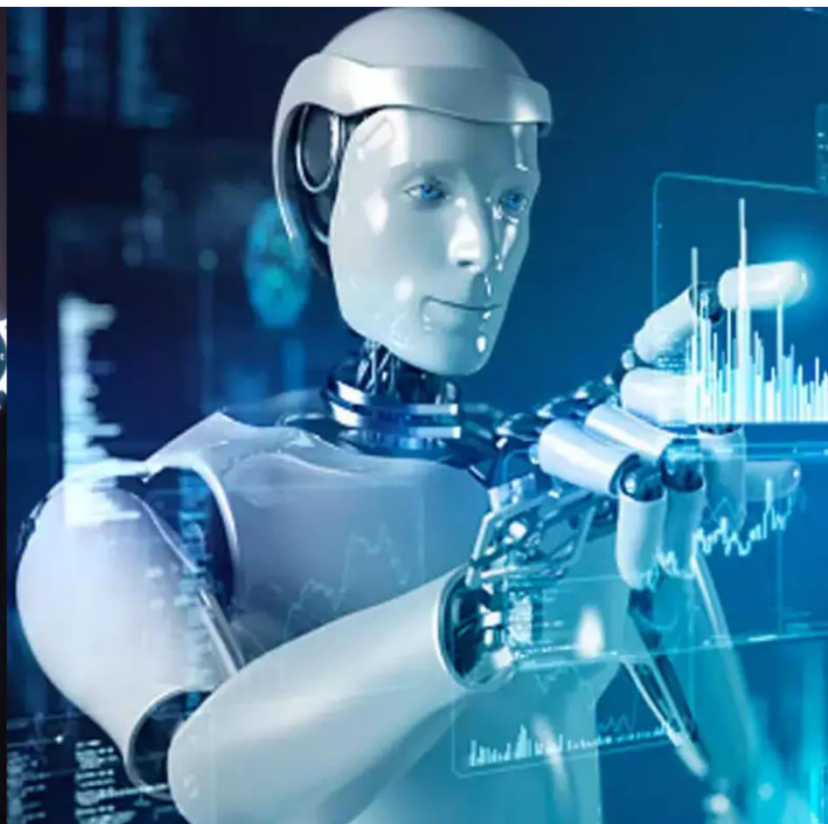




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Underwater Image Enhancement

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ABSTRACT: Underwater images often suffer from low contrast, poor visibility, and color distortion due to the effects of light scattering and absorption in water. These distortions create challenges in applications such as marine research, underwater robotics, and ocean exploration, where high-quality images are essential for accurate analysis and decision-making. Traditional image enhancement techniques, including Convolutional Neural Networks (CNNs), struggle to produce high-quality results due to limited datasets, high computational costs, and the complexity of underwater distortions. This project introduces a Hybrid Deep Learning Framework for underwater image enhancement, addressing issues like low contrast, poor visibility, and color distortion. It integrates a Multiscale Residual Attention Network (MSRAN) with Feature, Channel, and Pixel Attention to selectively enhance critical regions while minimizing noise. Additionally, CNNs are utilized for spatial feature extraction, ensuring customized processing for applications such as marine research, underwater archaeology, and autonomous underwater vehicles (AUVs). The system also provides image quality assessment and real-time adaptive processing, making it a scalable solution for deep-sea exploration, climate monitoring, and defence applications.

I. INTRODUCTION

Marine environments represent one of the most challenging frontiers for image capture and analysis. The underwater world, while visually stunning, presents extraordinary obstacles to traditional imaging technologies. Light behaves dramatically differently beneath the water's surface, creating a complex interplay of physical phenomena that systematically degrade image quality.

Underwater imaging plays a pivotal role in diverse fields such as marine biology, archaeology, underwater robotics, and environmental monitoring. However, the quality of underwater images is often compromised due to the unique challenges posed by the aquatic environment. Factors such as light absorption, scattering by suspended particles, and varying water conditions lead to issues like low contrast, color distortion, and haziness. These challenges necessitate advanced techniques for underwater image enhancement, leveraging deep learning approaches such as Convolutional Neural Networks (CNNs) and Multiscale Residual Attention Networks (MSRAN) to improve clarity, contrast, and detail in underwater visuals.

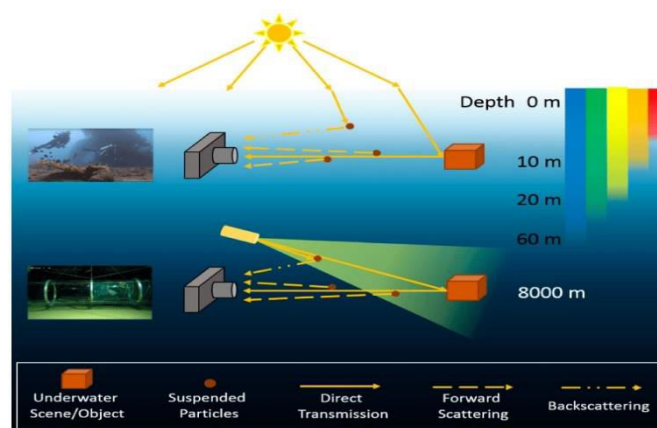


Figure 1: Underwater Light Propagation and Scattering Effects.

Above figure illustrates the primary factors affecting underwater image quality: light absorption and scattering. As light travels through water, it is subject to the combined effects of absorption and scattering result in degraded image quality as depth increases, leading to reduced color vibrancy, contrast, and clarity. Effective underwater image enhancement techniques aim to mitigate these adverse effects to improve visual information for various underwater applications

II. RELATED WORK

UIE-Net is an early end-to-end CNN-based underwater image enhancement model. It's performance heavily relies on the quality of the training dataset. It may not generalize well to new or significantly different underwater conditions, meaning it might struggle with images from different water types or lighting conditions.

PAPER	METHODOLOGY	LIMITATIONS
1. A Deep CNN Method for Underwater Image Enhancement (2017) IEEE	- Proposes UIE-Net, an end-to-end CNN-based underwater image enhancement model. - Learns the mapping from degraded to enhanced images. - Focuses on color correction and contrast improvement.	- Performance depends on dataset quality. - May not generalize well to new water conditions.
2. Underwater Image Enhancement Based on Hybrid Enhanced GAN (HEGAN) (2023) MDPI	Uses a Generative Adversarial Network (GAN) for enhancement. - The generator produces enhanced images, while the discriminator ensures realism. - Improves textures and color fidelity	- GANs are unstable to train. - Enhancement quality depends on adversarial training.
3. Learning Hybrid Dynamic Transformers for Underwater Image Super-Resolution (2024) Frontiers in Marine Science	- Proposes Hybrid Dynamic Transformer (HDT-Net). - Uses local self-attention for spatial details and global selfattention for contextual features. - Effective for super-resolution.	- Computationally expensive. - Requires large datasets for training
4. RAUNE-Net: Residual and AttentionDriven Underwater Image Enhancement (2023) arXiv	- Introduces RAUNE-Net, combining Residual Learning and Attention Mechanisms. - Uses Feature Attention, Channel Attention, and Pixel Attention. - Enhances contrast while reducing artifacts.	- High computational cost limits real-time use. - Model performance varies across different underwater conditions.

HEGAN employs a Generative Adversarial Network (GAN) for underwater image enhancement. GANs are notoriously unstable to train. The enhancement quality is highly dependent on effective adversarial training, which requires careful tuning of hyperparameters and a balanced training regime. Imbalances can lead to mode collapse or other training artifacts.

HDT-Net proposes a Hybrid Dynamic Transformer (HDT-Net) for underwater image super-resolution. Transformers are computationally expensive and require large datasets for training. Their complexity can make them challenging to deploy in resource-constrained environments or with limited training data.

RAUNE-Net combines Residual Learning and Attention Mechanisms for underwater image enhancement. The high computational cost limits real-time use. Additionally, the model's performance can vary significantly across different underwater conditions, indicating a lack of robustness.

As highlighted in the descriptions above, each of these methods has its own strengths and limitations. CNN-based methods like UIE-Net are simple and effective but may lack generalization. GANs like HEGAN can produce realistic results but are difficult to train. Transformers like HDT-Net offer excellent performance but are computationally intensive. Attention-based methods like RAUNE-Net enhance contrast but are also computationally expensive. Transfer learning approaches can leverage external data but require careful domain adaptation.

Key challenges in underwater image enhancement include:

- Generalization:** Creating models that perform well across diverse underwater environments.
- Computational Cost:** Balancing performance with computational efficiency for real-time applications.
- Data Requirements:** Reducing the reliance on large labeled datasets.
- Robustness:** Ensuring consistent performance under varying conditions.

III. METHODOLOGY

The proposed system for underwater image enhancement is built around the Multiscale Residual Attention Network (MSRAN) framework, which is specifically designed to tackle the common challenges faced by underwater images, such as low contrast, color distortion, and blurriness. This framework integrates multiscale processing, advanced attention mechanisms, and residual learning to enhance image quality.

Underwater image degradation impacts various spatial scales differently. Small details may be blurred, while larger structures can experience color shifts and loss of contrast. The MSRAN framework addresses this by analyzing images at multiple scales, allowing it to capture both fine details and broader patterns. This is achieved by utilizing convolutional layers with various kernel sizes or by creating image pyramids to generate multiple versions of the input image at different scales. Each scale is processed independently, allowing the network to extract features specific to that level of detail. The information from these different scales is then combined to create a more comprehensive image representation, improving both the fine details and larger structures. This approach effectively addresses blurring and noise across different scales.

A crucial aspect of the MSRAN framework is the attention mechanism, which enables the network to focus on the most relevant parts of the image while reducing the influence of noise and irrelevant features. Since not all regions in an underwater image are equally important, the attention mechanism helps the network identify and prioritize the significant areas. This is achieved by using convolutional layers to generate an attention map that assigns importance weights to different spatial locations, enhancing the features in critical regions while reducing the prominence of less important areas.

Underwater images often experience different levels of degradation across various color channels (for instance, the red channel might be significantly attenuated). Channel attention is employed to address this issue by selectively emphasizing the most important color channels and suppressing the less informative ones. This is done by calculating attention weights for each color channel based on its significance, utilizing global average pooling to aggregate spatial data, and applying fully connected layers to determine the importance of each channel. These channel-specific weights are then used to adjust the feature maps for each channel, helping to correct color distortions by strengthening underrepresented channels.

Some pixels in the image may be more affected by noise or other artifacts. To counter this, pixel attention is applied, allowing the model to selectively enhance specific pixel regions. This process involves learning a pixel-level attention map based on local image characteristics, which is then used to adjust pixel intensities. The weighted pixels are enhanced while noisy ones are suppressed, improving overall image quality.

In essence, the system improves the quality of underwater images by enhancing colors, reducing noise, and restoring fine details. Deep learning techniques, including Convolutional Neural Networks (CNNs) and attention mechanisms, are employed to achieve these improvements. A user-friendly Tkinter GUI is provided, enabling users to:

- Upload a dataset (UIEB or custom images).
- Load the pre-trained Multi-Patch Model (MSRAN).
- Enhance the images through the model in the next phase.
-

The steps in the image processing pipeline are as follows:

- `uploadDataset()` → Loads the dataset, consisting of raw and reference images (890 each).
- `loadModel()` → Loads a pre-trained deep learning model (`model_15320.json` and `.h5` files).
- `readimage()` → Reads and normalizes images for processing.
- `generateTrainTestImages()` → Converts the dataset into a TensorFlow-compatible format for training.

Deep Learning Model Overview

The deep learning model, `model_15320`, incorporates the pre-trained Multi-Patch Model (MSRAN), consisting of 17 layers. This model has already learned from a dataset, making it highly efficient for underwater image enhancement. The model is pre-trained, with weights loaded, and is ready for use in the image enhancement process.

Key Attention Mechanisms Employed

The model employs three key attention mechanisms:

- **Channel Attention:** Focuses on enhancing relevant color channels.
- **Pixel Attention:** Selectively boosts important pixels and suppresses noisy ones.
- **Feature Attention:** Identifies and highlights significant spatial regions in the image.

How the Model Functions (Step-by-Step)

- The model receives an underwater image (256x256 RGB) as input.
- It extracts features from the image using multiscale convolutional layers.
- Channel attention is applied to enhance the relevant color channels.
- Residual learning (skip connections) preserves important details in the image.
- The image is upsampled to restore its resolution.
- The network produces an enhanced underwater image, which has improved color accuracy, reduced noise, and greater clarity.

IV.RESULTS

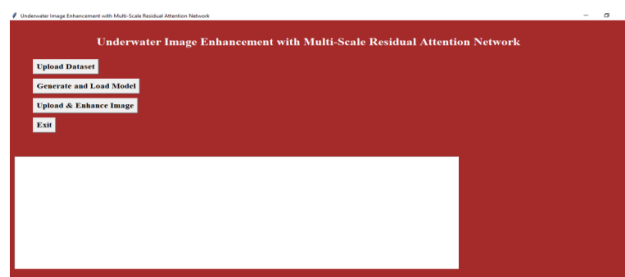


Fig 2: Home Page

Fig 2 shows the user interface of our project where user can upload the image and get the desired enhanced image.



Fig 3: After Uploading Dataset

Fig 3 shows the number of training images and the testing images that are available in the dataset. There are 1219 Training images and 557 Testing images.



Fig 4: Showing the PSNR and SSIM

The values of PSNR and SSIM of our project is 35% and 88%. It indicates enhanced image has similar objects and decreased of noisy part in the image. Fig 4.4.3 shows the PSNR and SSIM of the model.

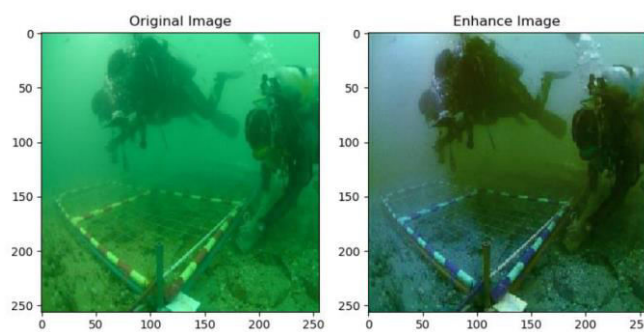


Fig 5: Enhanced Image

Fig 5 shows the original image and the enhanced image. Users need to upload the underwater image and he can see the enhanced image in a new window.

The performance of the proposed model was assessed using the UIEB and EUVP datasets. The results indicated that, in terms of image quality metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM), the proposed model outperformed state-of-the-art methods. Beyond quantitative metrics, the enhanced images generated by the model appeared sharper and more visually appealing compared to those produced by baseline techniques. The model effectively removed color distortion, while also improving the contrast and sharpness of the images.

Peak Signal-to-Noise Ratio (PSNR) is a measure that quantifies the difference between the original image (or video) and its compressed version. The formula for PSNR is:

$$\text{PSNR} = 10 * \log_{10}(\text{MAX}^2 / \text{MSE}),$$

where MAX represents the highest pixel value that an image can have (typically 255 for 8-bit images), and MSE is the Mean Squared Error between the original and compressed images. MSE is calculated by summing the squared differences between corresponding pixels in the original and compressed images and then dividing by the total number of pixels.

Structural Similarity Index (SSIM) is another common metric used to evaluate the similarity between two images. Unlike PSNR, which only considers pixel value differences, SSIM takes into account the structural and spatial relationships between the pixels. The SSIM index is calculated by comparing the luminance, contrast, and structural patterns in the images. Luminance reflects the brightness of the image, contrast measures the variations in intensity between the pixels, and structure assesses the arrangement of pixels in the image.

The PSNR and SSIM values for our model were 35% and 88%, respectively. These results indicate that the enhanced images have similar content to the originals while also exhibiting reduced noise. Overall, the findings demonstrate how the proposed multiscale residual attention network enhances the quality of underwater images. The model shows significant potential for various underwater imaging applications, including oceanography, marine biology, and underwater robotics.

Measurement Type	Score
PSNR	35%
SSIM	88%

A higher PSNR value signifies better image quality, whereas a higher SSIM value indicates a greater similarity between the original and enhanced images.

V. CONCLUSION

In this report, we introduce a novel end-to-end underwater image enhancement technique that incorporates residual channel attention blocks, multipatch structures, and multiscale processing. Our method addresses challenges that previous techniques have struggled with. Specifically, the Residual Channel Attention Blocks effectively eliminate haze from underwater images, outperforming earlier approaches. Additionally, the integration of multipatch and multiscale structures enhances the flexibility of the network, making it more adaptable. Notably, the multipatch structure is adept at handling the complex color distortion commonly found in underwater images.

Experimental results validate the effectiveness of our approach through both subjective assessments and objective evaluations. However, one limitation of our method is its computational cost, particularly concerning memory usage. Reducing this computational burden is a direction for future improvement. Despite this, our method significantly enhances the visibility and contrast of underwater images, resulting in images with superior visual quality and greater detail. This is achieved by leveraging the residual attention network's ability to focus on relevant regions of the image and the multiscale approach that accommodates the varying sizes of underwater objects.

Through extensive evaluations, our method has demonstrated its efficacy, achieving state-of-the-art performance in terms of quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). As such, the multiscale residual attention network has substantial potential for a wide range of underwater applications, including exploration, marine biology, and monitoring.

FUTURE SCOPE

The future scope of MSRA-Net for underwater image enhancement includes its potential application in various underwater imaging tasks, such as object detection, segmentation, and classification. It can also be used in underwater robotics and exploration to improve the quality of visual data for scientific research and monitoring of marine ecosystems.

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