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Technologies for granulometric analysis in Geoscience: From Photogrammetry and LiDAR to Deep Learning Approaches

Tecnologías para el análisis granulométrico en Geociencias: de la fotogrametría y el LiDAR a los enfoques de aprendizaje profundo

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ABSTRACT
Granulometry is essential for understanding geological granular flows, sediment transport, and deposition processes. Traditionally, sieving has been the standard particle-size analysis method; however, it presents limitations in accuracy and field applicability, particularly in inaccessible environments. This perspective article reviews emerging technologies for granulometric analysis in geosciences, covering studies published between 1967 and 2025 from Web of Science and Scopus. Over the last three decades, digital image analysis, Structure-from-Motion (SfM) photogrammetry, and Light Detection and Ranging (LiDAR) have enabled remote, high-resolution particle characterization. More recently, artificial intelligence and deep learning have accelerated this progress. Applications based on Convolutional Neural Networks (CNNs), transformer architectures, Graph Neural Networks (GNNs), and LiDAR-derived 3D point clouds are discussed. A comparative analysis of methods is presented considering spatial resolution, accuracy, particle-size range, processing time, cost, and Technology Readiness Level (TRL). Results indicate that hybrid approaches generally outperform single-method solutions. Future developments point toward hybrid systems, Bayesian uncertainty quantification, and autonomous field operations supported by edge computing.

Keywords: granulometry, LiDAR, photogrammetry, deep learning

RESUMEN
La granulometría es fundamental para comprender flujos granulares geológicos, transporte de sedimentos y procesos de deposición. Tradicionalmente, el tamizado ha sido el método estándar para determinar el tamaño de partícula; sin embargo, presenta limitaciones de precisión, tiempo y aplicabilidad en campo. En las últimas décadas han surgido técnicas basadas en análisis de imágenes, fotogrametría y tecnologías LiDAR, que permiten realizar granulometría mediante enfoques ópticos y modales más eficientes. Este artículo de perspectiva analiza tecnologías emergentes, destacando la integración de inteligencia artificial y aprendizaje profundo en el análisis granulométrico. Se discuten aplicaciones de Structure from Motion (SfM), redes neuronales convolucionales (CNN), arquitecturas transformador y Redes Neuronales de Grafos (GNN), así como metodologías LiDAR para generar nubes de puntos tridimensionales. Estas tecnologías permiten análisis no invasivos, rápidos y aplicables en entornos complejos, además de proporcionar información 3D detallada. El futuro apunta al desarrollo de sistemas híbridos con cuantificación de incertidumbre mediante enfoques bayesianos.

Palabras clave: granulometría, LiDAR, fotogrametría, aprendizaje profundo

INTRODUCTION

One of the most important textural characteristics of a sedimentary deposit composed of clasts or particles is the size of the grains that compose it, their distribution, and the degree of uniformity of their dimensions. The importance of particle size analysis is reflected not only in its early adoption in sedimentology but also in the extensive scientific literature devoted to it. The analysis of grain size (a term encompassing size and size distribution) was probably the first sedimentological study ever conducted, and the enormous number of publications on the subject amply demonstrates the importance geologists have always attached to this textural characteristic. According to a search conducted in Web of Science (https://www.webofscience.com) from 1967 to 2025, approximately 3,742 articles related to granulometry have been published across 21 disciplines; those with 90 or more publications are shown in Figure 1. Of these publications, 11.4% are in geosciences.

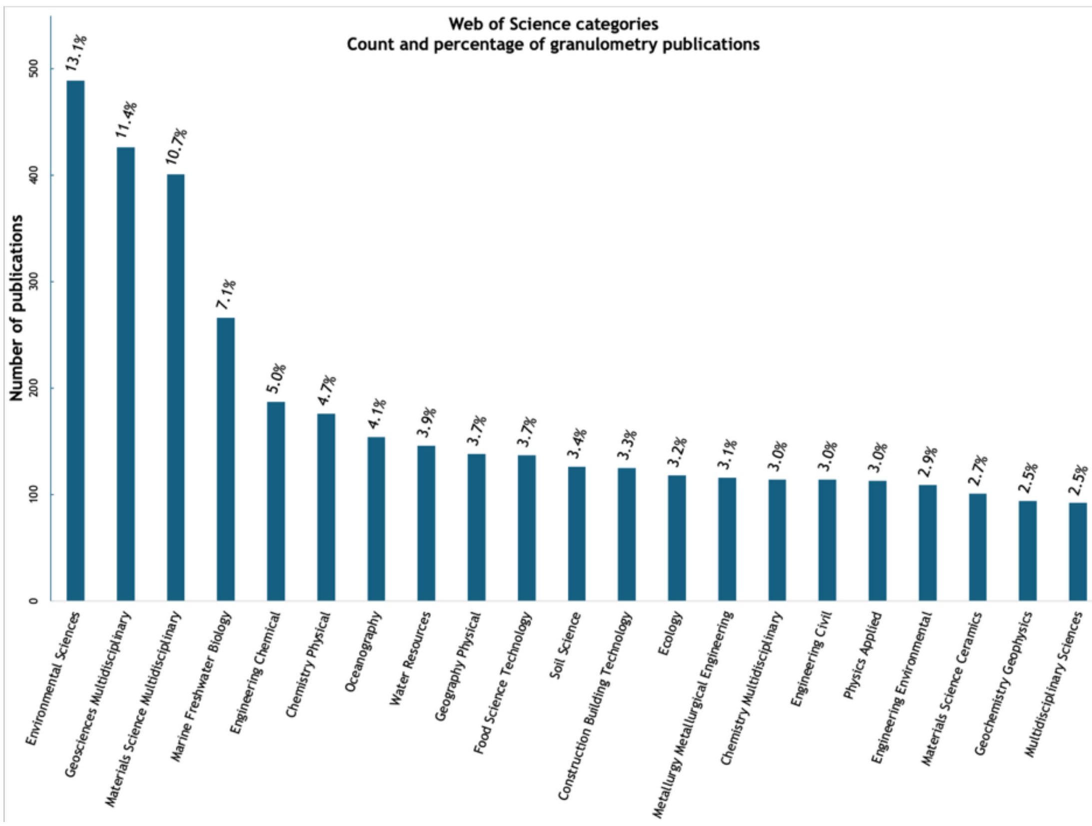

Fig. 1: The number of publications per area of study with more than 90 articles from 1967 to 2025 is shown, and at the top, the percentage represents the total analyzed.

Granulometry is a fundamental aspect of geosciences that focuses on characterizing particle-size distributions in materials such as soils, sediments, and rocks. Particle size is closely linked to sediment origin and is strongly influenced by transport and depositional processes, making it a key parameter for interpreting sedimentary environments and reconstructing geological histories (Folk, 1980; Friedman & Sanders, 1978; Blott & Pye, 2001; Oyedotun, 2022). Moreover, particle size distribution (PSD) plays a critical role in controlling sediment dynamics, including erosion, transport, and deposition, as well as key physical properties such as porosity and permeability (Dorrell *et al*., 2018).

Despite the extensive development of traditional granulometric techniques, recent studies have highlighted significant limitations in their application, particularly methodological inconsistencies and difficulties in comparing results across different analytical approaches (Di Stefano *et al*., 2010). These challenges arise because each technique is based on distinct physical principles and assumptions, leading to systematic discrepancies in particle-size estimates. In parallel, the rapid evolution of digital technologies and computational methods has introduced new opportunities for particle-size characterization, including image-based analysis, 3D reconstruction (Eshel *et al*., 2004; Di Stefano *et al*., 2010; Eltner *et al*., 2016), and data-driven approaches, offering improved resolution and flexibility in complex geological settings.

In this context, there is a growing need to critically evaluate and integrate emerging methodologies within the framework of geoscientific granulometry. This perspective article has three specific objectives: (1) to provide a structured comparative overview of emerging technologies for granulometric analysis in geosciences; (2) to evaluate their relative performance through quantitative comparison of accuracy metrics, spatial resolution, cost, and technological readiness; and (3) to identify research gaps and priorities for future development toward integrated hybrid approaches for autonomous field operations. The emphasis is on methodologies applicable in challenging field conditions, including inaccessible or hazardous environments, where traditional techniques may be impractical or impossible to implement.

METHODOLOGY

This study was conducted as a critical literature review of emerging technologies for granulometric analysis in geosciences, including traditional granulometric methods, image-based techniques, Structure-from-Motion (SfM) photogrammetry, LiDAR systems, and artificial intelligence approaches for particle characterization.

The review methodology was inspired by recommendations proposed for literature review papers by van Wee and Banister (2015), incorporating a structured search strategy, explicit selection criteria, and comparative analysis of methodologies.

Literature Search Strategy

The bibliographic search was conducted using the databases Web of Science, Scopus, Google Scholar, and ScienceDirect. The review considered publications from 1967 to 2025 to capture both seminal granulometric studies and recent developments in computer vision, remote sensing, and deep learning.

The search process combined keywords associated with granulometry, sedimentology, optical analysis, photogrammetry, LiDAR, and artificial intelligence. Examples of search terms included: “granulometry”, “particle size distribution”, “sediment analysis”, “image-based granulometry”, “Structure from Motion”, “SfM photogrammetry”, “LiDAR granulometry”, “deep learning particle segmentation”, “CNN granulometry”, “Graph Neural Networks geosciences”, “Earth Sciences”, and “geosciences”.

Boolean operators (AND, OR) were used to refine the search strategy and identify interdisciplinary studies.

Inclusion and Exclusion Criteria

The review included: peer-reviewed journal articles; conference proceedings of significant relevance; seminal methodological studies; recent studies focused on artificial intelligence and remote sensing applications in geosciences; studies related to particle-size analysis in geological, sedimentological, volcanological, and geomorphological contexts.

The review excluded: publications lacking methodological description; studies unrelated to particle-size characterization; duplicated studies; papers focused exclusively on industrial or medical applications without relevance to Earth Sciences.

Priority was given to studies presenting quantitative validation metrics such as RMSE, MAPE, IoU, precision, recall, or comparative performance analyses.

Classification Framework

The selected studies were grouped into five major methodological categories traditional granulometric methods; Optical and image-based techniques; SfM photogrammetry approaches; LiDAR-based methodologies; Artificial intelligence and deep learning approaches.

Within each category, the studies were comparatively analyzed considering spatial resolution, particle-size range, computational requirements, processing time, field applicability, accuracy metrics, operational limitations, and Technology Readiness Level (TRL).

Comparative Analysis

A comparative qualitative and quantitative analysis was performed to identify methodological trends, technological limitations, and emerging opportunities in granulometric analysis.

Special attention was given to methodological comparability, reproducibility, validation against traditional granulometric standards, applicability in complex geological environments, and integration of hybrid methodologies.

The review also examined the growing role of artificial intelligence in automating particle segmentation, classification, and three-dimensional reconstruction.

TRADITIONAL GRANULOMETRIC METHODS

Traditional granulometric analysis has primarily relied on sieving and sedimentation techniques. Sieving, dating back to the early 20th century (Wentworth, 1922; Krumbein, 1934), involves passing material through a series of mesh screens with progressively smaller openings; the process is shown in Figure 2. While this method provides direct measurement of particle sizes, it is time-consuming, requires substantial sample preparation, and is limited in its ability to characterize very fine particles or those with irregular shapes (Allen, 1997; Ludwick & Henderson, 1968).The sieving method is very important due to its practicality, ease of application, and reliability, and it can be replicated under standard conditions (Sarocchi, 2006). The principal limit for this method is that sieving is convenient for segregating particles coarser than 0.05 mm; when the material is shaking, the probability of a particle passing depends on a certain orientation (Day, 1965; Dellavalle, 1948; Epstein, 1954; Fournier-sowinski, 2024; Folk, 1980; Ludwick & Henderson, 1968; Houghton *et al*., 2024; Whitby, 1954). Additionally, sieve openings can vary in size, so accurate sieving requires careful standardization of the procedure, which is often performed in the laboratory. Figure 2 shows, in a simple way, the process of sieving: by depositing a sample of geomaterial on a mesh and performing different types of movements (up-down, left-right) or making small blows on the mesh support, the finer material is separated from the larger grains.

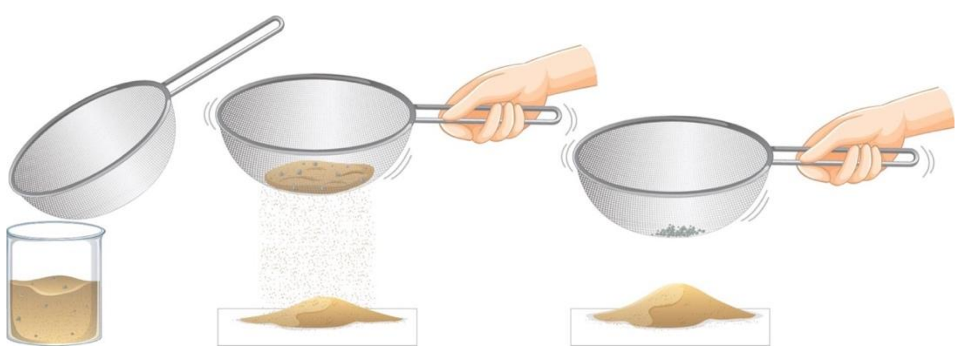

Fig. 2: A simple representation of the sieving process.

A complementary technique, Sedimentation, involves allowing a suspension of particles to settle under the influence of gravity (Figure 3). The settling rate is related to particle size, and the particle size distribution can be determined by analyzing the sedimentation curve. This curve is constructed using statistical methods for analyzing particle-size frequency distributions in sediments (Krumbein, 1934; Lines & Stanley-Wood, 1992).

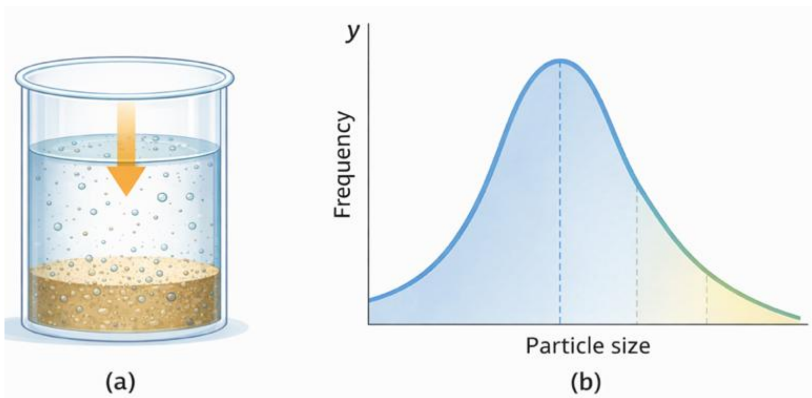

Fig. 3: Simplified representation of particle sedimentation and particle-size frequency analysis: (a) sedimentation process and (b) particle-size distribution.

When the particles are small and spherical with density ρ_s and diameter X, the sedimentation can be calculated through a liquid of density ρ_L and viscosity η at a rate of:

$$v = \frac{X^2 g (\rho_s - \rho_L)^2}{18\eta} \tag{1}$$

Where g is the gravitational constant. This relationship is known as Stokes' equation (Day, 1965). Sedimentation methods exploit this principle to characterize fine-grained material, though their application demands patience: once the soil suspension is homogenized, quantification relies on a sequential decanting procedure in which the residue must be repeatedly resuspended and allowed to settle, recovering by successive cycles the particles that had not yet reached the upper layer at the onset of each sedimentation interval (Day, 1965). Several authors note that the sedimentation diameter distribution is more appropriate than the sieving size distribution (Bridge, 1981; Middleton, 1976; Poizot *et al.*, 2008; Sedláčková *et al.*, 2024).

Altogether, sedimentation analysis occupies a well-justified place in granulometric practice. Its resolution for fine particles, independence from particle shape, and compatibility with a broad range of fluids and size classes give it a versatility that few competing techniques can match; the capacity for real-time monitoring reinforces its value in dynamic experimental settings. That said, the method is not without friction. Polydisperse samples complicate interpretation; thermal and viscosity fluctuations propagate into measurement error; coarse fractions fall outside their effective range; and the instrumentation can impose nontrivial operational demands. Being aware of these trade-offs is what distinguishes a well-designed particle size distribution protocol from one that merely generates numbers.

Despite their standardization, traditional techniques were designed with the laboratory in mind, and this origin becomes evident when they are applied in field conditions. Sample collection, the inevitable first step, becomes a real obstacle in environments where access involves risks: the slopes of active volcanoes, unstable debris slopes, or sites so remote that logistics are prohibitive. The problem is exacerbated by the destructive nature of the collection process itself; once a sample is extracted, the site's original spatial structure is altered, and with it, much of the stratigraphic and textural information needed to reconstruct deposition histories. Repeating measurements at the same location is also ruled out, which precludes any monitoring application requiring temporal resolution at a fixed point.

IMAGE-BASED GRANULOMETRIC ANALYSIS

In response to the limitations of traditional granulometric methods, several alternative approaches have been developed in recent decades, particularly those based on digital imaging and computer vision. The advent of digital photography and image processing techniques in the 1970s marked a significant advance in granulometric analysis. Early systems, such as those developed by Gallagher (1976), demonstrated the potential for automated particle-size measurement from images. The following decades saw rapid development in this field, and systems such as WipFrag became industry standards for applications such as blast fragmentation analysis (Maerz *et al*., 2018).

Image-based approaches enable automated particle detection and size estimation from digital images, significantly reducing processing time while preserving the spatial structure of sedimentary surfaces. However, these methods face challenges related to image quality, lighting conditions, particle overlapping, and the need for careful calibration. The accuracy of image-based grain size analysis depends largely on the quality of the image acquisition and the sophistication of the processing algorithms employed (Hunter *et al*., 1990; Russ, 1999). Image-based grain-size methods have been widely applied to sedimentary and granular-flow deposits, including fluvial gravels (Buscombe, 2013; Graham *et al*., 2005). Particle size distribution can be analyzed using instruments that collect data without coming into contact with the surface. In the field of earth sciences, this results in savings in time, financial resources, and laboratory analysis of geomaterials; therefore, it is a very useful tool for applied research. In this study, we have analyzed the most important remote sensing methods currently used for particle size analysis. In this section of the study, we have analyzed the various remote sensing methods used in grain size analysis.

Most remote sensing approaches to particle size analysis share a common underlying logic: the deposit is treated as a raster surface, and particle boundaries are inferred by counting and grouping pixels whose spectral or geometric properties cross a defined threshold (Sarocchi *et al*., 2005). Segmentation converts the original image into a binary representation in which each identified object (a grain, a clast, a fragment) can be measured individually. The conceptual lineage of these approaches is longer than it might appear; methods such as the Rosiwal traverse and the classical point-count technique predate digital imaging entirely, yet they operate on the same principle of sampling a two-dimensional surface and using the areal proportions of what is found there to estimate the underlying material. What changed with digital remote sensing was not the logic but the scale and speed at which it could be applied.

That combination of historical depth and expanding capability is what makes the intersection of granulometry and remote sensing worth taking seriously as a research area. Surface characteristics that once required physical sampling — with all the access constraints and spatial destruction that entails — can now be tracked across large areas, revisited through time, and analyzed at resolutions that manual field methods cannot approach. The tools are not equivalent substitutes for traditional granulometry, but they extend their reach into environments and at scales where no substitute previously existed.

Table 1 summarizes the physical principles, analytical capabilities, applications, strengths, and limitations associated with each granulometric technique.

STRUCTURE FROM MOTION (SFM) PHOTOGRAMMETRY

Structure-from-Motion (SfM) photogrammetry represents a revolutionary advancement in three-dimensional (3D) reconstruction from two-dimensional (2D) image sequences. Unlike conventional photogrammetry, which requires known camera positions and orientations, SfM photogrammetry automatically estimates camera parameters and 3D scene geometry simultaneously by identifying common features across multiple images (Carrivick *et al*., 2016). This technique has become increasingly accessible with the proliferation of high-quality digital cameras and powerful computational resources.

Table 1 Comparative overview of conventional and emerging particle-size analysis methods used in geosciences and related disciplines.

Table 2:Comparative overview of conventional and emerging particle-size analysis methods used in geosciences and related disciplines.

Method	Description	Application	Advantages	Disadvantages
Sieve analysis	They are classified by passing a sample through a stack of sieves with progressively finer mesh sizes, measuring the mass fraction retained on each sieve to determine the particle size distribution (Fournier-sowinski, 2024; Ludwick a& Henderson, 1968; Houghton *et al*., 2024; Whitby, 1954).		Simple and cost-effective. Suitable for a wide range of particle sizes. It allows to produce well-defined size fractions (Sarocchi, 2006).	Low resolution for small particles. Labor-intensive. Not ideal for highly cohesive or sticky materials (Callesen *et al*., 2023; Ludwick & Henderson, 1968; Houghton *et al*., 2024).
Sedimentation Analysis	In a liquid medium, particles aggregate under the influence of gravity. The particle size distribution is calculated based on the sedimentation rate (Folk, 1980; Friedman & Sanders, 1978; Krumbein, 1934; Sedláčková *et al*., 2024).	High precision for fine particles. Suitable for nanoparticle analysis. Performs well with non-spherical particles (Ludwick & Henderson, 1968; Houghton *et al*., 2024)	It requires a sedimentation process, which can be time-consuming. It is sensitive to agglomeration and flocculation. It can be affected by temperature and other factors (Poizot *et al*., 2008; Sedláčková *et al*., 2024).	Sedimentation Analysis
Point-counting method.	Counting the particles (or other minerals) that pass through the intersections of the grid when it is superimposed on a sample, whether in an image of the sample or on the sample itself (Sarocchi *et al*., 2005; Thomson, 1930).	Minerology, sedimentology, industry (Demirmen, 1971; Roufail & Klein, 2021; Sarocchi *et al*., 2005; Smieja-Król & Fiałkiewicz-Kozieł, 2014).	Easy to replicate and accurate. It does not require sophisticated equipment (Roufail & Klein, 2021; Smieja-Król and Fiałkiewicz-Kozieł, 2014).	A wide range of measurements would be necessary. The analysis would be very time-consuming (Demirmen, 1971; Sarocchi, 2006).
Rosiwal's method of intersections.	By superimposing straight lines onto a random geological cross-section and measuring the most prominent landforms along those lines, Rosiwal discovered that the ratio of the total length of the intersection to the total length of the lines used was equal to the ratio of the area of the landforms to the total measured area (Rosiwal, 1898; Sarocchi, 2006; Sarocchi *et al*., 2005).	Vulcanology, geology, sedimentology (Sarocchi, 2006; Sarocchi *et al*., 2005).	Easy to replicate. Results like those obtained using the sieving method (Chávez *et al*., 2015; Rosiwal, 1898).	It requires many measurements (Sarocchi, 2006).
Laser diffraction	The particles scatter a laser beam, and the scattering pattern is analyzed to determine the particle size distribution (Blott *et al*., 2004; Chávez *et al*., 2015).	Nanotechnology, industrial powders, and pharmaceuticals, Geosciences (Blott & Pye, 2001, 2006; Buurman *et al*., 1997; Shekunov *et al*., 2007).	High-speed analysis. Wide dynamic range. Measures numerous particles simultaneously (Zobeck, 2004).	It may present difficulties with asymmetric particles. In the case of nanoparticles, its use is limited. It must be calibrated using reference materials. The cost of the equipment (Eshel *et al*., 2004).
Dynamic Light scattering	The Brownian motion of particles and their particle size distribution are determined by analyzing variations in the intensity of scattered light (Artemyeva *et al*., 2017).	Characterization of proteins, polymers, colloidal systems, nanoparticles, biopharmaceutical formulations, soil colloids, clay minerals, suspended sediments, natural organic matter, environmental nanoparticles, and geochemical transport processes in aquatic and terrestrial environments (Bhattacharjee, 2016; Lerma et al., 2015; Knysh et al., 2023; Rodríguez-Loya et al., 2023).	Measures particle-size distributions from nanometers to micrometers, requires minimal sample preparation, and provides rapid, non-destructive analysis of colloidal and dispersed systems (Berne & Pecora, 2000; Bhattacharjee, 2016).	For accurate results, a A monodisperse sample is required. Sensitive to aggregate formation and polydispersity. Limited to opaque samples or those with high dispersion (Berne & Pecora, 2000; Bhattacharjee, 2016).
Microscopy	Optical or electron microscopy is used to measure and count each particle individually. Image analysis software is often employed (Allen, 1997; Balagurunathan *et al*., 2001; Ferreira & Rasband, 2012).	Studies on particle morphology, mineralogy, and biological materials (Allen, 1997; Goldstein *et al*., 2017; Russ, 2004; Vernon, 2018).	It provides detailed information on particle morphology. It allows for the analysis of a wide variety of materials. High-resolution images (Allen, 1997; Goldstein *et al*., 2017; Russ, 2004).	It is time-consuming for large datasets. It depends on the operator. For some materials, it is limited to optical and electron microscopy (Allen, 1997; Goldstein *et al*., 2017; Russ, 2004).

Recent studies have demonstrated the effectiveness of SfM for granulometric applications. Micheletti *et al*. (2015), showed that smartphone-based SfM can produce results comparable to those from professional equipment, significantly reducing costs and increasing accessibility. An *et al*. (2021; 2022), demonstrated the use of smartphone SfM to measure rock joint roughness, achieving precision levels suitable for geological characterization. The integration of SfM with unmanned aerial vehicles (UAVs) has further expanded the applicability of photogrammetric methods. Giordan *et al*. (2020), provided a comprehensive review of UAV applications in engineering geology, highlighting their utility in accessing hazardous or remote sites. This combination enables the creation of detailed 3D models of large-scale deposits without direct physical access, making it particularly valuable for studying active volcanic environments, unstable slopes, or other dangerous locations.

LiDAR TECHNOLOGY FOR GRANULOMETRIC ANALYSIS

LiDAR systems provide high-resolution three-dimensional representations of particle distributions, enabling precise characterization of surface geometry without requiring physical sample extraction. Unlike image-based methods, which infer three-dimensional information from two-dimensional images, LiDAR directly captures the spatial coordinates of surface points through laser scanning, generating dense point clouds that accurately represent the geometry of the particles. Figure 4 shows how LiDAR data can be obtained using a drone.

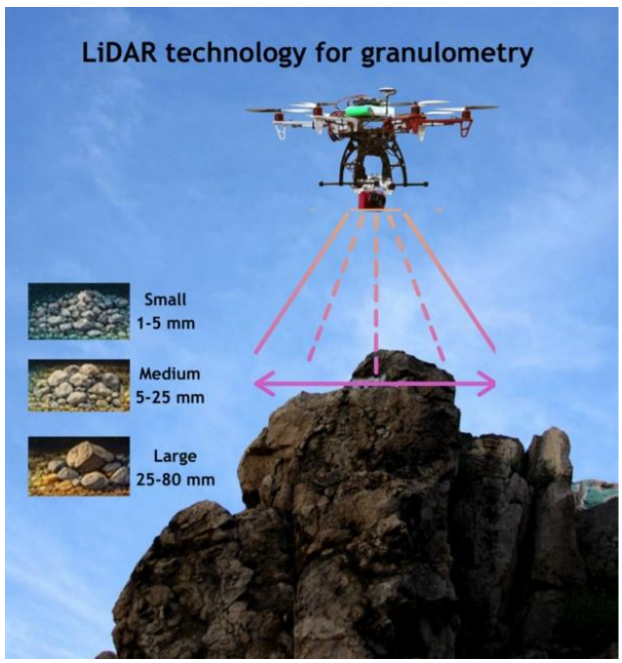

Fig. 4: Acquisition of granulometric data using drones for particle size analysis.

Engin (2019; 2020), pioneered the application of LiDAR to the analysis of particle sizes in aggregates and blasted rock, developing algorithms specifically designed to process LiDAR point clouds for granulometric analysis. His work demonstrated that LiDAR-based measurements achieve superior accuracy to traditional image analysis, with mean absolute percentage errors (MAPE) consistently lower than those from photographic methods. The accuracy stems from LiDAR's ability to capture comprehensive three-dimensional information, thereby reducing errors associated with particle overlap and edge detection that affect image-based approaches.

Thurley (2010), advanced the field by developing sophisticated algorithms for analyzing three-dimensional data, focusing on the separation and sizing of rock piles in mining operations. His work established fundamental methodologies for the processing of LiDAR point clouds, including segmentation algorithms that distinguish individual particles within complex aggregations. These techniques are particularly valuable for analyzing heterogeneous deposits in which particles of various sizes are intermixed.

The advantages of LiDAR extend beyond greater accuracy. Technology is less sensitive to lighting conditions than photographic methods and can effectively characterize particles in challenging environments. Furthermore, LiDAR point clouds provide rich datasets that enable not only the analysis of size distribution but also the detailed characterization of particle shape, orientation, and packing geometry. These additional parameters are crucial for understanding deposition processes and predicting the mechanical behavior of granular materials.

Artificial Intelligence and Machine Learning Applications

The integration of artificial intelligence (AI) and machine learning into particle size analysis represents a paradigm shift in this field, enabling automated, rapid, and highly accurate particle characterization. Deep learning approaches, particularly convolutional neural networks (CNNs), have demonstrated an extraordinary ability for image segmentation, particle detection, and size classification. Recent advances in image segmentation have been driven by deep learning architectures that have become fundamental to computer vision. Models based on convolutional neural networks, such as U-Net (Ronneberger *et al*., 2015) and Mask R-CNN (He *et al*., 2017), have demonstrated high performance in pixel-level segmentation tasks, including particle detection and boundary delineation. More recently, foundation models such as the Segment Anything Model (SAM) (Kirillov *et al*., 2023) have enabled segmentation without prior training across various domains, suggesting new possibilities for automated particle size analysis without the need for extensive labeled datasets.

Convolutional Neural Networks for Particle Size Analysis

Buscombe (2020), developed SediNet, a configurable deep learning model designed specifically for mixed optical grain size analysis, both qualitative and quantitative. This system demonstrates the ability of convolutional neural networks (CNNs) to handle complex grain size scenarios, including particles with varying shapes, colors, and lithologies. SediNet's architecture learns hierarchical features from training images, enabling it to accurately segment and classify particles even under challenging conditions, such as low contrast or overlapping particles. Li *et al*. (2024), extended the application of deep learning to particle recognition and the detection of shape parameters, demonstrating that modern neural networks can extract not only size information but also detailed morphological features. Their work shows how deep learning can automate tasks that previously required extensive manual analysis, significantly increasing throughput while maintaining or improving accuracy.

From a broader perspective, recent advances suggest a shift toward hybrid methodologies that integrate conventional image processing with machine learning techniques for particle size analysis. Rather than replacing traditional approaches, these methods build upon by incorporating data-driven models that enhance feature extraction and segmentation. This convergence appears particularly promising for addressing the challenges posed by irregular particle morphologies and complex geological environments, where purely deterministic or data-driven approaches are often insufficient (Ronkin *et al*., 2023).

Transformer Architectures and Advanced Neural Networks

Recent advances in neural network architecture, particularly Transformer models and graph neural networks (GNNs), are opening new frontiers in particle size analysis. Coenen *et al*. (2023), introduced the Granulometry Transformer, an image-based system for the automated control of concrete aggregate production. This approach leverages the self-attention mechanisms of Transformer architectures to capture long-range dependencies in images, enabling a more sophisticated understanding of particle distributions and relationships. Graph neural networks represent a particularly promising advancement for granulometric applications. Choi & Kumar (2024), developed GNN-based surrogate models for granular flows, demonstrating that these networks can capture spatial relationships between particles and predict collective behavior. This capability extends granulometric analysis beyond simple size distribution to understand how particle arrangement influences mechanical properties and flow dynamics. Wang *et al*. (2025), provided a comprehensive review of machine learning applications in granular material modeling, highlighting the breadth of AI techniques currently applied to granular systems. Their work emphasizes the potential of integrated approaches that combine multiple AI methods with traditional physical understanding to create more robust and interpretable models.

INTEGRATION OF TECHNOLOGIES AND HYBRID APPROACHES

The most promising advances in modern grain size analysis involve integrating multiple technologies and methodologies. Lianheng *et al*. (2020), demonstrated practical photogrammetric workflows that combine SfM with traditional geological techniques to construct three-dimensional databases of rock joint surfaces. Their work shows that hybrid approaches can leverage the strengths of different methods while compensating for their individual limitations.

Engin and Maerz (2022), compared LiDAR and image-analysis approaches for particle-size measurement, providing quantitative assessments of their relative strengths and weaknesses. Their findings suggest that optimal characterization strategies typically involve both technologies, as LiDAR provides high-precision reference measurements and image analysis offers rapid, large-scale coverage.

Ozturk and Rashidzade (2020), developed photogrammetry-based methods to determine three-dimensional morphological indices of coarse aggregates, demonstrating that detailed shape characterization is now possible using integrated approaches. Their methodology combines high-resolution images with sophisticated 3D reconstruction algorithms to extract morphological parameters crucial for understanding particle behavior.

Wei *et al*. (2024), explored the integration of deep learning with histogram-based methods for grain size analysis, demonstrating that combining traditional statistical approaches with modern AI can yield more robust and interpretable results. This type of hybrid methodology represents a pragmatic path forward, building on established techniques while incorporating new capabilities.

RESULTS AND DISCUSSION

Table 2 presents a comparative analysis of the main grain-size analysis methods used in the Earth sciences, considering their spatial resolution, accuracy, operational limitations, and technological maturity. This comparison provides a framework for understanding the advantages and limitations of each approach. The comparative analysis of granulometric methods (Table 1) and their associated quantitative performance metrics (Table 2) reveals a clear technological evolution from traditional approaches toward integrated, data-driven methodologies. This transition is characterized by improvements in accuracy, spatial resolution, automation, and scalability, although it is accompanied by increased computational and economic costs. Table 3 summarizes the quantitative performance metrics reported in the literature, including RMSE, MAPE, and segmentation accuracy (IoU and F1-score), enabling a more objective comparison between methodologies.

Comparison of Traditional and Digital Methods

Sieving and sedimentation have earned their place as reference techniques precisely because they are well understood, tightly standardized, and, under controlled conditions, difficult to beat in terms of repeatability: RMSE values typically stay below 5% and MAPE below 10%. The physical directness of these approaches is their greatest asset, since the measurement and the phenomenon being measured are essentially one and the same. Yet that same physicality is the source of their most stubborn constraints. Collecting a sample destroys the spatial fabric of the deposit; working in an active volcanic zone or on an unstable slope to do so may be simply out of the question. Sedimentation adds to its own layer of assumptions (spherical particles, predictable fluid behavior) that, when violated, push error in a direction that is hard to detect and even harder to correct.

Digital approaches sidestep many of these problems, though not without introducing new ones. Image analysis and SfM photogrammetry share the considerable advantage of leaving the deposit intact, and both compress processing time from a full day of laboratory work to a matter of minutes. Image-based methods do carry a real sensitivity to lighting, particle overlap, and calibration state, which shows up in MAPE figures that tend to cluster between 15 and 25% — workable, but noticeably wider than the traditional benchmark. SfM narrows that gap by reconstructing the surface in 3D, bringing RMSE values into the 5–15% range, especially when acquired from a UAV platform. The cost of that improvement is computational: both methods demand careful acquisition protocols and, in the case of SfM, processing pipelines that are far from trivial to set up and validate.

Table 2: Comparative analysis of grain-size analysis methods. Summary of the spatial resolution, accuracy, applicability, cost, and computational requirements of traditional, digital, and AI-based approaches. TRL: Technology Readiness Level (1 = conceptual, 9 = fully operational). As shown in Table 1, traditional methods, such as sieving, remain highly reliable but have limitations in terms of spatial representation and field applicability. In contrast, LiDAR and SfM techniques provide higher spatial resolution and enable non-invasive analysis, albeit at a higher computational and economic cost.

Method	Spatial Resolution	Accuracy (Typical Error)	Particle Size Range	Advantages	Limitations	Computational Requirements	Data Type	TRL*
Sieving	Low (mm-cm)	High (±5-10%)	>63 µm	Standardized, simple, reproducible	Destructive, time-consuming, not suitable for fine particles	None	Physical samples	9
Sedimentation (Hydrometer/Pipette)	Medium (µm scale)	Moderate (±10–15%)	<63 µm	Effective for fine particles; well-established theory	It depends on the assumptions (Stokes' law); it takes a long time	Low	Physical samples	9
Image Analysis (2D)	Medium-High (mm-µm)	Moderate (±10–20%)	mm-cm	Non-invasive, fast processing, preserves spatial structure	Light sensitivity, ghosting, and calibration issues	Medium	2D images	7-9
SfM Photogrammetry (3D)	High (sub-mm–cm)	Moderate-High (±5-15%)	mm-m	Low cost, 3D reconstruction, accessible (smartphones/UAVs)	It requires significant computational power and depends on the image quality	High (CPU/GPU)	3D point clouds	7-8
LiDAR	Very High (mm-cm)	High (±2-10%)	mm-m	Direct 3D measurement, high precision, less sensitive to lighting	It is expensive and requires specialized equipment	Medium	3D point clouds	8-9
CNN-based Methods	High (pixel-level)	High (IoU > 0.85 typical)	mm-cm	Automated segmentation, high accuracy, scalable	It requires labeled datasets and a complex training process	High (GPU)	Images / features	6-8
Transformers (Vision Transformers)	Very High	High (context-sensitive detection)	mm-cm	Captures long-range spatial relationships	It requires large amounts of data and is computationally intensive	Very High	Images / embeddings	5-7
Graph Neural Networks (GNNs)	High (relational)	High (model-dependent)	mm-m	Model particle interactions and structure	Complex implementation, limited datasets	Very High	Graphs / spatial data	4-6
Hybrid Methods (SfM + AI / LiDAR + AI)	Very High	Very High (±2–8%)	µm-m	Combine the benefits, improve strength and precision	Complexity of integration, high cost, and computation	Very High	Multi-source data	6-8

Table 3: Comparative analysis of particle size analysis methods. Summary of the spatial resolution, accuracy, applicability, cost, and computational requirements of traditional, digital, and artificial intelligence-based approaches.

Method	RMSE (Typical)	MAPE (%)	IoU / F1-score	Processing Time	Data Volume	Sensitivity Factors	Output Quality
Sieving	<5%	<10%	N/A	High (hours-days)	Low	Sample handling, human error	High (direct measurement)
Sedimentation	~10%	10-20%	N/A	Very High (days)	Low	Fluid properties, particle shape	Medium-High
Image Analysis (2D)	10–20%	15–25%	IoU: 0.6–0.8	Low (minutes)	Medium	Lighting, overlap, calibration	Medium
SfM Photogrammetry	5–15%	10–20%	IoU: 0.7–0.85	Medium-High (hours)	High	Image quality, overlap, camera geometry	High (3D reconstruction)
LiDAR	2–10%	5–15%	IoU: 0.8–0.9	Medium	High	Surface reflectivity, occlusions	Very High (dense 3D data)
CNN-based Methods	3–10%	5–15%	IoU: 0.85–0.95 / F1 > 0.9	Low (after training)	High	Training data quality, generalization	Very High
Transformers (ViT)	2–8%	5–12%	IoU: 0.88–0.96	Medium	Very High	Dataset size, computational cost	Very High
GNNs	Variable (model-dependent)	Variable	F1: 0.8–0.95	High	Very High	Graph construction, topology	High (structural insight)
Sieving	<5%	<10%	N/A	High (hours-days)	Low	Sample handling, human error	High (direct measurement)

LiDAR and High-Resolution 3D Characterization

Where image-based techniques infer depth from brightness and geometry, LiDAR measures it directly, and that distinction has consequences throughout the analysis chain. Errors from particle overlap and perspective distortion — two perennial headaches in photographic granulometry — are substantially reduced, and the resulting point clouds carry spatial information dense enough to resolve individual particle geometries with a fidelity that photographs rarely match. As reported in Table 2, RMSE values for LiDAR-based granulometry range from 2 to 10%, with MAPE in the 5–15% range, figures that hold up reasonably well across varying lighting conditions where purely optical methods would degrade.

The honest accounting, though, includes the equipment cost and the computational weight of handling dense point clouds. Segmenting individual particles out of a cloud that may contain tens of millions of points is still a genuinely hard problem, and no algorithm solves it cleanly in all cases. Recent progress from the deep learning community has helped considerably here: PointNet and PointNet++ (Qi *et al.*, 2017) introduced architectures that operate directly on raw point sets rather than requiring conversion to voxels or images, and their segmentation performance on complex granular assemblies has set a new practical standard. Even so, LiDAR remains the tool of choice mainly when precision justifies the overhead, which in practice means high-stakes geological or engineering applications were getting the size distribution wrong carries real consequences.

Artificial Intelligence and Automated Granulometry

The arrival of convolutional neural networks in granulometric workflows did not simply speed up existing analysis — it changed what kinds of problems were approachable at all. Tasks that previously required an expert to spend hours manually tracing particle boundaries can now be handled automatically, with IoU values routinely exceeding 0.85 and F1-scores above 0.90 across a range of particle shapes, textures, and degrees of overlap. The models are not sensitive to the same variables that trip up rule-based image processing: inconsistent illumination, irregular grain morphology, and heterogeneous surface textures tend to affect CNN performance far less than they affect threshold-based segmentation. Vision Transformers and Graph Neural Networks push the capability envelope further in different directions. Transformer architectures capture long-range context across an image — useful when particle size can only be inferred relative to neighboring grains — and have reached IoU values above 0.90 in some reported applications. GNNs take a different task, explicitly encoding the relational geometry between particles and using that structure to make predictions; the natural fit is for applications where the spatial arrangement of grains matters, not just their individual dimensions. Neither class of model comes cheaply: both require substantial annotated training data, significant GPU resources, and enough geological diversity in the training set to avoid models that perform brilliantly on the benchmark and poorly in the field.

Hybrid Approaches as the Optimal Strategy

No single method dominates across all the dimensions that matter — accuracy, cost, speed, environmental tolerance, and interpretability. What has emerged as the most defensible general strategy is combining the geometric rigor of 3D acquisition (SfM or LiDAR) with the classification power of machine learning, an integration that consistently produces the lowest error figures in the literature: RMSE between 2 and 8%, MAPE below 10%, and IoU above 0.90, as summarized in Table 3. Each component compensates for the other's weakness — the physics-based reconstruction provides a reliable geometric foundation that machine learning alone cannot guarantee, while the learned model handles segmentation complexity that no purely geometric algorithm manages cleanly.

The integration is not free. Feeding outputs from one pipeline into another introduces alignment and format-compatibility issues; the combined computational load is substantial, and operational costs rise accordingly. For routine, lower-stakes work, these barriers are real. For characterizing deposits in complex or hazardous terrain, where the cost of poor measurement is borne by downstream decisions rather than the measurement itself, the trade-off typically favors the hybrid approach.

Computational and Practical Considerations

Running a sieve stack requires no GPU, no training data, and no software license. That simplicity is not nothing — it is part of why sieving survived a century of competing proposals. The flip side is that simple tools reach their limits early: they cannot work remotely, cannot be automated beyond basic mechanical agitation, and cannot produce three-dimensional output. AI and hybrid systems flip this profile almost entirely, offering high throughput and spatial richness at the cost of infrastructure that many research groups do not yet have.

Choosing between these options is therefore not primarily a technical question but a contextual one. Laboratory work under controlled conditions with manageable sample sizes still has little reason to abandon sieving. Field campaigns targeting large, inaccessible, or actively dangerous deposits are where LiDAR and SfM earn their overhead. Machine learning methods become compelling — rather than merely interesting — when datasets are large enough to support meaningful training and when the volume or pace of analysis makes manual approaches impractical.

Implications for Future Research

Three practical gaps stand out from this review. The absence of shared benchmark datasets makes objective cross-method comparison more difficult than it should be, and the field would benefit from a concerted effort to produce annotated reference collections that cover a range of geological materials and imaging conditions. Physics-Informed Neural Networks offer a route to models that generalize better with less data by incorporating the physical constraints — sediment transport equations, particle interaction rules — that purely data-driven approaches must rediscover from scratch for each new context. And Bayesian uncertainty quantification, still underused in applied granulometry, would bring the field into alignment with risk-assessment frameworks that routinely require not just an estimate but a principled description of how wrong that estimate might be.

The broader trajectory is toward broader access. UAV platforms have dropped in price faster than almost anyone predicted; open-source implementations of most major deep learning architectures are freely available; and the processing power of a mid-range laptop today exceeds what filled a server room a decade ago. Granulometric analysis, once confined to specialist laboratories, is gradually becoming something a field team can carry out on-site.

Future perspectives and emerging trends

Several converging developments suggest that granulometric practice over the next decade will look quite different from the current state of the art — not through any single breakthrough, but through the accumulation of incremental advances across several fronts simultaneously.

The most immediate is the push toward autonomous field acquisition. Pairing UAVs and ground robots with edge-computing hardware and compact AI models means that data collection and preliminary processing no longer need to wait for a laboratory; the system does it in place. For monitoring applications — tracking sediment flux through an active channel, watching a volcanic flank respond to new activity — this capacity for continuous, unattended measurement is genuinely new, not simply faster than what came before.

Scientific Machine Learning, and PINNs in particular (Raissi *et al*., 2019), address a problem that has long lurked behind data-driven granulometry: a model trained in one geological setting may perform poorly in another if the physics of transport and deposition differ sufficiently. Encoding the governing equations into the learning objective ensures that predictions remain physically plausible even when extrapolated beyond the training distribution—a meaningful safeguard when field data are sparse, and the cost of a wrong inference is high. Bayesian frameworks complement this by replacing point estimates with probability distributions, which is precisely what engineering and hazard-assessment workflows need when using granulometric outputs to inform decisions.

Neural operators and advanced GNN architectures are still closer to research tools than to field instruments, but the direction they point is clear: toward methods that connect particle-scale measurements to bulk mechanical behavior without requiring the intermediate step of expensive physical testing. If that connection can be made reliably, granulometry becomes not just a descriptive exercise but a predictive one.

What ties these threads together is accessibility. The hardware and software infrastructure that once made advanced granulometric analysis the province of well-funded institutions is becoming routine, and that shift will matter as much for the breadth of geological problems studied as for the depth with which any individual problem is examined.

CONCLUSIONS

Granulometric analysis is undergoing a profound transformation driven by advances in remote sensing, three-dimensional reconstruction, and artificial intelligence. Traditional methods such as sieving and sedimentation remain essential because of their standardization, reproducibility, and direct physical interpretation. However, their limitations in terms of field applicability, spatial representation, and automation have motivated the development of alternative approaches based on digital imaging, photogrammetry, LiDAR, and machine learning.

The comparative review presented in this study indicates that image-based methods, SfM photogrammetry, and LiDAR technologies provide significant advantages for non-invasive particle-size characterization, particularly in hazardous, remote, or large-scale geological environments. Among these approaches, LiDAR offers the highest geometric accuracy and spatial detail, while SfM provides an attractive balance between cost, accessibility, and three-dimensional reconstruction capabilities. Recent advances in deep learning, including convolutional neural networks, transformer architectures, and graph neural networks, have further improved particle segmentation, classification, and morphological characterization, enabling levels of automation and scalability that were previously unattainable.

The evidence reviewed suggests that the future of granulometric analysis lies in hybrid methodologies that integrate high-resolution 3D acquisition technologies with artificial intelligence. Such approaches combine the geometric reliability of LiDAR and photogrammetry with the analytical power of data-driven models, resulting in improved accuracy, robustness, and operational efficiency. Future research should focus on creating benchmark datasets, incorporating physics-informed machine learning frameworks, quantifying uncertainty through Bayesian methods, and developing autonomous field systems supported by UAVs and edge computing. These advances have the potential to transform granulometry from a predominantly descriptive discipline into a predictive and real-time tool for geoscientific investigation and decision-making.

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