A Survey on SEM Image Analysis Techniques

Naveen Bharadwaj
Department of Electrical and Computer Engineering
University of Delaware
Newark, DE, USA
naveen@udel.edu

***Abstract*—This survey delves into the utilization of deep learning methods for the analysis of scanning electron microscopy (SEM) images. The paper concentrates on the enhancement of image quality and the detection of defects, exploring the Use of Deep Learning Methods for Image Enhancement and Restoration and examine the effectiveness of generative adversarial networks (GANs), convolutional neural networks (CNNs), and other deep learning methods in improving the signal-to-noise ratio, denoising images, restoring degraded images, and enhancing image contrast. Several studies in this area are reviewed and analyzed to determine the potential of these techniques for image enhancement and restoration. Automated defect detection and classification have been applied in several studies, with potential applications in materials science and engineering. This paper presents a comprehensive analysis of the effectiveness of deep learning techniques in enhancing SEM image quality and identifying defects. The findings indicate that these approaches have significant potential for broader application in the field.**

***Index Terms*—Scanning electron microscopy (SEM), Deep learning, Image analysis, Image quality enhancement, Defect detection, Generative adversarial networks (GANs), Convolutional neural networks (CNNs), Signal-to-noise ratio (SNR), Denoising, Image restoration.**

I. Introduction

Scanning electron microscopy (SEM) is a widely adopted imaging technique used for high-resolution imaging and analysis of various materials in engineering. However, SEM images may be affected by noise, low contrast, and other forms of degradation, thus reducing their quality and usefulness for analysis. This survey presents an overview of the recent research on the application of deep learning and other methods for SEM image analysis. Traditional methods such as filtering and thresholding are limited and require extensive manual tuning. In recent years, deep learning-based approaches have shown great potential in addressing these challenges. Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Autoencoders are deep learning models that can learn to extract and represent high-level features from noisy and distorted SEM images. These models can generate high-quality images with improved resolution, contrast, and signal-to-noise ratio. In this literature survey, we review and compare various deep learning-based techniques for SEM image restoration and enhancement, including their advantages and limitations. We also highlight the open research challenges and opportunities in this field, including the need for explainable deep learning models and real-time analysis of SEM images.

II. Deep Neural Networks

Deep neural networks (DNNs) are a class of machine learning algorithms that are particularly well-suited for tasks such as image processing and analysis. In the context of scanning electron microscopy (SEM), DNNs can be used to perform a variety of tasks, such as image restoration, enhancement, segmentation, classification, and object detection.

A. Convolutional Neural Networks (CNNs)

The process of using CNNs for SEM image analysis typically involves several steps. The first step is to prepare the SEM image dataset for training and evaluation. This involves preprocessing the images to remove noise and artifacts, and dividing the dataset into training, validation, and test sets. The next step is to design the CNN architecture, which typically consists of multiple layers, including convolutional, pooling, and activation layers. The input to the network is the SEM image, and the output is the predicted label or the transformed image. Kim et al. (2020) developed a deep learning-based SEM image restoration method using a denoising autoencoder, which achieved significant improvements in signal-to-noise ratio compared to traditional methods. Similarly, Lee et al. (2019) proposed an unsupervised deep learning approach for enhancing low-quality SEM images, which utilized a CNN for feature extraction and denoising.

CNNs have also been used for image segmentation in SEM images. Jung et al. (2019) developed a deep learning-based segmentation method for SEM images using a U-Net architecture, which achieved high accuracy in identifying different regions of the SEM image. Liu et al. (2020) developed an automated defect detection and classification method using a CNN, which achieved high accuracy in detecting and classifying different types of defects in SEM images.

B. Generative Adversarial Networks (GANs)

A Generative Adversarial Network (GAN) is a deep learning model used to generate new data, such as images or videos, that are similar to a training dataset. GANs consist of two neural networks - a generator and a discriminator - that work in tandem to learn the underlying distribution of the training data and generate new data that follows that distribution

Generative Adversarial Networks (GANs) can be utilized to generate synthetic images that contain defects. This approach involves training a GAN on a dataset of defect-free SEM images and introducing defects into the generator network to simulate various types of defects. The resulting synthetic images can be used to evaluate the performance of algorithms for detecting and classifying defects in SEM images. A study proposed a defect simulation method using GANs, and the results showed that the proposed method effectively simulated different types of defects.

Another study proposed a GAN-based SEM image restoration method to enhance the signal-to-noise ratio (SNR) of low-quality SEM images. The authors trained a GAN on a dataset of clean and noisy SEM images and used the generator network to restore the noisy images. The proposed method was shown to significantly improve the SNR and image quality of the SEM images, as compared to other restoration methods.

C. *Autoencoders*

Autoencoders are a type of neural network used for reconstructing input data, such as images, from a compressed representation. In the context of SEM image analysis, autoencoders can be applied for tasks such as image denoising and restoration. One study proposed an unsupervised deep learning approach for SEM image quality enhancement using an autoencoder, where the network was trained on low-quality SEM images, and the encoder network was used to extract features from the input images, and the decoder network was used to reconstruct the images for quality enhancement. Another study proposed a high-performance denoiser based on deep learning trained using precisely reproduced SEM noise. In this study, an autoencoder was used to learn the noise distribution of SEM images and generate realistic noise patterns to train the denoising network, which was evaluated on a dataset of noisy SEM images and shown to significantly improve image quality. A similar study proposed a high-performance denoiser based on deep learning trained by precisely reproduced SEM noise, where an autoencoder was used to learn the noise patterns of SEM images and denoise them accordingly, and the proposed method was shown to achieve superior performance in terms of both visual quality and signal-to-noise ratio, when compared to other denoising methods.

Table 1 provides an overview of several scanning electron microscope (SEM) imaging techniques and their applications. The table lists the mode of operation, whether machine learning (ML) or non-ML, as well as the disadvantages, throughput, and signal-to-noise ratio of each technique. Techniques such as Convolutional Neural Networks (CNN), Generative Adversarial Networks (GAN), Autoencoders, and Transfer Learning all use ML to perform tasks such as image restoration, enhancement, generation, and classification. Wavelet Transform is a non-ML technique used for denoising, compression, feature extraction, and restoration. Feature Extraction Techniques and Hybrid Techniques can use either ML or non-ML methods for classification, object recognition, and image processing. However, these techniques may not capture all relevant image features, may be sensitive to noise and lighting conditions, and may require extensive computational resources.

III. Pre-processing Techniques

A. *Image processing*

Preprocessing SEM images using image processing techniques such as filtering, thresholding, and morphological operations can improve the quality of the images and reduce the computational requirements for subsequent deep learning analysis. For instance, filtering can help to remove noise and artifacts from the images, which can improve the quality of the images and reduce the computational requirements for subsequent analysis. Thresholding can convert grayscale images to binary images, which can make it easier to identify and separate objects of interest from the background. Morphological operations like erosion and dilation can help modify the shape and size of objects in the images, which can fill gaps or remove small features that may not be relevant for the analysis.

Several studies have applied these preprocessing techniques to SEM images before using deep learning techniques such as CNNs, autoencoders, and GANs. For example, researchers have used median filtering to remove salt and pepper noise from SEM images, followed by adaptive thresholding to convert the images to binary format. However, there are limitations to these techniques, such as potential information loss during the preprocessing step, which can impact the accuracy of subsequent analysis. Additionally, selecting appropriate parameters for these techniques can be challenging and time-consuming, requiring expert knowledge. Nonetheless, using image processing techniques for preprocessing SEM images remains a valuable tool to enhance the quality of input data for subsequent deep learning analysis.

B. *Edge Detection and Segmentation*

Edge detection and segmentation are essential preprocessing steps for SEM image analysis that are often employed in conjunction with deep learning techniques, such as convolutional neural networks (CNNs). These methods aim to identify and extract object boundaries in SEM images by detecting abrupt changes in pixel intensity, known as edges. The edge detection process involves convolving the image with a filter to enhance the edges, followed by thresholding the filtered image to create a binary image where object pixels are represented by ones and background pixels by zeros.

CNNs can be trained on these binary images to automatically learn how to segment objects from their backgrounds. In some cases, CNNs can be trained end-to-end to perform both edge detection and segmentation tasks simultaneously, without the need for explicit preprocessing steps. However, in some cases, morphological operations such as dilation and erosion can still be applied to refine the segmentation results obtained from CNNs. Overall, combining image processing techniques such as edge detection and segmentation with deep learning methods can lead to more accurate and efficient SEM image analysis.

TABLE I
OVERVIEW OF SEM IMAGING TECHNIQUES

Techniques	**Applications**	**Advantages**	**Disadvantages**	**ML/Non-ML**	**Training Data Required**	**Throughput**	**Signal-to-Noise Ratio**
SEM Restoration with CNN	Image Restoration and Enhancement	Provides high-quality results, superior to other traditional techniques	Computationally expensive, requires large amounts of training data, prone to overfitting	ML	Large amounts of high-quality training data required	High	High
GAN for SEM Image Processing	Image Generation, Style Transfer, Super-resolution, and Image Editing	Can produce high-quality images, can learn complex image distributions	Can be difficult to train, can suffer from mode collapse, can produce unrealistic images	ML	Can work well with small amounts of training data	Low	High
Autoencoders for SEM Imaging	Image Compression, Reconstruction, and Anomaly Detection	Can capture subtle image details, can learn useful image representations	May not capture all image details, can suffer from overfitting	ML	Requires large amounts of training data, specialized architecture	High	High
Transfer Learning in SEM Imaging	Image Classification and Object Detection	Can improve performance on new and related tasks, reduces the amount of training data required	Pre-trained models may not be applicable to all tasks, may require fine-tuning	ML	Pre-existing models and large datasets required	High	High
Wavelet Transform for SEM Imaging	Denoising, Compression, Feature Extraction, and Restoration	Can effectively reduce noise in SEM images, can efficiently capture high-frequency features	Can be computationally intensive, requires careful selection of wavelet basis functions	Non-ML	Not applicable	High	High
Feature Extraction Techniques for SEM Imaging	Classification and Object Recognition	Can capture complex image features, can be used with different types of data	May not capture all relevant image features, may be sensitive to noise and lighting conditions	ML/Non-ML	May require significant computational resources	High	Low
Hybrid Techniques for SEM Imaging	Image Processing, Segmentation, and Classification	Can provide more accurate and comprehensive results, can address complex image processing tasks	Can be complex to implement and optimize, may require extensive computational resources	ML/Non-ML	Large amounts of high-quality training data required	Varies	Low

C. Feature Extraction

In deep learning techniques, feature extraction is usually performed using convolutional neural networks (CNNs), which automatically learn and extract features from raw image data. The CNN architecture consists of multiple layers of interconnected neurons, where each layer is responsible for learning and extracting specific features at different levels of abstraction. The first layers of the CNN learn basic features such as edges, corners, and curves, while the deeper layers learn more complex features such as shapes, textures, and patterns.

In CNNs, the feature extraction process is performed as part of the network training process, where the weights of the neurons in the different layers are adjusted to optimize the performance of the network on a given task. By training the network on a large dataset of SEM images, the CNN can learn to identify and extract the relevant features automatically, without the need for manual feature engineering. This approach has been shown to be effective for a wide range of SEM image analysis tasks, such as classification, segmentation, and detection of specific features or defects in the images.

D. Wavelet Transform

Wavelet transform is a mathematical tool that can be used in the preprocessing step of deep learning models for SEM image analysis. It is particularly useful for signal and image processing and can be applied to SEM images to improve their quality before training a deep learning model.

Wavelet transform can be used for image denoising, feature extraction, and image segmentation. Wavelet transform decomposes an image into a series of coefficients, which represent the image at different scales and frequencies. This allows for the identification of important image features at different scales, which can be used for various image analysis tasks.

Researchers have used wavelet transform in combination with deep learning for various SEM image analysis tasks, such as image denoising, restoration, and enhancement.

IV. Hybrid Techniques

Deep learning techniques, such as convolutional neural networks (CNNs) and generative adversarial networks (GANs), are known for their ability to automatically learn complex features from data. On the other hand, classical machine learning techniques, such as Support Vector Machines (SVM) and Random Forests (RF), are better suited for handling small and noisy datasets and are more interpretable.

To compensate for the limitations of each approach and improve overall performance, a hybrid approach that combines both techniques can be used. For example, in SEM image restoration, a CNN can be used for noise reduction while a GAN can be used for image enhancement. Similarly, a CNN can be combined with the wavelet transform for feature extraction and image decomposition in SEM image restoration.

In SEM image segmentation, a pre-trained CNN can be used for feature extraction and an unsupervised learning algorithm can be used for clustering. In SEM image analysis, a CNN can be used for feature extraction, and an autoencoder can be used for dimensionality reduction.

However, implementing a hybrid approach requires careful consideration of several factors, such as the choice of deep learning architecture and the selection of classical machine learning algorithms. The hybrid approach has been reported to outperform deep learning or classical machine learning alone in some cases, but the suitability of this approach should be evaluated on a case-by-case basis.

V. Transfer Learning

Transfer learning is a technique used in deep learning that involves leveraging pre-trained models, typically convolutional neural networks (CNNs), to improve the performance of a new model for a specific task. The pre-trained model has already learned to extract features from a large dataset of images, and these learned features can be transferred to the new model to improve its performance on a similar task.

VI. Deep Reinforcement Learning

Deep reinforcement learning (DRL) can be used to optimize the quality of SEM images by adjusting imaging parameters. One way to use DRL in SEM image analysis is to train an agent to adjust parameters such as focus, brightness, and contrast to maximize a reward signal based on image quality. Another way is to train an agent to detect and correct defects by applying filters or adjusting contrast to maximize the reward signal.

A recent study used DRL to optimize SEM imaging parameters for the detection of surface defects in metal materials, while another used DRL to optimize the imaging parameters for the SEM-based inspection of printed circuit boards. Both studies found that DRL-based optimization approaches achieved higher accuracy and efficiency compared to traditional methods.

VII. Limitations

A. Convolutional Neural Networks

Transfer learning is a valuable technique in computer vision that capitalizes on pre-trained models trained on extensive datasets. However, this approach encounters certain challenges that necessitate suitable remedies. To ensure effective training, transfer learning necessitates substantial quantities of labeled scanning electron microscope (SEM) data. Addressing this issue involves acquiring and utilizing ample labeled SEM data. Another challenge arises from the risk of overfitting, which can occur when the model is excessively complex or when the training data is limited or biased. To mitigate overfitting, incorporating regularization and data augmentation techniques proves effective. Additionally, transfer learning can become computationally demanding, particularly when dealing with high-resolution SEM images. This challenge can be resolved through the utilization of graphics processing units (GPUs), parallel processing, and distributed computing techniques, which significantly enhance computational efficiency.

B. Generative Adversarial Networks

Generative Adversarial Networks (GANs) are powerful models that generate data by training a generator and a discriminator simultaneously. However, GANs often face challenges related to training difficulties and stability, potentially leading to mode collapse, where the generator fails to capture diverse modes of the target distribution. To address these issues, alternative loss functions, such as Wasserstein loss or hinge loss, can be employed, along with the integration of Support Vector Machines (SVMs) to enhance training and stabilize GANs.

Moreover, GANs may generate scanning electron microscope (SEM) images that lack the fine details present in the original data, resulting in output that is visually dissimilar. To mitigate this limitation, visualization techniques and clustering algorithms can be applied to GAN-generated samples, aiding in the exploration and enhancement of fine details in SEM images.

Furthermore, GANs require substantial computational resources for effective training. To address this computational burden, various techniques can be employed, including weight initialization methods to optimize training efficiency, batch normalization to accelerate convergence, and the utilization of skip connections to facilitate information flow and gradient propagation, thereby mitigating the resource requirements of GAN training. These measures collectively contribute to the improvement of GAN performance and alleviate the computational demands involved.

VIII. Recommendations

A. Standardised Datasets

There is a need for the development of standardized datasets for SEM image analysis. This will enable the comparison of results across different studies and facilitate the development of more accurate and robust deep learning models.

B. Transfer Learning

Transfer learning has been shown to be an effective way of improving the performance of deep learning models in SEM image analysis. Future research should explore the use of transfer learning techniques to improve the accuracy and robustness of deep learning models.

C. Explainable deep learning

Deep learning models are often considered as black boxes, making it difficult to interpret the results. Future research should focus on developing explainable deep learning models that can provide insights into the decision-making process of the models.

D. Integration with other techniques

Deep learning techniques can be combined with other image processing techniques to improve the accuracy and robustness of SEM image analysis. Future research should explore the integration of deep learning techniques with other techniques such as wavelet transform and denoising.

E. Real-time analysis

Real-time analysis of SEM images is essential for many applications. Future research should focus on developing deep learning models that can provide real-time analysis of SEM images.

F. Generalisation

Deep learning models are often trained on a specific dataset and may not generalize well to new datasets. Future research should focus on developing deep learning models that can generalize well to new datasets.

IX. Conclusion

In conclusion, deep learning techniques have shown significant potential in SEM image analysis, providing accurate and efficient results in various applications such as detection, classification, segmentation, and reconstruction. The use of deep learning methods, such as CNNs, GANs, autoencoders, transfer learning, and deep reinforcement learning, have demonstrated superior performance compared to traditional machine learning methods in handling complex SEM images.

However, several technical and practical constraints still exist, including the need for large and standardized datasets, explainable deep learning, integration with other techniques, real-time analysis, generalization, and validation and evaluation. Additionally, pre-processing techniques, such as filtering, thresholding, and morphological operations, as well as feature extraction techniques, have been used to enhance the quality of SEM images before applying deep learning algorithms.

References

[1] A. Yilmaz et al., ”Scanning SEM Restoration using Convolutional Neural Networks,” 2021.

[2] D. Jung et al., ”Image Enhancement and Segmentation in SEM by Deep Learning,” 2017.

[3] A. Pathak et al., ”Automated SEM Image Restoration using Deep Learning and Wavelet Transform,” 2019.

[4] N.H. Kim et al., ”Deep Learning Based Restoration and Enhancement of SEM Images,” 2020.

[5] Liangjiang Yu et al., ”SEM image quality enhancement: an unsupervised deep learning approach,” 2020.

[6] J. Park et al., ”A Novel Method for Scanning Electron Microscope Image Restoration using Deep Learning,” 2018.

[7] X. Liu et al., ”Automated defect detection and classification of SEM images using deep learning,” 2020.

[8] Joohyung Lee et al., ”Enhancing Low Quality SEM Images using Deep Learning,” 2019.

[9] Yilmaz et al., ”Precisely Reproduced SEM Noise Dataset and High-Performance Denoiser Based on Deep Learning,” 2021.

[10] Zhe Wang et al., ”Defect simulation in SEM images using generative adversarial networks,” 2019.