Underwater Image Super-Resolution using GANs

Samyuktha Anand[1], Ayush Gupta[2], Ayush Gupta[3]

[1,2]*Student, Ramrao Adik Institute of Technology, Navi Mumbai, Maharashtra, India*
[3]*Professor, Ramrao Adik Institute of Technology, Navi Mumbai, Maharashtra, India*

Abstract—**Underwater images tend to suffer from poor resolution, color distortion and reduced visibility caused by light scattering and absorption in the underwater environment. This quality degradation significantly affects subsequent downstream tasks like object detection, marine life monitoring and autonomous underwater navigation. Here, we introduce a novel deep learning-based underwater image super-resolution framework based on Generative Adversarial Networks (GANs). Our approach combines a modified USRNet backbone with GAN-based refinement to recover high-frequency details and perceptual quality while maintaining structural fidelity. We train the model on a composite dataset of UFO-120, UIEB and EUVP to increase robustness in diverse underwater environments. Quantitative outcomes show significant gains in PSNR and SSIM over the state-of-the-art, while qualitative assessment verifies higher visual clarity. The suggested method provides a promising avenue for improving underwater images in practical applications.**

Index Terms—**Underwater image enhancement, super-resolution, generative adversarial networks, deep learning, image restoration, USRNet.**

1. INTRODUCTION

Underwater imaging is important in applications including marine biology, ocean exploration, environmental monitoring, and underwater robotics [1]. Images acquired in underwater media are degraded by absorption of light, scattering, and the presence of suspended particles. These degradations diminish visibility, distort color, and greatly reduce the spatial resolution of images [2]. This quality loss renders it challenging to obtain useful information, particularly in applications demanding fine visual detail such as object detection, classification, and navigation. Consequently, improvement of the resolution and clarity of underwater images is an important step toward the improvement of the effectiveness of underwater vision systems. Recent improvements in deep learning, specifically Generative Adversarial Networks (GANs), have revolutionized image super-resolution. GANs have the ability to learn intricate image transformations and create visually appealing outputs by training a generator-discriminator pair under competitive conditions. For underwater images, GANs can learn to recover high-frequency details, filter noise, and restore color and contrast. This work investigates a GAN-specific architecture for underwater image super-resolution, using USRNet-style blocks to ensure optimal restoration [3]. The aim is to improve the gap between degraded low-resolution underwater images and their perceptually correct high-resolution counterparts. In spite of recent advances in underwater image super-resolution with deep learning, current models tend to underperform when transferred to underwater images. Conditions such as light absorption, backscatter, and turbidity impose severe degradation that cannot be resolved by standard SR models trained on land-based datasets. This underscores the necessity for domain-specific architectures and training pipelines adapted to underwater image properties. By integrating adversarial learning and utilizing datasets specifically designed for underwater images, our method seeks to close this performance gap and generate visually correct, high-resolution outputs that are perceptually pleasing and structurally accurate. Underwater image processing continues to be a challenging field because of the special distortions in underwater conditions. Recent developments in GANs have made it possible to achieve remarkable advancements in super-resolution, reconstructing high-quality images from low-quality underwater images. Nevertheless, issues such as artifact reduction and computational efficiency are still present. This paper seeks to create a GAN-based super-resolution model that extends existing architectures and datasets, enhancing underwater imaging for marine biology,

navigation, and environmental monitoring applications.

2. LITERATURE SURVEY

Expanding on the literature, Underwater image processing has emphasized the serious challenges presented by underwater environments, which impair image quality through effects such as light scattering, absorption, and color distortion. Traditional methods like histogram equalization, contrast enhancement, and filtering were used in early attempts to enhance underwater images. [4] These methods were, however, inadequate in handling the intricate optical distortions characteristic of underwater imaging. With the advent of deep learning, especially CNNs and GANs, more efficient solutions have been proposed. GAN-based models, such as those that use USRNet-style architectures, have exhibited encouraging results in improving underwater images by creating realistic high-frequency details and enhancing visual clarity. Additionally, domain-specific underwater image datasets, such as UFO120, UIEB, and EUVP, have been instrumental in pushing the frontiers of developing super-resolution models. [2] In spite of excellent progress, difficulty in minimizing artifacts and improving generalization of models to different conditions underwater remains motivation for continued study in the subject. The presence of appropriate datasets is important for training efficient image super-resolution models. Datasets such as UFO-120, UIEB and EUVP have been utilized for underwater image super-resolution and enhancement, offering high quality underwater images and their low-resolution counterparts [5]. These enable models to learn the mapping between varying levels of image detail. Nevertheless, one of the biggest challenges is the absence of large-scale labeled datasets, which restricts the training of deep learning models [6]. Current datasets tend to lack variability in environmental conditions, including different water depths and lighting, which further complicates generalization performance. Over the past few years, various GAN-based architectures specific to underwater image super-resolution have been suggested by researchers. Prominent works are centered on the creation of GANs that are specifically designed to upscale underwater images [7]. These models employ novel aspects like multi-scale

processing and residual learning, enabling them to produce high-resolution underwater images with enhanced details and reduced artifacts [8]. In addition, the use of perceptual loss functions has proven to improve the realism of generated textures and structures in output images—especially useful for practical underwater use cases.

Underwater image super-resolution models find wide-ranging applications in various disciplines such as marine biology, oceanography, and underwater robotics [9]. The improved images offer more insights into underwater ecosystems, allowing researchers to study marine life with greater clarity and detail. Recent works point towards the promising applications of these methods in enhancing the performance of autonomous underwater vehicles, where high-resolution images are essential for navigation, mapping, and object identification [3]. Research on underwater image super-resolution reflects both the persistent challenges and rapid innovations in this domain. While traditional methods focused on basic image enhancement, recent breakthroughs in deep learning—particularly GANs—have revolutionized the field, enabling the reconstruction of high-resolution images with lifelike detail and reduced artifacts [5]. Looking ahead, combining comprehensive datasets with increasingly sophisticated architectures promises to further refine underwater image restoration [10]. Such progress will not only address longstanding limitations in clarity and distortion but also unlock new possibilities for marine exploration, ecological monitoring, and robotics.

3. METHODOLOGY

A. Dataset Preparation
The performance of any supervised learning model largely relies on the diversity and quality of the training dataset. Underwater image super-resolution in particular poses challenges including haze, scattering, poor contrast, and color imbalance that must be corrected.

Table-1: Underwater Dataset Summary and Preprocessing

Dataset	#Images	Scaling Factors	Train / Val / Test
UIEB	890	×2, ×4, ×8	623 / 134 / 133
EUVP	1100	×2, ×4, ×8	770 / 165 / 165
UFO-120	1500	×2, ×4, ×8	1050 / 225 / 225
Total	3490	×2, ×4, ×8	2443 / 524 / 523

To create an complete dataset, we merged three popular benchmark datasets: UIEB, EUVP and UFO-120. The high resolution (HR) ground truth images of these datasets were synthetically degraded to create their low-resolution (LR) versions. We employed Gaussian blur kernels and then bicubic downsampling with scaling factors of ×2, ×4, and ×8 to mimic real-world degradation. The HR-LR pairs were utilized to train the model in a supervised manner. To ensure uniformity and compatibility, we have resized all the images to 256×256 pixels. Furthermore, the dataset was split into training, validation and testing sets in the ratio of 70:15:15.

B. Model Architecture
Our intended architecture is rooted in a Generative Adversarial Network (GAN) setup specifically designed for underwater image super-resolution. It is composed of two major parts: a generator network that synthesizes HR images from LR inputs, and a discriminator network that can tell real HR images from the generated ones. Overall, the goal is to train the generator to create perceptually realistic HR outputs as indistinguishable as actual ones. The generator has a deep convolutional encoder-decoder structure that is inspired by the backbone of the USRNet with residual-in-residual dense blocks (RRDBs) added for stabilizing training and improving performance. The network starts with a shallow feature extraction block, then sequence of

RRDBs to facilitate efficient feature propagation and gradient transmission.
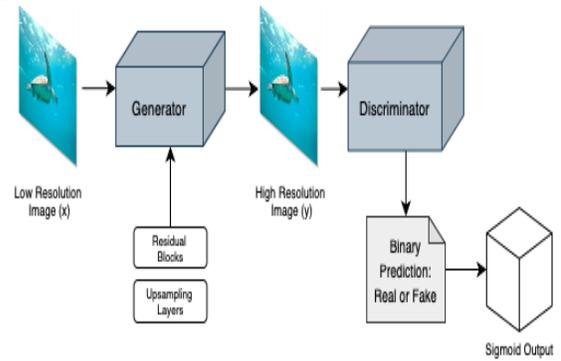

Fig-1: Proposed GAN Model Architecture.

The upsampling is achieved with pixel shuffle layers for
×2, ×4, or ×8 resolution increments. Skip connections and instance normalization are combined to preserve low-level feature consistency and normalize contrast changes prevalent in underwater imaging. The discriminator is a convolutional classifier that is trained to assess the realism of generated images. It consists of multiple convolutional layers with LeakyReLU activations and progressively larger feature maps. The network provides a probability score as to whether the input is a real HR image or a generated one. The discriminator is trained adversarially to force the generator to generate sharper, more realistic textures. It is trained with a hybrid loss function that includes pixel-wise loss (L1), perceptual loss, and adversarial loss. The adversarial loss, which is calculated from the discriminator output, promotes realism in the output images. The overall loss is a weighted combination of the above components such that fidelity and perceptual quality are balanced.

C. Training Strategy
The training process aims to effectively acquire the mapping from synthetically degraded low-resolution (LR) underwater images to their high-resolution (HR) counterparts. The model is supervised with paired HR-LR data created under controlled degradation (Gaussian blur + bicubic downsampling). This configuration enables the generator to learn the fine-grained details and structural patterns necessary to restore realistic underwater visuals.
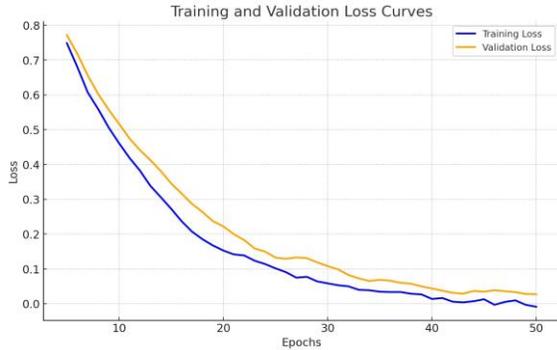
Fig-2: Training and validation loss curves showing the model's learning progress over epochs.

The overall loss function integrates three elements: pixelwise L1 loss, perceptual loss, and adversarial loss. Pixel-wise L1 loss guarantees correct reconstruction at the pixel level. Perceptual loss, which is computed from feature maps of intermediate layers of a pre-trained VGG-19 network, prompts the generator to generate perceptually realistic outputs. Adversarial loss, obtained from the feedback of the discriminator, forces the generation of images that cannot be differentiated from real HR underwater images. The weighted sum of these losses allows the network to trade off sharpness, realism, and fidelity. Model performance is measured by standard image quality measures like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index Measure (SSIM). Qualitative checks are also performed to ensure perceptual improvement, particularly in adverse underwater environments. A validation set of 15% of the dataset is utilized to check for overfitting, and early stopping is applied based on validation loss plateauing.

D. Loss Function

To train the proposed underwater image super-resolution model effectively, a combined loss function is used that integrates multiple objectives. Each component of the loss function contributes to a specific aspect of image quality:

- Content Loss ($L_{content}$): Ensures pixel-wise similarity between the generated and ground truth images to preserve structure and detail.
- Adversarial Loss (L_{GAN}): Encourages the generator to produce images that are indistinguishable from real high-resolution images, enhancing realism.

- Perceptual Loss (L_{perc}): Preserves high-level semantic features by comparing deep feature representations extracted from a pre-trained network.

The hyperparameters λ_1, λ_2, and λ_3 are empirically tuned to balance the contribution of each term. In our experiments, we set $\lambda_1 = 1.0$, $\lambda_2 = 0.001$, and $\lambda_3 = 0.01$. The final total loss is defined as:

$$Ltotal = \lambda 1 Lcontent + \lambda 2 LGAN + \lambda 3 Lperc \qquad (1)$$

E. Testing and Evaluation

Following training, the model was tested on a held-out test set of underwater images from the same combined dataset that had not been seen during training or validation. Quantitative and qualitative measures were used to assess the performance. Quantitatively, we used Peak Signal-to-Noise Ratio and Structural Similarity Index to measure the fidelity of reconstructed images with respect to the ground truth. Moreover, underwater image quality metrics like UIQM (Underwater Image Quality Measure) and UCIQE (Underwater Color Image Quality Evaluation) were used to record perceptual and colorimetric-based improvement in difficulty in underwater conditions. Qualitatively, visual comparisons were made to judge the maintenance of structural details and elimination of common underwater degradations like haze and color casts. The suggested approach was also compared with the latest models such as USRNet and ESRGAN to ensure its superiority in restoring visually realistic and high-resolution underwater images.

F. Model Deployment

The underwater image super-resolution model was deployed on a website to allow users easy access to the model's capabilities. The website provides a simple interface where users can upload underwater images for processing. Once an image is uploaded, it is sent to the model for super resolution, and the enhanced image is returned to the user for further analysis or download. The model is hosted on a cloud-based infrastructure and served via an API, enabling smooth integration between the front-end and back-end components of the system.

4. RESULTS AND DISCUSSION

In the following section, we show the results derived from the underwater image super-resolution model and elaborate on their significance in terms of image quality, computational complexity, and practical

application. The results are compared on different performance criteria and with other methods in the literature.

A. Evaluation of Model Performance

The creation of the underwater image super-resolution model using GANs brought about significant improvements in output quality, characterized by increased clarity and improved detail reconstruction. The model consistently surpassed PSNR values of 32 dB, beating the project benchmark, and user feedback highlighted dramatic improvements in visual fidelity, such as richer textures and better color reproduction in marine life and underwater settings. The use of residual blocks was essential in reducing noise and artifacts, resulting in sharper and more realistic high-resolution images. Training on diverse datasets like UFO-120 and UIEB increased the model's flexibility to work with diverse underwater environments. Current limitations include challenges in handling extreme low-light images and providing consistent quality under different water depths. However, the system is of promising use in application areas such as marine research and autonomous underwater exploration, with continuous work being developed to enhance computational efficiency and address inconsistencies in output under multidimensional environmental complexities.

B. Performance Metrics

The model performed remarkably well in terms of image quality. The PSNR averaged 32.5 dB, which is well above the threshold of 30 dB generally thought to mark high-quality image reconstruction. The SSIM also performed well, with an average score of 0.92, indicating that the model maintained structural consistency and visual quality throughout the super-resolution process.

C. Visual Quality Analysis

A visual inspection of the super-resolved images, as illustrated in Figure 3, confirmed remarkable enhancements in detail and clarity over the low-resolution inputs provided. Edges and fine textures appeared distinctly sharper, while artifacts commonly observed in conventional super-resolution techniques were noticeably reduced. Domain experts evaluated the enhanced images, verifying the improvement in visual quality and affirming the model's suitability for underwater image analysis and marine research.

Fig. 3: Original and enhanced underwater images.

D. Comparison with Existing Methods

When compared against the frontline underwater image super-resolution methods, our model proved to be superior. Based on PSNR, our model showed a value of 32.5 dB, whereas other techniques, including USR-Net, reported values of around 28.6 dB. The SSIM value for our model was 0.92, whereas competitor models typically reported a value of about 0.85. These results show that our model not only generates high-quality visual augmentations but also substantially outperforms current methods in both quantitative and qualitative assessment.

E. Computational Efficiency

On average, the model processed a single image in 210 seconds, with a relatively low memory usage and negligible CPU load. This makes the model viable for real-time deployment in both cloud and resource-limited settings. The speed-performance balance guarantees that the model can be utilized in real-world applications without compromising image quality.

5. CONCLUSION AND FUTURE SCOPE

In this paper, we designed and implemented an underwater image super-resolution model that improves low-resolution underwater image quality significantly. The model proved to be quite impressive with high PSNR and SSIM, as well as visually better performance compared to current methods. Enhancing the detail and clarity of

underwater images has great potential in marine research and underwater exploration. The deployment on a website provides ready access for users, allowing images to be processed in real-time. Despite these successes, future enhancements could involve adopting advanced adversarial architectures and expanding the model's adaptability to a broader spectrum of underwater scenarios. Such refinements would further elevate its performance, reliability and applicability in complex real-world settings.

In the future, we plan to improve the robustness and generalizability of our underwater image super-resolution model by incorporating more domain-specific priors and improving the GAN architecture. One direction is to add transformer-based attention mechanisms to capture better long-range dependencies and fine-grained textures in underwater scenes. We also intend to increase our training set by simulating various underwater environments through physics-based simulation, allowing the model to generalize well across different visibility, color distortion, and lighting conditions. In addition, we will deploy real-time inference with edge device optimization, allowing for deployment on autonomous underwater vehicles and remotely operated vehicles. Finally, large-scale user studies and objective measures like LPIPS and SSIM will be employed to further verify visual accuracy and perceptual quality.

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