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Underwater Image Enhancements Using CNN And U-Net

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Abstract: Due to environmental scattering, images taken in the underwater environment still exhibit color distortion, loss of resolution, and decreased contrast. The paper presents a method for enhancing the aesthetic appeal of underwater photography. Yet, because of unwanted staining, decreased contrast, and detail loss brought on by light scattering and absorption, photos that are directly taken in the marine environment are still highly damaged, drastically limiting the amount of information that can be extracted from the image. This study introduces the U-Net, a CNN-based network, and provides an end-to-end framework for subaquatic picture improvement to address this problem. The two workouts that are utilized to train the U-net are colour correction and haze removal. It is possible to simultaneously acquire a potent feature representation for both tasks using this dual training strategy. To manage the training of U-net, we generate 1000 synthetic training images based on the physical underwater imaging model. Depending on the language and framework used.

Index Terms* - Machine Learning, CNN algorithm, *Feature Extraction, Image Classification.

I. INTRODUCTION

The quality of underwater images is vital for tasks like monitoring marine life, assessing the geological environment, and carrying out underwater archaeology. The physical properties of underwater environments make it challenging to capture crisp underwater photographs.

Underwater photos have poor visibility and colour distortion because of light attenuation and scattering [1].

The two primary categories of underwater picture enhancement techniques now in use are image-based and model-based algorithms. [2]. algorithms based on images to adjust the colours and remove the haze, [3] [4] [5] [6] [7] estimate the transmission map straight from the underwater image that was obtained. algorithms based on models [8] [9] [10] [11] [12] better describe the imaging process by taking underwater optical qualities into account. The two types of approaches have one thing in common: they both make use of different presumptions and constraints. They also have the same disadvantage in that the accepted assumptions might not be appropriate for some settings. The purpose of underwater picture enhancement methods is to lessen these difficulties and improve the aesthetic appeal of underwater images. Colour correction, Contrast improvement, Dehazing, Noise reduction, Image fusion, etc. are a few popular methods used in underwater image enhancement. The Convolution Neural Networks (CNN) and UNet are the foundation of the end-to-end system we suggest in this paper for cross-scene underwater image improvement. It is our intention to learn how to map underwater photographs to color-corrected images and transmission maps, and then to apply that mapping to improve underwater images across scenes. We suggest a framework for underwater image enhancement that is based on CNN to overcome the issues. The underwater imaging model is used to create the underwater images that are used to train the projected CNN Network and U-Net.

II.RELATED WORK

In their end-to-end architecture for improving subaquatic images, Yang Wang et al. [13] present the CNN-based network known as UIE-Net. The two exercises used to train the UIE-net are colour correction and haze removal. By using a single training strategy, both tasks can simultaneously learn a reliable feature representation. The suggested learning architecture significantly increases convergent speed and accuracy by extracting intrinsic features more effectively in small patches using a pixel's disruptive strategy. They create 200000 training photos using the physical underwater imaging model to manage the training of UIE-net.

S. Dhar et al. [14] describe a unique enhancement method for underwater images that makes use of a Convolutional neural network (CNN) and a set of enhancement functions. The resulting enhancement function is produced by combining the four functions. The four functions of the proposed network are clearly intelligible and capable of effectively enhancing various aspects of an underwater image, making it interpretable.

The innovative improved depth estimate method for underwater photos based on image blurriness and light absorption was proposed by Bhagyashree P Hanmante et al. [15]. We proposed a novel method for estimating image blurriness to increase processing efficiency. First, we performed image normalization and double precision conversion to speed up the conversion process. Next, we applied the edge-stopping pyramid technique rather than Gaussian filtering to enhance image quality.

In their ground-breaking two-stage network for underwater image restoration (UIR), Yufei Lin et al. [16] separate the restoration process into two stages: horizontal distortion restoration and vertical distortion restoration. The subsea physical model is first directly incorporated into a model-based network to address horizontal distortion. They propose a special attenuation coefficient prior attention block (ACPAB) to adaptively recalibrate the RGB channel-wise feature maps of the image in order to correct vertical distortion and reconstruct the clear underwater image.

The Ye Tao [17] underwater imaging method consists of two steps: an enhanced white-balancing approach and an artificial multiple underexposure picture fusion technique. The Underwater Colour Image Quality Evaluation (UCIQE) and the Underwater Image Quality Measure (UIQM), in conjunction with our artificial multiple underexposure image fusion strategy, which first uses the gamma-correction operation to generate multiple underexposure versions, determine the best color-compensated strategy for our white-balancing method..

The underwater image enhancement network (named Water-Net) suggested by Chongyi Li et al. [18] uses benchmark training as a baseline, indicating the generalizability of the proposed UIEB for training Convolutional Neural Networks (CNNs). Future research in underwater picture enhancement will benefit from understanding the performance and constraints of cutting-edge algorithms through benchmark assessments and the proposed Water-Net.

A reliable and effective underwater image enhancement technique termed MLLE is proposed by W. Zhang et al. [19]. Specifically, use a minimum colour loss concept and an extreme diminution map-guided fusion technique to locally alter an input image's colour and details first. The mean and variance of local picture slabs are then calculated using integral and squared integral maps, and the input image's contrast is changed adaptively as a result.

Shiqiang Tang et al. [20] introduce a novel colour correction method based on a colour filter array (CFA) and an enhancement method based on Retina with dense pixels and adaptive linear histogram processing for deteriorating color-biased underwater photos. Each RGB-space digital image acquired by a digital camera using CFA will include RGB values that are related and dependent on one another because of the interpolation method. They therefore make an effort to make up for the underwater image deterioration attenuation in the red channel in the green and blue channels. The retina model has been widely applied to manage dim and hazy images.

The Underwater-ready Dark Channel Prior Algorithm's capabilities and constraints are proposed to be verified by Rony Caballero [21]. Additionally, a few improvements to this technique are suggested for use with underwater photographs taken in various illumination scenarios. To authenticate or deny the usage of any of the Dark Channel Prior modified algorithms, a blurriness-based index is also suggested.

Yan Wang [22] describes the main reasons for underwater image quality loss in terms of the underwater image formation model (IFM). After that, they examine techniques for underwater restoration, considering both IFM-free and IFM-based strategies.

Jiaying Xiong [23] presents a two-step technique to find regions of underwater photos that have greater details: To recover more details and avoid partial over-enhancement, they first develop a linear model related to the underwater image's mean and variance. Then we provide a nonlinear adaptive weight scheme employing this locating information.

Donghui Wei [24] proposes a novel two-step method to improve the visual appeal of underwater photographs. First, the overall contrast of the image is increased using a transmission map-based enhancement, like the picture defog method. Second, by employing an edge-preserving filter, picture details are retrieved, and local contrast is improved.

3.METHODOLOGY

The project model is used for underwater image enhancement in which Convolution Neural Networks (CNN) for classification and multi-class U-Net for feature extraction. The system is accomplished on a dataset of paired undersea images, where each image is paired with its ground truth. The methodology is shown in the System architecture in Fig 1 below.

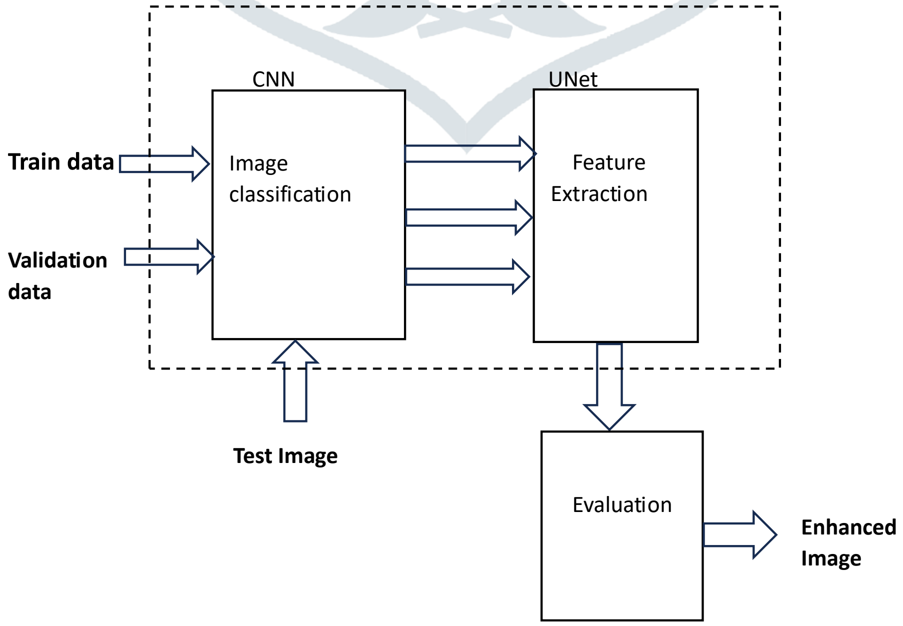

Fig1. Block diagram of Proposed Network Architecture

A) Data Collection and Preprocessing:

Gather a large dataset of paired underwater images, consisting of degraded images and their corresponding high-quality references. Preprocess the images by removing noise, correcting color distortion, and applying necessary adjustments to enhance the quality of the reference images. It's important to have enough image pairs for training. Kaggle [25] is an online platform that hosts a wide range of datasets for machine learning and data science projects. The dataset consists of a total of 1,000 underwater images in JPEG format. The images have resolutions, 512x512 pixels.

B) Classification:

CNN-Based Classification Model: Train a CNN-based classification model to classify underwater images into different categories such as shallow, medium, and deep. The CNN model serves as a feature extractor to capture discriminative features from the input underwater images. During the training process, the model learns to extract relevant features that are important for differentiating between various classes of underwater images. Training a machine learning model on labeled data, incorporating depth characteristics as input features, can help automate the categorization process. CNNs trained using a loss function that measures the discrepancy between the predicted outputs and the ground truth labels. Loss functions for tasks include categorical cross-entropy for multi-class classification.

The categorical cross-entropy [26] loss is then calculated as the average of the cross-entropy loss across all samples or data points in the dataset.

$$Cross - Entropy\ Loss\ =\ -\Sigma\ [true\_class\_label\ *\ log(predicted\_probability)]$$

where the sum is taken over all classes.

CNN model trained using backpropagation, which computes the gradients of the network's parameters with respect to the loss function. Optimization algorithms, such as Adam [27], are then used to update the network's parameters iteratively, minimizing the loss function and improving the network's performance. The learning rate is 3e^-4.

C)Feature Extraction:

U-Net Architecture: Utilize the U-Net architecture, known for its ability to capture both low-level and high-level features, for feature extraction and image enhancement. An encoder-decoder structure with skip links makes up the U-Net architecture., enabling effective information propagation and feature fusion across different scales. The encoder part of the U-Net captures contextual information and extracts hierarchical features, while the decoder part reconstructs the enhanced image from the extracted features. Apply the U-Net architecture to each class separately, so create multiple U-Net models, with each model specifically designed for a particular class. Train each U-Net model separately using the corresponding class of images and their ground truth labels or enhanced images. The loss function such as mean squared error (MSE) [28] calculated as,

$$MSE\ =\ (1\ /\ N)\ *\ \Sigma\ (y\_true\ -\ y\_pred)^2$$

Optimization algorithms, such as Adam, are then used to update the network's parameters iteratively, minimizing the loss function and improving the network's performance. The learning rate is 0.002.

Apply the trained CNN and U-Net model to enhance new, unseen underwater images. Process the images through the network to obtain the enhanced versions, which should exhibit improved visual quality and clarity compared to the original underwater images.

This methodology aims to effectively restore underwater images, reduce noise, correct color distortion, and enhance the visibility of details. The approach can have practical applications in various domains that require high-quality underwater image analysis and decision-making.

4. EXPERIMENTAL SETUP:

The system is developed in Python using the generic code to co-ordinate with the utilities of the system. The system will be supported with software Windows 10 onwards, VS Code, for GUI Tkinter and Hardware VRAM: 12GB NVIDIARTX A6000, video card GeForce RTX 3080 and graphics card AMD Radon RX580. The data set required is downloaded from Kaggle.

5. RESULTS AND DISCUSSION

F-measure, also known as F1 score [29], is an evaluation metric used in information retrieval, and multiclass classification tasks to measure the trade-off between precision and recall. It combines these two metrics into a single value that represents the harmonic mean of precision and recall. Evaluate the F-measure [29] for each class.

To calculate the F-measure for each class, we need to compute precision and recall.

For the shallow images:

Precision = TP / (TP + FP) = 240 / (240 + 30) ≈ 0.8889
Recall = TP / (TP + FN) = 240 / (240 + 60) ≈ 0.8

For the medium images:

Precision = TP / (TP + FP) = 260 / (260 + 40) ≈ 0.8667
Recall = TP / (TP + FN) = 260 / (260 + 40) ≈ 0.8667

For the deep images:

Precision = TP / (TP + FP) = 270 / (270 + 50) ≈ 0.8438
Recall = TP / (TP + FN) = 270 / (270 + 30) ≈ 0.9

Now, calculate the F-measure in Table I using the precision and recall values for each class:

F-measure for shallow images = 2 * (precision * recall) / (precision + recall)
= 2 * (0.8889 * 0.8) / (0.8889 + 0.8) ≈ 0.8428

F-measure for medium images = 2 * (precision * recall) / (precision + recall)
= 2 * (0.8667 * 0.8667) / (0.8667 + 0.8667) ≈ 0.8667

F-measure for deep images = 2 * (precision * recall) / (precision + recall)
= 2 * (0.8438 * 0.9) / (0.8438 + 0.9) ≈ 0.8714

Table I: F-measure for different category of underwater images

Underwater Image Types	Precision	Recall
Shallow	0.8889	0.8
Medium	0.8667	0.8667
Deep	0.8438	0.9

Peak Signal-to-Noise Ratio (PSNR) [30] is a metric used to measure how well augmented or reconstructed images compare to a reference image. The PSNR [30] metric compares the maximum signal power to the power of the difference between the reference image and the enhanced/reconstructed image.

$$PSNR = 10 * log10((MAX\char`^2) / MSE)$$

A statistic for assessing the effectiveness of picture enhancement or reconstruction techniques is mean squared error (MSE) [28]. The average squared difference between the improved image and the related reference image, also known as the ground truth image, is measured.

$$MSE = (1 / N) * \Sigma\, (y_{true} - y_{pred})$$

The results for MSE and PSNR are presented in Table II

Images	MSE	PSNR
Image 1	70.48	29.65
Image 2	71.62	29.58
Image 3	55.09	30.72
Image 4	31.92	33.09
Average	57.27	31.13

Figure displays the qualitative comparison between UWCNN, IUIECNN, and our suggested approach. On some photos, the results from UWCNN(b) and IUIECNN(c) demonstrate observable colour and contrast improvements. Results from our suggested method(d) were more precise and clearer, as shown in Fig 2.

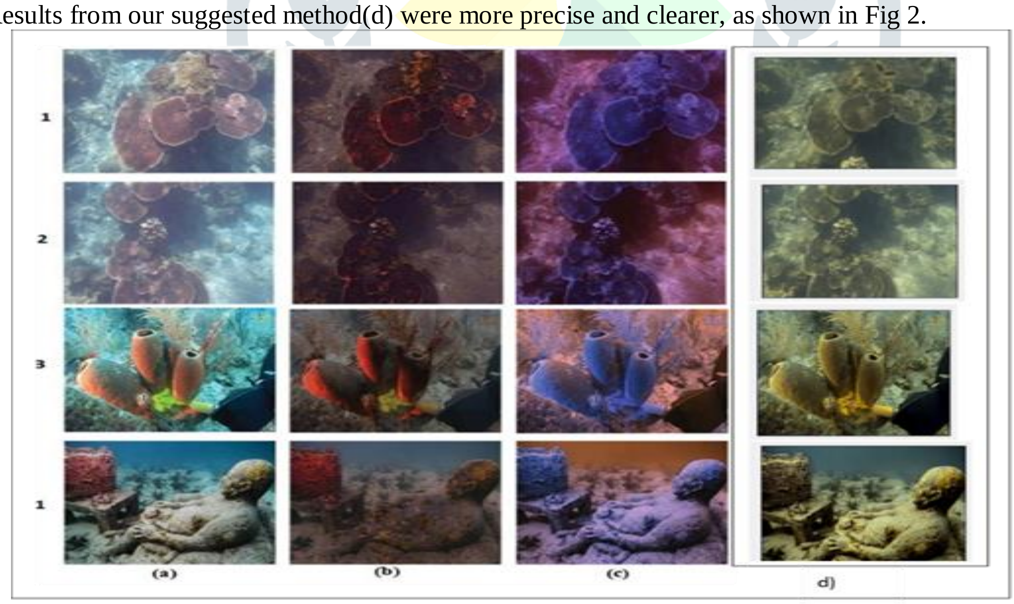

Fig2. (a)Input trial images (b) UWCNN results(c)IUIECNN results (d)proposed technique results.

Greater image quality is indicated by lower numbers. The average squared difference between the enhanced image and the reference image is what the MSE values reflect. On the other hand, bigger values denote greater image quality. The PSNR [30] values show the ratio of the maximum achievable power of a signal to the power of the difference between the enhanced and reference images. You may evaluate the performance and efficacy of the approaches in terms of the quality of image enhancement by contrasting the MSE [28] in Table III and PSNR values in Table IV for each image.

Table III: Average MSE of different techniques on the underwater images

UWCNN	UIBLA	cGAN	IUIECNN	Proposed Method
728	2557	1100	564	57.27

UWCNN	UIBLA	cGAN	IUIECNN	Proposed Method
19.512	14.052	17.715	20.611	31.13

Table IV: Average PSNR of different techniques on the underwater images

V. CONCLUSION:

The suggested work offered a strategy for improving underwater image clarity utilizing a network based on CNN and U-Net, which will enhance the visual quality of the photos. Colour adjustment and haze subtraction are the two tasks used to train the network.

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