Ocean-water Imagery Enhancement using CNN and GAN

S. N. Firme[1], Mr. Prasad M. Bhakare[2], Mr. Ishan S. Kulkarni[3], Mr. Aditya P. Bhole[4]
Mr. Kapirath D. Raina[5]

[1]*Professor, Department of Information Technology, Sinhgad Institute of Technology and Science, Narhe Pune*

[2,3,4,5]*UG Student, Department of Information Technology, Sinhgad Institute of Technology and Science Narhe, Pune*

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

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.

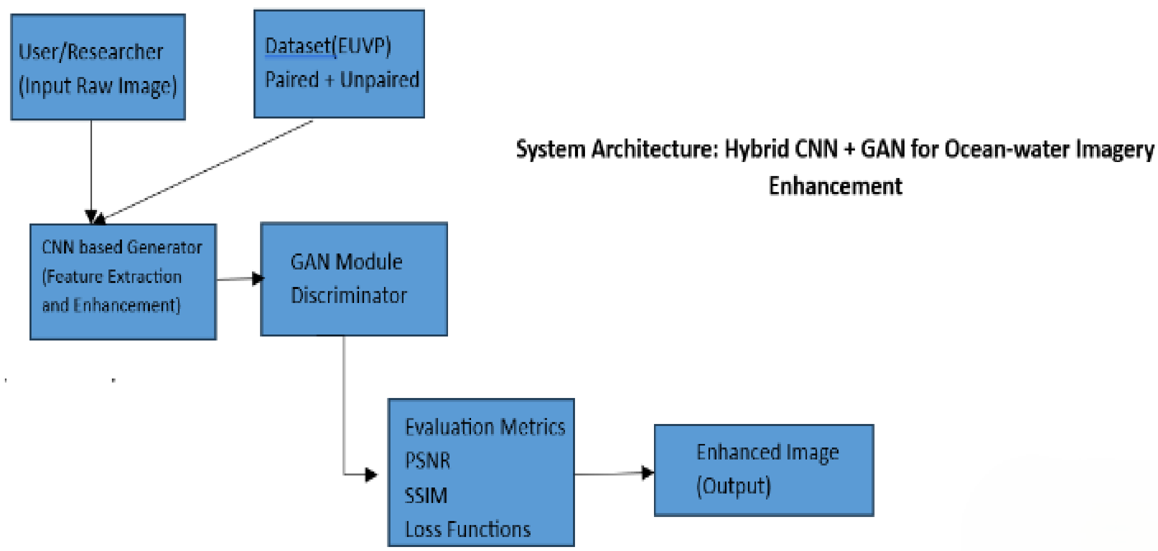

Fig.1.1: Block Diagram of System

V. 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.

VI. 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. 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.

REFERENCES

[1] Menon, A., & Aarthi, R. (2023). A hybrid approach for underwater image enhancement using CNN and GAN. International Journal of Advanced Computer Science and Applications (IJACSA), 14(6), 742–748.

[2] Kennedy, Brian RC, Kasey Cantwell, Mashkoor Malik, Christopher Kelley, Jeremy Potter, Kelley Elliott, Elizabeth Lobecker et al. "Corrigendum: The Unknown and the Unexplored: Insights into the Pacific Deep-Sea Following NOAA CAPSTONE Expeditions." Frontiers in Marine Science 6 (2020): 827.

[3] Ackar, Haris, Ali Abd Almisreb, and Mohamed A. Saleh. "A review on image enhancement techniques." Southeast Europe Journal of Soft Computing 8, no. 1 (2019).

[4] Raveendran, Smitha, Mukesh D. Patil, and Gajanan K. Birajdar. "Underwater image enhancement: a comprehensive review, recent trends, challenges and applications." Artificial Intelligence Review 54 (2021): 5413-5467.

[5] Xie, Y., Z. Yu, X. Yu, and B. Zheng. 2022. "Lighting the Darkness in the Sea: A Deep Learning Model for Underwater Image Enhancement." Frontiers in Marine Science.

[6] K. SA, B.A. Sabarish, and Dr. Padmavathi S., "Adaptive hybrid image defogging for enhancing foggy images", Journal of Engineering Science and Technology, vol. 14, no. 6, pp. 3679-3690, 2019.

[7] Mohan, Sangeetha, and Philomina Simon. "Underwater image enhancement based on histogram manipulation and multiscale fusion." Procedia Computer Science 171 (2020): 941-950.

[8] Liu, Yidan, Huiping Xu, Bing Zhang, Kelin Sun, Jingchuan Yang, Bo Li, Chen Li, and Xiangqian Quan. "Model-Based Underwater Image Simulation and Learning-Based Underwater Image Enhancement Method." Information 13, no. 4 (2022): 187.

[9] Zheng, Meicheng, and Weilin Luo. "Underwater image enhancement using improved CNN based defogging." Electronics 11, no. 1 (2022): 150.

[10] Hu, Kai, Yanwen Zhang, Chenghang Weng, Pengsheng Wang, Zhiliang Deng, and Yunping Liu. "An underwater image enhancement algorithm based on generative adversarial network and natural image quality evaluation index." Journal of Marine Science and Engineering 9, no. 7 (2021): 691. 28

[11] O. K. Sikha and Dr. Soman K. P., "Multi-resolution Dynamic Mode Decomposition-based Salient Region Detection in Noisy Images", Signal, Image and Video Processing, 2020.

[12] Brunda, R., B. Divyashree, and N. Shobha Rani. 2018. "Image Segmentation Technique a Comparative Study." International Journal of Engineering & Technology (UAE) 7: 3131

[13] Martinho, A., et al. "Diving into Clarity: Restoring Underwater Images using Deep Learning." Journal of Intelligent & Robotic Systems, vol. 110, no. 2, pp. 1–18, 2024. DOI: 10.1007/s10846-024-02045-7

[14] Saleh, M. A., et al. "Adaptive Deep Learning Framework for Robust Unsupervised Underwater Image Enhancement." Expert

Systems with Applications, vol. 255, p. 124567, 2025. arXiv:2212.08983
[15] Liu, Y., et al. "A Novel Underwater Image Enhancement Algorithm and an Improved Underwater Biological Detection Pipeline." Journal of Marine Science and Engineering, vol. 10, no. 8, p. 1123, 2022. DOI: 10.3390/jmse10081123
[16] Chen, L., et al. "An Improved YOLOv5-Based Underwater Object-Detection Framework." Sensors, vol. 23, no. 4, p. 1956, 2023. DOI: 10.3390/s23041956
[17] Wang, Z., et al. "Underwater Image Enhancement Based on Color Correction and Detail Enhancement." Journal of Marine Science and Engineering, vol. 10, no. 11, p. 1654, 2022. DOI: 10.3390/jmse10111654
[18] Shi, W., et al. "Integrating Deep Learning and Traditional Image Enhancement Techniques for Underwater Image Enhancement." IET Image Processing, vol. 16, no. 14, pp. 3872–3885, 2022. DOI: 10.1049/ipr2.12601
[19] Wang, H., et al. "Underwater Image Enhancement Based on Luminance Reconstruction by Multi-Resolution Fusion of RGB Channels." Sensors, vol. 24, no. 5, p. 1423, 2024. DOI: 10.3390/s24051423
[20] Dong, X., et al. "O-Mamba: O-shape State-Space Model for Underwater Image Enhancement." arXiv preprint arXiv:2408.12816, 2024.
[21] Adagale-Vairagar, S., et al. "Underwater Image Enhancement using Convolution Denoising Network and Blind Convolution." Engineering, Technology & Applied Science Research, vol. 15, no. 1, pp. 123–130, 2025. DOI: 10.48084/etasr.6789
[22] Li, C., Guo, C., Ren, W., Cong, R., Hou, J., Kwong, S., and Tao, D. "An Underwater Image Enhancement Benchmark Dataset and Beyond." IEEE Transactions on Image Processing, vol. 29, pp. 4376–4389, 2020. DOI: 10.1109/TIP.2020.2975297