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Deep learning–based analysis of scanning electron microscopy images in nanomedicine and biomedical materials: a critical review

Abstract

Scanning electron microscopy (SEM) is widely used for characterizing the surface morphology of nanostructured biomaterials, drug delivery systems, and biomedical devices at micro- and nanoscales. Despite its ability to provide high-resolution structural information, the interpretation of SEM images remains largely dependent on manual analysis, which is time-consuming and susceptible to operator-dependent variability. Recent advances in artificial intelligence, particularly deep learning approaches based on convolutional neural networks (CNNs), have created new opportunities for automated and reproducible analysis of SEM data. This review critically examines recent studies that apply deep learning techniques to SEM image analysis in nanomedicine and biomedical materials research. Core principles of CNN-based image analysis are briefly introduced, followed by an overview of commonly investigated morphological features and classification tasks. The review discusses reported strategies for dataset construction, image preprocessing, model training, and performance evaluation, highlighting both methodological trends and recurring limitations in the literature. Key challenges, including limited dataset sizes, non-independent data sampling, variability arising from imaging conditions, and issues related to model interpretability and generalizability, are also addressed. Finally, the review outlines future directions for improving the robustness and translational relevance of AI-assisted SEM analysis, with particular emphasis on reproducibility, validation across instruments, and potential applications in preclinical research and quality control.

Keywords: scanning electron microscopy, deep learning, convolutional neural networks, nanomedicine, biomedical materials, image analysis

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Introduction

Advances in nanomedicine and biomedical materials science increasingly depend on the precise design and characterization of structures at the micro- and nanoscale. Morphological properties such as surface topography, porosity, particle shape, fiber alignment, and coating uniformity extend beyond purely structural descriptors, as they directly influence biological interactions including protein adsorption, cellular adhesion, inflammatory responses, and drug release behavior.[1–3] For this reason, imaging techniques capable of resolving fine structural details play a central role across the translational pipeline, from material development and preclinical evaluation to manufacturing and quality control.

Among available imaging modalities, scanning electron microscopy (SEM) remains one of the most widely used techniques for morphological characterization of biomedical materials. Its high spatial resolution, large depth of field, and versatility have established SEM as a routine tool for the analysis of nanofibrous scaffolds, porous matrices, implant surface coatings, pharmaceutical particles, and micro- and nano-engineered medical devices.[4–6] By enabling direct visualization of surface features and structural organization, SEM provides insights that are often inaccessible through bulk or ensemble-averaged analytical methods.

Despite these advantages, SEM image interpretation in biomedical research is still predominantly performed through manual inspection by trained experts. Morphological assessments are frequently qualitative or semi-quantitative, relying on visual judgment to identify structural features, defects, or irregularities. Such evaluations are inherently time-consuming and subject to inter- and intra-observer variability, particularly when analyzing large datasets or when morphological differences between samples are subtle.[7] These limitations pose significant challenges in high-throughput research settings and industrial environments, where objective, rapid, and reproducible analysis is increasingly required.

In parallel with advances in imaging technologies, artificial intelligence (AI) has emerged as a powerful framework for the analysis of complex biomedical data. Machine learning (ML), and in particular deep learning (DL), has demonstrated strong performance in diverse medical imaging domains, including radiology, digital pathology, and ophthalmology.[8–10] Convolutional neural networks (CNNs), which are specifically designed for image-based tasks, have become the dominant architecture for visual classification, segmentation, and feature extraction. Unlike traditional image analysis approaches that rely on handcrafted features, CNNs learn hierarchical representations directly from pixel-level data, enabling the identification of complex, multiscale patterns.

More recently, DL-based methods have begun to attract attention in the context of SEM image analysis. SEM images contain rich textural and structural information, making them well suited for CNN-driven approaches. An increasing number of studies have reported the use of DL models for tasks such as nanostructure classification, surface defect detection, particle segmentation, and discrimination between biomedical materials based on SEM-derived morphology.[11–13] These studies suggest that AI-assisted SEM analysis has the potential to reduce subjectivity and improve the efficiency and consistency of morphological characterization workflows.

From a translational perspective, the integration of DL with SEM is particularly relevant for nanomedicine and biomedical materials development. Automated and reproducible analysis of SEM images could support standardized evaluation of implant surfaces, scaffold architectures, and drug delivery carriers, thereby contributing to manufacturing consistency and quality assurance. In addition, data-driven approaches may enable more systematic screening of design variables, facilitating the optimization of materials intended for clinical use.

However, several methodological and practical challenges currently limit the broader adoption of DL-assisted SEM analysis. SEM image characteristics are highly sensitive to acquisition parameters such as accelerating voltage, working distance, detector configuration, and sample preparation protocols. Variations across instruments and laboratories can introduce domain shifts that degrade model performance and restrict generalizability.[14] Furthermore, many published studies rely on relatively small, highly curated, or non-independent datasets, raising concerns related to selection bias, overfitting, and limited external validation.

Model transparency and interpretability represent additional critical considerations, particularly in biomedical applications. It is essential to understand which image features drive model predictions and to ensure that performance is not influenced by confounding factors such as scale bars, imaging artifacts, or instrument-specific signatures. Recent guidelines for AI-based biomedical research emphasize the importance of transparent reporting of data sources, preprocessing steps, model architectures, and evaluation protocols in order to promote reproducibility and trust.[15]

Given the rapid growth of research at the intersection of SEM, deep learning, and nanomedicine, a structured and critical synthesis of the literature is timely. The objectives of this review are to:

(i) outline the methodological foundations of deep learning–based SEM image analysis;

(ii) summarize SEM-derived morphological features relevant to biomedical and nanomedical applications; and

(iii) critically assess current limitations and emerging opportunities for robust and translational implementation.

Representative SEM morphology classes and their biomedical relevance are summarized in Table 1, while an overview of a typical AI-assisted SEM analysis workflow is provided in Figure 1.

Deep learning methodologies applied to SEM images

Data acquisition and dataset construction

The performance and generalizability of deep learning models are strongly influenced by the characteristics of the datasets used for training and evaluation. In studies involving scanning electron microscopy, datasets typically consist of images acquired under heterogeneous experimental conditions, including variations in magnification, detector type, accelerating voltage, working distance, and sample preparation protocols. While such diversity can, in principle, promote model robustness, insufficient control or documentation of acquisition parameters may introduce confounding factors that obscure true morphological learning and negatively affect reproducibility.[16]

In biomedical SEM applications, dataset construction often relies on manual curation to ensure acceptable image quality. Images are commonly selected based on criteria such as adequate resolution, proper focus, and limited presence of imaging artifacts. Samples exhibiting severe charging effects, contamination, or excessive noise are frequently excluded to facilitate stable model training and to reduce the risk of learning spurious correlations.[11,12] Although this practice improves internal consistency, it may also lead to overly curated datasets that do not fully reflect real-world variability encountered across laboratories or instruments.

Annotation strategies vary widely across the literature. Labels are often assigned based on visual morphology (e.g., fibrous, particulate, porous structures) or according to processing- or function-related categories, such as coated versus uncoated surfaces. In some cases, annotations are derived from expert judgment without explicit quantitative criteria, introducing subjectivity and inter-observer variability. The lack of standardized labeling conventions remains a major limitation and complicates direct comparison of reported model performance across studies.

Dataset size and sample independence represent additional methodological concerns. Many published studies rely on relatively small datasets, often comprising tens to a few hundred SEM images. To compensate for limited data, patch-based extraction from larger images is frequently employed. While this approach increases the number of training samples, it can inadvertently introduce non-independent data points if patches derived from the same original image are distributed across training and testing sets. Such data leakage may lead to inflated performance estimates and overoptimistic conclusions regarding model generalization. Explicit reporting of specimen-level data splitting and dataset composition is therefore essential for meaningful evaluation.

Preprocessing and data preparation

Preprocessing is a critical step in ensuring consistency among SEM image inputs and enabling reliable deep learning model training. Common preprocessing operations include resizing images to uniform spatial dimensions and normalizing pixel intensity values to a defined range. Although SEM images are intrinsically grayscale, some studies retain three-channel representations to maintain compatibility with convolutional neural network architectures pretrained on natural image datasets.[17] While this strategy facilitates transfer learning, it does not inherently introduce additional morphological information and should be interpreted with caution.

Beyond basic normalization, SEM-specific preprocessing considerations are often underreported. Differences in magnification, pixel-to-length calibration, and field of view can substantially affect feature representation, particularly in texture-dominated classification tasks. Inadequate normalization of spatial scale may cause models to associate morphology with magnification rather than intrinsic structural characteristics. Similarly, frequency-domain biases arising from detector configuration or noise filtering can influence learned representations and limit cross-instrument applicability.

A persistent methodological issue is the inclusion of image elements unrelated to sample morphology, such as scale bars, textual annotations, and manufacturer logos. If retained during training, these features may serve as unintended shortcuts for classification, enabling models to exploit acquisition-specific cues rather than genuine morphological differences. This phenomenon can result in artificially high performance metrics that fail to reflect true predictive capability.[18] As a result, careful cropping, masking, or removal of non-morphological regions is strongly recommended prior to model training.

CNN architectures and training strategies

A wide range of convolutional neural network architectures has been applied to SEM image analysis, encompassing both custom-designed models and transfer learning–based approaches. Custom CNN architectures offer flexibility and reduced computational complexity, making them suitable for smaller datasets commonly encountered in SEM studies. In contrast, pretrained architectures such as ResNet, VGG, and EfficientNet leverage feature representations learned from large-scale natural image datasets and may improve convergence when appropriately fine-tuned.[19,20]

However, the substantial domain differences between natural images and SEM data warrant careful consideration. SEM images are dominated by texture, contrast, and surface topology rather than object-centric shapes, which form the basis of many pretrained representations. Consequently, transfer learning may yield suboptimal feature extraction if early layers are not adequately adapted or if domain mismatch is not explicitly addressed. Comparative analyses of architecture suitability for SEM-specific tasks remain limited in the literature.

Model training is typically conducted using gradient-based optimization algorithms such as Adam or RMSprop. Hyperparameters including learning rate, batch size, and number of training epochs strongly influence convergence behavior and generalization performance.[21] To mitigate overfitting—particularly in scenarios with limited or non-independent data—regularization strategies such as dropout, batch normalization, and data augmentation are frequently employed. Nevertheless, the effectiveness of these techniques is rarely evaluated systematically across studies.

Evaluation practices reported in the literature remain heterogeneous. Overall classification accuracy is often presented as a primary metric, yet it provides limited insight in multi-class settings or in the presence of class imbalance. More informative evaluation strategies include class-wise precision and recall, macro-averaged F1-scores, confusion matrices, and, where possible, external validation on independent datasets. The absence of statistical significance testing and cross-instrument validation further limits the interpretability and comparability of reported results (Table 1).[15]

Table 1 Summarizes representative SEM-derived morphological categories that are frequently reported in nanomedicine and biomedical materials research, together with typical application domains and associated functional relevance. The classification adopted in this review is intentionally morphology-driven rather than material- or chemistry-specific. This choice reflects the nature of image-based deep learning workflows, which primarily rely on visual patterns such as texture, topology, and spatial organization rather than compositional information.

Table 1 Representative sem-derived morphological categories commonly investigated in nanomedicine and biomedical materials research, together with typical application areas and functional relevance.

SEM morphology	Representative applications	Biomedical relevance
Nanofibrous structures	Tissue engineering scaffolds	Cell adhesion, alignment, guidance
Porous architectures	Regenerative biomaterials	Nutrient diffusion, tissue ingrowth
Coated surfaces	Implants, drug-eluting devices	Biocompatibility, controlled release
Patterned surfaces	Biosensors, cell-instructive substrates	Modulation of cell response
Particles / powders	Drug delivery systems	Dissolution, biodistribution
MEMS / electrode structures	Implantable devices	Signal stability, device reliability

Nanofibrous and porous structures are grouped according to their dominant architectural features, as these morphologies are commonly investigated in tissue engineering and regenerative medicine. Although these categories are visually distinct at certain magnifications, substantial intra-class heterogeneity exists, arising from variations in fiber diameter, pore size distribution, and structural anisotropy. Such heterogeneity can complicate supervised classification tasks and may limit the separability of classes in CNN-based models unless scale and imaging conditions are carefully controlled.

Surface-engineered materials, including coated and patterned substrates, are treated as separate categories due to their relevance in implant technologies and biointerface design. In these systems, relatively subtle morphological differences—such as coating continuity, pattern fidelity, or edge definition—can have disproportionate effects on biological response and long-term functionality. From a deep learning perspective, distinguishing meaningful surface features from imaging artifacts remains a key challenge.

Particle- and powder-based systems represent an important class of pharmaceutical and nanomedicine formulations. In these applications, particle size, shape, surface roughness, and aggregation state strongly influence dissolution behavior and biodistribution. However, reported morphology classes often span wide size ranges and imaging magnifications, which can hinder consistent feature learning across datasets.

Finally, micro- and nano-fabricated components, including MEMS structures and electrode geometries, are presented as a distinct category. These systems are increasingly relevant for implantable sensors and biomedical electronics, yet their complex geometries and strong dependence on imaging parameters can challenge generalization of CNN-based approaches across instruments and laboratories.

Overall, the categories summarized in Table 1 should be regarded as conceptually useful but not universally separable. Explicit reporting of imaging conditions, scale, and quantitative descriptors is essential when these morphology classes are used as targets for supervised deep learning (Figure 1).

Figure 1 presents a conceptual overview of a typical deep learning–assisted SEM image analysis workflow. The figure is intended as a generalized framework rather than a prescriptive pipeline, as specific implementations vary widely across studies and applications. The workflow begins with SEM image acquisition, a stage at which variations in magnification, detector configuration, accelerating voltage, and sample preparation protocols can introduce substantial variability into the dataset.

This acquisition-related heterogeneity underscores the importance of preprocessing, which aims to reduce non-morphological sources of variation and to standardize image inputs prior to model training. Following preprocessing, convolutional neural network–based models

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are applied for automated feature learning. Through hierarchical representation learning, CNNs extract texture- and topology-related features directly from pixel-level data, without reliance on manually defined descriptors.

As illustrated in Figure 1, model evaluation constitutes a critical intermediate step and extends beyond single summary metrics. Class-specific performance measures are necessary to assess reliability across different morphology categories and to identify systematic failure modes. In many published studies, this stage is limited by the absence of independent external validation, which restricts conclusions regarding generalizability.

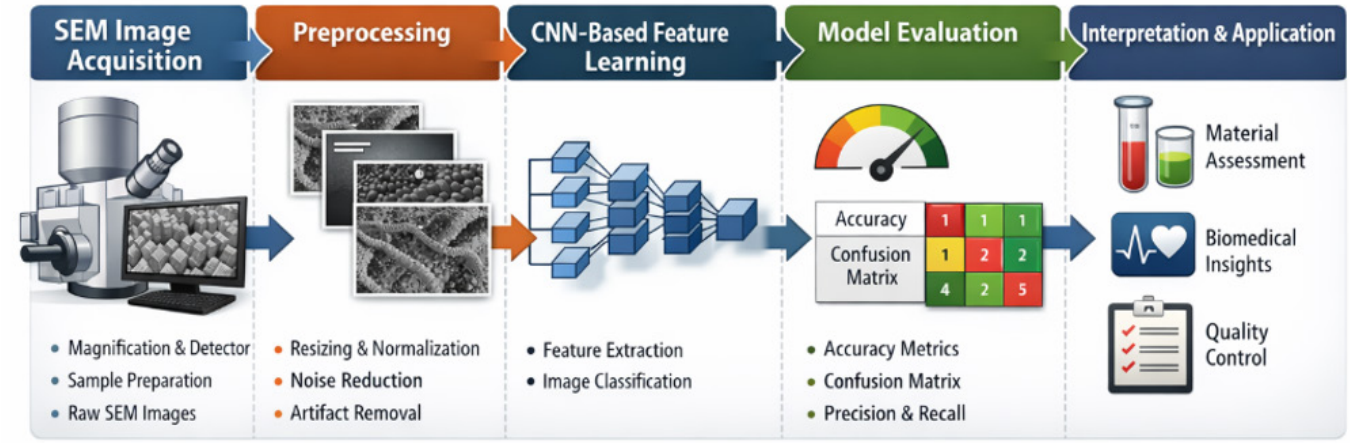

Figure 1 Conceptual workflow of deep learning–assisted SEM image analysis, illustrating data acquisition, preprocessing, CNN-based feature learning, model evaluation, and biomedical interpretation.

The final stage of the workflow focuses on interpretation and application. At this point, model outputs are linked to material characterization, quality assessment, or design optimization tasks. For biomedical applications, this step requires careful consideration of model interpretability and robustness to ensure that predictions reflect true morphological differences rather than acquisition-specific artifacts. By explicitly connecting SEM-derived image analysis with functional and translational objectives, the workflow in Figure 1 highlights both the potential and the current limitations of deep learning approaches in this domain.

Challenges and limitations of deep learning–based sem analysis

Despite the encouraging results reported in recent studies, the integration of deep learning approaches with SEM image analysis in biomedical and nanomedical research is accompanied by a number of methodological and translational challenges. Careful consideration of these limitations is essential to avoid overinterpretation of model performance and to support meaningful deployment in research, industrial, or clinical contexts.

One of the most significant challenges arises from variability in SEM image acquisition. Differences in accelerating voltage, working distance, detector configuration, and sample preparation protocols can substantially alter image contrast, texture, and apparent morphology. While controlled variability may improve model robustness when adequately represented during training, unaccounted differences between training and deployment conditions frequently introduce domain shifts that degrade performance and limit generalizability across instruments or laboratories.[16,17] Although preprocessing strategies, as outlined in Figure 1, aim to reduce such effects, complete normalization across heterogeneous acquisition conditions remains difficult to achieve in practice.

Dataset size and class distribution represent additional constraints. In biomedical SEM applications, datasets are often limited in scale due to the cost, time, and expertise required for image acquisition and expert annotation. Small datasets increase susceptibility to overfitting, particularly when complex CNN architectures are applied. Moreover, class imbalance—commonly encountered in realistic biomedical materials datasets—can bias model predictions toward dominant categories. In such cases, overall classification accuracy may appear high while performance on underrepresented but scientifically or clinically relevant classes remains poor.[18] Reliance on accuracy as a sole performance metric therefore risks masking critical failure modes.

Model interpretability constitutes another major limitation, especially in translational and medically oriented applications. CNNs are frequently characterized as "black-box" models, as the internal representations driving their predictions are not inherently transparent. For SEM-based biomedical analysis, it is crucial to determine whether model decisions are informed by meaningful morphological features rather than coincidental patterns. Techniques such as class activation mapping, saliency analysis, and gradient-based visualization have been proposed to enhance interpretability; however, their application to SEM data remains inconsistent and their limitations—particularly in texture-dominated images—are not always acknowledged.[19]

Closely related to interpretability is the risk of models exploiting non-morphological visual cues present in SEM images. Elements such as scale bars, textual annotations, detector-specific noise patterns, or instrument signatures may inadvertently correlate with class labels. If these cues are not removed or controlled during preprocessing, models may achieve high apparent performance by learning acquisition-specific shortcuts rather than genuine morphological distinctions. This issue has been increasingly recognized as a source of artificially inflated performance and underscores the need for rigorous preprocessing and transparent reporting, in line with recent guidelines for AI-based biomedical research.[15]

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Finally, reproducibility and standardization remain unresolved challenges within the field. Substantial variation in dataset composition, labeling schemes, preprocessing pipelines, model architectures, and evaluation protocols complicates direct comparison across studies. The lack of publicly available benchmark datasets and standardized evaluation frameworks for biomedical SEM image analysis further limits objective assessment of methodological progress and hinders broader translational adoption.

Clinical and translational ımplications

Despite the methodological challenges discussed above, deep learning–assisted analysis of SEM images presents notable opportunities for advancing nanomedicine and biomedical materials research, particularly at the interface between experimental characterization and translational application. By enabling more automated, quantitative, and reproducible interpretation of nanoscale morphology, AI-driven approaches may help bridge the gap between materials design and functional performance assessment.

In the context of implantable medical devices, surface morphology is a critical determinant of biological integration, corrosion resistance, and long-term biocompatibility. Parameters such as surface roughness, coating continuity, and micro- or nanoscale pattern fidelity are known to influence osseointegration and host response. CNN-based analysis of SEM images has the potential to support more standardized evaluation of implant surfaces during manufacturing and quality control, complementing conventional inspection methods. Morphology-oriented classification frameworks, such as those summarized in Table 1, may provide a structured means of relating SEM-derived features to functional performance indicators relevant to preclinical testing and device development. However, the role of such approaches should currently be viewed as supportive rather than substitutive, pending further validation.

Tissue engineering and regenerative medicine represent another area where AI-assisted SEM analysis may offer translational value. Scaffold architecture—including fiber orientation, pore size distribution, interconnectivity, and surface texture—plays a central role in regulating cell adhesion, migration, and tissue maturation. Automated analysis of SEM images could facilitate systematic comparison of scaffold designs and assist in identifying morphological features associated with favorable biological responses. In this context, deep learning approaches may function as research tools that accelerate iterative design and optimization processes, rather than as standalone decision-making systems.

Pharmaceutical and nanomedicine formulations may similarly benefit from deep learning–based SEM image analysis. In particulate drug delivery systems, particle size, shape, surface morphology, and aggregation state strongly influence dissolution behavior, bioavailability, and biodistribution. Automated particle detection, segmentation, and classification from SEM images could support high-throughput formulation screening and enhance process understanding. From a translational perspective, these capabilities may contribute to improved batch-to-batch consistency and manufacturing robustness, particularly for complex nanomedicine products where subtle morphological differences can have disproportionate functional consequences.

Beyond individual application domains, deep learning–assisted SEM analysis has broader implications for regulatory science and standardization. Algorithm-driven interpretation of SEM data may contribute to more objective and reproducible characterization workflows, supporting comparability across studies and manufacturing sites. Nevertheless, meaningful regulatory or clinical adoption will require rigorous validation, clear definition of intended use, and transparent documentation of data provenance, model development, and performance limitations. Close collaboration among materials scientists, clinicians, and regulatory stakeholders will be essential to establish confidence in AI-assisted SEM methodologies and to determine their appropriate role within clinical development pipelines and regulatory frameworks.

Future perspectives

The integration of deep learning with scanning electron microscopy represents a rapidly developing area in nanomedicine and biomedical materials research. To date, most reported studies have focused on feasibility demonstrations and proof-of-concept applications. Future work is expected to expand beyond these initial implementations toward more robust, generalizable, and translationally relevant frameworks.

One important direction for future research is the incorporation of multimodal data. SEM provides detailed surface morphology, but biological performance is often governed by a combination of structural, mechanical, and chemical properties. Integrating SEM data with complementary techniques such as transmission electron microscopy (TEM), atomic force microscopy (AFM), or energy-dispersive X-ray spectroscopy (EDS) may enable deep learning models to jointly analyze morphological, mechanical, and compositional information. Multimodal learning strategies could therefore support a more comprehensive understanding of structure–function relationships in complex biomedical materials, particularly in systems where morphology alone does not fully explain biological outcomes.

Another promising avenue involves the adoption of federated and distributed learning approaches. In biomedical research, SEM datasets are often fragmented across institutions due to data ownership, intellectual property, or regulatory constraints. Federated learning enables collaborative model training without centralized data sharing by allowing models to learn from decentralized datasets while keeping raw images local. This strategy may be particularly well suited to SEM applications, where inter-laboratory variability is high and access to large, diverse datasets is limited. By leveraging distributed data sources, federated approaches could improve model generalizability and reduce sensitivity to instrument- or site-specific imaging conditions.

Explainable artificial intelligence (XAI) is also expected to play a central role in the future adoption of deep learning–based SEM analysis. As models become more complex and are applied in translational settings, the ability to interpret and validate model predictions will be increasingly important. Techniques such as attention mechanisms, saliency mapping, and feature attribution methods can provide insight into which morphological characteristics influence model decisions. Improved interpretability will not only enhance scientific understanding but also support confidence in AI-assisted analysis for downstream biomedical and regulatory applications.

Standardization represents another critical challenge and opportunity. The absence of widely accepted benchmark datasets, annotation guidelines, and evaluation protocols currently limits objective comparison between studies. Community-driven efforts to develop well-curated, publicly available SEM image repositories with standardized morphological labels could substantially accelerate

progress in the field. Such benchmarks would support fair assessment of algorithmic performance and promote reproducibility across research groups.

Finally, advances in computational efficiency and deployment strategies are likely to expand real-world applicability. The development of lightweight neural network architectures and edge computing solutions may enable near-real-time SEM image analysis directly at the point of acquisition, such as in manufacturing facilities or research laboratories. These developments could reduce analysis time, lower computational costs, and facilitate integration of AI-assisted SEM analysis into routine biomedical workflows.

Collectively, these emerging directions suggest that deep learning–based SEM analysis is poised to evolve from exploratory research toward more mature, standardized, and impactful applications. Continued interdisciplinary collaboration among materials scientists, data scientists, clinicians, and regulatory stakeholders will be essential to ensure that future developments are both scientifically rigorous and translationally meaningful.

Conclusions

This review has examined the expanding role of deep learning–based analysis of scanning electron microscopy images in nanomedicine and biomedical materials research. While SEM remains a cornerstone technique for nanoscale morphological characterization, conventional analysis workflows are often constrained by subjectivity, limited scalability, and variability in expert interpretation. Deep learning approaches, particularly convolutional neural networks, offer a compelling alternative by enabling automated, quantitative, and reproducible extraction of morphological information from complex SEM datasets.

By adopting a morphology-oriented classification framework (Table 1) and outlining a generalized AI-assisted SEM analysis pipeline (Figure 1), this review illustrates how deep learning can provide a unifying analytical paradigm across diverse biomedical material systems. Existing studies demonstrate that CNN-based models are capable of distinguishing and interpreting SEM images of fibrous architectures, particulate systems, porous scaffolds, surface-modified materials, and micro- and nano-fabricated devices. These findings highlight the potential utility of AI-assisted SEM analysis in both exploratory research and translational settings.

At the same time, several challenges continue to limit widespread adoption. Variability in image acquisition conditions, limited dataset sizes, class imbalance, and persistent concerns regarding model interpretability and reproducibility must be addressed to ensure robust and reliable deployment. Addressing these issues will require careful experimental design, transparent reporting practices, and alignment with emerging standards for AI-based biomedical research.

Future directions

Future developments in deep learning–assisted SEM analysis are expected to expand both methodological sophistication and translational relevance. One important direction involves the integration of SEM data with complementary imaging and analytical modalities. The combination of SEM with techniques such as transmission electron microscopy, atomic force microscopy, or spectroscopic methods may allow deep learning models to jointly analyze morphology, composition, and mechanical properties, enabling a more comprehensive understanding of structure–function relationships in biomedical materials.[11,12]

Explainable artificial intelligence is likely to play a central role in this evolution. As deep learning models move closer to clinical and regulatory use, interpretability becomes essential. Methods that provide insight into feature importance or activation patterns can help researchers and clinicians assess whether model predictions are driven by biologically meaningful morphological characteristics. Such transparency will be critical for building trust in AI-assisted analysis and for supporting regulatory acceptance.[13]

Data-related considerations will also shape future progress. The development of large, well-annotated, and publicly accessible SEM image repositories would facilitate benchmarking, improve cross-study comparability, and enhance generalizability across laboratories and imaging platforms. In parallel, federated learning strategies offer a promising solution for collaborative model development without centralized data sharing, addressing privacy and intellectual property concerns while increasing dataset diversity.[14]

Advances in computational efficiency and model deployment are expected to further enhance real-world applicability. Lightweight neural network architectures and optimized inference pipelines may enable near–real-time SEM image analysis in manufacturing and clinical laboratory environments. Such capabilities could support on-site quality control, rapid material assessment, and iterative design optimization.

In the longer term, the integration of deep learning with SEM has the potential to transform nanoscale characterization from a largely qualitative practice into a data-driven, standardized, and clinically informed discipline. Achieving this transition will require sustained interdisciplinary collaboration among materials scientists, data scientists, clinicians, and regulatory experts to ensure that methodological advances translate into meaningful biomedical and clinical impact.

This review has examined the growing role of deep learning–based analysis of SEM images in nanomedicine and biomedical materials research. SEM remains a cornerstone technique for nanoscale morphological characterization, yet traditional analysis approaches are limited by subjectivity, scalability constraints, and variability in expert interpretation. The application of convolutional neural networks offers a powerful alternative, enabling automated, quantitative, and reproducible extraction of morphological information from complex SEM datasets.

By organizing SEM images into morphology-driven categories (Table 1) and outlining a general AI-assisted analysis workflow (Figure 1), this review highlights how deep learning can serve as a unifying framework across diverse biomedical applications. Recent studies demonstrate that CNN-based models can effectively classify and interpret SEM images of fibers, particles, porous structures, coated surfaces, and microfabricated devices, underscoring their potential utility in both research and translational contexts.

At the same time, significant challenges remain. Variability in image acquisition, limited dataset sizes, class imbalance, and issues of interpretability and reproducibility must be addressed before widespread adoption can be achieved. Careful experimental design, transparent reporting, and adherence to emerging AI reporting standards are essential to ensure scientific rigor and clinical relevance.

Looking forward, the integration of multimodal data, explainable AI techniques, and federated learning paradigms is expected to further enhance the robustness and translational value of AI-assisted SEM analysis. As these methodologies mature, they have the potential to reshape how nanoscale imaging data are interpreted and applied,

ultimately contributing to more efficient material design, improved quality control, and accelerated translation of nanotechnologies into clinical practice.

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Conflicts of interest

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