J.Natn.Sci.Foundation Sri Lanka 2024 52 (4): 527 - 540
DOI: http://dx.doi.org/10.4038/jnsfsr.v52i4.12150

RESEARCH ARTICLE

Communication Engineering

Unveiling the depths of underwater image enhancement with spatial blended CNN: Diving into clarity

R Ahila Priyadharshini*, S Arivazhagan and K Ramajeyam
Mepco Schlenk Engineering College, Mepco Nagar, Sivakasi, Tamil Nadu 626005, India.

Submitted: 29 July 2024; Revised: 05 December 2024; Accepted: 09 December 2024

Abstract: This study introduces a pioneering approach called spatial blended convolutional neural network (SBCNN) tailored specifically for enhancing the visual quality of underwater images. Traditional methods often struggle with the challenges posed by underwater environments, such as light absorption, scattering, and colour distortion. SBCNN addresses these challenges by combining spatial techniques with convolutional neural networks (CNNs), leveraging the strengths of both approaches. The architecture of SBCNN is designed to effectively capture spatial details and structural information inherent in underwater images. It incorporates spatial CNN branches, which are specialized components dedicated to analyse and enhance spatial features within the image. By integrating these spatial branches with traditional CNN layers, SBCNN can effectively address the unique characteristics of underwater imagery. To assess the performance of SBCNN, the study conducted comprehensive experimental evaluations using three different datasets: UIEB, EUVP, and UFO-120 and quantitative metrics such as peak signal-to-noise ratio (PSNR), mean square error (MSE), and Structural Similarity Index (SSIM) were utilized to compare the results with existing methods. The findings from these evaluations demonstrated significant improvements achieved by SBCNN over traditional techniques, indicating its effectiveness in enhancing the visual quality of underwater images. Furthermore, to validate the generalizability of the proposed method, cross-dataset testing was conducted on the EUVP ImageNet dataset and UIEB dataset.

Keywords: Contrast enhancement, Contrast stretching, convolution neural network, deep learning, Homomorphic filtering, underwater images.

INTRODUCTION

Underwater image enhancement is a field of research focused on improving the quality and visibility of images captured in underwater environments. Underwater imaging presents unique challenges due to the interaction of light with water. These challenges include light absorption, scattering, and colour distortion, which degrade the visible quality of underwater images. When light enters the water, it undergoes absorption by water molecules and dissolved substances. Different wavelengths of light are absorbed to different extents, resulting in colour changes and loss of originality in underwater images. As a result, underwater scenes often appear dominated by shades of blue or green, making it difficult to accurately perceive and differentiate objects (Ancuti *et al.*, 2012). Scattering is another significant challenge in underwater imaging. When light encounters suspended particles, plankton, and other impurities in the water, it scatters in different directions. This scattering causes a reduction in contrast, making objects appear blurry or hazy, and reducing the visibility of fine details. As a result, underwater images often lack sharpness and low clarity, making it more challenging to discern objects and structures (Liu *et al.*, 2019). In addition to absorption and scattering, water also introduces haze and reduces contrast in underwater images. Haze is caused by the presence of suspended particles and dissolved organic matter, which scatter light

* Corresponding author (rahila@mepcoeng.ac.in; https://orcid.org/0000-0001-9265-4842)

and create a hazy appearance. This haze further reduces visibility and limits the depth perception in underwater scenes. Overcoming these challenges and enhancing underwater images is crucial for various applications. In scientific research, underwater images provide valuable information about marine ecosystems, species behaviour, and environmental changes (Prasath & Kumanan 2020). By improving the visibility and quality of these images, researchers can extract more accurate data and gain a better understanding of underwater environments. In fields such as underwater archaeology, enhanced images enable the documentation and analysis of submerged artifacts and structures, aiding in the preservation and interpretation of our cultural heritage.

Over the years, researchers have explored both traditional methods and deep learning methods to address this problem. Traditional image enhancement methods can be divided into two categories: physical models and non-physical models. Physical models attempt to restore an image to its original state, while non-physical models enhance the image without attempting to restore it. Newer deep learning-based image enhancement methods can be divided into two categories: convolutional neural network (CNN)-based models and generative adversarial network (GAN)-based models. CNN-based models learn to enhance images by analyzing a large dataset of images. GAN-based models use two neural networks to compete, one network trying to generate realistic images and the other network trying to distinguish between real and fake images.

Initially, traditional methods aim to address challenges in underwater imagery, such as colour casts, low contrast, and haze caused by light absorption and scattering. For instance, Hitam *et al.* (2013) proposed an adaptive histogram equalization technique specifically designed for underwater image enhancement. Unlike traditional histogram equalization, which applies a single transformation to the entire image, this method adaptively divides the image into smaller regions and performs histogram equalization independently in each region. By considering the local characteristics of an image, this approach can effectively enhance the contrast and visibility of the underwater images. Bianco *et al.* (2015) adopted a colour correction technique that considers the physical properties of light absorption in water. It models the light absorption process using the properties of water, and uses this information to estimate and correct the colour cast in underwater images. By considering the specific wavelengths of light absorbed by water, this method can effectively restore true colours and enhance the visual quality of underwater images. In the work proposed by Abin *et al.* (2021), a fusion-based technique that combines information from multiple underwater images to enhance visual quality was proposed. By capturing multiple images with different exposure settings or from different viewpoints, this method overcomes the limitations of a single image and extracts more accurate scene detail. The captured images were aligned and fused using advanced image-fusion algorithms, resulting in an enhanced image with improved colour, contrast, and visibility. Zhou *et al.* (2022) developed a retinex theory, which aims to decompose an image into its reflectance and illumination components, to enhance underwater images. This approach employs multiscale analysis to capture both local and global image information. By manipulating the illumination component, which represents global lighting conditions, this method can alleviate the colour cast and significantly improve the overall appearance of underwater images. The approach of Muniraj and Dhandapani (2021) drew inspiration from image-dehazing techniques and adapted them for underwater image enhancement. It is assumed that the degradation of underwater images is similar to the effects of atmospheric haze in land-based images. This method employs dehazing algorithms to estimate and remove underwater haze, thereby enhancing the contrast, clarity, and visibility of underwater images. It considers the unique characteristics of underwater scenes and properties of light scattering in water.

Traditional methods struggle to address the complex combination of light absorption, scattering, and colour distortion in severely degraded underwater images. Their simplistic enhancement techniques often fail to recover details from such images. Basic colour correction methods (*e.g.*, white balance adjustment) often fall short in underwater conditions because they cannot accurately restore colours in images with severe wavelength-dependent absorption, especially when red wavelengths are completely lost. Many traditional methods rely on manually tuned parameters (*e.g.*, filter sizes, contrast enhancement levels), which can be difficult to optimize for different underwater conditions. This manual tweaking makes it hard to automate the enhancement process for a wide variety of images

In recent years, deep learning has gained significant popularity due to its effectiveness in various image processing tasks, including computer vision, image segmentation, pattern recognition, and image enhancement (Priyadharshini *et al.*, 2021, 2023; Arun *et al.*, 2024). CNN-based algorithms focus on preserving the original underwater image, while GAN-based approaches are designed to enhance the perceptual quality of the images. However, the need for a large number of labelled images poses a challenge in real-world deep learning-based underwater image enhancement (Yang *et al.*, 2019). Hashisho *et al.* (2019) developed a real-time underwater image-enhancement model based on an end-to-end deep neural network. Their approach utilized a U-Net architecture with skip connections to capture both low- and high-level image features, resulting in an accurate enhancement. Although the model achieved real-time performance and showed practical applicability, a drawback of this method is its dependence on large-scale annotated datasets, which can be time consuming and resource intensive. Consequently, the generalizability of this model to diverse underwater conditions is limited.

With the advent of deep convolutional neural networks, Li *et al.* (2020) proposed a deep learning-based method for enhancing underwater images using underwater scene priors. By incorporating these priors into their deep neural network architecture, they successfully improved visibility and restored colour in underwater images. However, one drawback of this approach is its limited effectiveness when applied to underwater scenarios with different characteristics. WaterNet is a deep learning-based approach proposed by Li *et al.* (2020) for underwater image enhancement. It utilizes a fully convolutional network (FCN) architecture to enhance the visual quality of underwater images. WaterNet effectively enhances the image clarity, colour correction, and overall visibility by training on a large dataset of paired underwater and reference images. Underwater convolutional neural network (UWCNN) is another deep learning method for underwater image enhancement introduced by Anwar *et al*. (2018). UWCNN employs a deep convolutional neural network with skip connections to capture and restore both low-level and high-level features in underwater images. By incorporating skip connections, the UWCNN effectively preserves fine details during the enhancement process. This model was trained using a dataset of paired underwater and reference images to learn the mapping between degraded and enhanced image domains.

GAN-based methods, such as underwater GAN, proposed by Wang *et al.* (2019), leverage an adversarial learning framework to generate realistic and visually pleasing enhanced images. GAN-based methods produce visually appealing enhancements by capturing the statistical properties of the underwater scenes. In addition, CycleGAN, proposed by Du *et al.* (2021), is another popular deep learning model used for underwater image enhancement. CycleGAN is an image-to-image translation model that can learn mappings between different domains without requiring paired training data. By training on unpaired datasets of underwater and reference images, CycleGAN can learn to transform underwater images to resemble the characteristics of reference images, thereby effectively enhancing the visibility and overall quality of underwater images. While GANs offer significant potential in underwater image enhancement, their limitations such as the need for large datasets, training instability, potential artifacts, and computational complexity must be carefully considered and mitigated in practical applications.

In this study, we propose a spatial blended convolutional neural network (SB-CNN) technique by leveraging deep learning, specifically convolutional neural networks in combination with the traditional spatial enhancement technique, to enhance underwater images. The main contributions of this study are as follows.

- Integration of deep CNN architecture with spatial enhancement technique to enhance image quality by preserving consistent colouring, structural similarity of scene content, and image sharpness.
- Experiments are conducted using spatial techniques and deep learning techniques individually as well as in a combined manner.
- Experiments, conducted on widely used datasets such as UEIB, UFO-120, and EUVP, demonstrate that our method delivers competitive performance while ensuring interpretability.
- Cross validation on different datasets is carried out to prove the potential efficiency of this approach

MATERIALS AND METHODS

In this section, the datasets used for the experimentation, the proposed deep CNN architectures and the concept of transforming underwater images with spatial blended CNN enhancement are discussed.

UIEB dataset

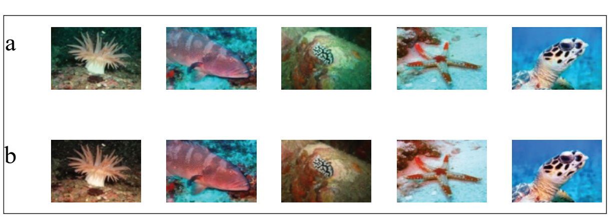
The underwater image enhancement benchmark (UIEB) dataset comprises raw underwater images alongside their corresponding pseudo-reference images, which are used as a standard for evaluating real-world underwater image enhancement. For each raw image, the pseudo-reference is selected from results produced by various UIE algorithms, aiming to identify the best possible enhancement. The subjective quality evaluation study of Li *et al.* involved gathering 890 raw underwater images and their associated mean opinion scores (MOSs) through repeated assessments. This dataset offers a wide range of underwater scenes, showcasing diverse image content, resolutions, and quality degradation patterns (Li *et al.*, 2020). Furthermore, the dataset also includes an additional set of 60 challenging images, which play a vital role in evaluating the efficacy of image enhancement algorithms. The sample images of UIEB dataset are shown in Figure 1.

Source: Li *et al.*, 2020

Figure 1: Sample images of UIEB dataset (a) raw images (b) reference images

UFO-120 dataset

The UFO-120 dataset is a specialized collection of underwater images designed for research and development in the field of underwater image enhancement and restoration. It was developed to address the challenges posed by underwater environments, such as colour distortions, poor visibility, and noise, which degrade image quality due to the scattering and absorption of light underwater (Jahidul Islam *et al.*, 2020). Each image is accompanied by an associated ground truth image, resulting in a collection of 120 ground truth images. The images showcase a diverse range of underwater scenes, encompassing different settings, lighting conditions, and subject matter. The sample images of UFO-120 dataset are shown in Figure 2.

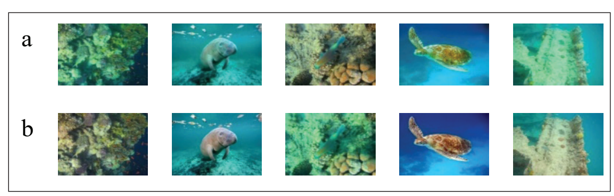


Source: Islam *et al.*, 2020

Figure 2: Sample images of UFO-120 dataset (a) low-resolution distorted images (b) high-resolution ground truth images

EUVP dataset

The enhanced underwater visual perception (EUVP) dataset contains an extensive collection of both paired and unpaired underwater images, including around 12,000 paired underwater dark, underwater ImageNet and underwater scenes and 8,000 unpaired samples. These images exhibit a wide range of perceptual quality, spanning from low to high. The dataset was created using seven different cameras, capturing images under diverse lighting conditions and water types. To generate distorted images from high-quality ones, the authors (Islam *et al*., 2020) utilized a learned underwater distortion model based on CycleGAN, ensuring realistic representation of underwater visual degradation. The EUVP underwater scene dataset includes various real and synthetic underwater environments like coral reefs, marine life, and wrecks, showcasing typical underwater challenges such as colour distortion, low contrast, and lighting issues. The EUVP ImageNet dataset consists of underwater-degraded images derived from ImageNet (a large-scale visual database for object recognition) scenes. These images have been artificially degraded to simulate underwater conditions. In this dataset, clear ImageNet images are transformed to mimic underwater distortions such as colour degradation, blurring, and contrast reduction: mimicking light attenuation in water. The EUVP underwater dark dataset contains underwater images captured in dimly lit or deep-sea environments where natural light is minimal or absent. These images exhibit extreme darkness, low contrast, and significant noise. The sample images of EUVP underwater scene dataset are shown in Figure 3.



Source: Islam *et al*., 2020

Figure 3: Sample images of EUVP underwater scene dataset (a) Input images (b) Ground truth images

Proposed SBCNN approach

This research work deals with two different approaches: non-physical model enhancement methods and transforming underwater images with spatial blended CNN enhancement methods for underwater image enhancement.

Proposed spatial enhancement methods

The proposed methodology aims to improve the visual quality of underwater images using a combination of techniques, as shown in Figure 4. The methodology consisted of several interconnected stages. In the first stage, colour correction (Tarhate, 2020) was applied to address colour distortion issues commonly found in underwater images. This step mitigates the distortions caused by the absorption and scattering of light in water, thereby restoring the original colour of the scene. White balancing involves both eliminating unwanted colour casts and adjusting white light to appear cooler. According to the white patch theory, the white balance algorithm relies on the maximum value of the combined blue, green, and red channels to adjust colours. Padding is then applied by adding empty pixels around the image's edges to preserve its original dimensions, ensuring the image's size and shape remain intact. Gamma correction is applied to control the overall brightness of an image, improving results when the image appears too dark or overly bright. The gamma value is typically set to 0.7 based on observation. The mathematical formula for gamma correction is shown in equation 1:

$$F' = 255 \times \left(\frac{F}{255}\right)^{\gamma} \quad ...(1)$$

where F' represents the corrected intensity, F is the original intensity, and γ is the gamma value.

Unsharp masking (USM) is a popular technique used to enhance image sharpness. Despite the name, it is designed to make an image look sharper by increasing the contrast along edges and fine details. The formula for unsharp masking is shown in equation 2:

$$F_s = F + \beta(F - G * F) \quad ...(2)$$

where: F_s is the sharpened image, $G * F$ is the blurred (Gaussian-filtered) version of the image. In this work, β (scaling factor controlling the sharpness intensity) is set as 1.

Homomorphic filtering (Seow & Asari, 2004) is used to enhance image quality further. This technique operates in the frequency domain by modifying the amplitudes of the frequency components in the image. Homomorphic filtering improves the clarity and detail of underwater images by selectively amplifying specific frequency ranges. The subsequent stage focuses on fusion, in which multiple images or image components are combined to create a single composite image with improved visual quality. Fusion techniques help integrate information from different images captured under varying conditions, reduce noise, enhance details, and improve the overall image quality. The fusion used here is average fusion. Finally, contrast stretching (Samir, 2020) was employed to address the poor contrast that is often observed in underwater images. This technique expands the range of intensity values in an image and improves the contrast and object visibility in underwater scenes. To evaluate the performance of the methodology, full-reference metrics (Guo *et al.*, 2022) were utilized to objectively measure the image quality.

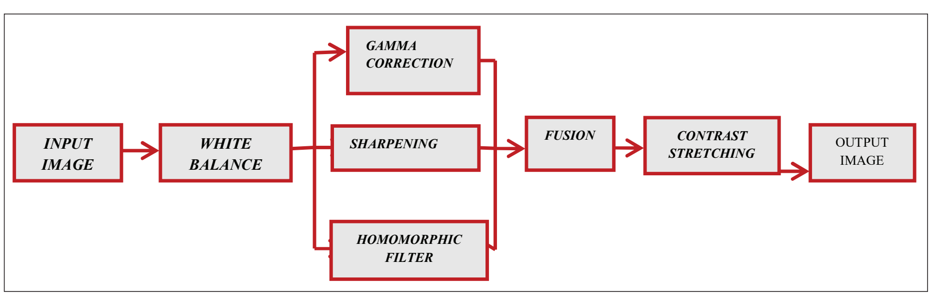


Figure 4: Block diagram of proposed spatial enhancement technique

Proposed spatial blended CNN enhancement method

A novel method called spatial blended CNN is introduced for enhancing the sharpness and detail of images. The approach involves blending information from different scales to improve spatial resolution. The CNNs are used in this approach for feature extraction at different scales. The CNN learns to identify key features such as edges, textures, and other details from the input image. These features are extracted at various resolutions, which are then combined to form a sharper, more detailed output. Feature maps from different scales are concatenated along the channel dimension. This approach preserves all information from each scale, giving the network more flexibility. The spatial blended CNN architecture stands out by omitting normalization techniques and fully connected layers, providing a unique approach to enhance underwater images. Normalization layers (Batch Normalization) are often used to stabilize training and accelerate convergence. However, they may inadvertently suppress or distort fine image details, which are critical for high-quality image enhancement tasks. By omitting normalization, the architecture retains the raw range of feature values, potentially preserving subtle details crucial for the enhancement process. Fully connected layers are typically used for tasks like classification or regression, where global image context is more relevant than spatial relationships. For image-to-image tasks like enhancement, spatial relationships and local features are more important. Fully connected layers, being inherently global, can lead to loss of spatial details. Instead, the architecture likely relies on convolutional layers that retain spatial information. The spatial blended CNN enhancement method is illustrated in Figure 5.

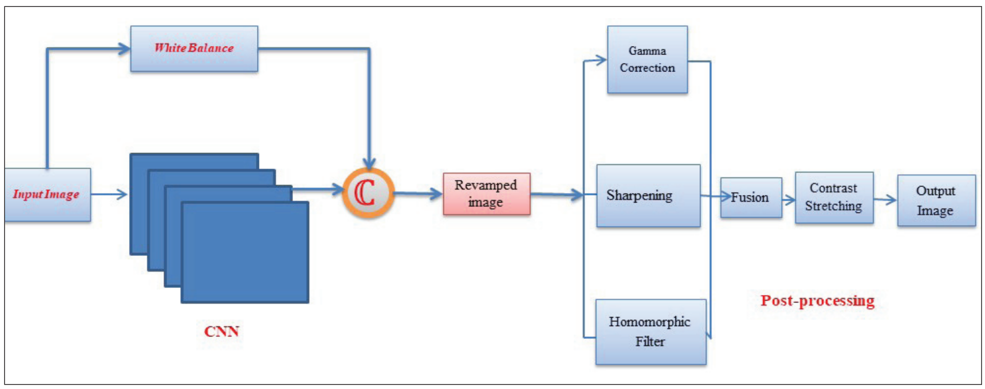


Figure 5: Block diagram of proposed spatial blended CNN enhancement method

The method starts by preprocessing the input images. The images were resized to standardized dimensions of 256 × 256 pixels. To address colour distortion, red and blue channels are corrected with respect to green channel. First the RGB channels are normalized using the equation 3.

$$C'_i = C_i \times \frac{m_{Gray}}{m_{C_i}} \quad ...(3)$$

Where C_i': The normalized value of the colour channel *i* (either Red, Green, or Blue).

C_i: The original value of the colour channel *i*.

m_{Gray}: The mean of the grayscale version of the image.

m_{C_i}: The mean of the colour channel *i*.

Then the colours in red and blue channels are corrected using equation 4 and 5 respectively.

$$R = C_R - 0.3(m_{C_G} - m_{C_R})C_G(1 - C_R) \quad ...(4)$$

$$B = C_B - 0.3(m_{C_G} - m_{C_B})C_G(1 - C_B) \quad ...(5)$$

This colour correction step aims to restore accurate colour information and enhance overall visual quality.

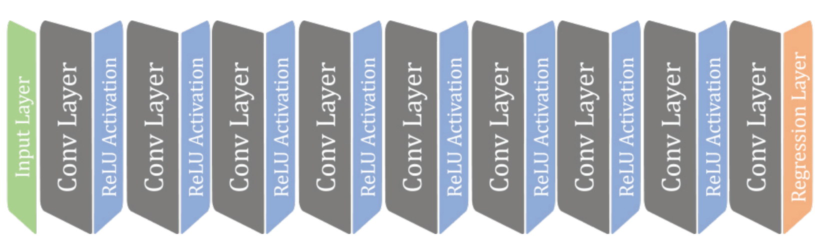


Figure 6: Proposed CNN architecture

Following the preprocessing stage, the method incorporates a deep CNN architecture, as shown in Figure 6, to learn the complex mapping between the original and enhanced images. A CNN consists of eight convolutional layers, typically followed by rectified linear unit (ReLU) activation, which introduces nonlinearity into the network. A regression layer is then added with the ninth convolutional layer to enable direct image enhancement. In each convolutional layer 128 filters with size 3 ×3 are used. By training the CNN with 600 epochs and a batch size of 128, the model learned to extract high-level features and generate enhanced images with improved visibility, reduced colour distortion, and enhanced overall quality. The learning rate is set as 0.001. Once the CNN model is trained, it is used to predict the enhanced images of the original underwater inputs. To further refine the quality of the predicted images, a series of post processing techniques were applied (Mousavi *et al.*, 2023). These techniques include gamma correction to adjust pixel intensities, unsharp masking to enhance image sharpness, and contrast stretching to expand the dynamic range of the pixel values. The combination of these techniques results in enhanced underwater images with improved brightness, contrast, and visual appeal.

The training method involves pairing each input image with a corresponding reference image that serves as the target for training. The root mean square error (RMSE) is used as the loss function to measure the discrepancy between the enhanced and target images (Anwar *et al.*, 2018). The RMSE loss function is represented by equation 6,

$$RMSE = \sqrt{\frac{1}{MNO} \sum_{i,j,k=1}^{M,N,O} [h(x) - y(x)]^2} \quad ...(6)$$

where *M, N,* and *O* denote the height, width, and number of channels in the image, respectively. The variables *i, j*, and *k* represent the coordinates within the three dimensions of the image. *h(x)* represents the original image, and *y(x)* represents the output image from CNN. The summation is performed over all pixel locations in the image.

RESULTS AND DISCUSSION

In this study, a method for enhancing underwater images is developed using a combination of spatial analysis and deep learning. Experiments were conducted to evaluate the effectiveness of the proposed approach by using three datasets: UIEB, UFO-120, and EUVP. The method was compared with existing techniques, and the results were measured using various metrics, such as PSNR, SSIM. This method showed significant improvements in image quality, reduced artifacts, and enhanced detail. A visual inspection confirmed the effectiveness of this approach.

Metrics

We performed a quantitative evaluation of the output of spatial blended CNN using well-established metrics commonly used in previous studies. These metrics include the mean square error (MSE), peak signal-to-noise ratio (PSNR), and structural similarity index (SSIM). The PSNR metric quantifies the similarity between an image *x* and a reference image y by calculating the mean-squared error (MSE) between them. The PSNR is given in equation 7:

$$PSNR(x,y) = 10 \log_{10} \left[{256^2}/{mse(x,y)} \right] \quad ...(7)$$

In this formula, MSE measures the average squared difference between the pixel values of *x* and *y*. The PSNR measures the ratio of the maximum possible pixel value squared (256^2 for an 8-bit image) to MSE. A higher PSNR value indicates greater similarity and better reconstruction quality between the images. The structural similarity index (SSIM) compares image patches based on their luminance, contrast, and structure. It quantifies the similarity between two images, *x* and *y*, using equation 8.

$$SSIM(x,y) = \frac{\left((2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)\right)}{[(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)]} \quad ...(8)$$

In this equation, μ represents the mean value, σ^2 represents the variance, and σ_{xy} represents the cross-correlation between images x and y. The constants c_1 and c_2 are included to ensure numerical stability and are calculated as $c_1 = (255 \times 0.01)^2$ and

An SSIM value of 1 signifies identical images (which are undesirable in image enhancement); it should not be excessively low. In most cases, an SSIM value between 0.5 and 1 is considered desirable, striking a balance between preserving image structure and achieving desired enhancements.

Analysis

In this section, we analyze our proposed approach and evaluate its performance both qualitatively and quantitatively. We compare the results of our spatial approach and white balancing CNN with the Spatial Blended CNN in Table 1, 2, and 3. Additionally, we compare the performance of the spatial blended CNN with four state-of-the-art methods on the underwater image datasets mentioned earlier, as shown in Table 4 and 5. To assess the effectiveness of our method, we use a separate test set comprising two different dataset images that were not used during the training of the colour model in the spatial blended CNN pipeline. The results presented in the tables clearly demonstrate that the spatial blended CNN outperforms all other methods in terms of the MSE, PSNR, and SSIM metrics, establishing itself as the top-performing technique for underwater image enhancement on the above mentioned datasets.

Spatial approach

A spatial approach mentioned in Figure 4 was employed to enhance underwater images by applying various filters. These filters aimed to address issues such as low contrast, colour distortion, and noise. The results of the enhancement process were evaluated using several metrics, which are presented in Table 1. Additionally, a sample output image is provided to visually demonstrate the improvements achieved through the spatial approach. The sample image enhanced using this approach is shown in Figure 7.

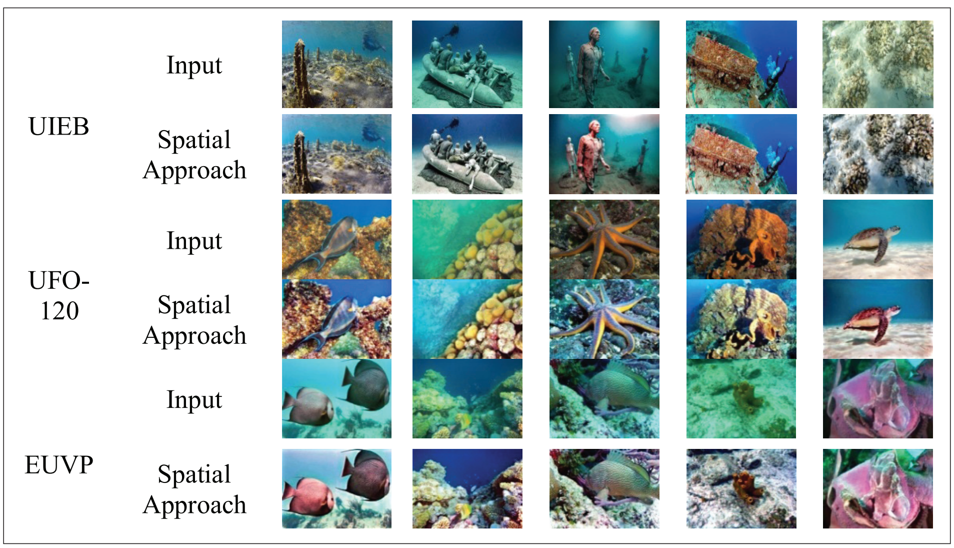


Figure 7: Sample enhanced image using spatial approach with different dataset

When evaluated on the EUVP test image dataset, the method achieves better PSNR, MSE, and SSIM results compared to the UIEB and UFO-120 datasets.

Table 1: Evaluation metrics for spatial approach

Dataset	Spatial approach		
	MSE ($\times 10^3$)	PSNR	SSIM
UIEB	1.292	17.542	0.7197
UFO-120	1.220	17.043	0.719
EUVP	1.179	18.641	0.7961

White balancing CNN

A white balancing CNN was developed to enhance underwater images by improving their colour accuracy and reducing colour casts caused by water's properties. This approach is similar to SB-CNN without post processing. The CNN was trained using a dataset of RGB underwater images and corresponding ground truth images with white balance adjustments. The trained network was then used to enhance new underwater images, resulting in improved colour accuracy and reduced colour casts. Figure 8 displays the output image generated by the white balancing CNN, and Table 2 provides a summary of the evaluation metrics. The white balancing CNN exhibited effectiveness in enhancing underwater images, yielding higher PSNR and SSIM values, as well as lower MSE values, compared to the spatial approach. Notably, when examining the performance across different datasets, the EUVP dataset consistently yielded superior results compared with the UIEB and UFO-120 datasets within the white balancing CNN network.

Table 2: Evaluation metrics for white balancing CNN approach

Datasets	White balancing CNN		
	MSE ($\times 10^3$)	PSNR	SSIM
UIEB	0.831	19.721	0.758
UFO-120	1.102	18.659	0.752
EUVP	0.738	21.178	0.778

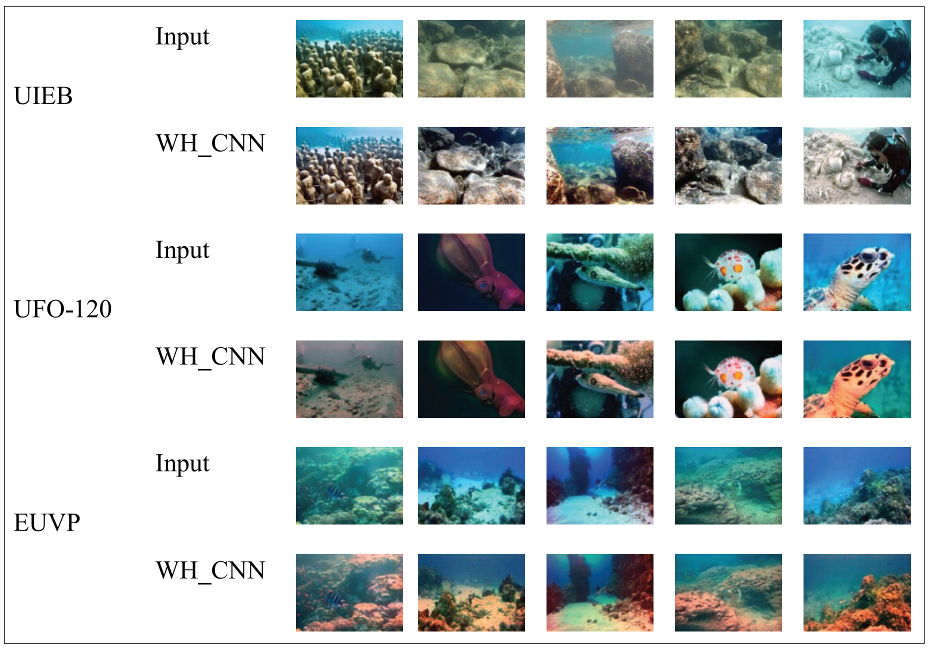


Figure 8: Sample enhanced image using white balancing CNN with different datasets

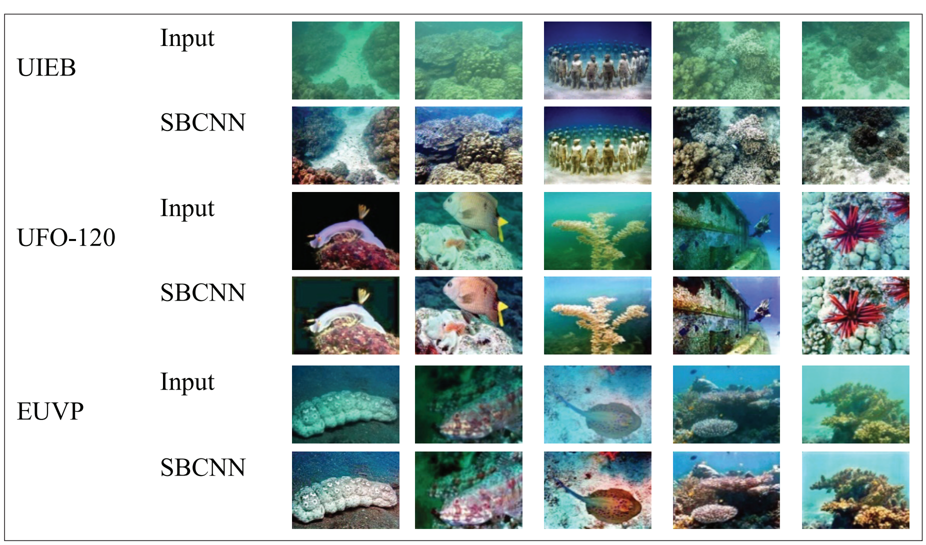


Figure 9: Sample enhanced image using spatial blended CNN with different datasets

Spatial blended CNN

The spatial blended CNN shown in Fig 5 is used to enhance underwater images, combining spatial processing techniques with convolutional neural networks. The sample image enhanced using this approach is shown in Figure 9. Table 3 displays the evaluation metrics for the spatial blended CNN. The results in Table 3 demonstrate the effectiveness of the spatially blended CNN in enhancing underwater images. The higher PSNR and SSIM values, along with the lower MSE values, indicate improved image quality, better similarity to the reference images, and reduced errors. Notably, the spatial blended CNN performed exceptionally well on the EUVP, UIEB, and UFO-120 datasets, producing high-quality images comparable to the reference images. These results clearly establish the superiority of the spatial blended CNN over both the spatial approach and white balancing CNN in the arena of underwater image enhancement. Figure 10 depicts the visual comparison of different underwater image enhancement methods adopted in this work.

Table 3: Evaluation metrics for spatial blended CNN

Datasets	Spatial blended CNN		
	MSE (×10^3)	PSNR	SSIM
UIEB	0.341	22.879	0.871
UFO-120	0.202	25.212	0.800
EUVP	0.160	26.380	0.789

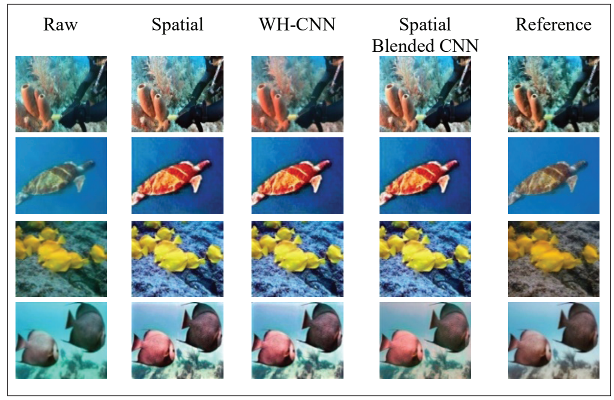


Figure 10: visual comparison of different underwater image enhancement methods including spatial approach, white balance CNN, and spatial blended CNN

While the spatial approach may have obtained lower metric scores, it demonstrated exceptional performance in enhancing the image quality. In contrast, the white-balancing CNN achieved a higher overall image quality. However, it is a spatially blended CNN that has proven to be the most effective method for producing high-quality images that closely resemble the reference images. The spatial blended CNN achieved higher metrics, indicating superior image quality. To further evaluate its performance, a comparison can be made between the metrics (PSNR and SSIM) and visual quality of the spatial blended CNN with other existing methods.

Table 4: Performance comparison of SBCNN with existing approaches.

Dataset	Metrics	WaterNet (Li *et al* 2020)	FUnIE-GAN (Islam *et al* 2020)	Deep SESR (Jahidul *et al* 2020)	Shallow-UWnet (Naik *et al* 2021)	FUnIE-GAN-UP (Islam *et al* 2020)	UGAN (Fabbri *et al* 2018)	UGAN-P (Fabbri *et al* 2018)	iDehaze (Mousavi *et al* 2023)	SBCNN
UIEB	MSE (×10^3)	0.843	0.824	0.803	0.890	-	-	-	1.062	**0.341**
	PSNR	19.110	19.130	19.260	18.990	-	-	-	17.960	**22.878**
	SSIM	0.790	0.730	0.730	0.670	-	-	-	0.800	**0.871**
UFO-120	MSE (×10^3)	0.293	0.231	**0.153**	0.198	0.299	0.238	0.248	1.217	0.202
	PSNR	23.120	24.720	**26.460**	25.200	23.290	24.23	24.110	17.550	25.212
	SSIM	0.730	0.740	0.780	0.730	0.670	0.690	0.690	0.720	**0.800**
EUVP	MSE (×10^3)	0.226	0.142	0.193	**0.104**	0.196	0.155	0.155	0.322	0.16
	PSNR	24.430	26.190	25.300	**27.390**	25.210	26.530	26.530	23.010	26.379
	SSIM	0.820	0.820	0.810	0.830	0.780	0.800	0.800	**0.840**	0.789

This comprehensive assessment will provide a more comprehensive understanding of the effectiveness of spatial blended CNN's in enhancing underwater images.

Table 4 presents a comprehensive comparison between the spatial blended CNN and various existing methods, including WaterNet, FUnIE-GAN, deep SESR, Shallow-UWNet, UGAN and iDehaze. In terms of SSIM, the SBCNN showed a slight advantage over Shallow-UWNet, but it exhibited a relatively higher standard deviation, indicating less stability in its results. The qualitative analysis on UIEB, EUVP and UFO-120 datasets are shown in Figures 11, 12 and 13 respectively. Interestingly, when specifically compared to WaterNet using the UIEB dataset, the SBCNN demonstrated more accurate SSIM results and higher stability. It is worth noting that the comparison with the UIEB dataset showed better results for the spatial blended CNN, while the average results of the approach were obtained by evaluating it with the UFO120 and EUVP datasets.

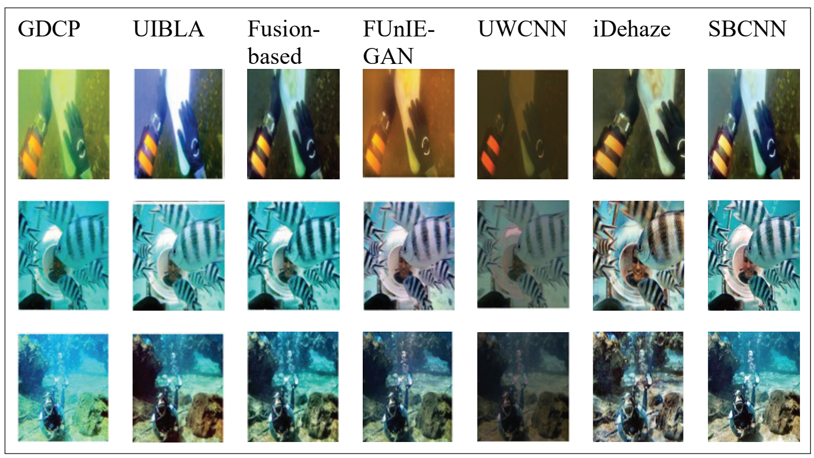


Figure11: Qualitative analysis on UIEB dataset. Existing approaches include Red Channel (Galdran *et al* 2015), GDCP (Peng *et al* 2018), UIBLA (Peng & Cosman 2017), Fusion-Based (Ancuti *et al* 2012), FUnIE-GAN (Islam *et al* 2020) ,UWCNN (Li *et al* 2020) and iDehaze (Mousavi *et al* 2023)

Figure12: Qualitative analysis on EUVP dataset. Existing approaches include deep SESR (Jahidul *et al* 2020), FUnIE-GAN and FUnIE-GAN-UP (Islam *et al* 2020), UGAN and UGAN-P (Fabbri *et al* 2018) and iDehaze (Mousavi *et al* 2023)

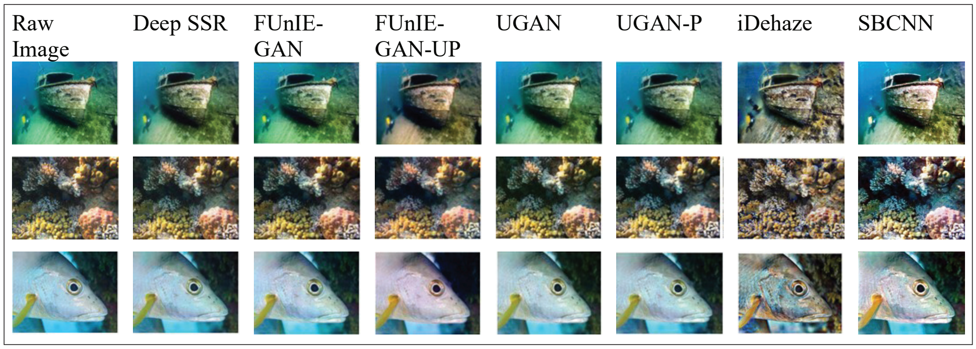


Figure13: Qualitative analysis on UFO-120 dataset. Existing approaches include Deep SESR (Jahidul *et al* 2020), FUnIE-GAN and FUnIE-GAN-UP (Islam *et al* 2020), UGAN and UGAN-P (Fabbri *et al* 2018) and iDehaze (Mousavi *et al* 2023)

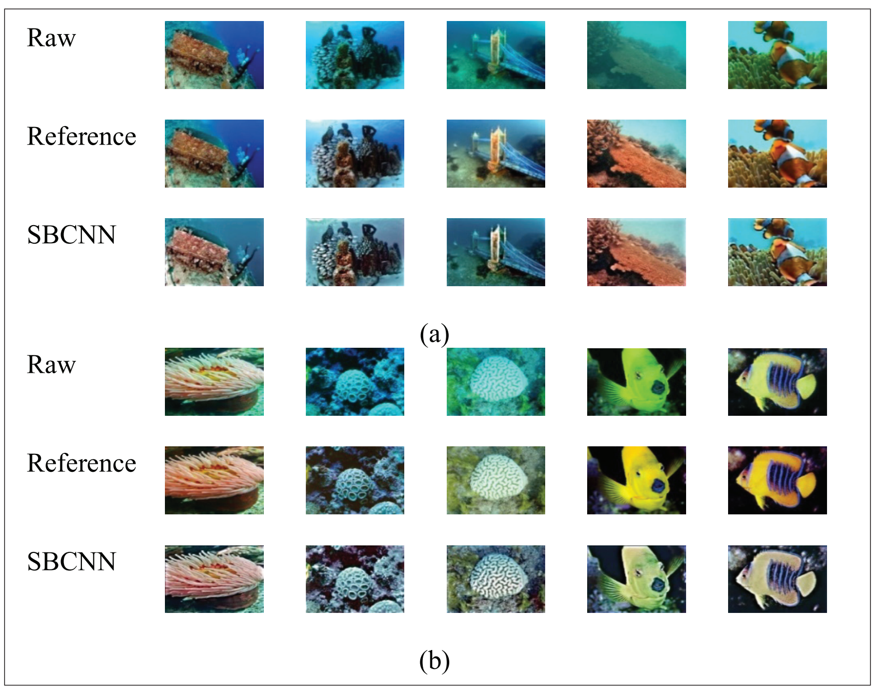


Figure14: Qualitative analysis of cross-validation on (a) UIEB dataset (b)EUVP ImageNet dataset

Cross-dataset Testing

The SBCNN trained on EUVP underwater scene dataset is evaluated with two extra datasets: the EUVP ImageNet dataset, containing underwater-degraded images derived from ImageNet database, and the UIEB dataset. By using these two distinct datasets in cross-testing, we can more rigorously assess the model's robustness, adjust hyperparameters as needed, and ensure that the enhanced images are consistent in quality across different types of underwater scenes. Figure 14 showcases the results of this cross-validation process, highlighting the performance and validation of the method in enhancing underwater images.

The cross-dataset testing results in Table 5 provide key quantitative insights into the SBCNN method's performance across the UIEB and EUVP ImageNet datasets. The lower mean squared error (MSE) values achieved on both datasets suggest that the SBCNN can closely reconstruct the ground truth images with minimal error, which is crucial for accurate underwater image enhancement. Specifically, the MSE value for the UIEB dataset is 0.809×10^3, while for the EUVP ImageNet dataset, it is slightly lower at 0.782×10^3. This small difference suggests a consistent performance across different underwater image sources, indicating the robustness of the method.

Table 5: Cross-dataset testing

Dataset	MSE ($\times10^3$)	PSNR	SSIM
UIEB	0.809	20.429	0.8283
EUVP imagenet	0.782	20.717	0.7538

CONCLUSION

In conclusion, the proposed method for enhancing underwater images demonstrates superior performance compared with existing techniques, as evidenced by improved objective metrics such as PSNR, MSE, and SSIM. By leveraging spatial processing techniques and a deep CNN architecture, this method effectively addresses common challenges in underwater imaging, including colour distortion, limited visibility, and scattered light, resulting in significant improvements in image quality. Moreover, innovative post-processing algorithms further refine the predicted images, enhancing brightness, contrast, and overall visual appeal. The combined use of deep learning techniques and spatial post-processing algorithms enables substantial improvements in colour accuracy, visibility, and overall image quality in the challenging domain of underwater imaging, making it a promising solution with diverse applications in marine research, underwater exploration, and related fields.

REFERENCES

Abin, D., Gulabani, B., Joshi, C., Damle, S., & Gengaje, S. (2021). Fusion based approach for underwater image enhancement. *2021 International Conference on Communication Information and Computing Technology (ICCICT)*. https://doi.org/10.1109/iccict50803.2021.9510127

Ancuti, C., Ancuti, C.O., Haber, T., & Bekaert, P. (2012). Enhancing underwater images and videos by fusion. *Proceedings of the 2012 IEEE Conference on Computer Vision and Pattern Recognition, Providence*, RI, USA, https://doi.org/10.1109/cvpr.2012.6247661.

Anwar, S., Li, C., & Porikli, F. (2018). Deep underwater image enhancement. *arXiv preprint arXiv:1807.03528*.

Arun M., Visvaja K., & Vidhya A. (2024). Implementing underwater image enhancement algorithms on resource constrained devices. *The Journal of Ocean Technology*, *19*(3), 100-116.

Bianco, G., Muzzupappa, M., Bruno, F., Garcia, R., & Neumann, L. (2015). A new color correction method for underwater imaging. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *XL-5/W5*, 25–32. https://doi.org/10.5194/isprsarchives-xl-5-w5-25-2015

Du, R., Li, W., Chen, S., Li, C., & Zhang, Y. (2021). Unpaired underwater image enhancement based on cyclegan. *Information*, *13*(1),1. https://doi.org/10.3390/info13010001

Fabbri, C., Islam, M. J., & Sattar, J. (2018). Enhancing underwater imagery using generative adversarial networks. *2018 IEEE International Conference on Robotics and Automation (ICRA)*. https://doi.org/10.1109/icra.2018.8460552

Galdran, A., Pardo, D., Picón, A., & Alvarez-Gila, A. (2015). Automatic red-channel Underwater Image Restoration. *Journal of Visual Communication and Image Representation*, *26*, 132–145. https://doi.org/10.1016/j.jvcir.2014.11.006

Guo, P., He, L., Liu, S., Zeng, D., & Liu, H. (2022). Underwater image quality assessment: Subjective and objective methods. *IEEE Transactions on Multimedia*, *24*, 1980–1989. https://doi.org/10.1109/tmm.2021.3074825

Hashisho, Y., Albadawi, M., Krause, T., & Freiherr von Lukas, U. (2019). Underwater Color Restoration using U-Net denoising autoencoder. *2019 11th International Symposium on Image and Signal Processing and Analysis (ISPA)*. https://doi.org/10.1109/ispa.2019.8868679

Hitam, M. S., Yussof, W. N., Awalludin, E. A., & Bachok, Z. (2013). Mixture contrast limited adaptive histogram equalization for Underwater Image Enhancement. *2013 International Conference on Computer Applications Technology (ICCAT)*. https://doi.org/10.1109/iccat.2013.6522017

Khanal, S. (2020). Contrast stretching. Medium. https://samirkhanal35.medium.com/contrast-stretching-f25e7c4e8e33

Islam, M. J., Xia, Y., & Sattar, J. (2020). Fast underwater image enhancement for improved visual perception. *IEEE Robotics and Automation Letters*, *5*(2), 3227–3234. https://doi.org/10.1109/lra.2020.2974710

Jahidul Islam, M., Luo, P., & Sattar, J. (2020). Simultaneous enhancement and super-resolution of underwater imagery for improved visual perception. *Robotics: Science and Systems XVI*. https://doi.org/10.15607/rss.2020.xvi.018

Li, C., Anwar, S., & Porikli, F. (2020). Underwater scene prior inspired deep underwater image and video enhancement. *Pattern Recognition*, *98*, 107038. https://doi.org/10.1016/j.patcog.2019.107038

Li, C., Guo, C., Ren, W., Cong, R., Hou, J., Kwong, S., & Tao, D. (2020). An underwater image enhancement benchmark dataset and beyond. *IEEE Transactions on Image Processing*, *29*, 4376–4389. https://doi.org/10.1109/tip.2019.2955241

Li, C., Anwar, S., & Porikli, F. (2020). Underwater scene prior inspired deep underwater image and video enhancement. *Pattern Recognit. 98*, 107038.

Liu, Y., Xu, H., Shang, D., Li, C., & Quan, X. (2019). An underwater image enhancement method for different illumination conditions based on color tone correction and fusion-based descattering. *Sensors*, *19*(24), 5567. https://doi.org/10.3390/s19245567

Mousavi, M., Estrada, R., & Ashok, A. (2023). iDehaze: Supervised underwater image enhancement and dehazing via physically accurate photorealistic simulations. *Electronics*, *12*(11), 2352. https://doi.org/10.3390/electronics12112352

Muniraj, M., & Dhandapani, V. (2021). Underwater image enhancement by combining color constancy and dehazing based on depth estimation. *Neurocomputing*, *460*, 211–230. https://doi.org/10.1016/j.neucom.2021.07.003

Naik, A., Swarnakar, A., & Mittal, K. (2021). Shallow-uwnet: compressed model for underwater image enhancement (student abstract). *Proceedings of the AAAI Conference on Artificial Intelligence*, *35*(18), 15853–15854. https://doi.org/10.1609/aaai.v35i18.17923

Peng, Y.-T., & Cosman, P. C. (2017). Underwater image restoration based on image blurriness and light absorption. *IEEE Transactions on Image Processing*, *26*(4), 1579–1594. https://doi.org/10.1109/tip.2017.2663846

Peng, Y.T., Cao, K., & Cosman, P.C. (2018). Generalization of the dark channel prior for single image restoration. *IEEE Trans. Image Process*. *27*, 2856–2868

Prasath, R., & Kumanan, T. (2020). Application of different techniques for underwater image processing- A systematic review. *IOP Conference Series: Materials Science and Engineering*, *925*(1), 012034. https://doi.org/10.1088/1757-899x/925/1/012034

Priyadharshini, R.A., Arivazhagan, S., & Arun, M. (2021). Ayurvedic medicinal plants identification: A comparative study on feature extraction methods. *Communications in Computer and Information Science*, *1377*, 268–280. https://doi.org/10.1007/978-981-16-1092-9_23

Priyadharshini, R.A., Arivazhagan, S., & Arun, M. (2023). Crack recognition on concrete structures based on machine crafted and hand crafted features. *Expert Systems with Applications*, *228*, 120447. https://doi.org/10.1016/j.eswa.2023.120447

Priyadharshini, R.A., Arivazhagan, S., Pavithra, K.A., & Sowmya, S. (2024). An ensemble deep learning approach for underwater image enhancement, e-Prime - Advances in Electrical Engineering, Electronics and Energy, Volume 9, 2024, https://doi.org/10.1016/j.prime.2024.100634.

Seow, M.-J., & Asari, V. K. (n.d.). (2024). Homomorphic processing system and ratio rule for color image enhancement. *2004 IEEE International Joint Conference on Neural Networks (IEEE Cat. No.04CH37541)*. https://doi.org/10.1109/ijcnn.2004.1381031

Tarhate, S. (2020). Weight maps guided underwater image enhancement by fusion technique. *Bioscience Biotechnology Research Communications*, *13*(14), 440–444. https://doi.org/10.21786/bbrc/13.14/99

The UFO-120 dataset. The UFO-120 Dataset | Minnesota Interactive Robotics and Vision Laboratory. https://irvlab.cs.umn.edu/resources/ufo-120-dataset

Wang, Nan, *et al.* UWGAN: underwater GAN for real-world underwater color restoration and dehazing. *arXiv preprint arXiv:1912.10269* (2019).

Yang, M., Hu, J., Li, C., Rohde, G., Du, Y., & Hu, K. (2019a). An in-depth survey of underwater image enhancement and restoration. *IEEE Access*, *7*, 123638–123657. https://doi.org/10.1109/access.2019.2932611

Zhou, J., Yao, J., Zhang, W. *et al.* (2022). Multi-scale retinex-based adaptive gray-scale transformation method for underwater image enhancement. *Multimed Tools Appl 81*, 1811–1831. https://doi.org/10.1007/s11042-021-11327-8.