ISSN: 2037-4445

Under water Image Enhancement and Classification

[1]Manoj Pandian GV, [2]Surendar M, [3]Raja Pandi L, [4]Bharath M,

B.E-CSE Final year, Velammal College of Engineering and Technology

[5]Dr.R.Deepalakshmi, B.E, M.E, Ph.D., Velammal College of Engineering and Technology, rdl@vcet.ac.in

Abstract--Attenuation, uneven, colour distortion, and reduced contrast in submerged images all manage disputing to analyse and define optical information. Diverse forms and algorithms have existed proposed to enhance the character of underwater figures and extract valuable information from ruling class, making important progress in the field of submerged figure enhancement and categorization in current years. We supply a inclusive overview of ultimate current methods for undersea representation enhancement and categorization in this place paper. The challenges and characteristics of underwater images are first discussed, and then various enhancement techniques like colour correction, contrast enhancement, and dehazing are presented. In addition, various feature extraction and classification algorithms, such as object recognition, texture analysis, and deep learning for underwater image analysis, are examined in this paper. The paper concludes with a critical evaluation of the current methods and recommendations for future research.

Keywords—Underwater images, image enhancement, image classification, feature extraction, and deep learning.

I. INTRODUCTION

In recent years, there has been a growing emphasis on the study of underwater imaging, as it holds great significance in various fields such as marine biology, oceanography, naval surveillance, underwater inspection and exploration, and underwater robotics. However, the process of underwater imaging is particularly challenging due to the intricate and ever changing nature of the underwater environment. This complexity arises from factors like light attenuation, backscatter, and water turbidity, among others. These factors can significantly impact the quality of underwater images, making it difficult to accurately identify and classify underwater objects and features. To overcome these challenges, researchers have devised a range of techniques and algorithms that aim to enhance and classify underwater images, with the ultimate goal of improving their quality and facilitating the precise identification and classification of underwater objects and features. This paper will provide an overview of the current cutting-edge techniques employed in underwater image enhancement and classification, specifically focusing on the utilization of deep learning techniques.

II.UNDERWATER IMAGE ENHANCEMENT

The quality of underwater images is often subpar due to the limited amount of light available in the underwater environment. This can lead to issues such as low contrast, poor visibility, and color distortion. To address these challenges, various techniques have been developed for underwater image enhancement. The objective of these techniques is to improve the quality and clarity of underwater images.

ISSN: 2037-4445

One commonly employed technique for underwater image enhancement is image preprocessing. This involves the elimination of noise and artifacts from the image. Techniques such as filtering and deconvolution can be utilized to remove noise and blur, thereby enhancing the sharpness and clarity of the image.

Another frequently used technique for underwater image enhancement is colour correction. The goal of colour correction is to rectify colour distortion in underwater images caused by the absorption and scattering of light in water. Techniques such as white balancing and colour correction algorithms can be employed to adjust the colour temperature and colour balance of the image, thereby enhancing its overall appearance and visibility.

Furthermore, image fusion techniques can be employed to merge multiple images of the same scene captured from different viewpoints or at different times. This can enhance the overall quality and clarity of the image. These techniques are particularly valuable for underwater imaging, where images can be distorted due to the complex and dynamic nature of the underwater environment.

III.UNDERWATER IMAGE CLASSIFICATION

Underwater image classification involves the identification and classification of objects and features in underwater images, based on their visual characteristics and properties. This can be achieved using various machine learning techniques, such as supervised and unsupervised learning, deep learning, and convolutional neural networks(CNNs).

One of the most commonly used techniques for underwater image classification is supervised learning, which involves the use of labeled datasets to train a classifier to identify and classify objects in underwater images. This approach is highly effective for underwater image classification, particularly when combined with feature extraction techniques such as the bag-of-features approach.

Another commonly used technique for underwater image classification is unsupervised learning, which involves the use of unlabeled datasets to identify patterns and clusters in underwater images. This approach can be particularly useful for identifying new and previously unknown objects and features in underwater images.

Deep learning techniques, such as CNNs, have also been shown to be highly effective for under water image classification, due to their ability to automatically learn and extract features from large datasets. These techniques have been used to classify a wide range of underwater objects and features, such as fish species, coral reefs, and ship wrecks.

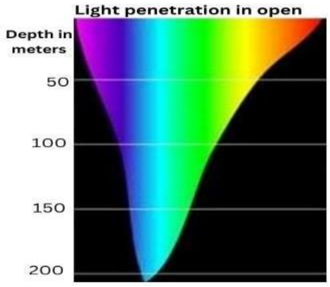


Fig 1

Figure: 1 Color penetration pattern It is obvious that because blue has the shortest apparent wavelength, it goes the farthest in the ocean and deep. This results in the bluehue dominating underwater photos, which has the unfavorable consequence of changing the original color of any underwater objects. The blurry photos also have an overwhelming amount of blue and minimal brightness, contrast, and other elements.

IV. LITERATURE SURVEY

A. *New underwater image dataset*:

Ashraf Shaleem Et.al[1] described the performance of selected models at different depths comparatively analyzed and got better-quality images than others at certain depths.

B. *Visual Perception:*

Md Jahidul Islam Et.al[2] suggest that the proposed model can learn to enhance underwater image quality from both paired and unpaired training saying visible guided underwater robot are suitable for real-time preprocessing in the autonomy pipeline.

C. Classification on Data Augmentation:

Yifeng Xu Et.al[3]described two augmentation methods that can improve classification probability by transforming raw data and increasing virtue data.

D. Classification on Data Augmentation:

According to Vimal Raj E.tal.[4], the classification of features in underwater optical images is challenging due to their low light intensity. To address this issue, the researchers have employed the SURF (Speeded-UP Robust Features) and SVM (Support Vector Machines) algorithms within bag of Features models. This approach aims to achieve the highest possible accuracy in feature classification.

E. Benchmark Dataset and beyond:

Chongyi Li Et.al[5]proposed an underwater image enhancement network Water-Net as a baseline for training CNNs and enhancement was done on Water-Net.

F. Image processing technique:

Arpit Wany Et.al[6]proposed to improve underwater images by using a technique to reduce medium scattering and absorption. It results in the sharpening of the image not being done to reduce noise issues.

V.PROBLEM STATEMENT

The Problem statement is identified and discussed below.
Enhancing and classifying underwater images poses a significant challenge due to the influence of environmental factors on the visual perception of underwater robots[7]. Underwater images often suffer from color distortion, low contrast, and lack of clarity[7]. To tackle these issues, researchers have put forth different image enhancement algorithms based on deep learning and image formation models[7][8][9].

In a recent study, Li et al. proposed the utilization of a deep neural network to classify and de-scatter underwater image data[9]. Their method employs a convolutional neural network to mitigate the scattering effect caused by the underwater environment and improve image quality[9]. Additionally, the authors employed a support vector machine classifier to categorize the enhanced images[9]. Experimental results demonstrated that their proposed method outperformed other state-of-the-art techniques in terms of image quality and classification accuracy[9].

Another approach to enhancing underwater images involves using particle swarm optimization to adjust the RGB values of the image[9]. AbuNaser et al. employed this method to enhance the illumination and true colors of underwater images[9]. Lu et al. proposed a weighted guided trigonometric filtering and artificial light correction approach to improve underwater images[9]. Their method incorporates a color correction algorithm to rectify color distortion and a guided filter to enhance image quality[9].

In conclusion, underwater image enhancement and classification is a significant research area that has garnered considerable attention in recent years. Researchers have proposed various algorithms based on deep learning, image formation models, and optimization techniques to address the challenges associated with underwater imaging. These methods have exhibited promising outcomes in enhancing image quality and classification accuracy of underwater images.

VI. METHODOLGY

In the ever-evolving educational landscape, the adoption of Deep Learning (DL) algorithms has sparked a renaissance in understanding students' learning patterns. By amassing a captivating array of underwater fish images, a remarkable Convolutional Neural Network (CNN) algorithm is summoned to wield its prowess in discerning and identifying the diverse marine species that dwell beneath the waves.

A. *Data selection and loading:*

The data selection is the process of selecting the underwater fish species’ digital image dataset. Recognizing the many undersea fish species is the focus of this study. The dataset contains information about the types of underwater images like, 'Corals', 'Crabs', 'Dolphin', 'Eel', 'Jelly Fish', 'Lobster', 'Nudibranchs', 'Octopus', 'Penguin', 'Puffers', 'Sea Rays', 'Sea Urchins', 'Seahorse', 'Seal', 'Sharks', 'Squid', 'Starfish', 'Turtle Tortoise', 'Whale'.

B. Data preprocessing:

Getting rescaled data from the dataset is the process of pre-processing image data. Data collection and picture dataset resizing. Rescale the size of the remote sensing scene dataset's picturesto100.Collectingdata: The variables in that categorical data are described as having a limited number of rescaled values. That array input and output variables are needed by the majority of deep learning techniques.

C. *Splitting Dataset Into Train And Test Data:*

The act of partitioning a set of available data into two distinct subsets, commonly done for the purpose of cross-validation, is referred to as data splitting. This involves the creation of a predictive model using one portion of the data, while the effectiveness of the model is evaluated using a separate portion. In the context of analyzing image processing models, a critical step involves dividing the data into training and testing sets. Typically, the majority of the image data is allocated for training, while a smaller portion is reserved for testing, when the dataset is divided into these two subsets.

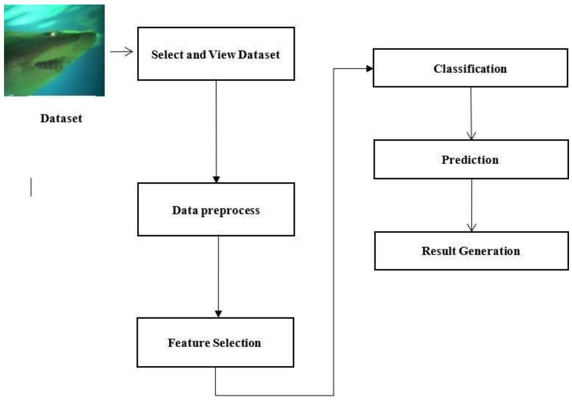


Fig 2: System Diagram

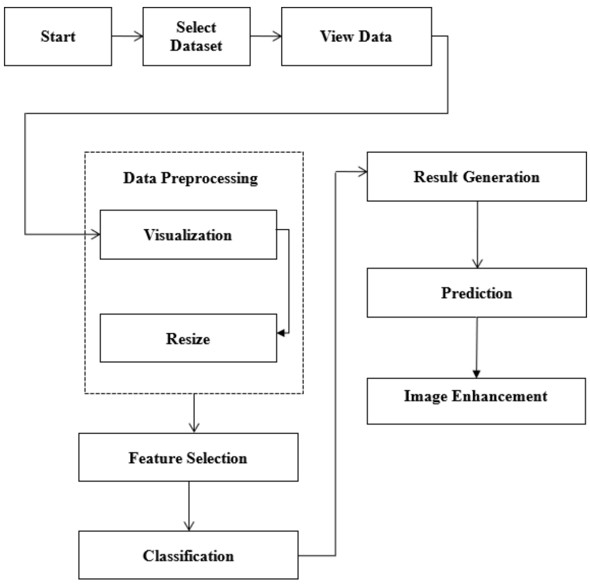


Fig 3: Flow Diagram

D.Classification:

The methodology for underwater classification using Convolutional Neural Networks (CNNs) involves several key steps. First, a diverse and representative dataset of underwater images is collected, containing various fish species, coral formations, and marine life. Data augmentation techniques may be applied to expand the dataset and enhance the model's generalization ability. The dataset is then split into training, validation, and testing sets. Next, a CNN architecture is designed, comprising multiple convolutional layers for feature extraction, pooling layers for dimensionality reduction, and fully connected layers for classification. The CNN model is trained on the training dataset using back propagation and optimization algorithms, aiming to minimize the classification error. Hyperparameter tuning and regularization methods are employed to prevent overfitting.

Transfer learning can also be considered, where pre-trained models on large-scale image datasets are fine-tuned for underwater classification. Once trained, the CNN model's performance is evaluated on the validation and testing datasets, using appropriate metrics such as accuracy, precision, recall, and F1 score. The final model is then deployed to classify underwater images, contributing to ecological research, conservation efforts, and better understanding of underwater ecosystems.

E. Prediction:

The approach involves utilizing a deep learning model to identify the type of undersea fish from the dataset. By optimizing the total prediction outcomes, this project will successfully fore cast the data from the dataset.

- White Balance:

White balancing is a subject that has been discussed quite a bit, however, most of the replies I have read discuss automatic white balancing methods for a complete image without a clear distinction between what is white, grey, and black.

This strategy is characteristic of the Color Constancy adaption, which works similarly to how the human visual system does by looking for the lightest patch to serve as a white reference. Keep in mind that each channel in your RGB color space needs to be at its highest value for white to be visible in the image.

- Gamma Correction:

Gamma correction is a technique used to adjust the overall brightness of an image. When photos are not properly adjusted, they may appear either too dark or washed out. Additionally, accurate color reproduction also requires an understanding of gamma. Gamma correction is employed to enhance the contrast of images. In the typical scenario where A = 1, the inputs and outputs are typically non-negative real numbers, with A being a constant ranging from 0 to 1. Conversely, gamma compression involves encoding with a compressive power-law nonlinearity, where a gamma value of 1 is commonly referred to as an encoding gamma value, while a gamma value greater than 1 is known as a decoding gamma. On the other hand, gamma expansion refers to the utilization of an expansive power-law nonlinearity. The formula for gamma correction is V_out = V_in^gamma.

- Histogram:

In underwater image classification, histogram equalization plays a pivotal role in enhancing image visibility and contrast. Underwater environments often suffer from poor lighting and water turbidity, resulting in images with limited visual information. By applying histogram equalization, the intensity levels of the underwater images are redistributed, leading to improved image quality and the revelation of hidden details. This preprocessing step effectively enhances the visibility of marine life, corals, and other underwater features, facilitating accurate classification. Histogram equalization proves to be instrumental in achieving higher classification accuracy, enabling a more comprehensive understanding of marine ecosystems and fostering advancements in underwater research and conservation efforts.

Fig 4: White Balance

Fig 5: Gamma correction

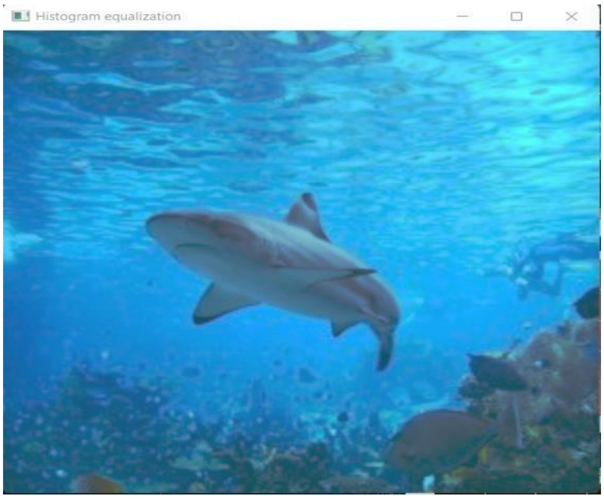


Fig 6: Histogram equalization

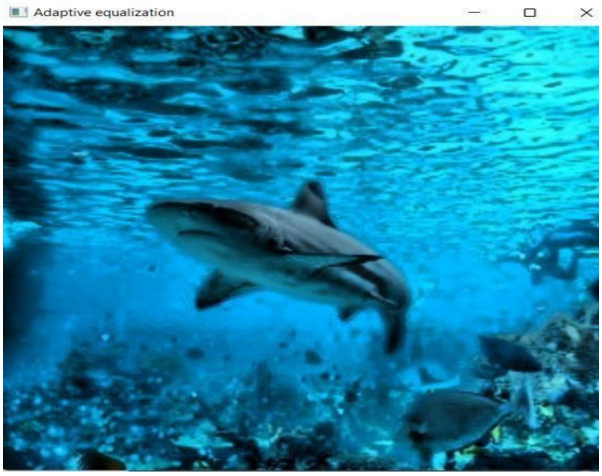


Fig 7: Adaptive Equalization

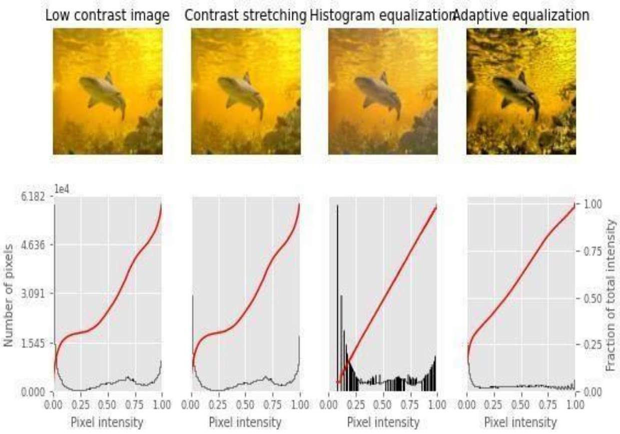


Fig 8: Enhanced Images

VII. RESULT & DISCUSSION

The main objective is to determine the accuracy of classifying pictures using clustered categories. A dataset consisting of 16,042 underwater photographs taken with a remotely operated vehicle (ROV) in a shallow area was used. The photographs were divided into seven unrelated classes, including corals, crabs, dolphins, eels, jellyfish, lobsters, nudibranchs, octopuses, penguins, puffers, sea rays, sea urchins, seahorses, seals, sharks, squids, starfish, turtle tortoises, and whales. 80% of the dataset was used for training, while the remaining 20% was used for testing or validation. The analysis considered the top 33,280 strongest characteristics in each category, resulting in a total of 186,368 features. The default setting of 500 clusters was used. Two methods were used to extract patches: the region of interest and the grid methods. In this case, the grid method was used to recover all the features, and a histogram was created to show the frequency of occurrences. The confusion matrix showed that the majority of true positive values were correctly classified, resulting in an overall accuracy of 97.9%. Sample images can be seen in Fig 9, and the dataset is listed in Table 1.

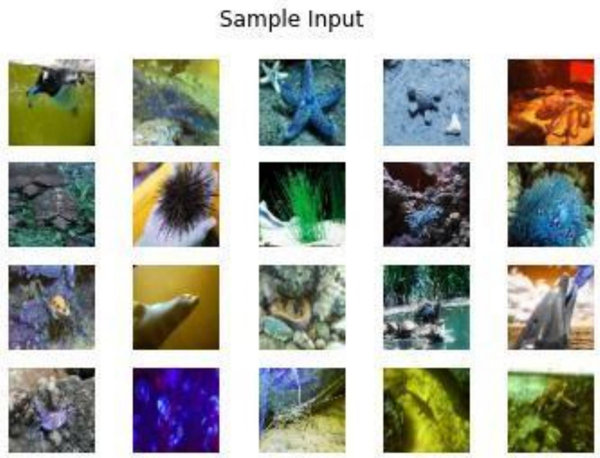


Fig 9: Sample Inputs

Data	IMAGES
Corals	500
Crabs	499
Dolphin	782
Eel	497
jelly fish	855
Lobster	499
Nudibranchs	500
Octopus	562
Penguin	482
Puffers	531
Sea Rays	517
Sea Urchins	579
Seahorse	4778
Seal	414
Sharks	590
Squid	483
Starfish	499
Turtle_Tortoise	1903
Whale	572
TOTAL	**16042**

Table 1: Dataset

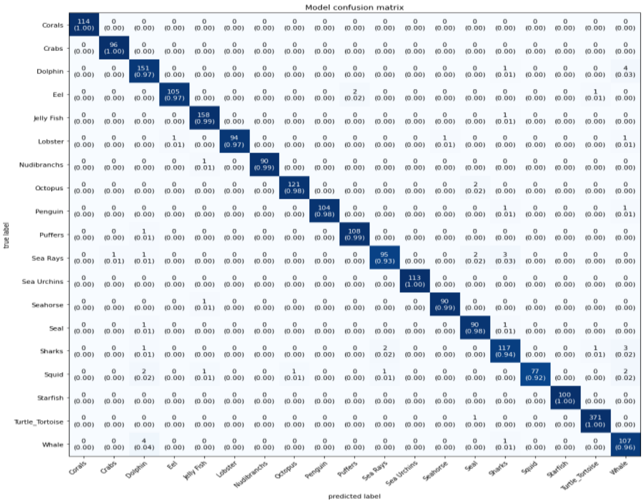


Fig 10: Confusion matrix

The model confusion matrix X as predicted label Y as a true label which gives merely 97.9 % accuracy the performance plot accuracy rises gradually and we can predict loss as rapidly are shown in the Fig 11 and classification on prediction found as shown as Fig 12.

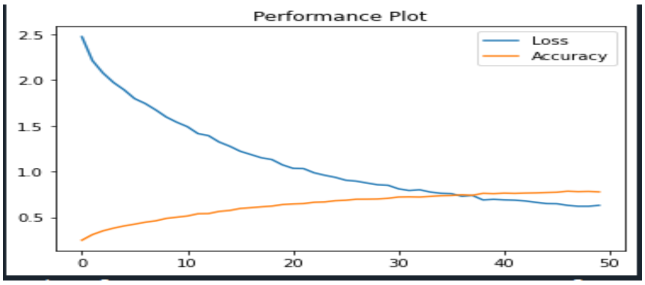
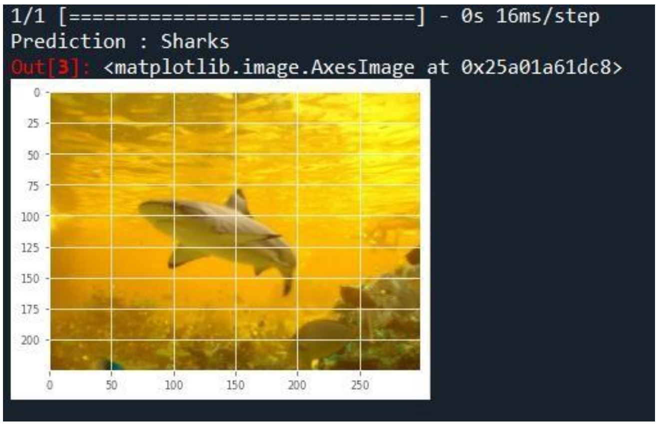


Fig 11: Performance Plot




```
Accuracy of the CNN is: 97.95657992362976 %
```

Fig 12: Output & Prediction

VII. CONCLUSION

In this study, a deep learning classifier is employed to analyze photographs of various underwater fish species. The pre-processing phase involves utilizing images of multiple underwater fish species as input data. These photos are resized and organized into an array. Subsequently, the dataset is divided into a training dataset and a testing dataset through the feature selection technique. All the photos are then downscaled and transformed into an array format. Finally, the classification approach is employed to classify the photos of underwater fish species. The deep learning method of Convolutional Neural Networks (CNN) is utilized to predict the outcome, employing metrics such as accuracy, precision, and recall f1-measure.

REFERENCE

[1] Underwater Image Enhancement Methods Using A New Underwater Image Dataset Ashraf Shaleemet.at., (2023)
[2] Md Jahidul Islam et.at., Fast Underwater Image Enhancement for Improved Visual Perception(2020).
[3] Yifeng Xuet.at., Underwater Image Classification Using Deep CNN and Data Augmentation (2018)
[4] M. Vimal Raj, et.at., "Underwater Image Classification using Machine Learning Technique" , International Symposium on Ocean Technology (SYMPOL), 2019
[5] Chongyi Li et.at., Underwater Image Enhancement Benchmark Dataset and beyond(2019)
[6] Arpit Wany et.at., Underwater Image Enhancement Using Image processing Techniques(2021)
[7] An Experimental-Based Review of Image Enhancement and Image Restoration Methods for Underwater Imaging Yan Wang et.at., (2019)
[8] Underwater Image Enhancement based on Deep Learning and Image Formation Model Xuelei Chen, et.at., (2021)
[9] Underwater image enhancement: a comprehensive review, recent trends, challenges and applications, Smitha Raveendran, (2021).
[10] Swati Sonawane, et.al.,, Underwater image classification and enhancement.IJSDR, October 2022.
[11] Devendar Marasakatla, et.at., Under Water Image Enhancement Using CNN ,ICAECIS, 2023
[12] Anushka Yadav, et.al.,, Underwater image enhancement using convolutional neural network. IEEE 18 September 2021.
[13] Shirin Shahana V, et.al.,, Underwater image enhancement and color correction a review. SEMANCTIC scholar, 2022.
[14] S.-B. Gao, et.al., Underwater image enhancement using adaptive retinal mechanisms. IEEE, 28 November 2019.
[15] [M. Han, et.al., A review on intelligence dehazing and color restoration for underwater images. IEEE, 23 January 2018.
[16] Changli Li, et at, Color correction based on CFA and enhancement based on Retinex with dense pixels for underwater images. IEEE, 2020.
[17] Zitong Kang, et at, Underwater image enhancement by maximum- likelihood based adaptive color correction and robust scattering removal.

[18] R Prasath, et at, Application of Different Techniques for Underwater Image Processing- A Systematic Review. ICCEMS, 2020.
[19] Yang Guan et.al., Fast underwater image enhancement based on a generative adversarial framework. IEEE, 2023.
[20] Chengquan Zhang et.al "Underwater image enhancement based on an integrated color model." IET Computer Vision -2017