



Research  
AI for Process Manufacturing—Review

# Future Manufacturing with AI-Driven Particle Vision Analysis in the Microscopic World



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## ARTICLE INFO

### Article history:

Received 4 August 2024

Revised 1 May 2025

Accepted 8 August 2025

Available online 12 August 2025

### Keywords:

Particle vision analysis

AI-driven microscopic imaging

Smart manufacturing

## ABSTRACT

Recent advances in artificial intelligence (AI) have led to the development of sophisticated algorithms that significantly improve image analysis capabilities. This combination of AI and microscopic imaging is transforming the way we interpret and analyze imaging data, simplifying complex tasks and enabling innovative experimental methods previously thought impossible. In smart manufacturing, these improvements are especially impactful, increasing precision and efficiency in production processes. This review examines the convergence of AI with particle image analysis, an area we refer to as “particle vision analysis (PVA).” We offer a detailed overview of how this technology integrates into and impacts various fields within the physical sciences and materials sectors, where it plays a crucial role in both innovation and operational improvements. We explore four key areas of advancement—namely, particle classification, detection, segmentation, and object tracking—along with a look into the emerging field of augmented microscopy. This paper also underscores the vital role of the existing datasets and implementations that support these applications, which provide essential insights and resources that drive continuous research and development in this fast-evolving field. Our thorough analysis aims to outline the transformative potential of AI-driven PVA in improving precision in future manufacturing at the microscopic scale and thereby preparing the ground for significant technological progress and broad industrial applications in nanomanufacturing, biomanufacturing, and pharmaceutical manufacturing. This exploration not only highlights the advantages of integrating AI into conventional manufacturing processes but also anticipates the rise of next-generation smart manufacturing, which is set to revolutionize industry standards and operational practices.

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## 1. Introduction

Advances in imaging technologies have revolutionized particle research by enabling detailed exploration of the temporal and spatial variations inherent in the microscopic world. Developments in optics have yielded microscopes capable of imaging across a wide range of spatial scales, from single molecules to entire organisms. Simultaneously, improvements in fluorescent probes have increased the brightness, photostability, and spectral range of fluorescent proteins and small-molecule dyes. These combined advances have facilitated dynamic measurements in living cells, including long-term imaging of single molecules [1,2], simultane-

ous measurements of multiple biosensors [3,4], and observations of organismal development [5,6]. Beyond live-cell imaging in life sciences, integrating advanced imaging techniques with materials and physical sciences is crucial for deepening our understanding of the microscopic world. High-resolution techniques such as cryo-electron microscopy (cryo-EM) [7] have provided unprecedented views of macromolecular complexes, facilitating detailed structural analyses of particles [8]. Additionally, super-resolution microscopy methods, including stochastic optical reconstruction microscopy (STORM) [9] and photoactivated localization microscopy (PALM) [10], have pushed the boundaries of spatial resolution, enabling the visualization of particles at the nanometer scale [9]. Such detailed observations are integral to the development of manufacturing systems that are not only efficient but also environmentally sustainable and highly adaptable.

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The rapid advancements in imaging technology have been paralleled by an increasing demand for quantitative image analysis in particle research. Modern imaging data require quantification to be truly informative [11]. This necessity has driven the development of sophisticated analytical tools capable of processing and interpreting large volumes of complex imaging data, allowing researchers to extract meaningful insights from their observations. Key tasks in this field include particle classification, which involves predicting labels for images, such as determining whether a stem cell has differentiated. Particle detection focuses on identifying the positions of particles within images, while particle segmentation aims to distinguish distinct objects within an image, such as isolating single particles. Particle tracking involves following an object, such as a single particle in a live embryo, across multiple frames of a movie. Additionally, super-resolution techniques, which are often enhanced by neural networks, significantly improve the clarity and detail of microscopy images, revealing features that were previously unresolvable. This increased capability is crucial for eco-manufacturing, where understanding material behaviors at the nanoscale can drive innovations in product design and manufacturing processes, leading to more sustainable production techniques.

Artificial intelligence (AI) has significantly broadened the scope of problems that computer vision can address. AI algorithms have demonstrated remarkable success in various image analysis tasks, including classification, detection, segmentation, tracking, and super-resolution. Recently, large-scale pretrained models have shown astounding capabilities in solving these tasks, combining a rich blend of knowledge and skills [12,13]. For instance, models reported in recent studies have demonstrated the ability to classify, detect, and segment new target objects without requiring extensive annotated data [14,15]. Additionally, a zero-shot deconvolution network for optical fluorescence microscopy has been proposed, which increases image resolution by over 1.5-fold without the need for high-quality training data, enabling unsupervised, high-fidelity imaging across various microscopy modalities [16]. These advancements have significantly improved the accuracy and efficiency of particle analysis, allowing for more detailed and comprehensive studies of microscopic phenomena. The integration of deep learning techniques into particle analysis represents a transformative leap forward, increasing the resolution and accuracy of imaging while reducing the dependence on extensive annotated datasets, which are often labor-intensive and time-consuming to produce. This paradigm shift could propel the fields of cyber-manufacturing, bio-manufacturing, and eco-manufacturing forward.

Given the central role of observation—and consequently imaging—in particle analysis, AI has the potential to revolutionize our understanding of the microscopic world. Currently, a metaphorical gold rush is underway, with numerous research groups leveraging AI methods to extract novel insights into particle behavior. Researchers are not only exploring new applications but also refining existing AI techniques to fully harness the potential of AI in particle analysis. These efforts have significantly increased the capabilities of microscopic image analysis tools [17–24]. For instance, TrackMate [17] offers both automated and semi-automated tracking solutions, along with advanced visualization tools. Furthermore, its architecture improves compatibility with advanced external segmentation tools such as ilastik [18], Trainable Weka Segmentation [19], and Cellpose [20], thereby increasing the accuracy and efficiency of segmentation in complex imaging studies. Innovative tools such as Cellpose, QuPath, and StarDist have been developed for specific segmentation and analysis tasks. Cellpose is optimized for cellular and nucleus segmentation [20], QuPath excels in whole slide image analysis in digital pathology [21], and StarDist employs novel star-convex shapes

for precise object detection in microscopy images [22]. In addition, tools such as DeepLIF and spatial transcriptomics tools leverage deep learning to improve the interpretation of immunohistochemistry images and analyze spatially resolved transcriptomics data, respectively [23,24].

This review aims to serve as a comprehensive introduction to AI in the analysis of microscopic images, with a focus on common use cases in quantitative microscopic research. By incorporating insights from relevant examples, we seek to demystify AI techniques for new adopters in the field. First, we define and analyze the applications of particle vision analysis (PVA) across various disciplines, exploring its directions and challenges. Next, we systematically summarize key tasks in particle image analysis, including classification, detection, segmentation, tracking, and super-resolution. We also provide an overview of popular open-source frameworks and datasets that support these tasks. Finally, we offer an assessment of the future development of PVA, with suggestions for potential research directions and advancements. Through this comprehensive review, we aim to underscore the transformative potential of AI in microscopic research, highlighting its pivotal role in advancing methodologies and revolutionizing approaches within the manufacturing sector (Fig. 1).

## 2. Particle vision analysis

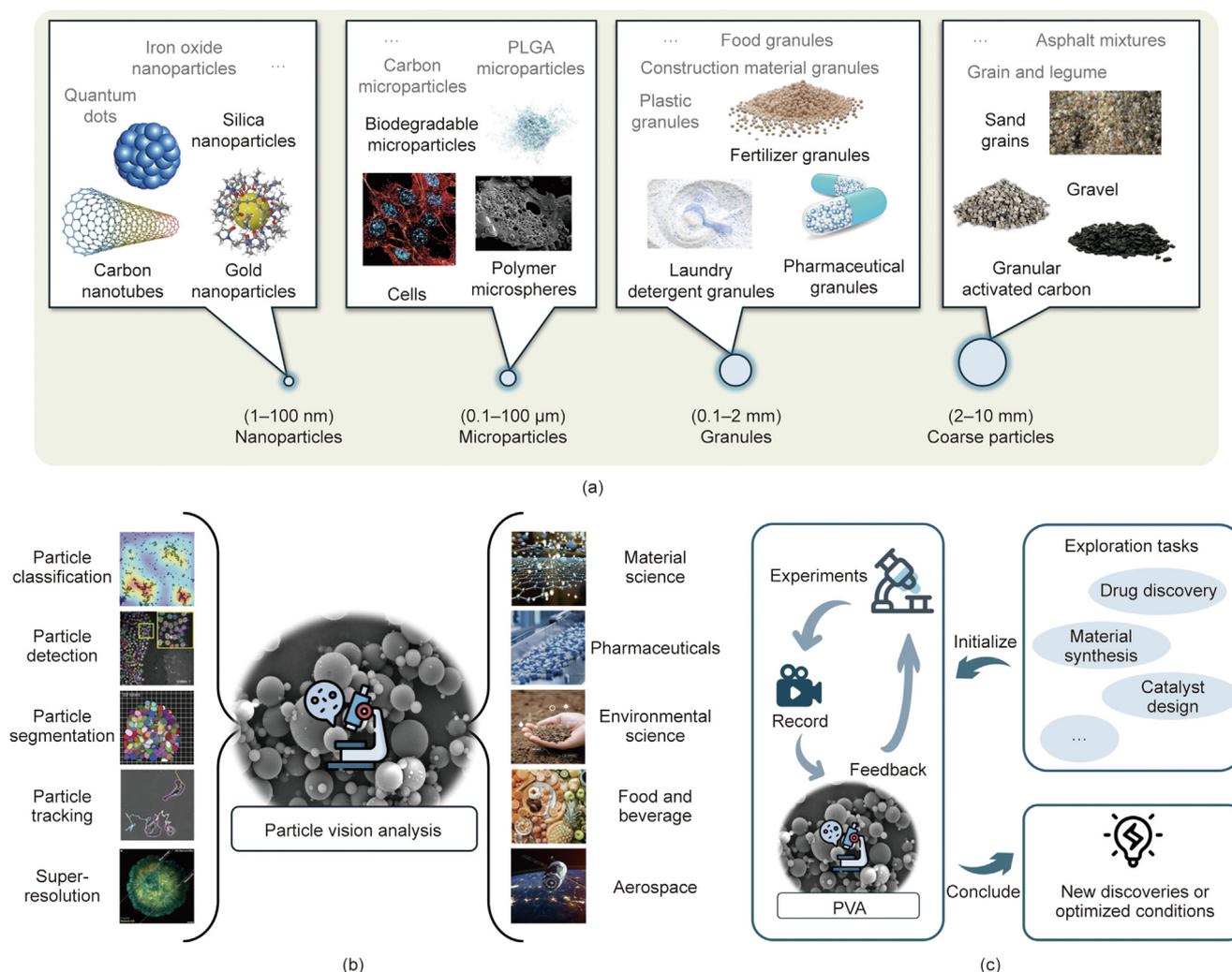
PVA merges AI-enhanced imaging and computational techniques to study particles across various media, serving as a cornerstone in our understanding of particles' complex properties and behaviors. This multidisciplinary field significantly impacts materials science, pharmaceuticals, environmental science, and industrial processing, contributing to the advancement of both technology and science by providing detailed quantitative and qualitative insights into particle size, shape, distribution, composition, and dynamics [25–31]. These insights are vital for exploring fundamental particle properties and their functional roles and thus increasing our scientific understanding and technological capabilities.

### 2.1. Manufacturing applications of PVA

#### 2.1.1. Materials manufacturing (nanoscale to microscale)

In materials science research, understanding particle size and distribution is fundamental for exploring the properties and functional behaviors of materials. Research typically spans particle sizes from nanometers ( $1\text{ nm} = 10^{-9}\text{ m}$ ) to micrometers ( $1\text{ }\mu\text{m} = 10^{-6}\text{ m}$ ), which crucially influence the mechanical, electrical, and optical characteristics of materials. Advanced techniques such as dynamic light scattering (DLS), scanning electron microscopy (SEM), and transmission electron microscopy (TEM) are utilized to measure and analyze particle size distributions accurately. This comprehensive investigation aids in the development of materials with tailored properties for specific applications, driving innovation in fields such as nanotechnology, electronics, and biomedicine.

PVA is an important tool for analyzing material properties at the granular level, which facilitates the design of materials with specific functions. This is particularly crucial in fields such as nanotechnology, where nanoscale properties greatly influence performance and innovation [32–36]. PVA enables the rapid and non-invasive quantification of particle size distributions in bulk materials, which is essential for monitoring manufacturing processes such as microcrystalline cellulose production [32]. The integration of PVA with deep learning accelerates the detection of key two-dimensional (2D) materials in microscopic images, significantly reducing identification times for materials that are critical in quantum information science, such as hexagonal boron nitride flakes [33]. The real-time dynamic characterization of particle size distributions



**Fig. 1.** Introduction of PVA. (a) Particle diversity: Particles range in size from nanoparticles (1–100 nm), such as the gold and silica that are crucial in medical therapies and drug delivery, to microparticles (0.1–100  $\mu\text{m}$ ), such as the polymer spheres and cells that are important in slow-release medications and biological research. Granules (0.1–2 mm), used in sectors from agriculture to cleaning, and coarse particles (2–10 mm), such as sand and gravel, are essential in construction and environmental management. PLGA: poly(lactic-co-glycolic acid). (b) PVA: This discipline focuses on the detection, segmentation, tracking, classification, and super-resolution imaging of particles. It utilizes advanced algorithms and imaging techniques to analyze particles ranging from microscopic cell structures to larger environmental samples, with applications spanning materials science, pharmaceuticals, environmental science, food and beverages, and aerospace. (c) Practical mechanism of PVA: Starting with exploration tasks such as drug discovery, material synthesis, and catalyst design, this cycle progresses through experimentation where observations and data are gathered and analyzed with advanced particle imaging techniques. The feedback loop from these experiments drives further refinements, enhancing insights or optimizing conditions, thus promoting continuous advancement in various fields.

on conveyor belts through tailored artificial vision systems exemplifies essential process control in manufacturing, improving both efficiency and product quality [34]. Additionally, sieveless computer vision techniques offer a direct, high-throughput method for particle size analysis, overcoming the inconsistencies of traditional mechanical sieving methods [35].

Modal analysis using three-dimensional (3D) vision-based measurements uses vibration data analysis to provide sophisticated assessments of material properties that are crucial for advancements in structural engineering [36]. TEM and computer vision are used for nanopore detection in 2D membranes, assisting in ion detection and DNA sequencing [37]. Visual vibrometry, which leverages vibration mechanics and computer vision, estimates material properties from videos of vibrating objects, providing a novel, non-invasive approach to material characterization [38]. Furthermore, an enhanced visual tracking methodology utilizing quantum-behaved particle swarm optimization (PSO) improves dynamic optimization problems within material contexts [39].

Lastly, an innovative algorithm for analyzing particulate materials from tomography images offers key insights into non-destructive material analysis and the internal structure of engineered materials [40].

### 2.1.2. Pharmaceuticals manufacturing (nanometers to several hundred micrometers)

Particles are a critical factor in pharmaceutical research, influencing drug formulation, delivery, and bioavailability. In this field, particle sizes typically range from submicron levels ( $< 1 \mu\text{m}$ ) up to several hundred micrometers. The smaller size domain, often targeted in the nanoscale range (1–100 nm), is particularly relevant for increasing the solubility and absorption rates of poorly water-soluble drugs. Techniques such as nanoprecipitation, high-pressure homogenization, and milling are utilized to achieve and control these fine particle sizes. Precise characterization of such particles is carried out using methods such as laser diffraction, nanoparticle tracking analysis (NTA), and electron microscopy.

The detailed control and analysis of particle size not only optimize the therapeutic efficacy but also improve the stability and overall performance of pharmaceutical formulations.

Recent advancements in PVA technologies have markedly bolstered the consistency and quality of pharmaceutical products. These improvements are not merely important for adhering to stringent regulatory standards but also increase the therapeutic effectiveness of medications. Among these technologies, IMAQ Vision Builder has emerged as a critical tool for the image processing of pharmaceutical powders. This technique facilitates the detection of surface defects and ensures the quality of particles, which is vital for streamlined manufacturing processes [41]. Furthermore, the integration of automated systems that perform multivariate texture analysis has revolutionized the estimation of size distribution in granulated pharmaceuticals. Such systems are instrumental in maintaining uniform drug formulations, thereby contributing significantly to product consistency [32]. In addition to static imaging, machine vision plays a key role in the online inspection of visual particles within pharmaceutical ampoules. This application not only increases the accuracy of defect detection but also minimizes production errors, thus safeguarding product integrity [42]. Moreover, particle tracking technologies are employed to monitor the dynamic behaviors of therapeutic nanoparticles. These techniques are invaluable for optimizing drug and gene delivery mechanisms, thus improving therapeutic outcomes [43]. The application of automated machine vision systems in inspecting liquid pharmaceuticals is another significant advancement. These systems drastically improve the detection of contaminants, achieving high accuracy and speed, which are essential for ensuring product safety [44]. Lastly, techniques such as frequency domain photon migration (FDPM) are utilized to meticulously analyze particle sizes and properties. This analysis is critical for ensuring compliance with regulatory standards and optimizing drug formulations [45].

### 2.1.3. Environmental science (nanoscale to microscale)

In environmental science, particles influence the behavior and impact of particulate matter on air quality, water pollution, and soil contamination. Within this field, particle sizes typically range from a few nanometers ( $1\text{ nm} = 10^{-9}\text{ m}$ ) to micrometers ( $10\text{ }\mu\text{m}$ ). Ultrafine particles ( $< 100\text{ nm}$ ) are of particular interest due to their ability to penetrate biological membranes and affect respiratory and cardiovascular health. Methods such as aerosol mass spectrometry and scanning mobility particle sizing are employed to comprehensively characterize these particles. Understanding the distribution and effects of different particle sizes is vital for developing strategies to mitigate environmental pollutants and assess their ecological and health impacts.

PVA plays a crucial role in pollution assessment and monitoring, where it is extensively used to characterize and track particulate matter in various ecosystems, including air, water, and soil. By systematically studying pollution levels and the dispersion patterns of pollutants, researchers gain valuable insights into the dynamics of environmental contamination. This analysis is essential not only for evaluating the effectiveness of current environmental regulations and remediation strategies but also for formulating future policies. Recent advancements include the application of quantum cascade laser-based hyperspectral infrared chemical imaging techniques in PVA studies—an innovative approach that has significantly improved the monitoring of microplastics in environmental samples, offering rapid and routine assessments. Hyperspectral imaging provides comprehensive data on the quantity, morphology, and chemical types of microplastics, which aids in improving our understanding and management of pollution sources [46,47]. Furthermore, techniques such as automated electron probe X-ray micro-analysis and laser microprobe mass spec-

trometry have been effectively employed to characterize aerosols and other particulate pollutants in the environment. These methods are pivotal in assessing air quality and overall environmental health, providing detailed elemental and molecular information about particles [48]. Additionally, the development and implementation of image-dehazing algorithms have significantly improved the clarity of environmental images compromised by particulates such as haze and fog. This improvement is particularly important in the fields of environmental monitoring and remote sensing, where accurate image analysis is necessary for the effective observation and management of ecological zones [49]. Deep learning models have also been adapted to increase the accuracy of particle source identification in environmental science. For example, models have been applied to differentiate between anthropogenic and natural magnetic particles in TEM images, offering new avenues for detailed environmental analysis [50].

### 2.1.4. Diverse manufacturing applications

PVA also plays a crucial role in several other manufacturing sectors, including food processing, chemicals, and mining. Particle sizes in these sectors range from the submicron scale to several millimeters, necessitating a wide range of applications and technologies. In manufacturing, particle size must be controlled to optimize product texture, strength, and functional properties. Advanced characterization methods such as laser diffraction and electron microscopy provide precise particle size distribution, aiding in the development of superior manufacturing techniques and materials. The application of PVA is essential for maintaining high standards of quality control, ensuring material purity, and optimizing manufacturing processes. These capabilities are key to increasing productivity and safety, making PVA an indispensable tool in industrial applications. In food processing, PVA techniques are useful for monitoring and controlling the quality of food products. Detailed analyses of particle sizes and their distribution during manufacturing ensure consistent quality and adherence to strict safety standards [51], which is important for consumer safety and maintaining brand trust. The cosmetics industry relies on PVA for stringent quality control, particularly to assess the uniformity and distribution of particles in products such as powders and emulsions. This scrutiny significantly impacts product safety and effectiveness, making PVA central to the development of reliable and high-quality cosmetic products [52]. Aerospace applications also benefit significantly from PVA techniques. Enhanced inspection methods ensure the reliability of aerospace components by analyzing surface particles and identifying defects—crucial tasks for ensuring safety and durability [53]. In the semiconductor industry, PVA is critical for monitoring the cleanliness of silicon wafers and for the precise deposition of silicon particles during device fabrication. Controlling these parameters affects the performance and yield of semiconductor devices, impacting the efficiency and cost-effectiveness of manufacturing processes [54].

## 2.2. Advancing scientific discoveries

More than just a practical tool, PVA is emerging as a foundational element in the advancement of scientific knowledge, its capabilities instrumental in driving the discovery and development of new scientific insights. As illustrated in Fig. 1(c), PVA underpins a cyclic process of scientific discovery and optimization. This cycle starts with exploration tasks such as drug discovery, material synthesis, and catalyst design. Next is the experimentation phase, in which observations and data are collected and scrutinized using advanced particle imaging techniques. Feedback from these experiments prompts further refinements, yielding new insights and optimized conditions. This iterative process fosters continuous advancement across various scientific fields.

### 2.2.1. Developing new theories

PVA enables scientists to observe and analyze particles under diverse conditions and interactions, merging automated data analysis with advanced visualization techniques. This integration is pivotal in revealing complex phenomena in fields such as physics, chemistry, and biology. For example, in physics, PVA has facilitated new insights into particle interactions at quantum levels; in chemistry, it has aided in the understanding of catalytic processes at the nanoscale [55,56]. In biology, applications of PVA have led to breakthroughs in understanding cellular structures and their dynamic interactions within tissues and environments [57,58]. When used to manage large, intricate datasets, PVA supports data exploration and knowledge discovery, driving the formulation of new theories about material behaviors and biological processes at the microscopic level [59]. These insights have the potential to revolutionize our understanding across these domains, profoundly impacting theoretical foundations and leading to novel experimental approaches in each field.

### 2.2.2. Improve experimental techniques

Recent advancements in PVA technology have significantly improved both resolution and processing speeds, enabling the real-time exploration of dynamic processes under conditions that closely mimic natural environments [60–63]. In particle physics, particularly at the Large Hadron Collider, PVA plays a crucial role in analyzing high-energy particle collision events. By integrating advanced image processing techniques with sophisticated deep learning algorithms, PVA increases the accuracy and efficiency of particle identification, deepening our understanding of fundamental physics phenomena [63]. ZeroCostDL4Mic [64] is an accessible platform that leverages free cloud resources to enable researchers without coding expertise to train and apply deep learning networks for microscopy tasks such as segmentation, object detection, and super-resolution. By simplifying access to powerful AI tools and providing performance evaluation metrics, ZeroCostDL4Mic democratizes advanced microscopy analysis and facilitates the study of complex biological processes. In the realm of materials science, Schwartzman et al. [63] have highlighted how large-scale graph networks are revolutionizing the discovery of inorganic crystals; such approaches have been used to identify over 2 million stable structures and expand the known materials space by an order of magnitude. This breakthrough significantly increases the efficiency of materials discovery by enabling the rapid screening of technologically relevant materials and supporting advanced modeling applications. These technological advancements not only broaden the scope and depth of scientific experiments but also transform previously infeasible studies into viable research opportunities. As a result, these developments yield more precise and detailed insights, potentially leading to groundbreaking discoveries and a deeper understanding of the fundamental principles governing natural phenomena.

### 2.2.3. Advancements in AI-driven science

The integration of machine learning and AI into PVA has markedly enhanced the sophistication of PVA, enabling the meticulous analysis of vast datasets. This advancement is especially transformative in sectors such as agriculture, where machine vision systems equipped with capabilities for image segmentation and feature extraction are being optimized, improving analysis and identification processes and boosting agricultural productivity and management efficiency [65]. Similarly, in fields such as epidemiology and climate science, PVA's ability to parse through and analyze complex, multifactorial datasets is invaluable. These data-driven approaches are essential for accurately predicting and effectively mitigating risks associated with public health and environmental changes [66], showcasing the pivotal role of

advanced data analysis in understanding and addressing global challenges.

In conclusion, PVA has emerged as a cornerstone in the advancement of scientific progress. By providing innovative tools for theory development and increasing experimental capabilities, PVA extends the frontiers of knowledge across disciplines. Its role in fostering interdisciplinary research integrates diverse scientific realms, facilitating collaborative solutions to complex global challenges. Moreover, through the integration of machine learning and AI, PVA significantly advances data-driven science, thereby enriching our understanding and management of complex systems. These contributions not only promote the continuous expansion of knowledge but also offer essential assistance in addressing emerging scientific and societal challenges.

## 2.3. Challenges in PVA

Despite its advantages, PVA presents several inherent complexities that pose significant challenges to its advancement. This section highlights the primary obstacles researchers encounter in refining this technology.

### 2.3.1. Particle complexity

As illustrated in Fig. 1(a), the wide variety of particle characteristics, including shape, size, and material composition, introduces significant analytical challenges. Each type of particle may demand distinct imaging and analysis techniques, which complicates the development of standardized methods across different studies [67]. This diversity necessitates the creation of highly adaptable analytical tools that are capable of delivering precise measurements and detailed characterizations under diverse conditions. The ability to effectively handle such variability is critical for the advancement of PVA methodologies and their application in real-world scenarios.

### 2.3.2. Dynamic environments

Analyzing particles within dynamic or unstable environments that replicate natural or industrial conditions presents formidable challenges. These environments require robust imaging techniques and advanced real-time processing capabilities to accurately capture and analyze data [68,69]. Precision in rapidly changing scenarios is essential for a wide array of applications, from environmental monitoring to industrial quality control. Successfully adapting PVA technologies to function reliably under such variable conditions increases their applicability and effectiveness, ensuring that data integrity is maintained even when external variables fluctuate significantly.

### 2.3.3. Scale of analysis

PVA often requires the processing of vast datasets containing high-resolution images, which poses significant challenges due to the time-consuming and computationally intensive nature of these tasks. The primary challenge is the development of more efficient computational strategies capable of managing extensive data volumes without compromising accuracy or processing speed [70]. Addressing this issue necessitates continual advancements in both hardware and software to adapt to the escalating demands of large-scale analysis. Improvements in data compression algorithms, parallel processing techniques, and the utilization of high-performance computing platforms are key in achieving these goals, thereby enabling researchers to analyze larger datasets more effectively and efficiently [71].

In response to these challenges, ongoing research and development efforts are concentrated on increasing the sophistication and adaptability of PVA systems. These efforts include improving image-acquisition techniques to capture higher quality data more

efficiently, refining machine learning algorithms for more accurate pattern recognition and predictive analysis, and optimizing data handling capacities to manage large-scale datasets effectively [70,72]. Such advancements are essential in order to overcome the current limitations of PVA and broaden its utility in diverse scientific and industrial applications. By continuously pushing the boundaries of technology, researchers aim to unlock new possibilities with PVA, making it a more powerful tool in the quest for scientific discovery and industrial innovation.

### 3. Advancing PVA with AI

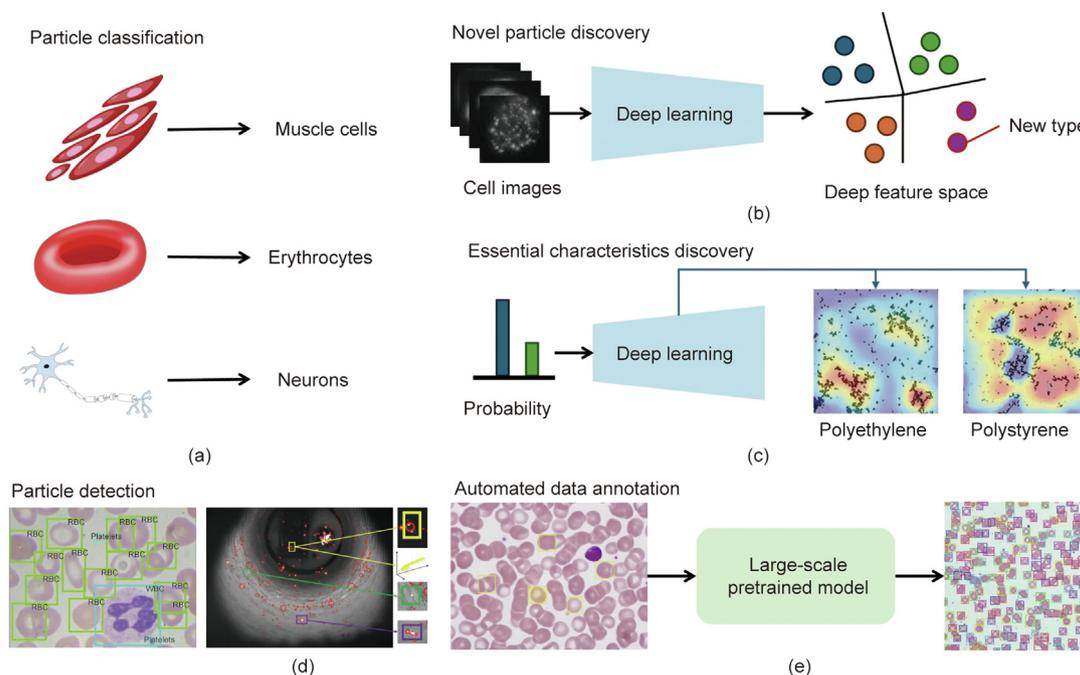
As shown in Fig. 2 [14,15,47,73–78] and Fig. 3 [16,27,79,80], AI methods in PVA have evolved to include the detection, classification, segmentation, tracking, and super-resolution imaging of particles. These methods utilize advanced algorithms and imaging techniques to analyze particles across a broad spectrum of scales, from microscopic cell structures to large-scale environmental samples. The application of AI in PVA extends across diverse sectors, increasing capabilities in materials science, pharmaceuticals, environmental science, the food and beverage industry, and aerospace. The versatility of PVA allows it to underpin significant scientific advancements, and its practical applications affect a wide array of industries. The inclusion of AI in PVA not only increases the efficiency and accuracy of particle analysis but also transforms how researchers and industry professionals approach complex problems involving particulate materials. For users interested in implementing these AI-driven PVA techniques, a comprehensive list of existing tools and resources is provided in Table 1 [20–24,27,28, 80–103].

#### 3.1. Particle detection and classification

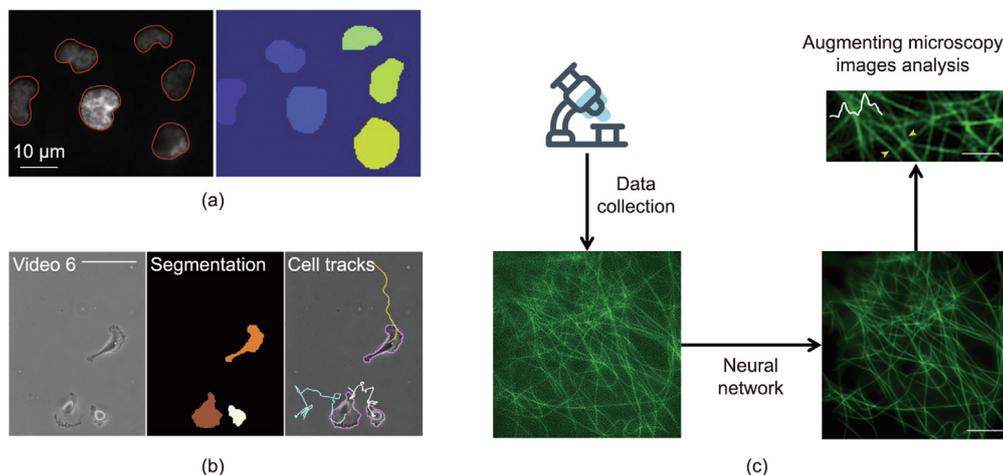
Recent studies have emphasized the expanding role of AI in particle detection and classification, where it significantly increases

analytical capabilities across various scientific domains, as shown in Fig. 2. Kim et al. [26] employed a state-of-the-art deep convolutional neural network (CNN) to classify the shapes of nanoparticles from SEM images. Their approach utilizes advanced image-processing algorithms to accurately estimate particle size, recognize scale bars, and extract text, significantly speeding up the analytical process. Similarly, Cao et al. [104] combined deep learning with the electrical sensing zone (ESZ) method to classify micron-sized particles in liquid–solid systems. By using a ResNet model, they achieved the high-accuracy differentiation of particle types based on varied pulse signals—an approach that proved ideal for industrial monitoring applications. In the field of microplastics analysis, von der Esch et al. [105] developed the TUM-ParticleTyper, a tool that automatically identifies, counts, and characterizes microplastic particles in microscopy images. This software significantly increases analytical precision and facilitates calibration across diverse microscopy techniques. In another innovative study, Mukherjee et al. [47] exploited liquid crystal (LC) aqueous interfaces to trap and classify colloidal microplastics, providing new insights into the aggregation behaviors of polyethylene (PE) and polystyrene (PS) and aiding in material identification. Their study utilized LC-mediated interactions to reveal distinct assembly behaviors of PE and PS microparticles at the LC interface. By enhancing these differences with surfactant additives, the researchers observed that the PS microparticles shifted from forming linear chain-like structures to becoming dispersed, while the PE microparticles consistently formed dense clusters. These differences in aggregation were captured and analyzed using deep learning, specifically through a CNN model, which accurately classified the particles based on their assembly patterns.

For the accurate reconstruction of granular particle shapes in three dimensions from X-ray computed tomography images, Lai and Chen [106] integrated machine learning with the level set method. This approach was demonstrated to be particularly effective for analyzing complex samples such as Martian soil simulants.



**Fig. 2.** Particle classification and detection. (a) A deep-learning-based classifier identifies protein expression patterns in fluorescence images with high accuracy. (b) Particle classification models are trained to perform tasks and extract feature vectors from images, enabling the clustering and identification of novel cell phenotypes [73,74]. (c) Utilizing interpretable deep learning methods, the trained model identifies critical features that contribute to classification performance [75–77]. Reproduced from Ref. [47] with permission. (d) Advanced image detection techniques powered by deep learning accurately identify various cell types and particles. RBC: red blood cell; WBC: white blood cell. Reproduced from Ref. [78] with permission. (e) Large-scale pretrained models leverage labeling information from small datasets to automate the labeling process for cell samples [14,15].



**Fig. 3.** Particle segmentation, particle tracking, and super-resolution. (a) Particle segmentation: Individual cells are distinctly outlined to demonstrate the precision of segmentation techniques in identifying cellular boundaries. Reproduced from Ref. [79] with permission. (b) Particle tracking: The trajectories of individual cells as recorded by advanced tracking algorithms are shown here, highlighting the paths and behaviors of cells in motion [80]. Reproduced from Ref. [27] with permission. (c) Super-resolution: Using cutting-edge super-resolution methods augmented by neural networks, the clarity and detail of features in microscopy images are significantly increased, revealing previously unresolvable elements. Reproduced from Ref. [16] with permission.

**Table 1**  
Source code and containers for AI-driven PVA.

Application	Particle size	Package	Comments	Refs.
Particle segmentation	Microparticles	Cellpose	A generalist algorithm for cell and nucleus segmentation	[20,81,82]
Particle segmentation	Microparticles or granules	QuPath	An open source software for bioimage analysis	[21]
Particle detection	Microparticles or granules	DeepTangle	Fast detection of slender bodies in high-density microscopy data	[83]
Particle detection and segmentation	Microparticles or granules	StarDist	A deep learning nuclei segmentation method originally developed for fluorescence microscopy, can be extended and successfully applied to histopathology images	[22,84,85]
Particle classification and segmentation	Microparticles or granules	TIAToolbox	A computational pathology toolbox developed by TIA Centre that provides an end-to-end API for pathology image analysis using best practices	[86]
Particle segmentation	Microparticles or granules	micro-sam	A tool for interactive and automatic segmentation and tracking of objects in multi-dimensional microscopy data	[87]
Particle segmentation	Microparticles or granules	DeepLIIF	Deep-learning inferred multiplex immunofluorescence for immunohistochemical image quantification	[23,88–91]
Particle segmentation	Microparticles or granules	Spateo	Multidimensional spatiotemporal modeling of single-cell spatial transcriptomics	[24]
Particle segmentation	Microparticles or granules	MEDIAR	Harmony of data-centric and model-centric for multi-modality microscopy	[92]
Particle tracking	Microparticles or granules	BigNeuron	A resource to benchmark and predict performance of algorithms for automated tracing of neurons in light microscopy datasets	[93]
Particle tracking	Microparticles or granules	Usiigaci	An all-in-one, semi-automated pipeline to segment, track, and visualize cell movement and morphological changes in phase contrast microscopy	[94]
Particle tracking	Microparticles or granules	TrackMate	An extensible platform where developers can easily write their own detection, particle linking, visualization or analysis algorithms	[27,80]
Particle tracking	Microparticles or granules	DeepTrack2	A comprehensive deep learning framework for digital microscopy	[28,95–97]
Particle tracking	Microparticles or granules	Bayesian tracker	A Python library for multi-object tracking, used to reconstruct trajectories in crowded fields	[98,99]
Super-resolution	Nanoparticles or microparticles	PSSR	A deep learning-based framework that facilitates otherwise unattainable resolution, speed, and sensitivity of point-scanning imaging systems (e.g., scanning electron or laser scanning confocal microscopes)	[100]
Super-resolution	Nanoparticles or microparticles	CAFI	Deep learning-based temporal super-resolution for fast bioimaging	[101]
Super-resolution	Nanoparticles or microparticles	FD-DeepLoc	Field dependent deep learning enables high-throughput whole-cell 3D super-resolution imaging	[102]
Super-resolution	Nanoparticles or microparticles	DeepSTORM3D	Dense 3D localization microscopy and PSF design by deep learning	[103]

TIA: tissue image analytics; API: application programming interface; PSSR: point-scanning super-resolution; CAFI: content-aware frame interpolation; PSF: point-spread function.

Advancing computer image analysis further, Raadnuhi [107] reported the use of Fourier analysis and fractal dimension extraction for classifying wear particles in mechanical systems, increasing the reliability of identifying distinct wear particle features. Expanding on these techniques, Stachowiak et al. [108] developed

an automated SEM-based system to classify wear particles by surface texture and shape, successfully distinguishing between fatigue, abrasive, and adhesive wear with greater accuracy than traditional manual methods. In cosmic-ray research, Garcia et al. [109] introduced an automated classification system using the

SciBar cosmic-ray telescope (SciCRT). By applying pattern recognition, neural networks, and clustering techniques, they distinguished various particle types and analyzed neutron spectra. In high-energy physics, Baldi et al. [110] demonstrated the superior performance of deep learning in classifying exotic particles, outperforming traditional machine learning methods by up to 8%. Carvalho et al. [111] used optical tweezers to classify particles via laser scattering signals, combining Fourier analysis, principal component analysis (PCA), and machine learning to achieve a classification accuracy of around 90% with minimal computational overhead. Furthermore, Alonso and Kirkegaard [83] developed DeepTangle, a toolbox for the rapid detection of slender bodies in dense microscopy data. The toolbox relies on CNNs with temporal context to process short video clips instead of single frames. It generates multiple independent centerline predictions for each slender body and uses a latent space to differentiate between overlapping organisms. Another significant contribution is TIAToolbox [86], an open-source library designed to simplify and increase the accessibility of computational pathology. By providing modular and user-friendly tools for whole-slide image analysis, TIAToolbox facilitates the implementation of advanced deep learning algorithms, democratizing research in computational pathology for a wide range of users. These advancements collectively underscore the transformative impact of AI in enhancing particle detection and classification across varied scientific domains.

### 3.2. Particle segmentation and tracking

In the life sciences, tracking technologies are useful for monitoring a wide range of biological entities, including single particles, subcellular organelles, bacteria, cells, and entire organisms (Fig. 3(b)). The diversity of imaging modalities in such studies necessitates a range of software solutions, as no single platform can address all tracking challenges. To accommodate this variety, flexible and extensible software platforms have been developed [27,80,112–115], enabling biologists to construct customized, automated tracking pipelines tailored to specific research needs. Tracking algorithms typically follow a two-step process of detection and linking. First, detection algorithms segment individual objects at each time point. Subsequently, linking algorithms connect these objects across time points to establish continuous tracks. Accurate object identification is essential for this process [25]. However, challenges arise in live-cell fluorescence microscopy, which is often compromised by low signal-to-noise ratios (SNRs), complicating object segmentation (Fig. 3(a)). Inaccurate detections may lead to fragmented tracks, resulting in multiple short tracks for a single object over time. Furthermore, high-density object regions pose additional difficulties due to overlapping or closely situated entities, with many algorithms mistakenly grouping these into a single object, leading to track interruptions or errors.

Recent advancements in biological image analysis have led to the development of sophisticated tools designed to increase the accuracy and efficiency of data interpretation. These tools leverage cutting-edge machine learning techniques and are tailored to specific analytical needs across various domains of the life sciences. Modern segmentation algorithms—particularly those integrating machine learning and deep learning—have been notably effective in addressing key challenges in the field. These algorithms excel at segmenting images with low SNRs and high object densities [79]. TrackMate, a user-friendly plugin for Fiji [80,116], provides both automated and semi-automated tracking solutions, along with advanced visualization and analysis tools. However, its reliance on Laplacian of Gaussian (LoG) filters, which are suitable for sub-resolved particles and blob-like objects [17], limits its effectiveness for textured objects, complex shapes, and

non-fluorescence modalities. These filters primarily measure the position, rather than the shape, of objects. TrackMate version 7 introduces a more modular architecture, increasing compatibility with external segmentation tools and offering an application programming interface (API) that supports integration with advanced tools such as ilastik [18], the Trainable Weka Segmentation plugin [19], StarDist [22], Cellpose [20], and MorphoLibJ [117]. This flexibility allows researchers to utilize state-of-the-art algorithms for more accurate and efficient segmentation, significantly improving the quality and reliability of tracking in complex imaging studies. Cellpose [20,81,82] is a versatile algorithm specifically designed for cellular and nucleus segmentation. It is optimized for user-specific data and includes capabilities for image restoration, making it highly effective for complex cellular structures. QuPath [21] is an open-source software platform that excels in bioimage analysis, particularly for whole-slide image analysis in digital pathology. It provides robust tools for processing large datasets, facilitating detailed tissue examination and diagnostics. StarDist [22,84,85] has introduced StarDist-3D, an innovative neural network model that extends 2D star-convex polygon representations to 3D star-convex polyhedra for the precise detection and segmentation of cell nuclei. This model effectively addresses key challenges, including the development of parameter-efficient shape representations, adaptation to the anisotropic voxel sizes common in fluorescence microscopy, and efficient computation of the polyhedra intersections required for non-maximum suppression. These advancements enable StarDist-3D to deliver superior performance on complex volumetric fluorescence microscopy datasets, outperforming both classical and existing deep-learning-based methods. Semantic annotation tools [87] increase the efficiency and detail of annotation processes in microscopy images to streamline research workflows and data categorization; they are especially suited for complex biological structures. DeepLIF [23,88–91] focuses on the advanced analysis of immunofluorescence imaging. By employing deep learning techniques, it improves the quantification and interpretation of immunohistochemistry images, supporting better diagnostic and research outcomes. Spatial transcriptomics tools [24] can be used to analyze spatially resolved transcriptomics data, providing insights into the cellular microenvironment and gene expression patterns, which are key in understanding tissue architecture and disease pathology. MEDIAR [92] advances multi-modality microscopy by integrating data-centric and model-centric approaches. It features robust predictive models and configurations that increase the analytical capabilities of microscopy, supporting diverse biological investigations. BigNeuron [93] addresses the challenges of analyzing and processing large-scale neuron imaging data. It focuses on optimizing feature extraction and computational efficiency, which are essential for neural network studies. Phase contrast microscopy enhancement [94] is a stain-free approach enabled by supervised machine learning to improve cell tracking; it provides clearer insights into cell dynamics without the need for invasive staining techniques. DeepTrack [28,95–97] facilitates the development and deployment of advanced optical microscopy techniques using deep learning, streamlining the study of cellular and subcellular structures. Bayesian tracking frameworks [98,99] utilize a Bayesian approach to robustly link object states across time in image datasets, increasing the reliability of biological particle tracking. These tools collectively represent significant contributions to the field of life sciences, each improving various aspects of particle research through technological innovation.

### 3.3. Super-resolution

Super-resolution techniques have significantly advanced PVA by improving spatial resolution and enabling the detailed

observation of complex systems (Fig. 3(c)). Keane et al. [118] pioneered super-resolution in particle image velocimetry (PIV), with a focus on particle spacing and displacement between light pulses, instead of conventional volume sizes. Validated through Monte Carlo simulations and re-analyzed turbulent flow data, this method improved resolution from 250 to 100  $\mu\text{m}$ , increasing measurement precision. von Diezmann et al. [119] expanded these techniques to 3D imaging in order to improve the visualization of nanoscale structures and motions, which aids in analyzing complex biological systems. Gungor et al. [120] introduced a deep learning approach with transformers to improve calibration in magnetic particle imaging (MPI); the approach speeds up system matrix recovery and MPI reconstruction by up to 64 times, thereby improving imaging efficiency. Chen et al. [121] investigated the impact of super-resolution imaging on single-molecule reactions and nanocatalysis; their work offers insights into chemical kinetics and nanocatalyst activities through enhanced spatial resolution and dynamic monitoring.

Recent advancements in super-resolution technologies have transformed particle imaging, increasing image resolution and analytical capabilities across various fields. These developments have enabled more precise observations at the nanoscale, leading to breakthroughs in both fundamental research and practical applications. Patil et al. [122] developed a method using conditional generative adversarial networks (cGANs) that increases the resolution of optical microscope images to match that of a scanning electron microscope. This approach notably improves particle size estimation in dense samples, demonstrating significant potential for industrial imaging applications. Similarly, Classen et al. [123] employed 3D structured illumination combined with intensity correlation microscopy to surpass the diffraction limit. Their technique provides superior resolution at lower illumination levels, which is valuable for detailed 3D biological imaging while minimizing phototoxicity. Additionally, Liu et al. [124] adapted the Visual Molecular Dynamics (VMD) software to analyze super-resolution and single-particle tracking data, thus facilitating efficient studies of biomolecular trafficking and complex intracellular structures. To further increase imaging capabilities, Nieuwenhuizen et al. [125] introduced a resolution measure based on Fourier ring correlation (FRC) for comparing nanoscopy methods. Their approach optimizes imaging strategies and expedites data acquisition by considering factors such as localization uncertainty, label density, and sample structure. Bahy et al. [126] increased the resolution of multi-focus low-resolution images using adaptive regularization and PSO. By optimally adjusting the regularization parameters, they achieved superior imaging results. Ghasemi-Falavarjani et al. [127] utilized particle filters to combine information from multiple low-resolution frames, significantly increasing image clarity and detail. Gray et al. [128] developed VirusMapper, an open-source tool integrated into Fiji for single-particle analysis in super-resolution microscopy. This software enables precise modeling of nanoscale biological structures, facilitating detailed studies of viral architecture and function. Laine et al. [129] innovatively integrated adaptive optics (AO) with deep learning to correct optical aberrations in single-molecule localization microscopy (SMLM). By compensating for tissue-induced distortions, they significantly increased 3D imaging accuracy and resolution in biological tissues. Their approach involves incorporating an AO system with deformable mirrors into the microscope's optical path to dynamically adjust and rectify wavefront distortions in real time. Complementing this hardware setup, they employed a U-Net [130,131] architecture known for its proficiency in image segmentation and enhancement tasks. The U-Net was trained on paired datasets of aberrated and corrected images, enabling the model to predict corrections for unseen aberrations in real time. This hybrid methodology not only improved image

resolution but also enhanced the SNR, making it particularly valuable for live-cell imaging applications where aberrations are prevalent. By combining AO with deep learning, they achieved precise corrections in dynamic imaging environments, thereby broadening the applicability of SMLM in complex biological systems.

Advancements in super-resolution imaging have significantly increased our ability to analyze microscopic structures across various scientific fields. Joseph [132] introduced a method integrating adaptive noise reduction with super-resolution techniques to enhance digital microscopy images, thereby improving microscopic structure analysis. In virology, McMahon et al. [133] applied fluorescence super-resolution microscopy combined with automated analysis to examine influenza virions. Their study revealed significant variability in filament size and viral protein distribution, suggesting a stochastic model of virus assembly. These findings enable a detailed understanding of virus morphology and its implications for transmission and pathogenicity. Comprehensive reviews have further highlighted progress in super-resolution microscopy. Liu et al. [134] reviewed recent advancements in the field, with a focus on technologies such as SMLM and minimal fluorescence photon fluxes microscopy (MINIFLUX), which achieve nanometer resolution in cellular imaging. They discussed technical developments, optimal experimental conditions, and diverse analytical methods, particularly the use of SMLM to study molecular machines and dynamic structural changes in living cells. Similarly, Lee et al. [135] provided an exhaustive overview of various super-resolution imaging techniques such as STORM, PALM, and stimulated emission depletion (STED) in cell biology, highlighting their impact on visualizing cellular structures with nanometer precision and increasing our understanding of cellular processes at the molecular level.

In environmental science, Offroy et al. [136] significantly advanced the Raman imaging of atmospheric aerosols by integrating super-resolution imaging with chemometric methods. Achieving a resolution of 200 nm, they provided detailed chemical composition maps of individual particles, offering new insights into atmospheric particle dynamics and their environmental and health implications. More specifically, the researchers used multivariate curve resolution-alternating least squares (MCR-ALS). By collecting a series of slightly shifted low-resolution hyperspectral images and reconstructing them into higher-resolution images through post-processing algorithms, they achieved detailed chemical characterization of submicron aerosols beyond the diffraction limit of traditional Raman imaging. Precise control over vibrations and sample motion—achieved with an anti-vibration system and a precise piezo motorized stage—was essential to ensure sub-nanometer stability during image acquisition. Despite challenges such as lengthy data acquisition times and significant computational demands, this approach provides a powerful tool for analyzing the heterogeneous structure and chemical composition of aerosols at the submicron scale. It holds broad applicability in fields such as environmental science, materials science, and pharmaceuticals, where detailed spatial chemical information is critical. Future efforts should focus on improving acquisition speed and computational efficiency to facilitate routine use in scientific research. In structural biology, Tokuhisa et al. [137] described the use of CNNs to significantly improve the resolution of X-ray diffraction images. Their approach improves the quality and interpretability of single-particle images in the analysis of biological macromolecules.

Interdisciplinary collaboration has played an important role in driving innovative solutions, particularly in the realm of augmented microscopy. For example, collaborative efforts between biophysicists and computer scientists have led to the development of super-resolution microscopy techniques such as PALM and STORM [135]. These approaches integrate advanced optical

methods with machine learning algorithms, providing sub-diffraction imaging capabilities that enable researchers to visualize individual protein molecules at nanometer scales. This has opened new frontiers in understanding cellular structures and molecular interactions that were previously inaccessible. Similarly, the collaboration between chemists and imaging specialists has resulted in advancements such as chemometric-enhanced Raman imaging [136], which allows detailed mapping of the chemical composition of atmospheric aerosols. This advance has significantly contributed to environmental science, particularly in understanding aerosol behavior and their effects on health and climate. In virology, interdisciplinary teams have utilized super-resolution microscopy to examine viral structures in unprecedented detail. One notable example is the previously mentioned open-source platform VirusMapper [128], which was developed through collaboration between software engineers, virologists, and optical physicists. Integrated with the ImageJ platform, this tool facilitates the construction of high-resolution models of viral architecture, providing critical insights into viral mechanisms and structural biology.

### 3.4. Smart manufacturing

AI-driven PVA is revolutionizing smart manufacturing by significantly increasing precision, efficiency, and innovation across a broad spectrum of industries, from nanomanufacturing and biomanufacturing to pharmaceutical and large-scale production systems. In these sectors, PVA is useful for scrutinizing and evaluating product quality at the microscopic scale, ensuring alignment with stringent predefined standards. Recent research [138] has investigated how machine learning can be seamlessly integrated to refine and optimize manufacturing processes, with a special focus on employing high-throughput technologies to handle the complex and voluminous data characteristic of modern manufacturing. Another key study [139] has examined the critical role of deep learning in overcoming challenges within smart manufacturing systems, detailing how these sophisticated AI techniques can enhance process optimization, predictive maintenance, and quality control—each essential for increasing manufacturing efficiency.

PVA's capabilities extend beyond simple monitoring to include the detailed analysis and characterization of particles, which aids in the design and decision-making processes that are central to the development of next-generation manufacturing technologies. By providing real-time feedback and control, PVA allows manufacturers to instantly adjust processes, making it possible to maintain exceptional product quality. Furthermore, its application in predictive maintenance helps in identifying particle anomalies that predict machinery wear and tear, preventing expensive downtimes, and ensuring continuous production flow. The deployment of AI in particle analysis not only accelerates the manufacturing process but also significantly improves the accuracy of defect detection and quality assurance. Overall, PVA is a transformative tool that advances the automation and optimization of manufacturing processes, leading to smarter, more efficient production lines. This technology represents a significant leap forward in manufacturing capabilities, setting new standards for quality and operational efficiency across diverse manufacturing domains.

### 3.5. Integrative analysis of AI techniques

The advancement of PVA has been significantly accelerated by the integration of state-of-the-art AI techniques across various applications, including super-resolution imaging, object detection, and object recognition. Several common methodologies have been pivotal in increasing the analytical capabilities of PVA, offering improvements in both efficiency and accuracy. In particular, object

detection and classification in PVA have greatly benefited from algorithms such as You Only Look Once (YOLO) [140–145], mask region-based convolutional neural network (Mask R-CNN) [146,147], and contrastive language-image pretraining (CLIP)-based detectors [148–152]. YOLO is renowned for its speed and accuracy in real-time object detection, being capable of processing entire images through a single neural network in one pass. This efficiency is valuable for large-scale particle detection tasks that require rapid processing to handle substantial data volumes [153,154]. Similarly, Mask R-CNN provides robust object detection with the added benefit of generating segmentation masks, enabling more detailed particle localization and classification. In contrast, CLIP-based detectors leverage CLIP [155,156] to create rich, multimodal representations by combining visual and textual data. These models enable zero-shot detection [157], which allows the identification of objects or particles without requiring explicit training on specific datasets. This capability is particularly advantageous in PVA, where the diversity of particles or contaminants can be vast and obtaining labeled datasets may be impractical. By using textual descriptions, CLIP-based models can detect novel particles, greatly expanding the flexibility and scalability of PVA applications in fields such as environmental monitoring and material science.

Several architectures, including U-Net [130] and UNet++ [131], can play a crucial role in object segmentation tasks. U-Net utilizes an encoder–decoder structure with skip connections, effectively preserving spatial information during segmentation, which is essential for accurately identifying and segmenting objects. UNet++ refines this architecture further by introducing nested and dense skip connections, improving the model's capability to segment objects with complex shapes and intricate boundaries. These features make U-Net and UNet++ particularly useful in PVA, where the precise segmentation of particles is vital for analyzing their morphology and behavior [158,159]. Moreover, the segment anything model (SAM) [160,161], with its promptable segmentation capabilities, has proven to be a powerful tool in PVA. SAM can generate accurate masks for any object within an image without requiring extensive additional training, making it highly adaptable for the varying shapes and sizes of particles in PVA [162,163]. By efficiently isolating particles from complex backgrounds, SAM increases the overall quality of downstream analyses such as particle tracking, classification, and behavior prediction, thus contributing to more comprehensive and accurate interpretations of particle data.

In super-resolution tasks, models such as enhanced super-resolution generative adversarial networks (ESRGANs) [164] and diffusion-based approaches [165,166] have been pivotal in advancing PVA. ESRGANs improve prior generative adversarial network (GAN)-based methods by incorporating a residual-in-residual dense block, which produces more realistic and detailed high-resolution images. In PVA, ESRGANs have been successfully employed to improve the resolution of particle images, allowing for more detailed and accurate analysis of particle characteristics and behaviors [122]. This improvement in image quality makes it possible to capture subtle particle features that were previously indiscernible with lower-resolution imaging. Diffusion-based models have also demonstrated significant potential in super-resolution tasks by iteratively refining images through the modeling of denoising processes. Approaches such as denoising diffusion probabilistic models (DDPMs) [166] and super-resolution via iterative refinement [165] are capable of generating high-fidelity, fine-detail images from low-resolution inputs. In PVA, these diffusion models have proven effective in reconstructing particle images with remarkable precision [167], thereby increasing the accuracy of subsequent analyses, such as particle classification, tracking, and behavior prediction. By overcoming the resolution limitations

of conventional imaging equipment, the super-resolution techniques of ESRGAN and diffusion-based models play a critical role in enabling more precise and insightful analysis of particles. The enhanced image quality afforded by these methods not only improves the visual clarity of particle data but also significantly contributes to the overall accuracy of PVA.

Transfer learning and few-shot learning methods provide effective solutions to the common challenge of limited annotated datasets in PVA. Transfer learning [168,169] enables models to utilize features learned from large-scale datasets, such as ImageNet, and adapt them to the specific domain of particle imagery with minimal additional training. This approach not only accelerates the application of cutting-edge AI research to PVA but also reduces the need for large, domain-specific annotated datasets, which are often time-consuming and expensive to collect. Few-shot learning techniques [170–173] further increase the model's capability by enabling it to generalize effectively from a limited number of samples. In PVA, such techniques are particularly valuable for recognizing new or rare particle types in cases where assembling extensive training datasets is impractical or impossible. Few-shot learning allows models to perform well even in data-scarce situations, which is critical for applications such as environmental monitoring, nanotechnology, and pharmaceutical research, where rare particle events may hold significant importance. By leveraging transfer learning and few-shot learning, PVA researchers can overcome the limitations of dataset scarcity, ensuring that AI-driven models can still deliver high performance across a wide range of tasks with minimal data.

These technologies have not only made significant contributions to the fields of computer vision and AI, but also established a critical foundation for their application in PVA. By accelerating the integration of AI into PVA, these advancements have expanded the scope of particle analysis, enabling more detailed, accurate, and scalable assessments of particle behaviors and characteristics across a wide range of research and industrial domains. As AI technologies continue to evolve, PVA is positioned to offer even deeper insights into the micro- and nanoscale world, unlocking new possibilities for scientific discovery and technological innovation.

#### 4. Discussion and outlook

One of the primary challenges in PVA is the complexity of particles. Particles vary widely in shape, size, and material composition, requiring tailored imaging and analysis techniques. Developing standardized methods that can accommodate this diversity is essential for advancing PVA methodologies. Additionally, the dynamic environments in which particles are often studied, such as natural or industrial settings, present further challenges. Robust imaging techniques and advanced real-time processing capabilities are required to capture and analyze data accurately under these conditions. Another significant challenge is the scale of analysis. PVA often involves processing vast datasets containing high-resolution images, which can be time-consuming and computationally intensive. Developing more efficient computational strategies, such as improved data-compression algorithms, parallel processing techniques, and high-performance computing platforms, is crucial in managing these extensive data volumes without compromising accuracy or speed. Looking ahead, future directions in AI-driven PVA hold promise for addressing these challenges through the following innovative solutions.

##### 4.1. Development of analytical tools and computational strategies

The evolution of PVA requires the development of versatile analytical tools and computational strategies to accurately measure and characterize particles under diverse conditions. Recent

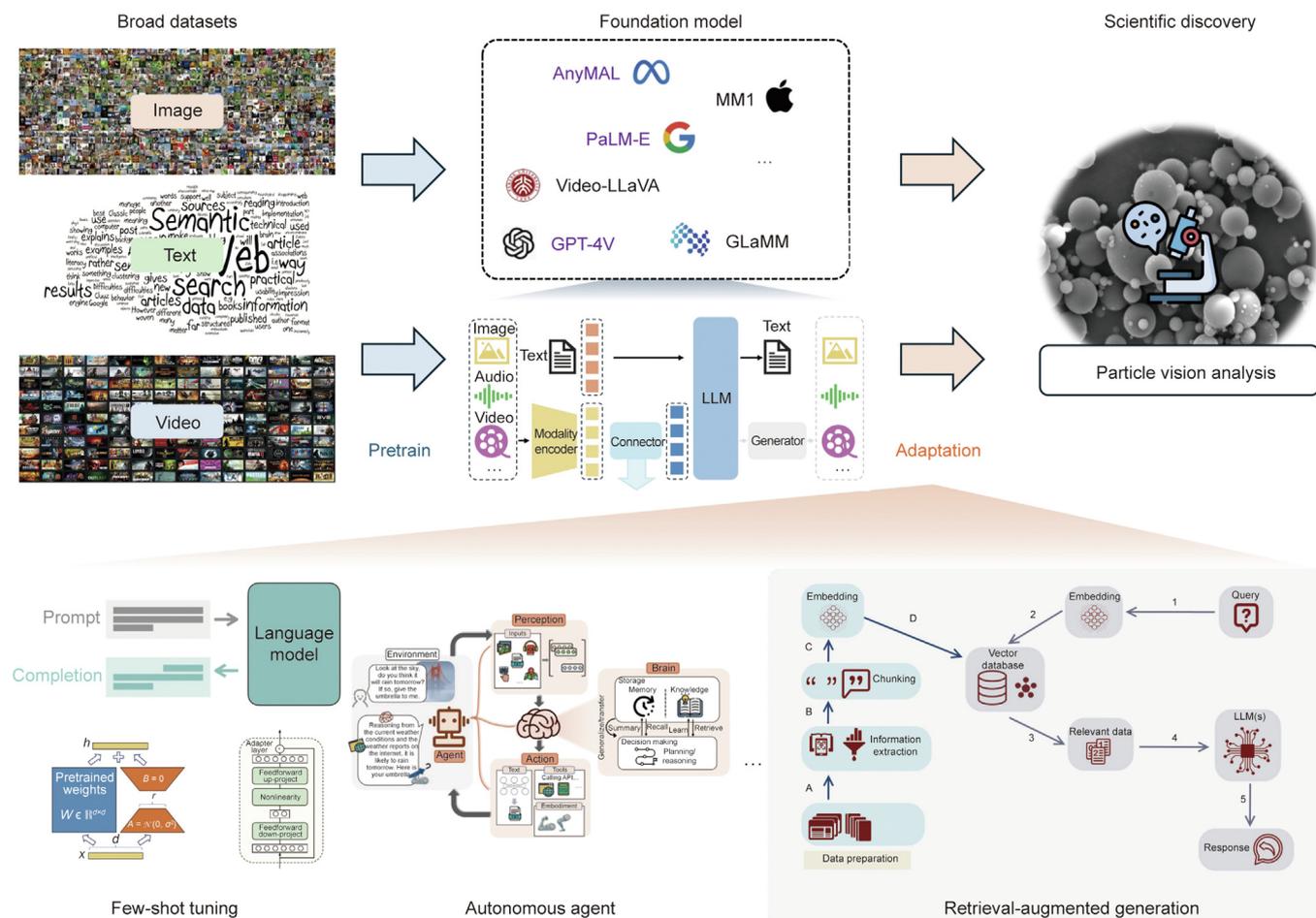
advancements in computer vision and machine learning have introduced more objective, quantitative, and general approaches for microstructural analysis, significantly reducing human bias and improving automation and precision in measurements [174]. These tools excel in generating numerical representations of images, such as feature vectors, which are essential for detailed characterization and analysis in materials science [175]. Moreover, the integration of computational methods plays a pivotal role in designing high-performance materials, optimizing synthesis processes, and interpreting complex datasets [175]. This computational capability extends the flexibility and scalability of software tracking platforms, enabling them to accommodate a wide range of imaging modalities and particle types. As shown in Fig. 4 [172,176,177], AI-driven models are increasingly being developed to predict particle behavior in various media, making significant contributions to fields such as manufacturing and biomedical engineering.

While these advancements in PVA tools are impressive, several limitations and technical challenges remain. First, the reliance on large, annotated datasets for training AI models can be a bottleneck, particularly in specialized fields such as PVA, where data is often scarce or difficult to label. This limitation hampers the development of highly generalized models capable of handling diverse particle types and environments. Additionally, although AI models have made strides in automation, they still struggle with generalization across different imaging conditions, requiring extensive fine-tuning to adapt to new experimental setups. Another critical challenge lies in the computational expense of real-time analysis, particularly for high-resolution images or videos. As the demand for real-time, *in situ* particle tracking and analysis increases, there is a need for more efficient algorithms that can process large volumes of data without compromising accuracy. Furthermore, while current models excel in static environments, dynamic and highly variable conditions, such as those encountered in biological or industrial processes, present significant hurdles in terms of tracking and predicting particle behavior. Future research should focus on addressing these limitations by developing more robust, generalizable models capable of operating with smaller datasets and under varying experimental conditions. Additionally, innovations in computational efficiency and the application of transfer learning and few-shot learning techniques could significantly increase the adaptability and scalability of PVA systems. By overcoming these challenges, the next generation of PVA tools will be better positioned to tackle complex scientific and industrial applications, pushing the boundaries of what is possible in particle analysis.

##### 4.2. Leveraging large-scale pretrained models

Recent progress in particle-vision analysis has embraced the paradigm of foundational models—large-scale, self-supervised networks pretrained on vast, heterogeneous datasets and later adapted to specific tasks via lightweight tuning strategies (Fig. 4). These models have revolutionized several computer vision tasks, including classification, detection, segmentation, tracking, and super-resolution. A critical aspect of their success is the utilization of vast, unlabeled datasets via self-supervised learning techniques, which substantially diminish the dependence on costly annotated data. Nonetheless, the rarity of specific scientific datasets presents a significant hurdle in training these models autonomously in specialized domains such as PVA.

To address these challenges, adaptation strategies such as few-shot learning and fine-tuning are essential. Fine-tuning, in particular, enables the customization of these models to specialized scenarios within PVA where data are scarce, expediting their deployment and efficacy in niche scientific fields [14,15,73,74]. In addition to fine-tuning, recent efforts have focused on leveraging



**Fig. 4.** Pretraining and application phases of foundational models in PVA. The pretraining phase utilizes a modality encoder to handle extensive multimodal datasets. Subsequently, the model is tailored to particular tasks through advanced adaptation methods such as few-shot tuning [172], autonomous agents [176], and retrieval-augmented generation [177]. These adaptations increase the model's functionality and performance in diverse sectors, including materials science, pharmaceuticals, environmental science, the food and beverage industry, and aerospace engineering. LLM: large language model. Reproduced from Ref. [176] with permission.

multimodal pretrained models, which are designed to handle and integrate data from various modalities—such as text, images, and audio—into a unified framework. Models such as CLIP [155], ALIGN [178], and Flamingo [179], which are pretrained on both visual and textual data, have shown the ability to transfer knowledge across domains, achieving state-of-the-art performance in tasks requiring cross-modal understanding [92,122,180].

Multimodal learning has emerged as a transformative approach that integrates diverse data modalities to create more comprehensive representations. For example, vision-language models (VLMs) such as CLIP [155] and ALIGN [178] have demonstrated the ability to align visual and textual inputs, significantly improving the performance of models in tasks such as image retrieval, captioning, and visual question answering. The incorporation of textual data into visual models enables more intuitive understanding and contextual reasoning, which is valuable in fields such as PVA, where visual observations must often be paired with domain-specific terminologies and annotations. These models allow for the exploitation of large-scale, multimodal datasets, facilitating transfer learning from general domains to highly specialized scientific applications.

Moreover, the growing trend of multimodal fusion models extends beyond traditional vision-language tasks to integrate additional sensory inputs, such as auditory or spatial data, creating more robust and flexible systems. For instance, models such as Flamingo [179] and Gato [181] can perform a wide range of tasks

across different domains by learning from multimodal data sources, including text, vision, and audio. This multi-source integration enriches the model's representational capacity and improves its performance in scenarios requiring comprehensive contextual understanding.

Despite these promising advancements in multimodal learning, several challenges remain, particularly in the context of scientific applications such as PVA. First, the integration of diverse data modalities is computationally expensive and often requires large-scale, well-annotated datasets that are difficult to obtain in niche scientific fields. Additionally, the complexity of aligning disparate data types, such as microscopy images with experimental metadata or sensor outputs, presents significant technical challenges. Moreover, while multimodal models excel in general tasks, their adaptation to specific scientific problems often requires extensive fine-tuning, which can be time-consuming and resource-intensive. In PVA, multimodal learning offers substantial potential, particularly for tasks that necessitate the correlation of various data types. By leveraging multimodal pretrained models, researchers can more effectively utilize scarce scientific datasets, improving model adaptability and prediction accuracy in complex tasks, as illustrated in Fig. 4. Techniques such as retrieval-augmented generation (RAG) [177], which allows models to retrieve relevant external information from large databases, offer a powerful means of enhancing decision-making in domains where complete data is not always available. Future research should prioritize the

development of more efficient and scalable multimodal learning models that can better handle the unique demands of scientific applications, ensuring that PVA continues to evolve and deliver further profound insights into particle behaviors and characteristics.

#### 4.3. Interdisciplinary research and AI-driven scientific discovery

The advancement of PVA in smart manufacturing depends on continuous progress in both hardware and software to support large-scale and complex analyses. Improvements in computational strategies and the integration of advanced machine learning algorithms are critical for effectively managing the vast datasets generated in PVA. Collaboration between fields such as physics, biology, engineering, and computer science is essential for developing holistic solutions that address key societal challenges [182]. State-of-the-art equipment, including electron microscopy and super-resolution imaging systems, plays a pivotal role in applying AI algorithms within PVA. These advanced tools facilitate the detailed analysis and characterization of materials at the nanoscale, offering valuable insights that drive innovation across a wide range of fields, from materials science to biomedical engineering [183]. The integration of data-driven science into PVA has greatly increased its capacity to analyze large datasets, enabling the extraction of meaningful information at unprecedented scales.

However, despite these advancements, several challenges persist. One major limitation is the overemphasis on biological images in current research, which leaves fields such as materials science, chemistry, and environmental studies underrepresented. The lack of diverse, high-quality datasets in these areas limits the generalizability and adaptability of PVA technologies. Expanding the scope of microscopic data collection in these fields is essential for realizing the full potential of PVA in areas such as nanomanufacturing, where detailed particle analysis is required for material optimization and quality control. Additionally, while PVA has made strides in increasing our ability to analyze complex data, significant computational challenges remain. The sheer volume and complexity of the data generated by high-resolution imaging systems can overwhelm current computational infrastructures, necessitating more efficient algorithms and hardware to enable real-time analysis. Furthermore, ensuring the accuracy of AI-driven models in dynamic environments, where particle behaviors may fluctuate due to varying external factors, is still a technical hurdle.

As PVA technologies evolve, fostering interdisciplinary collaboration will be essential for overcoming these limitations and developing innovative solutions to complex global challenges. Advancements in PVA are critical not only for accelerating research in smart manufacturing but also for accurately predicting and mitigating risks in public health, environmental sustainability, and beyond. By addressing these challenges, PVA can continue to contribute meaningfully to scientific discovery and technological innovation.

## 5. Conclusions

In conclusion, PVA has become a cornerstone of advancements in scientific progress across various scales, from the nanoscale (e.g., fine particles) to the megascale (e.g., big data). Its innovative tools facilitate not only the development of theoretical frameworks but also the enhancement of experimental techniques, thereby pushing the frontiers of knowledge across a multitude of disciplines. PVA's capacity to integrate data from diverse scientific fields fosters interdisciplinary research, enabling collaborative efforts to tackle complex global challenges such as climate change, environmental sustainability, and public health. Moreover, the integration

of machine learning and AI into PVA has transformed the landscape of data-driven science. By automating the analysis and characterization of complex datasets, PVA significantly accelerates the discovery process and increases precision in areas such as nanomanufacturing, materials science, and pharmaceuticals. PVA's ability to efficiently analyze and optimize particle interactions and behaviors at multiple scales provides critical insights into the design and control of complex manufacturing systems, driving innovation in both industrial and scientific applications.

However, to fully realize the potential of PVA, future research must address current limitations, such as the scarcity of annotated datasets and the computational challenges associated with high-resolution, real-time analysis. Advances in transfer learning, few-shot learning, and multimodal data integration will be key in overcoming these obstacles. Furthermore, interdisciplinary collaboration will remain essential for unlocking new applications of PVA, particularly in fields that require the correlation of diverse data types, such as combining microscopy images with experimental metadata or environmental monitoring data. As PVA continues to evolve, its role in expanding our scientific understanding and developing innovative solutions to pressing societal challenges will become increasingly significant. By integrating advanced AI techniques with cutting-edge imaging technologies, PVA is poised to drive breakthroughs in fields ranging from smart manufacturing to environmental science, ultimately shaping the future of both research and industry.

#### CRediT authorship contribution statement

**Guangyao Chen:** Writing – original draft, Validation, Investigation, Data curation, Writing – review & editing, Visualization, Methodology, Formal analysis. **Fengqi You:** Writing – original draft, Supervision, Project administration, Investigation, Writing – review & editing, Visualization, Resources, Methodology, Funding acquisition, Conceptualization, Formal analysis.

#### Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

#### Acknowledgments

The authors gratefully acknowledge the funding support from the US National Science Foundation (2229092). This project is also partially supported by the Eric and Wendy Schmidt AI in Science Postdoctoral Fellowship, a program of Schmidt Sciences, LLC.

#### Data availability

Relevant materials, including a comprehensive list of the papers reviewed and the associated codebase, are accessible via the following link: <https://github.com/PEESEgroup/Awesome-Particle-Vision-Analysis>.

#### Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used OpenAI ChatGPT in order to improve the language, grammar, and overall readability of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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