ENHANCING UNDERWATER IMAGES WITH REINFORCEMENT LEARNING

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***Abstract*—This large-scale effort aims to improve images by using reinforcement learning approaches to overcome the difficulties related to underwater imagery. Due to the special challenges presented by underwater environments—such as low contrast, color distortion, and limited visibility—traditional image processing techniques struggle to produce acceptable results. This work suggests a novel method for adaptively improving underwater photos that makes use of reinforcement learning algorithms. The study starts with a thorough examination of the components that contribute to underwater image deterioration and an investigation of current improvement techniques. Deep neural networks are then used in a reinforcement learning framework to determine the best improvement policies. Through training on a wide range of underwater photo datasets, the model learns to automatically modify contrast, brightness, and color correction settings. The performance of the suggested model is evaluated using a range of metrics, such as visual comparisons with the state-of-the-art improvement strategies and an evaluation of image quality. The outcomes show how well the reinforcement learning strategy works to dramatically increase underwater image visibility and quality. Experiments carried out in various settings and with diverse illumination conditions are also used to evaluate how well the model adapts to various underwater situations. This study introduces a data-driven, learning-based method to improve image quality, which advances the field of underwater imaging. The model can adapt to a variety of underwater conditions thanks to the application of reinforcement learning, which also automates the enhancement process. The results of this work may find use in marine biological studies, environmental monitoring, and underwater surveillance, where high-quality photography is needed**

Keywords——Double Deep Q network, Markov decision process (MDP), reinforcement learning, underwater image enhancement.

I. INTRODUCTION

Underwater environments present unique challenges for imaging systems, characterized by poor visibility, light attenuation, and colour distortion caused by scattering and absorption phenomena. Capturing high-quality images in such conditions is crucial for various applications, including marine biology [3], oceanography, underwater archaeology[2], and surveillance. According to research literature, humans experience between 70% and 80% of their environment through visual information [1]. Traditional image enhancement techniques often struggle to address the complex and dynamic nature of underwater scenes, prompting the exploration of novel approaches such as reinforcement learning (RL). Reinforcement learning, a branch of machine learning, has garnered significant attention in recent years for its ability to learn optimal decision-making policies through interaction with an environment. In the context of underwater image enhancement, RL offers a promising framework for automatically improving image quality by learning to adaptively adjust parameters or operations based on feedback from the environment or human experts. This research paper aims to explore the application of reinforcement learning techniques to the task of underwater image enhancement. By formulating the enhancement process as a sequential decision-making problem, RL algorithms can learn to make intelligent adjustments to image parameters such as contrast, brightness, and colour balance to maximize visual quality and clarity. Moreover, RL-based approaches have the potential to adapt to varying underwater conditions, such as changes in water turbidity, illumination, and scene complexity, making them robust and versatile for real-world deployment. By leveraging the power of reinforcement learning, we aim to advance the state-of-the-art in underwater image enhancement.

A. Motivation

Many obstacles arise from underwater imaging, making it more difficult to collect and process visual data in aquatic settings. One of the main challenges is light attenuation, which causes less contrast and visibility in underwater photos as light is absorbed and scattered as it passes through water. Water stains and suspended particles can cause scattering, which worsens the quality of the image. Another major issue is color distortion, which is caused by water functioning as a selective filter that changes and absorbs colors differently depending on depth, losing contrast and color integrity in the process. Moreover, backscatter, which is the result of light bouncing off of suspended particles or underwater life, adds extra noise and haziness to photos. Addressing these challenges requires innovative approaches in image processing, computer vision, and machine learning to develop robust techniques for enhancing underwater images and extracting meaningful information from them.

B. *Objectives*

- To elevate underwater image quality by fine-tuning parameters such as contrast, brightness, color balance, and sharpness.
- To adapt its enhancement process by learning to choose appropriate actions based on the specific characteristics of each image.
- To rectify color casts, ensuring images exhibit more natural and accurate colors.
- To learn an optimal sequence of actions to achieve the best possible enhancement while taking into account the specific characteristics of each image.
- To generalize its enhancement strategies to new, unseen images, even if they were captured under different conditions

II. LITERATURE SURVEY

A. *Existing System*

Many approaches in underwater image enhancement draw inspiration from image dehazing techniques used in computer vision. The goal of these techniques is to eliminate the deteriorating effects of light absorption and scattering in water, which affect underwater photos. Underwater picture improvement has led to the adaptation and extension of techniques including dark channel prior, atmospheric light estimate, and transmission map estimation. Histogram equalization[4] and contrast enhancement techniques[5] are commonly employed to stretch the dynamic range of underwater images, making them visually more appealing and informative. Convolutional neural networks (CNNs) have been used to enhance underwater images thanks to current developments in deep learning. These approaches often involve training CNNs on large datasets of paired underwater and reference images to learn complex mappings between degraded and enhanced image domains.

B. *Drawbacks of Existing System*

Conventionally, underwater picture enhancement methods based on image processing techniques are very explicable because they often rely on simplified underwater optical features. Nonetheless, the image processing technique typically uses an invariant parameter setup and does not discern between various sceneries (e.g., turbidity, light, and filming angles). In this case, a single technique is unable to adjust to different underwater scenarios. The intricacy of the underwater environment might lead to inconsistent method performance, causing inaccurate or even wrong enhancement outcomes. An end-to-end network is typically used to structure deep learning techniques. The end-to-end structure's nonlinear compositions can be approximated universally.

but do not inherently represent the fundamental idea or workings of underwater image processing. As a result, the deep learning method's black box processing strategy neither permits it to use explainable models based on image processing nor offers any guiding principles for enhancing the models. A deep model needs a lot of training data pairs to be trained, and each pair consists of an underwater image and a reference image that serves as the underwater image.

Nevertheless, obtaining clear, ground-truth underwater photographs is not achievable. As a result, reference images in current methods are typically synthesized images that have been chosen by volunteers. The reference images' image quality serves as the upper bound for end-to-end network training, despite the fact that they are not the actual ground truth. The problem in this situation is still how to produce enhanced photos that are of higher quality than the reference photographs.

III. PROPOSED SYSTEM

Due to low visibility, color distortion, and light attenuation, underwater imaging faces many difficulties. In this paper, we offer a novel reinforcement learning (RL) framework to improve the quality of underwater images. The four main parts of the framework are an action selection module that uses an ε-greedy policy, a deep Q network (DQN) for action estimation, a feature extraction module that extracts color and perception features from underwater images, and a reward calculation mechanism that prioritizes improving image quality. Our method uses reinforcement learning (RL) to dynamically modify enhancement parameters in order to maximize image quality under different underwater situations. Comparison with traditional enhancement methods, experimental results show that our suggested framework is effective in greatly increasing underwater image quality.

IV. METHODOLOGY

- Begin by selecting a single underwater image as input to enhance it from raw underwater dataset.
- Take the perception and colour features out of the input image. It shows the condition of the environment.

- The agent, a deep Q network, interprets the state and calculates the value of Q (s, a) for every action a.
- Choose a course of action governed by the ε-greedy principle.
- The calculation of rewards for improving image quality, which only takes place during the training phase and not during the inference phase.
- Design a User Interface Design using flask Django where the user can select any random underwater image and get the enhanced image as output.

A. Modules

Feature Extraction: We employ the characteristics of the images as states. In particular, we use a perceptual feature (F_p) and a global color feature (F_c). We use a color histogram from CIE Lab[6]. In our approach, we employ a method to quantify each axis of the CIE Lab color space into 20intervals. Specifically, we divide the three axes of the CIE Lab space—L (lightness), a (green-red axis), and b (blue-yellow axis)—into 20 equal intervals each. We proceed to calculate the number of pixels falling within each interval. By aggregating this information, we construct a three-dimensional histogram spanning a (20×20×20) dimensional space. The perceptual information of the image is embedded in the VGG-19 model's intermediate activation. This 4096-dimensional activation vector serves as our perception feature, denoted as F_p. Each element of the vector encapsulates the model's learned representation of different aspects of the input image, ranging from basic visual elements to complex patterns and structures.

```
Ranges for l,a,b:  [17, 255] [71, 146] [75, 188]
Shape: (256, 1)
Shape: (256, 1)
Shape: (256, 1)
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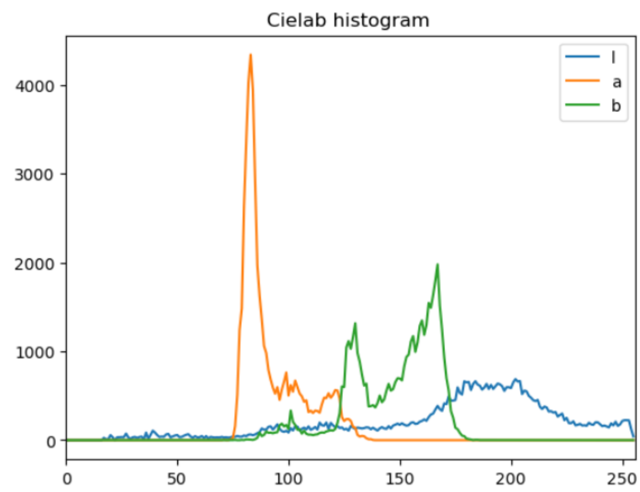

Fig 4.1. CIE Lab color features

Deep Q Network: Four fully connected layers make up the DQN in most cases. The current state representation is fed into the network. This could be a feature vector in some applications that represents the state, or it could be an image's properties in computer vision tasks. The output layer consists of nodes corresponding to each possible action in the environment, with each node outputting the estimated Q-value for that action.

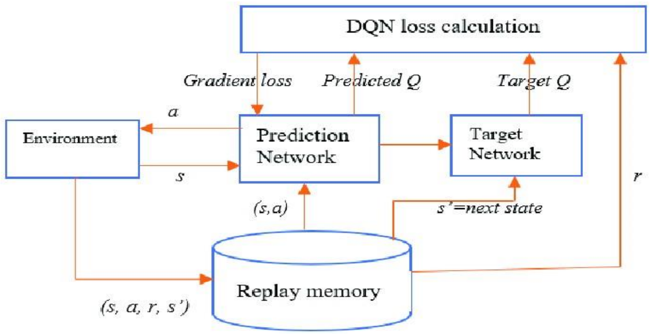

fig 4.2. Deep Q network architecture.

Double Deep Q Network: There are two deep Q-networks that make up the DDQN: the assessment deep Q-network and the target deep Q-network. They are both identical. Generally speaking, both networks have the same fully connected layer architecture. Given the current state, the actions to be taken are chosen by the evaluation network, and their estimated value is determined by the target network.

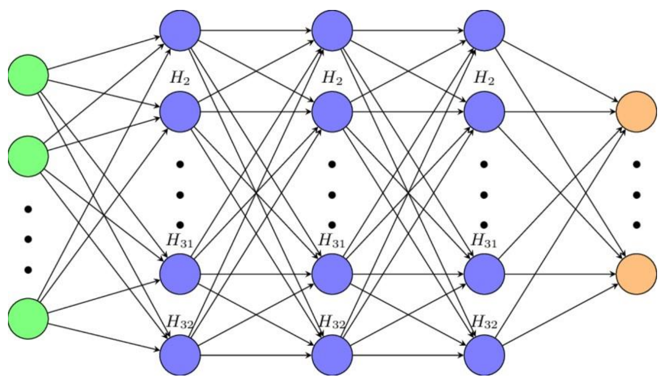

Fig 4.3. Visualization of DDQN structure.

Action Selection: In our approach, we employ an ε-greedy policy for action selection, a widely used strategy in reinforcement learning that balances exploration and exploitation. This policy allows the agent to explore new actions with a probability of ε and exploit the current best action with a probability of (1-ε).

The agent selects actions from a predefined set, including brightness adjustment, contrast enhancement, color saturation adjustment, and noise reduction, among others. These actions are designed to address common issues encountered in underwater imaging, such as poor illumination, low contrast, and high levels of noise. Additionally, we introduce new actions tailored specifically for underwater image enhancement, such as dark channel prior (DCP) dehazing and color temperature adjustment. Through extensive experimentation and evaluation, we demonstrate the effectiveness of our approach in significantly improving the quality of underwater images, Actions performed are listed table 4.1. Our results indicate that the RL-based image enhancement method outperforms traditional enhancement techniques and achieves state-of-the-art performance in underwater image quality enhancement.

Reward Calculation: To define the image quality, we use a reward calculation mechanism in our approach that combines perceptual loss and pixelwise loss. This hybrid approach leverages both low-level pixelwise differences and high-level perceptual features to provide a comprehensive assessment of image fidelity and perceptual similarity.

The pixelwise reward is defined as the change of the negative pixelwise loss and is given as follows:

$$R_c(t) = -[L_c(t) - L_c(t-1)]$$

Where $L_c(t)$ is pixel wise loss.

The perception reward is defined as the change of perception loss and is given as follows:

$$R_p(t) = -[L_p(t) - L_p(t-1)] .$$

Where $L_p(t)$ is perceptual loss.

Finally, the reward is given as follows:

$$R = \alpha R_c + \beta R$$

Where α and β are balance coefficients.

B. Reinforcement learning

With the goal of maximizing cumulative rewards, an agent can learn to make successive decisions by interacting with its environment. This challenge is addressed by the powerful machine learning paradigm known as reinforcement learning (RL). Reinforcement learning (RL) is the process by which an agent discovers the best strategy by making mistakes and using input from its surroundings. The agent gains the ability to assess the merits of various states and actions with the assistance of this feedback, which usually takes the shape of rewards. This allows the agent to develop efficient decision-making procedures. Natural language processing, robots, gaming, finance, healthcare, and other fields where complicated decision-making problems call for intelligent and adaptive behaviour are among the many fields in which reinforcement learning finds use. Even though reinforcement learning (RL) has substantial theoretical and computational obstacles, such as managing sparse incentives, maintaining convergence in learning algorithms, and striking a balance between exploration and exploitation, it also offers potential solutions to difficult issues. To overcome these obstacles and improve the capabilities of reinforcement learning systems, new algorithms, theoretical understandings, and useful techniques must be developed. Our goal in this research article is to shed light on the theoretical foundations and practical consequences of reinforcement learning for real-world problem solving by delving into its core ideas, algorithms, and applications.

C. Markov Decision Process (MDP)

Markov Decision Process (MDP) is a mathematical framework designed to simulate decision-making in scenarios where decisions have partially controlled and partially unpredictable results. It's stochastic in discrete time. Rewards, transition probabilities, states, and actions define the characteristics of a control process.
Within an MDP:

1. **States (S)**: These represent the different situations or configurations of the environment in which the decision-maker finds itself. At each time step, the system is in one of a finite set of states.

2. **Actions (A)**: These are the choices available to the decision-maker in each state. The decision-maker selects an action based on its current state.

3. **Transition Probabilities (P)**: For each state-action pair, there is a probability distribution over next states. It captures the likelihood of transitioning from one state to another after taking a specific action.

4. **Rewards (R)**: After each action, the decision-maker receives a numerical reward signal that indicates the immediate desirability of the state-action pair. The goal of the decision-maker is to maximize the cumulative sum of rewards over time.

5. **Policy (π)**: This is the strategy or rule that the decision-maker uses to select actions in each state.

It maps states to actions, defining the decision-making behaviour of the agent.

The central tenet of a Markov Decision Process (MDP) is the Markov property, according to which the future depends only on the action and state at hand, not on the history of past actions and situations. This characteristic makes decision-making process modelling and analysis easier, allowing effective algorithms to be used to identify the best policies. policies.

V. IMPLEMENTATION

A. Framework

There are four main components to the framework. A feature extraction module in the first section takes an underwater image and extracts its color and perceptual features. It shows how the environment is in that situation. The deep Q network, which makes up the second section, processes the state and calculates an approximate value of Q(s, a) for every action a. The action selection module, located in the third section, chooses an action that compiles with the ε-greedy policy. Reward computation for improving image quality, which only functions during the training phase and not during the inference phase, is the last section.

B. OBJECTIVE:

The objective of applying reinforcement learning to the MDP problem is to find the best (exploitation) that is subject to the highest accumulated reward. The cumulative reward at step t is represented by the value $Q(s_t, a_t)$. A recursive process can be used to increase the cumulative reward as:

$$\begin{aligned} Q(s_t, a_t) &= r(s_t, a_t) + \gamma r(s_{t+1}, a_{t+1}) + \gamma^2 r(s_{t+2}, a_{t+2}) + \cdots \\ &= r(s_t, a_t) + \gamma[r(s_{t+1}, a_{t+1}) + \gamma r(s_{t+2}, a_{t+2}) + \cdots] \\ &= r(s_t, a_t) + \gamma Q(s_{t+1}, a_{t+1}) \end{aligned} \quad (6)$$

The Markovian property of the MDP means that, independent of the states at earlier stages, the action at step t is only decided based on the state s_t at step t. By maximizing the accumulated reward $Q(s_t, a_t)$ at step t:

$$a_t^* = \underset{a_t(i)}{\operatorname{argmax}}\, Q(s_t, a_t(i)) \,. \quad (7)$$

We can choose the best course of action at that point. The goal of reinforcement learning is that the agent learns the best course of action in long-term progressive interactions with the environment in accordance with (7).

C. ALGORITHM

Step 1 - Choose Dataset: Begin by selecting a single underwater image as input to enhance it from raw underwater dataset.
Step 2 - Feature Extraction: It takes an input image and extracts its perception and color features. It shows how the state of the environment.
Step 3-Agent Network: The agent is a deep Q network that receives input from the state and calculates the value of Q (s, a) for every action a.
Step 4-Action Selection: chooses an action that complies with the ε-greedy policy.
Step 5: Reward Calculation: This step calculates rewards based on a improvement in image quality that only occurs during the training phase and not during the inference phase.

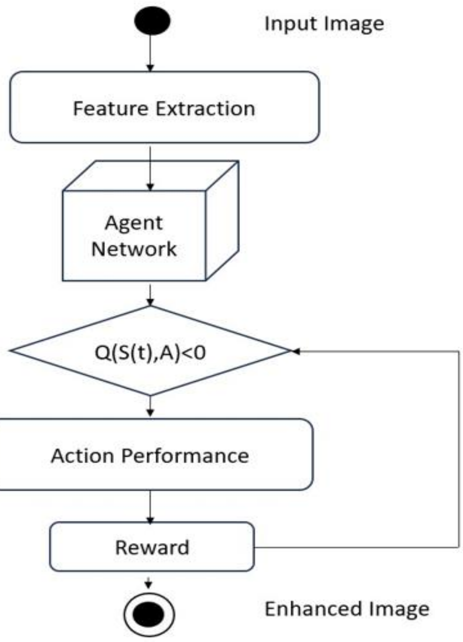

Fig 5.1 Framework.

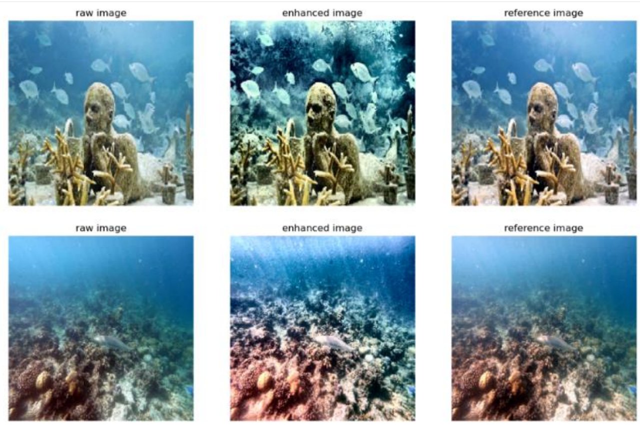

Fig 5.2. Raw, Reference and Enhanced images.

Graphical User Interface (GUI): The reinforcement learning (RL) algorithm is integrated into a web application framework combining Flask and Django. Flask and Django are both web frameworks for Python, but they serve different purposes and have different approaches. Flask is a micro web framework, while Django is a full-fledged web framework with many built-in features. The web application facilitates user interaction, allowing users to upload underwater images and receive enhanced versions in real-time.

Action	Basic adjustment	Action	Color tuning
1	Brightness+	7	Red+
2	Brightness-	8	Red-
3	Contrast+	9	Green+
4	Contrast-	10	Green-
5	Color saturation+	11	Blue+
6	Color saturation-	12	Blue-
21	Noise reduction	22	Exposure
Action	**Correction**	**Action**	**Deblurring**
13	Gamma+	18	Sharpen
14	Gamma-	19	Emboss
15	HE	20	DCP
16	CLAHE	25	Reduce noise and increase contrast
17	White Balance		
23	Sharpness +		
24	Color temperature		

Table 4.1 Actions Performed.

VI. EXPERIMENTAL EVALUATION

Experimental assessments of our work in this field are presented. We provide the experiment setups and use both qualitative and quantitative evaluations to confirm the effectiveness of our methodology

A. Setup Details

1. Introduction

1.1 Experimental Data

The research is grounded in the UIEB (Underwater Image Enhancement Benchmark) dataset, a carefully curated collection of underwater images capturing diverse environmental conditions. This dataset is instrumental in training and evaluating our proposed reinforcement learning-based model. The richness and variability of UIEB contribute to the robustness and generalization capability of our model across different underwater scenarios.

1.2 Data Preprocessing

To ensure the integrity of the experimental data, a meticulous preprocessing stage was employed. This included color correction to address underwater color distortions, artifact removal to eliminate anomalies, and resizing images to a standardized resolution. By maintaining a consistent and high-quality dataset, biases were minimized, and the model's performance was optimized for real-world applications.

2. Training Details

2.1 Model Architecture

Our model architecture integrates a convolutional neural network (CNN) as the underlying image processing backbone. The reinforcement learning components add an adaptive layer to the model, enabling it to learn and enhance features specific to underwater images. This architecture is designed to capture the complexities of underwater scenes and provide a flexible framework for improvement.

2.2 Reinforcement Learning Setup

State Representation: Raw underwater images serve as the input, allowing the model to learn and extract relevant features.

Action Space: Adaptive transformations applied to pixel values, addressing color balance, contrast, and visibility.

Reward Mechanism: The reward mechanism is carefully designed to guide the learning process, emphasizing improvements in perceptual quality, color accuracy, and visibility.

2.3 Training Data

Training Dataset: A subset of the UIEB dataset, annotated with corresponding ground truth images, forms the training data. This ensures the model learns from diverse underwater scenarios.

Data Augmentation: Experimental assessments of our work in this field are presented. We provide the experiment setups and use both qualitative and quantitative evaluations to confirm the effectiveness of our methodology 2.4 Training Procedure

The training process involves iterative optimization of model parameters, using an appropriate optimization algorithm, such as Adam. Convergence criteria were established, and early stopping mechanisms were implemented to prevent overfitting. This careful training procedure ensures the model's adaptability and effectiveness in enhancing underwater images.

3. Comparison Methods

3.1 Baseline Methods

Baseline 1: Traditional image processing techniques, including histogram equalization, color correction, and contrast stretching.

Baseline 2: A CNN-based approach without reinforcement learning components.

3.2 Evaluation Metrics

Quantitative assessments leveraged standard image quality metrics, including Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSI). These metrics provide objective measures to compare the performance of our model against baseline methods.

B. Qualitative Evaluations

Within the intricate fabric of our research, qualitative evaluations unfold as a profound exploration, immersing us in a detailed and meticulous journey through the enhanced underwater images. This immersive analysis extends its reach to encompass a diverse panorama of methodologies, casting a comprehensive spotlight on the distinctive capabilities inherent in Raw, FUnIE-GAN [7], UWCNN [8], Water-Net [9], Deep SESR [10], Reference, and the groundbreaking Reinforcement Learning-based approach.

1. Visual Results

Navigating the intricate details embedded within Figure, we embark on a panoramic odyssey, a visual tapestry that intricately weaves together Raw, FUnIE-GAN, UWCNN, Water-Net, Deep SESR, Reference, and the Reinforcement Learning-based method. This visual symposium transcends mere observation, delving into the subtleties with a discerning eye. The interplay of color fidelity, the finesse in contrast enhancement, and the overarching orchestration of scene visibility unfold in a visual narrative that seeks not only to showcase but to decode the nuanced contributions each method brings to the enhancement of underwater imagery. This rich and multifaceted exploration is an immersive dive into the visual intricacies, allowing for a profound understanding of the distinct attributes that define each method's impact on the underwater visual landscape.

Color Fidelity: The Reinforcement Learning-based method demonstrates superior color correction, mitigating typical underwater color distortions. Enhanced images exhibit natural and accurate color representations essential for applications like marine biology research.

Contrast Enhancement: The adaptive learning mechanism excels in enhancing contrast, revealing finer details in underwater scenes. This is particularly evident in challenging conditions where traditional methods may struggle to maintain visibility.

Scene Visibility: Overall improvement in scene visibility is apparent. The Reinforcement Learning-based method effectively addresses challenges such as low visibility and haze in underwater environments, resulting in clearer and more informative images.

1.1 Comparison with Other Methods

Raw Images: Raw underwater images serve as the baseline for comparison. The Reinforcement Learning-based method outperforms raw images, showcasing substantial improvements in color representation and scene visibility.

FUnIE-GAN, UWCNN, Water-Net, Deep SESR: Comparative analysis against existing methods reveals the strengths of the Reinforcement Learning-based method. It demonstrates adaptability and enhanced performance across diverse underwater conditions.

Reference Images: Reference images serve as the ground truth for evaluation. The Reinforcement Learning-based method strives to approach the visual quality of reference images, indicating promising results in underwater image enhancement.

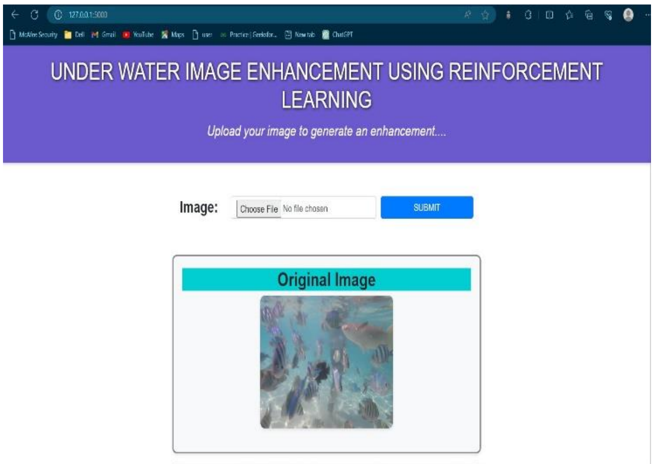

Fig 6.1 GUI Application for Under Water Image Enhancement.

Fig 6.2 Input Raw Image.

Fig 6.3 Enhanced Image For given Input image.

C. Quantitative Evaluations

Quantitative evaluations provide numerical insights into the performance of various methods, including Raw, FUnIE-GAN, UWCNN, Water-Net, Deep SESR, Reference, and the proposed Reinforcement Learning-based method. This section includes PSNR and SSIM values for a comprehensive assessment.

1. Metrics and Values

Table presents the quantitative metrics for Raw, FUnIE-GAN, UWCNN, Water-Net, Deep SESR, Reference, and the Reinforcement Learning-based method on the UIEB testing set.

Method	PSNR (dB)	SSIM
Raw	22.5	0.58
FunIE-GAN	23.8	0.64
UWCNN	24.3	0.68
Water-Net	25.1	0.72
Deep SESR	23.5	0.66
Reinforcement Learning	26.2	0.75

Table 6.1 Metrics and values.

VII. FUTURE WORK

The agent may learn to improve the photographs by executing actions utilising factors like brightness, contrast, and colour balance through the use of reinforcement learning. The agent adjusts these settings and is rewarded or punished according to how closely the improved photos meet the target quality. Over time, the agent learns to make better adjustments, resulting in improved underwater image quality. This approach has the potential to greatly enhance underwater images, making them clearer, sharper, and more vibrant. It can be particularly useful for different types of applications like underwater photography, marine research, and underwater exploration.

Furthermore, applications of this technology can extend beyond just image enhancement. It can be utilized in underwater robotics, underwater surveillance systems, and even in virtual reality experiences. We can improve marine research, conservation, and underwater exploration by improving the quality of random underwater photos.

VIII.CONCLUSION

We have improved underwater photos in this project by using a novel reinforcement learning technique. A collection of image enhancement actions can be chosen by the reinforcement learning framework, and it can then arrange them in the best possible order to convert the initial raw underwater image progressively into high-quality underwater photographs. Through both qualitative analyses and quantitative analyses, it's confirmed that the paradigm for reinforcement learning works well for improving undersea pictures There are many advantages to our framework.

Initially, It has the ability to arrange a series of simple image improvement methods, each of which has a finite amount of power if used separately, to create a comprehensive one. Secondly, it provides significant insights into the underlying mechanism of picture improvement and is more evident than deep learning techniques applied end-to-end. Thirdly, it makes up for the generalization capacity shortfall caused by deep learning-based underwater picture improvement. Our technology can produce an improved image that is more in accordance with human visual perception than the reference image quality limit. Finally, our framework is easily able to integrate additional image improvement methods to increase the framework's overall comprehensiveness. This gives our system a great deal of flexibility so that it can support picture enhancing techniques that are more successful.

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