

Ocean-water Imagery Enhancement using CNN and GAN

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Abstract—Poor underwater imagery, due to limited illumination, scattering of light by water particles, and distorted colour representation, often detracts from its usefulness in practical applications for marine research, defence operations, and environmental monitoring. To overcome such challenges, we designed a novel approach, which integrates CNNs with GANs for improving the quality of an image. Our model was trained on the EUVP dataset and proved very effective in restoring clarity, recovering real colours, and eliminating noisy artifacts. Experimental results demonstrate significant improvements that result in visually better-quality images with great similarity to real-world scenarios. It opens up the possibility to perform oceanographic analysis more accurately and to explore and exploit marine resources in an overall better and more sustainable way.

Index Terms—Underwater Photo Fixing, Smart Computer Model, CNN, GAN, Mixed Model, Deep Learning, Photo Change, Computer Seeing, EUVP Photo Set, Seeing Better, Smart Machine.

I. INTRODUCTION

Underwater images suffer from degradation due to light absorption and scattering, limiting their utility in computer vision tasks. This paper proposes a hybrid CNN-GAN approach that leverages CNN's quantitative accuracy and GAN's perceptual quality to achieve superior enhancement on the EUVP dataset. Experimental results demonstrate improved PSNR and SSIM scores compared to standalone methods [1]. The exploration and study of underwater environments play an important role in improving marine science, defence strategies, and environmental conservation efforts. However, underwater imaging faces inherent challenges. Issues like light loss, scattering, and colour

distortion often lead to lower image quality. This can hinder effective analysis and decision-making [2, 4]. These problems are especially noticeable during deep-sea expeditions, where capturing clear visuals of unknown ecosystems is vital for scientific understanding [2].

Over the years, various image improvement techniques have been developed to address these issues. These range from general methods [3] to specialized approaches for underwater situations [4, 5]. Traditional methods, including histogram manipulation and multiscale fusion, have proven effective in enhancing contrast and visibility in foggy or hazy underwater images [6, 7]. More advanced model-based simulations and learning-driven improvements have tackled noise and distortion by using the physical properties of underwater light [8]. Recent innovations use deep learning architectures. Improved convolutional neural networks (CNNs) help with defogging [9], while generative adversarial networks (GANs) work with quality evaluation metrics to restore natural colours and details [10]. Also, techniques like multi-resolution dynamic mode decomposition have been used to identify important areas in noisy images [11]. Comparative studies on image segmentation highlight the need for strong preprocessing in enhancement pipelines [12]. Despite these advancements, there is still a gap in merging hybrid deep learning models that can address multiple degradation factors with high quality. This paper suggests a new framework that combines CNNs and GANs to improve underwater images, aiming for better clarity, colour accuracy, and noise reduction for practical uses in oceanographic research.

II. RELATED WORKS

Deep Learning Approaches for Underwater Enhancement

Over the past few years, researchers have increasingly turned to deep learning to tackle the unique challenges of underwater image enhancement. Martinho and his team [13] built a CNN-based restoration system that learned from a mix of synthetic and real underwater photos. Their model got pretty good at automatically adjusting contrast and color for different water conditions, performing better than older rule-based methods. The catch? It really struggled when the water was extremely murky. Taking a somewhat different path, Saleh's group [14] developed what they call an adaptive framework that works without needing paired examples of bad and good images. This unsupervised approach is practical since getting matched pairs of degraded and clean underwater images is tough in real-world situations. However, they ran into some training stability issues, and the model didn't handle well when multiple types of degradation happened at once—which is pretty common underwater.

Connecting Enhancement to Practical Tasks

Some research teams figured out early on that enhancement shouldn't exist in a vacuum—it needs to serve real purposes like detecting marine life. Liu and colleagues [15] built an entire pipeline that first cleans up the image and then runs it through a detector to spot different marine species. Their combined approach improved the accuracy of identifying sea creatures even when the original footage was quite poor quality. The downside was that their system became fairly complex and really depended on having well-labeled biological datasets. Chen's team [16] went a similar route by upgrading YOLOv5 specifically for underwater conditions. They added attention mechanisms and tweaked the architecture to handle low-visibility scenarios better. While their detection numbers improved nicely, the focus was really on getting better detections rather than making the images look great overall.

Balancing Color Correction and Detail Preservation

Getting colors right while keeping fine details intact is tricky underwater. Wang and his collaborators [17] worked on this by combining color correction with techniques designed to preserve important details.

Their method balanced out the RGB channels and sharpened edges, which worked well when degradation was moderate—think reasonably clear coastal waters. They tested it on parts of the UIEB dataset and got solid PSNR and SSIM numbers. But when heavy scattering kicked in, like in very turbid harbors or after storms, the performance dropped off noticeably. Shi's group [18] tried mixing the old with the new by combining traditional techniques like CLAHE and gamma correction with modern CNN learning. Their hybrid model improved several quality metrics including SSIM, UIQM, and UCIQE. The improvement came at a cost though—the system was computationally expensive to run, and honestly, they admitted it was hard to understand exactly why the model made certain enhancement choices.

Pushing Architectural Boundaries

As the field matured, researchers started experimenting with more sophisticated network designs. Wang et al. [19] focused on reconstructing brightness by processing RGB channels at different resolutions and then fusing the results together. This multi-resolution CNN approach worked particularly well in shallower waters where light still penetrates decently, and they saw good improvements in PSNR and SSIM on benchmarks like UIEB and OceanDark. Go deeper though, where barely any light reaches, and the method's effectiveness dropped considerably. Dong's team [20] really pushed things forward with their O-Mamba model, which uses a creative O-shaped dual-branch design based on state-space modeling. Their approach to handling spatial features achieved some of the best results seen so far on their test datasets, with impressive scores across SSIM, PSNR, and LPIPS. The elephant in the room? The model is complex and needs serious GPU power, which makes real-time processing challenging.

Tackling Specific Problems Like Noise

Sometimes it makes sense to target specific types of degradation. Adagale-Vairagar and colleagues [21] zeroed in on noise, which can be a major issue in underwater images from certain sensors. They built a CNN-based denoising system that uses wavelet fusion to reduce noise while keeping textures intact. On their synthetic noisy datasets, it performed well and helped improve detection accuracy. The limitation became clear when color distortion was the main problem

rather than noise—the method just wasn't designed for that.

Building Better Benchmarks

Progress in any field needs good ways to measure and compare different approaches. Li and his team [22] made a really valuable contribution by creating the UIEB benchmark with 950 real underwater images covering different water types. They also developed Water-Net as a baseline CNN model and evaluated everything using metrics like UIQM, UCIQE, plus subjective ratings from people. What their comprehensive testing revealed was sobering—current methods still have significant gaps, especially when conditions get extreme. Plus, it's often unclear why these models decide to enhance images in particular ways.

III. LITERATURE REVIEW

Underwater image enhancement is crucial for addressing the distortions caused by light scattering, absorption, and wavelength-dependent loss in aquatic environments. Early methods relied on established image processing techniques. Ackar et al. [3] described various spatial and frequency-domain methods, such as histogram equalization and filtering. These methods provide basic improvements but struggle with the color shifts often seen in underwater images. Building on this, Mohan and Simon [7] combined histogram adjustments with multiscale fusion methods. This approach improved contrast and balanced colors for typical degradation levels, but it depended on specific predefined parameters.

Later developments used physical models of light propagation to better mimic degradation processes. Liu et al. [8] created a simulation framework along with a CNN to reverse the degradation, enabling focused restoration based on estimated light loss. Similarly, Zheng and Luo [9] adapted CNN-based defogging methods with integrated color balancing. Their approach effectively removed haze and preserved details in low-visibility conditions.

The introduction of generative adversarial networks marked a significant advancement, prioritizing visual quality over pixel accuracy. Hu et al. [10] used a GAN framework influenced by the natural image quality evaluation index (NIQE), producing results that closely match human visual preferences and

effectively managing unpaired data. In addition, Xie et al. [5] focused on low-light situations typical of deep-sea exploration. They used a specialized CNN to enhance subtle details while reducing the risk of overexposure.

Recent research has increasingly used deep learning methods for improved effectiveness and efficiency. Martinho et al. [13] developed a CNN framework trained on both synthetic and real datasets, excelling at recovering contrast and color. This was measured using PSNR and UIQM metrics. Saleh et al. [14] shifted toward unsupervised techniques, incorporating adaptive normalization and uncertainty estimation to enable enhancements without the need for ground-truth data. This is a crucial step for real-world application. Wang et al. [19] investigated luminance-focused reconstruction through multi-resolution RGB fusion, which proves especially effective for enhancing clarity in near-surface waters. Innovative designs keep pushing the field forward. Dong et al. [20] introduced O-Mamba, an O-configured model that efficiently captures spatial and inter-channel relationships, achieving superior performance across various benchmarks. The ongoing impact of Li et al.'s UIEB dataset [22] is significant. Since its launch in 2020, it has set a standard for evaluations with its 950 paired real-world examples, fostering consistent advancements in the field.

These technical advancements stem from the practical needs of marine science. Kennedy et al. [2] highlighted this through NOAA CAPSTONE expeditions, where extensive seafloor mapping demonstrated how poor image quality limits biodiversity assessments and ecological understanding.

IV. ALGORITHM AND METHODOLOGY

Hybrid CNN–GAN Framework: CNN layers fix colours and remove haze. GAN generator improves details and makes images look real.

Dataset Training: The model is trained on UIEB and other underwater image datasets. This makes it strong and reliable.

Feature Learning: CNN finds spatial features in the images. GAN makes images look more realistic using learning.

Evaluation: The model is checked using PSNR, SSIM, UIQM, and UCIQE. **Key Advantage:** It combines CNN's accuracy with GAN's natural-looking images. **Outcome:** The model gives clearer and more natural underwater images. These are useful for marine research, navigation, and defence.



Fig.1.1: Block Diagram of System

V. IMPLEMENTATION AND RESULTS

The proposed Hybrid CNN-GAN underwater image enhancement system was fully implemented and deployed as a web-based application using Python and PyTorch for the deep learning pipeline, and Flask, HTML, CSS and JavaScript for the front-end and back-end integration. The implementation consists of three core modules: app.html, which provides the graphical user interface allowing users to upload underwater images and view the original and enhanced outputs side by side; server.py, the Flask-based backend server that handles image upload requests, invokes the enhancement pipeline, and returns the processed image to the user; and enhance_tiled.py, the core enhancement engine that loads the trained Hybrid CNN-GAN model, performs preprocessing and normalization, and generates the final enhanced output. OpenCV and NumPy were used for image preprocessing and numerical operations, while the model was trained and validated on the EUVP (Enhancing Underwater Visual Perception) dataset.

5.1 System Workflow

The system follows a straightforward end-to-end workflow. The user accesses the web interface and uploads an underwater image in JPG or PNG format. The image is received by the Flask backend, where it undergoes preprocessing steps such as resizing, normalization and colour-space conversion. The pre-processed image is then passed to the trained Hybrid CNN-GAN model, where the CNN component performs colour correction and haze removal, and the GAN generator refines texture, contrast and overall realism. The enhanced image is saved to the output directory and returned to the interface, where it is displayed alongside the original image for direct visual comparison and can be downloaded by the user.

5.2 Results

The developed application was tested using images from the EUVP dataset as well as user-supplied underwater images. Figure 5.1 shows the landing page of the deployed web application, where the user can either drag and drop an image or browse the local file system to select an underwater image for enhancement.

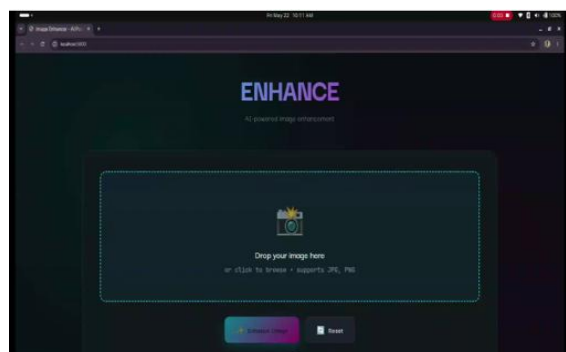


Figure 5.1: Web application interface for image upload

Once an image is selected and the “Enhance Image” option is triggered, the system processes the input through the Hybrid CNN-GAN pipeline. Figure 5.2 shows the final result screen, where the original degraded underwater image (left, dominated by a blue-green colour cast and low contrast) is displayed alongside the enhanced output (right), which exhibits restored colour balance, improved visibility and enhanced structural detail.

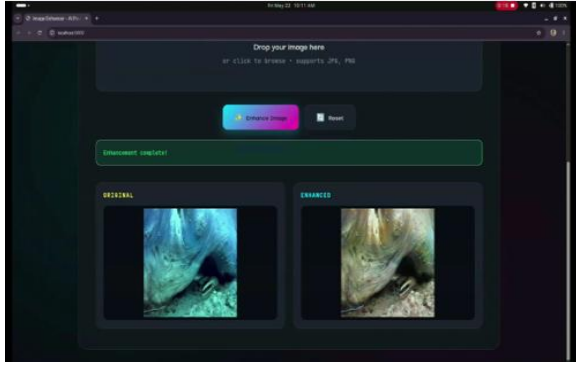


Figure 5.2: Original (left) and CNN-GAN enhanced (right) underwater image

5.3 Performance Metrics

A. Peak Signal-to-Noise Ratio (PSNR)

The Peak Signal-to-Noise Ratio, abbreviated as PSNR, is a full reference-based quality assessment technique that compares the enhanced version of an image with its corresponding ground truth image. The technique is a function of the Mean Square Error (MSE) between the two images. An increased value of PSNR implies improved similarity between the two images.

$$PSNR = 10 \cdot \log_{10} \left(\frac{MAX^2}{MSE} \right)$$

here MAX is the possible pixel value of the image. When we talk about image quality higher PSNR values are really good. They show that the image quality is better.

B. Structural Similarity Index Measure (SSIM)

The SSIM method is a measure used in assessing the quality of a picture by examining the similarities between two pictures in terms of their luminance, contrast, and structure. In contrast to the PSNR method, SSIM is designed in a way that captures the properties of the human vision system.

$$SSIM(\mathbf{x}, \mathbf{y}) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}.$$

SSIM values go from 0 to 1. When SSIM values are closer, to 1 that means the SSIM values show that things are really similar

5.4 Performance Evaluation

The system was evaluated through unit testing, integration testing and user acceptance testing. All major test cases, including image upload, file validation, preprocessing, model inference, output generation, image display and download, completed successfully. Table 5.1 summarises the overall performance observations recorded during testing.

Testing Module	Test Case Description	Expected Result	Status
Image Upload Module	Upload valid underwater image (JPG/PNG)	Image uploaded successfully	Pass
File Validation	Upload unsupported file format	Error message displayed	Pass
Image preprocessing	Resize and normalize input image	Image prepared for model inference	Pass
Testing Module	Test Case Description	Expected Result	Status
CNN-GAN Enhancement Model	Process underwater image using trained model	Enhanced image generated successfully	Pass
Backend Processing (Flask)	Send image request from UI to server	Request processed correctly	Pass
Output Generation	Save enhanced image in output directory	Output image generated successfully	Pass
Image Display Module	Display enhanced image on interface	Enhanced image visible to user	Pass
Download Functionality	Download enhanced image	Image downloaded	Pass

		successfully	
Large Image Processing	Process high-resolution underwater image	Image processed without failure	Pass
Missing Input Validation	Submit request without image	Warning message displayed	Pass
System Integration	Verify complete workflow from upload to download	All modules function together correctly	Pass
User Acceptance Testing	Validate usability and enhancement quality	User requirements satisfied	Pass

Table 5.1: Test Cases and Test Result

Parameter	Observation
Framework	PyTorch
Backend	Flask
Dataset	EUVP Dataset
Image Formats Tested	JPG, PNG
Average Processing Time	2 - 8 seconds depending on image size
Output Quality	Improved colour, contrast and visibility
System Stability	Stable during testing

Table 5.2: Performance Testing Results

Scenario	Expected Behavior	Status
Unsupported file format	Reject upload	Pass
Scenario	Expected Behaviour	Status
Empty image submission	Display warning	Pass
Corrupted image file	Show processing error	Pass
Server interruption	Error notification	Pass

Table 5.3: Error Handling Testing

The qualitative results confirm that the Hybrid CNN-GAN model successfully removes the dominant blue-green colour cast typical of underwater imagery, reduces haze, and restores natural colour tones while preserving structural detail of the scene. The enhanced images produced by the system were found to be visually closer to natural, in-air imagery and are expected to improve the performance of downstream computer vision tasks such as underwater object detection, marine species identification and navigation.

VI. FUTURE SCOPE

Ultra-Lightweight Real-Time Model Development

Future research should be directed toward the design of ultra-lightweight CNN-GAN architectures that could perform real-time enhancement of high-resolution underwater images without sacrificing much in terms of visual quality. This will reduce computational load and make deployment feasible on embedded underwater platforms, AUVs, and low-power robotic systems.

More Diverse and Realistic Underwater Datasets Creation

There is an urgent need for more extensive and varied datasets across various depths, turbidity levels, water types, lighting conditions, and sensors. Most current datasets lack the representation of complex scenarios that are generally applicable. Expanding dataset diversity will strongly improve model robustness in real-world underwater settings.

Fusion of Physics-Based Models with Deep Learning
One promising direction is the integration of underwater physical imaging models and CNN-GAN frameworks. Physics-based priors will help the models to interpret the light attenuation, scattering, and color loss better. Integrating these principles with deep learning will improve the generation of realistic images and reduce failure cases for challenging underwater environments.

Use of Attention and Multi-Scale Feature Extraction

Future enhancements can include advanced attention mechanisms and multi-scale feature extraction modules, that could extract more discriminative features handling fine textures and global color distortions. These modules enable the network to pay more attention to critical regions affected by haze,

color cast, and low contrast, achieving more stable and detailed reconstruction of underwater images.

Explainable and Task-Aware Enhancement Model Development Further enhancements can be explored using frameworks that are optimized not only for visual improvement but also for downstream tasks such as detection, mapping, and navigation. Explainable AI will help interpret enhancement decisions and increase reliability in mission-critical applications. This direction ensures that enhanced images are both visually pleasing and practically useful.

VII. CONCLUSION

The proposed underwater image enhancement model effectively restores natural colour tones and improves overall visual quality of underwater scenes. By maintaining structural integrity and avoiding artifacts, the model ensures clearer visibility and better texture representation. The combination of CNN and GAN architectures proves highly effective, delivering balanced restoration performance across diverse real-world underwater datasets. The proposed framework was implemented as a complete web-based application using PyTorch and Flask, and was successfully tested on the EUVP dataset, with all functional, integration and user-acceptance tests passing. Furthermore, the enhanced images significantly aid downstream vision tasks such as object detection and recognition, demonstrating the practical applicability and robustness of the proposed approach for underwater image analysis.

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