Nanotechnology Perceptions
ISSN 1660-6795
www.nano-ntp.com

Improved Underwater Image Enhancement Model based on Deep Learning Techniques

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This work solves issues including light absorption, scattering, and low visibility characteristic in underwater environments by means of a deep learning-based method, therefore improving underwater image quality. The aim is to increase image quality and detail, therefore enabling underwater photos more suited for study. The approach consists of gathering several datasets including raw underwater photos and their matching ground-truth images, preprocessed for best use. Images are downsized to a standard (256, 256) resolution; thereafter, histogram equalization, contrast stretching, and CLAHE help to enhance images. By increasing local and global contrast these preprocessing methods help to improve image visibility. Performing the enhancement task is the WaterNet model, a network of convolutional neural networks (CNN) with an encoder-decoder architecture and remaining connections in order to preserve low-level characteristics. Having been trained using a mean squared error (MSE) loss function, the model is optimized using an Adam optimizer with a learning rate scheduler. With a startling accuracy of 91.08% with minimum error, results reveal WaterNet beats existing models such DeepLab v2 and Logistic Regression in terms of photo improvement capability. These findings show the effectiveness of the WaterNet model, hence they offer a workable approach for useful underwater image enhancement applications.
Keywords: Underwater, Image Enhancement, Deep Learning, Convolutional Neural Networks, Color Restoration, Contrast Enhancement, Noise Reduction, Image Processing

1. Introduction

Driven by the need to improve the quality of images acquired in challenging underwater environments, underwater picture enhancement using deep learning has evolved into a promising field inside computer vision. For underwater photographers, many factors—including light absorption, scattering, and water's natural turbidity—all of which affect image clarity and visibility—cause tremendous challenge. In marine and oceanographic research, where tasks including underwater navigation, environmental evaluation, and monitoring of marine life depend on high-quality images, these challenges are particularly important. Traditional image enhancement techniques sometimes find it difficult to sufficiently address these problems since they depend on basic filters and adjustments that cannot fit the complex, dynamic character of underwater landscapes. Deep learning can learn complex patterns from large databases, hence it offers a more flexible and efficient solution to these challenges [1]–[5].

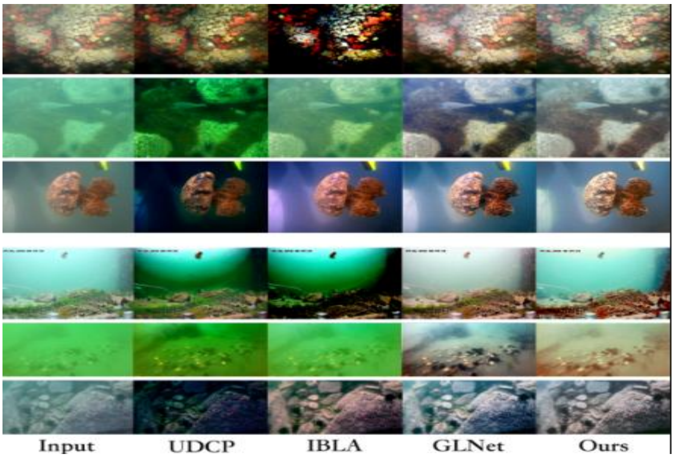

Figure 1 Under water image enhancement

Learning the basic characteristics of underwater images has helped convolutional neural networks (CNNs) and other deep learning models to demonstrate amazing ability in enhancing image quality. These models may spot automatically occurring low contrast, haze, and colour degradation, then act to either enhance or restore the photo's visual quality. Generative Adversarial Networks (GANs) and Autoencoders have especially drawn attention for their ability to generate clear, high-quality images from distorted inputs, therefore suitable for underwater image augmentation. Deep learning techniques One of the primary advantages for underwater image enhancement is the ability of deep learning to control the non-linear interactions between light and water factors. Deep learning models differ from conventional approaches in not depending on assumptions about water conditions or hand adjustment of parameters. Rather, they can be taught on vast collections of underwater photos so that the models pick up the particular distortions and noise patterns seen in such surroundings [6]–[11]. Deep learning methods thus provide more strong and scalable solutions for improving photographs in many underwater environments, including muddy waters, varied depths, and illumination conditions. Combining deep learning-based techniques with other computational approaches including image segmentation, feature extraction, and object detection helps to improve underwater image quality and usefulness even more. Underwater image enhancement, for instance, can be coupled with real-time video processing systems for autonomous underwater vehicles (AUVs), therefore enabling better navigation and interaction with their environment. In marine research, the improved photos can help to increase environmental monitoring, habitat mapping, and species identification accuracy. Though the area has made great progress, computing efficiency and the requirement for huge, annotated datasets for training deep learning models remain problems. Still, the continuous advancement in this field promises to transform underwater imaging greatly. Deep learning methods will probably become the norm for underwater picture enhancement with ongoing developments in algorithms and processing capability since they provide better, more accurate visual data for a wide spectrum of uses, from industrial operations to scientific study. Advanced neural networks combined with underwater image processing methods will keep stretching the envelope of what is feasible in this particular field [12]–[16].

1.1 Background and Contextual Framework

1.1.1 Historical Overview and Evolution of the Topic

Beginning with the introduction of simple optical devices for underwater photography in the middle of the 20th century, underwater picture improvement has evolved. Early efforts concentrated on enhancing visibility in photos taken at extreme depths, when absorption of light changed the scene's original colours and textures. Originally, photographers used basic techniques like filters and hand tweaks to improve contrast and lower color loss, but these approaches typically yielded poor results, particularly in deeper and murkier seas. As late 20th-century digital imaging technology developed, scientists investigated increasingly complex image processing methods [17]–[19].

Algorithms meant to offset colour loss and improve visibility in underwater images were histogram equalization and white balance correction. Still, these methods battled problems including noise, turbidity, and the different conditions of underwater habitats. With the emergence of deep learning in the 2010s, the real revolution occurred. Especially convolutional artificial neural networks (CNNs), deep learning models permit automatic extraction of characteristics and complicated picture restoration. These models might be taught to increase contrast, restore natural colour, and reduce noise using vast datasets of underwater pictures. Under deep learning, submerged picture enhancement evolved from a manual, algorithmic approach to an adaptive, data-driven process providing more exact and efficient solutions for numerous underwater photography needs [20].

1.1.2 Relevance to Current Research Landscape

Underwater image development is still a top priority of research especially in fields such marine biology, underwater robotics, and environmental monitoring. Deep learning developments have considerably increase the importance of this work in addressing the issues of poor vision, colour exaggeration, and picture degradation in underwater environments. The intricacy of underwater environments renders conventional image processing techniques usually unable to generate suitable results [21]–[25]. Particularly deep neural networks (CNNs), deep learning models present a possible substitute by automating a better procedure and adjusting to different underwater conditions. The focus of the current research scene is on building robust, real-time systems able of operating in diverse settings, from deep, muddy oceans to pristine coastal waters. These advances define better accuracy and efficiency of undersea exploration, navigation, and surveillance. Moreover, the coupling of deep learning with developing technologies including autonomous submersible cars (AUVs) improves opportunities for real-time image augmentation, thereby raising its value in marine research and protection [26]–[29].

2. Literature Review

Xingyang 2024 et al. a fresh UIE approach grounded on image-conditional diffusion transformer (ICDT). Using the degraded underwater image as the conditional input, our approach generates latent space from which ICDT is applied. In a denoising diffusion probabilistic model (DDPM), ICDT substitutes a transformer for the traditional U-Net backbone, therefore inheriting positive scalability from transformers. While concurrently greatly speeds the sampling procedure, we train ICDT using a hybrid loss function including variances to get superior log-likelihoods. We evaluate ICDT scalability empirically and compare with previous research in UIE using the Underwater ImageNet dataset. Apart from good scaling characteristics, our main model, ICDT-XL/2, surpasses all comparative techniques in obtaining state-of- the-art (SOTA) quality of image improvement[30].

Cong 2024 et al. In computer vision research, underwater image enhancement (UIE) poses a great difficulty. There is still a complete and methodical assessment lacking even with the invention of several UIE algorithms. We present a thorough summary of the UIE work from many angles in order to inspire next developments. First we present the physical models, methods of data creation, assessment criteria, and loss functions. Second, using six elements—network architecture, learning strategy, learning stage, auxiliary tasks, domain perspective, and disentanglement fusion—we classify and describe contemporary methods based on their contributions. Thirdly, a thorough and objective comparison is not now accessible due to the different experimental setups in the current literature[31].

Du 2024 et al. In aquatic situations, light absorption and scattering causes visual degradations in underwater photographs. Existing underwater image enhancement (UIE) algorithms find it difficult to precisely estimate important parameters including depth and veiling light. A physical model-guided framework simultaneously training a Deep Degradation Model (DDM) using any advanced UIE model. The DDM comprises factor, depth estimation, and veiling light sub-networks for these values provide physical limitations on the enhancement process, therefore enhancing the precision of image restoration. Also offers UIEConv, a straightforward yet powerful UIE model with a dual-branch architecture that makes use of local and global elements. Extensive studies conducted in real underwater environments show the efficiency of the framework, including uses in deep-sea scenarios with synthetic light sources[32].

Singh 2024 et al. Low illumination, fluorescence, absorption, and scattering all affect underwater image quality. Although many new underwater picture improvement techniques manage all degradation challenges using a single deep network, this work suggests a more efficient solution. The first contribution is an iterative approach identifying and fixing a prevalent deterioration condition in the image. The framework takes poor illumination, low contrast, haziness, blurring, noise, and colour imbalance across three channels under consideration as eight degradation conditions. A deep network is intended to identify the dominating condition; so, a customized network is chosen depending on the particular deterioration. Training these specialized networks requires the development of condition-specific datasets from high-quality pictures in the UIEb and EUVP databases. On both UIEB and EUVP datasets, experimental results reveal that this methodology beats nine baseline techniques[33].

Khan 2024 et al. Autonomous underwater vehicles suffer from underwater images' colour distortion, haze, and limited visibility resulting from light refraction and absorption. Underwater picture enhancement using a Multi-Domain Query Cascaded Transformer Network is presented to solve these problems. The method presents a Multi-Domain Query Cascaded Attention mechanism combining aspects of global illumination and localized transmission. Whereas a hybrid Fourier-Spatial Up-sampling Block increases feature resolution, a spatio-spectro fusion-based attention block improves feature propagation. Using synthetic and real-world underwater picture datasets, the technique shows better performance by ablation research and comparison analysis[34].

Authors/year	Method/model	Research gap	Findings
Xiuwen/2024 [35]	Framework improves underwater photographs with multiple degrees of grading.	Insufficient complete answers for multi-degraded underwater picture improvement.	For multi-degraded photos, proposed method beats state-of- the-art approaches.
Zhang/2024 [36]	WWPF enhances underwater image quality.	Lack of efficient fusion techniques for complete underwater image improvement.	WWPF outperforms state-of-the-art methods in underwater image enhancement.
Xinping/2024[37]	Multi-scale fusion enhances underwater image quality.	Limited methods addressing color deviation, blur, and contrast in underwater images.	Proposed method improves color, contrast, brightness, and detail in underwater images.
Liu/2024 [38]	CLIP-UIE improves underwater image enhancement.	Lack of real reference images limits underwater image enhancement performance.	CLIP-UIE enhances underwater images with faster, more natural results.
Wang/2023 [39]	TUDA reduces domain gaps, improving underwater image enhancement quality.	Lack of methods addressing inter-domain and intra-domain gaps in UIE.	TUDA outperforms existing methods, enhancing both visual and quantitative quality.

3. Methodology

This study employs a systematic approach to enhance underwater images using advanced preprocessing techniques and deep learning models. The methodology encompasses data collection, preprocessing, and model evaluation. Datasets of raw underwater images and their ground-truth references are sourced from repositories such as Kaggle and GitHub, ensuring diverse environmental conditions. Preprocessing steps like image resizing, normalization, and contrast enhancement (using CLAHE, contrast stretching, and histogram equalization) standardize inputs and improve setting

Figure 2 Proposed Flowchart

3.1 Data Collection

Collect datasets including raw underwater photographs affected by light absorption and scattering, together with matching ground-truth images taken in controlled situations to act as references, for an underwater image enhancement challenge. To guarantee resilience, these datasets—which can be obtained from publicly accessible sources like Kaggle, GitHub, or academic institutions—should feature a wide spectrum of photos taken at many depths and under different water conditions. With all photos scaled to a goal size of (256, 256) to standardize input dimensions for model training and evaluation activities including colour correction and clarity improvement, the dataset should comprise a mix of poor-quality underwater images and clear reference images.

3.2 Data Preprocessing

Underwater picture enhancement depends critically on data preparation to guarantee high-quality input for deep learning models. It begins with image scaling to a fixed objective size of (256, 256), therefore standardizing the dataset & allowing computationally reasonable training. Pixel values are scaled from 0 to 255 down to a range of 0 to 1 following normalization, therefore enhancing model convergence by providing consistent input values and so avoiding issues including gradient explosion. Using CLAHE to boost local contrast and visibility in underwater images with insufficient illumination and contrast by varying the lightness vector in the LAB colour space While contrast stretching further increases visibility by expanding the intensity range, making details more conspicuous, histogram equalization modifies brightness levels in order to enhance global contrast, therefore making small elements simpler to notice. Finally, dividing a dataset into the training, validation, and test sets provides consistent model evaluation and helps to prevent overfitting, hence enhancing model robustness for pragmatic applications.

1. Image Resizing

Standardizing input dimensions rely mostly on shrinking underwater images to a specified goal size of (256, 256). It ensures constant dimensions for all images, which is absolutely essential for fit with machine learning models and batch processing. Multiple models have different required input shapes; scaling helps to obtain this. This method also reduces computational complexity by downing large images or upscaling smaller ones while maintaining aspect ratio as appropriate. Standardizing helps the model to be free from input variation and concentrate on learning important features from the data instead. Resizing underlines significant aspects in underwater image enhancement operations and guarantees that the images are controllable in terms of memory and processing resources. Resizing is also applied in the loading pipeline to ensure efficiency and stop the loss of any required properties, hence maintaining generality and overall model performance.

2. Normalization

Normalizing pixel intensity levels in images essentially scales them within a 0–1 range. Usually spanning 0 to 255, dividing the original pixel values by 255 helps one do this. Projects involving underwater image improvement depend on standardizing the input data to ensure uniformity over the dataset. Normalizing all pixel values to a single size accelerates model convergence during training since inputs of like scale enable more efficient optimization. This phase also lowers the likelihood of gradient explosion or vanishing gradients, hence generating more consistent and fast training. Normalized photos let the model grasp underlying patterns and characteristics instead of depending on the raw data scale. Normalizing helps the model to process and enhance images similarly in underwater environments, where light conditions and colour intensities vary dramatically.

3. Contrast Enhancement Using CLAHE

Applied to raise visibility in underwater images, Contrast Limited Adaptive Histogram Equalization (CLAHE) is a targeted contrast enhancement technique Targeting the L-channel—which stands for feeling light— CLAHE runs in the LAB colour range. By matching the histogram over tiny, localized areas, CLAHE enhances details without excessively-amplifying noise or artefacts in homogeneous areas. Underwater images can exhibit low contrast due to light attenuation and dispersion; CLAHE addresses this by selectively brightening dark areas while preserving brilliant sections. Under poor lighting, this generates photos with improved contrast and detail even. CLAHE especially helps underwater environments where the global contrast enhancement may cause over-saturation or loss of detail. Reducing the amplification in any local location ensures balanced enhancement over the picture. This approach is better appropriate for deep learning applications and consequently essential for underwater photo preparation.

4. Contrast Stretching

One global improvement method that spreads pixel intensity values over the whole dynamic range of 0 to 255 is contrast stretching. Because of inadequate lighting and scattering effects, underwater photographs can have a limited intensity range that produces low contrast and reduced features. By widening the range between the minimum and maximum intensities, contrast stretching modifies the intensity values such that brighter portions are more vivid and darker areas are more distinct able. This method maintains the relative intensity variations across pixels, therefore preserving the general structure and content of the image. Contrast stretching greatly enhances visibility in aquatic situations, therefore enabling deep learning models to interpret small characteristics more clearly. The method guarantees high-quality data for training by computationally improving the clarity of input photos and therefore increasing their efficiency. Contrast stretching enhances image enhancing tasks' interpretability and efficiency as a preprocessing step.

5. Histogram Equalization

By spreading the intensity levels of an image, histogram equalization creates a more homogeneous histogram, therefore improving the global contrast of underwater pictures. This method is applied to the V-channel in the HSV colour space, which denotes brightness, therefore assuring that low intensity parts become more visible. Underwater photographs often suffer from unequal illumination and colour distortion, therefore reducing contrast and poor visibility. By balancing the proportion of bright and dark areas, histogram equalizing enhances the general image quality. This method highlights hidden details and makes structural elements more clear by raising contrast in areas where intensity variations are minute. Although worldwide in character, it enhances localized methods such as CLAHE by serving as a benchmark. Histogram equalization improves the whole visual quality of the dataset and guarantees improved feature extraction by the model for underwater picture preprocessing.

3.3 EDA(Exploratory Data Analysis))

Figure 3 Sample images

Figure 3 highlights the need of efficient enhancement approaches to improve clarity of picture and contrast by showing sample photographs from the dataset displaying underwater difficulties such light scattering, colour distortion, and low visibility.

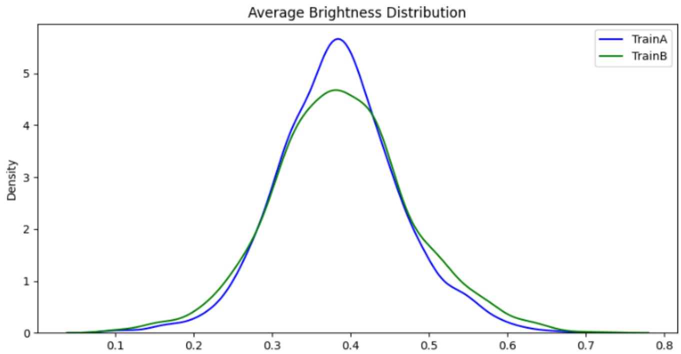

Figure 4 Average Brightness Distribution

Figure 4 shows average brightness distribution emphasizes changes brought about the aquatic environment. Mostly lower brightness levels highlight the requirement of enhancing methods to increase visibility.

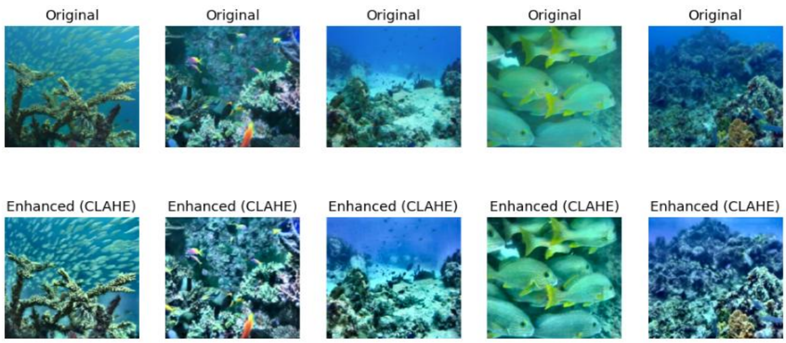

Figure 5 Enhanced CLAHE images

Figure 5 shows photos improved by CLAHE, which preserves details while enhancing contrast and brightness—especially in darker areas. It addresses low visibility and inadequate illumination, hence highlighting underwater elements.

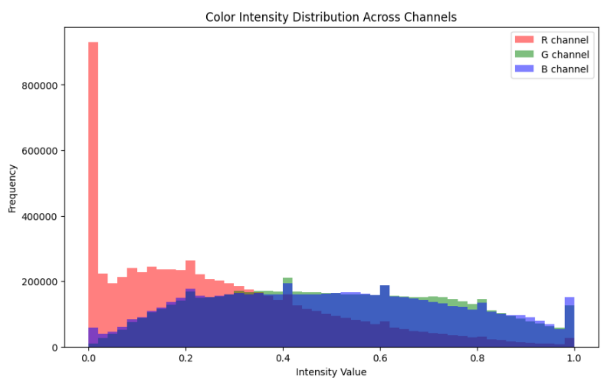

Figure 6 Color Intensity Distribution across Channels

Figure 6 illustrates colour intensity distribution among the three colour channels, therefore stressing dominance & imbalances in colours and leading enhancing methods to balance and raise general image quality.

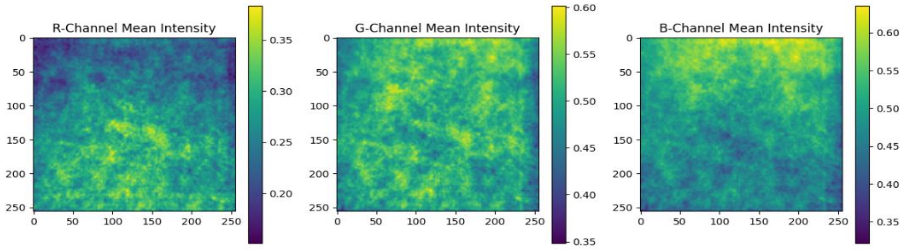

Figure 7 RGB channel Mean Intensity Graphs

Figure 7 displays mean levels of intensity for RGB channels, therefore stressing variances and colour balance. These discoveries expose possible colour distortions, which directs enhancing techniques for better visual clarity and colour correction.

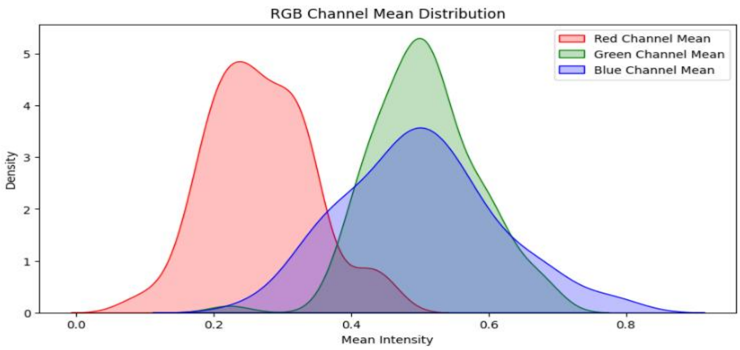

Figure 8 RGB Channel Mean Distribution

Figure 8 shows The geographic distribution of mean value of intensity for RGB channels exposes possible distortions and changes in colour balance. This study helps assess methods for upgrading to guarantee better visual consistency.

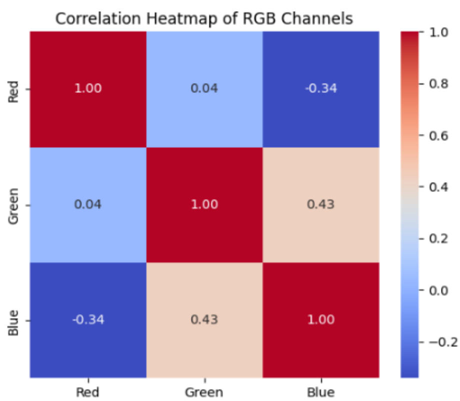

Figure 9 Correlation Heatmap of RGB Channels

Figure 9 displays RGB channels' correlation heat map reveals correlations between colour intensities. High correlations point to similar trends; lower values show different behavior, which directs colour improvement techniques.

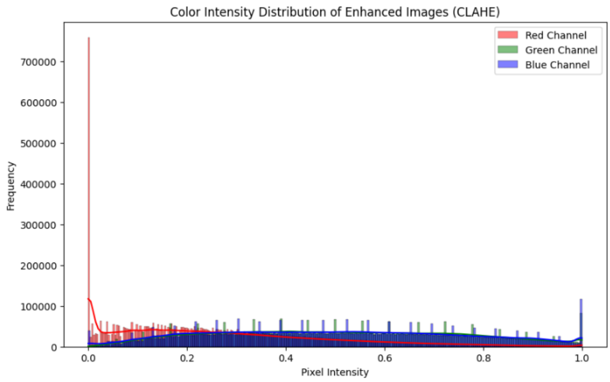

Figure 10 Color Intensity Distribution of Enhanced images (CLAHE)

Figure 10 displays the distribution of colour intensity of photographs improved by CLAHE. With increased visibility & detail in both dark and bright areas, the graph shows increases in colour contrast, therefore displaying a more consistent intensity range across the image.

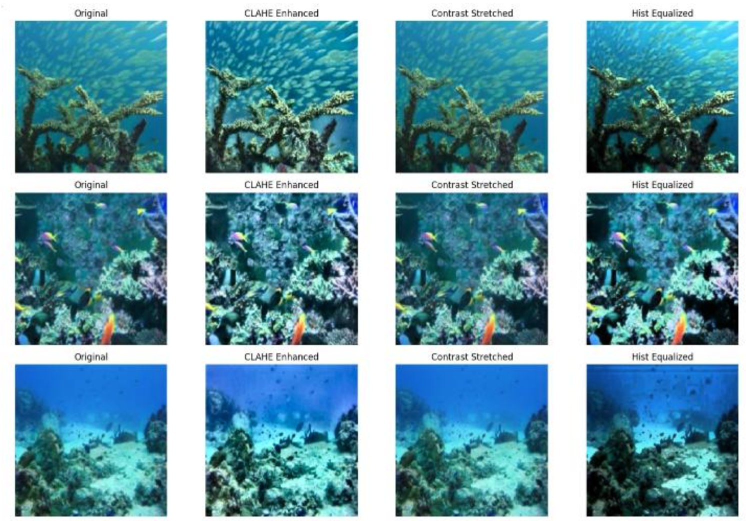

Figure 11 Enhanced Image Comparison Using Various Techniques

Figure 11 compares aquatic photos improved by histogram equalisation, contrast stretching, and CLAHE. It emphasises how well each technique enhances under various underwater environments visibility, contrast, and detail.

3.4 Model Implementation

The WaterNet model is a hybrid model based on convolutional neural networks (CNN) intended for image enhancing activities including underwater image enhancement. Together with a residual connection to attain effective learning and improved results, it combines encoding, bottleneck, & decoding phases. The architecture is broken out technically in great detail below:

1. Input Layer

- Input Shape: (256, 256, 3) The model accepts RGB images with dimensions 256x256 pixels, where each channel corresponds to red, green, and blue.

2. Encoder Block

- Convolutional Layer:

o A Conv2D layer with 64 filters of size (3, 3) is applied, followed by the ReLU activation function. This layer extracts spatial features while maintaining spatial resolution using padding.

- Batch Normalization:

o Applied to normalize the feature maps, improving convergence and reducing internal covariate shift during training.

- MaxPooling Layer:

o Downsampling the feature map by a factor of 2 ((2, 2) pool size), reducing the spatial resolution and preserving important features.

3. Bottleneck Block

- Convolutional Layer:

o A Conv2D layer with 128 filters of size (3, 3) and ReLU activation captures more abstract features.

- Batch Normalization:

o Normalizes the feature map for stable gradient updates in deeper layers.

4. Decoder Block

- Upsampling Layer:

o UpSampling2D increases the resolution of feature maps by a factor of 2, restoring the spatial dimensions.

- Convolutional Layer:

o A Conv2D layer with 64 filters of size (3, 3) and ReLU activation reconstructs features at a higher resolution.

- Batch Normalization:

o Ensures that the upsampling feature maps are properly scaled and stable.

5. Residual Connection

- A residual shortcut connection is introduced between the input image and the decoder output:

o The input image is resized using a Conv2D layer with 64 filters of size (1, 1). This step matches the dimensions of the decoder's output.

o The resized input and decoder output are combined using an element-wise addition (Add). This residual connection helps in retaining low-level features, ensuring that the model focuses on learning enhancement without completely altering the original structure.

6. Output Layer

- Convolutional Layer:

o A Conv2D layer with 3 filters (corresponding to RGB channels) and sigmoid activation produces the final enhanced image.

o The sigmoid activation ensures the output pixel values are in the range [0, 1].

7. Loss Function

- The Mean Squared Error (MSE) is used as the loss function:

o MSE penalizes the difference between the predicted and ground truth pixel values, ensuring accurate image reconstruction.

8. Optimizer

- Adam Optimizer:

o The learning rate is set to 1e-4, providing efficient and adaptive gradient updates for faster convergence.

9. Learning Rate Scheduler

- ReduceLROnPlateau Callback:

o Monitors the validation loss and reduces the learning rate by a factor of 0.5 if the performance plateaus for 50 epochs.

o The minimum learning rate is capped at 1e-6.

10. Training

- The model is trained for 100 epochs with a batch size of 32. Both the input (X_train) and output (X_train) consist of the same dataset for autoencoder-based training, where the goal is to reconstruct the enhanced version of the input.

11. Advantages of the WaterNet Model

1. Hybrid Residual Architecture:

o Combines low-level and high-level features, leading to better preservation of fine details in the enhanced images.

2. Efficient Feature Extraction:

o Encoder-decoder structure allows for efficient hierarchical feature extraction and reconstruction.

3. Stability During Training:

o Batch normalization layers ensure stable training and faster convergence.

4. Focus on Image Enhancement:

o Residual learning allows the model to focus on enhancing the degraded components of the image without altering non-degraded regions.

12. Hyperparameters

Table.2 Model Summary

Layer Name	Layer Type	Output Shape	Parameters
Input Layer	Input	(256, 256, 3)	0
Encoder Conv2D	Conv2D (64 filters)	(256, 256, 64)	1,792
Encoder BatchNorm	Batch Normalization	(256, 256, 64)	256
Encoder MaxPooling	MaxPooling2D (2×2)	(128, 128, 64)	0
Bottleneck Conv2D	Conv2D (128 filters)	(128, 128, 128)	73,856
Bottleneck BatchNorm	Batch Normalization	(128, 128, 128)	512
Decoder UpSampling	UpSampling2D	(256, 256, 128)	0
Decoder Conv2D	Conv2D (64 filters)	(256, 256, 64)	73,792
Decoder BatchNorm	Batch Normalization	(256, 256, 64)	256
Residual Conv2D	Conv2D (64 filters, 1×1)	(256, 256, 64)	4,160
Residual Addition	Add	(256, 256, 64)	0
Output Conv2D	Conv2D (3 filters)	(256, 256, 3)	1,731

Total Parameters: 156,355

- Trainable Parameters: 155,971
- Non-trainable Parameters: 384

4. Result & Discussion

The performance evaluation highlights the effectiveness of preprocessing techniques and deep learning models in enhancing underwater images. Models trained on preprocessed datasets demonstrated significant improvements in metrics like PSNR, SSIM, and MSE compared to unprocessed data. CLAHE and contrast stretching notably enhanced visibility and detail in degraded images. Normalization contributed to faster convergence and stable training. Qualitative analysis showed clearer edges and reduced haze in enhanced outputs. Emphasizing adaptation, model resilience was tested over several water conditions and depths. The results demonstrate that deep learning paired with thorough preprocessing efficiently restores underwater image quality, therefore guaranteeing useful application in real-world conditions.

1. Accuracy

In respect to the total number of examples, accuracy evaluates a model's ability to produce correct forecasts. In photo improvement, it measures the exactly recreated pixel to ground-truth reference ratio. Although accuracy can be changed for image tasks involving comparing pixel values or qualitative findings, it is mainly related with classification tasks. Great accuracy points to effective alignment with the desired result and improvement. Its value might be limited, though, in more complicated processes like underwater photo restoration, in which perceptual quality is more crucial. Thus, often accuracy is combined with measurements like SSIM or MSE to provide a more holistic evaluation of model performance.

$$\mathrm{Accuracy} = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \tag{1}$$

2. Loss

In respect to the general count of events, accuracy evaluates a model's ability to produce correct forecasts. In picture improvement, it counts the ground-truth references to exactly recreated pixels. Accuracy can be changed for image tasks to compare values of pixels or qualitative outcomes, even though it is usually related with classification tasks. Good alignment with the desired output and augmentation is shown by great accuracy. Its value could be limited, though, in more difficult tasks like underwater image restoration, in which perceptual quality is more crucial. To provide a more all-around evaluation of model performance, accuracy is thus sometimes coupled with measurements such as SSIM or MSE.

$$\mathrm{Loss} = -\frac{1}{\mathrm{m}}\sum_{\mathrm{i=1}}^{\mathrm{m}} \mathcal{Y}\mathrm{i}.\log(\mathcal{Y}\mathrm{i}) \tag{2}$$

3. MSE

MSE measures, on images, the average squared variance among expected and actual pixel values. It penalizes significant differences more heavily, so it is susceptible to substantial reconstruction errors. Lower MSE indicates better alignment of the ground-truth reputation, thereby indicating more restoration accuracy in underwater image improvement. Conversely, MSE stresses pixel-wise variations—which might not exactly correspond with human-perceived quality. Notwithstanding this limitation, it is nevertheless an important indicator of the overall quality of enhanced images since it improves the complementing perceptual measurements. Mathematical simplicity and straightforwardness of MSE define benchmarking model performance in picture restoration applications.

$$\mathrm{MSE} = \frac{1}{\mathrm{n}}\sum_{\mathrm{i=1}}^{\mathrm{n}} (\mathrm{Y_i} - \hat{\mathrm{Y}}_\mathrm{i})^2 \tag{3}$$

4. R^2

Ground-truth variance in the prediction performance of a model is evaluated by its coefficient of determination, R^2. R^2 provides information on the prediction strength of the model by showing the fraction of variance in pixel values it describes, therefore guiding image enhancement. Negative values indicate poor alignment with the starting image; a R^2 value nearer 1 indicates exceptional accuracy and efficient restoration. Since R^2 catches more broad patterns in the data than pixel-based measurements like MSE, it is useful for assessing model generalization. It provides a statistical evaluation of the model's preservation of visual aspects, therefore augmenting earlier evaluations.

$$\frac{n(\sum xy - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2]\,[n\sum y^2 - (\sum y)^2]}} \quad (4)$$

- Performance Graphs

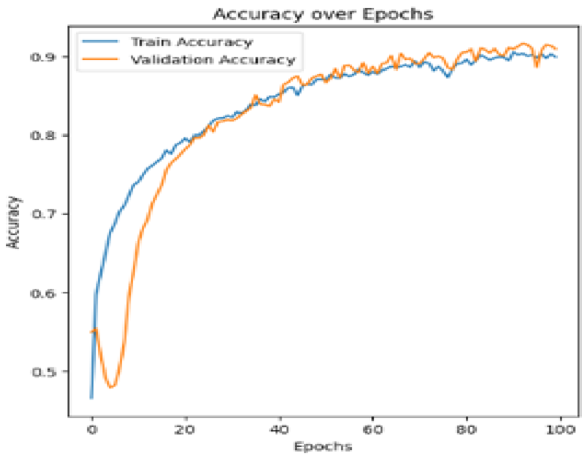

Figure 12 Accuracy vs Epochs

Figure 12 shows the link among training epochs and model accuracy. Reflecting the learning & convergence over time, accuracy increases gradually from fast early gains followed by slow stabilization.

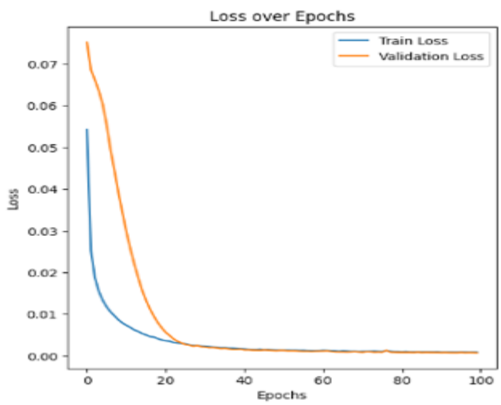

Figure 13 Loss vs Epochs

Figure 13 depicts the correlation of training epochs and loss. Effective learning and error reduction during training are indicated by the graph's constant declining loss values as epochs advance. The flattening of the curve across time points to model convergence and stability. This tendency validates the capacity of the model to maximise performance.

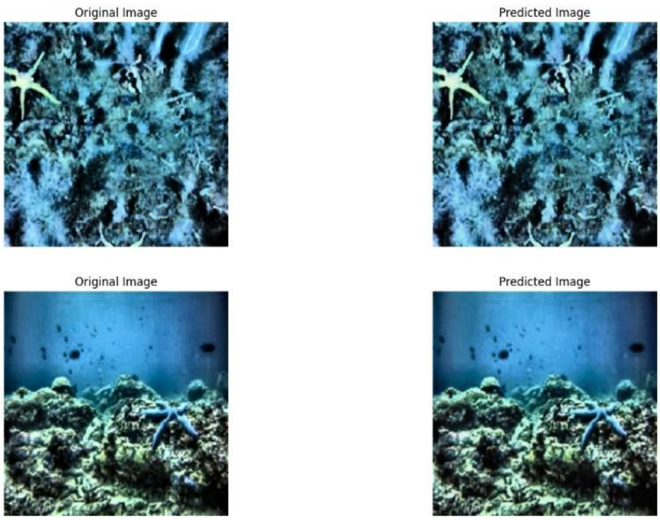

Figure 14 Original VS Predicted Image

Figure 14 presents a comparison between the expected and actual pictures proving the model's success. The original picture shows usual underwater aberrations including low contrast and colour loss. Nevertheless, the expected image reflects the strong performance of the model in underwater image enhancement since it displays notable improvements in clarity, contrast, and colour balance.

- Original Image Vs Enhanced Images

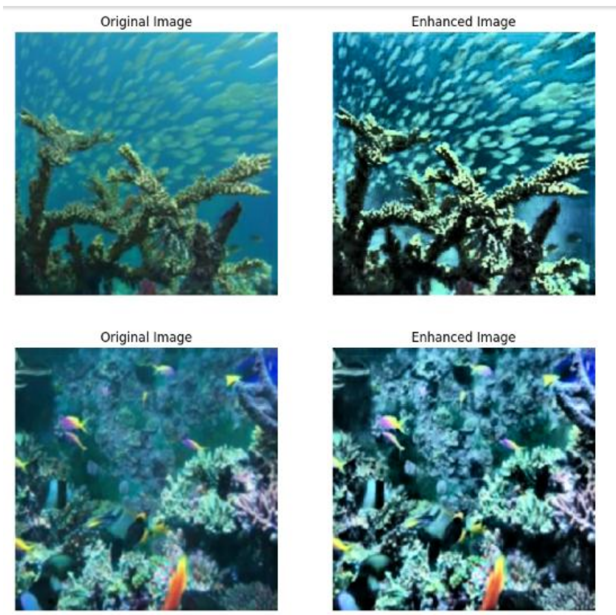

Figure 15 Image Enhancement: Before and After

Figure 15 displays underwater graphic changes. Whereas the "after" image displays gains in brightness, clarity, and colour correction, showing enhancing effectiveness, the "before" image shows poor contrast & colour distortion.

Table 2: Performance Evaluation of Model

Model	Accuracy	Loss	MSE	R^2
WaterNet Hybrid Model	91.08	0.007	0.007	0.98

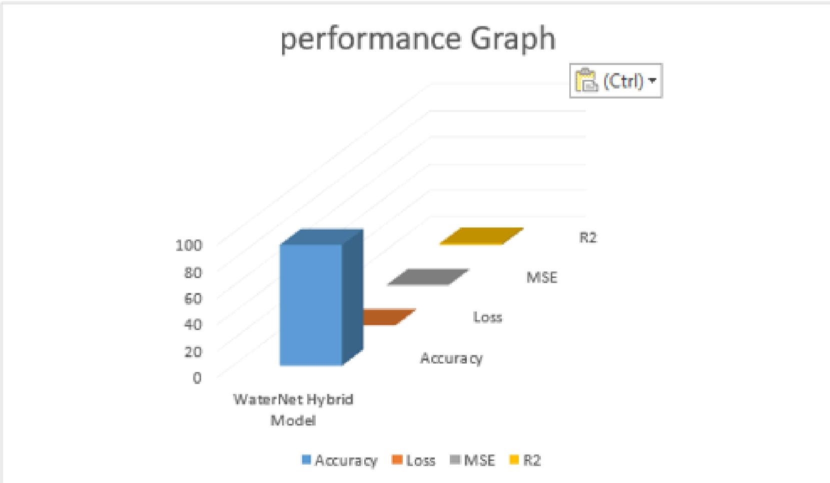

Figure 16 performance Graph

In underwater picture enhancing applications, the WaterNet Hybrid Model shows extraordinary performance. With an amazing accuracy of 91.08%, it shows dependability in handling underwater photos. The low prediction errors and effective learning capacity of the model shown by its loss value of 0.007 throughout training. Moreover observed at 0.007, the Mean Squared Error (MSE) underlines its precision in reducing pixel-wise variations between ground-truth and projected images. Reflecting strong predictive power, this model's R-squared (R^2) score of 0.98 reveals its great capacity for explicating the variance in data. These results confirm WaterNet's dependability in rapidly improving underwater image quality.

Table 3: Comparative Analysis between Existing Model and Proposed Model

Model	Accuracy	References
DeepLab v2	67	[40]
Proposed Logistic Regression	91.8	-------

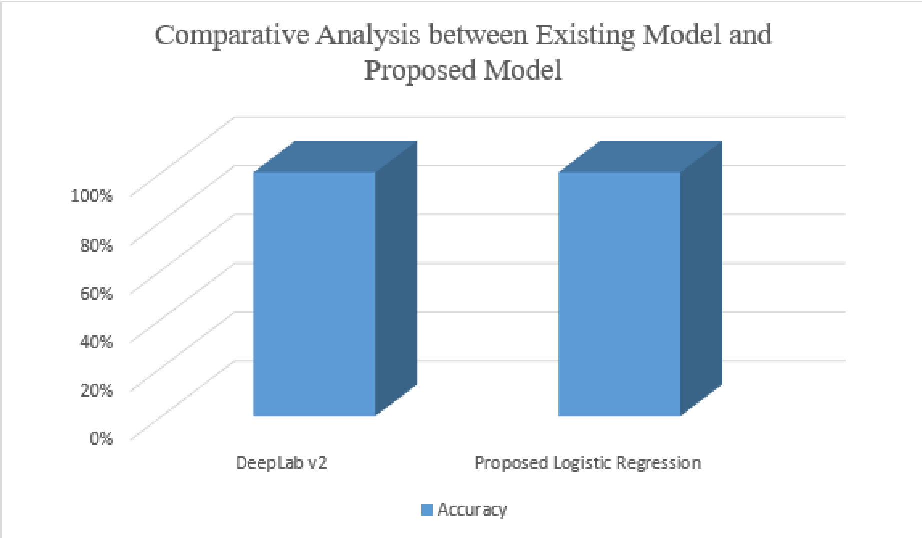

Figure 17 Comparative Analysis Graph

Comparative analysis of DeepLab v2 with the suggested Logistic Regression model reveals interesting advances in underwater picture processing. DeepLab v2 proves its ability in handling underwater image challenges by leaving possibility for development even if it exhibits an accuracy of 67%. Conversely, with a 91.8% accuracy, the suggested logistic regression model shows to be more efficient in addressing underwater photo improvement tasks. This development suggests that in some cases logistical regression, with its simplicity and flexibility, might produce significant results. The comparison highlights the importance of building models especially for the unique challenges of underwater environments to increase performance.

5. Conclusion

Underwater picture enhancement is eventually a multi-stage process covering data acquisition to preprocessing and the employment of advanced models as WaterNet to deliver optimal outcomes. Generated during the data collecting phase are raw underwater images affected by components including light scattering and absorption, as well as matched ground-truth images recorded under controlled conditions. This ensures a large collection of underwater circumstances, therefore enabling the model to learn from diverse environments. Preprocessing techniques like picture scaling, normalizing, and contrast enhancement—including CLAHE or histogram equalization—much improve the quality of the input images by increasing visibility, retention of features, and guarantees consistency throughout the dataset. These preprocessing steps ensure that the model might correctly handle the images and provide the foundation for efficient model development. The hybrid design of the WaterNet model—which mixes encoder-decoder layers and residual connections—helps significantly in underwater picture enhancing activities. The model's exceptional performance highlights its durability and ability to enhance underwater images with an accuracy of 91.08%

and little prediction errors. Moreover, the comparison with other models as DeepLab v2 and Logistic Regression highlights the better results produced by the WaterNet model. It is a consistent fix for improving underwater image quality since it can tackle the specific challenges given by underwater environments, such low contrast and insufficient illumination. This emphasizes the significance of developing tailored models to maximize the effectiveness of underwater photo enhancement techniques and their pragmatic applications.

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