UNDERWATER IMAGE RESTORATION USING MIRNET

Group No - 12S

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ABSTRACT

- This project focuses on assessing the effectiveness of MIRNet(Multi-Scale Image Restoration Network) for enhancing underwater images and comparing its performance with other advanced image enhancement algorithms.

- To conduct this evaluation, we utilized a comprehensive dataset of underwater images known as the UIEB dataset.

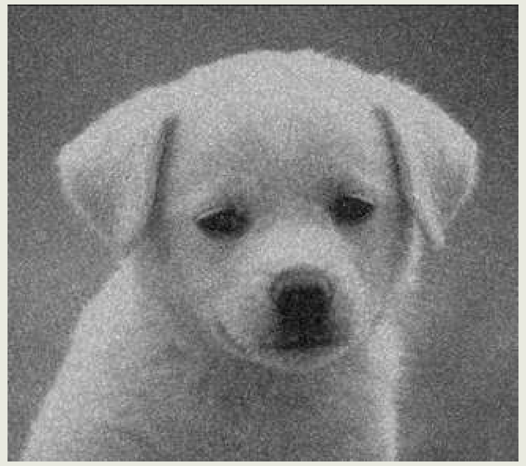
- Furthermore, we applied enhancement techniques, including CLAHE[3], UDCP[12] and White Balancing algorithms[6] to the same dataset for a thorough comparative analysis.

- The performance of these algorithms was evaluated using quantitative metrics such as PSNR, SSIM, and UIQM and UCIQE[8].

INTRODUCTION

During image acquisition, degradations are often introduced because of:

Physical limitations of cameras



Noise

Low contrast

Unsuitable lighting conditions

Low light

Bright

INTRODUCTION

AIM : This project's main goal is to improve the visual quality and usefulness of photos taken in underwater situations by applying the MIRNet (Multi-Scale Image Restoration Network) framework.

OBJECTIVE :

1.Developing a deep learning model based on MIRNet for underwater image enhancement.

2.Comparing the quality of normal sky images and underwater images to highlight the challenges in underwater image processing.

3.Comparing different methods like White Balancing, CLAHE, UDCP and Evaluating the performance of the trained MIRNet model using quantitative and qualitative metrics.

INTRODUCTION

1. **Importance of Underwater Imaging[1] :**

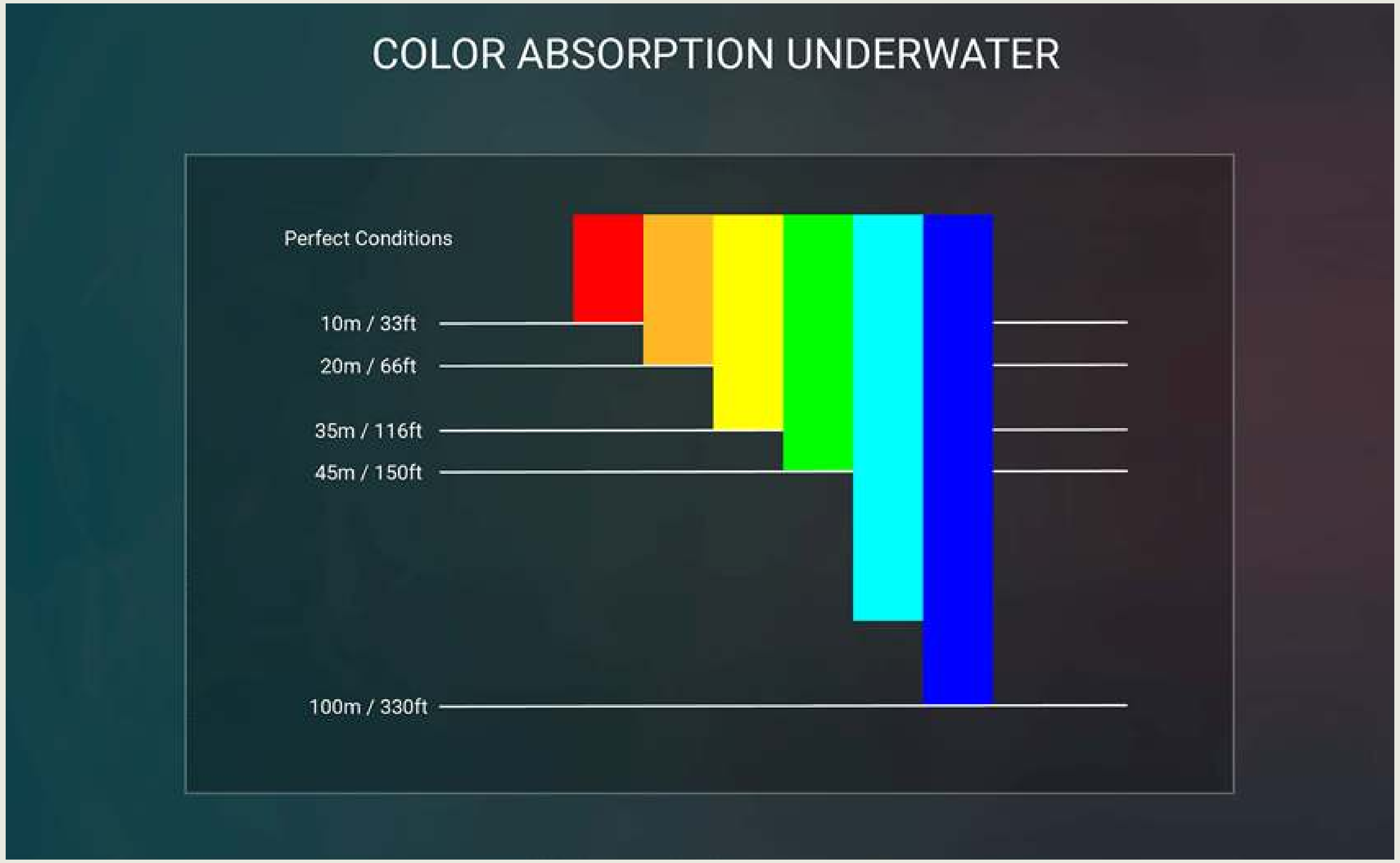
- Crucial for exploring valuable aquatic resources
- widely used for inspecting submarine infrastructure, detecting objects, controlling underwater vehicles, and research in various fields.

2. **Challenges in Underwater Imaging :**

- Scattering and Absorption
- Poor Color Contrast and Visibility

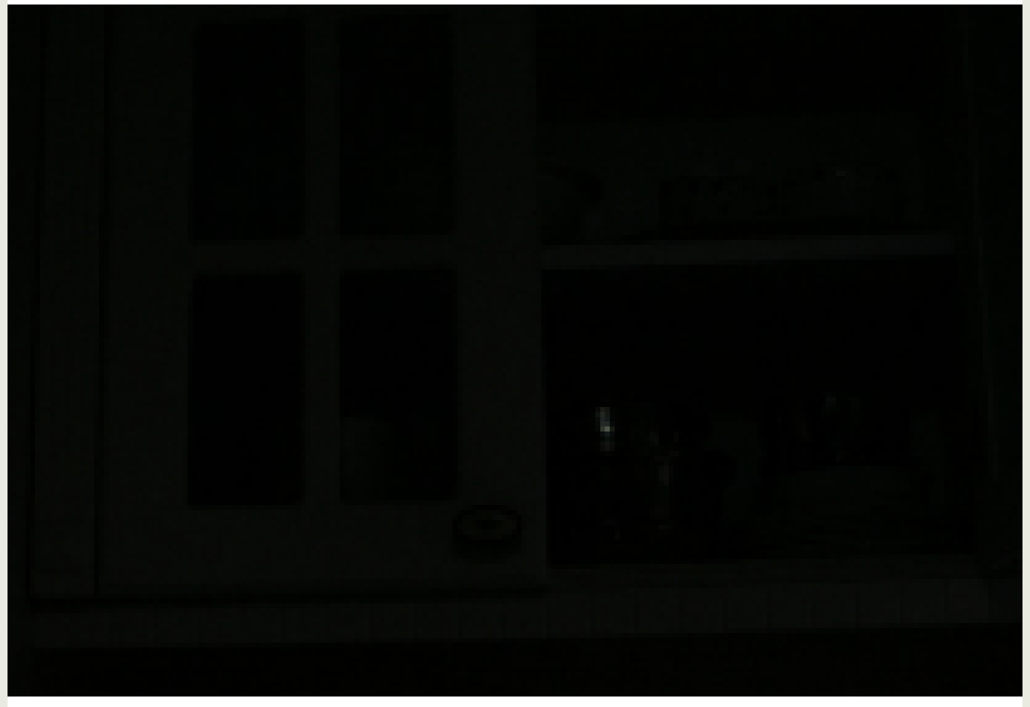
3. **Effects of Light in Water :**

- Turbidity absorbs red light first, allowing deeper blue light, leading to greenish and bluish photos.
- Fog in underwater images arises from air light and attenuation, affecting brightness and contrast.



LIMITATIONS OF UNDERWATER IMAGES

Performance of MIRNet for normal images



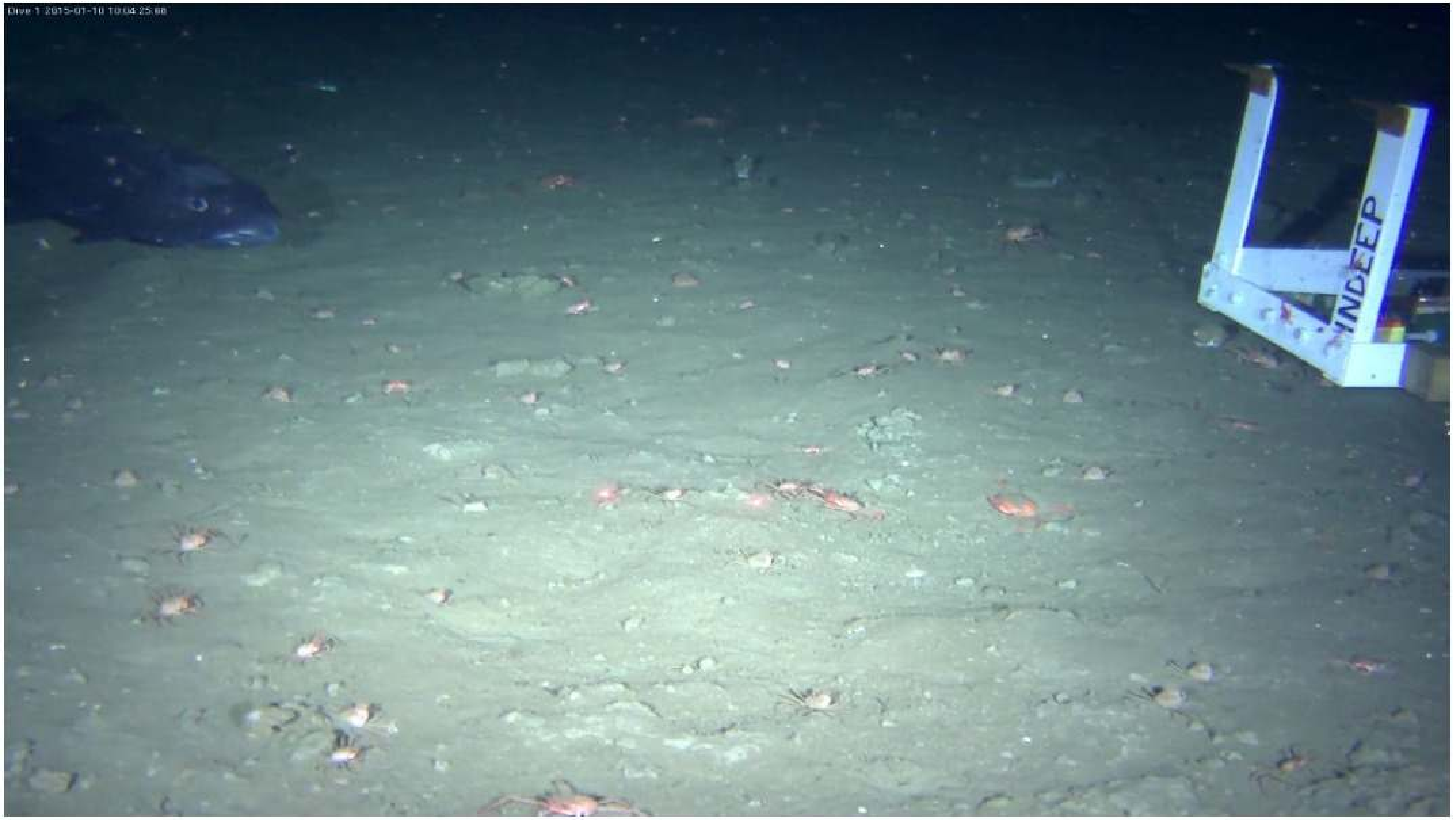
Input

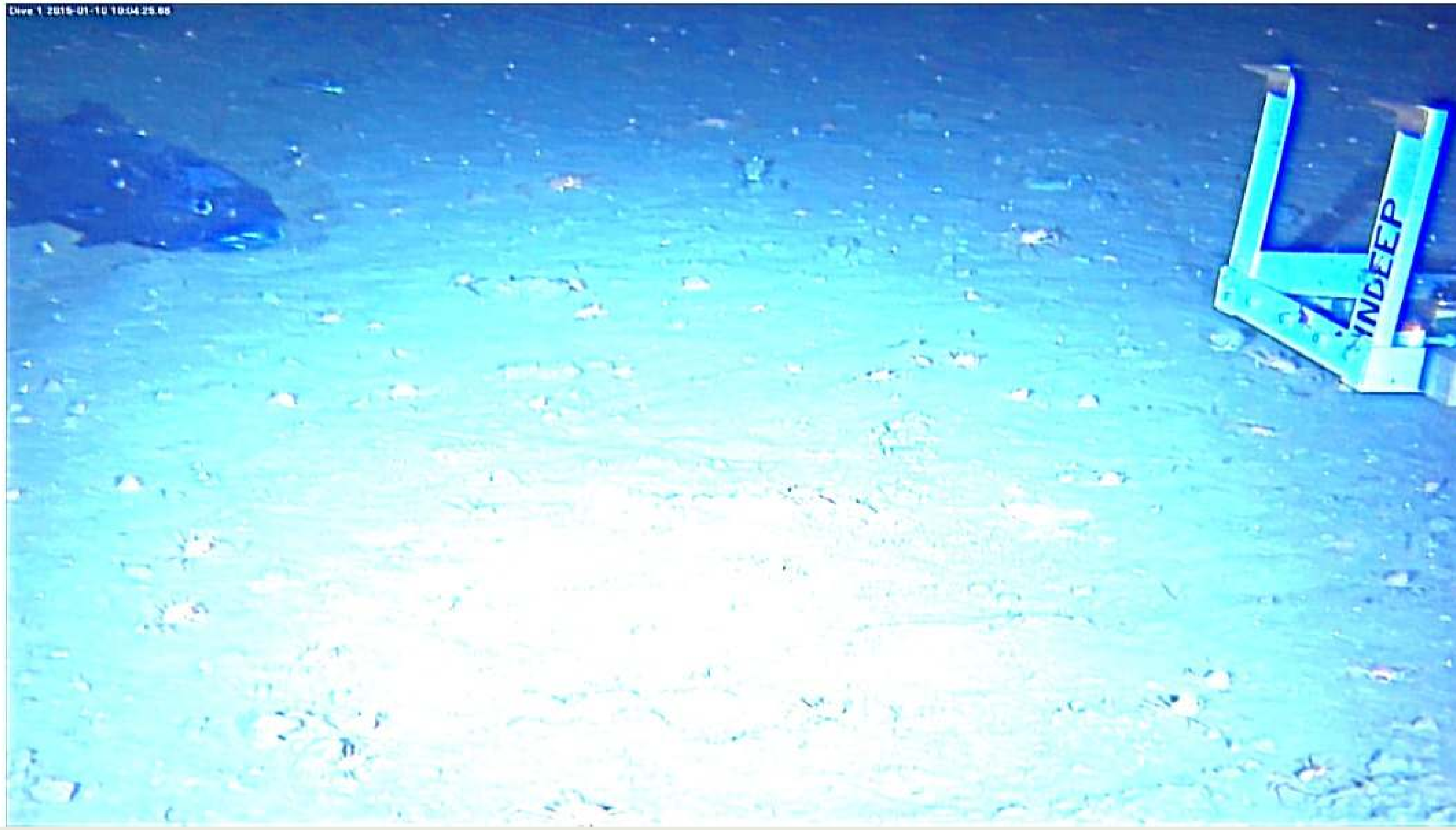
MIRNet

Ground Truth

PSNR for LOL (LOw Light) dataset - 27.89 dB

LIMITATIONS OF MIRNET FOR UNDERWATER





Underwater Cameras

challenges like low light, color distortion, and pressure. Here are the key types and examples of underwater cameras commonly used:

Types of Underwater Cameras

1. **Compact Cameras:**
   - Portable and user-friendly.
   - Often paired with underwater housings for water resistance.
2. **Action Cameras:**
   - Small, rugged, and often waterproof without additional housing.
   - Ideal for casual underwater photography or videos.
3. **DSLR and Mirrorless Cameras:**
   - Professional-grade cameras paired with specialized underwater housings.
   - Provide superior image quality and flexibility with interchangeable lenses.
4. **360-Degree Cameras:**
   - Capture immersive spherical underwater footage.

Literature Survey

SrNo	Title of paper	Methodology
1	Learning enriched features for real image restoration and enhancement:Computer Vision–ECCV 2020: 16th European Conference	1. Proposed MIRNet for image restoration, combining high-resolution precision with strong contextual features. 2. Utilizes multi-scale residual blocks with: • Parallel multi-resolution streams. • Attention mechanisms for feature enhancement. Achieves state-of-the-art results on image denoising, super-resolution, and enhancement tasks.
2	Underwater Image Enhancement Using MIRNet. Journal of Electronic Information Systems, 5(1), 36–44	1. Pre-processed underwater images using: • White balance for color correction. • Contrast enhancement to improve image contrast. 2. Enhanced images with MIRNet, a deep learning model for low-light image enhancement. 3. Evaluated quality using PSNR, RMSE, and SSIM metrics.
3	A Survey on Underwater Images Enhancement Techniques 2020 IEEE 9th Inter-national Conference on Communication Systems and NetworkTechnologies (CSNT)	1. Addressed noise, haziness, and color loss in underwater images using Generative Adversarial Networks (GANs). 2. Evaluated various GAN models: WaterGAN, PAMSGAN, UWGAN, SpiralGAN, and GANs for LiDAR and real-time underwater images. 3. Demonstrated superior performance of GANs over traditional enhancement methods.

Literature Survey

SrNo	Title of paper	Methodology
4	A retinex based enhancing approach for single underwater image	• Proposed a retinex-based approach to enhance underwater images with: 1. Color correction to fix distortion. 2. Variational framework for retinex to decompose and optimize reflectance (details) and illumination (brightness). 3. Enhancement of reflectance and illumination to address under-exposure and fuzziness. • Combines enhanced components for improved edges, details, and naturalness. • Applicable to other degraded images, like sandstorm images.
5	Underwater image enhancement via extended multi-scale Retinex	• Proposed LAB-MSR, a Retinex-based underwater image enhancement method inspired by the human visual system. • Modified Retinex algorithm using bilateral and trilateral filters on CIELAB color space channels. • Addressed scattering and absorption effects to improve visibility, contrast, and clarity. • Demonstrated competitive results on real-world data with varying turbidities.
6	Single Image Haze Removal Using Dark Channel Prior	• Introduced the Dark Channel Prior for single-image haze removal. • Utilized the observation that haze-free image patches have low-intensity pixels in at least one color channel. Combined this prior with the haze imaging model to estimate haze thickness and restore clear images and Achieved high-quality haze removal and generated a depth map as a byproduct.

Literature Survey

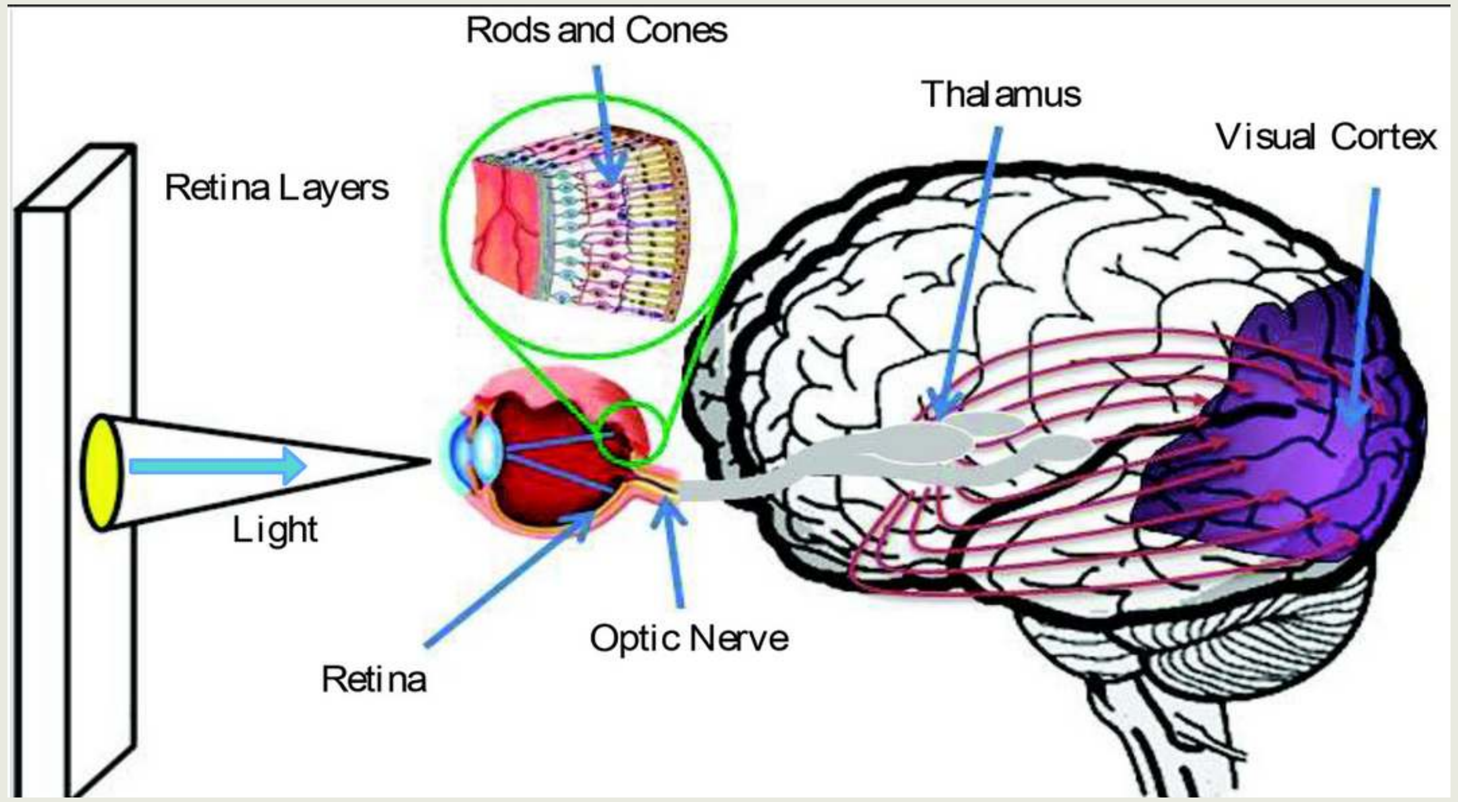
SrNo	Title of paper	Methodology
7	Underwater Image Enhancement Techniques: An Exhaustive Study	-Comparative Study of Techniques -techniques are WCID,CLAHE,DCP -Address problems such as low contrast, blurring, limited visibility, haziness, and color variations. -Utilize preprocessing and image restoration techniques to reduce noise and improve clarity.
8	An Underwater Image Enhancement Benchmark Dataset and Beyond,in IEEE Transactions on Image Processing,	-Significance of Underwater Image Enhancement -Underwater Image Enhancement Benchmark (UIEB): -The paper introduces Water-Net, an underwater image enhancement network trained on UIEB.
9	Color Correction and Local Contrast Enhancement for Underwater Image Enhancement	• Proposed an underwater image enhancement method addressing color cast, low contrast, an blur,Demonstrated effective blur removal, color correction, and improved clarity through qualitative and quantitative results. • Method includes: 1. Multi-channel color compensation and color correction. 2. Detail sharpening using Gaussian differential pyramid. 3. Contrast enhancement through contrast-limited adaptive histogram equalization.

Retinex Theory

Concept: Explains how the visual system perceives lightness by comparing receptor cell responses.

Mechanism: Evaluates lightness across different regions, enabling color perception based on surrounding contexts.

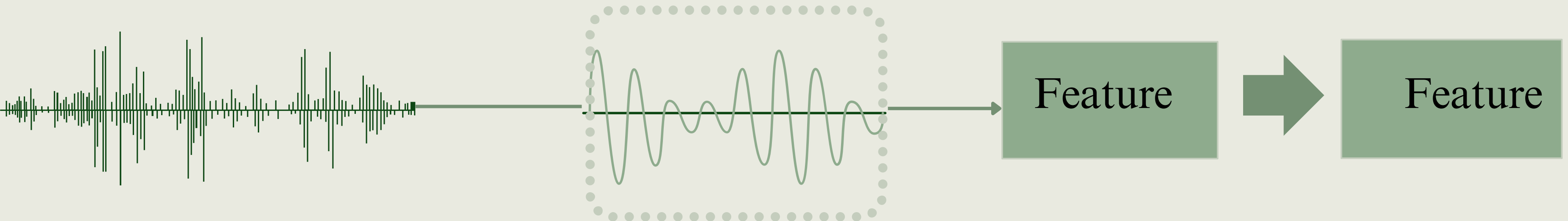
Research Status: Ongoing studies challenge its assumptions and explore applications in image processing[11].



src: https://santhalakshminarayana.github.io/blog/retinex-theory-of-color-vision

Single Scale and MultiScale Feature Extraction

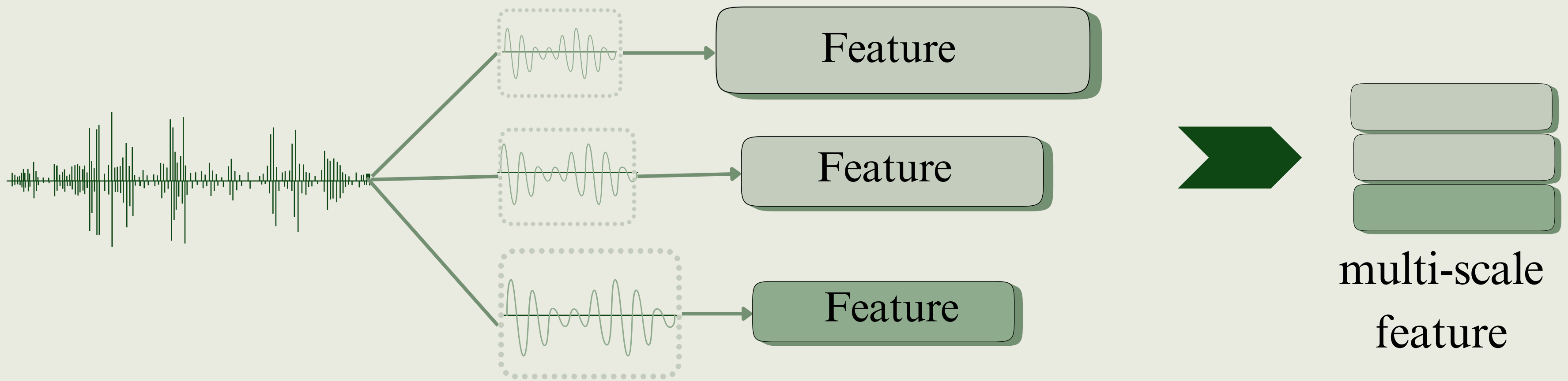
- Single-scale feature extraction is a technique that extracts features at a single scale [4]
- A filter (or kernel) of a fixed size (e.g., 3x3, 5x5) is convolved over the entire image.
- Features that are too small or too large compared to the filter size may not be captured effectively.



(a) single-scale feature extraction

filters **max pooling** **multi-scale poolingand concatenate**

- Multi-scale feature extraction is a tehnique that analyzes images at multiple scales to capture information at different levels[4]
- The image is processed with multiple filters of different sizes
- Captures features at multiple levels of detail, providing a more robust and comprehensive understanding of the image.



(b) multi-scale feature extraction

1x Scale

2x Scale

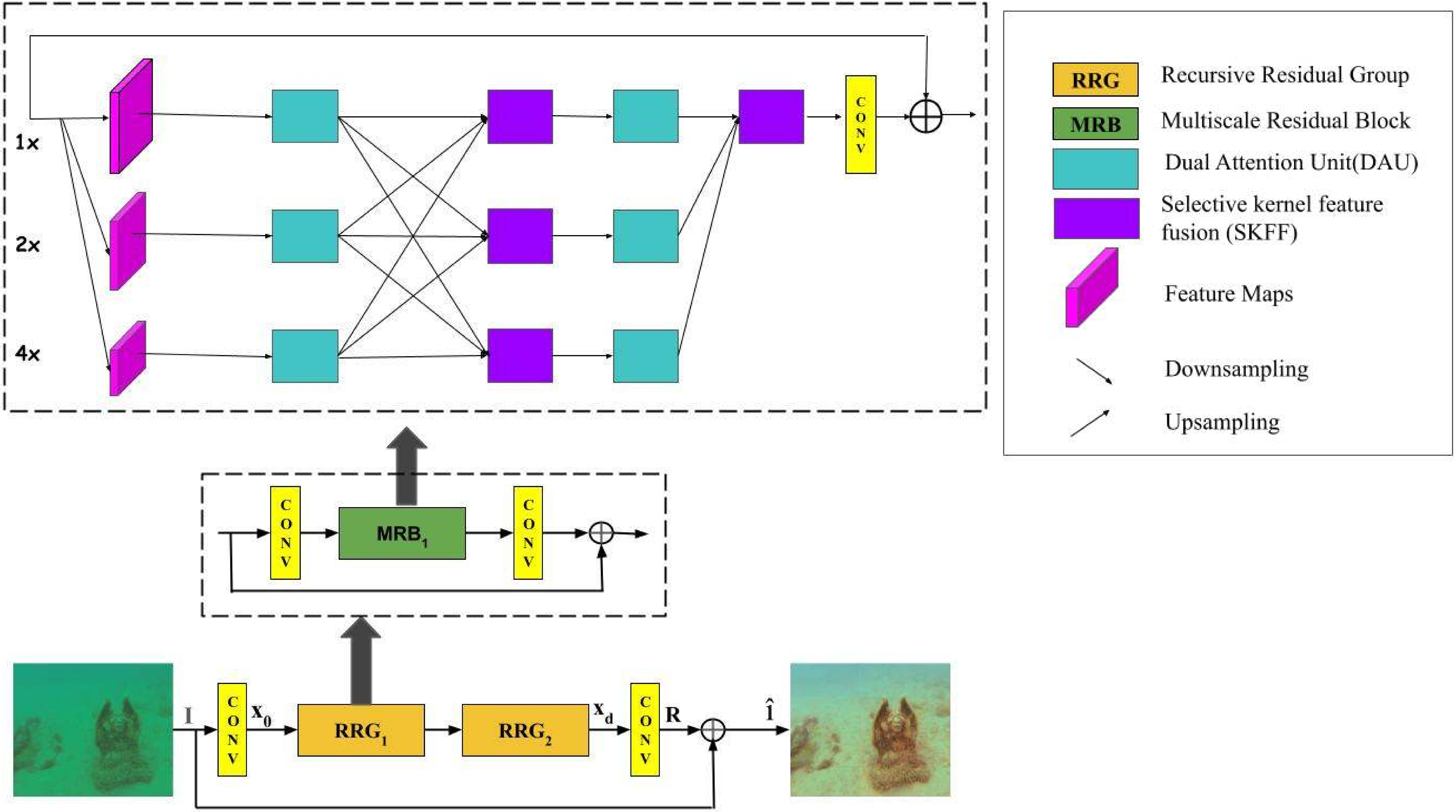
4x Scale

Modified MIRNet Design

The original MIRNet consists of 3 Recursive Residual Groups (RRGs) and 2 Multi-Scale Residual Blocks (MRBs). In this implementation, it was modified to include 2 RRGs and 1 MRB to achieve:

1. **Optimized Efficiency:** Reduced computational complexity for faster performance.
2. **Avoided Overfitting:** Simplified design suited for domain-specific datasets like UIEB.
3. **Domain Adaptation:** Maintained restoration quality while improving processing time.

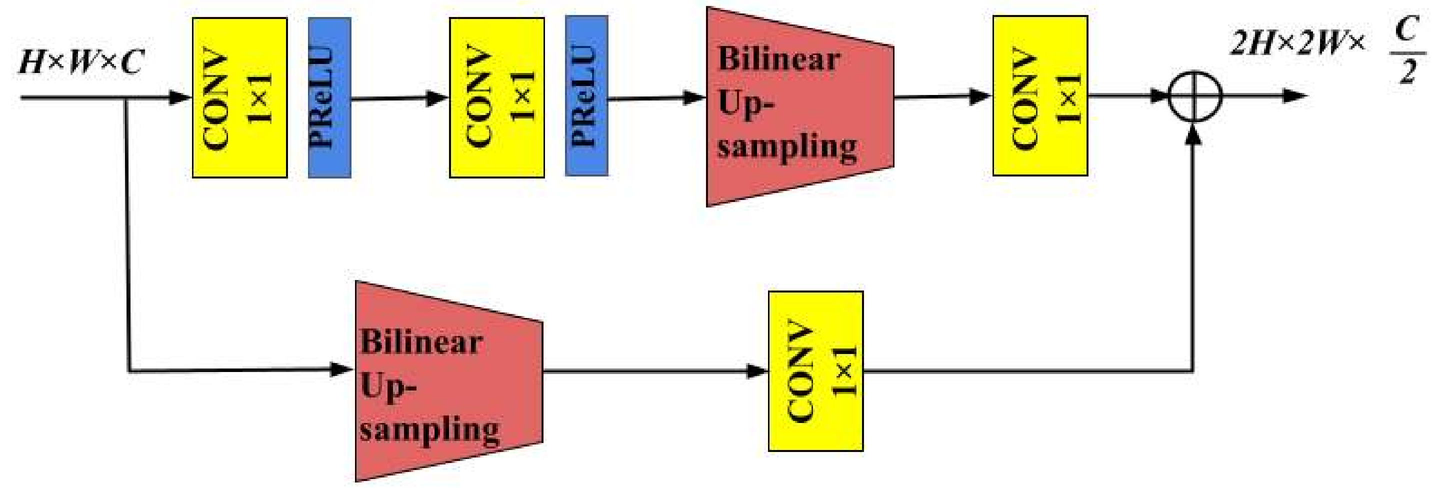
-The trained MIRNet outputs significantly enhanced images with improved color and visibility.


1×
2×
4×
CONV
RRG
Recursive Residual Group
MRB
Multiscale Residual Block
Dual Attention Unit(DAU)
Selective kernel feature fusion (SKFF)
Feature Maps
Downsampling
Upsampling
CONV
MRB1
CONV
I
CONV
x0
RRG1
RRG2
xd
CONV
R
Î

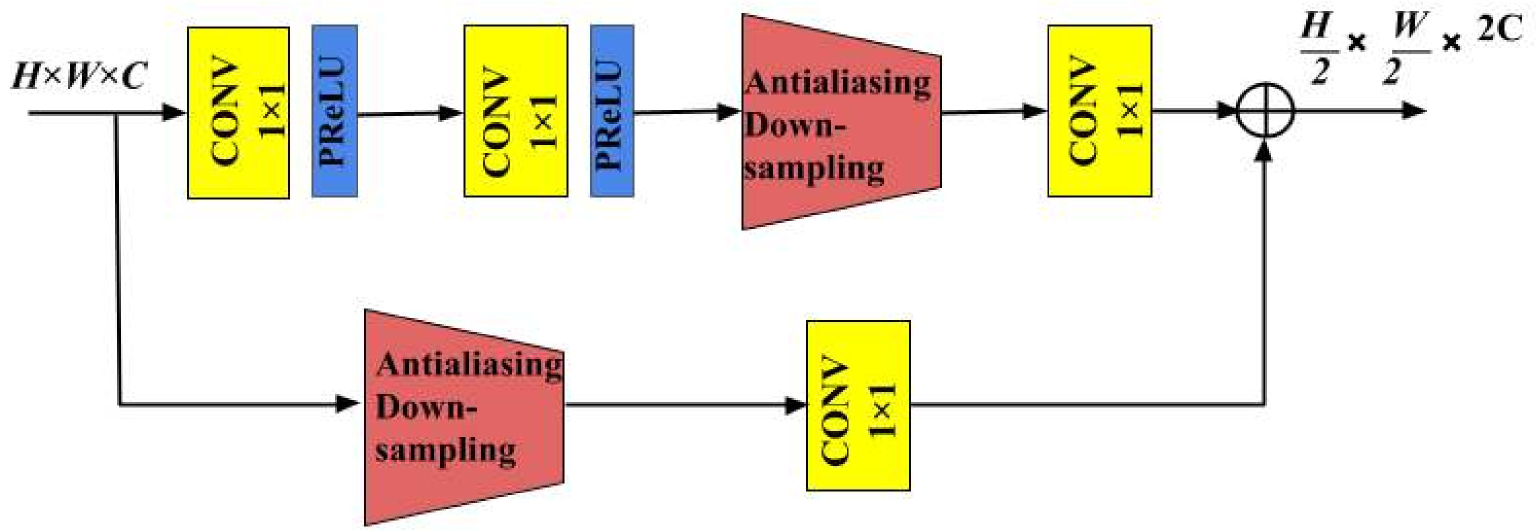
Residual Resizing Modules.

Framework Overview:

1. Recursive Residual Design with skip connections for efficient information flow.
2. Introduced Residual Resizing Modules (RRM) for downsampling and upsampling operations.
   - Downsampling: 2× or 4× by applying the module once or twice, respectively.
   - Upsampling: 2× or 4× by applying the module once or twice, respectively.
3. In MRB (Multi-Resolution Block), feature map size remains constant within convolution streams.
4. Feature map size changes across streams based on input and output resolution indices:
   - $i < j$: Downsample input. i, j=resolution indices of input and output feature maps resp.
   - $i > j$: Upsample input.
5. Integrated anti-aliasing downsampling to improve network shift-equivariance.



(b) Upsampling module



(a) Downsampling module

Multi-Scale Residual Block

Objective -

- In order to detect the image features at different scales, we propose multi-scale residual block (MSRB).
- Maintain spatially-precise high-resolution representation through the entire network.
- Generate multi-scale features in 1x,2x,4x etc.
- Information exchange among parallel streams for feature consolidation.

Dual Attention Unit

Attention modules are used to make CNN learn and focus more on the important information, rather than learning non-useful background information.

DAU

Spatial Attention

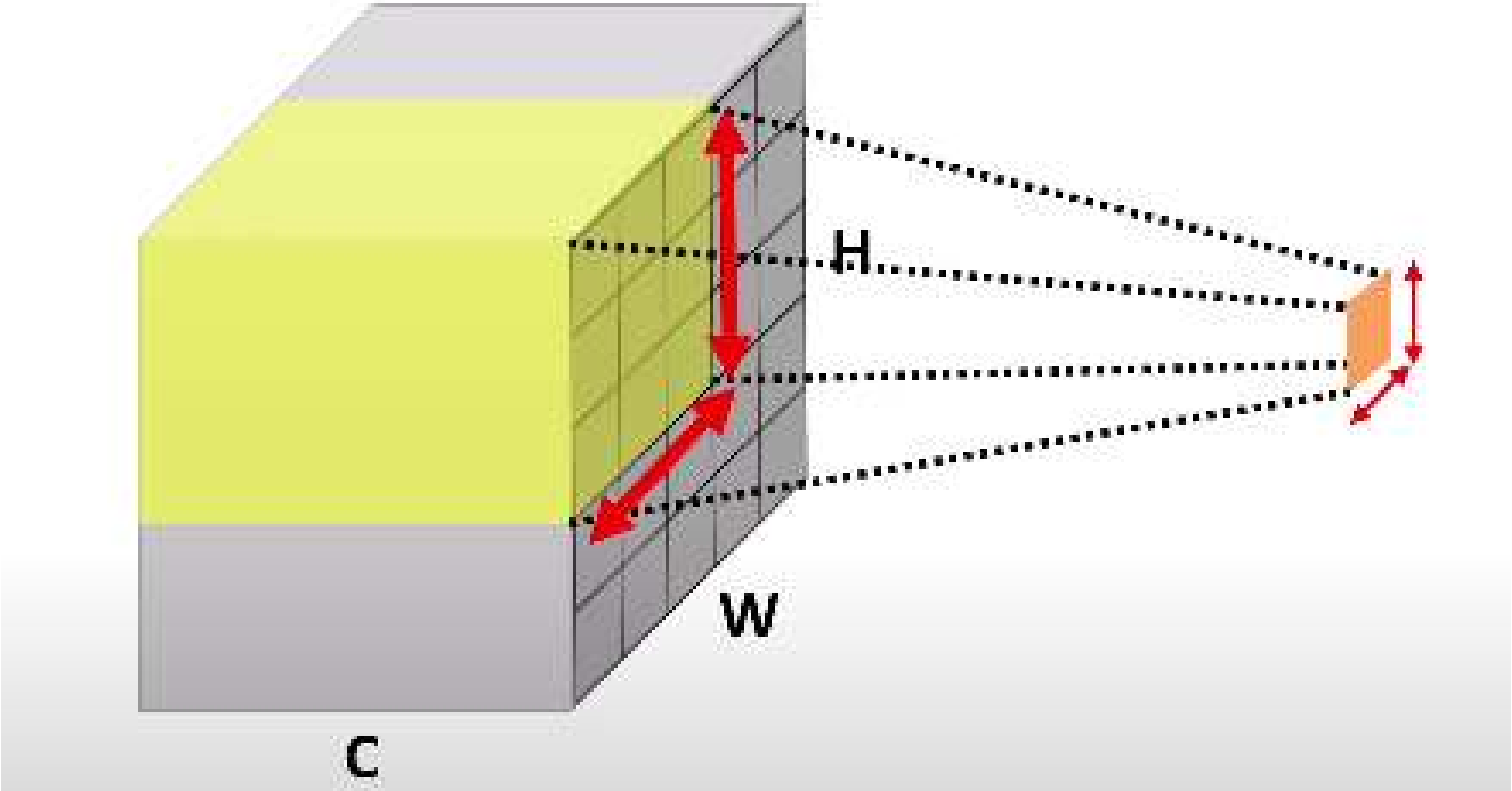
Captures **where** the key features in the image are.

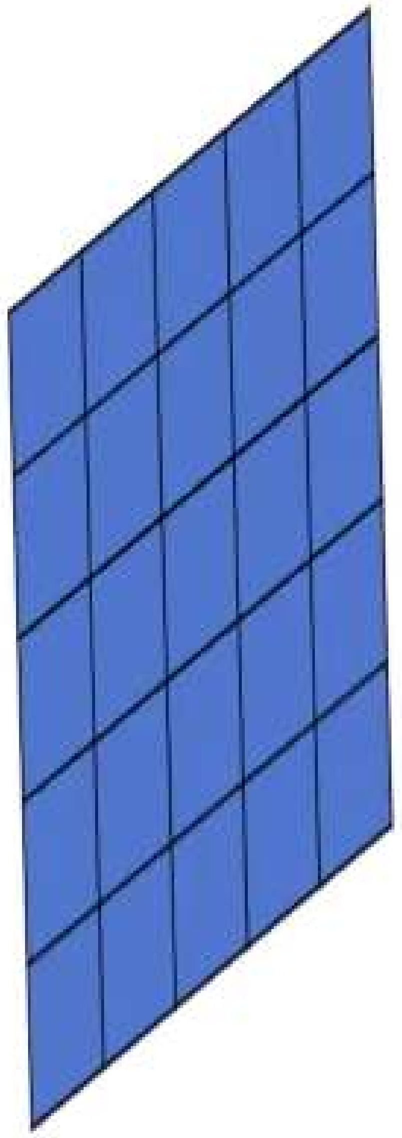
Channel Attention

Captures **what** the key features in the image are.

Spatial Attention

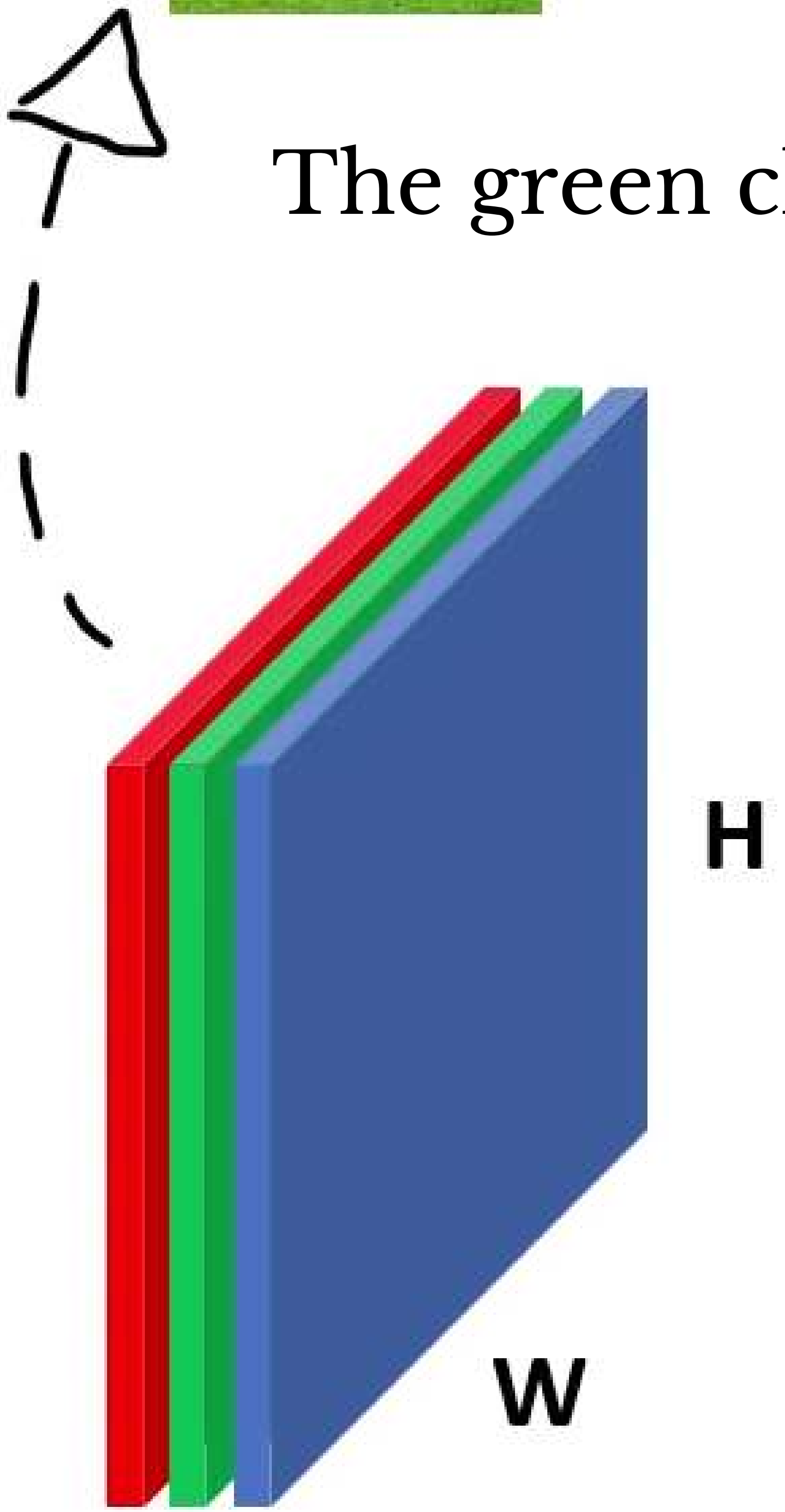
Only the part where the dog is located becomes useful than the rest.

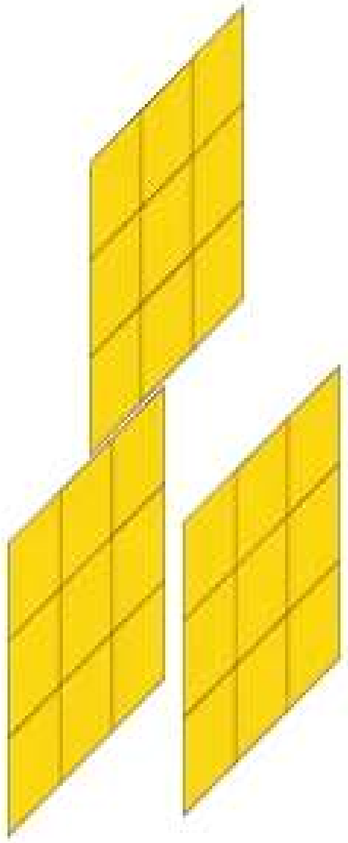




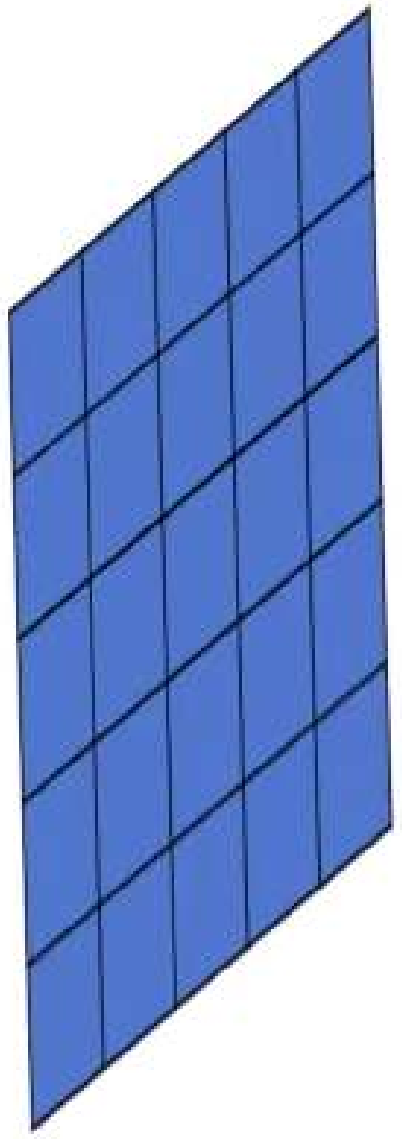
Channel Attention

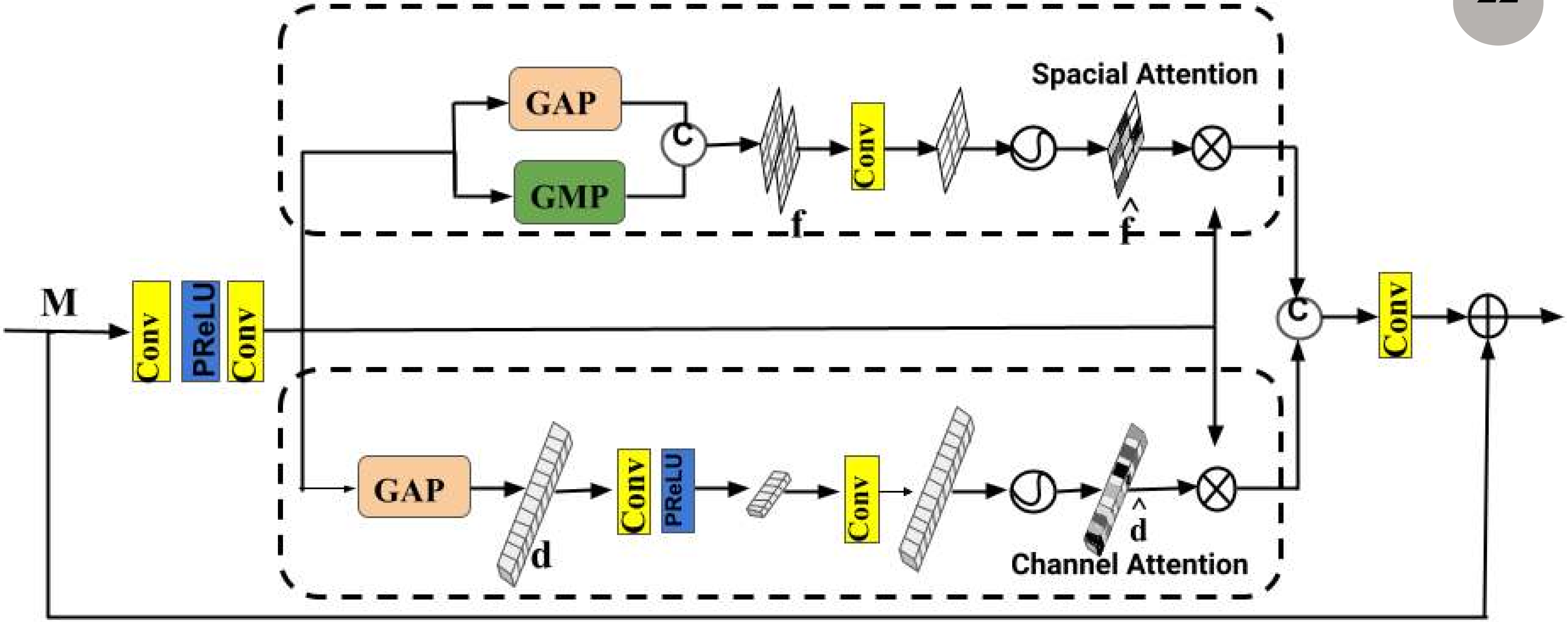
The green channel is important here for the given grass field image





The middle kernel is responsible to gain this information





GAP - Global Avg. Pooling
GMP - Global Max. Pooling

SELECTIVE KERNEL FEATURE FUSION

Selective Kernel (SK) convolution, which allows neurons to adaptively adjust their receptive field (RF) sizes. This SK convolution is implemented through three key operators: Split, Fuse, and Select.

1. **SPLIT OPERATION:**

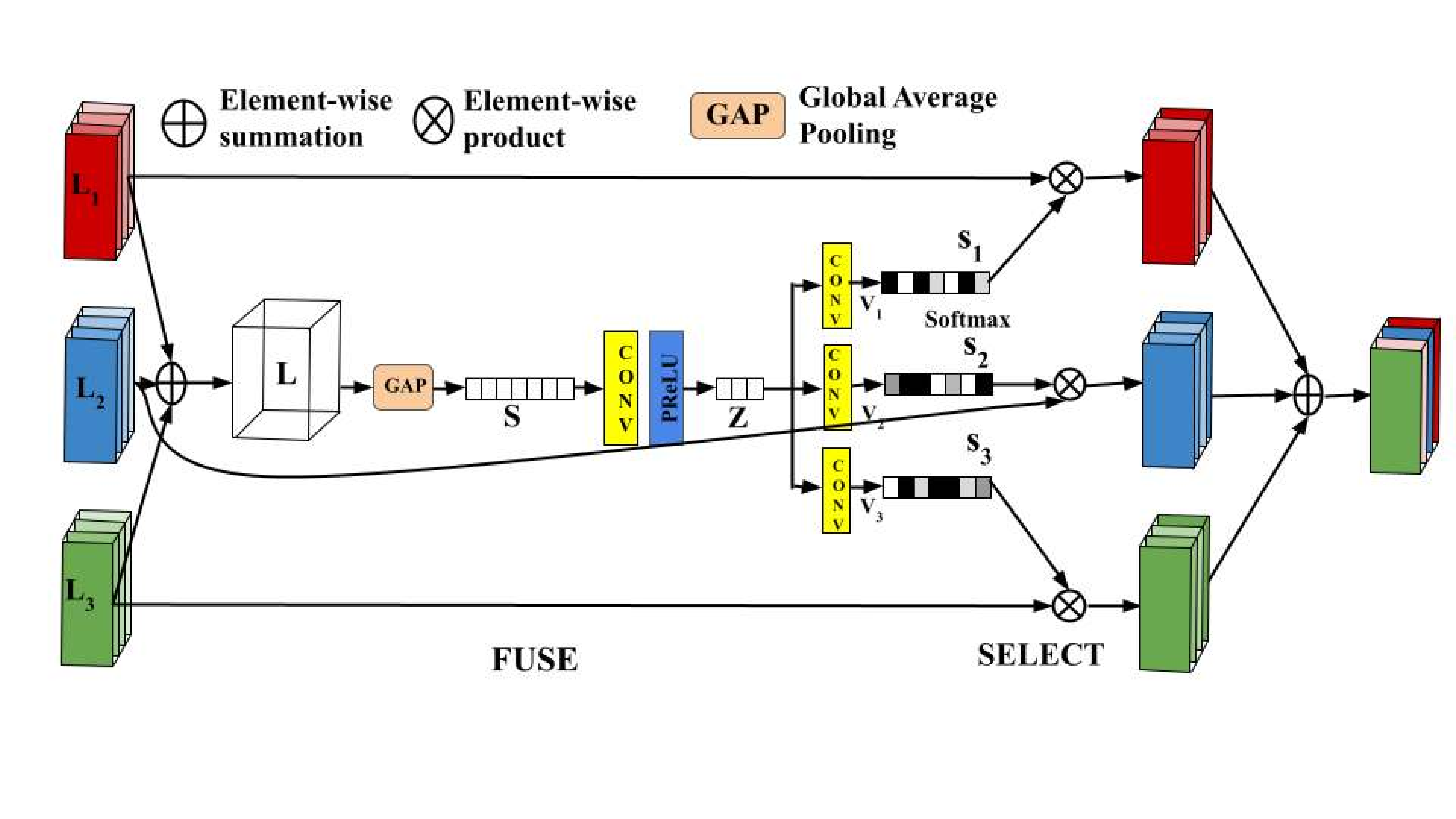
- Conduct transformation on feature map with different kernel sizes (3 , 5, 7)
- Convolutions are followed by Batch Normalization and PReLU activation function

2. **FUSE OPERATION:**

- The Fuse operation lets neurons adaptively select relevant receptive field sizes.
- Fuse results from multiple branches via an element-wise summation
- applied global average pooling to to generate channel-wise statistic
- A compact feature z is created to guide precise and adaptive selections.

3. **SELECT OPERATION:**

- The operator applies the softmax function to v1, v2, v3, producing attention activations s1, s2, s3
- These activations are used to adaptively recalibrate the multi-scale feature maps L1, L2, L3, respectively.


Element-wise summation
Element-wise product
GAP Global Average Pooling
L1
L2
L3
L
GAP
S
CONV
PReLU
Z
CONV
CONV
CONV
V1
V2
V3
s1
s2
s3
Softmax
FUSE
SELECT

UIEB DATASET

The UIEB (Underwater Image Enhancement Benchmark) dataset includes 950 images where 890 are paired(have corresponding ground truths) and 60 challenging samples. The dataset addresses challenges like color imbalance, visibility loss, and texture degradation, making it a standard benchmark for underwater image restoration.

Proposed Methodology

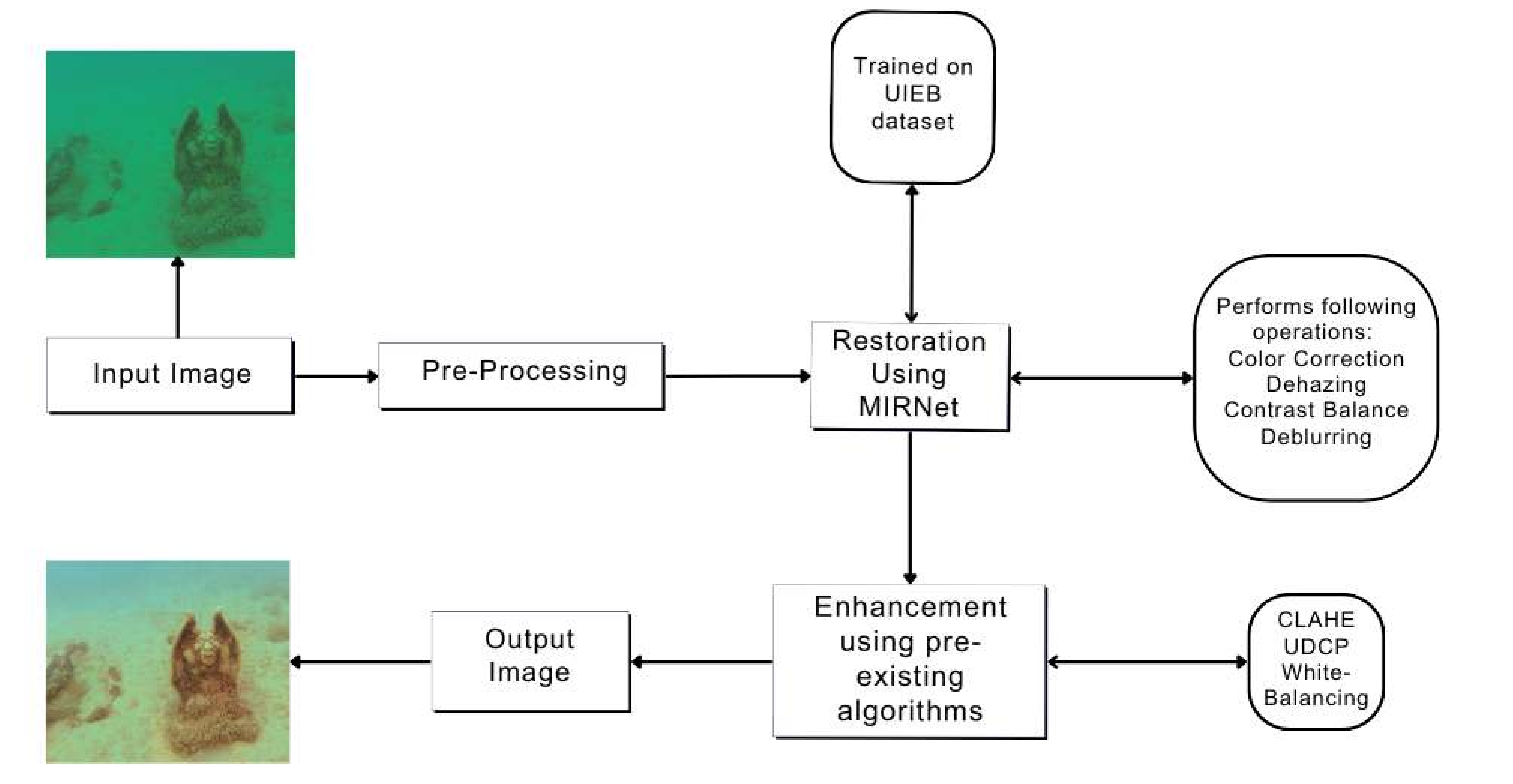
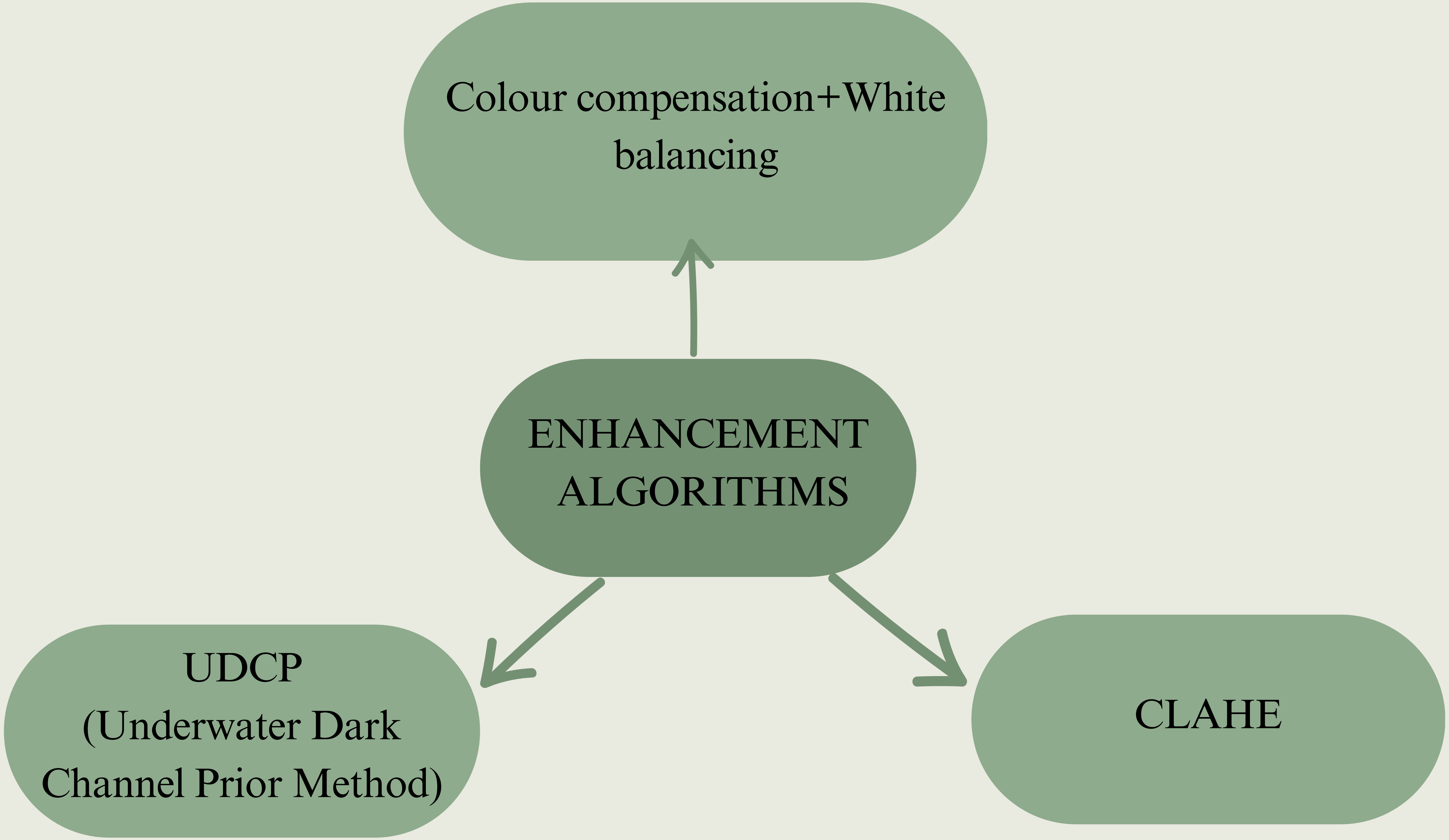


FIG.1

ENHANCEMENT TECHNIQUES



COLOR COMPENSATION + WHITE BALANCE

Color compensation is a technique used to correct and balance the colors in an image, ensuring that they appear natural and consistent under varying conditions.

Formula :

$$\mathbf{meanC = (1/n)\sum_{i=1}^{n} Ci}$$

[where C indicates Channel(R,G,B) and i is the intensity value (0-255)]

If meanG>meanR and meanG > meanB : Greenish Tint

meanB>meanR and meanB>meanG: Bluish Tint

Otherwise: Neutral Tint

COLOR COMPENSATION + WHITE BALANCE

- Color Compensation: Based upon the tint found (greenish/bluish) it compensates other channels.

For Greenish Tint: $R'(x,y) = R(x,y) \times uG/uR$ and $B'(x,y) = B(x,y) \times uG/uB$

C' - new pixel value

C - original pixel value

For Bluish Tint: $R'(x,y) = R(x,y) \times uB/uR$ and $G'(x,y) = G(x,y) \times uB/uG$

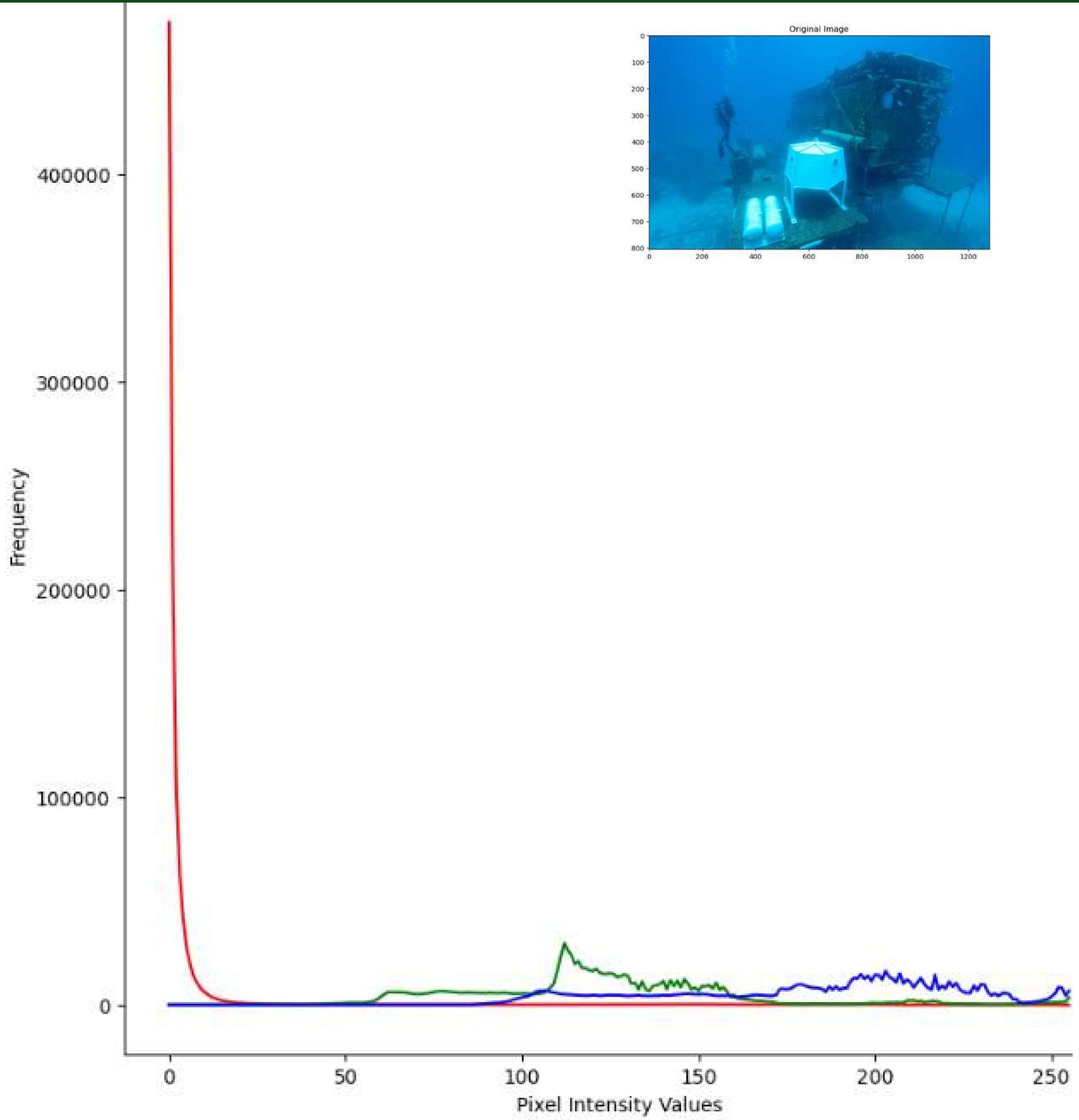
where u -> mean of that Channel

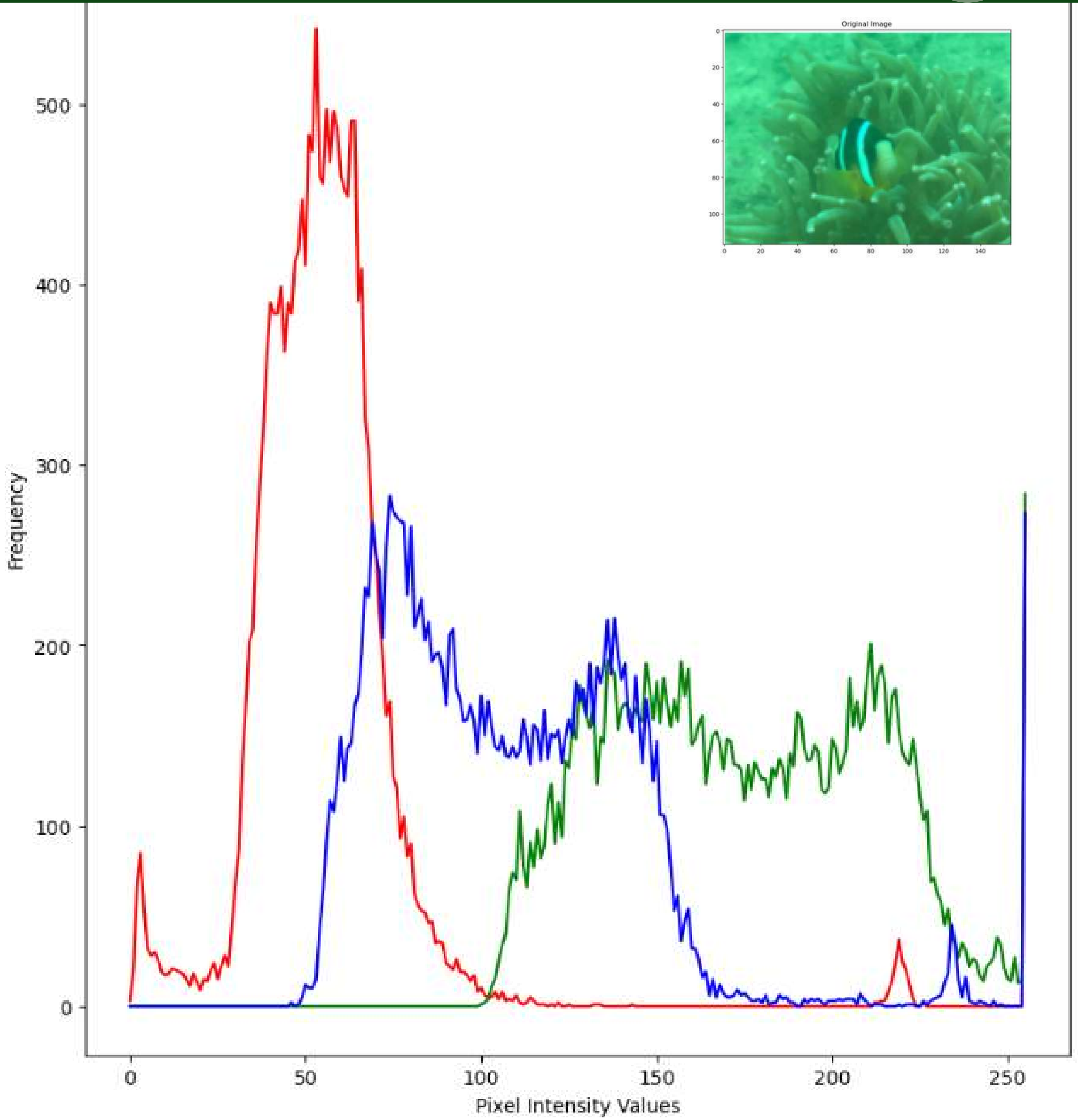
- White Balancing (Gray World Algorithm): Balances the image by ensuring the average color in the image is neutral gray.[5]

Gray World : $uGray = 1/3\,(uR + uG + uB)$

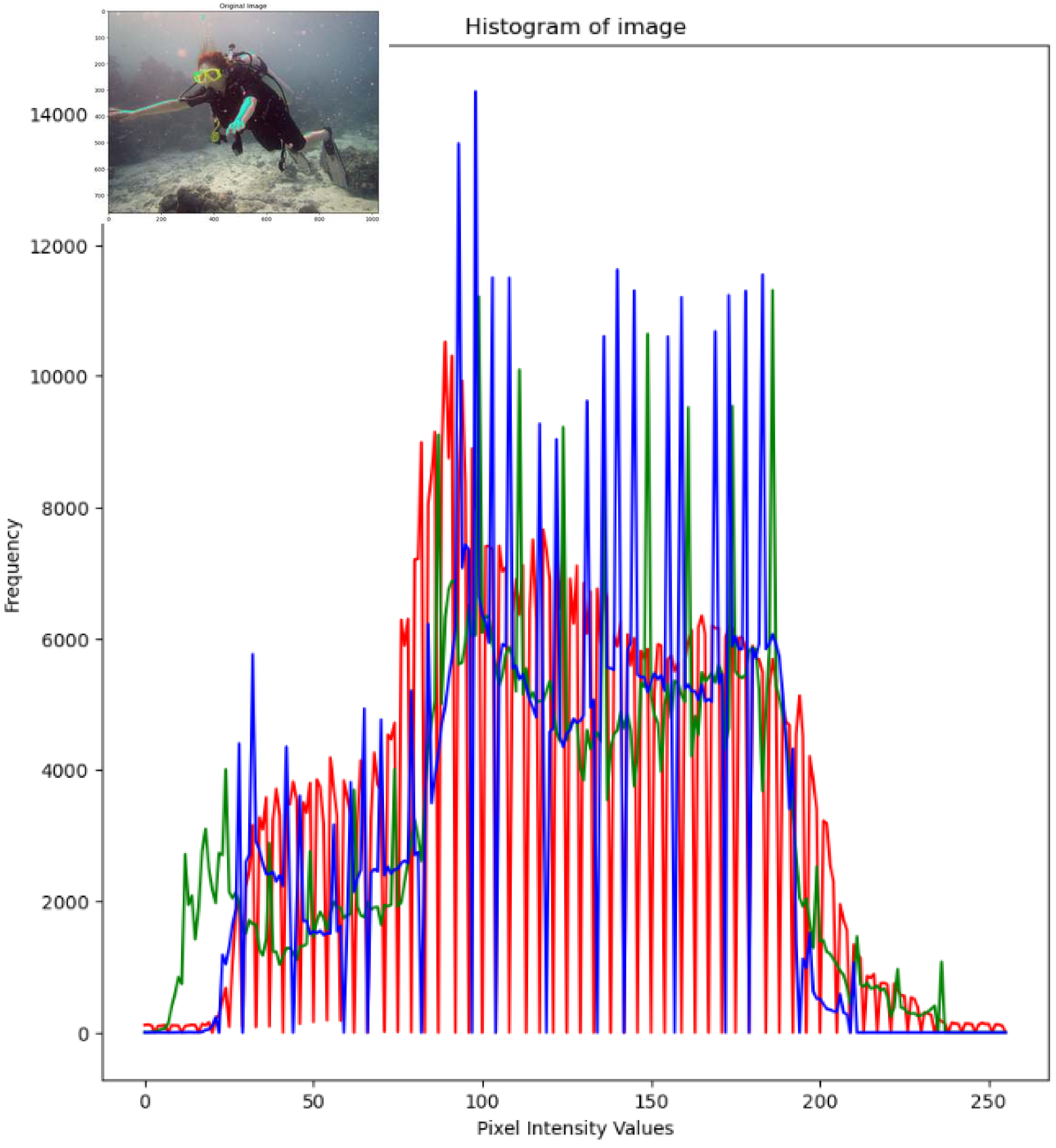
Each channel is then scaled using this mean : $C'(x,y) = C(x,y) \times uGray/uC$

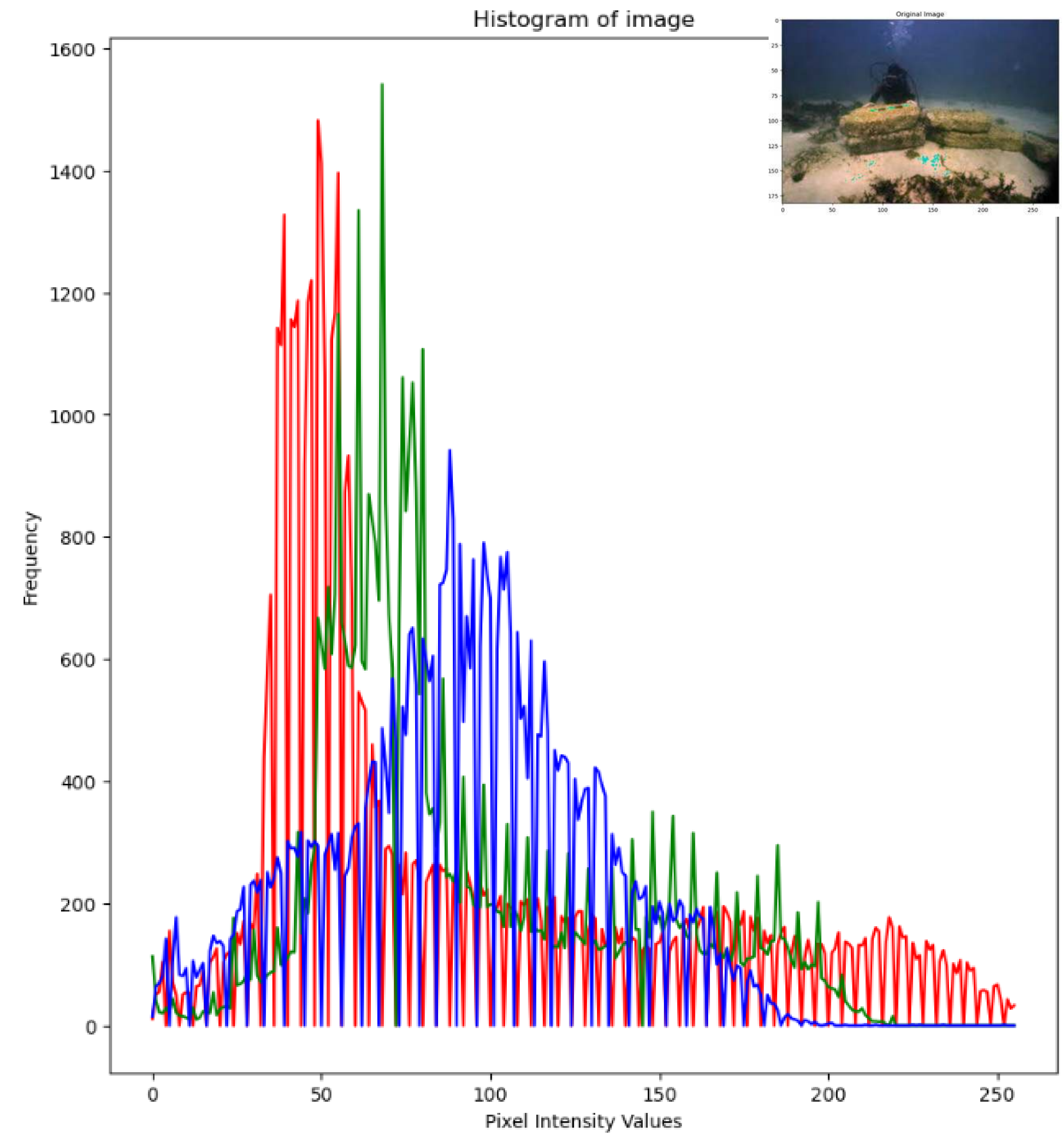
Histogram Plots of Bluish and Greenish Images Indicating Pixel Distribution





Histogram Plots of the same images after enhancement





Input Image

Enhanced using White balancing

Input Image → Restored by MIRNet → Enhanced

UDCP (UNDERWATER DARK CHANNEL PRIOR)

-Specifically designed for underwater image enhancement to address visibility issues caused by light absorption and scattering[12].

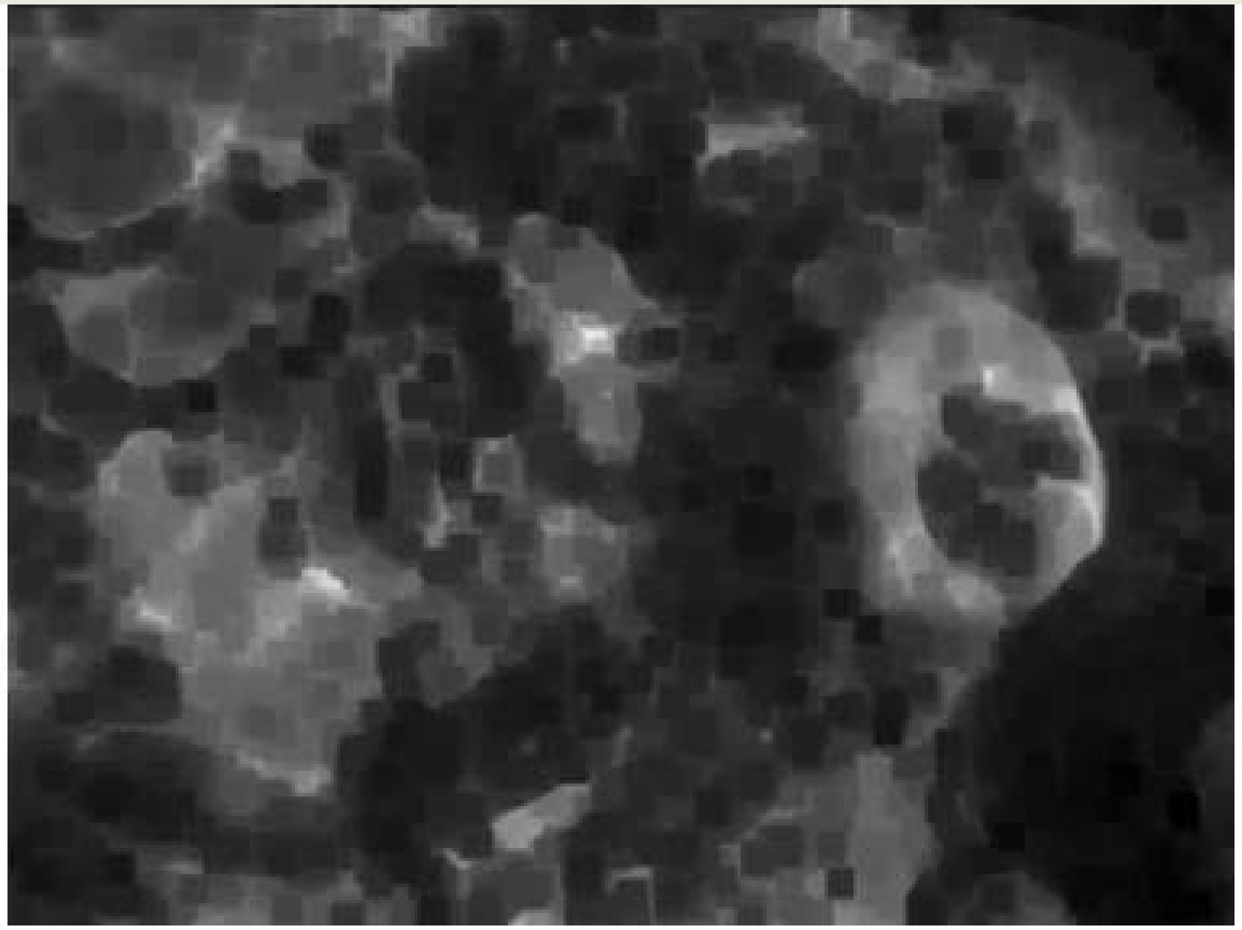
- Utilizes the blue and green channels for calculations, as red light is absorbed rapidly underwater.

- Extends the Dark Channel Prior (DCP) to account for the specific challenges of underwater environments.

- Used in underwater photography, marine exploration, and underwater surveillance to restore and enhance images.

UDCP Results

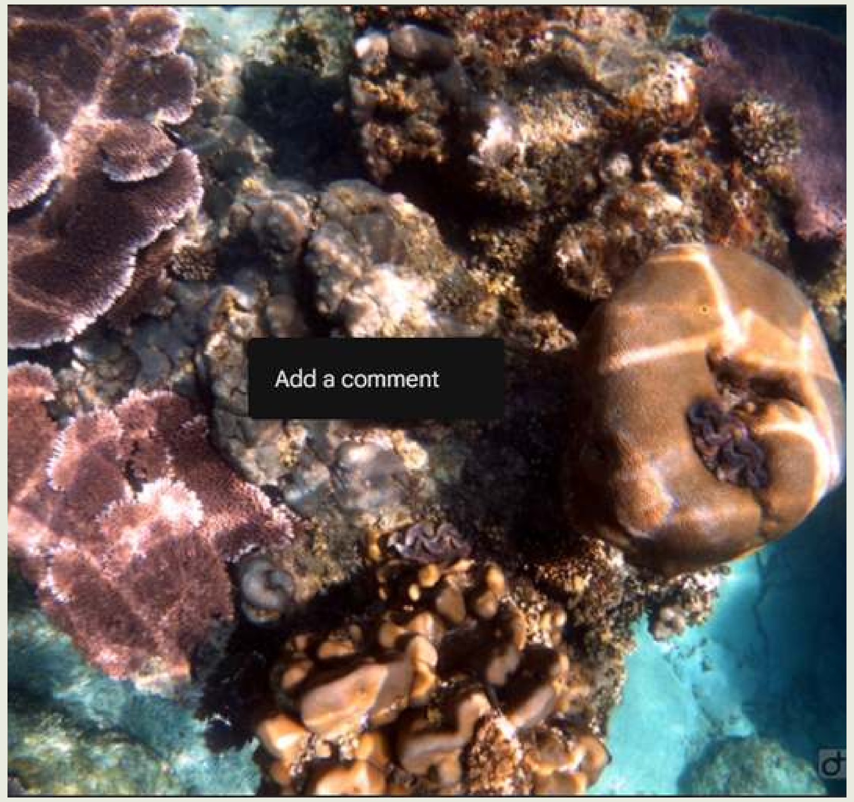
Input Image → Dark Channel → Output Image



MKSSS's Cummins College of Engineering for Women, Pune

UDCP Results

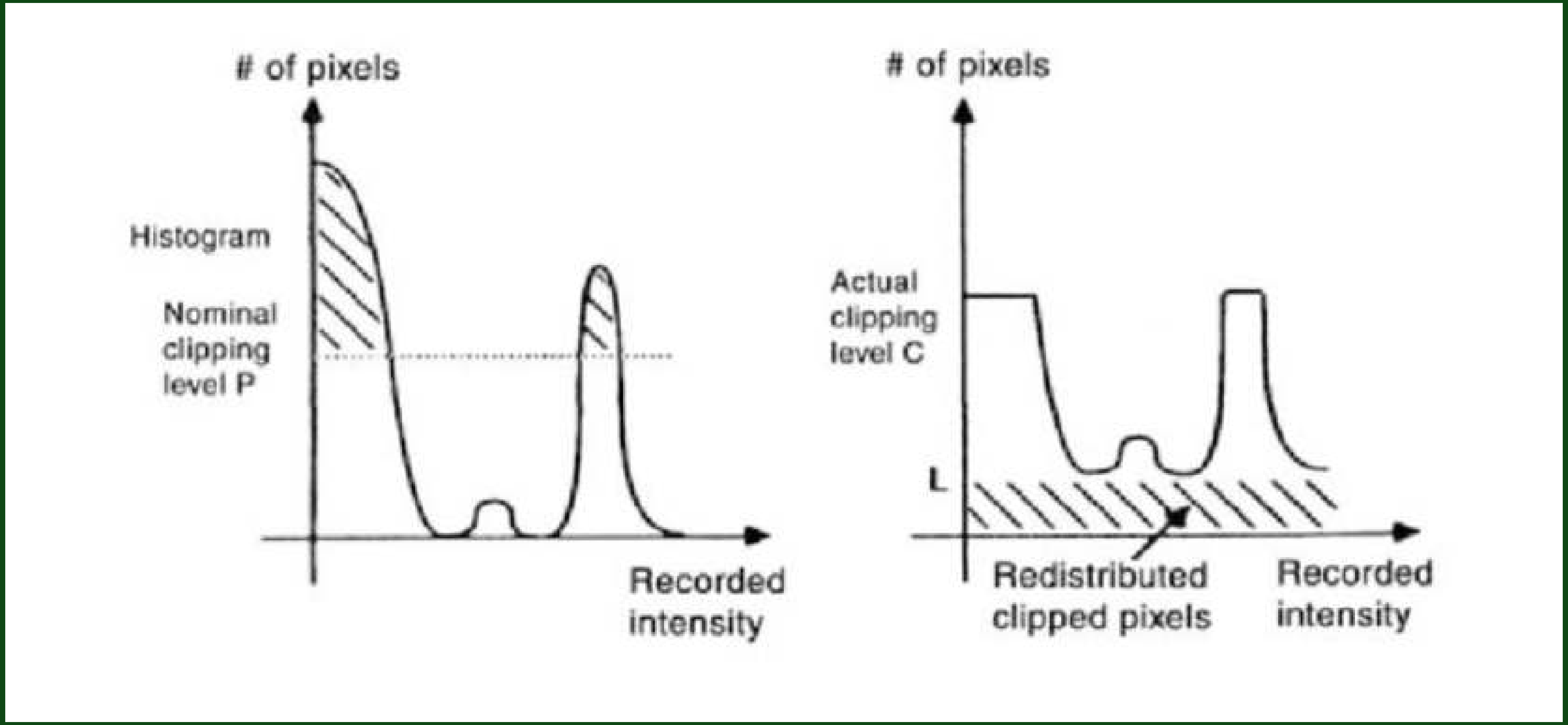
Input Image → Restored by MIRNet → UDCP → Ground Truth



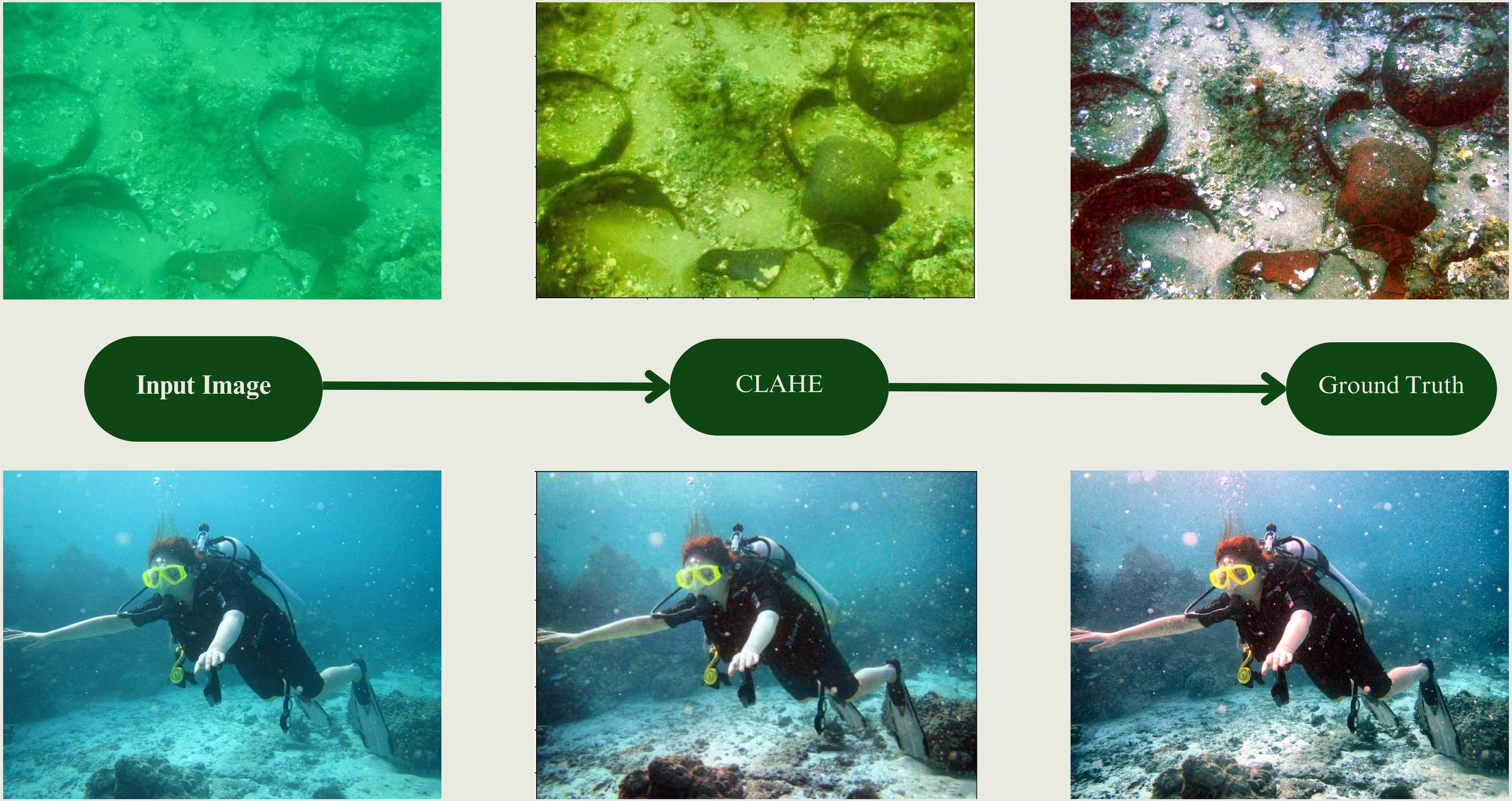
CLAHE

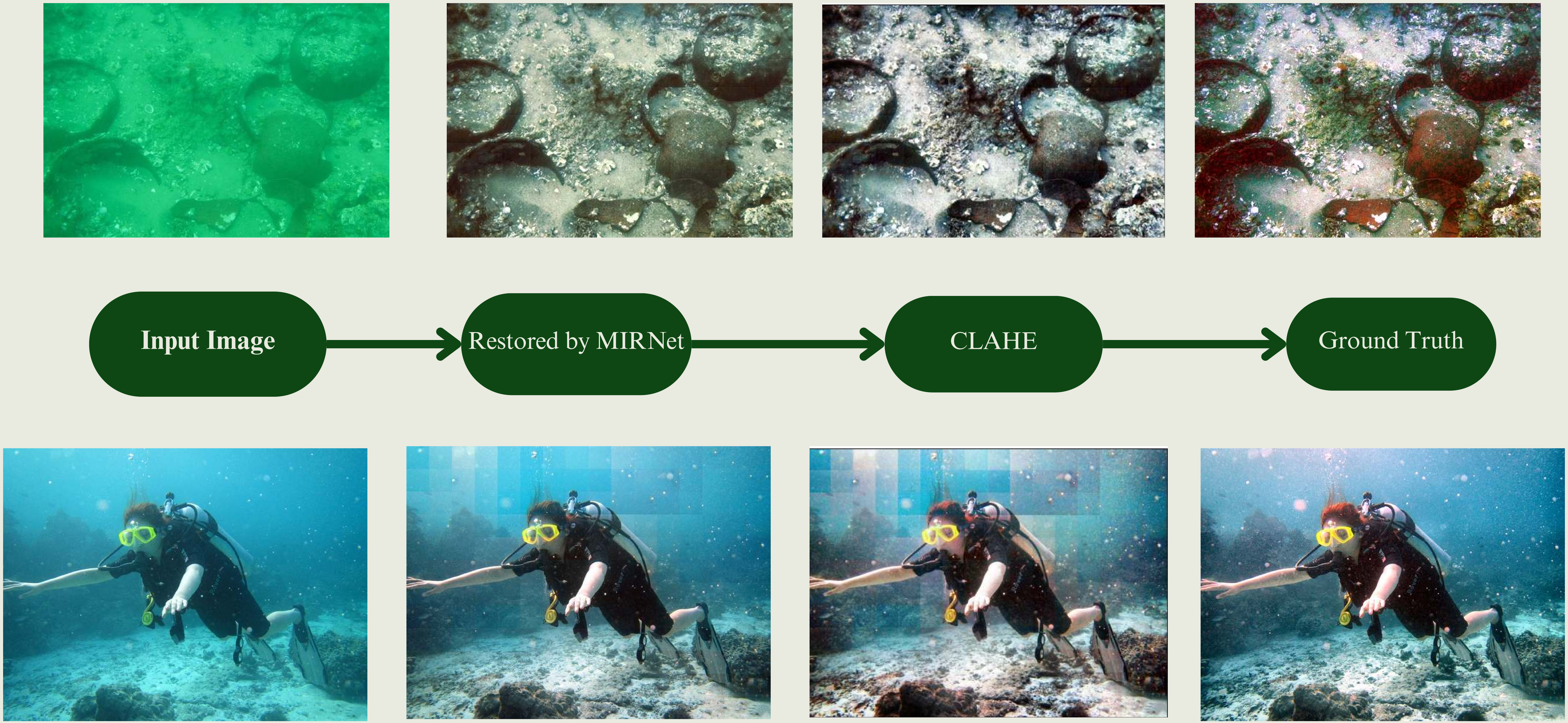
- **Division into Tiles:** CLAHE enhances local contrast by dividing the image into smaller tiles.
- **Contrast Limiting:** Histogram equalization is applied to each tile with a clip limit to control noise amplification.
- **Histogram Equalization Process:** Excess histogram values are redistributed for balanced enhancement.
- **Merging Tiles with Interpolation:** Bilinear interpolation merges the tiles seamlessly, ensuring smooth transitions and improved clarity

CLAHE



# of pixels
Histogram
Nominal clipping level P
Recorded intensity
# of pixels
Actual clipping level C
L
Redistributed clipped pixels
Recorded intensity


Input Image
CLAHE
Ground Truth



Input Image
Restored by MIRNet
CLAHE
Ground Truth

EVALUATION METRICS

PSNR (Peak-Signal-to-Noise-Ratio) -

20log10(MAX2/MSE)

For an 8-bit image PSNR can vary from 30-50dB.

SSIM(Structural Similarity Index Measure) - Range from -1 to 1.

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

EVALUATION METRICS

UIQM(Underwater Image Quality Measure) - Range from 0 to 5.

$$\mathrm{UIQM} = c_1 \times \mathrm{UICM} + c_2 \times \mathrm{UISM} + c_3 \times \mathrm{UIConM}$$

c1 = 0.0282, c2 = 0.2953, and c3 = 3.5753 are application-dependent coefficients.

UCIQE(Underwater Color Image Quality Evaluation) Range from 0 to 1.

$$UCIQE = c_1 \times \sigma_c + c_2 \times con_l + c_3 \times \mu_s.$$

where, σc is the standard deviation of chroma, conl is the contrast of luminance and μs is the average of saturation, and c1, c2, c3 are weighted coefficients. c1 = 0.4680, c2 = 0.2745, and c3 = 0.2576.

TRAINING

1. Extracted patches of size 128x128 making upto 30,000 train and 7000 validation images.
2. Adam optimizer with learning rate = 1e-4.
3. Loss function - Charbonnier Loss commonly used for restoration tasks.

$$\mathcal{L}(\hat{\mathbf{I}}, \mathbf{I}^*) = \sqrt{\|\hat{\mathbf{I}} - \mathbf{I}^*\|^2 + \varepsilon^2},$$

where I* denotes the ground-truth image, and ε is a constant which we empirically set to 10−3.

4. Metrics monitored - PSNR (Peak-Signal-to-Noise-Ratio)
5. Trained for 100 epochs using backup-callback

RESULTS ON UIEB Dataset

1.Performance of MIRNet On UIEB Dataset

PSNR	SSIM	UIQM	UCIQE
23.85	0.84	2.8802	0.5987

2.Comparison with state-of-the-art models

Method	WaterNet	FUnIE	UGAN	U-Shape Transformer	Our
PSNR(dB)	17.73	19.37	19.79	24.16	23.85

RESULTS ON UIEB Dataset

RESULTS ON UIEB Dataset

Image	UDCP		White Balancing		CLAHE	
	PSNR	SSIM	PSNR	SSIM	PSNR	SSIM
a	13.3	0.68	7.61	0.909	18.23	0.86
b	14.25	0.82	18.14	0.906	15.9	0.85
c	9.60	0.69	19.63	0.95	19.4	0.9
d	13.18	0.63	17.85	0.94	16.77	0.82
e	12.75	0.71	13.86	0.83	19.53	0.93
f	17.73	0.88	16.43	0.92	19.5	0.91

RESULTS ON UIEB Dataset

Image	UDCP		White Balancing		CLAHE	
	UIQM	UCIQE	UIQM	UCIQE	UIQM	UCIQE
a	1.8189	0.6308	3.1617	0.6402	3.1648	0.6397
b	2.4910	0.6917	3.3125	0.6502	3.5639	0.6387
c	2.0367	0.7287	2.6834	0.5864	2.8232	0.6355
d	1.5577	0.6576	2.6449	0.6499	2.9766	0.6542
e	1.9743	0.6603	2.6138	0.648	3.0655	0.6602
f	1.5773	0.6400	2.5156	0.6489	3.2343	0.6425

CONCLUSION

1. Exceptional Performance: MIRNet addresses underwater imaging challenges like poor visibility, color distortion, and noise, producing visually appealing and informative results.Enhancement algorithms are used to significantly improve image quality, resulting in visibly superior images.
2. Lightweight Design: Optimized for reduced computational complexity without compromising performance.
3. Superior Results: Consistently outperforms across benchmarks with remarkable precision and clarity in restoring underwater images.
4. Real-World Applicability: Robust, scalable, and suitable for scenarios with limited computational resources.
5. Future Potential: Can be adapted for other challenging imaging conditions to broaden its impact.

Application/Usage

Applications of Underwater Image Restoration Using MIRNet:

1.Marine Biology and Research:
Enhanced visibility allows researchers to study marine life, coral reefs, and underwater ecosystems in greater detail.
2.Underwater Exploration:
Improves visual clarity for underwater exploration missions, including shipwreck discoveries and archaeological studies.
3.Underwater Robotics and Autonomous Vehicles:
Helps autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) navigate and perform tasks effectively in low-visibility conditions.
4.Aquaculture:
Provides clearer images for monitoring fish farming activities, identifying diseases, and ensuring optimal conditions in underwater enclosures.
5.Search and Rescue Operations:
Assists in locating objects or individuals in underwater environments with poor visibility, improving success rates in critical missions.

WEB APPLICATION LINK

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12 Underwater Dark Channel Prior Method (UDCP) For Compensating Red Channel Degradation In Underwater Images

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