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Underwater Image Quality Enhancement and Object Detection using Deep Learning Techniques

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Abstract:

Underwater images often suffer from poor visibility, low contrast, and color distortions due to light absorption and scattering, making object detection a challenging task. This research presents a deep learning-based framework that combines image enhancement and object detection to overcome these limitations. A UNet-based enhancement model optimized with a hybrid loss function (L1 loss + SSIM index) is employed to restore visual clarity and improve structural details in degraded underwater images. The enhanced outputs are then processed using the YOLO 8l detection model to accurately identify and classify underwater objects. Experimental results demonstrate significant improvements in image quality and detection accuracy, with clear recognition of objects such as shipwrecks and divers. The proposed approach establishes a reliable pipeline for underwater visual analysis, offering potential applications in nautical exploration, archaeology, surveillance, and ecological monitoring.

Keywords— Underwater imaging, image segmentation, denoising techniques, visual quality enhancement, Peak Signal-to-Noise Ratio (PSNR), Mean Squared Error (MSE), Structural Similarity Index (SSIM), and image filtering.

Introduction

Over the past decade, underwater data and image acquisition technologies have advanced rapidly, and the application of underwater object recognition has become increasingly widespread. These technologies are now used in diverse fields such as laying submarine optical cables, constructing and maintaining offshore oil platforms, salvaging sunken submarines, marine organism harvesting, and environmental monitoring of the oceans. Optical imaging in underwater environments provides high resolution and rich detail, making it particularly effective for detecting objects at close range. However, such images frequently suffer from noise interference, blurred textures, low contrast, and color distortion due to light absorption and scattering. These limitations reduce the amount of usable information, creating challenges for tasks like target detection in marine industries and fisheries. Enhancing submerged images can greatly improve their quality and support demanding tasks, such as tracking and monitoring marine life. Therefore, strengthening the visual features of underwater imagery is essential to produce high-resolution, color-rich images suitable for advanced marine research and industrial applications.

I. LITERATURE SURVEY

In [1] a deep learning-based approach for underwater metallic object detection is presented, using input image data with multiple steps to enhance model performance. The TURBID dataset, consisting of 100 images, was employed for evaluation. To assess effectiveness, the model was tested across different validation levels. Initially, input images undergo preprocessing, followed by KFCM-based segmentation to isolate key regions. The segmented outputs are then processed through DWT feature extraction, capturing essential characteristics. Finally, a Convolutional Neural Network (CNN) performs classification to identify the objects. This technique can be effectively applied to locate submerged metallic components, such as machine parts from ships or aircraft that have sunk into the sea.

In [2] for clearer insight, the key challenges in vision-based underwater detection are categorized into four groups: degraded image quality, detection of small-scale objects, limited generalization across environments, and the need for real-time processing. We examine recent progress in this field and discuss the strengths and shortcomings of existing techniques in addressing these challenges.

The [3] aim of this paper is to introduce a structured framework for analyzing underwater pipeline images through deep learning techniques. The approach is systematically organized around the identified objects, along with a description of the deep learning models applied. Leveraging deep neural networks for interpreting seafloor imagery shows great promise in automation, especially for the detection and monitoring of underwater pipelines.

These challenges primarily arise because particles in underwater environments scatter and absorb light, reducing visibility. The advent of deep learning has enabled researchers to tackle numerous problems, such as protecting marine ecosystems, supporting rescue operations, preventing underwater hazards, and detecting or tracking submerged objects. Despite these advancements, the strengths and limitations of deep learning models in this domain are not yet fully understood [4].

In [5] the improved outputs produced by RCARN are subsequently forwarded to the detection phase, where the existing YOLOv3 model is employed. To attain superior detection accuracy, YOLOv3 is first trained on the extensive COCO dataset and then refined with the improved underwater photos. This research utilizes a dataset encompassing six kinds of aquatic objects: dolphin, jellyfish, octopus, seahorse, starfish, and turtle, consisting of genuine field photographs collected from various sources.

According to [6] Several new algorithms have recently been introduced to enhance underwater images. However, most of these methods are tested only on limited datasets or a small selection of real-world images, making it difficult to evaluate their true effectiveness and track their progress in practical applications. A thorough perceptual study and analysis of submarine imagery is therefore essential. Alongside enhancement, object detection in underwater images is also a major challenge, as low lighting conditions and noise significantly reduce detection accuracy. In this work, we propose the use of deep learning techniques to both enhance image quality and identify underwater objects. Since the dataset includes noisy samples, preprocessing and normalization are applied to filter and balance the data. The refined dataset is then fed into a Convolutional Neural Network (CNN), where convolution and pooling layers extract features, and a fully connected layer performs classification based on the trained model.

According to [7] Underwater video footage serves as the primary source of information for human endeavors in ocean research and development. This work initially explores the imaging principles governing underwater visuals, elucidates the factors contributing to their quality degradation, and offers a concise classification of current augmentation strategies. It subsequently underscores the significance of contemporary deep learning methodologies in enhancing underwater image quality and accentuates progress in underwater video improvement technology.

In [8] the findings of this study confirm that unexplored underwater environments can be effectively analyzed using both traditional methods and deep learning techniques. Advanced deep learning models, such as complex neural networks, have proven capable of identifying and classifying various underwater elements, even when image quality is suboptimal. Enhancing and refining underwater images is also crucial, as clearer visuals can simplify feature extraction and lead to improved classification accuracy. Further exploration of these enhancement methods would be valuable, as they can significantly reduce the complexity of later detection tasks. The combined application of conventional classifiers and DL-based approaches for identifying marine species—and subsequently evaluating their surrounding environments in both qualitative and quantitative terms—represents a meaningful step forward in this research domain.

In [9] modified variation of MIRNet is specifically designed for underwater circumstances, successfully mitigating vision concerns by controlling random brightness fluctuations. The suggested approach, in contrast to the original, not only adjusts brightness but also augments the color richness of underwater photos. UICE-MIRNet fundamentally incorporates an UI-CEB, which detects low-color areas in underwater images and does color restoration while maintaining critical contextual information.

According to[10] Underwater picture data from the Korean seas was improved using deep learning models specifically developed for underwater image restoration, including CycleGAN, Underwater GAN, and Fast Underwater Picture Enhancement GAN. An image fusion methodology was employed to enhance optical underwater photos using conventional image processing methods. To objectively analyze performance, two standard metrics were utilized: Underwater Image Quality Measure, which measures colorfulness, sharpness, and contrast, and UCIQE, which checks chroma, brightness, and saturation.

II. PROPOSED SYSTEM

The proposed system integrates underwater image enhancement with deep learning-based object detection to improve visibility and recognition in challenging underwater environments. The framework is divided into two main stages:

Image Enhancement: A UNet-based model is employed to restore degraded underwater images by correcting color distortions, reducing noise, and enhancing structural details. The model is optimized using a hybrid loss function combining L1 loss and the SSIM index, ensuring both pixel-level accuracy and perceptual quality.

Object Detection: The enhanced images are passed to the YOLO 8l detection model, which provides real-time and accurate identification of underwater objects. YOLO 8l is chosen for its lightweight architecture, high detection accuracy, and ability to process multiple object categories simultaneously.

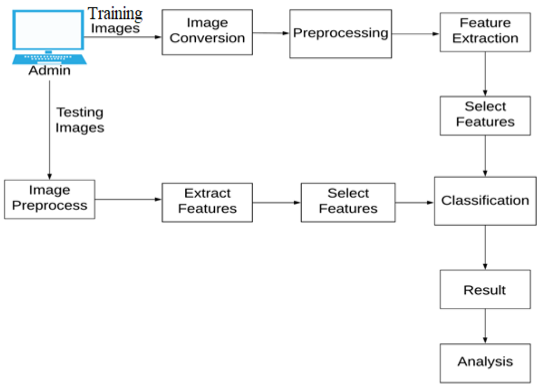

Figure 1: Architecture of our model

The YOLOv8l detection model is a large variant of the YOLOv8 family, designed for object detection, segmentation, and classification tasks. It balances accuracy and speed, making it suitable for high-performance detection scenarios.

- Architecture: YOLOv8l uses a CSP Darknet-based backbone with convolutional layers, SPPF (Spatial Pyramid Pooling – Fast), and a PAN-FPN neck for multi-scale feature fusion, followed by detection heads.
- Input Size: Typically 640×640 pixels (but configurable).
- Performance: Compared to smaller YOLOv8 versions (n, s, m), the l (large) model achieves higher accuracy (mAP) but requires more GPU memory and computational resources.
- Use Cases: Suitable for applications requiring high accuracy, such as medical image detection, traffic surveillance, and industrial defect inspection.

III. RESULTS

The detection performance of the YOLOv8l model was evaluated on the test dataset, demonstrating accurate object identification across various scenarios. To further improve image quality and detection reliability, researchers applied a U-Net-based image enhancement algorithm and analyzed its effectiveness using the combined L1 loss and SSIM index. The resulting loss curve indicates that the model converges steadily, with L1 loss decreasing over epochs while the SSIM index consistently improves, reflecting enhanced structural similarity and reduced reconstruction errors in the processed images. Overall, the integration of YOLOv8l detection with U-Net enhancement provides a robust framework for precise detection and improved image clarity.

The set of images showcases the steps involved in detecting objects beneath the water. The first frame displays the original view of a sea ship, which appears somewhat blurred due to underwater visibility limitations. In the second frame, an image enhancement algorithm is applied, resulting in clearer details and improved contrast. The final frame illustrates the detection phase, where the YOLO model successfully identifies the ship and diver, assigning confidence scores of 0.85, 0.27, and 0.84, each marked with bounding boxes.

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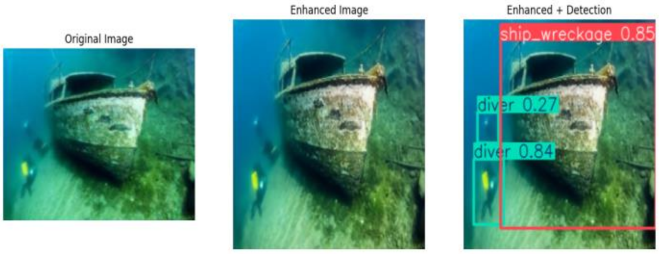

Figure 2: Enhanced and Detection Results

The series of images depicts the steps involved in detecting objects underwater. The initial frame displays a sea turtle, slightly obscured by underwater conditions. In the next frame, an image enhancement algorithm is applied, resulting in improved clarity and contrast. The final frame shows the detection outcome, where the YOLO model successfully recognizes the turtle, marking it with a bounding box and a confidence score of 0.89.

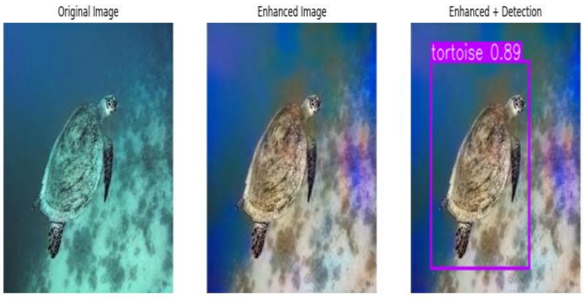

Figure 3: Enhanced and Detection Results

The x-axis (Epoch) denotes the total number of complete iterations over the dataset, whereas the y-axis (Loss) reflects the discrepancy between anticipated and actual outputs. During the initial phase (epoch 0–10), the training loss decreases significantly from about 0.36 to below 0.15, indicating that the model rapidly acquires fundamental patterns within the data. As training advances over 50 epochs, the loss diminishes at a slower rate, signifying the refinement of the weights. After approximately 200 epochs of training, the loss stabilizes at 0.06, indicating that the model has converged and that further training yields minimal improvements.

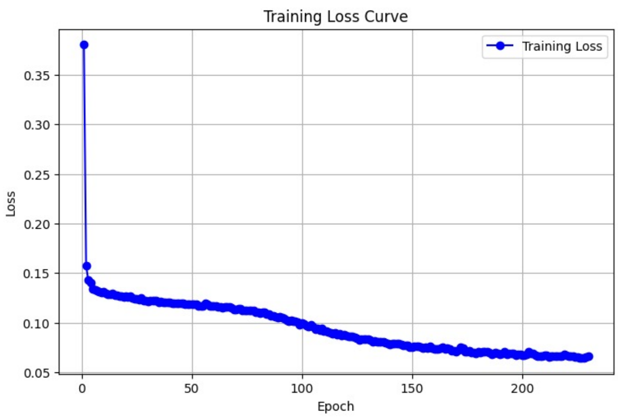

Figure 4: Training Loss Curve Results

IV. CONCLUSION

The research effectively illustrates that deep learning methodologies may markedly elevate underwater image quality and augment item detection efficacy. The UNet-based enhancement technique, refined with a composite L1 loss and SSIM index, efficiently diminishes noise and recovers intricate features, as seen by the convergence of the loss curve. Augmented photos, when processed using the YOLO 8l detection model, produced very precise identification of underwater entities, including shipwrecks and divers. The testing findings confirm that the combination of picture enhancement and object detection establishes a strong foundation for evaluating difficult underwater situations, thereby improving visual clarity and detection reliability.

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