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An Efficient Deep Learning Technique based Underwater Image Color Restoration

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***Abstract*— Underwater image processing plays a critical role in marine exploration, environmental monitoring, and underwater robotics. However, the inherent challenges of underwater environments, such as light absorption and scattering, result in degraded image quality with color distortion and reduced visibility. These challenges hinder effective analysis and interpretation of underwater images. This study introduces an efficient deep learning technique based on Convolutional Neural Networks (CNNs) for underwater image color restoration. The proposed method utilizes a robust architecture designed to address color distortion by enhancing color balance, improving contrast, and recovering fine details. By leveraging a dataset of underwater images with varying degrees of degradation, the CNN model is trained to predict corrected versions of input images. Extensive evaluations demonstrate the model's ability to achieve superior restoration performance compared to traditional image enhancement techniques. The results highlight the model's effectiveness in handling diverse underwater conditions, paving the way for advancements in underwater imaging applications such as marine biodiversity assessments, archaeological explorations, and underwater inspections.**

Keywords*—*DL, Underwater, CNN, Image, Color, Restoration, AI.

I. INTRODUCTION

The underwater world holds immense scientific, economic, and ecological value, yet its exploration and monitoring remain challenging due to the unique properties of water. Unlike terrestrial environments, underwater settings present obstacles that significantly affect the quality of captured images. These challenges primarily stem from the physics of light propagation in water, which causes absorption and scattering. As light penetrates water, longer wavelengths, such as red, diminish rapidly, while shorter wavelengths, such as blue and green, dominate, leading to the characteristic bluish or greenish hue of underwater images. Scattering further degrades visibility by distorting image clarity, particularly in turbid waters. These factors result in underwater images that are often plagued by poor contrast, reduced sharpness, and significant color distortion, making them unsuitable for critical applications.

Traditional approaches to underwater image restoration rely on physical models of light propagation, such as dehazing and white-balancing techniques. While these methods address some aspects of underwater image degradation, they often struggle to adapt to diverse environmental conditions or fail to restore fine details and natural colors

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comprehensively. The advent of deep learning, particularly Convolutional Neural Networks (CNNs), has revolutionized the field of image processing by enabling automatic feature extraction and transformation. CNNs have demonstrated exceptional capabilities in tasks such as image enhancement, object detection, and image classification, making them promising candidates for underwater image restoration.

In this work, we propose an efficient CNN-based approach for underwater image color restoration. Our model is designed to mitigate the effects of light absorption and scattering by learning complex color correction mappings from a large dataset of degraded and reference images. Unlike traditional methods, the CNN-based approach leverages its ability to capture spatial and contextual information, ensuring the restoration of natural colors and details in underwater images. The network architecture incorporates multiple layers of convolution, activation, and pooling operations, which are fine-tuned to address the unique challenges of underwater imaging. Additionally, the model employs techniques such as data augmentation and loss function optimization to enhance its generalization across various underwater scenarios.

The proposed technique is rigorously evaluated on benchmark datasets and real-world underwater images. The results demonstrate its superiority over traditional image restoration methods in terms of visual quality and quantitative metrics such as Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). Moreover, the CNN model exhibits robustness across different water conditions, including clear, turbid, and deep-sea environments. These findings underscore the potential of the proposed approach to advance underwater imaging technologies.

The importance of underwater image restoration extends beyond improving image aesthetics. High-quality underwater images are crucial for applications such as coral reef monitoring, marine biodiversity assessment, underwater surveillance, and shipwreck documentation. By addressing the challenges posed by underwater environments, this research contributes to the broader goal of enabling effective exploration and conservation of marine ecosystems. The combination of deep learning techniques with domain-specific underwater image processing paves the way for innovative solutions to longstanding challenges in marine research and technology.

II. PROPOSED METHODOLOGY

The proposed methodology is explained using following flow chart-

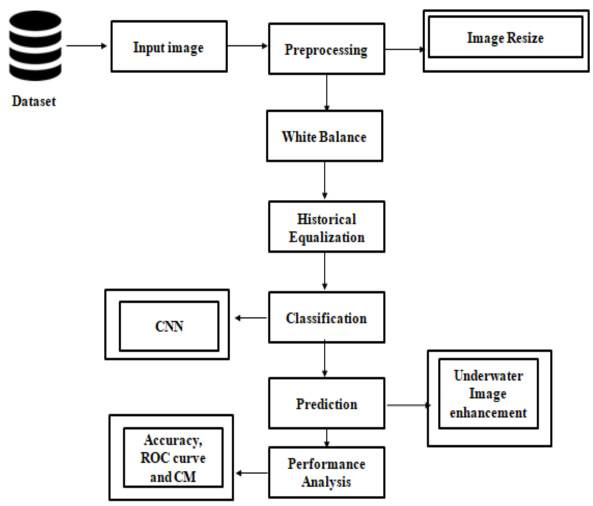

Figure 1: Flow chart

1. Dataset

The process begins with a dataset comprising underwater images with varying levels of degradation. These images serve as the input for the entire restoration pipeline. The dataset typically includes images captured in diverse underwater conditions to ensure the model's robustness and generalization.

2. Input Image

The underwater images from the dataset are loaded into the system for processing. These images are then forwarded to the preprocessing stage to enhance their suitability for restoration and analysis.

3. Preprocessing

This step includes techniques to prepare the input images for subsequent processing. The primary objectives of preprocessing are to reduce noise, standardize image dimensions, and improve overall quality. It consists of two sub-steps:

a. Image Resize

The images are resized to a fixed resolution to ensure uniformity across the dataset. This step is essential for maintaining consistency in the input size for the CNN model, as deep learning architectures typically require fixed input dimensions.

b. White Balance

White balancing is applied to correct the color cast caused by the dominance of blue or green wavelengths in underwater images. This step ensures that the colors in the image appear more natural and balanced.

4. Histogram Equalization

Histogram equalization is performed to enhance the contrast of the underwater images. This technique redistributes the intensity levels across the image, making darker areas more visible and improving the overall clarity of the image. It helps in revealing details that are otherwise obscured due to low contrast.

5. Classification

The preprocessed images are fed into a Convolutional Neural Network (CNN) for classification. The CNN is trained to distinguish between different categories or classes of degradation, such as "lightly degraded," "moderately degraded," or "heavily degraded." This step is crucial for tailoring the restoration process to the specific type of degradation present in the image.

6. Prediction

Based on the classification output, the CNN predicts the appropriate corrections required for each image. These predictions guide the enhancement process to ensure optimal restoration results.

7. Underwater Image Enhancement

The predicted corrections are applied to the input images to restore their colors and improve their overall visual quality. This stage involves operations like color correction, detail enhancement, and noise reduction. The result is a visually enhanced underwater image that closely resembles its original appearance.

8. Performance Analysis

The restored images are evaluated using various performance metrics to assess the effectiveness of the proposed approach. This step involves:

a. Accuracy

Measures the correctness of the model's predictions in restoring underwater images.

b. ROC Curve

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The Receiver Operating Characteristic (ROC) curve evaluates the model's ability to distinguish between different classes or levels of degradation.

c. Confusion Matrix (CM)

The confusion matrix provides insights into the classification accuracy by showing the number of true positive, true negative, false positive, and false negative predictions.

9. Output

The final output includes the restored underwater images along with a detailed performance analysis report. This output serves as the basis for evaluating the method's practical applicability and its potential for real-world deployment.

III. SIMULATION RESULTS

The simulation is performed using the python software.

Figure 2: Original Image

Figure 2 is presenting another sample of the original image of underwater from the dataset.

Figure 3: White balance

Figure 3 is presenting the white balance of the pixel. In this step the image removing unrealistic color casts sothat the object can be more cleared.

Figure 4: Balanced images

Figure 4 is presenting the balanced image, this is the clear image after the processing step.

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Figure 5: Enhanced image

Figure 5 is presenting the histogram equalization of the pixel. In this step the image is enhanced and colour restoration process is completed.

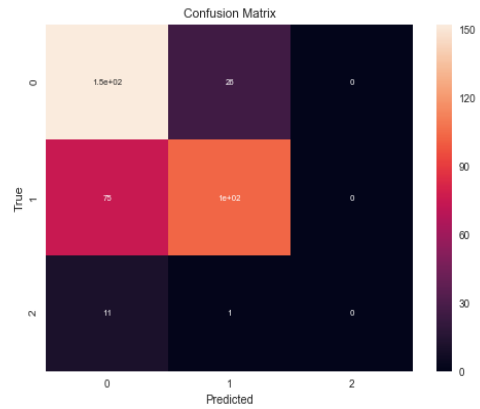

Figure 6: Confusion matrix

Figure 6 is showing the confusion matrix or the predictive matrix of the proposed research work. This matrix includes the values of true and false prediction.

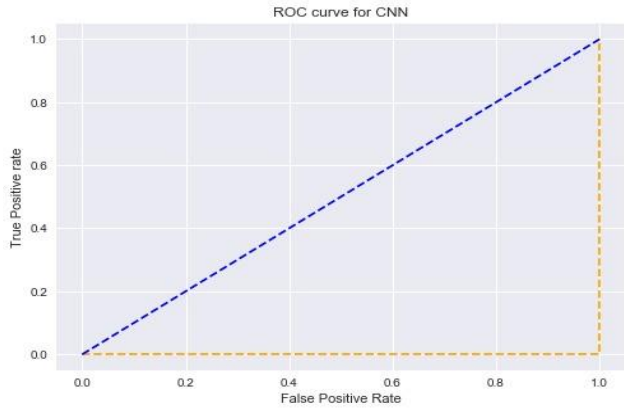

Figure 7: ROC curve

Table 1: Simulation Result

Sr. No.	**Parameters**	**Simulation Result**
1	Method	CNN
2	Accuracy (%)	96
3	Classification Error (%)	4
4	Loss	0.494
5	Epoch	10

Table 2: Result Comparison

Sr. No.	**Parameters**	**Previous Work**	**Proposed Work**
1	Method	Deep Neural Network	CNN
2	Accuracy (%)	96	99.70
3	Classification Error (%)	4	0.30

Table 1 is showing the result comparison of the previous and proposed work. The overall accuracy achieved by the proposed work is 99.72% while previous it is achieved 96%. The error rate of proposed work is 0.28% while 4% in existing work. Therefore it is clear from the simulation results; the proposed work is achieved significant better results than existing work.

IV. CONCLUSION

This paper presents a convolution neural network based deep learning technique for underwater image enhancement. The simulation is performed using the python spyder IDE 3.7 software. The dataset is trained and tested successfully. Generated the confusion matrix and optimized better accuracy. The overall accuracy achieved by the proposed work is 99.70% while previous it is achieved 96%. The error rate of proposed work is 0.30% while 4% in existing work. Therefore it is clear from the simulation results; the proposed work is achieved significant better results than existing work.

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