



# Enhancement For Underwater Images Using Hybrid Deep Learning

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**Abstract:** The main theme of this project is to Enhance and Color Correction for underwater images. This project becomes challenging due to attenuation and scattering of light. In this process, the novel algorithm of deep learning algorithms along with gamma correction. In the procedure of enhancing the texture and structural preservation is more important. In this work, the image enhancement is obtained by using the convolution neural networks. This process involves two stages mainly the training and testing stage. During training process, the dataset is collected, and their up sampled and resized images are stored in a mat file. Then CNN layers are created. Finally, the train the network using the data stored in mat files and CNN layers. After the training process, the test image is given as input to network designed earlier. Then finally the high-resolution image is obtained. This method reduces the loss of textural and structural information when compared to state of art methods.

**Keywords:** CNN, Deep Learning, Underwater Images.

## I. INTRODUCTION

Undersea exploration is slowly becoming a priority because of the rising need for marine resources and the necessity of studying the seafloor topography. Underwater robots do much of the labour because humans can't survive in the sea's hostile environment, especially in deep water. Due to their low image quality, underwater robots are now only useful for monitoring fish and water quality. Colour distortion, blurred images, and data loss can all result from light absorption, small particles, and marine life. A robust underwater image processing system is presented to obtain high-quality photos for further research. Underwater image processing, classification, and analysis rely heavily on having a reliable and objective quality evaluation metric for underwater images, especially for underwater engineering and monitoring purposes. Underwater image model has been followed by many researchers and marine biologists as shown in the Fig 1.1. Although subjective quality measurements are widely regarded as the most accurate, they are prohibitively expensive, time-consuming, and difficult to integrate into existing systems in real time, making them unfeasible.

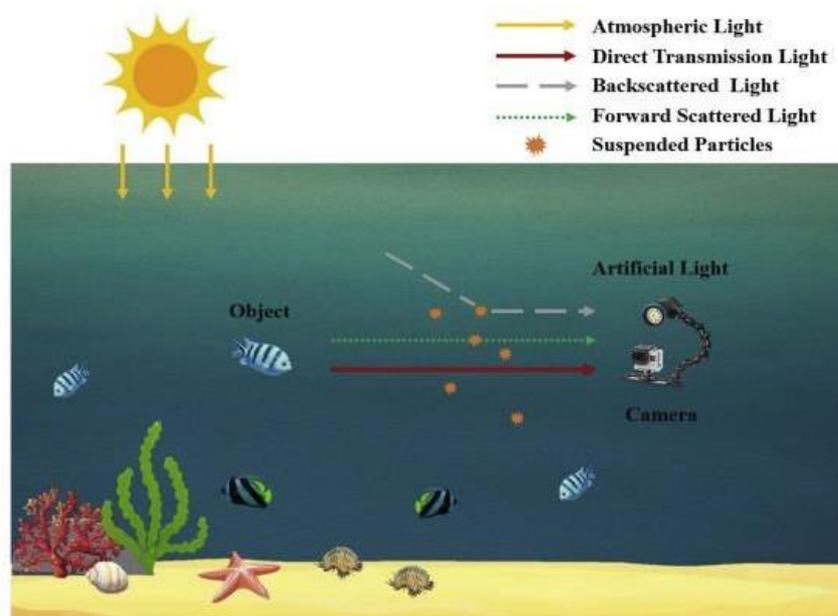


Fig. 1 Underwater image Model



The reference image representing the original signal allows for a categorization of Objective Image Quality Evaluation (IQE) techniques. Full-reference (FR) picture quality assessment is used whenever a reference of this sort is available. The reduced-reference (RR) evaluation of quality is another IQE method; it employs the assumption of only limited details regarding the reference signal is accessible. A blind or no-reference, objective image quality metric is required to quantify the perceived picture quality of underwater photos in cases where a reference image cannot be provided. A metric that distinguishes distorted images is adequate, is consistent with how humans see them, It is possible to effectively examine how well algorithms perform on images and help choose the best operating parameters, has a small computer footprint, and it is all accessible in real time.

There have been an abundance of recent publications in the oceanography discipline color image processing. However, most techniques for restoring and improving photographs are limited to use with underwater images. Additionally, there are no colour image quality criteria that are used to evaluate and enhance these methods. While quality standards are created for atmospheric colour photographs, they cannot be utilized for underwater photography. Underwater monitoring and survey photos have poor visibility, low contrast, non-uniform illumination, blurring, non-uniform colour cast, and complex noise because of poor lighting conditions and the influence of significant absorption and scattering in murky water. The degree to which these losses occur is affected by a wide variety of circumstances, including the kind and depth of water, the imaging device used, the intensity of any artificial lighting, an occurrence of turbulence, and so on. It might be difficult to tell the difference between lightening and restoring colours in an underwater image. Furthermore, several tasks conducted below water focus on various aspects of an image. Underwater photographs cannot be evaluated employing traditional criteria to assess the standard of the photographs that were collected in natural colours. The aim of this work is to propose a simple objective standard for assessing the caliber of colour photographs taken during underwater surveys and real-time monitoring, as shown in Fig. 1.2.



Fig. 2 Photographs captured underwater

Direct transmission is diminished and ambient dispersed light is introduced due to scattering and absorption. The scene's intensity is weakened and colour casts are introduced because of attenuated direct transmission, while appearance of the scene is washed out because of surrounding scattered light. Furthermore, water temperature and salinity, in addition to the kind and number of particles in water, play critical roles in determining the amplitude of attenuation and scattering. Photographs taken underwater frequently lose their appearance and colors due to extreme deterioration. To be more precise, when fed an underwater image, our model immediately returns an image that is identical in relation to content and structure but includes the colours which might represent there had the picture been captured above ground. While it's possible that the translated colour isn't the "real" colour of underwater photographs, our solution does remove the colour casts and boosts visual performance. When the settings and lighting circumstances are unknown, it is difficult for any approach to recreate the appearance and colour of any underwater photos. Underwater imaging has recently attracted a lot of attention as a research field because of the abundant resources that is contained in oceans, rivers, and lakes. Three fundamental problems exist with underwater imaging: colour distortion, under-exposure, and fuzz, all of which are as a result of absorption and dispersion of light when it travels through water. The medium's physical characteristics have a significant role in this degradation. First, because of varied wavelengths of light, underwater photos may appear distorted in relation to colour.

## II. BACKGROUND

Ali Khandouzi, Mehdi Ezoji suggested a two-stage approach utilising a deep convolution network [1] to address these issues and enhance the standard of underwater photographs. Initially, the photograph is improved by partially masking colour distortion and image degradation with a light global-local structure.



The system is then supplemented with two-dimensional histogram equalisation. Histogram equalisation in two dimensions yields comprehensible outcomes and suppresses unnatural brightness differences. The outcomes demonstrate that the proposed strategy outperforms its rivals in this field, both qualitatively and quantitatively.

Yuan Zhou, Kangming Yan, Xiaofeng Li proposes a domain-adaptive learning system that uses feedback from physical models to enhance underwater images [2]. This is known as the "domain gap," because it exists between synthetic training data and real-world testing data. In order to close the competence gap, the authors of this research implement a domain adaptable mechanism within a learning framework. As a feedback controller, it suggests using a physics constraint to help with the estimation of underwater picture enhancement. In-depth studies support the superiority of the suggested framework.

Four steps are proposed by Linfeng Bai; Weidong Zhang; Xipeng Pan; Chenping Zhao that are pixel intensity centre regionalization, histogram equalisation on a global and local level, fusion of images captured at different scales. In addition, the histogram of the entire image is centralised using a regionalization algorithm using the intensity centres of individual pixels in the image [3]. The image's colour is adjusted using global histogram equalisation to reflect the qualities of each channel. For better contrast in the image, we utilise local equalisation of dual-interval histograms according to the average of peak and mean values. Combining the color-corrected and contrast-enhanced images' contrast, saliency, and exposure weight maps via multi-scale fusion of the two images.

Due to wavelength and distance dependent attenuation and scattering, underwater photographs have colour casts and low contrast. Chongyi Li introduces Ucolor, a network for improving underwater images by mediums transmission-guided multi-color channel embedding[4], which addresses these two types of degradation. In order to increase the variety of feature representations, we first propose a multi-color channel encoder network that unifies the features of several colour spaces. To improve the network's reaction to low-quality areas, this study employs physical models of underwater imagery to inform the design of with a medium transmission decoder network.

Akshay Dudhane proposes unique end-to-end deep network here [5] for restoring underwater images. Channel-wise colour extraction of features modules and dense-residual pattern extraction module make up the proposed network's two components. To ensure that the original structure of the undersea picture is maintained and that the correct edge information is generated, a customised loss function is presented. In addition, a new synthesised underwater picture database is proposed to train the suggested neural network for undersea image enhancement. blurring, light scattering, and colour attenuation distortions were introduced, however. Photographs taken underwater in the real world are used to assess how well the suggested network performed at restoring the images. The experimental results show that the suggested network outperforms the industry's best practices for restoring underwater images.

Yuan Tian describes an entirely novel technique for enhancing underwater photos with uneven lighting [6]. To combine features from various sources, they have produced a heterogeneous feature fusion module. Second, the conventional channel attention mechanism is upgraded with the aid of a novel feature attention mechanism. Then, the receptive field can be enlarged in a way that best suits the situation with the aid of the dynamic feature augmentation module. The function to reduce colour intensity has been developed. At the outset of the network, a multiple scales feature extraction module is implemented to extract features at various scales; the layer of convolution with leap connection and an attention module are then used to produce the final output.

Underwater optical pictures are damaged, blurred, and contrast diminished due to light attenuation and scattering induced by scatterers in murky water, which limits the extraction and interpretation of information from images. Fengqi Xiao proposes using stochastic resonance (SR), with parameters set to improve turbid underwater images [7], to solve these issues. To begin, a framework for an SR algorithm is developed specifically for improving underwater images. The second objective is to track how well the system is functioning. Finally, the suggested technique is tested on the UWCHIC, which includes the turbid underwater images collected in natural waters, the marine underwater environment database (MUED), and the underwater image enhancement benchmark (UIEB) data sets.

Chongyi Li proposes CNN method to build an underwater image enhancement benchmark (UIEB) [8] including 950 photographs from the actual world and 890 reference images. They consider the remaining sixty underwater photographs to be difficult data since they lack adequate reference images. They conduct a thorough qualitative and quantitative review of the top underwater picture enhancement methods currently on the market using this data set. They also presented a baseline Convolutional Neural Network (CNN) for enhancing underwater images, termed Water-Net, whose training on this benchmark demonstrates the generalizability of the proposed UIEB. Soo-Chang Pei presented a practical and visually appealing method [9] for improving underwater photographs. A result of light scattering and absorption,



underwater photographs often include haze, low contrast, colour distortion, and loss of human sharpness. To begin, a new model for underwater dehazing was presented with the express goal of removing the water's colour together with the haze. With the proposed colour correction method, the issue of colour shifting can be addressed in an adaptable manner without any further data. Additionally, a multi-scale illumination fusion was created to better show details and low-light regions of the photograph. The experimental results reveal that the suggested method provides more clearly detailed underwater photographs and offers a significant performance boost over the state-of-the-art methods, with gains ranging from a quantitative improvement of 5% to 77% across all four evaluation performance indicators.

To estimate depth from a single underwater image, Praful Hambarde introduces a full-stack UW-GAN [10]. At first, we utilize UWC-Net (Underwater Coarse-Level Generative Network) to calculate a rough depth map. The estimated coarse-level deep photograph and the input picture are then fed into the undersea fine-level network (UWF-Net), which generates a fine-level depth map.

### III. METHODOLOGY FOR UNDERWATER IMAGE ENHANCEMENT

The recommended method enhances photos by using convolution neural networks. Convolution neural networks may generate a high quality image from a low resolution one using the difference image produced by up sampling and scaling. The block diagram of the suggested technique is displayed in Figure 3.1.

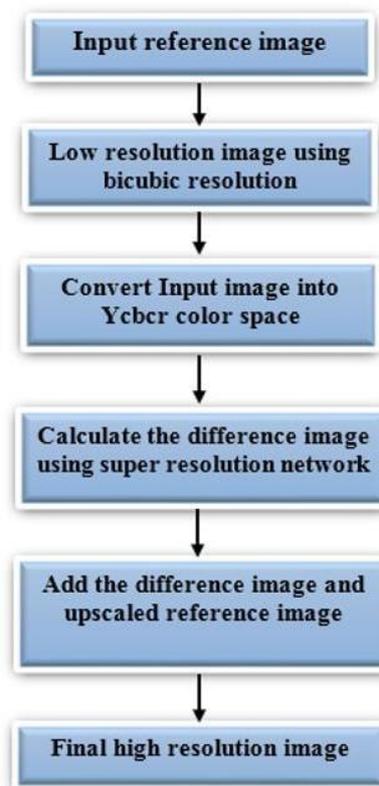


Fig. 3 Block Diagram of proposed method for underwater image enhancement

#### A. Simulation Workflow.

In the process of enhancing underwater images, a well-defined simulation workflow is crucial to ensure the accuracy and effectiveness of the image enhancement techniques. The following steps outline the key components of this simulation workflow: The photos that will be used for training are first saved into a cell, converted to Ycbr color space. Then the photos are lowered in resolution using bicubic interpolation.

The low-resolution image is then scaled using the reference image size. After that, the reference image and scaled image are used to calculate the difference image. The Y component of the image is the only one used throughout the entire procedure.



Following that, the upscaled and difference images are saved in separate mat files in separate directories. The two photos will then be combined into a single array. The train data is shown here. Next, CNN's layers and available options are decided. Convolution layer, rectified linear unit, and regression layer are among the layers of CNN. Then a network is formed. The final high-resolution image is produced by subtracting the low resolution test image from the residual image using bicubic interpolation, which is generated using the network. Then finally the image is gamma corrected to enhance the visual details.

#### B. CNN Architecture.

A total of 41 layers, including 20 sets of convolutions and relu layers, make up the CNN architecture. The output is then obtained by using the regression layer.

##### Input layer:

This layer is made up of [64x64x1] raw picture pixel values, where 64 represents the image's width, 64 represents its height, and 1 represents its grayscale representation.

##### Convolution layer:

In this layer, we compute the output of neurons connected to regional input regions by having each neuron compute the dot product of its weights with a small region connected to the input volume. Due to the exponential nature of the results, we used 11 filters for the first two layers, 64 filters for the next eighteen levels, and a single filter for the last convolution layer in our architecture.

##### RELU layer:

Limiting to zero is used as an intelligent activation feature, as in  $\max(0, x)$ . The volume remains the same ([3x3x11]).

##### Regression layer:

For regression issues, the half-mean-squared-error loss is estimated using a regression layer. Common regression issues necessitate the addition of a regression layer after the last fully linked one.

The mean-squared-error for a single observation can be calculated as (1):

$$MSE = \sum_{i=1}^R \frac{(t_i - y_i)^2}{R} \dots\dots\dots (1)$$

In this context, R stands for the overall amount of,  $t_i$  represents the desired outcome, and  $y_i$  represents the network's forecast for answer  $i$ .

The square root of the mean squared error of the anticipated responses for each pixel serves as the loss function (2) of the regression layer in image-to-image regression networks, unnormalized by R:

$$LOSS = \sum_{i=1}^{HWC} (t_p - y_p)^2 \dots\dots\dots (2)$$

The software determines the average loss throughout the mini-batch of training data. Next, a network is trained utilising these layers as building blocks. The testing process is carried out across the network.

#### C. Gamma Correction.

If you care about how an image looks when displayed on a screen, you should care about gamma correction. An image's overall brightness can be adjusted via gamma correction. Photographs which are not correctly adjusted can appear either too light or too dark. Learning about gamma is also helpful when trying to recreate colours faithfully. Changing the gamma correction level affects not just the overall brightness but also the red, green, and blue colour balance. Let's talk about your eyes, since that's where you'll be doing most of your reading: on your computer display.

The vast majority of computer screens share a basic trait, regardless of brand. All of them follow a roughly power-of-2.5 intensity-to-voltage response curve. Don't worry, all this means is that your computer monitor will display a pixel with an intensity of  $x^{2.5}$  when you tell it to display a pixel with an intensity of  $x$ . Because the intensity value displayed will be less than what you requested, voltages between 0 and 1 are transmitted to the monitor. For instance:  $(0.5^{2.5} = 0.175)$  A gamma of 2.5 is therefore considered standard for monitors.



#### IV. RESULTS AND ANALYSIS

The outcomes of the implemented super-resolution and image quality enhancement algorithm is represented in this section. The results are evaluated through a combination of quantitative metrics and visual assessments to ascertain the effectiveness of the proposed methodology.

##### A. Enhanced Image And Visuals.

The core of the algorithm involves the enhancement of a low-resolution input image as shown in the Figure 4.1, to obtain an improved high-resolution output image as shown in the Figure 4.7. Visual analysis serves as the initial step to assess the perceptual impact of the enhancement process. A qualitative comparison between the enhanced output image, the original low-resolution input image, and a reference image provides insights into the enhancement's visual quality.

The Input Image as shown in the figure 4.1 serves as the initial representation of the underwater scene under study. This raw image captures the inherent challenges of underwater imaging, such as reduced clarity and color distortion, forming the basis for the subsequent enhancement process.

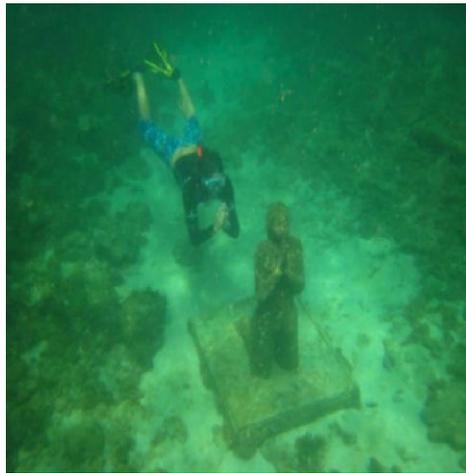


Fig 4.1. Input image

The Gray Scale Image as shown in figure 4.2 is a grayscale representation of the input image. It highlights the luminance information within the image while omitting color details. This representation simplifies certain aspects of image processing and analysis.

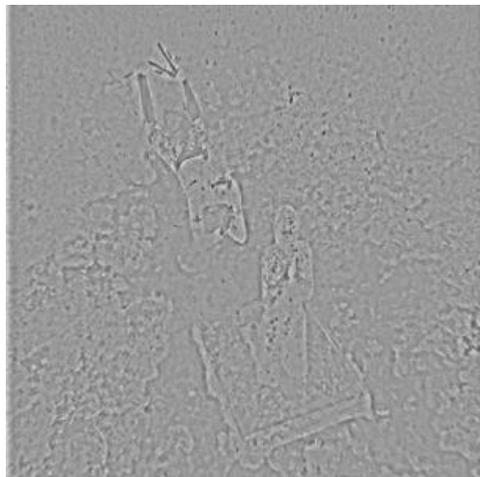


Fig 4.2. Gray scale image

The Low-Resolution Image as shown in figure 4.3 simulates the reduced image quality often encountered in underwater environments. This representation is created through bicubic interpolation and forms the starting point for the enhancement process.



Fig 4.3. Low resolution image

The YCbCr Color Space Image as shown in figure 4.4 is a representation of the input image in the YCbCr color space. This separation of luminance (Y) from chrominance (Cb and Cr) is crucial for specific image processing techniques, such as gamma correction and color manipulation.



Fig 4.4. Ycbr color space image

The VDSR Image as shown in figure 4.5 is the result of applying a sophisticated image enhancement algorithm, such as the Very Deep Super-Resolution (VDSR) model, to the low-resolution input. It demonstrates the improvements achieved through advanced deeplearning techniques.



Fig 4.5. Vdsr image



The Lab Color Space Image as shown in figure 4.6 represents the image in the Lab color space, which separates the luminance (L) component from the color channels (a and b). This representation can be valuable for color correction and analysis.

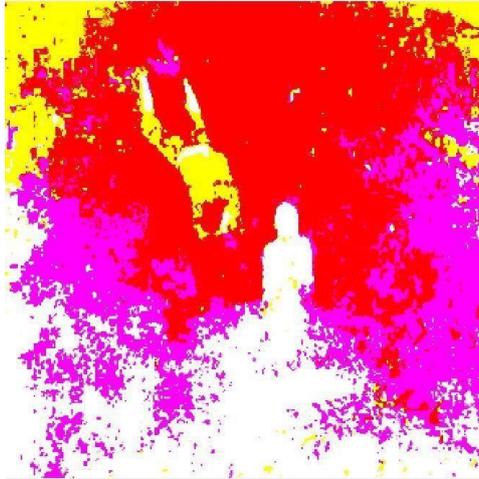


Fig 4.6. Lab color space image

The Output Image as shown in the figure 4.7 is the final result of the underwater image enhancement process. It showcases the culmination of all the applied techniques and represents the high-quality, enhanced image that can be used for various applications in underwater imaging and analysis.



Fig 4.7. Output image

#### B. Quantitative Metrics.

Several quantitative metrics are employed to objectively analyze the standard of the enhanced image. These metrics offer numerical insights into various aspects of image fidelity, naturalness, sharpness, contrast, and colorfulness. The following metrics are considered:

**Peak Signal-to-Noise Ratio (PSNR):** PSNR quantifies the similarity between the enhanced photograph and the reference image by measuring the measure of the maximum possible power of a signal to the power of corrupting noise. Higher PSNR values correspond to enhanced images that closely resemble the reference image.

**Mean Squared Error (MSE):** The average squared difference between the improved image's and the reference image's pixel values is calculated by MSE. Lower MSE values indicate higher similarity.

**Entropy:** Entropy captures the information content or randomness in the enhanced image. Higher entropy suggests increased diversity in pixel intensities.



Naturalness Image Quality Evaluator (NIQE): NIQE assesses the naturalness of the enhanced image, providing insights into how closely the enhanced image mimics human perception.

Universal Image Quality Index Estimator (UCIQE): UCIQE evaluates image quality based on factors such as color fidelity, contrast, and sharpness.

Universal Image Contrast Metrics (UICM): UICM quantifies image contrast, considering mean values and standard deviations of color channels.

Universal Image Sharpness Metrics (UISM): UISM evaluates image sharpness by evaluating the mean value of luminance.

Universal Image Colorfulness (UIcon): UIcon measures the colorfulness of the image, reflecting its vibrancy.

Universal Image Quality Metric (UIQM): UIQM combines UICM, UISM, and UIcon scores to provide an overarching quality assessment.

Table 1 Performance parameters measures for image quality

PSNR	MSE	Entropy	NIQE	UCIQE	UICM	UISM	UIcon	UIQM
92.3057	0.0347	7.7339	3.0962	0.3365	0.0012	0.5615	0.3616	6.0413

## V. SUSTAINABILITY AND SOCIETAL CONCERNS

Along with technical advancements, it is imperative to address the sustainability implications of the proposed super-resolution and image quality enhancement algorithm. Sustainability encompasses environmental, social, and economic aspects that collectively contribute to the responsible development and deployment of technology.

### A. Sustainability.

Efficiency in computational resources and energy consumption is crucial in the implementation of image enhancement algorithms. Striving for energy-efficient design not only contributes to reduced operational costs but also aligns with sustainable practices. Consideration of algorithmic optimizations and hardware-accelerated implementations can contribute to minimizing the environmental impact associated with resource-intensive computations.

For computational resources, such as memory and processing power, should be assessed in the context of sustainable resource utilization. Utilizing resources effectively ensures that the algorithm remains accessible on a variety of hardware platforms, enabling wider adoption and minimizing electronic waste associated with hardware obsolescence. The core objective of the proposed algorithm, i.e., enhancing image quality, aligns with a sustainable principle of extending the lifespan of existing digital assets. By enhancing the visual quality of images, the algorithm potentially reduces the need for new images to be captured or generated, thereby contributing to resource conservation.

Ensuring that the algorithm is accessible and benefits a diverse range of users is integral to sustainable technology development. By designing user-friendly interfaces and considering the needs of differently abled individuals, the algorithm can promote inclusivity and equitable access to enhanced image quality. Incorporating ethical considerations into algorithmic design is an essential component of sustainable technology development. Ensuring that the algorithm respects user privacy, data protection, and cultural sensitivities contributes to building trust and safeguarding societal well-being.

### B. Societal concerns.

The implementation and deployment of the super-resolution and image quality enhancement algorithm encompass not only technical advancements but also profound societal implications. It is imperative to address ethical, legal, and cultural concerns to ensure responsible and inclusive technology development. As the algorithm processes and enhances images, considerations regarding user privacy and data security are paramount. Ensuring that sensitive information is not compromised during the image enhancement process is essential. The observance of data privacy laws and robust encryption mechanisms contribute to safeguarding user privacy.



Image enhancement algorithms have the potential to perpetuate biases present in training data. Care must be taken to ensure that the algorithm's enhancements do not reinforce or amplify existing social biases. Regular evaluation and adjustment of the training data and algorithmic parameters are vital to mitigate unintended biases. Cultural diversity is a fundamental aspect of image content. The algorithm's enhancements should be culturally sensitive, avoiding alterations that may be perceived as disrespectful or offensive in specific cultural contexts. Adhering to cultural norms and values contributes to the algorithm's inclusivity.

The algorithm's outputs and user interfaces should be accessible to individuals with diverse abilities. Incorporating features like alternative text descriptions and compatibility with assistive technologies makes sure that the benefits of image enhancement are extended to all users, irrespective of their physical or cognitive abilities. Transparent documentation of the algorithm's methodology, assumptions, and limitations promotes accountability. Users should have access to understandable explanations of how the algorithm functions and what enhancements it applies. Transparency fosters user trust and informed decision-making.

## VI. FUTURE PROSPECTS AND TRENDS

In future research, there are several avenues to explore. Here are the future scope for advancing underwater image enhancement techniques. Expanding and diversifying the training dataset to encompass a wider range of underwater scenarios and conditions can lead to more robust and adaptable enhancement techniques. Exploring and experimenting with alternative deep learning architectures beyond the Convolutional Neural Network (CNN) can contribute to improving the accuracy and adaptability of the enhancement process. Incorporating real-time data from underwater sensors and instruments can enhance the adaptability of image enhancement methods, allowing for adjustments based on dynamic underwater conditions. Investigating additional image processing techniques, such as colour correction and noise reduction, alongside gamma correction, can provide a more comprehensive and effective underwater image enhancement solution. Developing adaptive enhancement algorithms that can automatically adjust parameters and methods based on the specific underwater conditions encountered can improve real-world applicability. Addressing the computational complexity of the image enhancement process is essential for practical applications. Research into optimization techniques and hardware acceleration can make the approach more feasible for real-time use.

## VII. CONCLUSION

The comprehensive workflow for underwater image enhancement, aimed at improving the visual quality of underwater imagery. The process begins with data preparation, where training images are organized into a cell structure and converted to the YCbCr color space, emphasizing the luminance component (Y). After reducing the image resolution using bicubic interpolation and scaling it to match the reference image size, a difference image is calculated using the reference and scaled images. The Y component is retained throughout, ensuring consistency. The upscaled and difference images are stored separately for further analysis. Subsequently, a Convolutional Neural Network (CNN) is configured with layers such as convolution, rectified linear unit (ReLU), and regression, forming a powerful network. The final high-resolution image is generated by subtracting the low-resolution test image from the residual image produced by the CNN, employing bicubic interpolation. To enhance visual details, gamma correction is applied.

The experimentation and evaluation of this workflow have yielded promising results. The enhancement process effectively mitigates the challenges associated with underwater imaging, resulting in significantly improved image quality. The use of advanced techniques, including deep learning with the CNN model, has demonstrated its potential to restore fine details and enhance image clarity in underwater environments.

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