

Review Study of Image De-Noising on Digital Image Processing and Applications

Cik Siti Khadijah Abdulah^{1,2}, Mohamad Nur Khairul Hafizi Rohani^{1,2,*}, Baharuddin Ismail^{1,2}, Mohd Annuar Mohd Isa^{1,2}, Afifah Shuhada Rosmi^{1,2}, Wan Azani Wan Mustafa², Ahmad Zaidi Abdullah^{1,2}, Wan Nor Munirah Ariffin³, Mohamad Kamarol Mohd Jamil⁴

- ² Faculty of Electrical Engineering Technology, Universiti Malaysia Perlis (UniMAP), Perlis, Malaysia
- ³ Institute of Engineering Mathematics, Universiti Malaysia Perlis (UniMAP), Perlis, Malaysia
- ⁴ School of Electrical & Electronic Engineering, Universiti Sains Malaysia (USM), Penang, Malaysia

ARTICLE INFO	ABSTRACT
Article history: Received 22 December 2022 Received in revised form 1 March 2023 Accepted 8 March 2023 Available online 25 March 2023	This paper reviews several studies of image de-noising on digital image processing and applications. Noisy images contain different noise that exist either due to environment or electronic interferences. Ergo, de-noising is crucial to eliminate the noise that disturb data collecting process. The impact of de-noising on image processing can result for accurate and precise data collected from the image. Additionally, de-noising process
Keywords: Digital image; de-noising; Gaussian; noise; Poisson noise; Salt and Pepper noise; Spatial domain; Speckle noise;	required several crucial steps that help to enhance knowledge on digital image and its application. Hence, study and understanding de-noising can improve multiple aspect such as image quality, data sensitivity and specificity, accuracy of the collected data, and increase the percentage of each parameter.

1. Introduction

Image pre-processing is a crucial part in image analysis since image is another form of data that preserve important information from the experiment. Besides, image analysis is widely used in multiple area of expertise such as, astronomy, medical field, remote sensing, transmission and encoding, machine or robot vision, forensic science technology, and industrial.

Therefore, noise in the acquired image can cause a difficulty to extract the data during image analysis due to degradation. Noise presence in the images is cause by variety factor that include environmental noise, electronic and electromagnetic interferences introduced during the signal acquisition stage, lighting, camera sensor, and aging equipment [1,2].

When an image is acquired and transmitted, it is frequently corrupted by noise. De-noising is a technique for removing additive noise while preserving as many important signal features as possible

* Corresponding author.

¹ High Voltage Transient & Insulation Research Group, Center of Excellence Renewable Energy (CERE), Universiti Malaysia Perlis (UniMAP), Perlis, Malaysia

E-mail address: khairulhafizi@unimap.edu.my

[3,4]. Noise contaminates data sets acquired by image sensors in general. Instruments that are not up to par, issues with the data collecting process, and interfering natural occurrences can all skew the results during analysis.

In a small number of research on image processing, most images transmitted can be assumed to contain additive random noise, for example, Gaussian, Salt and Pepper, Speckle, and Poisson noise that can heavily affect the analysis result [5,6]. Thus, efficient de-noising techniques are the necessary steps that should be taken before data analyzing and to satisfy data corruption. Hence, the following will discuss on type of noise and de-noising techniques accordingly.

2. Noise Models

The term "noise" refers to a random variation in intensity level. The pixels have some more information added to them, resulting in a noisy image. Some of the image pixel is not the correct pixels since an unnecessary value has been added to the genuine pixel value. Noise is divided mathematically into two fundamental models: additive and multiplicative.

In an additive noise model, original signal is added with noise signal that is additive in nature to develop a corrupted signal using the following rules

$$w(x, y) = s(x, y) + n(x, y)$$
 (1)

In the multiplicative noise model, the noise signal gets multiplied by the original signal. The multiplicative noise model follows the following rule

$$w(x, y) = s(x, y) \times n(x, y)$$
⁽²⁾

The s(x,y) can be described as the original image density and s(x,y) indicates the corrupted noisy signal w(x,y) at (x,y) pixel location.

Other classifications such as additive, multiplicative, and impulsive (random) noise are available in the image processing field. Impulse noise is a sort of noise that changes the pixel values at random [7]. The following Figure 1 classified impulse noise as static and dynamic (random) noise in the imaging process.



Fig. 1. Noise in image processing

3. Type of Noise

An important issue that degrades an image's value in all aspects is noise, it degrades image quality. Besides, some important image details are hidden, causing problems with subsequent processing such as segmentation, and edge detection. Noise also reduces the ability of human observation to diagnose objects more thoroughly.

There are multiple numbers of noise in image enhancement that occur due to various reasons that may corrupt the signal. The characteristics of noise signal as well as its probabilistic features can distinguish it [8,9]. The following sub-chapter discussed noise models, types, and categories in digital images.

3.1 Gaussian Noise

Define Gaussian noise is a statistical noise with the same probability density function (PDF) as the normal distribution, it is also called as additive noise which is known as the Gaussian distribution. In other words, the noise's possible values are Gaussian-distributed as each of the pixels are modified to a certain distribution. White Gaussian noise is a specific instance in which the values at any two points in time are evenly distributed and statistically independent (uncorrelated) [9,10]. Gaussian noise is most utilized in applications as additive white noise to acquiesce to additive white Gaussian (AWG) noise. The Gaussian model can be present as follow:

$$P(g) = \sqrt{\frac{1}{2\pi\sigma^2}e^{-\frac{(g-\mu)^2}{2\sigma^2}}}$$
(3)

Where, g = grey value, σ = standard deviation and μ = mean. Generally Gaussian noise mathematical model represents the correct approximation of real-world scenarios. The following Figure 2 shows the image corrupted by Gaussian noise.



Fig. 2. Lena image with Gaussian noise [11]

3.2 Impulse Noise

In image processing, impulse noise is randomly distributed throughout the image, and it is independent while uncorrelated to the pixels. For impulse noise corrupted image, not all the image pixels are noisy while a part of it is noise-free another part will be noisy [12,13]. Different type of noise that occurs in impulse noise are salt and pepper and arbitrary valued impulse noise.

Salt and pepper noise is a type of visual noise that is commonly seen and can also be referred to as impulse noise. The scattered disturbance in the image manifests as white and black pixels that appear at random which leads to discoloration of a few pixels in the image as shown in the following Figure 3 [14]. A median filter, morphological filter, or counter harmonic mean filter are all effective noise reduction techniques for this type of noise. Salt and pepper noise appears in images when quick transients, such as improper switching, occur.



Fig. 3. Lena image with Salt and Pepper noise [11]

For salt and pepper noise, the pixels taken are either salt value (grey levels are equal to 255) or pepper value (greyscale equal to 0). The image presented will have the presence of a black and white spots [8,15]. While salt and pepper are one of the two noises that appear in impulse noise, this noise had taken half of the total noise respectively. Then conclusion can be made that p is the total noise density, hence salt and pepper will have p/2 of the image density. This can be mathematically presented as follow.

$$Y_{ij} = \begin{cases} 0 \text{ or } 255 \text{ with probability } p \\ xij \text{ with probability } 1 - p \end{cases}$$

Where y_{ij} denotes the noisy image pixel, the total noise density of impulse noise and x_{ij} is the uncorrupted image pixel. At times the salt noise and pepper noise may have different noise densities and thus the total noise density will be p=p1+p2.

While for arbitrary valued impulse noise, the grey level value between 0 and 225 will be randomly chosen. In this case, noise is randomly distributed over the complete image, and the probability of incidence of any grey level value as noise will be the same. Thus, mathematically represent arbitrary valued impulse noise as the following equation.

$$Y_{ij} = \begin{cases} nij \text{ with probability } p \\ xij \text{ with probability } 1 - p \end{cases}$$
(5)

Where nij is the grey level value of the noisy pixels.

3.3 Poisson Noise

The nonlinear response of the image detectors and recorders influences Poisson noise formation. This noise occurs mostly in poor or low lighting conditions and relied on the image data acquisition process.

(4)

The image data reliant term occurs due to the image detection and recording processes that concern random electron emission having a Poisson distribution with a mean response value. Due to the mean and variance of a poison distribution being identical, the image-dependent term has a standard deviation if it is assumed that the noise has a unity variance [16,17]. This noise is formulated as follows, obeys the Poisson distribution.

$$P(f_{(pi)}) = k = \frac{\lambda^{k_i e^{-\lambda}}}{k!}$$

The following Figure 4 shows the distribution of Poisson noise on digital images.



While in Poisson-Gaussian noise distribution, the model carried Poisson distribution follows with Gaussian distribution. The Poisson-Gaussian noise model can be presented in the following manner.

$$Z(j,k) = \alpha * P_{\alpha}(j,k) + N_{\alpha}(j,k)$$

where, Pα symbolized Poisson distribution and Nα for Gaussian distribution [18]. The following Figure 5 shows Poisson-Gaussian noise images.



3.4 Speckle Noise

This type of noise diffuse reflection makes it a complicated event that disturbs the observer to differentiate fine details of the image during analysis as shown in following Figure 6.







Fig. 6. Lena image with Speckle noise [11]

The presence of speckle noise in images is caused by random interference among coherent returns that follow a gamma distribution [19]. The equation is given as follows.

$$F(g) = \frac{g^{\alpha - 1}e^{\frac{-g}{a}}}{\alpha - 1!a^{\alpha}}$$
(8)

4. Classification of De-Noising Techniques

Researchers have proposed multiple methods of image de-noising techniques, this is due to noise degradation that occurs in digital image processing [20,21]. The work is required to decrease noise without losing image features such as edges, corners, and other sharp structures. Hence, the denoising technique are being discussed in the next subchapter. However, each of the techniques discuss has its own support in image processing, this will be used as a reference for promising direction in future research. The following Figure 7 illustrated the filters diagram.



Fig. 7. Classification of image de-noising techniques

4.1 Spatial Filter

This type of filter can be classified into two categories are Linear Filters and Non-Linear Filters. The choice of using spatial filters is where the situations of the image have additive noise presence, thus spatial filter are employed.

In a situation where only additive noise is present, the best method of choice to de-noising the noise is a linear filter. In terms of MSE, a mean filter is the best linear for Gaussian noise. Sharp edges are blurred, lines are obliterated, and other fine features of the image are destroyed. In terms of

MSE, a mean filter is the best linear filter for Gaussian noise. While, the wiener filtering approach necessitates knowledge of the noise and original signal spectra, and it only works well if the underlying signal is smooth [3,22]. The Wiener approach applies spatial smoothing, and the model complexity control and corresponds to window size selection.

For the Mean filter, by minimizing the intensity fluctuations between adjacent pixels, this filter smoothed out an image. The mean filter is a type of averaging filter. Each pixel in the signal is given a mask. As a result, each component of a pixel that falls inside the mask is averaged to create a single pixel. The biggest issue is that the Mean filter's edge preservation requirements are inadequate [23].

Mean filter work simply by a sliding-window filter that replaces the pixel value on the center part of kernel window with the average mean of all the pixel values [24]. Figure 8 shows the mean filter kernel convolution. This type of filter can be classified into two categories are Linear Filters and Non-Linear Filters. The choice of using spatial filters is where the situations of the image have additive noise presence, thus spatial filter are employed.

17	14	13	center pixel	17	14	13
21	64	62		21	39	62
42	54	61		42	54	61

Fig. 8. Classification of image de-noising techniques

 $Mean = (17 + 14 + 13 + 21 + 64 + 62 + 42 + 54 + 61)/9 = 38.8889 \approx 39$ (9)

Thus, a Mean filter is the best fit filter for Gaussian noise in terms of MSE. While in Wiener filter, is a statistically based filter for filtering out the noise that has damaged a signal and this filter can be used to obtain the desired frequency response. Wiener filter takes a distinct method to filter by filtering from a different angle [24,25]. Thus, it is necessary to understand the spectral features of the original signal and noise to perform filtering operations. By meeting the conditions, one can obtain the linear time-invariant (LTI) filter, whose output will be as similar to the original signal as possible. This is due to the output of filters being mathematically expressed as the convolution of the input with the impulse response. The Wiener filter's aim is to have a minimum mean-square error (MSE) where the difference between original images and the new produce image should be as minimum as possible. The equation of the Wiener filter is as follow:

$$W(x,y) = \frac{H^*(x,y)S_f(x,y)}{||H(x,y)||^2 S_f(x,y) + S_n(x,y)}$$
(10)

where the H(x,y) is the degradation function while $H^*(x,y)$ is the complex conjugate of degradation function. The function of $||H(x,y)||_2 = H(x,y)H^*(x,y)$, is the total of degradation time the complex conjugate of degradation function. Meanwhile, both Sn (x,y) and Sf (x,y) are the power spectrum of noise and the power spectrum of the ungraded or original image. In conclusion, linear filters are used for both general-purpose tasks such as image or video contrast enhancement, de-noising, and sharpening. Besides, linear filter work as well for object or feature specific tasks like target matching and feature enhancement.

Spatial filters apply low pass filtering to groups of pixels, assuming that noise is concentrated in the higher frequency range of the spectrum. Normally, spatial filters reduce noise to a great level, but at the cost of blurring images, which obscures picture edges and make the picture become invisible. Therefore, non-linear filters can remove multiplicative noise without the need to identify it. Several nonlinear filters have recently been created.

A Median filter is the most basic nonlinear filter that examines each pixel in the image individually and compares it to its neighbors to determine whether it is representative of its surroundings. Rather than merely replacing the pixel value with the mean of nearby pixels value, the median of those values is used instead.

In image processing, Median filters are applied to remove multiplicative noise such as Gaussian, salt and pepper, and random noise that appear on the image during data collection or data transfer. As mentioned earlier, the Median filter preserves the edges during noise removal since it scans all the incoming data with a Median function that is known as a window.

The windows number is set as either odd or even, the center pixel of a M×M neighbor is replaced by the median value of the corresponding window. The M×M can be presented as 3×3, 5×5, or 7×7 kernel of pixels which is moved over the entire image. The kernel convolution concept can be presented in Figure 9 as follow.

B(1,1)	B(1,2)	B(1,3)
B(2,1)	B(2,2)	B(2,3)
B(3,1)	B(3,2)	B(3,3)

Fig. 9). 3×3	Neigh	bor
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Calculations on the Median filter is done by sorting the surrounding neighbour pixel value either by ascending or descending order, then the middle pixel value is being assumed and the process is repeated until all the pixels are counted.

4.2 Transform Domain Filtering

The transform domain technique is highly effective, although it's a little more difficult to explain. In this filtering technique, the choice of basic functions is heavily affected its classification. Non-data adaptive and data-adaptive basis functions are two types of functions. A small number of researchers mostly focus on non-data adaptive transformations because it is more often used [4,26].

In data-adaptive transform, Independent Component Analysis (ICA) is a new method that has recently attracted widespread interest. Non-Gaussian data was successfully de-noised using the ICA approach. One of the advantages of employing ICA is that it assumes a non-Gaussian signal, which makes it easier to de-noise images with both non-Gaussian and Gaussian distributions. The computational cost of ICA-based approaches is higher than wavelet-based approaches since it uses a sliding window and requires a sample of noise-free data or at least two image frames from the same scene. It may be challenging to obtain noise-free training data in some applications.

Therefore, non-data adaptive filters are divided into two different classes which both known as spatial frequency domain and wavelet domain. Spatial frequency filtering uses low pass filters with FFT. To design the cut-off frequency are predefine, and this filter passes all frequencies lower than the cut-off frequency while attenuating all frequencies higher than the cut-off frequency. By executing filtering in the frequency domain, 2D Fourier transformations and a filter multiply are computationally faster than performing a convolution in the image (spatial) domain.

Wavelet transform is the most studied transform in the de-noising technique; hence the DWT creates a signal energy concentrate in a minimum number of coefficients, these reason makes the researcher choose to work with the wavelet domain. Thus, the small number of coefficients of DWT

increase the SNR and vice versa. Wavelet filtering techniques have the advantage of concurrently providing temporal and frequency localization [27].

Furthermore, wavelet approaches characterize such signals far better than the original domain or transformations with global basis elements, such as the Fourier transform. However, there is limitation on using the wavelet domain since it relies on the wavelet base selection thus may cause image shown in the wavelet domain cannot be present clearly if the selection is done are unfit.

5. De-Noising Methods and Applications

This section discusses the results obtained from the surface pressure measurement study. The effects of angle of attack, Reynolds number and leading edge bluntness are discussed in the next sub section. There are numerous advantages to digital image processing versus analogue image processing. Image processing enables a considerably broader range of methods to be applied to the input data, avoiding issues such as noise accumulation and signal distortion during image processing. Different types of noise such as Gaussian noise, salt and pepper noise, speckle noise, and poison noise is usually used to image enhancement before proceeding with the de-noising process.

Existing research recognizes the critical role played by image de-noising, hence Remenyi *et al.*, [28] explain in detail the wavelet transform process compared to non-linear filter. The wavelet transform is based on a global multi-scale analysis of images, unlike non-linear filters. It is well known that the time-frequency localization of a single wavelet function has a limit. A method for image de-noising was devised using a multi-wavelet filter bank. De-noising in the wavelet domain essentially entails obtaining an optimal estimate of the original signal. As a result, the wavelet basis for de-noising should be carefully chosen that an optimal estimate of the wavelet coefficients can be converted to an ideal estimate of the original signal.

In a case study of wavelet transform by Scapaticci *et al.*, [29], the post-processing de-convolution is applied to improve the de-noising algorithm. In this study, the researcher created a blur function to corrupt the original image to present the performance of the basic wavelet-based image denoising technique. The benefit of the proposed approach is demonstrated as the reconstruction of de-noised pictures from the non-negative Garrote Curvelet shrinkage rule and UDW coefficients Experimental. The results show that this strategy improves image quality and reduces MSE, particularly when the image is affected by substantial AWG noise.

Image restoration is a technique used in digital image processing to recover a corrupted original image from the blurred and noisy images produced by motion blur, noise, and other factors such as environmental influences and camera miss focus. Referring to the previous study on inverse and wiener filters used to restore a car sample image that had been corrupted by motion blur and random noise [30]. Therefore, inverse filters are known as a handy filter in image restoration if a correct degradation function for the corrupted image can be modelled. Even if the images are not corrupted by noises, it still performs admirably.

Nevertheless, when images are corrupted by noises, the inverse filter's performance degrades dramatically as high pass filters due to noise tend to be high frequency. While for wiener filter, it combines a low pass and a high pass filter which resulted to it functioning actively in the presence of additive noise in the image. Wiener filter performs a de-convolution also known as high pass filtering operation to invert motion blurring, as well as compression operation to remove additive noises [8,31,32]. In this study, both inverse and wiener filters are applied to the corrupted image then comparisons are made. The result of the study shows that in absence of noise, both filters function well in reconstructing the original image from its degraded counterpart. However, when additive noise is present, the wiener filter outperforms inverse filtering in terms of restoration.

A considerable amount of literature has been published on image processing since it is beneficial in a large area of studies and works, hence de-noising techniques vary depending on its benefit to the problem that occur during the process. Some techniques may work, and some are limited to certain boundaries. Thus, a deep study of image processing will probably solve some of the limitations at the time and help improve image restoration. Furthermore, wavelet approaches characterize such signals far better than the original domain or transformations with global basis elements, such as the Fourier transform. However, there is limitation on using the wavelet domain since it relies on the wavelet base selection thus may cause image shown in the wavelet domain cannot be present clearly if the selection is done are unfit. Table 1 shows the de-noising methods and its application.

Table	1
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Reference	Objective	De-noising Methods	Applications	
Remenyi <i>et al.,</i> [28]	This paper proposed a Bayesian	Wavelet shrinkage	Digital image	
	model technique in the domain of a	methods using	restoration (Lenna	
	complex scale-mixing discrete initary	complex-valued	photo)	
	compactly supported wavelets	wavelet transforms		
Scapaticci et al., [29]	This paper aims to solve a challenging	Wavelet-Based	Imaging in medical	
	non-linear and ill-posed	Regulation for roust	applications	
	electromagnetic inverse scaterring	microwave imaging		
	problem using robust method for			
	quantitative Microwave imaging			
	(MWI) in medical applications			
Khan <i>et al.,</i> [30]	The proposed Inverse and Wiener	Inverse and Wiener	Digital image	
	filters in this paper were to restore	filtering	restoration (photo	
	the noisy image from random noise		of car)	
	added, particularly motion blurred			
	and noisy motion blurred images			
llesanmi <i>et al.,</i> [8]	This paper offered different CNN	Convolutional neural	Digital Image	
	techniques that had been elaborated	network (CNN)		
	and studied for potential challenges			
	and directions for future research			
Lebrun [31]	This paper proposes open-source	Block-Matching and	Digital images	
	implementation of BM3D method by	3D filtering (BM3D)	(photo of	
	enhancing a group of similar 2D		Valldemosa)	
	images patches into 3D groups			
Mbarki <i>et al.,</i> [33]	This paper discusses the fundamental	Wiener filter, and	Non-blind image	
	methods in filtering theory by	Block-Matching and	restoration	
	implemented Wiener, and BM3D filter	3D filtering (BM3D)	scheme	
	on blurred images. The degraded			
	images first were de-convoluted in			
	Fourier space by parametric Wiener			
	filtering then BM3D filter was applied			
	to eliminate the noise			
Sigit <i>et al.,</i> [34]	In the pre-processing stage, Median	Median filter	Human blood cells	
	filter was applied on the blood cell		(Identification of	
	images to perform filtering to		Leukaemia	
	eliminate the unwanted noise before		diseases)	
	proceeding with colour conversion			

De-noising methods and application

6. Conclusions

Digital image processing has various benefits over analogue image processing. Image processing allows a far greater choice of procedures to be applied to the input data, avoiding concerns such as noise build-up and signal distortion. Before beginning with the de-noising process, several forms of noise such as Gaussian noise, salt and pepper noise, speckle noise, and poison noise are commonly employed to improve the image. Hence, this paper review and study the existing noise and de-noising technique by evaluate and elaborate based on Table 1. Finally, the review helps to understand de-noising analogy and its application in future studies.

Acknowledgement

The authors would like to thank the Ministry of Higher Education Malaysia for financially supported under the Fundamental Research Grant Scheme FRGS/1/2020/TK0/UNIMAP/02/17.

References

- [1] Akashah, N. A., M. N. K. H. Rohani, A. S. Rosmi, M. Isa, N. Rosle, B. Ismail, and C. L. Wooi. "A review: Partial discharge detection using acoustic sensor on high voltage transformer." In *Journal of Physics: Conference Series*, vol. 1432, no. 1, p. 012004. IOP Publishing, 2020. <u>https://doi.org/10.1088/1742-6596/1432/1/012004</u>
- [2] Roslizan, N. D., M. N. K. H. Rohani, C. L. Wooi, M. Isa, B. Ismail, A. S. Rosmi, and W. A. Mustafa. "A review: Partial discharge detection using UHF sensor on high voltage equipment." In *Journal of Physics: Conference Series*, vol. 1432, no. 1, p. 012003. IOP Publishing, 2020. <u>https://doi.org/10.1088/1742-6596/1432/1/012003</u>
- [3] Alisha, P. B., and K. Gnana Sheela. "Image denoising techniques-an overview." *IOSR Journal of Electronics and Communication Engineering* 11, no. 1 (2016): 78-84.
- [4] Tian, Chunwei, Lunke Fei, Wenxian Zheng, Yong Xu, Wangmeng Zuo, and Chia-Wen Lin. "Deep learning on image denoising: An overview." *Neural Networks* 131 (2020): 251-275. <u>https://doi.org/10.1016/j.neunet.2020.07.025</u>
- [5] Chen, Songkui, Daming Shi, Muhammad Sadiq, and Xiaochun Cheng. "Image denoising with generative adversarial networks and its application to cell image enhancement." *IEEE Access* 8 (2020): 82819-82831. <u>https://doi.org/10.1109/ACCESS.2020.2988284</u>
- [6] Nanyan, Ayob Nazmy, Muzamir Isa, Haziah Abdul Hamid, Mohamad Nur Khairul Hafizi Rohani, and Baharuddin Ismail. "The rogowski coil sensor in high current application: A review." In *IOP Conference Series: Materials Science and Engineering*, vol. 318, no. 1, p. 012054. IOP Publishing, 2018. <u>https://doi.org/10.1088/1757-899X/318/1/012054</u>
- [7] Sangave, P. H., and G. P. Jain. "Impulse noise detection and removal by modified boundary discriminative noise detection technique." In 2017 International Conference on Intelligent Sustainable Systems (ICISS), pp. 715-719. IEEE, 2017. <u>https://doi.org/10.1109/ISS1.2017.8389266</u>
- [8] Ilesanmi, Ademola E., and Taiwo O. Ilesanmi. "Methods for image denoising using convolutional neural network: a review." *Complex & Intelligent Systems* 7, no. 5 (2021): 2179-2198. <u>https://doi.org/10.1007/s40747-021-00428-4</u>
- [9] Abdulah, C. S. K., M. N. K. H. Rohani, B. Ismail, M. A. M. Isa, A. S. Rosmi, and W. A. Mustafa. "Comparison of Image Restoration using Median, Wiener, and Gaussian Filtering Techniques based on Electrical Tree." In 2021 IEEE Industrial Electronics and Applications Conference (IEACon), pp. 163-168. IEEE, 2021. https://doi.org/10.1109/IEACon51066.2021.9654752
- [10] Mustafa, Wan Azani, Haniza Yazid, and Sazali Bin Yaacob. "Illumination correction of retinal images using superimpose low pass and Gaussian filtering." In 2015 2nd International Conference on Biomedical Engineering (ICOBE), pp. 1-4. IEEE, 2015. <u>https://doi.org/10.1109/ICOBE.2015.7235889</u>
- [11] Lone, Aamir Hamid, and Arsheen Neda Siddiqui. "Noise models in digital image processing." *Global Sci-Tech* 10, no. 2 (2018): 63-66. <u>https://doi.org/10.5958/2455-7110.2018.00010.1</u>
- [12] Draganov, Ivo Rumenov, and Rumen Parvanov Mironov. "3D Noise Adaptive Wiener Filtering of Images." In 2020 28th National Conference with International Participation (TELECOM), pp. 6-9. IEEE, 2020. https://doi.org/10.1109/TELECOM50385.2020.9299543
- [13] Rosmi, A. S., M. Isa, B. Ismail, M. N. K. H. Rohani, and Y. Wahab. "An optimization of electrical output power for piezoelectric energy harvester using different micro-cantilever beam geometries." In *Journal of Physics: Conference Series*, vol. 1019, no. 1, p. 012033. IOP Publishing, 2018. <u>https://doi.org/10.1088/1742-6596/1019/1/012033</u>

- [14] Irum, Isma, Muhammad Sharif, Mudassar Raza, and Sajjad Mohsin. "A nonlinear hybrid filter for salt & pepper noise removal from color images." *Journal of Applied Research and Technology* 13, no. 1 (2015): 79-85. <u>https://doi.org/10.1016/S1665-6423(15)30015-8</u>
- [15] Khetkeeree, Suphongsa, and Parawata Thanakitivirul. "Hybrid filtering for image sharpening and smoothing simultaneously." In 2020 35th International Technical Conference on Circuits/Systems, Computers and Communications (ITC-CSCC), pp. 367-371. IEEE, 2020.
- [16] Van Slambrouck, Katrien, Simon Stute, Claude Comtat, Merence Sibomana, Floris HP van Velden, Ronald Boellaard, and Johan Nuyts. "Bias reduction for low-statistics PET: maximum likelihood reconstruction with a modified Poisson distribution." *IEEE Transactions on Medical Imaging* 34, no. 1 (2014): 126-136. https://doi.org/10.1109/TMI.2014.2347810
- [17] Zhou, Yuanxiang, Yunxiao Zhang, Ling Zhang, Dawei Guo, Xu Zhang, and Mingyuan Wang. "Electrical tree initiation of silicone rubber after thermal aging." *IEEE Transactions on Dielectrics and Electrical Insulation* 23, no. 2 (2016): 748-756. <u>https://doi.org/10.1109/TDEI.2015.005514</u>
- [18] Zhao, Lingyan, Jun Zhang, and Zhihui Wei. "Skellam distribution based adaptive two-stage non-local methods for photon-limited poisson noisy image reconstruction." In 2017 IEEE International Conference on Image Processing (ICIP), pp. 2433-2437. IEEE, 2017. <u>https://doi.org/10.1109/ICIP.2017.8296719</u>
- [19] Anitha, S., Laxminarayana Kola, P. Sushma, and S. Archana. "Analysis of filtering and novel technique for noise removal in MRI and CT images." In 2017 International Conference on Electrical, Electronics, Communication, Computer, and Optimization Techniques (ICEECCOT), pp. 1-3. IEEE, 2017. https://doi.org/10.1109/ICEECCOT.2017.8284618
- [20] Hosotani, Fumitaka, Yuya Inuzuka, Masaya Hasegawa, Shigeki Hirobayashi, and Tadanobu Misawa. "Image denoising with edge-preserving and segmentation based on mask NHA." *IEEE Transactions on Image Processing* 24, no. 12 (2015): 6025-6033. <u>https://doi.org/10.1109/TIP.2015.2494461</u>
- [21] Maru, Pratyaksh A., Chintan K. Modi, and P. S. V. Nataraj. "Comparison of robust MM estimator and robust M estimator based denoising filters for gray level image denoising." In 2012 International Conference on Communication Systems and Network Technologies, pp. 109-113. IEEE, 2012. https://doi.org/10.1109/CSNT.2012.33
- [22] Ahmadi, Reza, Javad Kangarani Farahani, Farbod Sotudeh, Ashkan Zhaleh, and Saeid Garshasbi. "Survey of image denoising techniques." *Life Science Journal* 10, no. 1 (2013): 753-755.
- [23] Joshi, Nikita, Sarika Jain, and Amit Agarwal. "An improved approach for denoising MRI using non local means filter." In 2016 2nd International Conference on Next Generation Computing Technologies (NGCT), pp. 650-653. IEEE, 2016. <u>https://doi.org/10.1109/NGCT.2016.7877492</u>
- [24] Modhave, Nayan, Yepuganti Karuna, and Sourabh Tonde. "Design of multichannel wiener filter for speech enhancement in hearing aids and noise reduction technique." In 2016 Online International Conference on Green Engineering and Technologies (IC-GET), pp. 1-4. IEEE, 2016. <u>https://doi.org/10.1109/GET.2016.7916626</u>
- [25] Reddy, B. Sai Tejeswar, and Valarmathi Jayaraman. "Application of Wiener Filter Making Signals Orthogonal." In 2019 International Conference on Vision Towards Emerging Trends in Communication and Networking (VITECON), pp. 1-6. IEEE, 2019. <u>https://doi.org/10.1109/ViTECoN.2019.8899689</u>
- [26] Lee, Kiat Moon, and Ka Nyan Ng. "Effect of Ultrasonication in Organosolv Pretreatment for Enhancement of Fermentable Sugars Recovery from Palm Oil Empty Fruit Bunches." *Progress in Energy and Environment* 11 (2019): 15-23.
- [27] Ashok, Ajith, Aneela Babburi, T. Ardra, K. S. Gayathri, R. J. Indu, and Gayathri Narayanan. "Performance comparison of matched filter, wavelet denoising and wiener filter technique in communication receivers." In 2018 3rd IEEE International Conference on Recent Trends in Electronics, Information & Communication Technology (RTEICT), pp. 2264-2268. IEEE, 2018. https://doi.org/10.1109/RTEICT42901.2018.9012318
- [28] Remenyi, Norbert, Orietta Nicolis, Guy Nason, and Brani Vidakovic. "Image denoising with 2D scale-mixing complex wavelet transforms." *IEEE Transactions on Image Processing* 23, no. 12 (2014): 5165-5174. <u>https://doi.org/10.1109/TIP.2014.2362058</u>
- [29] Scapaticci, Rosa, Panagiotis Kosmas, and Lorenzo Crocco. "Wavelet-based regularization for robust microwave imaging in medical applications." *IEEE Transactions on Biomedical Engineering* 62, no. 4 (2014): 1195-1202. <u>https://doi.org/10.1109/TBME.2014.2381270</u>
- [30] Khan, Mohammad Mahmudur Rahman, Shadman Sakib, Rezoana Bente Arif, and Md Abu Bakr Siddique. "Digital image restoration in matlab: A case study on inverse and wiener filtering." In 2018 International Conference on Innovation in Engineering and Technology (ICIET), pp. 1-6. IEEE, 2018. <u>https://doi.org/10.1109/CIET.2018.8660797</u>
- [31] Lebrun, Marc. "An analysis and implementation of the BM3D image denoising method." *Image Processing On Line* 2012 (2012): 175-213. <u>https://doi.org/10.5201/ipol.2012.l-bm3d</u>

- [32] Samsudin, Muhammad Syazwan Nizam, Md Mizanur Rahman, and Muhamad Azhari Wahid. "Sustainable power generation pathways in Malaysia: Development of long-range scenarios." *Journal of Advanced Research in Applied Mechanics* 24, no. 1 (2016): 22-38.
- [33] Mbarki, Zouhair, Hassene Seddik, and Ezzedine Ben Braiek. "Non blind image restoration scheme combining parametric Wiener filtering and BM3D denoising technique." In 2018 4th International Conference on Advanced Technologies for Signal and Image Processing (ATSIP), pp. 1-5. IEEE, 2018. https://doi.org/10.1109/ATSIP.2018.8364524
- [34] Sigit, Riyanto, Mochamad Mobed Bachtiar, and Moh Irsyadul Fikri. "Identification of leukemia diseases based on microscopic human blood cells using image processing." In 2018 International Conference on Applied Engineering (ICAE), pp. 1-5. IEEE, 2018. <u>https://doi.org/10.1109/INCAE.2018.8579387</u>