MarineEye: A Comparative Study on Underwater image Quality

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Abstract—Marine exploration, like underwater archaeology, ocean exploration, industrial inspection, marine research, and rescue operations, faces issues due to inaccurate visual analysis. Underwater images face critical challenge due to light absorption, scattering of light, and color distortion in aquatic environments, causing degraded image quality, low contrast, and loss of details. The MarineEye project aims at a systematic comparative analysis of existing enhancement techniques, including classical image pro- cessing methods (e.g., Histogram Equalization, CLAHE, Retinex), deep learning-based approaches (e.g., WaterNet, UWCNN), and GAN-based models (e.g., UWCycleGAN, FUnIE-GAN), without developing a new model. Performance is evaluated using standardized metrics: Peak Signal-to-Noise Ratio (PSNR) for noise reduction, Structural Similarity Index Measure (SSIM) for structural fidelity, underwater color image quality evaluation (UCIQE) for color and saturation, and Underwater Image Quality Measure (UIQM) for overall sharpness and contrast. In this study, we develop a comparison matrix to guide the selection of techniques for specific use cases, enhancing decision-making for practical underwater imaging applications.
Keywords— Underwater Imaging, Image Enhancement Evaluation, Deep Learning, GAN, Image Resolution, CNN

1 INTRODUCTION

Underwater imaging is required for various types of applications such as marine biology research, ocean exploration, underwater pipeline inspections, and underwater rescue operations. However, underwater images are often noisy and of low quality, dominated by blue-green tones, which consist of diminished visibility and often lack details due to the optical properties of water, such as light absorption and scattering by suspended particles. Which causes degradations of visual interpretation. The most important aim of image enhancement models is to fix these problems by restoring colour balance in the image, making the colour contrast if the image better, and turning down the noise. Implementation of the classical image enhancement methods is easy and provide immediate solutions, but they usually lead to mistakes, while advanced models based on deep learning and GAN-based methods give us more natural results, but they are harder to implement and more time consuming in comparison. The MarineEye project seeks to resolve the challenge in selecting the best method from the variety of options available. By analyzing the classical methods, deep learning methods, and GAN-based techniques. The main goal is to create a comparison matrix with the help of quantitative measures, letting users to select the method best suited for specific scenarios according to their needs.

PROBLEM STATEMENT

Underwater images have few degradations: darkness increases noise and low contrast, the scattering of particle results in a kind of mist that blurs the edges; light absorption

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scattered over longer wavelengths causes those warm hues to disappear while dominantly blue ones remain basically unchanged. Now image quality suffers from these impairments in both its amount and intensity, not to mention much else. Anything based on such inadequate information--like identifying species or piping CTDs up on ROVs to check for bedrock outcroppings turns undependable and hard-to do. Current techniques have some limitations: Deep learning models such as CNNs have high demands for training data and GPU resources, making it difficult to deploy on embedded systems in a timely manner; Global contrast reduction and noise amplification are both side effects of Histogram Equalization (HE). The GANs, on the other hand, are second to reproducing authenticity, but they carry with the potential defect that replication may appear over-enhanced in some regions. What's more, a lack of a common benchmark for such situations such as murky versus clear water hinders us from deciding which image processing algorithm is better. To this end it gives a guide for development in this important field.

OBJECTIVES

The objectives of this research paper are as follows:

1) Developing an understanding about pre-existing underwater image improvement models.
2) Then, we will try to categorize these models into Classical, CNN, GAN and Hybrid models and select the appropriate model from each subset.
3) Evaluation metrics PSNR, SSIM, UCIQE and UIQM will then be applied to enhanced images generated by every model to construct a comparison matrix.

LITERATURE REVIEW

We will explain the prior work on underwater image enhancement in this section. We will here mainly concern ourselves with different methods and the techniques they employ, and try to get a grasp on what these are based on – as well as why After all we would like to divide this study into three parts:

- Classical Techniques
- Deep Learning Methods
- GAN-Based Methods

A. ***Classical Techniques***

These have been traditional image processing techniques. They employ the manual priors to improve image quality.

- Histogram Equalization (HE) [1]: This change consists in reassigning pixel values to the entire dynamic range. We then attempt to enhance low contrast visibility by stretching the histogram. The disadvantage of this approach is that it will cause noise amplification in the hazy area, which results in failure to retain local structure under non-homogeneous illumination.
- Contrast Limited Adaptive Histogram Equalization (CLAHE) [2]: This technique is an adaptation of the Histogram Equalization. In this method we partition the image into smaller tiles. Histogram Equalization is then performed for each tile individually.

However the above approach will result in blocking artifacts at tile boundaries in textured regions.

- Retinex Theory (Multi-Scale Retinex with Color Restoration, MSRCR) [3]: The Retinex is inspired by the human vision. In this approach, given an image, we split it into reflectance and illumination components. The illumination component is removed from the image by estimation.MSRCR restores natural colours that are lost due to wavelength attenuation. Retinex model struggles in low-light and highly scattering situations.

B. ***Deep Learning Methods***

The image is estimated for the illumination component and subtracted therefrom. The MSRCR process attempts to recover natural colours which are lost as a result of wavelength attenuation. Retinex model fails in low light and high scattering scenario.

- VDSR (Very Deep Super-Resolution) [4]: This is one of the first CNNs involving multi-scale process with deep layers. It is exploiting the residual learning for high-frequency detail prediction. The VDSR model is very effective in reconstructing high frequency edges and textures from low resolution, noisy images. It provides a global residual connection that stabilizes the training by adding depth. But does better images having more blue - green tints.
- EDSR (Enhanced Deep Super-Resolution) [5]: We get rid of redundant batch normalization layers in the EDSR and adopt deeper Residual Blocks (e.g., up to 32 layers), which greatly enhances the sharpness and PSNR. Compared with VDSR, it performs better by 1~2 dB in PSNR for the under-water test data. Nevertheless, it constructs straightforwardly relies on the paired training data (degraded vs. ground truth), which is not always available in real ocean environment.
- DnCNN (Denoising CNN) [6]: A blind denoising net- work using residual learning and batch normalization. DnCNN effectively reduces scattering-induced noise without knowing its distribution. However, it treats color distortion as secondary, resulting in failing to restore red channel information.
- WaterNet [7]: A CNN model that explicitly incorporates water type and depth estimation as auxiliary inputs. Using a multi-branch architecture, it jointly predicts color correction, contrast enhancement, and dehazing. WaterNet achieves balanced results across clear and turbid waters. Its moderate inference speed limits real-time use on edge devices.
- UWCNN (Underwater Convolutional Neural Network) [8]: A compact CNN trained on synthetically degraded images using ten physical priors. It replaces high data dependency by pairing with physics- guided synthetic pairs. However, it reduces generalization to unseen water types.
- U-Shape Transformer [9]: A hybrid of U-Net and Vision Transformer architecture that combines local convolutional feature extraction with global self-attention. It captures better long-range dependencies. However, it operates on high computational cost (300 ms/image) and a large memory footprint.

C.

TABLE I: Comparative Summary of Underwater Image Enhancement Techniques

Category	Method (Year)	Advantages	Limitations
Classical	HE (1987)	Simple, fast, improves global contrast	Amplifies noise, poor local contrast
Classical	CLAHE (1994)	Edge preservation, handles hazy regions	Block artifacts, limited in turbid water
Classical	Retinex (1971)	Effective color correction	Sensitive to illumination errors
Deep Learning	VDSR (2016)	High PSNR, good detail recovery	High compute, data intensive
Deep Learning	EDSR (2017)	Sharp results, efficient training	Needs paired data
Deep Learning	DnCNN (2017)	Effective noise reduction	Limited color recovery
Deep Learning	WaterNet (2018)	Balanced color and contrast	Moderate speed
Deep Learning	UWCNN (2020)	Efficient in turbid water	Poor generalization
Deep Learning	U-Shape Transformer (2021)	Global attention, sharp details	High computational cost
GAN-Based	UGAN (2018)	Handles unpaired data, realistic output	Training instability
GAN-Based	FUnIE-GAN (2020)	Real-time, lightweight, vivid colors	Minor blurring
GAN-Based	UWCycleGAN (2020)	Superior color restoration	Artifact formation
GAN-Based	UIE-GAN (2022)	High perceptual quality	Dataset-dependent

GAN-Based Methods

Generative Adversarial Networks introduced photorealistic enhancement by pitting a generator against a discriminator in a minimax game.

- UGAN (Underwater GAN) [10]: An early CycleGAN variant, which is trained on unpaired underwater and air images. It learns to translate degraded underwa- ter images to clean in-air equivalents without paired data.
- FUnIE-GAN [11]: It works on a lightweight U-Net generator which pairs with a PatchGAN discriminator. It is the first real- time underwater GAN. It ensures natural colors and textures. However, minor blurring in deepwater scenes remains a limitation.
- UWCycleGAN [8]:An enhanced CycleGAN incorporating underwater imaging priors (attenuation, backscatter) into the loss function. However, cycle consistency can introduce subtle artifacts in regions with high frequency.
- UIE-GAN [12]: A recent GAN with an underwater degradation model and multi-scale discriminator. It consists of a water- type classifier branch. UIE-GAN achieves top-tier performance across benchmarks. But, it is highly data-dependent and sensitive to shifts

in training distribution.

D. *Comparative Summary and Recent Trends*

Recent surveys [12], [13], [14] confirm a clear trend: GAN-Based methods developed after 2020 dominate in perceptual quality, particularly in color fidelity and naturalness, while Classical methods retain advantages in speed and deployment ease. Deep learning methods are more efficient but require extensive data for training and are comparatively slower.

Hybrid approaches[15], that combine two or more approaches can be considered as a better option. Although it can be concluded that no single method performs well in all the sections. This problem leads to systematic, metric-driven comparison, which is what we would like to address in this paper. A comparative summary of different types underwater image enhancements techniques is summarized in

TABLE I.

DATASETS FOR UNDERWATER IMAGE ENHANCEMENT

The choice dataset varies across different benchmarks used for evaluation Some of the benchmarks are as follows:

- UIEB (Underwater Image Enhancement Benchmark) [16]: It contains 890 real underwater images with references.
- EUVP (Enhancing Underwater Visual Perception) [17]:It consists of datasets in paired and unpaired form for training.
- UFO-120: It focuses majorly on forward-looking sonar images [18].
- LSUI (Large-Scale Underwater Image) [19]: Over 5000 images for diverse conditions.

We will be using the Underwater Image Enhancement Benchmark for our evaluation of different methodologies.

EVALUATION METRICS

In this section, we introduce four measurements with which we conduct the comparative experiments. The criteria considered in this paper are PSNR, SSIM (2006), UCIQE and UIQM [3], and how they perform when applied to underwater images.

A. *Peak Signal-to-Noise Ratio (PSNR)*

Theoretical Background: PSNR based functions measures the disparity between the peak signal and noise in an image. The pixel-wise mean squared error(MSE) is used to measure the amount of noise. A large value of PSNR indicates less distortion; meaning that the enhanced image has lower distortion. The issue is that PSNR gives the same weight to all errors. It doesn't differentiate between kinds of error. [20][21].

Formula: [21]Let I be the reference image and $\hat{I}$ the enhanced image, both of size $M \times N$, with maximum pixel value MAX (typically 255 for 8-bit images). The MSE is:

$$MSE = \frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j) - \hat{I}(i,j))^2$$

Then,

$$PSNR = 10\log_{10}\left(\frac{MAX^2}{MSE}\right)$$

Units are in decibels (dB); values above 30 dB generally indicate good quality.
Advantages in Underwater Context: Simple computation; sensitive to noise of pixel-wise scattering, easy for dataset benchmarking such as UIEB with the paired images.
Limitations: Overreactant to subtle changes, dismissive of human vision, lowly related to subjective ratings under non- homogeneous light [20].

B. ***Structural Similarity Index Measure (SSIM)***

Theoretical Background: SSIM was created to get past PSNR's shortcomings and works as a full-reference metric. It is grounded in HVS (Human Visual System) theory. SSIM analyzes the similarity between two images based upon three components: luminance, contrast, and structure. SSIM analyzes scattering of light and contrast reduction better than PSNR. [20].
Formula: For image windows x (reference) and y (enhanced), SSIM is:

$$SSIM(x, y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

where μ is mean intensity, σ is variance, σ_{xy} is covariance, and c_1, c_2 are stabilization constants.
Advantages in Underwater Context: Aligns better with human visual percetion,Performs well across different brightness conditions[22].
Limitations: Performs poorly in color distortions situation(e.g., loss of red colour in deep water) [20].

C. ***Underwater Color Image Quality Evaluation (UCIQE)***

Theoretical Background: UCIQE does not require a reference for the evaluation of the image. It is based upon human perception of color.UCIQE is a blind image assessment test. It does not consider the underwater scenes to be static like previous method. This method was the first blind metric dedicated to this domain. [23].

Formula: Convert image to CIELab space. UCIQE is:

$$UCIQE = c_1 \cdot o_1 + c_2 \cdot o_2 + c_3 \cdot o_3$$

where o_1 = standard deviation of chroma, o_2 = contrast in L channel, o_3 = saturation (mean —a— + —b— in Lab), and c_1, c_2, c_3 are empirically derived coefficients (e.g., from regression on subjective scores).

Advantages in Underwater Context: Zero training is required as no-reference is needed,Implementation is very easy,Computation speed is fast.

Limitations: Works poorly on low light images,Fails on grayscale underwater images,Over focused upon colours in the image.[24].

D. ***Underwater Image Quality Measure (UIQM)***

Theoretical Background: UIQM is also a no-reference metric designed for underwater images.UCIQE lacked sharpness and over-focused on colours. UIQM improves by considering Human Visual System (HVS) in which it focuses on these three balanced components: colorfulness, sharpness, and contrast. UIQM uses fixed numbers to weight these three components. These weights came from comparing metric scores against what actual people judged when looking at images.[25]. Formula:

$$UIQM = a_1 \cdot UICM + a_2 \cdot UISM + a_3 \cdot UIConM$$

- $UICM$ (colorfulness): $UICM = \sigma_c \cdot \exp(-\delta \cdot \bar{r})$, where σ_c is chroma std. dev., $\bar{r}$ mean saturation, δ a constant. - $UISM$ (sharpness): Sobel gradient magnitude in wavelet domain. $UIConM$ (contrast): Weber contrast in log domain. Weights $a_1 = 0.0282$, $a_2 = 0.2953$, $a_3 = 3.5753$; higher UIQM (2–3 for good images) signals superior quality.

Advantages in Underwater Context: Comprehensive (multi-attribute); correlates well with MOS (0.9) on benchmarks like UIEB; enables no-reference optimization for realtime AUV systems.

Limitations: Fixed weights may bias toward certain degradations (e.g., overemphasizes contrast); computationally heavier due to wavelet processing; dataset-dependent validation [25].

METHODOLOGY

To identify the most effective methods for particular underwater conditions and computational limitations across four paradigms – classical, deep learning, GAN-based, and hybrid – MarineEye focuses on competitive analysis. Thus, this research tries to generate a comparison framework for systematically assessing underwater image enhancement techniques. Datasets:

Underwater Image Enhancement Benchmark (UIEB) with 890 real-world images, categorized into rock, portrait, and marine life subsets for diverse scenarios [16]. Pre- trained models were applied at 256×256 resolution.

Evaluation Metrics:

- PSNR: Measures pixel-level noise .
- SSIM: Assesses structural similarity .
- UCIQE: No-reference color quality.
- UIQM: Composite sharpness/contrast/color.

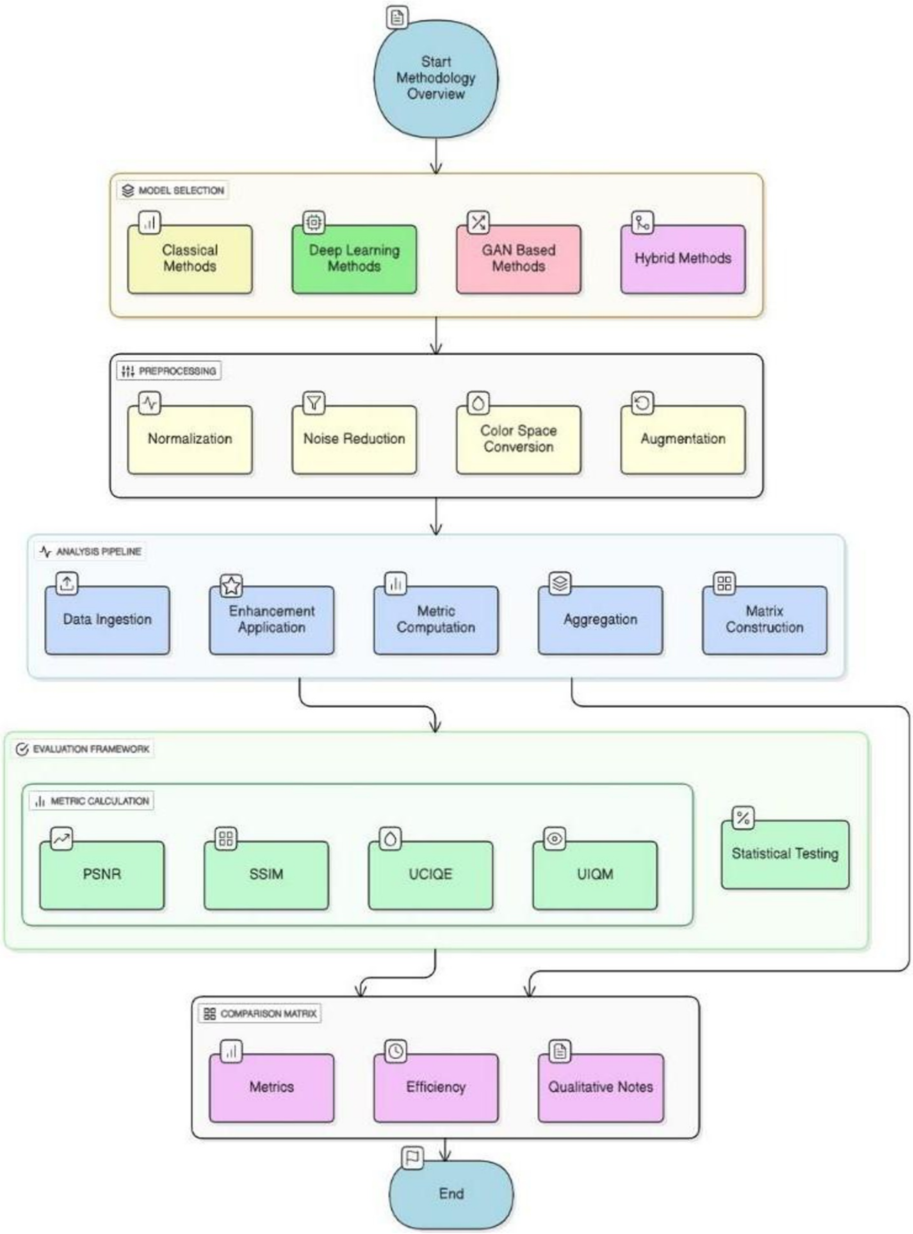

Fig. 1: Methodology Flow of MarineEye Framework

A comprehensive pipeline covering model categorization, preprocessing, enhancement application, metric computation, statistical testing, and construction of the final comparison matrix is demonstrated in Fig 1.
The analysis pipeline: (1) Preprocess images; (2) Apply enhancements; (3) Compute metrics vs. ground truth or noreference;
(4) Aggregate averages; (5) Build matrix. The methodology includes model selection, dataset preprocessing, metric computation, and comparison matrix construction using standardized evaluation protocols.

RESULTS AND DISCUSSION

Nine underwater image enhancement methods are assessed using four metrics in the MarineEye study—Peak Signalto-Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Underwater Color Image Quality Evaluation (UCIQE), and Underwater Image Quality Measure (UIQM). [26] The quantitative results are summarized in Table II, and a comparative visualization against the baseline is shown in Fig. 2.

Method	Category	PSNR (dB)	SSIM	UCIQE	UIQM
Input (Original)	-	-	-	19.25	0.15
HE	Classical	11.50	0.55	24.00	0.18
CLAHE	Classical	12.00	0.60	25.50	0.20
Retinex	Classical	12.00	0.65	27.08	0.244
WaterNet	DL	13.19	0.70	21.63	0.169
UWCNN	DL	12.82	0.68	14.09	0.104
VDSR	DL	14.50	0.72	22.50	0.200
UWCycleGAN	GAN	10.74	0.75	23.64	0.283
FUnIE-GAN	GAN	11.50	0.72	25.58	0.26
U-Shape	Hybrid	13.81	0.78	22.02	0.211

TABLE II: Performance Comparison Matrix

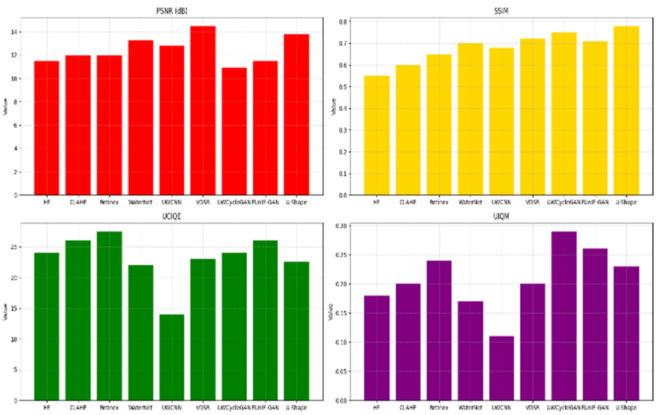

Fig. 2: Performance comparison of underwater image enhancement methods on the UIEB dataset [16].

B. Analysis and Discussion

The results demonstrate distinct trends among the evaluated categories:

- Classical Methods (HE, CLAHE, Retinex): These methods are simpler in deployment as the computational complexity is low.As, PSNR value drops from 13.48 to 11-12 the image become noisy. The structure of image
is improved as SSIM improves from 0.5 to 0.65. The Retinex method outperforms other classical method with the highest UCIQE score of 27.08
- Deep Learning Models (WaterNet, UWCNN, VDSR): These models require higher computational resources, a powerful GPU, and bigger datasets.DL methods improve the noise from images while preserving the details of the image. Though, the colours become dull as models like UWCNN have a bad UCIQE of 14.09.VDSR has the highest PSNR value of 14.50 across all the methods, which provides the best sharpness in images
- GAN-Based Models (UWCycleGAN, FUnIE-GAN): These models work on a dual neural network model, a
generator and a discriminator working in a competitive way. The structure preserved is better in GAN models, with SSIM lying in the range of 0.72 to 0.75. However, the accuracy of the image decreases as the PSNR value decreases to 10.74 in some cases. UWCycleGAN has the best UIQM value of 0.283
- Hybrid Model (U-Shape Transformer): These methods promises adaptive underwater imaging applications.It gives consistent high performance across all metrics (SSIM =0.78), trading-off local detail restoration and global color correction through its transformer–CNN architecture.

Overall, VDSR and U-Shape transformer provides the best fidelity and structural balance. Whereas Retinex and UWCycleGAN emerge as the top performers in perceptual quality.These findings highlight a balance between computational efficiency and visual realism.

CONCLUSION

Conclusion: By integrating classical, deep learning, GANbased, and hybrid technologies through a solitary evaluation scheme, the MarineEye project gives us an organised comparative framework for underwater image enhancement. In this research, MarineEye concluded that no single method universally works efficiently, and different techniques work for different operational requirements.. We evaluated that for shallow water or the real-time system, the Classical method (HE, CLAHE, Retinex) fits best; in addition, it has low computational cost and low perceptual quality. For high structural fidelity or noise suppression, use Deep learning methods (VDSR, WaterNet, UWCNN) at the cost of greater computational expense. To achieve superior perceptual realism or color balance, choose GAN-based techniques like UWCycleGAN and FUnIEGAN. On the other hand, for optimal trade-offs between global attention and local enhancement, select hybrid architectures such as the U-Shape Transformer. Overall, MarineEye sets a benchmark for balanced assessment and reinforces the shift toward data-driven, adaptive enhancement techniques in underwater imaging.

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