# Hybrid Image Denoising with Wavelet and Deep Learning Model

**D.M. Madhura[1], A.V. Krishna Mohan[2]**

[1]PG Student, Department of CSE, SIT, Tumkur, Karnataka, India. E-mail: madhuradm11398@gmail.com

[2]Assistant Professor, Department of CSE, SIT, Tumkur, Karnataka, India. E-mail: krishnamohansit@gmail.com

## Abstract

Underwater image enhancement restores corrupted underwater photos so that clean images can be produced. Deep learning-based image super resolution reconstruction has beena prominent issue in the near past. To enhance the efficiency and effectiveness of deep learning-based solutions, this research puts forth an enhanced picture deep convolutional neural networks-based super-resolution reconstruction technique. Deep learning-based image improvement techniques normally use paired data to train the model; however, in the underwater environment, paired data,such as damaged photographs and their corresponding cleanimages, is difficult to collect simultaneously. Another significant issue is how to effectively keep specific information in the improved image. We provide a neural network-based model for an approach to unpaired underwater picture enhancement to overcome these issues.

**Index Terms:** Component, Formatting, Style, Styling, Insert.

**DOI: 10.47750/pnr.2022.13.S03.201**

## INTRODUCTION

Underwater laser imaging technology is crucial for undersea information discovery, that is identifying underwater data. Though, because of the unique aqueous medium, the images will be exposed to air pollution, lowering the resolution. Many countries, including the United States and the former Soviet Union, have committed a significant amount of labour and equipment in underwater laser range, imaging, and other areas, and significant progress has been made in some important directions.

Imaging detection is a prominent subject in the realms of maritime defence, undersea resource development, and environmental monitoring. According to a recent study, turbulence degradation is the most important issue in natural waters. Scattering, light absorption, turbulence distortion, suspended particles and other problems all contribute to a significant loss of underwater image quality. An effective method to boost image quality while lowering hardware costs is to set up a degradation model to optimise picture enhancement algorithms.

Image enhancement and restoration algorithms are examples of traditional underwater image processing approaches [1]. In recent years, researchers have proposed a variety of mathematical approaches to raise the standard of underwater image reconstruction and restoration [2], colour correction, combining estimation, fusion and the deployment of the deep neural network [3].

To improve underwater photography, deep learning-based algorithms can make use of a computerized training system that picks up on the basic underwater characteristics from a collection of underwater photos. Instead of using handmade elements for picture representation, [6] employed non-parametric deep elements.

The convolutional neural network (CNN) [7] was brought into underwater picture enhancing applications by other re- searchers. Furthermore, by building an encoding–decoding framework, [3] created a deep pixel-to-pixel network.

Fig. 1. The dataset of unpaired undersea pictures.

Figure 1 shows various unpaired underwater picture samples.The dataset of unpaired undersea pictures. The top row shows the underwater photos that have been damaged, while the bottom row shows the photos that have been cleaned up. In both rows, there are no pairs.

Examining the effects of turbulence, route scattering, and suspended particles on underwater optical imaging and to investigate the implications of turbulence, route scattering, and suspended particles, Hou et al. [4] built an underwater imaging degradation model. Gero et al. [5] developed a laboratory settings under water turbulence experimental setup, and used field measurements to investigate the effect of optical turbulence on the resolution of underwater imaging systems.

## SYSTEM MODEL

### A. Convolution Neural Network

A particular kind of neural association called persuading neural organisation (CNN) is used to recognise and react to an obviously designed image in order to handle pixel data [6] [7]. CNN takes into account visual acuity, computer-assisted (AI) imag- ing, which is employed both internally and remotely to decide a plan's plan and delivery, as well as a vision machine that contains picture and video endorsement, NLP praising, and the executive's frameworks.

To avoid the difficulty of picture preparation using usual neural connections, layers of neurons are coordinated to span the whole field of investigation. CNN employs a multi- part perceptron technology that aims to reduce management overhead. Three sorts of layers make up CNN: data, yield, and a distinctive layer that incorporates a range of synchronization layers, mixing layers, fully integrated layers, and conventional layers. Obstacles and more complete image exploitation methodologies result in a more direct, points that is restricted to on-the-board trains that are only interested in image processing and local languages [8].

CNN employs a multi-facet perceptron structure to reduce handling requirements. Input layer, yield layer, and secret layer are among the CNN layers, which include various synchronisation layers, mix layers, entirely coordinated layers, and standard layers. Constraints are removed, image handling skills are improved, and a very effective, simple framework that is limited to training sessions concentrated on picture preparation and local language handling is created [9]. Figure 2 depicts the Convolution Neural Network's evolution. A number of layers make up the CNN architecture, which converts the information volume into a yield volume with split capacity. There are typically several distinct sorts of layers employed.

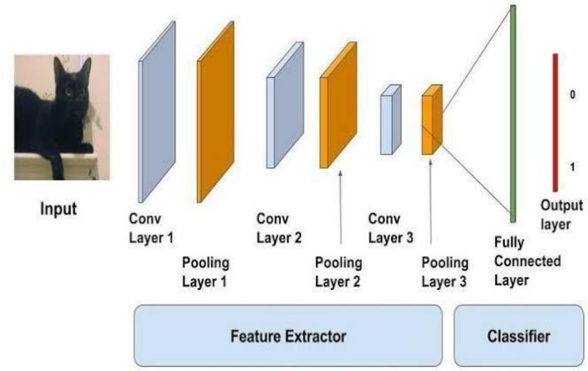


Fig. 2. CNN Model.

#### Convolutional layer

The structural square of CNN is the convolutional layer. Layer boundaries are made up of a group of significant channels (or characters) that have a small gathering field but stretch to the depths of the data volume. During a change, each channel is displayed in the information volume's width and height, with a mechanised dab yield between the info channel and the input, and a double guide chipping away at that channel [10]. As a result, when the company recognises a given type of piece ina specific data location, it learns which channels operate. Setting its initiation maps with all channels to the depth of profundity allows the convolution layer's whole yield volume to be obtained. All of a neuron's contributions to the return region can be recorded as its output if it scans the statement's comment section and then shares borders with neurons in the same implementation map [11].

#### Pooling layer

One more significant idea for CNN is joining, which is a type of nonlinear down-examining. There are a few nonstraight be- ginning capacity blends between various max mixes generally normal. It parts the inclusion picture into a bunch of visually impaired square shapes and, in each such area, yields the top [12].

According to several regulations, the particular area of a component is less relevant than its definite area. This is a theory that may be applied to the use of mix in convolutional neural networks. In order to control overburden, the mix layer attempts to shrink the depiction region, minimise the number of borders, analyse the organization's memory and PC count, and lower the size of the depiction region [13]. It isn't unexpected to occasionally apply a mix layer. The arrangement work gives an option in contrastto reliable interpretation. Pool addition is a significant piece of convolutional neural organizations for object securing depen- dent on Fast CNN plan.

### Fully connected layer

After numerous layers of blending, considerable level intuition in the neural organisation is finally finished with layers that are fully connected. Typical neural (non-convolutional) networks demonstrate that neurons in a completely linked layer have connections to every significant element in the preceding layer. They are presented in a manner that can be characterised as relative change, with predisposition offset coming after network reiteration (vector expansion of read or cut word).

## B. Working of CNN layers

Convolutional Neural Networks (CNN) [14] have a number of layers, as shown in the diagram. The first stage merges a reduced level image obtained during the colour transformation project with the established channels to estimate the factor of restrict association with potential traffic signal locations. [15].

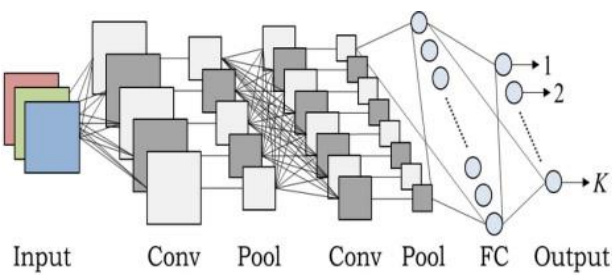


Fig. 3. Working of CNN Layers.

To assess whether or not the separator belongs to the appropriate class of traffic signals, its multi-sided features are displayed in layers that are easy to understand. When rotated, the condition of these pictures is not fragile. As a result of their non-roundness, we only apply one channel to each category of limiting photos. Figure 3 depicts hazardous channels.

The motivation behind why we utilize five channels to coordinate with one shape is that pivot significantly affects the arrangement of this part. Since the size of the traffic signs in the images ranges from 16 x 16 to 128 x 128, consistency with the largest size is necessary. Since this value can produce a pleasing result in enough PC time, we opted 1.05 as the channel scale for our test. [16].

For every uncommon channel in each scale, it produces an entire fix with a coefficient of contact more prominent than the breaking point. By changing the limit, we can create a gathering of intriguing areas (ROI). Since this calculation doesn't recognize dispersed bundles, there might be various ROIs almost a solitary traffic light. To tackle this issue, a straightforward ROI combination calculation was presented. In each graph, the ROIs are arranged by the coefficient of association with the slipping framework, and the greatest worth is chosen as the positive district and every one of the areas nearest to this locale are barred. Rehash this progression until there are no circuits left.

## C. Working Flow of Proposed Model

The Deep Convolution Neural Network flow is depicted by the aforementioned model in Figure 4.

- The wavelet transform is used to decompose the input and clean label pictures into four sub-bands.

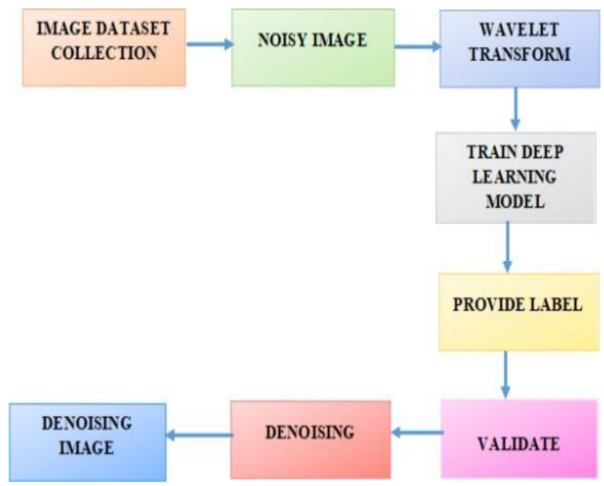


Fig. 4. Working Flow of Model

- By contrasting the input and cleaning label images in the wavelet domain, the wavelet residual images which are now utilised as new labels are created.
- Newly processed input and label are then instructed to the network to recognise functional links between many inputs and multiple outputs.
- In each wavelet sub-band, four patches at the same location are obtained and employed as training data.
- Between the initial and the final stages of the network, there are five components.
- There are three batch normalizations, ReLU and convolution layers in each module.
- The first stage is composed of two layers: a convolution layer with ReLU and a convolution layer with batch normalisation and ReLU.
- The final stage consists of three layers: a terminal convolution layer, a batch normalisation layer, and two convolutional layers. Residual learning framework to learn "R" and batch normalisation to expedite training and improve denoising performance are the two main aspects of this approach.
- Now, in order to obtain a complete image, we join all of the denoised patches. Our hybrid model will first divide the image into

frequency bands using wavelets, and then it will train feature maps using a deep learning model before performing inverse transform denoising.

- Denoising image is achieved.

Figure 5 depicts the model's system architecture. The suggested design is based on deep learning methods like convolution neural networks. The input layer of the neural network will receive input images, and it will identify noisy images and send them on to the hidden layer. In the CNN model's output layer, a denoised image is obtained.

### D. System Architecture of the Model

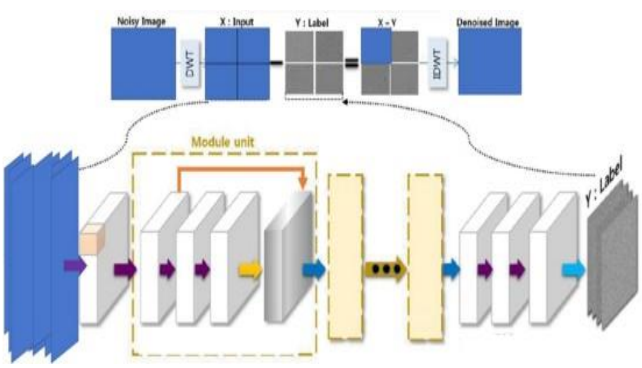


Fig. 5. System Architecture of the Model.

The Figure 6 shows a graph of the execution of the proposedframework. Utilize a case graph that portrays the capacity and conduct of the framework such that clients and designers consistently see best. Committed to assisting creators withcementing your thought, to fulfill client's necessity. Can getto all application exercises.

### E. Use Case Diagram of the Propose System

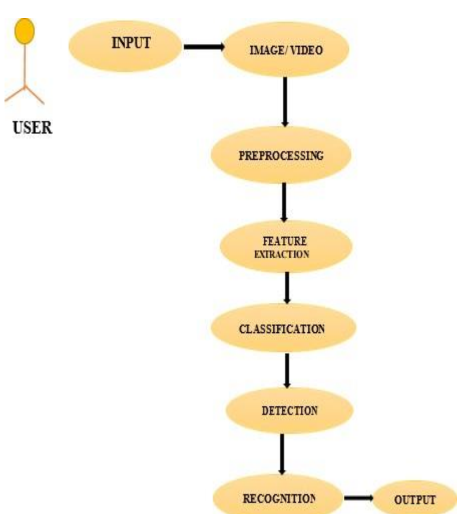


Fig. 6. Use Case Diagram of the Propose System.

## RESULTS AND DISCUSSION

The image processing is examined using MATLAB in this research. Some widely used filtering functions are contrasted in terms of their filtering effects. Figure 7 shows the original image, Figure 8 illustrates the noisy image. Figures 9, 10, 11, and 12 display pictures of low-low band, low-high band, high-low band, and high-high band, respectively. Figure 13 represents the reconstruction of the residual images. Figure 14 displays the filtered image that separates the reconstruction image's high and low characteristics. Patches are produced in the sampled layer by combining the high and low features, This patches are labeled as low-low, low-high, high-low, high-high images. The low-low labelled image, low-high labelled image, high-low labelled image, and high-high labelled image are shown in Figures 15, 16, 17, and 18. We obtain the denoising image depicted in Figure 19 after using the inverse discrete wavelet transform.

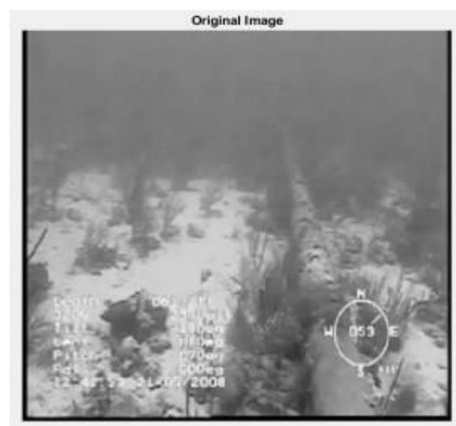


Fig. 7. Represents the original image.

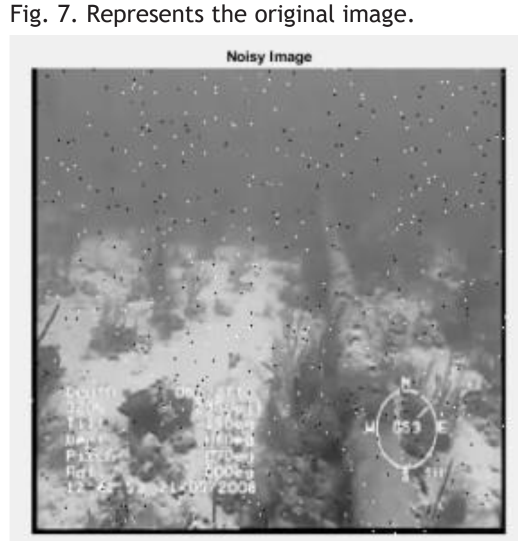


Fig. 8. Represents the noisy image.

## CONCLUSIONS

This research proposes an enhanced deep intensive convo- lution neural network based on the concept of deep learning.

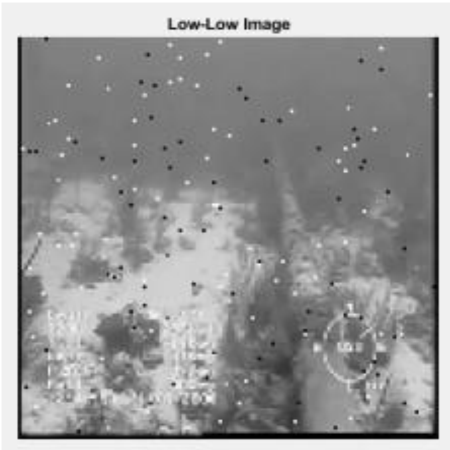


Fig. 9. Represents the low-low band image.

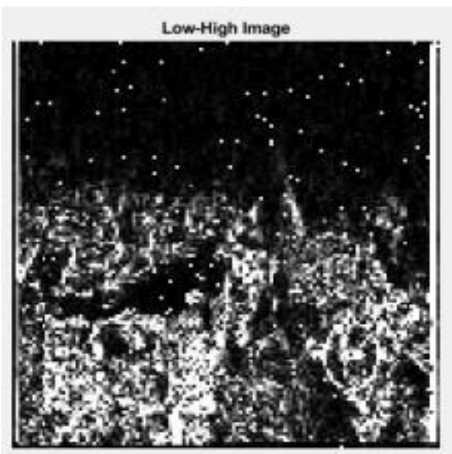


Fig. 10. Represents the low-high band image

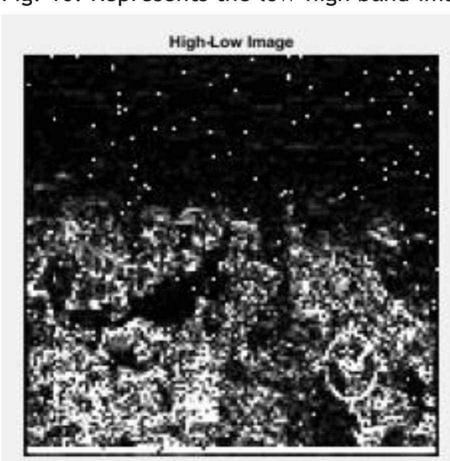


Fig. 11. Represents the high-low band image

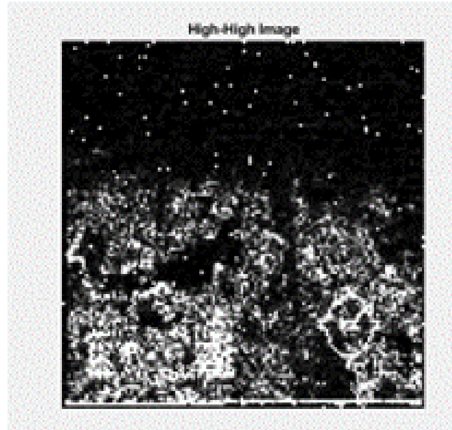


Fig. 12. Represents the high-high band image

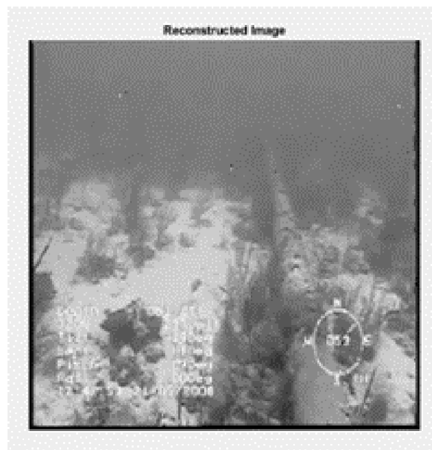


Fig. 13. Represents the reconstruction of the residual images.

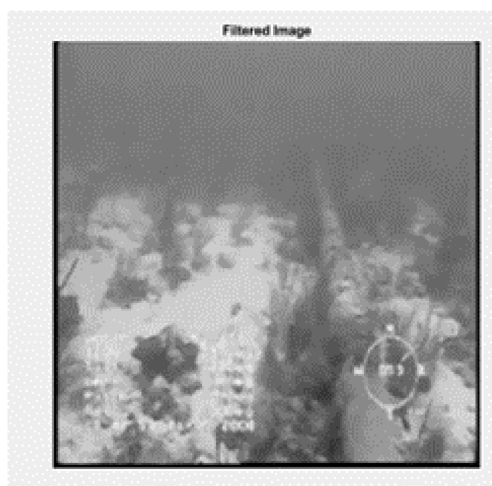


Fig. 14. Represents the filtered image.


Fig. 15. Represents low-low labeled image

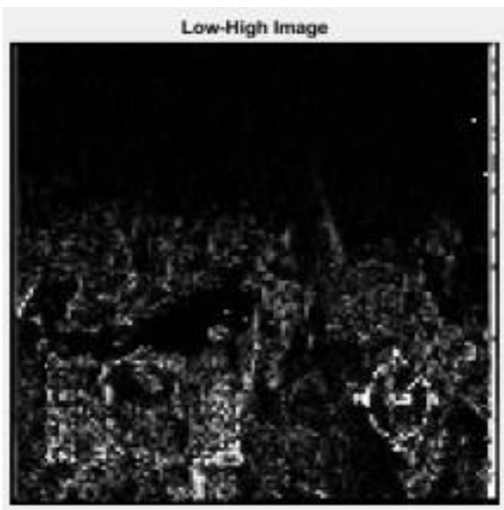


Fig. 16. Represents low-high labeled image.

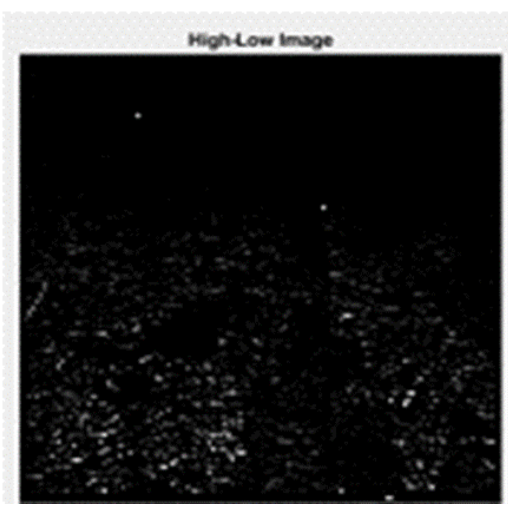


Fig. 17. Represents high-low labeled image.

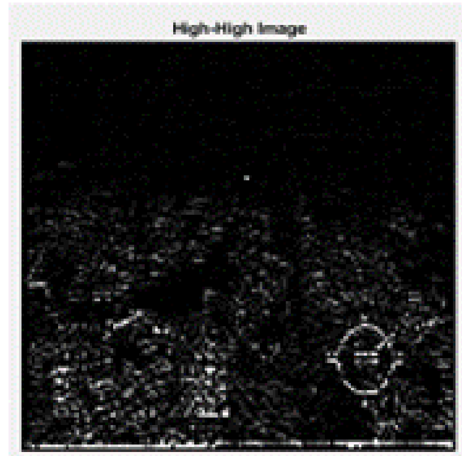


Fig. 18. Represents high-high labeled image.

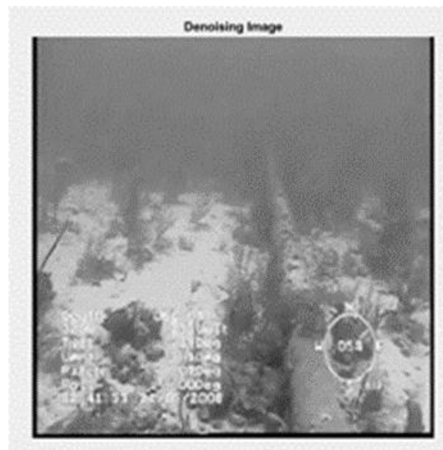


Fig. 19. Inverse discrete wavelet to obtain denoising image.

Based on the turbulence structure, the deep learning convolution kernel incorporates the wavelet basis, and a more dense block structure is supplied as the major innovation. In this paper, many noise reduction strategies were examined, median filtering, wiener filtering, and mean filtering are just a few examples. Each algorithm's benefits and drawbacks are also discussed. Using the three suggested wavelet denoising techniques, the snr, peak signal, the normalized mean square error of each strategy were calculated, and the execution times of each method are compared. Thus, it is shown that the wavelet threshold filtering approach reduces noise both effectively and inexpensively.

## References

J. Kim, J. K. Lee, and K. M. Lee, "Accurate image super-resolution using very deep convolutional networks," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) IEEE, 2016.

J. Kim, J. K. Lee, and K. M. Lee, "Deeply-recursive convolutional network for image super-resolution," 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR) IEEE, 2016.

X. Sun, L. Liu, Q. Li, J. Dong, E. Lima, R. Yin, "Deep pixel-to-pixel network for underwater image enhancement and restoration," IET Image Process., vol.13, no. 3, pp. 469–474, 2019.

W. Hou, Z. Lee, and A. D. Weidemann, "Why does the Secchi disk disappear? An imaging perspective," Opt. Express, vol. 15, no. 6, pp. 2791–2802, 2007.

G. Nootz, E. Jarosz, F. R. Dalgleish, W. Hou, "Quantification of optical turbulence in the ocean and its effects on beam propagation," Appl. Opt., vol. 55, no. 31, pp. 8813–8820, 2016.

Mukherjee, S.; Valenzise, G.; Cheng, I. Potential of deep features for opinion-unaware, distortion-unaware, no-reference image quality assess- ment. In Smart Multimedia. ICSM 2019; Lecture Notes in Computer Science; Springer: Cham, Switzerland, 2020; pp. 87–95.

Wang, Y.; Zhang, J.; Cao, Y.; Wang, Z. A deep CNN method for underwater image enhancement. In Proceedings of the International Conference on Image Processing, Beijing, China, 17–20 September 2017.

Y. Peng, P. Cosman, "Underwater image restoration based on image blurriness and light absorption," IEEE Trans. Image Process., vol. 26, no. 4, pp. 1579–1594, 2017

C. Ancuti, C.O. Ancuti, P. Bekaert, "Enhancing underwater images and videos by fusion," In Proceedings of the 2012 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), Providence, RI, USA, 16–21 June 2012; pp. 81–88.

A. Ghani, N. Isa, "Underwater image quality enhancement through integrated color model with Rayleigh distribution," Appl. Soft Comput., vol. 27, pp. 219–230, Feb. 2015.

C. Li, J. Guo, C. Guo, R. Cong, J. Gong, "A hybrid method for underwater image correction," Pattern Recognit. Lett., vol. 94, pp. 62–67, Jul. 2017.

Y. Chen, and J. Chen, "Spatial adaptive regularized MAP reconstruction for LD-based night vision," Optik - International Journal for Light and Electron Optics, vol. 125, no. 13, pp. 31623165, 2014.

A. Duarte, F. Codevilla, J. D. O. Gaya, S. S. C. Botelho, "A dataset to evaluate underwater image restoration methods," OCEANS 2016 – Shanghai, Shanghai, China, 2016.

Hou W,Gray D J,Weidemann A D, et al. Automated underwater image restoration and retrieval of related optical properties. Geoscience and Remote Sensing Symposium, 2007. IGARSS 2007. IEEE International. 2007:1889-1892.

He Duo-min, Seet Gerald G.L. Laser gated-ranging for underwater robot vision in turbid waters. Proceedings of SPIE - The International Society for Optical Engineering. 2002, 4546: 11-22

C. S. Tan, G. Seet, A. Sluzek, D. M. He,"A Novel Application of Range Gated ULIS in Near Target Turbid Medium", Journal of Optics and Laser in Engineering, Vol. 43, 995-1009, 2005.