A NEW VARIATIONAL AND GUIDED FILTERING APPROACH FOR SINGLE UNDERWATER IMAGE QUALITY ENHANCEMENT

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Abstract--Underwater images suffer from color distortion and contrast loss due to light absorption and scattering in water.The traditional restoration methods fail because different wavelengths attenuate at varying rates underwater. To address this, we propose a novel restoration method combining color correction and dehazing. Our approach estimates global background light using a quad-tree subdivision and ocean optical properties. Light scattering and absorption cause significant color shifts, reducing image visibility. These distortions alter the natural distribution of underwater images, affecting tasks like object detection and segmentation. Our method enhances image quality for improved underwater vision. In this project, we present an innovative underwater image restoration approach utilizing a variational framework and a guided filter. To address color degradation, the hazy patterns of altered colors are decomposed to estimate the transmission map, while a color loss prior is employed to refine it. Furthermore, a first-order gradient guided filter is introduced to enhance the transmission map's accuracy. Finally, a variational model is developed to restore underwater images and suppress noise based on an improved imaging model and image priors. To assess the effectiveness of our method, we conduct a comparative analysis across multiple metrics, including visual quality, color accuracy, noise robustness, and computational efficiency, demonstrating the advantages and limitations of different approaches.

Index Terms-- Underwater image enhancement, Variational approach, Guided filtering, Image dehazing, Color correction, Contrast enhancement

I.INTRODUCTION

This makes it more difficult to evaluate and comprehend the undersea environment. Techniques for image dehazing have become an essential part of underwater image enhancement (UIE). Both conventional techniques, which have their roots in the physics of light transmission in water, and more recent developments in learning-based methodologies—specifically, deep learning architectures like Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Transformers—are thoroughly examined in this review. Additionally, we discuss the main obstacles and potential paths forward for both conventional and learning-based approaches, emphasizing real-time processing, domain adaptation, and the incorporation of physical priors into deep learning models. For those studying and working in the field of underwater image improvement, this review offers insightful analysis and helpful suggestions.

Because it supports a variety of habitats on more than 71% of the Earth's surface, the underwater environment is extremely important from a scientific and ecological standpoint [1]. However,

because of the intricate way that light interacts with water, taking sharp images underwater is extremely difficult. Light scattering, absorption, and attenuation deteriorate image quality, resulting in diminished contrast, color distortion, and restricted visibility, as seen in Figure 1. Due to these constraints, important details and information are obscured, which reduces the efficiency of underwater image analysis in a variety of applications. In order to restore these features and enhance image quality for visual interpretability, image enhancement techniques—dehazing in particular—are crucial.

Researchers have started looking into the use of deep learning for underwater image enhancement, motivated by recent advances in the field in image processing tasks like dehazing and low light enhancement (e.g. [3], [6]). These methods make use of deep neural networks' capacity to learn the intricate adjustments required to restore the original scene from underwater photos that have deteriorated. Specifically, some investigations combine deep image improvement frameworks with physics-based models that mimic underwater light behavior, with encouraging outcomes. Underwater applications include marine resource exploitation and archeology, underwater infrastructure inspection, underwater vehicle control, and environmental monitoring have rapidly expanded during the past 20 years.

Since collecting and analyzing underwater data has become more important, researchers have been more interested in image theory and related methods. Since underwater images contain a multitude of information, including color, texture, and shape, they have emerged as the main medium for information transmission. Low contrast, color distortion, and information loss due to light absorption and dispersion are among the degradation problems that underwater images commonly face compared to outdoor photos [1], [2]. The light that the camera records is composed of three components, as shown in Fig. 1: the direct component, the forward scattering component, and the backward scattering component. Forward scattering results from a random fluctuation in the light reflected from the target object. Back scattering occurs when light enters the camera before it reaches an object due to reflections from suspended particles. Furthermore, the term "direct component" refers to the light component that the target object reflects into the camera. One way to conceptualize a damaged underwater image is as a linear combination of the three previously mentioned components.

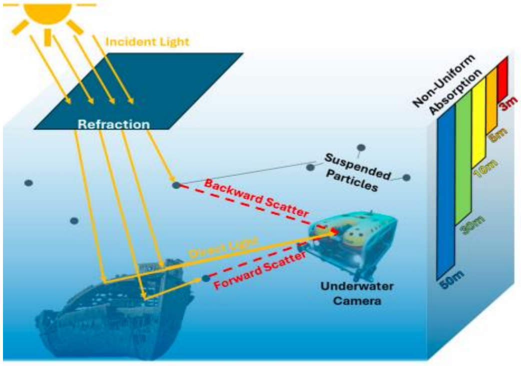

Figure 1: Scattering and Attenuation of Light Underwater.

While backward scattering results in low contrast and poor image vision, forward scattering introduces blurriness. Additionally, absorption lowers light energy, which influences color rendering. For instance, as light passes through water, the red component with the longest wavelength quickly vanishes, but the blue and green components continue to travel farther. Because of this, photos taken underwater typically seem green or blue and are rarely suitable for use in subsequent applications without some sort of pre-processing. Researchers have started looking into the use of deep learning for underwater image enhancement, motivated by recent advances in the field in image processing tasks like dehazing and low light enhancement (e.g. [3], [6]). These approaches harness the ability of deep neural networks to learn the complicated transformations needed to restore the original scene from damaged underwater photos.

Specifically, some studies combine deep image improvement frameworks with physics-based models that mimic underwater light behavior, with encouraging outcomes (e.g., [3], [6]). Many methods for improving images have been proposed in the last few decades. Historically, image enhancing efforts have included dehazing techniques, which are based on the principles of light transmission in water. The discipline has seen a revolution in recent years due to the introduction of deep learning, specifically Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs). They have exhibited extraordinary ability in learning the complex characteristics and patterns that characterize underwater imagery, yielding impressive dehazing results.

A restoration-based technique is put forth to address the degradation in underwater photos by integrating an imaging model with noise and a variational framework to recreate underwater images with high quality (RVFN). In order to restore underwater images and reduce noise, the suggested technique seeks to create an underwater imaging model with noise and a variational framework. Several examples restored by the proposed RVFN are shown in Fig. 2. The following is a summary of the study's contributions. (1) By isolating noise from the actual underwater scene, a novel underwater imaging model is developed, which helps to effectively remove noise while preserving underwater photos.

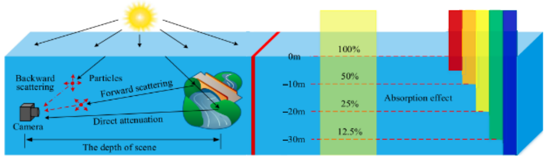

Fig 2. Underwater image formation model, comprising direct attenuation, forward scattering, and backward scattering components.

To restore underwater photos, a variational framework is created that takes into account the color deviation, intense noise, and reduced visibility.To precisely identify the background area, an evaluation formula incorporating illumination, contrast, and color deviation parameters is developed. In addition, the transmission map is refined using a gradient guided filter of the first order. With a significant quantity of research available, numerous attempts have been undertaken to enhance the quality of underwater photos in order to address these issues. These investigations fall into three categories: deep learning-based techniques, image restoration, and image enhancement. Real underwater sceneries are sought after by image restoration systems [5], which are based on the underwater image generation paradigm [3], [4]. On the other hand, image augmentation systems [6], [7] are dedicated to obtaining aesthetically acceptable photographs and do not rely on underwater image generation models. Because of their exceptional performance, various deep learning-based techniques [8], [9] have been used more recently to enhance the quality of underwater photos. It is still difficult to minimize information loss and prevent over-enhancement, even with recent advancements. In particular, the single assumption of water qualities prevents restoration-based approaches from being applied to all types of degradation circumstances.

Similarly, enhancement-based procedures typically provide outcomes that are over-saturated. Deep learning-based techniques can produce satisfactory results in some underwater landscapes, but their practical constraints include the need for a large number of label images, lengthy training periods, and generalization issues. Most significantly, in certain instances, these techniques fail to take into account the structural variations present in the image. Furthermore, the majority of current techniques are unable to prevent texture blurring while enhancing image visibility. For high-level visual applications, the texture of an image really contains some useful information that may be utilized to define the properties of objects. Consequently, it is desirable and significant to find an efficient way to get beyond these restrictions.

II. RELATED WORKS

Numerous methods have been developed over time to enhance underwater image visibility and clarity. These strategies fall into three categories: CNN-based, restoration-based, and enhancement-based techniques. Based on an underwater imaging model, these techniques use previous knowledge to predict physical attributes, flipping the imaging model to produce high-quality photos. A number of prior-based techniques were put out for underwater image restoration, drawing inspiration from dark channel prior [19]. Chiang and Chen [20] compensated for the attenuated wavelength in order to reconstruct underwater images based on the unequal absorption of light with different wavelengths. In order to assess the scene's depth, or the underwater dark channel previously, Drews et al. [21] eliminated the red channel due to the significant absorption of red light. To prevent overexposure, Galdran et al. [22] suggested saturation before correcting the scene's depth and inverted the red channel. In order to determine the physical characteristics for restoring underwater photographs, Li et al. [23] reduced the amount of color information lost in recovered images.

To estimate FIGURE 2, Peng et al. [24], [25] suggested a prior using light absorption and image ambiguity. restored outcomes from several scenes using the suggested strategy. restoration of underwater images using a transmission map and generalized DCP (GDCP). In order to repair the wavelength-based degradation in underwater photos, Berman et al. [2] created haze lines from deteriorated underwater photographs. Furthermore, additional previous data was suggested in order to precisely estimate the scene depth. In order to assess the depth of underwater scene (ROPU), Liu et al. [5] investigated the rank-one prior of underwater photos. Dai et al. [14] estimated transmission maps (DCAC) by breaking down deteriorated color curves into RGB axes. Zhou et al. [3] used adaptive dark pixels to remove back scattering and suggested channel intensity before estimating the depth map. Restoration-based techniques are sensitive to planned prior information and rely significantly on the characteristics of the physical imaging model. Therefore, a strong imaging model and presumptions are essential for fixing underwater image contamination.

Without using underwater imaging models, enhancement-based techniques directly modify gray values to produce aesthetically pleasing photos. Histogram-based, fusion-based, and Retinex-based techniques are common in this group. A thorough technique for modifying underwater image histograms was proposed by Hitam et al. [26]. It uses contrast-limited adaptive histogram equalization across a range of color spaces. Inspired by fusing multi-exposure photos, Wang et al. [31] presented an adaptive framework for improving low-light images. To improve underwater photos, Li et al. [7], [32] suggested the hybrid framework (HFUE) and adaptive color and contrast enhancement technique. In order to estimate light and reflectance, Zhuang et al. [6] created a variational framework that explores underwater image prior information in terms of multi-order gradient. Furthermore, because of their outstanding performance, a number of variational frameworks have also been used for hazy image enhancement.The optical characteristics and mechanism of underwater imaging are ignored by enhancement-based techniques. As a result, these techniques are prone to overexposure and underexposure in local areas and cannot precisely correct for the colors lost due to attenuation.

We thoroughly examined 167 excellent, immediately applicable research papers in order to assess the state of the field. We selected the top 10% of the most cited publications from this pool and, as shown in Figure 5, plotted their distribution on a bar chart. The publication sites of these highly referenced publications further support this increase in research effort. These important discoveries and cutting-edge methods are widely shared by prestigious journals like IEEE Transactions on Image Processing and IEEE Access, which further establish their status as important forums in the field. Additionally, Figure 6 highlights the broad and interdisciplinary interest in overcoming the difficulties of underwater imaging during the past ten years by listing the journals and conferences with the greatest number of papers in this field. While conventional image enhancing methods can be useful, the particular difficulties of underwater imaging frequently necessitate the use of specialized dehazing techniques in order to successfully reduce the effects of light scattering.

This focused analysis offers a better comprehension of the complexities and difficulties particular to underwater dehazing. • Comparative Insights: This review clarifies the advantages, disadvantages, and possible future paths of both conventional and state-of-the-art learning-based dehazing methods by a thorough comparative analysis. Our goal is to give scholars and practitioners a thorough road map by analyzing breakthroughs in the field and drawing lessons from foundational publications.Thorough Assessment: This evaluation is more than just a description. In order to comprehend the relative performance of dehazing algorithms across important criteria, we examine the theoretical frameworks that support them and examine actual data. This thorough analysis highlights the trade-offs present in various strategies and the obstacles still standing in the way of realizing underwater dehazing's full potential. Engaging Guide: This review is not intended to be merely a dull academic exercise. It aims to be an engaging manual that navigates the complex relationship between human perception and physics computation.

We hope to provide researchers and practitioners a better grasp of the state-of-the-art and open the door for future developments in this crucial area by illuminating the complexity of underwater dehazing in an approachable and entertaining manner. The combined goal of these contributions is to offer a useful tool for practitioners and researchers involved in underwater image dehazing. This review paper aims to shed light on the way to a better understanding and future developments in undersea exploration and analysis by providing a targeted analysis, comparative insights, thorough evaluation, and an engaging presentation computation as well as human perception. We hope to provide researchers and practitioners a better grasp of the state-of-the-art and open the door for future developments in this crucial area by illuminating the complexity of underwater dehazing in an approachable and entertaining manner. The combined goal of these contributions is to offer a useful tool for practitioners and researchers involved in underwater image dehazing. This review paper aims to shed light on the way to a better understanding and future developments in undersea exploration and analysis by providing a targeted analysis, comparative insights, thorough evaluation, and an engaging presentation.

This section offers a thorough summary of the current research on underwater image quality improvement, covering deep learning-based, restoration-based, and enhancement-based approaches. In order to recover the intended outcomes, image restoration-based approaches use specific priors to estimate various imaging model parameters [3], [4], and then reverse-deduce the deterioration process. Dark channel prior (DCP) [10], which was first suggested to eliminate fog for outside scenes, served as the model for several underwater image restoration techniques. A red channel prior (RCP) technique was presented by Galdran et al. [11], in which the distorted colors were restored in order to enhance contrast and make up for the lost visibility range. Cheng et al. then proposed a red-dark prior [12] to estimate the transmission map (TM) and background light (BL). A straightforward yet effective low-pass filter was used to deblur deteriorated sceneries and compensate for the distorted colors in order to recover the images.

Underwater DCP (UDCP), a modified dark channel prior that disregards the detrimental effects of degraded red channels, was used to recover underwater scenes concurrently while taking into account the attenuation of green and blue channels [13]. For transmission estimate, Chang et al. [14] created a submerged dark channel prior (SDCP) in the process. To fix the bright hue and lessen the absorption reaction, they used a point spread function deconvolution. However, due to light attenuation and different lighting circumstances, these DCP-based methods might not be able to reconstruct degraded sceneries. When evaluating the scene depth and BL, Peng et al. [15] considered image blurriness to counteract the impacts of illumination changes.

They recovered scene radiance by first obtaining BL from areas that were fuzzy, and then calculating the depth map and TM. A nonlocal adaptive attenuation-curve prior was developed to estimate the TM in Wang et al.'s [16] effective signal underwater picture restoration technique. In [17], colors of the light source were used in place of the conventional global BL, and the TM is calculated by a unique joint prior. In contrast, Park et al. [18]

reconstructed the photos using an integrated underwater image creation model, which helps remove hazy in damaged images by taking forward scattering into account. Adaptive histogram equalization (AHE) [19], [20], gray world [21], [22], and retinex-based techniques are examples of enhancement-based techniques that, in contrast to restoration-based techniques, concentrate on modifying picture pixel values to improve image quality. [23], [24].

In order to enhance the quality of underwater photographs, Iqbal et al. [25] first used linear stretching to alter the distribution of color channels and then incorporated HSI's saturation and intensity stretching. In order to divide the image under observation into many layers, Liu et al. [26] suggested using a deep sparse non-negative matrix factorization (DSNMF). They obtained the improved results by applying the estimated illumination to each level of the original image. In order to provide lucid results from the blurred images, Ma et al. [27] developed two innovative algorithms: single scale difference backtracking (SSDB) and multiple scale difference backtracking (MSDB). These conventional augmentation techniques, however, are limited to addressing a certain kind of deterioration issue. Luan et al. [28] present a hybrid technique for underwater image enhancement that removes different degradations.

By combining the wavelet domain denoising algorithm, homomorphic filtering algorithm, and contrast stretching algorithm, they sought to enhance contrast and reduce noise. Marques et al. [29] developed a two-branch model to eliminate darkness and accentuate minute features in low light underwater photos. Although this technique can increase the visibility of images in low light, it can also magnify noises and frequently produces an artificial appearance. Ancuti et al. created a novel multi-scale fusion technique in [30] to eliminate the color cast and reduce sounds in the reconstructed image at the same time. In order to adjust color, preserve features, and eliminate fog, Liang et al. [31] also used the effects of wavelength-dependent color attenuation and suggested a multi-scale dehazing algorithm. A color correction and bi-interval architecture was then introduced by Zhang et al. [32] to enhance image visibility and remove underwater disturbance.

III. PROPOSED SYSTEM

Depth map estimation for underwater image restoration. Prior to obtaining a depth map, image blurriness is utilized. The blurriness of an image grows with depth. In this case, backlight is extracted from the regions with the highest blurriness and the lowest variance. The brightest pixel at the top is used to estimate a backlight. Foreground things appear brighter than background objects when artificial lighting is utilized for illumination. Therefore, choosing the brightest pixels could produce inaccurate findings. The scattering of suspended particles, minerals, and rocks in the water causes blurry images. The relationship between depth and blurriness is linear. Therefore, determining the image's blurriness provides information about depth. There are five different methods for measuring visual blurriness. Image blurriness in the first category is determined by measuring the image's energy. A comparison of the energy of the original and deteriorated image yields the blurriness metric since blurring can smooth the image's edges and reduce the energy of high-frequency coefficients.

Since blurriness can make sharp edges in an image smooth, the second category takes the image's edge into account. Its breadth and edges are derived from horizontal and vertical gradients. Pixel intensity distribution is the subject of the third category. This approach takes into account that a sharper image has higher variance and entropy values. Local gradient metrics are part of the blurriness evaluation for the fourth category. One local gradient metric for estimating blurriness is singular value decomposition. Combinations of the previous four categories are used in the fifth category. However, because noise can intensify high-frequency material in an image, these techniques are vulnerable to noise. The aforementioned techniques for calculating blurriness cannot be applied to underwater image restoration since there is no reference image available. The supplied image is first transformed into the YCbCr color format. Luminance is represented by Y, whereas chrominance values are represented by Cb and Cr. Instead of taking chrominance values into account, blurriness is computed just utilizing the luminance component. Based on Y, it is simple to distinguish between sharp and hazy areas because it is more representative of the human senses. A sharp edge in the picture means there is less blur. then determines how much the brightness component differs from its Gaussian-filtered counterpart.

As a lowpass filter, Gaussian filtering keeps low-frequency information while eliminating high-frequency elements like noise or edges. There are delicate features and sharp things in this difference. This difference is then subjected to a maximum filter. This window is moved over after this filter determines the maximum value inside it. Any image size can be used with a window size of 7 to 31. Here, a window size of seven is used. Hole filling is used to recreate the output image. Only crisp details remain in the final image after the blurred areas have been eliminated. Therefore, a tiny value on the blurriness map indicates that the relevant pixels in the image are blurry, while a big value indicates that they are not. Thus, a smooth area would have tiny values and sharp edges would have large values. However, since they all belong to the same object, a smooth area surrounded by sharp edges would not be regarded as blurry. Fig. 3 displays the blurriness of the image.

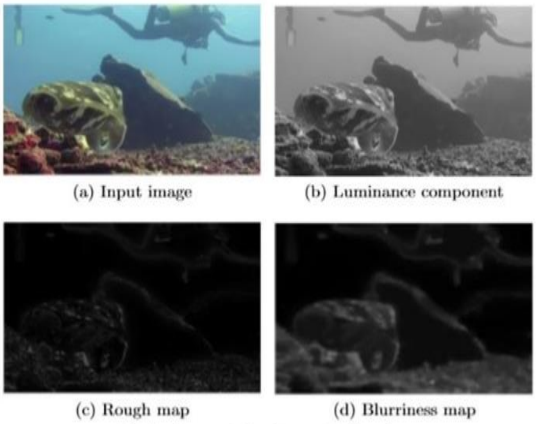

Fig. 3. Estimating Image Blurriness

A. Estimating Backlight:

The backlight is caused by light being scattered by water particles. It lessens image contrast and provides a fuzzy overlay. This method takes into account variance and blurriness in addition to one percent of the top brightest pixels in order to overcome the limitations of backlight estimate techniques (in the event of artificial lighting or brighter foreground objects). Here, the regions with the highest blurriness and the lowest variance are taken into account; quadtree subdivision is used to obtain these regions. Pixel values do not vary significantly in low variance regions. It is hence more likely to discover backlight. Although low variance does not always indicate that a region is fuzzy, blur zones always have low variance. Therefore, the requirements for the biggest blurriness and low variance are not equivalent. Because ambient light scatters more when one travels deeper into the water, the backlight is dependent on depth. Backlight estimation takes into account the biggest blurriness zone in order to account for this reliance.

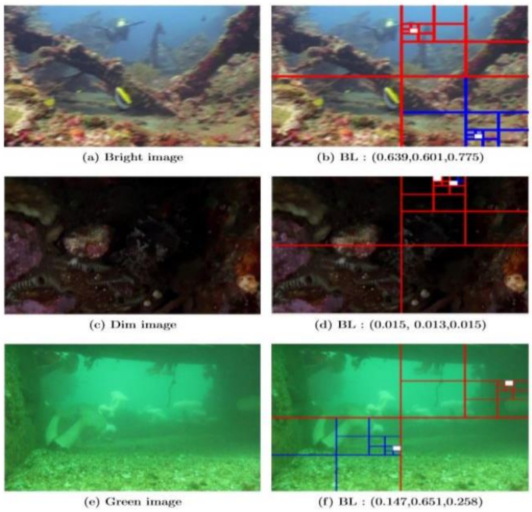

Fig 4. Estimation of Backlight

First, the image is evenly split into four quadrants based on variation or blurriness. Next, in the case of the blurriness zone with the highest value, the quadrant with the lowest variance is selected. The variation of individual pixels is averaged to determine the variance within a quadrant. Four additional quadrants are created from the one with the least deviation. Until the quadrant size falls below a predetermined threshold, this process is repeated. The maximum value of backlight is selected as the estimated backlight since it is more appropriate when the percentage of brilliant pixels is high. The lowest backlight value is used as the estimated backlight if the picture was captured with insufficient lighting (smaller ratio). The backlight is computed as the sum of these maximum and minimum values in the intermediate range between these extreme circumstances.

Backlight estimation is depicted in the figure, with the red line denoting blurriness and the blue line representing variation. The region with the biggest blurriness and the lowest variance is indicated by the white part. Backlight estimation for bright, dim, and green input images is displayed in Fig. 3. In all RGB color channels, a bright image has higher backlight values; the BL for fig. 3a,b is [0.639,0.601,0.775]. All three channels have lower backlight values for the dim input image, and the backlight produced for figures 3c and d is [0.015, 0.013, 0.015]. Only the green channel in the green input image has a higher backlight value than the other channels. Figure 3e, f's obtained backlight is [0.147, 0.651, 0.258].

B. Estimating Depth:

Underwater light attenuation is dependent on the wavelength and distance of the light. Here, three approaches are combined to measure depth. The third approach is based on visual blurriness, while the first two are based on different wavelengths having different attenuation rates. 1) Making use of red channel content: Red light attenuates more quickly than other colors since it has the longest wavelength in the visible spectrum. The majority of the red channel content may be lost as the light gets deeper. Therefore, an estimate of depth is obtained using a measure of red channel richness. An image was taken at a lesser depth if it has a significant amount of red channel value. The red channel information is nearly lost when the image I c (y) is taken at a deeper depth.

Red channel content is,

$R(x) = \max_{y \varepsilon \omega(x)} I^c(y)$ (2)

where ω(x) is a window of size 7,centered about x and c ε{r,g,b}. Then depth map is,

$d_R = 1 - K(R)$ (3)

Since three diff erent depth maps are combined, for them to be in the same range [0, 1] stretching function K is used. It is given by

$K(L) = L - L_{min} / L_{max} - L_{min}$ (4)

Using a three-color channel: Since light attenuates depending on color, the difference in attenuation of the various color channels (red, green, and blue) can be utilized as a precondition to compute a depth map. Compared to green and blue light, red light has a higher attenuation constant.

C. PROPOSED METHODOLOGY:

Because of light absorption, dispersion, and noise, underwater photographs frequently exhibit distortion, which lowers visibility and color fidelity. In order to successfully restore single underwater photos, this project presents a variational framework that is led by an underwater imaging model. Our method delivers accurate color restoration and improved image clarity by integrating noise models. The Schematic block overview of the proposed system is illustrated in fig(5).After considering the distorted underwater image as an input, the proposed system preprocesses it to remove any noise and then presents it to the color correction phase, which corrects for color distribution disturbances caused by undesired atmospheric light scattering at water molecules.The impact of light scattering and attenuation on the altered image quality is then assessed and statistically predicted.

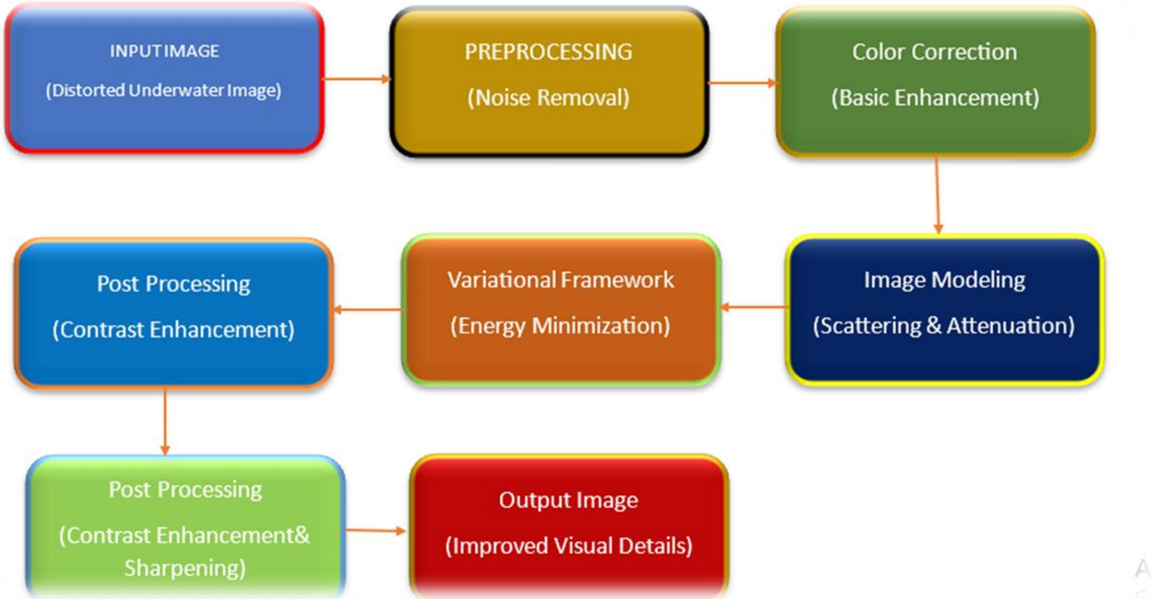

Figure 5 shows an overview of the proposed underwater image enhancement system's schematic blocks.

A key factor in raising the visual quality of underwater photos is the variational method, which is based on energy reduction concepts. By improving the structural characteristics of the image, this method helps to reduce the distortions that occur in underwater photos as a result of light absorption and scattering. In order to ensure that the improved image retains a natural appearance, guided filtering is next used to sharpen the image features by maintaining edges and lowering noise. By combining variational techniques with directed filtering, color distortion may be efficiently corrected, visibility can be improved, and crucial image elements that are frequently lost in underwater environments can be restored.

A post-processing stage is carried out to further improve the outcomes after the conceptual quality repair techniques are applied to the underwater image. In order to increase the image's overall clarity and make the smaller details easier to see, more contrast enhancement techniques are used during this step. Additionally, object borders and textures are improved through the use of sharpening procedures, giving the image a more defined and appealing appearance. The final quality-corrected underwater image is produced after these post-processing procedures are finished. Performance evaluations are conducted to verify the efficacy of the suggested enhancement strategy. The processed image is compared to conventional enhancement methods to show improvements in visibility, contrast, and overall image quality.

IV.RESULTS AND DISCUSSION:

The proposed underwater picture quality restoration system is designed, developed, coded, implemented, and simulated in the Matlab environment. The results of the simulation are displayed below. A picture's overall perception is influenced by its visual quality, which includes color correctness, contrast, detail preservation, and naturalness. Recent advances in variational framework-based underwater image enhancement have significantly improved visual quality in comparison to traditional methods.

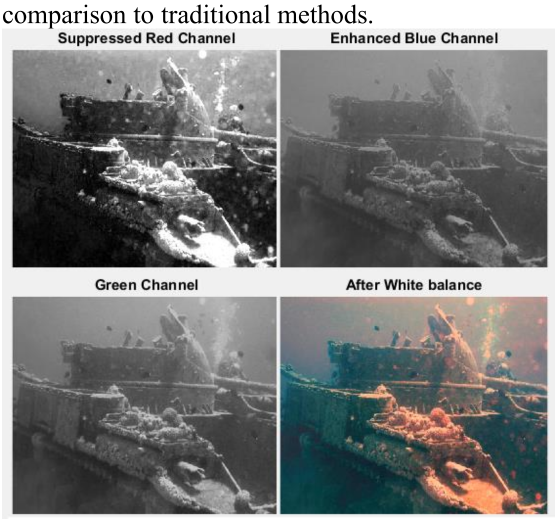

Fig. 6. Distorted underwater image color correction.

The photos depict a variety of underwater conditions, emphasizing typical issues such as low contrast, blurred features, and blueish/greenish casts. Deep learning has become a potent tool for improving underwater images, although not all methods use it.

Figure 7: Using the Variational Framework to improve the conceptual quality of an underwater image.

Figure 8 shows the underwater image's higher order enhancement following variational framework with a guided filter.

Color correction is the main function of the underwater picture enhancement system, and Fig. 6 shows the outcomes of this process. On the other hand, Fig. 7 displays the primary enhancement results using the variational framework of the suggested underwater picture enhancement system, and Fig. 8 displays the Higher Order enhancement results further produced with a guided filter. Figure 9 displays the final improved underwater image, and Figure 10 displays the quality score graph for the suggested underwater image enhancement approach.

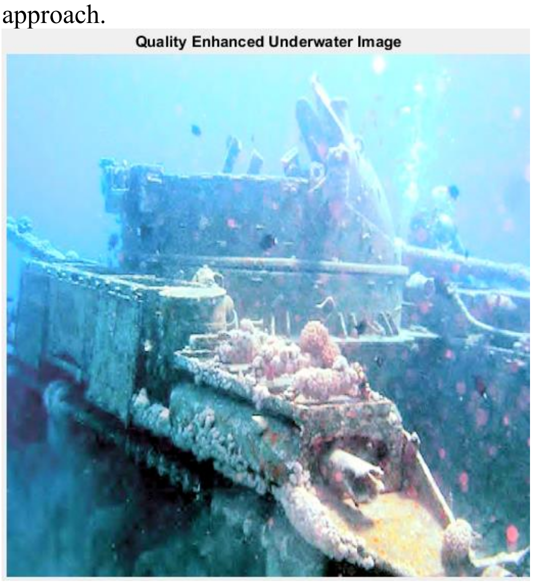

Fig. 9. After the post-processing stage, the underwater image quality was improved.

However, when it comes to visual quality, deep learning-based techniques typically do better than conventional methods. The model's internal and external representation learning stages are responsible for this achievement. The total image appears more realistic thanks to the interior stage, which enables differential improvement of damaged areas. Furthermore, the restoration of finer features in object structure and edges is made easier by the external information from related photos.

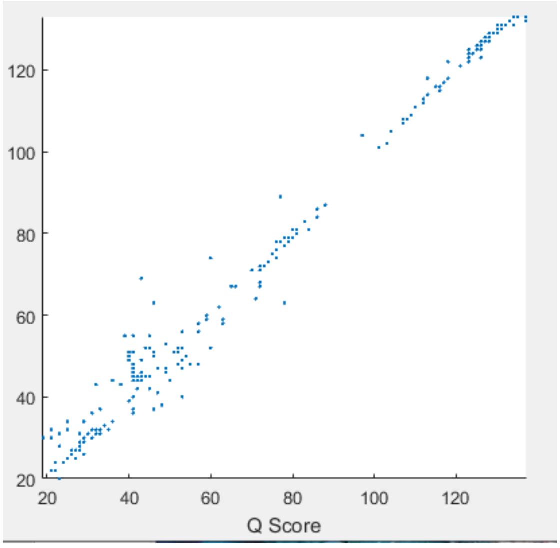

Figure 10: The suggested underwater image enhancement system's improved quality score graph.

These results demonstrate how deep learning-based techniques have improved the visual quality of underwater photos. The precision and naturalness of underwater picture restoration will continue to be enhanced as the field develops thanks to additional improvements made to these models.

V. CONCLUSION:

Because light scattering and absorption severely degrade image quality, underwater image augmentation is still a major difficulty. This research proposes a new framework for underwater image enhancement that uses directed filtering and variational energy minimization. In order to accomplish color correction, foreground enhancement, detail preservation, and texture expansion for underwater photos, the Variational model and total guided filters are combined here. Additionally, for implementation efficiency, we build two fast techniques based on gradient descent and ADMM with FFT acceleration methodology. Numerous tests conducted on actual underwater photos have validated the efficacy of our methodology. With PLCC of 0.9670, SROCC of 0.9525, SSIM of 0.9627, UQI of 0.9481, and MLSSIM of 0.9862, the suggested approach performs at its peak.Furthermore, a thorough examination that includes both qualitative and quantitative components guarantees that our suggested approach performs at the cutting edge. The conclusion would be strengthened if the effect of low underwater image quality on certain applications, such marine biology or underwater archaeology, could be quantified. The importance of this field of study could be highlighted, for example, by presenting data on the monetary losses brought on by erroneous image interpretation or the shortcomings of the available equipment for underwater exploration.

VI. FUTURE SCOPE:

Future studies should concentrate on creating reliable models that can manage a variety of underwater conditions, processing in real time for real-world uses, and integrating physical priors into deep learning frameworks. Researchers can greatly improve underwater imaging capabilities by tackling these issues, which will lead to advances in underwater archaeology, marine biology, and other disciplines. Future research will concentrate on examining new methods to increase computational stability and efficiency, particularly minimizing the impact of iterations and input parameters. Furthermore, it is recommended that more research be done with a focus on creating an effective algorithm for certain harsh underwater situations.

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