A novel surface denoising approach based on deep learning for freeform structured surface in metrology

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Abstract

Noise produced in manufacturing and measuring process are often high-frequency components and outliers, these will cause the inaccuracy of feature determination. Surface denoising is a crucial metrological operation in surface characterisation to suppress noise from areal surface. It usually called filtration for processing profile data. ISO standards filters such as Gaussian filters and wavelets filters have been proved successful on stochastic surfaces. PDE diffusion filter has been subsequently raised to address edge distortion in structured surface denoising. The main issue is that they all require manual parameter tuning for individual surface. This process costs time and relies on expert-knowledge of users. To date, the deep learning techniques are becoming dominated in image processing tasks including denoising, object detection and classification, which would also have great potential to benefit surface metrology. This paper proposed a deep learning-based method applying a classic deep Convolutional Neural Network to perform surface denoising task. The model is trained on a small training dataset of freeform structured surface measurements. The experimental results show that retrained neural network can automatically suppress unknown noises and outliers of the surfaces, meanwhile well retain the geometry of structures on the surface. The major contribution is that we newly apply a deep convolutional neural network to replace traditional filters and achieve automatic surface denoising. It can output denoising results within average one second, which shows a high application value for constructing future smart metrology system. The training process can be efficiently implemented on GPU at a low cost.

1 Introduction

Metrology is the science of measurement aims to increase measurement speed, accuracy and cost-effectiveness in order to improve production efficiency and control many operations on engineering components. Surface characterisation as a crucial metrological operation is defined to quantify the surface topography and texture with feature extraction and pattern analysis using a set of parameters that indicate the quality of the surface and interpret functional properties such as optical quality, service life, and reliability of the surface [1]. Engineered surfaces can be divided into two categories: structured surfaces and stochastic surfaces [2]. Surfaces with a dominant stochastic feature pattern are termed 'stochastic surfaces', and well-established characterisation techniques, such as filtration and spectral analysis, are available for this type of surface [3]. Structured surfaces are surfaces with a deterministic pattern that usually have a high aspect ratio to achieve a specific function [4]. A general surface characterisation scheme for the complex freeform structured surface is shown in fig. 1. Three steps are usually conducted prior to feature characterisation: form removal, denoising and segmentation. F-operator is the initial procedure that separates reference form from surface topography data to diminish the effects of nominal geometry on denoising. Denoising is the next step, aiming to reduce the impact of measurement noise and help identifying the features from surface texture.

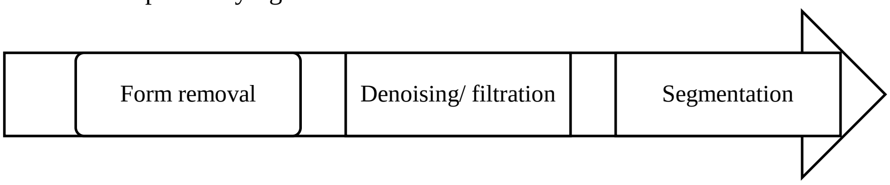

Figure 1: A general surface characterisation scheme for freeform structured surface

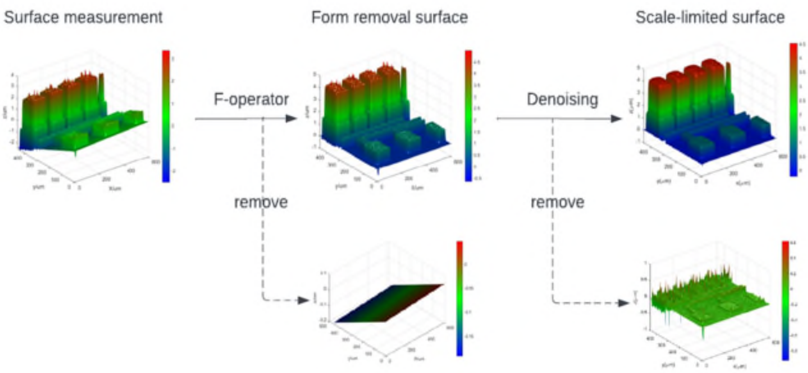

Figure 2: Areal surface decomposition process for characterisation

In the measurement of many real engineering surfaces, noise distribution is more diverse and hybrid. The most widely used filters include Gaussian/spline filters, wavelets and morphological filter, all performing well on stochastic surfaces with appropriately chosen parameters [5]. However, for engineering surfaces with structured features such as steps and grooves, as the high-frequency noise and outliers still exist, it is difficult for these traditional filters to accurately decompose structure from noise and outliers without any edge distortion [2]. PDE-based diffusion has been proved to have good structured-preservation property on step features [1]. The major drawback is that we need to choose appropriate filter for each input surface according to the type and feature based on expert-experience, then tuning parameters through trials. Furthermore, it’s hard to filter different-level noise using one identical value of parameter, which means filters cannot achieve automatic denoising for multiple surfaces. To address these challenges, we apply deep learning techniques to construct a smart denoising framework due to its unique characteristics. Firstly, the Convolutional Neural Networks (CNNs) are usually designed to process image or volumetric data, which are also the typical data representations of the freeform structured surface [1]. In addition, CNN's deep design boosts its flexibility and capability for exploiting surface features [6].

This paper proposes a novel surface denoising approach based on the Denoising Convolutional Neural Network (DnCNN) [7] to remove unknown mixed noise from the freeform structured surfaces without the requirement of manually filter selection and parameter tuning. Once the network has been trained, it can denoise an arbitrary input surface within the average time of 1s automatically. Due to the limited number of engineering surface samples, data augmentation techniques are integrated in network to enlarge the training data to improve performance and uniform data size. The results show that our neural network has remarkable denoising effects on various types of freeform structured surfaces with good structure-preservation property. Image quality full reference metrics (PSNR and SSIM) are here used to evaluate the denoising performance for model optimisation.

2 Brief literature review of CNN denoising

Deep learning-based approaches feature the characteristics of generalisation and robustness, which implies they can be employed for different data types and applications. During past years, DL applied for image denoising has received more attention due to its effectiveness in removing diverse types of noise from images, including real noise, blind noise, additive white Gaussian noise and hybrid noise [8]. One of the traditional neural networks structures is the multilayer perceptron (MLP) [9] consisting of hidden layers and nonlinear activation functions which use the backpropagation algorithm [10] and the loss function to train the model. The main disadvantages are disregarding of spatial information and inefficiency due to redundancy in high dimensions. Compared with MLP, convolutional neural network (CNN) is one of the most powerful models for performing various image processing tasks due to its end-to-end and local connectivity properties [11]. CNN-based methods are not only able to preserve spatial information but also offer a more effective and efficient way to match complicated patterns for matrix data. Chiang and Sullivan [12] were the first to utilise DL techniques for image denoising tasks, with the known shift-invariant blur function and additive noise to reconstruct the latent clean image, then using weighting factors to remove complex noise. The denoising CNN (DnCNN) proposed by Zhang et al. [7] has been verified as an efficient model, which can handle unknown mix-level noise based on residual learning strategy and batch normalization (BN) [13]. In terms of blinding denoising, a fast and flexible denoising CNN (FFDNet) can be presented with noisy image patches and different noise level masks as the input of the network to improve denoising speed and process blind denoising [14]. A convolutional blind denoising network (CBDNet) is proposed to remove noise from the given real noisy image by two sub-networks, one responsible for estimating the noise and the other estimating the latent clean image [15]. Due to most surface noises are folloing Gaussian distribution in mixed-level, DnCNN is adopted to denoise surface as an efficient and simple model to handle different levels of Gaussian noise, and it is also friendly to the small training dataset because its architecture design has higher flexibility and capability for exploiting surface features [16]. Therefore, it is employed here as the fundamental neural network to perform the surface denoising task.

3 Framework of deep learning denoising method

3.1 Architecture of DnCNN

DnCNN is proposed to process different levels of unknown noise, hence which is selected to employ into performing the denoising task for freeform structured surface. The denoising objective can be written as $y = x + n$, where y denotes noisy image; x denotes the clean image; and n means noise map. It is constructed based on two techniques to get better performance, that are residual learning [16] and batch normalization [17]. The integration of these two strategies can result in better denoising performance. The pre-defined DnCNN is a supervised learning with a total of 59 layers, including one input layer and one regression output layer, 20 convolutional layers for feature mapping, 18 batch normalization layers for mini-batch training and 19 rectified linear units (ReLU) layers [18] for limiting exponential growth of computational cost. Fig.3 depicts the basic architecture of DnCNN. The output of network is to estimate the noise distribution from training data. To meet the metrological requirements for surface denoising, we need to retrain the network using our surface data and optimise model to achieve the denoising accuracy with conserving structures.

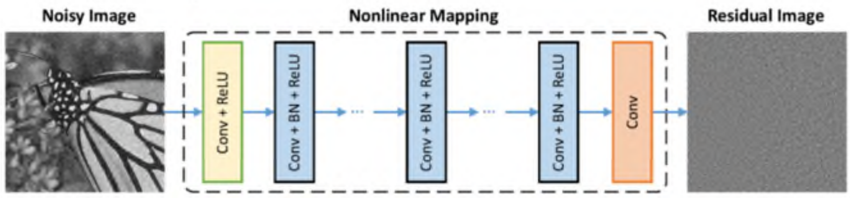

Figure 3: Basic architecture of pre-defined DnCNN [7]

3.2 Framework of surface denoising

The quickest and most straightforward method for noise removal application on surfaces is using the pre-trained DnCNN model. However, it is not trained based on freeform structured surface data samples, and the noise level and distribution are not the same as the general images, so the performance is not acceptable for metrological requirements. In terms of the kinds and intensities of noise it can identify, the pre-trained network also does not offer a lot of flexibility. To train a denoising DnCNN that can handle unknown hybrid noise of engineering surfaces based on pre-defined layers, the model is constructed in three parts: data pre-processing, model training workflow and denoising workflow. Starting from data pre-processing, the raw dataset will be first processed by filters to get noisy-clean pairs, and then divided into training, validation and test dataset. Training and validation datasets are enlarged using data augmentation technique which randomly crops raw images into patches with rotations, each image with a square patch size 50×50. Then adding different-level Gaussian noise into each patch and forming to mini-batch for training in each epoch. To improve performance, we define some training options to customise the denoising neural network for satisfying metrological requirements. The specific optimisable parameters are listed in Table 1 with definitions and default values (range). The 'GaussainNoiseLevel' is used to specify the noise deviation scope and distinct values are chosen within it for every patch. 'MiniBatchSize' decides the training dataset size per iteration and 'N_layers' constructs the network depth that denotes the number of Conv layers. 'MaxEpoch' and 'training method' impact the model accuracy and convergence. Training optimiser can be chosen from stochastic gradient descent with momentum (SGDM), root mean square propagation (RMSProp) [19] and adaptive moment estimation (ADAM) [20]. The trained DnCNN network is evaluated by test dataset including different types of freeform structured surfaces with features, using image quality metrics intuitively.

Table 1. Parameters options for DnCNN training

Training parameters	**Definition**	**Default**
'PatchesPerImage'	Number of random patches per image	512
'GaussianNoiseLevel'	Range of standard deviation of Gaussian noise	[0, 1]
'MiniBatchSize'	Size of mini batch to use for each iteration	128
'N_layers'	Number of 'conv' layers	20
'MaxEpochs'	Maximum number of epochs	30
'Training methods'	'adam'(selected), 'sgdm', 'rmsprop'	'adam'

Based on above, the framework of our DnCNN-based surface denoising model is designed based on the above model architecture, as shown in fig. 4. Steps of our implementation are following:

i. Collect raw surface measurements and obtain noisy-clean surface pairs.
ii. Establish 'Image Datastore' to store greyscale images converted from surface data and divided into the training dataset and the validation dataset.

iii. Create 'Denoising Image Datastore' to store generated training patches from the raw dataset using data augmentation techniques.
iv. Load predefined DnCNN layers as the fundamental network.
v. Retrain and optimise the surface denoising network by defining training options.

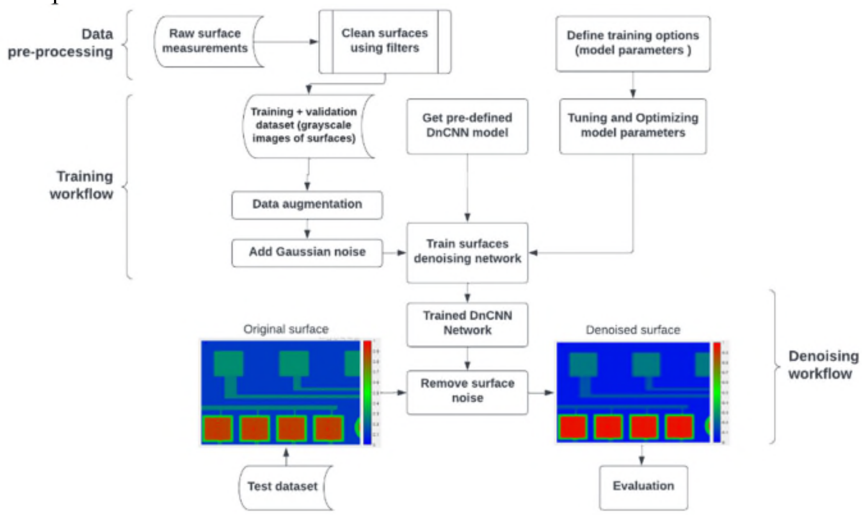

Figure 4: Framework of DnCNN-based surface denoising approach

4 Experiments

4.1 Training with parametric analysis

The raw dataset contains a small amount of grayscale images (30 samples) which are converted from various measured freeform structured surfaces in latticed-grid data representation. The neural network is trained in MATLAB platform (2022a) on GPU. The average training time is 95.26 mins. The metrics used for evaluation are PSNR and SSIM. Peak Signal to Noise Ratio (PSNR) is to calculate the ratio between the maximum possible power and corrupting noise [21]. The larger PSNR value, the better reconstruction. Structured Similarity Indexing Method (SSIM) [21] is an assessment index which converges to 1 indicating higher similarity with ideal clean surface and better structure-preservation.

To optimise model with parametric analysis, a typical MEMS surface from validation dataset is selected to show results for different parameters settings. We choose nine groups of settings for comparison and analysis as shown in fig.5. The sectioned profiles show the results more institutively with edge conditions and structure smoothing. From the profile analysis it shows the denoising accuracy is acceptable that only removing non-relative and high-frequency noise but conserving feature patterns for surface parameterisation. The red stars in metrics shown in fig.6 indicate the fourth group of parameters have highest scores. Hence, the optimal settings are 'PatchesPerImage' = 512, 'GaussianNoiseLevel' = [0.001, 0.999], ‘MiniBatchSize’ = 16, ‘N_layers’ = 10, ‘MaxEpochs’ = 10. To deeply obtain the optimum option, it needs model selection process to choose from hundreds of parameter combinations.

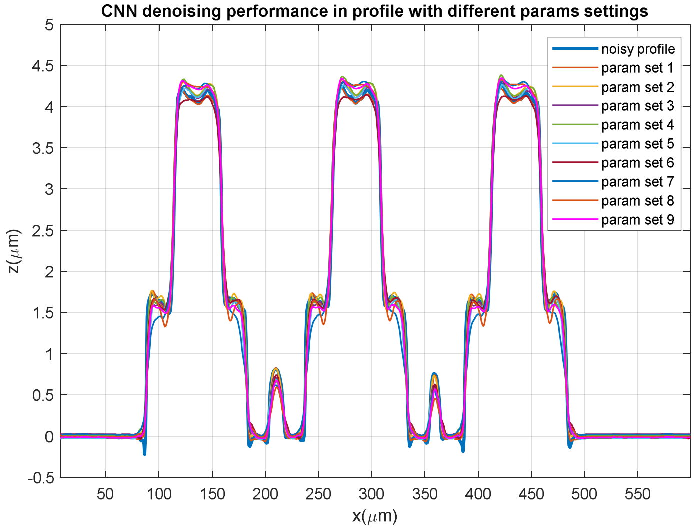

Figure 5. Section profiles of denoised surfaces for different parameters settings

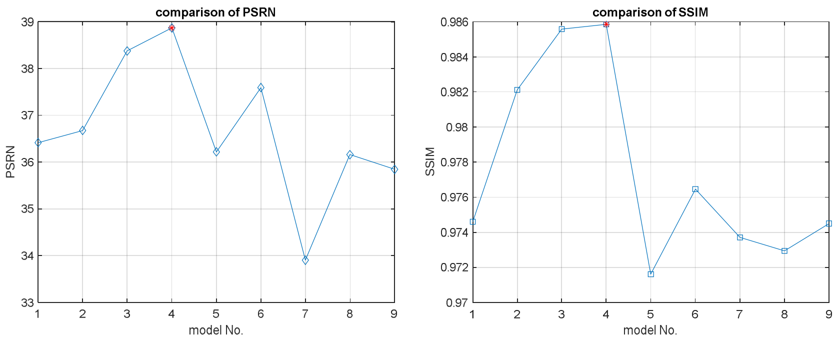

Figure 6. Metrics comparison of models

Fig.7 shows the 2.5D areal surface denoising performance verified with optimal model. Both high-frequency noise and significant outliers in structures and reference form are reduced remarkably.

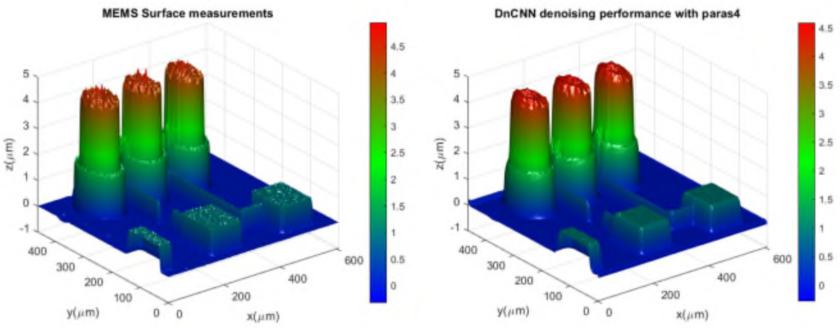

Figure 7. Test performance on areal surface

Increasing the "GaussianNoiseLevel" will typically result in more diverse training patches and improved accuracy. The higher "MiniBatchSize" is more able to cause local minima convergence, then some inconsequential noise cannot be recognised and filtered, while the smaller "MiniBatchSize" value delivers the better denoising effect due to more gradient updates. Deeper "N layers" will achieve more precise fitting with a lower RSME value, while still preserving some small-scale noise in structures. A proper trade-off between "MiniBatchSize" and "N layers," where the smaller "MiniBatchSize" should balance out the higher value of "N layers," is crucial. In order to improve training accuracy and effectiveness, it is preferable to shorten the "MaxEpochs" time.

4.2 Test model

Figure 8 shows results of applying optimised model on some other freeform structured surfaces. Seen from figure 8 that the deep learning model works well on more complex freeform structured surfaces. The profile section clearly verifies the denoising performance with property of pattern-conservation, which guarantees the accuracy for further parameterisation operation to assess the attributes of features. For those it is not easy to select appropriate filters and parameters values to meet requirements. Therefore, our deep learning-based surface denoising approach has a certain degree of universality for various freeform structured surfaces with only a small number of samples for training, which means it has high generality and applicability to potential practical applications.

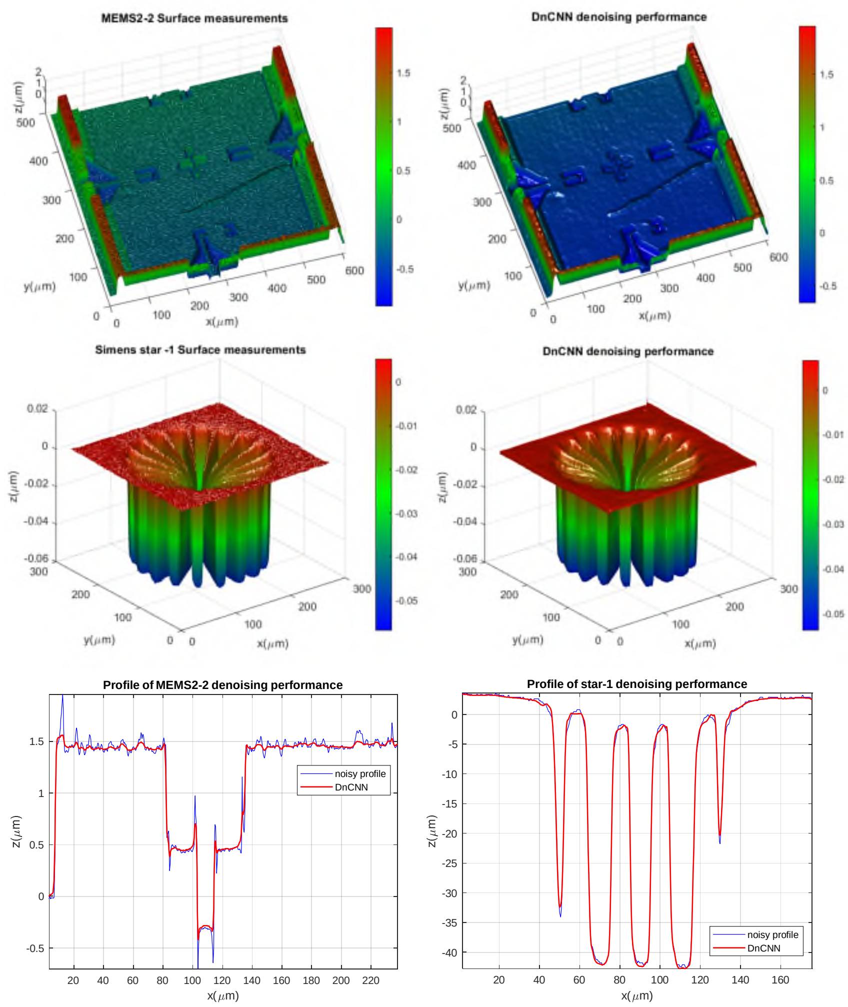

Figure 8. Test performance on areal surface

5 Conclusion

Overall, surface denoising task is firstly accomplished using a deep convolutional neural network-based method that includes data augmentation, residual learning, batch normalisation, and parameter optimization. In order to achieve noise estimation with better denoising performance and training efficiency, residual learning integrating batch normalisation is used; data augmentation is used to increase training accuracy; parameter optimization serves as a guide for training customised models based on various datasets. According to the experiments, our approach successfully denoises various types of freeform structured surfaces while maintaining their structural integrity. Additionally, once the model has been trained, neural networks can automatically handle the unknown hybrid noise at diverse levels under one second on average, and they exhibit remarkable noise reduction effects by separating mix-level noise with structures. This is in contrast to classic filters, which require parameter tuning for each unique input. The outcomes demonstrate the capability and usefulness of the suggested neural network for surface metrology. The training process' optimization, which is based on parametric analysis, provides users with application assistance. The ability to achieve intelligent denoising without the need to choose appropriate filters based on the different input surfaces and get ideal parameters through the test phase is a key benefit that is user-friendly for non-expert users.

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References

[1] Jiang, J., & Scott, P. (2020). Advanced Metrology: Freeform Surfaces. (1st ed.) Academic Press Inc. https://doi.org/10.1016/C2019-0-04832-7.

[2] Jiang, X. J., & Whitehouse, D. J. (2012). Technological shifts in surface metrology. CIRP Annals - Manufacturing Technology, 61(2), 815–836.

[3] Jiang, X., Scott, P. J., Whitehouse, D. J., & Blunt, L. (2007). Paradigm shifts in surface metrology. Part II. The current shift. Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences, 463(2085), 2071–2099.

[4] Evans, C. J., & Bryan, J. B. (1999). `Structured', `textured' or `engineered' surfaces. CIRP Annals - Manufacturing Technology, 48(2), 541–556.

[5] Lou, S., Zeng, W. H., Jiang, X. Q., & Scott, P. J. (2013). Robust filtration techniques in geometrical metrology and their comparison. *International Journal of Automation and Computing*, *10*(1), 1–8. https://doi.org/10.1007/s11633-013-0690-4

[6] Srinivas, B., & Rao, G. S. (2020). A Speckle Denoiser: Deep Convolutional Neural Network for MR Image Denoising. SSRN Electronic Journal, January. https://doi.org/10.2139/ssrn.3561333

[7] Zhang, K., Zuo, W., Chen, Y., Meng, D., & Zhang, L. (2017). Beyond a Gaussian denoiser: Residual learning of deep CNN for image denoising. IEEE Transactions on Image Processing, 26(7), 3142–3155. https://doi.org/10.1109/TIP.2017.2662206

[8] Tian, C., Fei, L., Zheng, W., Xu, Y., Zuo, W., & Lin, C. (2020). Deep learning on image denoising: An overview. Neural Networks, 131, 251-275.

[9] H. C. Burger, C. J. Schuler and S. Harmeling, "Image denoising: Can plain neural networks compete with BM3D?," 2012 IEEE Conference on Computer Vision and Pattern Recognition, 2012, pp. 2392-2399, doi: 10.1109/CVPR.2012.6247952.

[10] Hirose, Y., Yamashita, K., & Hijiya, S. (1991). Back-propagation algorithm which varies the number of hidden units. Neural Networks, 4(1), 61–66.

[11] L. O. Chua and T. Roska, "The CNN paradigm," in IEEE Transactions on Circuits and Systems I: Fundamental Theory and Applications, vol. 40, no. 3, pp. 147-156, March 1993, doi: 10.1109/81.222795.

[12] Y. -. Chiang and B. J. Sullivan, "Multi-frame image restoration using a neural network," Proceedings of the 32nd Midwest Symposium on Circuits and Systems,, 1989, pp. 744-747 vol.2, doi: 10.1109/MWSCAS.1989.101962.

[13] Residual learning of deep CNN for image denoising. IEEE Transactions on Image Processing, 26(7), 3142–3155. https://doi.org/10.1109/TIP.2017.2662206

[14] Zhang, K., Zuo, W., & Zhang, L. (2018a). Ffdnet: Toward a fast and flexible solution for cnn-based image denoising. IEEE Transactions on Image Processing, 27(9), 4608–4622.

[15] Guo, S., Yan, Z., Zhang, K., Zuo, W., & Zhang, L. (2019). Toward convolutional blind denoising of real photographs. In Proceedings of the IEEE conference on computer vision and pattern recognition (pp. 1712–1722).

[16] Residual learning of deep CNN for image denoising. IEEE Transactions on Image Processing, 26(7), 3142–3155. https://doi.org/10.1109/TIP.2017.2662206

[17] S. Ioffe and C. Szegedy, “Batch normalization: Accelerating deep network training by reducing internal covariate shift,” in International Conference on Machine Learning, 2015, pp. 448–456.

[18] A. Krizhevsky, I. Sutskever, and G. E. Hinton, “Imagenet classification with deep convolutional neural networks,” in Advances in Neural Information Processing Systems, 2012, pp. 1097–1105.

[19] Ruder, S. (2016). An overview of gradient descent optimization algorithms. 1–14. http://arxiv.org/abs/1609.04747

[20] Kingma, D. P., & Ba, J. L. (2015). Adam: A method for stochastic optimization. 3rd International Conference on Learning Representations, ICLR 2015 - Conference Track

[21] Sara, U., Akter, M., & Uddin, M. S. (2019). Image Quality Assessment through FSIM, SSIM, MSE and PSNR—A Comparative Study. Journal of Computer and Communications, 07(03), 8–18. https://doi.org/10.4236/jcc.2019.73002