.²¹¹ Meanwhile, vision transformers and hierarchical transformer variants such as Swin transformer leverage global self-attention mechanisms to capture long-range and texture-rich defect patterns¹⁰², demonstrating strong performance in complex vision tasks, including multi-category plastic waste sorting, where Swin transformer-based models achieve high accuracy and mean average precision, outperforming traditional CNN-based approaches in classification and detection tasks.²¹² The rise of multimodal foundation models such as CLIP⁴ and transformer-based models, such as the segment anything model^{213,214} allows simultaneous integration of visual,

spectral, and textual data for cross-domain understanding, providing new pathways for defect-material correlation through joint representation learning across modalities. Multimodal foundation models pre-trained on large visual language datasets learn generalized representations that bridge image and text domains, enabling efficient cross-modal reasoning and reducing the need for task-specific annotated data.²¹⁵ Additionally, digital twin simulations-to-real DRL enables the training of robotic inspection and control policies in simulation before real-world deployment, dramatically reducing data acquisition costs and safety risks, and facilitating effective transfer of learned policies to real systems via sim-to-real transfer techniques and digital twin frameworks.²¹⁶ Collectively, these approaches indicate a paradigm shift toward adaptive, data-efficient, and multimodal AI inspection frameworks that bridge research and industry. Future efforts should emphasize low-power deployment, domain adaptation, and standard benchmarking datasets for plastic defect detection to accelerate industrial adoption, aligning with ongoing research that underscores the importance of scalable representation learning, cross-modal integration, and robust simulation-to-real methodologies in industrial CPS robotics, inspection, and intelligent systems.²¹⁷

11. Conclusion

Artificial intelligence and advanced vision sensory technologies have dramatically improved plastic inspection, delivering unprecedented levels of accuracy, speed, and efficiency in quality control. CNNs excel at feature learning and extracting an image's most complex properties, making them efficient for detection, material classification, and recyclability assessment. SVMs complement CNNs by delivering impressive performance on small datasets, particularly when accuracy is paramount, and data are noisy. Hybrid models that combine CNNs with SVMs further enhance these capabilities, yielding superior results in both classification and defect identification. While these directions seem extremely promising, there are still challenges, such as high computational requirements, reliance on large datasets, and real-time latency, that hinder their broader adoption. Nevertheless, some of these limitations are being slowly addressed by developments such as hardware accelerators, lightweight algorithms, and optimized hybrid frameworks.

The use of DRL and a newly developed vision transformer in robotic systems¹⁰² opens new opportunities for autonomous decision-making, enabling system integrators and production managers to identify the best approaches for fast-changing¹⁰² production conditions in Industry 5.0 scenarios. As AI algorithms and hardware chips' computational capabilities advance, it

is anticipated that they will boost industrial productivity and help tackle challenges, such as enhancing future work environments for plastic sorting and recycling through a human-centric AI robot in an optimal, interactive way, utilizing concepts such as hybrid intelligence.⁸ The rapid progress of AI technologies is transforming the plastic sorting and manufacturing industry, enabling improved productivity and higher quality, as well as economically and environmentally sustainable “greener” manufacturing systems that support circular business ecosystems. Future research in AI models should prioritize the development of low-power, lightweight models that can operate efficiently on embedded and edge Internet-of-Things-enabled devices²¹⁸ for real-time inspection in Industry 5.0 environments. Adopting a few-shot transfer learning techniques and multimodal approaches will help overcome the challenge of limited annotated data, enabling models to generalize across different polymer types, defect classes, and imaging modalities. Conversely, with the anticipated advent of quantum computing⁹, the ultra-high performance computational capabilities of such computers are anticipated to enable the training of computationally expensive multimodal generative AI models with extremely large data sets. This will support enhanced inference capabilities in hybrid human-robot CPS and facilitate the development of new plastic materials and processes with tailored characteristics, further advancing both economic and environmental sustainability.

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Conflict of interest

Michail J. Beliat is an Editorial Board Member of the journal but was not involved in the editorial and peer review process conducted for this paper, directly or indirectly. Separately, other authors declared that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

Author contributions

Conceptualization: Michail J. Beliat is

Visualization: Michail J. Beliat is

Writing – original draft: All authors

Writing – review & editing: All authors

Ethics approval and consent to participate

Not applicable.

Consent for publication

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Availability of data

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Further disclosure

The authors disclosed that AI tools were used to generate higher-quality images for certain figures and to proofread text.

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