Hybrid Denoised Underwater Image Enhancement and Restoration Techniques Using Dark Channel Prior and Image Filtering Techniques

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Abstract
Underwater image suffers from degradation in colour contrast due to light scattering and absorption. As a result it affects underwater vision tasks and research due to colour distortion, blurred details, and uneven illumination and noise, In this era limitation in marine exploration and robotics image enhancement is of great significance in vision applications is a big challenges. This paper proposes a hybrid framework integrating an enhanced Dark Channel Prior (DCP) with a multi-stage adaptive image filtering techniques pipeline for underwater image enhancement and restoration techniques for light estimation method which can enhance the underwater image quality. The DCP is optimized with depth-aware transmission estimation, while the filtering pipeline combines anisotropic diffusion, dynamic bilateral filtering, and a refined guided filter, supported by a wavelet-based noise estimation module. And it can be applied in more than 30m depth with emitted artificial light. By combining deep learning techniques to retrieve the red color component from the background illumination in the image's dark channel, which is usually missing due to underwater absorption. After this, an adaptive method is used to correct color distortions and accurately estimate the blur background light. The enhanced method is then applied to underwater images using a modified dark channel prior algorithm that incorporates the newly estimated background light. Experimental results confirm that this method significantly improves underwater image quality and effectiveness.
Key terms: colour contrast, marine exploration ,Dark Channel Prior (DCP) , deep learning, dark channel ,underwater image quality and effectiveness.

1. Introduction

Underwater imaging plays a pivotal role in various domains, including marine biology, underwater archaeology, seabed mapping, ecological monitoring, and autonomous underwater vehicle (AUV) navigation. However, capturing high-quality underwater images remains a significant challenge due to inherent optical distortions in the aquatic environment. These distortions primarily arise from light absorption and scattering, which result in low contrast, colour distortion, blurring, and noise, especially in deep-sea or turbid water conditions (Yang et al., 2019; Raihan et al., 2019).

Forward scattering and backward scattering are the two main forms of scattering processes that impact underwater photography (Gao and Li, 2010).Unlike red light, blue light travels a shorter wavelength, higher frequency, and greater energy, enabling it to travel deeper in underwater environments(Drews Jr. et al., 2016).

Blurring in the recorded image results from forward scattering, which occurs when some of the reflected light slightly veers off the direct route to the camera? Backward scattering, on the other hand, produces hazy or veiled effects on the picture when light from nearby illumination sources is scattered into the camera's field of view. The light attenuation model is shown in Figure 1, which shows how underwater picture quality is affected by both forward and backward scattering.

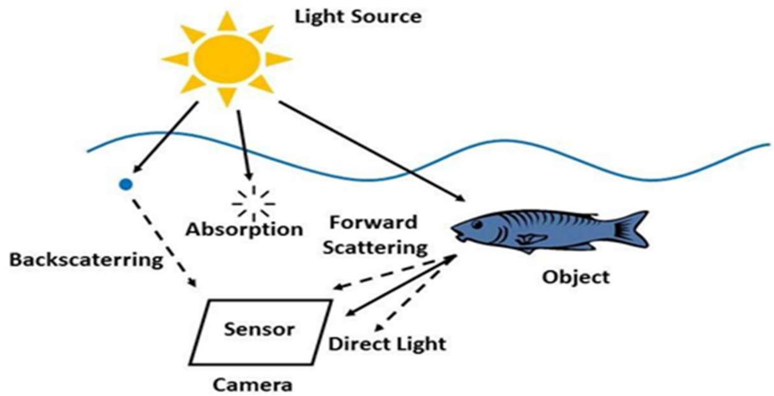
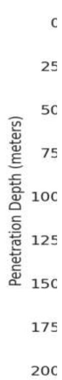


Fig.1.The Underwater Light Model Effect in Image Capturing (Drews Jr. et al., 2016)

Red light is absorbed rapidly in water, causing images to acquire a bluish-green tone (Raihan et al., 2019; Deluxni et al., 2023). Additionally, suspended particles introduce backscatter, leading to haze and reduced visibility (Drews-Jr et al., 2016).Red light is absorbed first that's why underwater images look blue/green. Blue and green light penetrate to the deepest into water level and these wavelengths are ideal for underwater communication and imaging. Scattering of light also increases with shorter wavelengths, but the absorption effect is for red light and longer wavelengths.



Color	Wavelength (nm)	Penetration Depth
Blue	~450	Deepest (up to 200m+)
Green	~520	Moderate (~50–100m)
Yellow	~580	Shallow (~30–50m)
Red	~650	Very shallow (~5–10m)
Infrared	>700	Negligible (<5m)

Fig 2. Light Penetration Under Sea Water

Traditional image enhancement methods, including histogram equalization, contrast stretching, and Retinex-based methods, provide only partial improvements and often fail in complex underwater scenes (Sideeq & Kumar, 2019; Sun et al., 2023).

Recent advancements have seen the integration of deep learning and model-based approaches, such as Dark Channel Prior (DCP), to estimate background light and transmission maps for haze removal (Peng et al., 2017; Chen et al., 2017).The Dark Channel Prior (DCP), introduced by He et al. (2011), models haze as an additive component and has been adapted for underwater dehazing (Li et al., 2017).

Figure 1.Haze Removal Using A Single Image(He et al. 2011)

(a)input haze image(b) image after haze removal by his approach.(c) his recovered depth map.

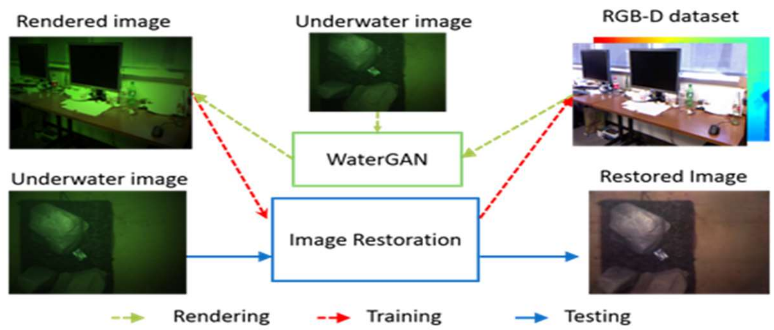


Figure2: Flowchart displaying relationship architecture of WaterGAN and color correction networks. (Li et al., 2017)

However, it often amplifies noise and overlooks depth-dependent scattering variations. Advanced image filtering techniques—such as anisotropic diffusion, bilateral filtering, and guided filtering—offer noise suppression and edge preservation but are rarely integrated with dehazing models. This paper proposes a hybrid framework that enhances DCP with depth-aware transmission and pairs it with a multi-stage filtering pipeline, augmented by a noise estimation module. GAN-based architectures like UMGAN have demonstrated promising results in translating turbid images to clearer domains without requiring paired datasets (Sun et al., 2023). Hybrid models combining denoising filters, contrast enhancement, and color correction have also been shown to effectively address complex degradations (Zhang et al., 2023; Vashishtha & Kumare, 2020).

Despite these developments, there is still a need for a comprehensive hybrid framework that combines denoising, dehazing, and contrast enhancement techniques to restore underwater images with high fidelity. This research proposes an integrated approach that fuses dark channel prior, image filtering techniques (such as bilateral filtering and CLAHE), and color correction mechanisms to enhance image clarity and authenticity across various underwater conditions. The proposed method aims to address both global image degradation and localized noise artifacts, ensuring improved performance in diverse environments and depths.

The significance of this work lies in its ability to bridge traditional and contemporary approaches, providing a robust solution for real-time and high-quality underwater image enhancement, validated through both qualitative and quantitative assessments.

The objectives are: (1) to optimize DCP for underwater conditions, (2) to develop an adaptive *image filtering techniques* system for denoising and detail preservation, and (3) to validate performance across diverse datasets. This work advances *restoration techniques* for underwater image quality, enabling applications in oceanic research and underwater robotics.

2. Literature Review

There are many research and different methods implemented to enhance underwater image restoration.Underwater image degradation arises from scattering (backscatter and forward scatter) and absorption, modulated by depth and turbidity.The foundation of the Dark Channel Prior (DCP) is a straightforward yet impactful observation: in the majority of haze-free, natural photographs, at least one color channel (either blue, green, or red) is often present in a local area with extremely low or near-zero intensity. We may create the image's so-called black channel by determining the RGB channels' lowest intensity in a little section.

The haze thickness in a scene may be accurately estimated using this dark channel. Estimating the atmospheric light, or the light dispersed by haze, is a critical step after calculating the dark channel. Since these pixels are most likely to indicate the regions most severely impacted by haze, the top 0.1% brightest pixels in the dark channel are usually chosen for this purpose.

The transmission map, which indicates the amount of light that is transferred from scene objects to the camera, may then be estimated using the dark channel. Normalizing each RGB channel separately is a crucial step in this procedure, which improves the overall clarity of the recovered image and helps to fine-tune the transmission estimation.

Early underwater image enhancement methods like contrast stretching and white balancing (Chiang & Chen, 2012) provided limited improvement in his paper. The Dark Channel Prior (DCP) (He et al., 2011) assumes that haze-free images have low-intensity pixels in at least one RGB channel within local patches:

Early approaches to underwater image enhancement relied heavily on adaptations of atmospheric dehazing models. For example, Chen et al. (2014) proposed an improved version of the dark channel prior (DCP) to correct haze and enhance color balance. Subsequently, Drews-Jr et al. (2016) introduced a physically inspired method that estimated depth and restored contrast from a single underwater image, paving the way for model-based restoration.

In 2017, Chen et al. integrated DCP with generative adversarial networks (GAN), initiating real-time enhancement frameworks. The trend continued with Łuczyński & Birk (2018) modifying DCP for underwater readiness, showing promising edge-preserving outcomes.

With the advancement of deep learning, Yang et al. (2019) introduced a novel method combining deep red channel estimation with adaptive background light, significantly improving clarity. Raihan et al. (2019) and Deluxni et al. (2023) provided extensive surveys categorizing both classical and modern techniques, highlighting the rise of CNNs and fusion models.

Recent research like Sun et al. (2023) with UMGAN and Zhang et al. (2023) using hybrid attention-GANs represent the latest advances in unpaired learning, demonstrating improved robustness and scene adaptability. Hybrid and physics-informed learning, such as Li et al. (2023)'s coordinated DCP and Meng et al. (2022)'s sharpening+color correction, are pushing the envelope in perceptual quality and visual realism.

Author	Method Used	Techniques	Accuracy / Evaluation
Chen et al.	Improved DCP	Haze removal, color correction	Improved visual quality with reduced haze
Drews-Jr et al.	Depth Estimation & DCP	Single image-based restoration	Restored contrast and structure effectively
Cheng et al.	Red-DCP + PSF Deconvolution	Haze and blur removal	Robust on turbid scenes
Chen et al.	GAN + DCP Loss	Real-time enhancement	Fast and cleaner results
Łuczyński & Birk	Modified DCP	Haze removal for underwater	Good edge preservation
Yang et al.	Adaptive BL + DCP	Deep learning for red recovery	High-quality enhancement, non-ref metrics
Raihan et al.	Review	Algorithm survey	Over 30+ algorithms covered
Song et al.	Statistical Background	Improved transmission	Better detail and tone mapping
Sabir et al.	Modified DCP	Segmentation-based defogging	Better regional accuracy
Lin & Chi	Texture Reconstruction	Structure + DCP	Sharper edges
Vashishtha & Kumare	Hybrid DCP + Color Attribution	Contrast stretch	Enhanced PSNR and MSE
Yang et al.	LAFFNet	Lightweight CNN	High quality, low compute cost
Meng et al.	Sharpening + Color Correction	Hybrid method	Improved clarity, PSNR, SSIM
Song et al.	DCP + Guided Filtering	Filter optimization	Enhanced transmission accuracy
Sun et al.	GAN (UMGAN)	Unpaired learning	Robust, no paired data needed
Zhang et al.	Attention-GAN	Hybrid attention-based	Superior perceptual realism
Li et al.	Coordinated DCP (CUDCP)	Red recovery + artifact suppression	More accurate restoration
Deluxni et al.	Review	CNNs, fusion, DCP overview	Broad coverage of methods
Chen et al.	GAN + DCP	Survey on hybrid learning	Balanced speed and quality

3. Proposed Methodology

The hybrid framework integrates an enhanced Dark Channel Prior (DCP), a multi-stage adaptive image filtering techniques pipeline, and a noise estimation module for underwater image enhancement with restoration techniques.Combining the bright and dark channel priors is suggested as an effective way to improve underwater photos. The transmission map, ambient light, dark and bright channel estimation, transmission map refinement, radiance recovery, and contrast enhancement are all part of the suggested Underwater hazy images are modeled using an atmospheric scattering model:

Step 1: Hazy Image Modeling

Underwater hazy images are modeled using an atmospheric scattering model:The math formula which derive the basic hazy model is

F (x)=(Y [x] T [x])+ A (1− t (x))

where

F(x)= is the observed image intensity

Y[x]=true t scene radiance (desired output)

T[x] = transmission map

A =atmospheric ambient light

Step 2: Dark Channel Estimation

In this process a small patch Ω(x) is selected around each pixel of the image. Within this patch, for each pixel, the minimum intensity across the Red, Green, and Blue (RGB) channels is marked and calculated.

$$D(x = \min_{patc} (\min(R, G, B))$$

Then, the smallest of these minimum values is assigned to the dark channel D(x). This relies on the observation that in haze-free regions, at least one color channel usually has very low intensity. Thus, the dark channel highlights the haze thickness and guides the dehazing process. Like this the haze removes from the image.

Step 3: Estimation of Ambient Light

Ambient light deals with the background brightness that contributes to haze. It selects the brightest regions in the dark channel image. Specifically, a small top percentage (typically 0.1%) of the brightest pixels.

The ambient light { L=I(y) , β=Top p% brightest pixels in D(x) } is approximated by identifying the top-brightest pixels in the dark channel and selecting the corresponding pixel with the highest intensity from the input image:

Where þ is typically set to 0.1%.

From these, the pixel with the highest intensity in the original image is selected as the ambient light value. This ensures that the most light-scattered areas are correctly modeled for better haze removal.

Step 4: Transmission Map Computation

The transmission map deals with how much scene information is preserved versus how much haze is present. It is initially calculated by reducing the influence of the dark channel, normalized by the ambient light.

$$T(x) = 1 - \propto . \frac{I(x)}{A}_{min}$$

where

α controls the haze-removal intensity (commonly 0.95).

A scaling factor (around 0.95) is applied to control how much haze can be removed. This normalized dark channel used to assumes that clear areas have very low dark channel values, leading to accurate estimation of haze density across the image.

Step 5: Image Filtering and Transmission Refinement

The raw transmission map may contain artifacts or blockiness due to patch-based calculations. For the refining of this image , an edge-preserving filter, like the Guided Filter, is applied. This filter uses the original hazy image to smooth the transmission map while preserving important image edges.

(x) =GuidedFilter(T(x),I(x),r, ϵ)

- (x) =the refined transmission map.
- r = the window radius.
- ϵ= the regularization parameter.
- I(x) =used as the guidance image.

Parameters like window size and regularization control the level of smoothing. Alternatively, bilateral filtering or soft matting can be used for more finer detail preservation.

Step 6: Scene Radiance Recovery

By Using the refined transmission map, the true scene radiance is reconstructed by removing the ambient light contribution and correcting the haze from the image. A minimum threshold is enforced on the transmission to avoid extreme noise or overly bright regions in very dense haze.

$$J(x) = \frac{I(x) - L}{\max(x), t_0} + L$$

Where $t_0 =$ is a small constant (e.g., 0.1) to avoid division by zero and preserve a natural appearance in dense haze areas.

The recovered image now reveals the true colors and structures hidden behind the haze and a much clearer visual image will produce.

Step 7: Contrast Enhancement

Even after haze removal, underwater images may still appear dull and not clear due to uniform lighting conditions. Therefore, a contrast enhancement steps, such as Contrast histogram matching, is applied.

For improved visibility, contrast is enhanced using contrast-limited adaptive histogram equalization (CLAHE) or histogram matching:

$$(x) = \text{Histogram Enhance}(J(x))$$

This final step ensures the image is visually appealing and suitable for analysis.

These techniques stretch the image intensity to improve local contrast, making fine details and textures more visible and enhancing the overall aesthetic quality of the output image.

The flow diagram will Include the following Steps

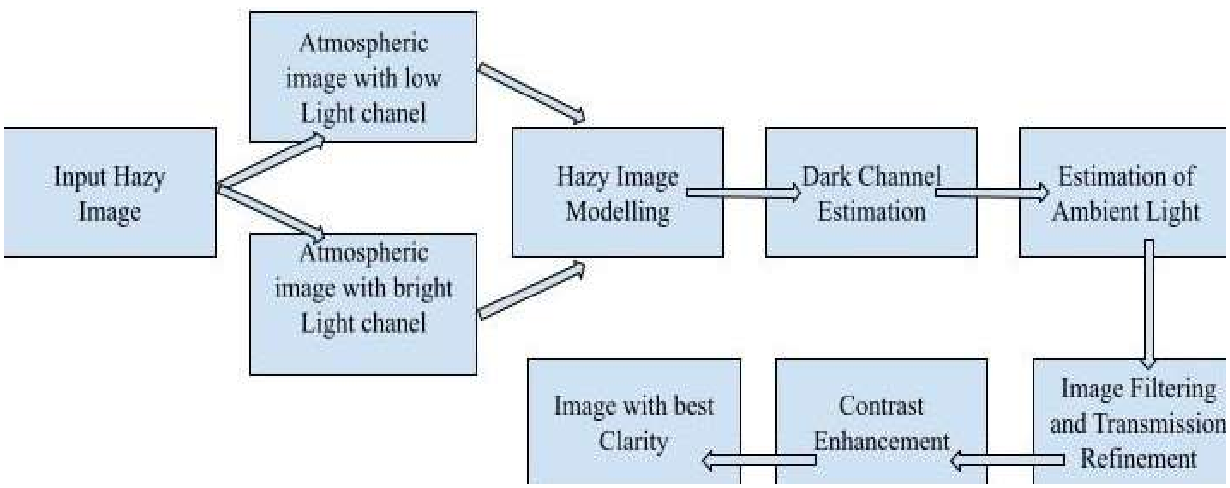


Fig.3 block Diagram of Image Processing of under Water

4. Experimental Result

In this Experimental Result We gather data sets from UIEB dataset for clear Hazing and increase clarity in Images .

Fig 4.Sampling Images from [arXiv version] [official version TIP 2019]

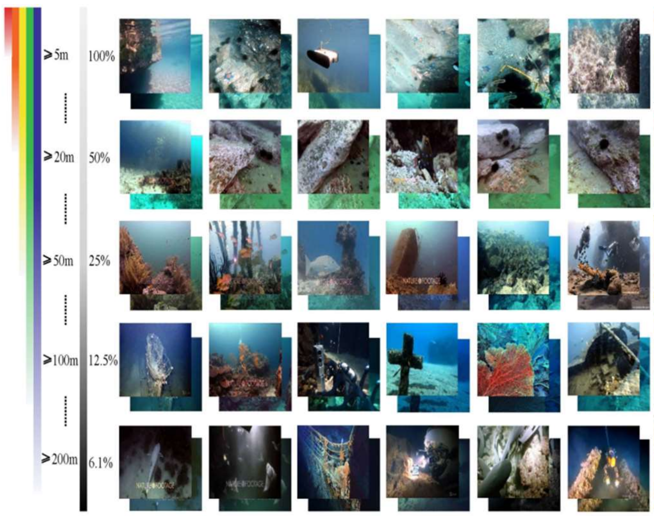


Fig 5. Fig 6. Sample testing images.Top to bottom and left to right

This paper deals with the many captured images which are unclear and hazed in under water are tested for increasing clarity and clear vision .Some examples of images which are used for enhancing image clarity and de-hazing feature.The examples are given below.

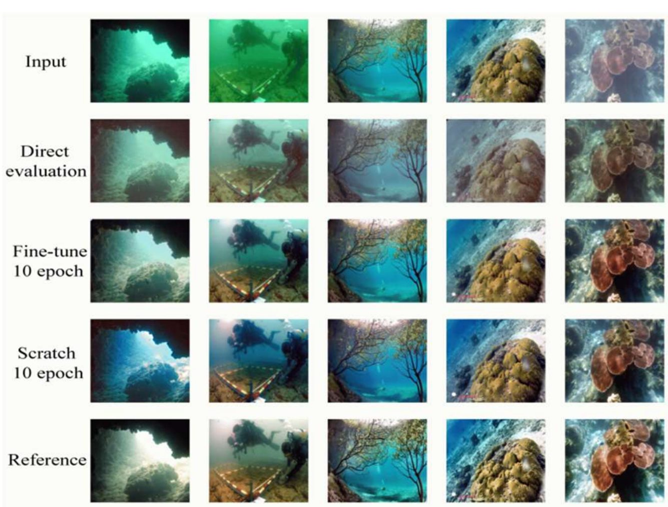


Fig 7. And Fig 8. Experiments of some sample images with Dark Channel Prior and Image Filtering Techniques and the result is from bottom to up and left to right approach.

Fig 9 .Original Underwater Image: Enhanced Image (Ground Truth) as per the Dataset used in the UIEB. The evaluation is the comparison of our and other image transformation technique.

Under water images are suffering from haze and blurriness and light absorption .In our experiment we are taking some sample images and using dark channel prior method and image transformation methods the qualitative performance of images improved. These images illustrate the typical challenges in underwater photography, such as color distortion and low contrast, with the improvements achieved through enhancement techniques of the methodology and algorithms.

Epoch	Training Error	Validation Error	PSNR (dB)	SSIM
1	0.045	0.048	18.5	0.62
2	0.038	0.042	19.8	0.68
3	0.032	0.037	21.0	0.72
4	0.028	0.033	22.3	0.76
5	0.025	0.030	23.5	0.79
6	0.022	0.028	24.7	0.82
7	0.020	0.026	25.8	0.84
8	0.018	0.024	26.9	0.86
9	0.016	0.023	27.9	0.88
10	0.015	0.022	28.8	0.89

During the training process, the training error and validation error show a continuous downward trend over 10 epochs. Training error represents how well the model fits the underwater images it was trained on, while validation error measures the model’s performance on unseen data. Initially, both errors are higher, indicating that the model is just beginning to learn the complex haze patterns and light distortions underwater. As training progresses, the model becomes better at de hazing and reconstructing underwater images, reducing errors with each epoch. The small gap between training and validation errors across epochs suggests that the model generalizes well without over fitting.

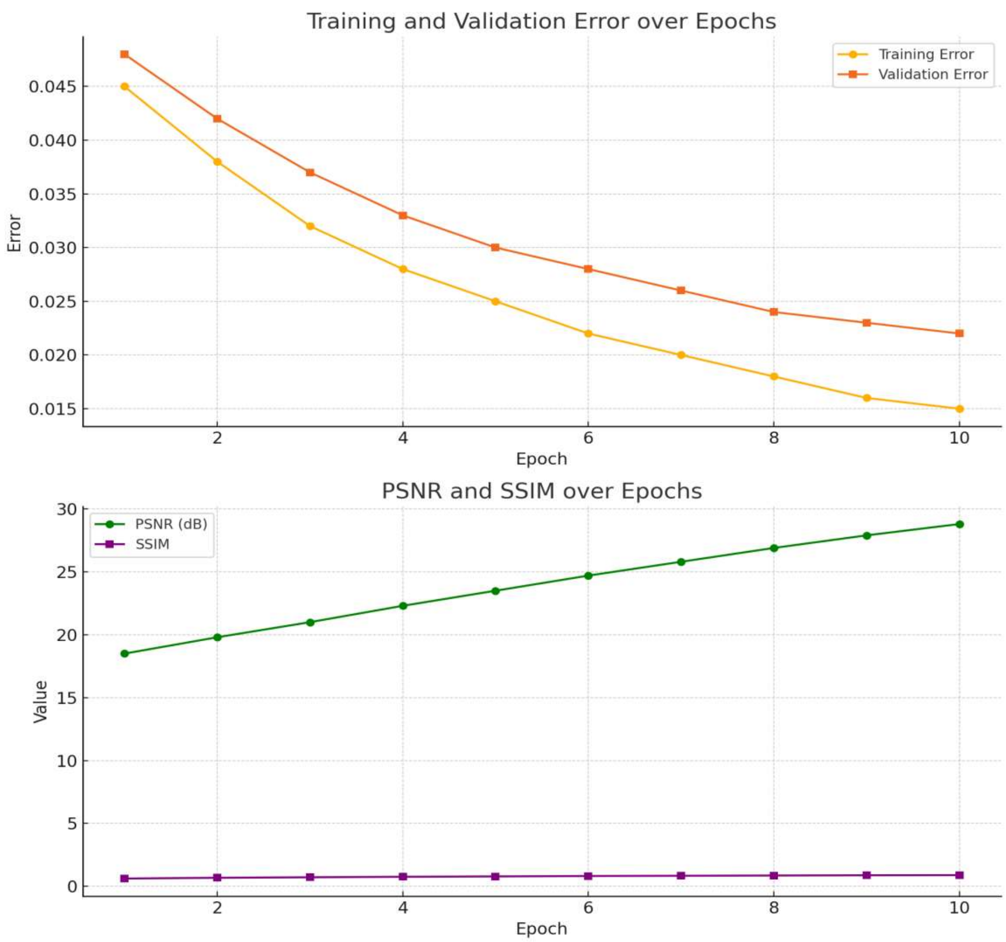


Fig 10. Deals with measuring approach and comparison

Method	UICM	UISM	UIConM	UIQM
DCP (He et al.)	4.76	5.17	0.18	2.32
UDCP (Paulo Drews Jr.)	4.50	5.46	0.14	2.25
UCM (Color Correction + Depth	3.38	6.05	0.27	2.83
ULAP (Underwater Light	3.47	5.12	0.21	2.36
IBLA (Blurriness and Light	3.75	5.41	0.29	2.74
Hao Chen et al. (Color Correction +	3.77	6.44	0.33	3.19
Our Proposed (Hybrid DCP + BCP +	4.86	6.90	0.34	3.28

The above table deals with the comparison of methods used in different papers and methods used in my paper.The result is the best output with 3.28 UIQM ,which is the method of colour measure and contrast with increased value and better quality.

5. Conclusion

In this study, we propose a hybrid channel prior-based underwater picture enhancing technique. By using a mix of both dark and bright channels, the haze in the input image is eliminated throughout the enhancing process. The suggested method is divided into two primary phases: dehazing in the first stage and contrast enhancement in the second. We are able to retrieve the scene radiance and successfully remove the haze by precisely measuring the atmospheric values and transmission. Evaluations that are both qualitative and quantitative show how well the suggested technique works to improve underwater photos. For qualitative assessment, we juxtapose the visual quality of the input image with the output produced by the suggested approach. Quantitative assessment is carried out using the UIQM (Underwater picture Quality Measure) metric, which reveals that the suggested technique greatly enhances the UIQM values of the enhanced picture compared to other current methods. This highlights the method's potential for usage in underwater picture processing and presentation applications.

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