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A Hybrid model of ResNet50 integrated U-Net for image Denoising for Polymer and Composite Microstructure Analysis

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Abstract

In digital era a high-quality imaging plays a very important role in polymer and composite material characterization features such as fiber-matrix interfaces, voids, microcracks cause problems in mechanical and functional properties. Polymer imaging includes optical microscopy and scanning electron microscopy, due to sensor limitation, environmental conditions add noise to the image and reduce quality of image. The noise degrades image quality, and it leads to reduce reliability in material analysis. So, there is need to reduce noise while preserving image features are desperately needed. To solve this problem, a hybrid model is introducing that uses deep learning models for noise reduction. Proposed method improves feature extraction by using skip connections and an attention mechanism, which prioritizes important information that is important for noise reduction. The method utilizes a diverse multimodal data set to train a robust noise reduction model based on the refined U-Net architecture, making it suitable for noise-prone imaging scenarios encountered in polymer science and materials engineering. Performance further enhanced with transfer learning from ResNet50. This approach successfully reduces noise. The proposed method shows strong capabilities to handle multi noise type and data quality across diverse applications, including polymer microstructure analysis, defect detection, and material quality assessment.

Keywords: Image denoising, skip connections, U-Net, ResNet-50, polymer processing, microstructure inspection

INTRODUCTION

Polymer Science and composite engineering imaging techniques play an important role in understanding material microstructure quality. Optical Microstructure, scanning electron microscopy and other polymer imaging modules. examination of polymer phase and fiber orientation, void distribution and interfacial bonding in composite materials. But due to the presence of unwanted noise, captured due to transmission or sensor flaws, analysis of these polymer and composite images is a challenge. Noise can be caused due to fluctuation in pixel values, distorting features, or blurring edges. Generally, image noise can be categorized into salt and pepper noise, speckle noise, and gaussian noise. Figure 1 shows difference between original and noisy polymer and composite images. Therefore, a generalized denoising technique is required to restore polymer and composite images.

Image denoising is a widely studied core problem that is still open, in the sense that existing work has numerous limitations and flaws to be addressed.

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Figure 1. (a)–(c) Original polymer microstructure image (Leica Microsystems, cryo-BIB-SEM) and its Gaussian-noisy counterpart used for model evaluation. (a) Original polymer image; (b) Gaussian noise; (c) Salt and pepper noise.

Given that noise, texture, and edges are high-frequency elements, separating these elements from the vital characteristics or structures is a challenge for the existing techniques used to denoise polymer and composite images. Filtering of noise can be thought of as a process in which noisy pixels are changed into a new value relying on the surrounding pixels.

Deep learning technologies and systems involving neural networks and autoencoders, which can learn highly intricate structures and representations of data, are more efficient for such tasks. To investigate methods for noise removal in an image, based on an autoencoder using a multimodal dataset to train a robust noise reduction model leveraging on the refined U-Net architecture. To be more specific, we employ ResNet50 in U-Net architecture to eliminate gaussian, speckle and salt and pepper noise. As a result, deep neural network training can be used for turning polymer and composite images with noise into original clean polymer and composite images. By digging into autoencoder theory from both mathematical and engineering perspectives, the aim is to find out how successful deep learning is for removing polymer image noise and its peculiar necessities. Polymer image denoising is Important to enhance reliability of polymer and composite imaging.

- Our study focuses on employing an autoencoder with ResNet50 within a U-Net architecture for polymer image denoising.
- The model aims to eliminate Gaussian, speckle, and salt and pepper noise from polymer and composite images.
- Deep learning techniques are utilized to train the model on a multimodal dataset.
- The research investigates the efficacy of our model in removing noise and its specific requirements for polymer imaging denoising
- This research comprises five main sections: introduction, review of existing literature, description of the proposed methodology and network architecture, presentation and analysis of experimental results, and concluding with future scope.

LITERATURE SURVEY

Past few decades, significant progress has been made in the field of image denoising. So, several denoising techniques were developed during this period such as Gaussian method, median method, mean method, and non-local mean method. These methods are widely used due to their simplicity and effectiveness, but these methods lack in maintaining the structural integrity of the image and face difficulty in preserving important information of image in high noising scenarios. Due to this limitation, there is a need to develop new and more robust and advanced image denoising methods.

Recent research is more focused on implementing mathematical models and learning based methods to develop more effective denoising algorithms. Use of mathematical concepts gives a new direction to overcome these limitations, Cetinkaya et al [1] introduced a deep convolutional autoencoder featuring a component based on feature pyramid network. The introduction of GAN by Goodfellow et al [2] in 2016 sparked a significant surge in the related research endeavors. Cycle GAN introduced by Gonog and Zhou et al [3], addresses challenge of translating polymer and composite images between different styles. Orest Kupyn et al [4] presented Deblur GAN for blind motion deblurring tackling task of

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restoring blurred polymer and composite images caused by motion. Christian Ledig et al [5] propose a single polymer image super resolution by utilizing SRGAN. More advancements in polymer image denoising techniques by J. Zhu et al [6] they introduced a deep residual network using deep fusion and local linear regularization for guided depth enhancement. This method utilizes a deep feature space to extract correlations between depth maps and color polymer and composite polymer images. The efficacy and reliability of this approach were demonstrated across various applications, including depth denoising, super-resolution, and inpainting. P. Riot et al [7] tackled the challenge of denoising polymer and composite images corrupted by additive white Gaussian noise by proposing a novel variational approach. This approach defines generic fidelity terms to locally regulate residual distribution using statistical moments and patch correlations. R. Li et al [8] presented a feature extraction technique based on the PCA denoising concept, which extracts principal components from original noise residuals. Y. Gan et al [9] introduced a brush let-based block matching 3D (BM3D) method for collaborative denoising of ultrasound polymer and composite images. L. Scholefield et al [10]A reported using a support vector machine (SVM) to select from multiple high performing denoising algorithms for each pixel in a noisy polymer image [11]. Table 1 summarizes the more research work we referred to while working on our own model.

METHODOLOGY

This section explores the use of transfer learning approach to perform polymer image denoising more precisely by repurposing a pre-trained deep learning model, like U-Net, ResNet50 & fine-tuning their features. Fine-tuning adapts the model to specific noise patterns, while feature extraction uses the pre-trained model as a feature extractor for subsequent denoising models. This method boosts denoising accuracy, particularly beneficial when limited clean data or complex noise types are present, enhancing overall polymer image quality.

Transfer Learning

Using the machine learning technique of transfer learning, one problem's solution is applied to another that is similar yet distinct. This involves executing pre-trained models on huge datasets and tuning them into tasks or domains in deep learning. For handling new dataset, the approach focusses on fine tuning on some new layers of network, learning useful features at early stages and managing the model weights accordingly. For the U-Net and ResNet50 are combined and used for polymer image denoising task as they both are suitable for learning local and high-level polymer image features.

Proposed Workflow

This section is divided into 3 parts: Dataset Preparation, Model Fine Tuning & Model Evaluation and each part explains the important phases of model development.

Data Preparation

In the data preparation phase, dataset is carefully selected as that data is used only for polymer image denoising applications. In training samples to improve diversity, data augmentation techniques are apply in this stage, like flipping scaling rotation, cropping, adding noise and color jittering. To reduce overfitting, a different type of noise is added to different intensity levels and ratios. Gaussian noise is included in this study with noise values of 0.1, 0.2, and 0.3. In the context of polymer image denoising, it is important to take additive and multiplicative properties of different noising types. Understanding the additive and multiplicative characteristics of different types of noise is essential for choosing the best denoising methods and to know how well denoising algorithms work on polymer image denoising. For algorithms to preserve polymer image details and decrease noise caused by additive and multiplicative noise sources, they must be able to discriminate between signal and noise components. Below explain the details of different type of noise.

Table 1. Detailed literature review.

S.N.	Methodology used	Tech Gap	Data set	Result
[12]	A generalized CNN model was proposed to help classify the noisy polymer and composite images using-ADAM optimizer & SGD optimizer.	Focus on improving learning rate and reducing the losses of the CNN model along with different types of noises	MNIST handwritten dataset (70k polymer and composite images)	SGD optimizer gave better accuracy score by a small margin for different noise types.
[13]	Deployment of an automated detection model, CADTra, designed to effectively diagnose diseases related to pneumonia	Using GAN's to improve the classification ability	Covid Dataset	FCNN model achieved accuracy on X-ray image is 98.42% and CT Image is 98.34%
[14]	Employing autoencoder networks that rely on the ORL face database to bolster face recognition systems.	this image denoising methods for autoencoder cannot be used in outdoor recognition systems in real time.	ORL face dataset (400 polymer and composite images)	This model eliminates the noise from facial polymer and composite images in face recognition systems effectively.
[15]	Addressing the impact of Gaussian noise in polymer and composite images, a common challenge in image processing and computer vision applications.	lack of comprehensive evaluation across various noise levels or types.	MNIST, Cifar-dataset, mini MIAS	For auto encoders, the accuracy in classification is higher with denoised image for MNIST, MiniMias, Cifar-10 which only increase by increasing noise factor
[16]	Explains how they can remove different types of noise from the polymer and composite images using filters	Non-linear filtering approaches such as median and weiner filter can be used to perform denoising on polymer and composite images subjected to different types of noise.	BSD68(68 polymer and composite images)	For Gaussian Noise Median Filter performed the best with a PSNR value of 26.4
[17]	A review of traditional machine learning techniques and deep learning technologies used for picture denoising.	Can also work on finding other types of noise like salt-and-pepper noise, speckle noise, or poisson noise on CNN models.	BSD68(68 polymer and composite images)	DnCNN method achieves the highest PSNR (29.23) among other popular denoising methods used the same dataset "BSD68".
[18]	The method uses Python language and machine learning techniques for image denoising.	This method cannot work with nonlinear filtering methods. Such as median filtering and Wavelet transform.	OpenCV samples	Python Libraries such as NumPy, OpenCV, TensorFlow, and PyTorch offer essential functionalities for data manipulation, image processing, model training,and evaluation.
[19]	To finish the image denoising task, a deep residual network based on generative adversarial (GAN) network was suggested.	Can work on developing design models that require fewer labeled polymers and composite images for training.	ImageNet dataset (3k polymer and composite images)	PSNR (30.58), SSIM (0.9207).
[20]	Uses the auto-encoder based neural network structure for feature extraction in restoration process.	There is always room for exploring alternative architectures tailored to specific restoration tasks or types of image degradation.	Berkeley segmentation dataset	Stacked non-local auto-encoders' architecture is used and along with ADAGRAD to optimize the whole neural network.
[21]	An LSTM model was proposed for image denoising task which generates future frames by giving a sequence of input frames.	For dealing with blurriness in the predicted frames an LSTM model can be combined with Denoising Autoencoders. The loss function can be improved by increasing the number of epochs.	MNIST dataset	The Denoising Autoencoder has an accuracy of 50% for the given dataset.

Gaussian Noise

The characteristic that differentiates Gaussian noise is that a random value is added to each pixel of polymer image, which is taken from a Gaussian distribution. The mean (μ) and standard deviation (σ) of this noise are commonly used to find it. Gaussian noise frequently appears in pictures denoising jobs as a soft, continuous distortion that degrades the polymer image's overall smoothness and clarity. Mathematical equations used to find additive noise by Gaussian probability density function which is shown in equation 1.

$$f(x) = \frac{1}{\sqrt{2\pi\sigma^2}} exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \tag{1}$$

Salt-and-Pepper Noise (S&P)

Salt and pepper noise, include both additive and multiplicative. It introduces random presence of bright (salt) or dark (pepper) pixels within the polymer image. S&P noise reduces feature activation and adds irregularity to the polymer image, simulating impulsive noise found in real-world imaging systems.

Poisson Noise (PN)

PN is a multiplicative noise source and is commonly found in low-light imaging sources, such as medical imaging or astronomical observations. PN is due to random nature of photon arrivals during the polymer image acquisition process. Poisson noise can result in both over- and under-exposed regions the polymer image, leading to loss of detail and contrast. Poisson probability mass function is explained in equation 2.

$$P\ (X = x) = \frac{\lambda^x e^{-\lambda}}{x!} \tag{2}$$

Where $x\ = 1,2,3,4 \ldots\ , \lambda = mean\ rate, e = Euler's\ constant$

Model Architecture

Proposed method includes a baseline denoising autoencoder architecture and explains how it enhances the model performance.

Denoising Autoencoder Architecture

The architecture combines the encoder and decoder, where the encoder compresses the input polymer image into a latent representation, and the decoder reconstructs the denoised polymer image from this representation. To achieve optimal denoising performance, first incorporate skip connections within the autoencoder make it better gradient flow and feature preservation to capture both high-level and low-level polymer image details [22]. Further attention mechanisms are incorporated, that can concentrate on visually important areas of the polymer image while denoising, which improves its capacity to distinguish between signal and noise components. Using extended encoder-decoder for multi-scale feature extraction, and this makes the model capture fine details for spatial scales, which is important for reconstructing the denoised polymer image. Combining these architectural elements the autoencoder provides denoising different kinds of noise while maintaining polymer image structure.

Enhancing the Model Performance

To improve the model's denoising process an advanced architectural such as skip connections and attention mechanisms are used. The autoencoder design as skip connections—also known as residual connection and act as direct connections between layers. The gradient flow is used while training, it helps mitigate the issue of disappearing gradients and promote efficient information transfer between layers. Skip connections allow the autoencoder to have important polymer image details and features during the denoising process, which improves the quality of the reconstruction.

Attention methods are very important for improving the denoising process for the autoencoder. The model can reduce noisy components and concentrate on informative polymer image part. Attention methods help the autoencoder to make effective resource allocation, it gives priority to the reconstruction of important features, also dynamically modifying the different polymer image regions during the denoising process. The autoencoder can efficiently remove noise and maintain integrity of the polymer image.

Including skip connections and attention mechanisms for denoising polymer image autoencoder architecture, makes it difficult for polymer image denoising and effectively addressed in a synergistic manner. These improvements in architecture allow the autoencoder to take advantage of the information in the polymer image, make the denoised output noise free and closely match the original polymer and composite polymer images. Skip connections and attention mechanisms use denoising autoencoder architectures to get good results in different real-world denoising applications, which makes them indispensable instruments in the fields like medical imaging, surveillance, and photography.

Designing a U-Net model that includes multi scale feature extraction through encoder-decoder and skip connections. The improved architecture makes the model to catch important information in noisy polymer and composite images of different size and this model outperforms standard methods.

Model Training

The proposed method adopts a transfer learning–based supervised training approach. Pre-trained convolutional neural networks, including ResNet18, ResNet34 and ResNet50, are utilized to initialize the encoder weights for improved feature extraction. The autoencoder is trained using paired noisy and clean polymer and composite microstructure images under a supervised learning framework to enhance denoising performance.

ResNet Architecture in Polymer Image Denoising

The combination of ResNet18 and ResNet34 is designed for denoising auto-encoder architecture. It is used of deep convolutional neural networks (CNNs) for denoising applications. ResNet18 and ResNet34 are Residual Network (ResNet) architectural designs that are known for their deep and effective design, which makes it possible to extract features and learn representations. This model also works as intermediate for evaluating deeper residual models such as ResNet50 used in this proposed system [23].

Convolutional layers, batch normalization ReLU activation functions, and residual blocks represent 18 layers that make ResNet18. Having skip connections in these blocks, the network can work on some layers and lessen the effects of the vanishing gradient issue. Skip connections which allow information to move directly between layers, ResNet18 can find and maintain polymer image features while denoising. This capability stable features learning and serves as a lightweight baseline for denoising performance comparison.

Similarly, ResNet34 uses 34 layers to the ResNet model, creating a network that can extract complex polymer image information due to of its greater depth, ResNet34 can learn more important representations of polymer image characteristics, which makes it an excellent choice for difficult denoising tasks where minute details must be maintained. ResNet34's skip connections allow gradients to propagate during training, which helps the network denoise polymer and composite images maintaining textures and structures. Increasing depth beyond a certain level motivates the use of more advanced architectures such as ResNet50 for enhanced multi-scale feature extraction. Figure 2 shows the architecture difference of ResNet34 and ResNet50.

ResNet18 and ResNet34 function as impotent feature extractors when sends into denoising autoencoder architectures, allowing the autoencoder to learn detailed representations of noisy polymer image. The denoising autoencoder can efficiently separate noise from signal by utilizing the hierarchical features that ResNet18 and ResNet34 have learned.

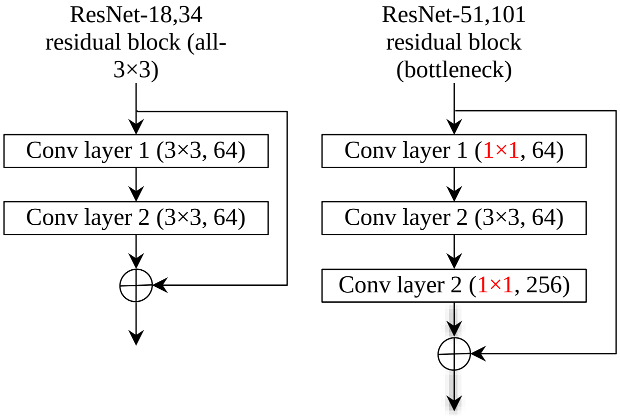

Figure 2. Architecture variations of ResNet34 ResNet50.

This leads to denoised polymer and composite images that have improved perceptual quality. These observations justify the transition toward ResNet50, which offers superior representational capacity while retaining the benefits of residual learning. Combining ResNet18 and ResNet34 architectures into denoising autoencoder frameworks seems like a good way to push the boundaries of polymer image denoising technology [24]. This optimization reduces problems such as vanishing gradient problem and improves model efficiency and forms the basis for adopting deeper residual backbones in application domains such as polymer imaging smart grid surveillance and industrial inspection.

Model Evaluation

Models are trained in a range of noise levels, and performance is assessed using industry-standard metrics like the Structural Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR) as shown in equation (3 and 4).

$$PSNR = 10\log_{10}\left(\frac{(Maximum)^2}{MSE}\right) \tag{3}$$

Where, Maximum is the largest probabilistic value of polymer image.

$$MSE = \frac{1}{mn}\sum_{p=0}^{m-1}\sum_{q=0}^{n-1}[I(p,q) - R(p,q)]^2 \tag{4}$$

Where $I(p,q)$ *is original image* and $R(p,q)$ is restored (denoised) polymer image of dimension $m\ x\ n$.

While SSIM evaluates structural similarity and offers information about the denoised polymer image's perceptual quality, PSNR gauges the denoised polymer image's quality in relation to the original. Mathematical equations for SSIM are shown in equation 5.

$$SSIM(p,q) = \frac{(2\mu_p\mu_q + c_1)(2\sigma_{pq} + c_2)}{(\mu_p^2 + \mu_q^2 + c_1)(\sigma_p^2 + \sigma_q^2 + c_2)} \tag{5}$$

This thorough assessment makes it possible to compare and analyze different architectures, such as the standard autoencoder, U-Net with enhanced features, and models that make use of transfer learning. The workflow is summarized in Figure 3.

PROPOSED METHOD APPLICATIONS IN POLYMER AND COMPOSITE IMAGING

The proposed model frameworks are well suited for polymer and composite material image. Microstructure features are important for material evaluations. In polymer microstructure analysis imaging noise masks fine boundaries and morphological variations that are very important for crystalline. The proposed model reduces the noise and prevents structural integrity and efficient identification of features.

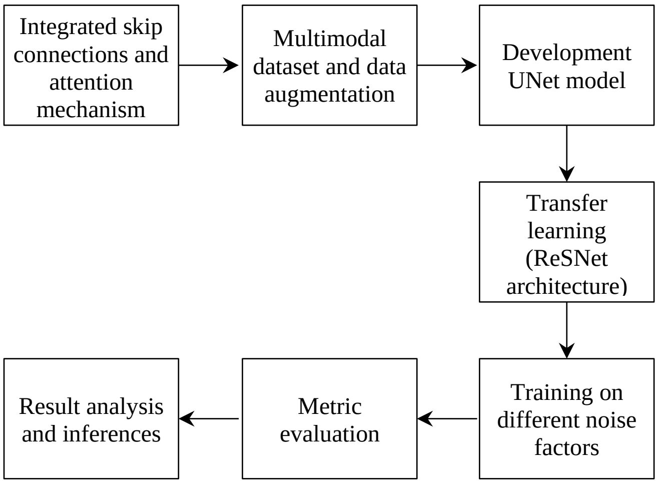

Figure 3. Methodology workflow.

The fiber-reinforced polymer composites defects such as voids, delamination, matrix cracks, and weak fibers matrix have a strong impact on mechanical strength and durability. So noisy image leads to the misdetection of the material structure. Proposed methods maintaining image edge continuity and spatial coherence enhance defect visibility and supports robust composite quality. This method gives nondestructive evaluation in polymer manufacturing by improving automated inspections and machine vision-based analysis. It makes it suitable for industry polymer processing and materials research applications.

EXPERIMENTAL RESULTS AND ANALYSIS

The evaluation metrics used include Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), and Mean Squared Error (MSE), which are standard quantitative measures for image denoising performance assessment.

The proposed model was implemented using Python and the PyTorch deep learning framework. Training was conducted on Google Colab utilizing an NVIDIA Tesla T4 GPU with 16 GB VRAM. The system environment included 12 GB RAM and an Intel Xeon CPU.

The training hyperparameters used for model optimization are presented in Table 2 to ensure reproducibility of the experimental setup.

We assessed polymer image denoising models like Autoencoder, U-Net, and U-Net implemented using ResNet50 across different noise levels, using PSNR and SSIM as evaluation metrics. PSNR denotes Peak Signal-to-Noise Ratio (in dB), and SSIM represents Structural Similarity Index Measure. Gaussian noise with standard deviations (σ) of 0.1, 0.2, and 0.3 was added to evaluate denoising robustness. The comparison of PSNR and SSIM values obtained for different models at varying noise levels is summarized in Table 3. To further analyze the stability of the proposed model a robustness evaluation was conducted on 310 test polymer and composite polymer images under varying noise intensities the average PSNR and SSIM values were computed to assess performance consistency.

Table 2. Training hyperparameters.

Parameter	**Value**
Epochs	100
Batch Size	16
Optimizer	Adam
Learning rate	1×10^{-4}
Pretraining	ImageNet

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Table 3. Comparative analysis of noise factors with other existing models.

Noise factor	**σ =0.1**		**σ =0.2**		**σ =0.3**	
Models	***PSNR (db)***	***SSIM***	***PSNR (db)***	***SSIM***	***PSNR (db)***	***SSIM***
Autoencoder	26.36	0.91	26.04	0.90	25.47	0.90
ResNet18	27.42	0.90	26.12	0.89	25.32	0.88
ResNet32	28.73	0.91	27.02	0.90	25.78	0.89
U-Net	29.05	0.9187	27.32	0.8935	26.02	0.8736
U-Net using ResNet50	29.89	0.9188	28.91	0.963	28.54	0.93

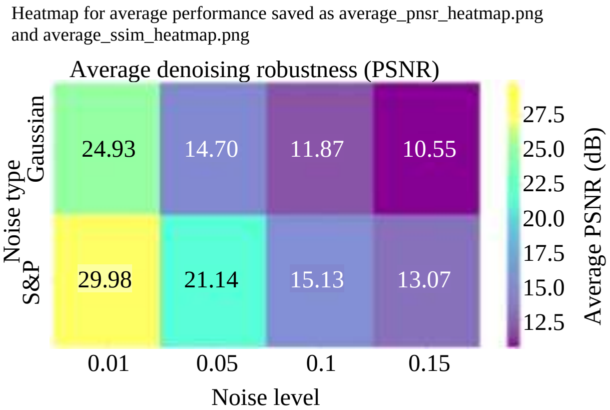

Figure 4. Average PSNR-based robustness analysis of the proposed U-Net–ResNet50 model under Gaussian and Salt-and-Pepper noise at different noise levels.

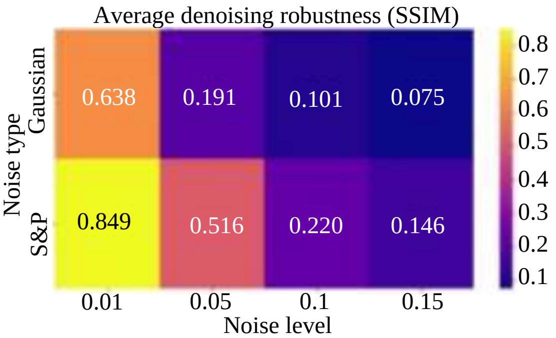

Figure 5. Average SSIM-based robustness analysis of the proposed U-Net–ResNet50 model under Gaussian and Salt-and-Pepper noise at different noise levels.

At 0.1 noise level, the U-Net model using ResNet50 gave superior performance, achieving 29.89 PSNR and 0.9188 SSIM as shown in Table 3. These results exceeded those of the standard U-Net, which recorded 29.05 PSNR and 0.9187 SSIM, and were significantly higher showed a PSNR of 26.36 and an SSIM of 0.91.

As the noise level increased from 0.2 and 0.3, the trend persisted, with the U-Net model and ResNet50 maintaining the highest scores in both metrics. Specifically, at a noise level of 0.3, this model reported a PSNR of 27.91 and an SSIM of 0.93, indicating its robust performance even under higher noise conditions. To visually summarize this behavior, heatmap representation of average PSNR and SSIM values across noise types and levels are presented in Figure 4 and 5. These heatmaps clearly illustrate the gradual performance degradation with increasing noise while highlighting the superior robustness of the U-Net-ResNet50 model.

Primitive versions of standalone ResNet50 model like ResNet18 and 32 as well as U-Net model cannot preserve its effectiveness when intensity of noise is increased (0.3). Our findings reveal that integrating ResNet50 into the U-Net architecture markedly improves noise reduction effectiveness and polymer image detail preservation compared to standard U-Net and Autoencoder models. This enhancement suggests that the application of advanced backbone architectures in U-Net frameworks could be a promising avenue for further improving polymer image denoising techniques.

CONCLUSION

This paper presents a new method for training deep learning models to reduce noise in polymer image. In this model skip connections and an attention mechanism are combined, to improve feature extraction and focus on important information. A multimodal dataset with various noise factors is used. U-Net-based model with ResNet50 transfer learning gives good performance compared to traditional methods like Autoencoder. Propose method achieves higher PSNR (29.89 vs. 26.36) and SSIM (0.988 vs. 0.91), that indicate better noise reduction and preservation of polymer image details. The model also shows stable performance for more noisy level, it concludes with strong robustness across different noise conditions. Overall, proposed methods highlight the potential for real life polymer image denoising applications, particularly in noise prone polymer imaging techniques—including optical microscopy and scanning electron microscopy.

Declaration of Interest

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

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AI Usage Disclosure

The authors used AI-assisted language tools (e.g., ChatGPT) solely for grammar refinement and language improvement. All experimental design, implementation, analysis, and scientific conclusions were independently developed and verified by the authors.

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