AP-GAN: Attention PatchGAN for Low Light Underwater Image Enhancement

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Declaration

It is hereby declared that

1. The thesis submitted is our own original work while completing degree at Brac University.

2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.

3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.

4. We have acknowledged all main sources of help.

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Abstract

Many pictures taken underwater suffer from low brightness, inadequate contrast or loss of fine details due to turbid waters and light absorption. Hence, this paper introduces **AP-GAN** (Attention PatchGAN), a deep learning framework which is specifically composed for the enhancement of underwater pictures. In this method, a U-Net generator is used to ensure enhanced structural fidelity and global colour correction. The adversarial feedback is delivered by a PatchGAN discriminator which again performs a local critic role, evaluating overlapping patches of the image to actively enforce the preservation of realistic textures and fine details. The proposed approach is applied on several underwater image databases and compared to classical enhancement strategies. Experimental results indicate that our model based on GAN is better than current methods, especially in colour preservation, contrast enhancement, and detail preservation. This paper focuses on the value of deep learning methods, specifically generative adversarial networks (GANs) with customised architectures such as U-Net and PatchGAN, in improving underwater images and recovering the fine details and structure of objects contained in them.

Keywords: Attention PatchGAN, Generative Adversarial Networks (GANs), U-Net, PatchGAN, Color Preservation, Detail Retention.

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Chapter 1

Introduction

1.1 Background

Underwater imagery is an important tool in marine biology, underwater archaeology, infrastructure inspection and defence. However, the medium of water itself presents considerable challenges to getting clear visuals. Light is affected by wavelength-dependent absorption and scattering by suspended particles, resulting in the typical degradations of underwater photographs: a dominant blue-green colour cast, greatly diminished contrast, haze, and an inability to distinguish fine detail. These problems not only affect the visual quality, but also the performance of computer vision algorithms for object detection and segmentation.

The quest for solutions has gone through a number of phases. Early methods have relied on non-physical techniques such as Histogram Equalisation (HE) and Contrast Limited Adaptive HE (CLAHE) to stretch the contrast, often at the expense of unnatural colours and magnified noise. Subsequently, physical model-based techniques, like that based on the Underwater Dark Channel Prior (UDCP) were developed to try to reverse the optical degradation by estimating parameters such as a transmission maps and background light. While effective in certain situations, these model-based approaches do not always work in different water situations and may give rise to artefacts.

The coming of Deep Learning changed the paradigm. Convolutional Neural Networks (CNNs) began to learn the complex mapping from degraded image to clear image directly from the data. Architectures such as U-Net, with their skip connexions, were thus able to do an excellent job of preserving the structural information while performing enhancement. More recently, Generative Adversarial Networks (GANs) have pushed the limit on perceived quality. The frameworks like pix2pix proved that the combination of a U-Net generator and a PatchGAN discriminator could be highly effective in image-to-image translation tasks. The significance of the PatchGAN as a local critic is great since it motivates the generator to produce realistic high frequency textures, which is a main criterion for the restoration of underwater details. This project builds upon this cutting-edge foundation by introducing **AP-GAN**, which exploits synergistic capabilities of U-Net and PatchGAN while incorporating attention mechanisms to address the persistent challenges in underwater image enhancement.

1.2 Rational of the Study or Motivation

Degradation in images underwater has real world consequences. For marine scientists it makes identifying species and tracking habitats difficult. For roboticists, this gets in the way of autonomous navigation and manipulation. Existing enhancement techniques often present a trade-off: improving the contrast can introduce inaccurate colours, while reducing the haze can make fine details more difficult to see. There is a definite and urgent need for a robust and generalised solution that can correct colour and improve contrast at the same time as preserving critical structural details without introducing significant artefacts.

The motivation for this study is the proved potential of GANs in generating images that are perceptually better looking, and the architecture-specific strengths of the U-Net and PatchGAN. In order to resolve this problem, by constructing a designed underwater image enhancement model according to this combination, this paper hopes to fill the gap between global colour correction and local details retention. The success of this approach has the potential to greatly enhance the clarity and utility of underwater visual data, providing support for a huge range of academic, industrial and environmental applications.

1.3 Problem Statement

Classical histogram-based approaches and physical model-based restoration are the existing underwater image enhancement techniques that are usually difficult to apply to different underwater environments. They are often known to generate outputs with unrealistic colour rendition and insufficient contrast enhancement or losing fine text details. While deep learning approaches have improved, many of them do not include a mechanism to explicitly ensure global structural fidelity and local texture realism. Therefore the particular problem this research is addressing is the creation of a strong deep learning model which can comprehensively improve underwater images by accurately restoring the colour and contrast while faithfully preserving and enhancing the finest details.

1.4 Objective

The objective of this work is to create, implement and test a Generative Adversarial Network (GAN) for improved restoration of underwater images. The specific objectives are:

- A GAN structure was developed that is composed of a U-Net generator for global structural and colour correction, and PatchGAN discriminator which is responsible for local realism of detail.
- To train the proposed model on a curated dataset of underwater images.
- • To adopt a quantitative model performance evaluation approach based on standard image quality metrics like PSNR, SSIM, and LPIPS, UIQM and UCIQE, while a qualitative measure is provided by visual inspection.

- A study of the methods comparing the proposed one with the previous classical as well as deep learning methods reveals the excellent quality of the colour preservation, enhancement of the contrast and the detail being preserved, and also we prove our method to be the best in the case of these performances over the existing technologies.

1.5 Methodology in Brief

This paper presents a deep learning-based method based on a Generative Adversarial Network (GAN) architecture called **AP-GAN** to address the underwater image enhancement problem. The methodology was implemented in several main steps:

- **AP-GAN Network Architecture:** The basic model consists of a U-Net generator and a PatchGAN discriminator. Finally, a Residual Block and a CBAM (Convolutional Block Attention Module) are introduced to U-Net to facilitate effective global structure and colour restoration. The PatchGAN discriminator is a local critic, which forces the creation of high frequency realistic details.

- **Data Collection & Processing:** A curated dataset of paired underwater images (degraded inputs and ground truths) was used. The dataset was preprocessed by using a custom pipeline including data augmentation, and partitioned into training (85%), validation (10%), and testing (5%) sets.

- **Training & Analysis:** An NVIDIA RTX 4090 GPU was utilized for the model training, where a combination of pixel-wise loss (MAE, MSE), perceptual loss (VGG-based) and adversarial loss was used. Mixed precision training (BF16) was employed for computational efficiency. The performance of the proposed model in terms of colour preservation, contrast enhancement and detail preservation was tested by the model's quantitative evaluation through the metrics Peak Signal to Noise Ratio (PSNR), Structural Similarity Index (SSIM), LPIPS, and Underwater Image Quality Measure (UIQM) and Underwater Colour Image Quality Evaluation (UCIQE).

1.6 Scopes and Challenges

Scope

This work is restricted to the enhancement of static underwater images by a supervised deep learning approach. The LSUI dataset is mostly used for training and evaluation. The majority of research is focused in the following areas:

- **Architecture Exploration:** Comparative analysis of different architectures of GAN including enhanced U-Net with PatchGAN, U-Net3+, and dual discriminator architecture was conducted, to determine the best architecture of GAN for underwater image restoration.

- **Final Model:** The AP-GAN (Attention PatchGAN for Low Light Underwater Image Enhancement) proved to be the configuration that provided the best overall performance.
- **Image Processing:** Focus is given to the enhancement of still single images, including global colour correction, contrast enhancement and local detail restoration.
- **Evaluation:** Both the quantitative and moreover the qualitative assessment is carried out using standard image quality assessment metrics, such as PSNR, SSIM, LPIPS, UIQM and UCIQE.

Challenges

Multiple challenges have been encountered and addressed during the course of this study:

- **Architectural Selection:** Preliminary experiments of complex models like U-Net3+ and dual discriminator GAN did not perform better than the final U-Net + PatchGAN model. These alternatives often had the effect of driving up a computer's cost without significant increases in performance, and emphasised the challenge of finding a balance between performance and efficiency.
- **Computational Limitations:** Training and comparing multiple deep GAN architectures requires a lot of computational power. Although a Nvidia RTX 4090 is used for the GPU card, this constrained the ability to a large number of hyper-parameter tuning and experimentation.

Chapter 2

Literature Review

2.1 Preliminaries

This section outlines the fundamental concepts and architectures that form the foundation of this research. A clear understanding of these components is essential to perceive the design and mechanics of the proposed AP-GAN model.

2.1.1 Generative Adversarial Networks (GANs)

Generative Adversarial Networks (GANs) are a form of a deep learning model that is based on a game-theoretic principle. A conventional GAN comprises two neural networks which are Generator (G) and Discriminator (D), and they are trained one against the other in a kind of warlike manner. The generator gets trained in such a way that it produces synthetic data samples that closely resemble the training data, and the discriminator gets trained to be able to tell the difference between the real data in the training set and the synthetic ones. In the case of image enhancement applications, this framework gets applied to the situation where the generator is to change a degraded input image into an enhanced output and the discriminator is to evaluate the quality of the enhanced output.

2.1.2 U-Net Architecture

U-Net is a convolutions neural network algorithm for image processing tasks. It comes with a symmetric architecture of encoder-decoder structure with skip connections. The encoder first extracts features and then gradually reduces the input image's spatial dimensions. The decoder takes these features and up-scales them to get back the original image resolution. Meanwhile, the skip connections are merging the high-resolution data from the encoder with the processed features of the decoder. This design is suitable for the underwater image enhancement problem, because it helps to preserve the structural details from the input to the output.

2.1.3 PatchGAN Discriminator

A PatchGAN discriminator is a form of discriminator which makes judgments based on local image patches instead of an entire image. It computes a matrix of outputs in which each element is the amount of resemblance of a particular patch with the input image. Thus, the generator receives a stimulus to produce the textures and structures that are realistic to the local area in all of the local regions. The technique is efficient in terms of computation and has also been established to enhance the visual quality of the generated images through the use of local features.

2.1.4 Attention Mechanisms: CBAM

Attention mechanisms are ways in which a network gives focus to what is important during processing. **Convolution Block Attention Module (CBAM)** is a channel and spatial attention module for handling feature maps. The channel attention module detects the informative features through the inter-channel relationship analysis. The spatial attention component identifies the salient areas in the feature maps. By using such attention mechanisms, the model is able to pay attention to relevant details in degraded underwater images, which may result in better enhancement.

2.1.5 Evaluation Metrics

The performance of image enhancement models is measured based on a number of standard measures.

- **Peak Signal to Noise Ratio (PSNR)**: It is basiclly pixel to pixel measurement of difference between two images. The better the reconstruction the higher are the values of PSNR.
- **Structural Similarity Index Measure (SSIM)**: This value measure the perceptual similarity of images which based on the structure, luminance and contrast features of the images. Values are between 0 and 1, the value is high if the characteristics are preserved in the structure well.
- **Learned Perceptual Image Patch Similarity (LPIPS)**: computes the perception distance of images by the features of a pre-trained network. The lower the score, the better the perception of similarity.
- **Underwater Image Quality Measure (UIQM)**: It evaluates underwater image quality based on the colorfulness, and sharpness, also the contrast. Higher values indicate better overall image quality.
- **Underwater Color Image Quality Evaluation (UCIQE)**: Quantifies underwater image quality using colorfulness, saturation, and contrast of chroma. Higher values represent better visual quality and color balance in underwater scenes.

2.2 Review of Existing Research

Opposing issues of light absorption, in which red light is reduced within several meters creating blue-green images with low penetration, and scattering due to particulate matter that reduces image quality and contrast are all challenges for underwater imaging. These lead to texture and feature loss, colour distortion of the images and distorted generation of visual data, making tasks such as navigation and mapping challenging [35]. In order to overcome these issues, the study employed the Generative Adversarial Networks (GANs), such as the WaterGAN, CycleGAN, whilst DenseGAN that generated realistic underwater images by altering colour and compensating for light loss and recreating small details. By training these models with EUVP and UIEBD datasets, we observed enhancements in PSNR, SSIM and other factors that determine color contrast, structural detail and realism in images that were used in robotic navigation and marine studies. However, the methods are dependent on the quality of the training data, which is computationally intensive, sensitive to variations in underwater environment, and synthetic outputs occasionally contain artifacts; these results underscore the importance of improving the methods for various underwater conditions, as stated by [35]. In the study by [33] entitled Lightweight Underwater Image Adaptive Enhancement Based on Zero-Reference Parameter Estimation Network, the work has addressed some challenges such as the issue of poor and complex lighting condition in underwater image that leads to certain degree of color attenuation and contrast reduction. Typical deep learning approaches entail encountering paired train data, hence they create complex networks, high computational time for model training and lengthy duration. To address these issues, the study developed the Zero-Reference Parameter Estimation Network (Zero-UAE), which is basically a low complexity model intended for the under-water image enhancement. The Zero-UAE employs an underwater adaptive curve model involving light attenuation to equalize perhaps lighting and colour bleaching. The quality is further optimized by using other specific non-reference loss functions and an adaptive changing lightweight parameter estimation network for additional parameters. Concerning effectiveness in three realistic datasets, Zero-UAE achieved performance on par with prior techniques, with a sparse architecture of 17K parameters – appropriate for low-power underwater detection applications. But, the model might require more clarification to it for better underwater environment execution [33].

The paper by [34] named 'Underwater Image Enhancement Algorithm Based on Adversarial Training' addresses problems of underwater image degradation due to factors like color shift distortion, blurriness, and varying brightness levels caused by light attenuation, scattering, and underwater turbulence. Most classical enhancement methods neglect the intricate distortions, particularly the trivial distortions, that exist in the real ocean environments. In order to achieve this, the paper presented a technique that blended adversarial learning in a data pre-processing step which could lead to dramatic color casting improvement, in addition to GANS improvement. Which is constituted by the design of a new high-dimensional semantic cyclic loss function, and the adaptation of the size of the generator towards imitating the features. Outcomes from experiments on three public datasets showed that all general approaches proposed in this paper were effective compared to existing methods concerning the quality assessment metric measurements such as subjective and objective measures including UCIQE, UIQM, entropy and other. However, the model is not able to identify big underwater areas, and for good results, significant hardware is required as stated by [34].

PUGAN: "Physical Model-Guided Underwater Image Enhancement using GAN with dual discriminators." by [29] states that light absorption and scattering in water make it difficult to improve underwater photos with low contrast, color distortion, and inadequate information on objects. Previous approaches concentrated on either improving visual quality using GAN loss functions or increasing robustness through physical regression models, but not at the same time.For this purpose, the research introduced PUGAN: a GAN framework guided by physical models that features Dual Discriminators. The model comprises a Parameters Estimation subnetwork that determines the parameters of the physical model for image inversion and a Two-Stream Interaction Enhancement subnetwork that enhances the crucial areas using a Degradation Quantization module. The Dual-Discriminators implement style-content adversarial constraints to improve realism and aesthetics. Thereafter, the effectiveness of PUGAN was validated on three benchmark datasets, achieving considerably higher PSNR and reduced lower MSE in comparison to alternative methods. Nonetheless, obstacles such as a large model size, increased computational complexity, and comparatively low reliability in highly turbid water or varying light condition environments persist [29].

In “UnderWater Image Enhancement with Capsules Vectors Quantization” by [26], obstacles have been faced in addressing the deterioration of underwater images resulting from wavelength-dependent light attenuation, scattering, and variations in water types.Generally, conventional techniques encountered challenges in scalability, especially with different dataset formats, and frequently necessitated either large amounts of data or intricate physical models. To address these issues, the study introduced UW-CVGAN, an innovative framework that integrates a VAE with a capsule layer in the latent space to achieve quantization goals. This approach leverages the clustering ability of capsule layers to differentiate important features from images while also reducing the image sizes by a factor of three. In contrast to other models, UW-CVGAN allows encoders to operate independently in image compression, resulting in improved memory efficiency. The algorithm’s experimental evaluation on benchmark datasets like EUVP, HICRD, UIEB, and USR248 has shown that the suggested UW-CVGAN surpassed the leading methods in terms of UCIQE (Urban Color), UIQM (Unified Image Quality Metric), and PSNR (Peak Signal-to-Noise Ratio) Nonetheless, it has certain drawbacks, particularly in color restoration regarding the red component of images, and better methods for handling extreme underwater distortions must be developed [26].

In the paper, ”Separated Attention: The underwater image enhancement method proposed in ”An Improved Cycle GAN Based Underwater Image Enhancement Method” by [31] has faced issues associated with underwater image degradation due to the absorption and scattering of light and color distortion, which affects basic tasks such as object detection and navigation for AUVs. The canonical enhancement techniques were not very effective when it came to generalization, and computational complexity hampered the ideal contrast and features reconstruction. To overcome these issues, the study put forward an improved CycleGAN model with a new loss function including depth-oriented attention. This method uses depth maps produced by the novel Depth Anything model to accomplish primarily adaptive contrast enhancement with secondary benefits of preserving content, color, texture, and style information in the background. For the model training, the researchers used a data set referred to as Enhancing Underwater Visual Perception (EUPV), which encompass pair and/or non pair underwater images. The comparative analysis of the results obtained by the proposed method with those of the state-of-the-art methods such as CycleGAN, Pix2Pix, FUnIE-GAN showed the efficiency of the developed approach, revealing better performance in terms of PSNR, SSM, and UIQM. However, the model had a heavier time for processing and a shift in background and foreground boundaries which could be solved in [31].

In the paper titled, "Multi-Level Attention GAN for Enhanced Underwater Visibility" authored by [22] has been constrained in dealing with the underwater image degradation where colors are distorted, contrast reduced, and images blurry which affects visual analysis in under water conditions. The traditional approaches were designed with poor means of achieving the existing goals of preserving the features of the image while enhancing it, which led to noise as well as artifacts in the image being restored. To address these problems, the study developed a new Generative Adversarial Network (GAN) model called MuLA-GAN. Compared to the original model, this model promotes more precise feature learning that concentrates on spatial and channel-wise features while also effectively preserving image details and restoring the images. Substantial experiments on various data sets consisting of UIEB, U45, UCCS and a species specific bio-fouling data set revealed that MuLA-GAN had superior performance over current benchmark in terms of quality and quality and also in terms of quantitative measures of PSNR value of 25.59 and SSIM value of 0.893. As powerful as it is, MuLA-GAN has disadvantages in terms of its computational speed owing to the depth of the model and may have to be optimized for real-time modelling [22].

The study titled: "Underwater Image Enhancement and Restoration Using Cycle GAN " presented by [23] has its challenges in degradation of the underwater images due to light scattering, absorption effects and color shift. They produce low contrast, unwanted color changes and blurring which makes activities like underwater, object detection, assessment of scene to be tricky. To overcome these issues, the study introduced an unpaired underwater image enhancement technique based on the CycleGAN. This model uses a generator with a content loss regularizer to ensure important details in the low-resolution underwater image are retained as the image is transformed from a low resolution to high resolution image. The model was trained with the help of the ADAM optimizer and on the data of the Enhancing Underwater Visual Perception (EUVP) dataset. The results indicate that the improvement of image quality is achieved, based on MSE and MAE, when the proposed model is used instead of state-of-the-art approaches. However, the desired performance of the model level is achieved with the help of hyperparameters tuning to manage the overfitting problem that still persists and real-time implementation issue, and extreme circumstances of underwater environment [23].

In a study done by [32] entitled, "A Novel Lightweight Model for Underwater Image Enhancement." it is shown that quality of underwater image has been degraded when it is affected by color shift, low contrast, and low-resolution which are as a result of light absorption and scattering. In traditional deep learning, models with high computations were used which caused problems of real-time detection in an underwater environment. To tackle these issues, the research introduced a compact model called Rep-UWnet, which integrates a fully connected convolutional network with three densely connected RepConv blocks, incorporating multi-scale hybrid convolutional attention modules. This design improves useful features and at the same time greatly shrinks the model size and computational costs. Rep-UWnet reduces parameters by about 83% from 2.7 M to 0.45 M while achieving higher PSNR, SSIM and sometimes a higher UIQM than state-of-the art methods.

The proven disadvantage of this technique however is its capability of performing sub optimally in highly complex underwater scenarios and requires further enhancement for real-time features [32].
In the research paper, "Simultaneous Restoration and Super-Resolution GAN for Underwater Image Enhancement" by [27] has experienced the problem in under water imagines that includes blurriness, noise and color distortion which limits tasks like object detection and recognition. Previous approaches were ineffective in combining image enhancement and super-resolution when dealing with underwater images and varying and challenging conditions. To address these challenges, the researchers created the Simultaneous Restoration and Super-Resolution GAN (SRSRGAN), which is a fully trainable model utilizing a two-stage generative adversarial network. The initial phase utilizes a multi-level degradation restoration generator (MLDRG) to restore degraded images, whereas the final phase employs a high-frequency learning module (HFLM) to improve image details.Unlike other approaches that work based on preknown degradation types, this unified approach works better with higher adaptability.Another comparison shown that the suggested SRSRGAN outperformed other methods used for image restoration and enhancement in terms of PSNR, SSIM, UCIQE, and UIQM rank. However, [27] state that the model is not the best under severe underwater circumstances and may need to be employed further.
The study "DGD-CGAN: A Dual Generator for Image Dewatering and Restoration" by [19] focuses on problems with underwater picture quality brought on by light attenuation and scattering as well as color distortion that causes blurriness and decreased contrast. Earlier approaches struggled with color correction and dehazing, most likely due to their reliance on depth information and the absence of an easily accessible training dataset. In light of these difficulties, this paper introduces the Dual Generator Dewatering Conditional Generative Adversarial Network, or DGD-cGAN. Two U-Net-based generators are employed in this model: one predicts the dewatered picture, while the other assesses transmission and veiling light using the image generation model for underwater images. Compared to the traditional methods and the existing work, the proposed RRDNet can operate without the water column parameters or depth inputs while using two decoders for color correction and haze reinforcement. Based on the authors' studies, DGD-cGAN outperformed some other algorithms on some benchmarks and criteria, such as PSNR, SSIM, and UIQM. Yet, the presented model has several drawbacks, among which the absolutely limited size of the training sample is the most striking one. Furthermore, there could be situations where Change Detection is less effective; this is in instances where there is high levels of under water movement or turbulence [19].
[25] study, "A Hybrid Approach for Underwater Image Enhancement Using CNN and GAN", addressed issues including low resolution, light scattering, color distortion, and poor lighting that deteriorate underwater images. Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs), two independent deep learning models, and other conventional techniques have had difficulty striking a balance between numerical accuracy and perceptual quality when enhancing underwater images. In order to address these issues, the study proposed a hybrid model that combines the advantages of both CNN and GAN frameworks. With the GAN component, visual quality is improved, while the CNN component concentrates on improving numerical metrics. This hybrid model was trained and tested

using the EUVP picture dataset, which comprises a range of underwater image sets with different image quality. The proposed hybrid technique performed better in terms of PSNR and SSIM than the CNN and GAN models when applied alone, according to experimental data. But because of its vast training dataset and high computational complexity, it is not well executed, which might lead to a decline in scalability and performance [25].

The 2018 paper "Enhancing Underwater Images using Generative Adversarial Networks" by [10] covered a number of topics, including color shifting, light refraction, light absorption, and scatterers in water. Vision-based tasks, which are essential for autonomous underwater vehicles (AUVs), are difficult because of these problems, as demonstrated by the example of object detection and recognition. The study suggested employing Generative Adversarial Networks (GANs), particularly CycleGAN, to create paired datasets of underwater clear and foggy images in order to address these issues. With this method, unsupervised learning may be used in place of ground truth data, which can be difficult to collect and occasionally time-consuming. The utilized GAN model was presented as Underwater GAN called UGAN with the optimization of one modified Gradient Difference Loss for the underwater images enhancement. From the data collected by the authors they stated that the Quantity of the main idea of the suggested advanced UGAN technique over the CycleGAN in the images quality and mentioned that it has better performance in the algorithm of tracking of underwater divers. However, some of them are inherent in the use of artificial data for model creation and can pose problems with adapting version changes to different types of water bodies [10]

In the underwater image enhancement technique in [14] study titled "Towards Real-Time Advancement of Underwater Visual Quality with GAN," the authors encountered several issues caused by light absorbance, scattering, and color changes to the images. These aspects, to some extent, define the prospects for using underwater robotic vision in practice. In response to these difficulties, the authors proposed a new Restoration Scheme known as the Generative Adversarial Networks which is commonly mentioned as GAN-RS with a Discriminator structural design that offers a branch with adversarial content evaluation of results and another branch with critic and noise reduction capacities. Also, for controlling the training process, a new loss named dark channel prior (DCP) loss together with the underwater index loss were used, so the generator can enhance underwater images in real-time. Experimental findings indicated that GAN-RS demonstrated superior visual quality compared to the state-of-the-art methods, with a computational rate of 133:77 FPS. Moreover, the realized effectiveness of the proposed method was demonstrated through the presentation of actual practical real-life tests to perceive the underwater objects. However, there are limitations in the model because it is challenging and pricey to collect underwater training data, and the parameters have to be tuned to avoid artifacts in the edited images [14].

[16] identified a number of problems in their study "Super-Resolution Reconstruction of Underwater Image Based on Image Sequence Generative Adversarial Network." They explained that while previous research attempts to address the distortion and low quality of underwater images caused by light scattering, absorption loss, and environmental factors, they also identified some particular difficulties. This type of SR commonly uses two traditional SR techniques, interpolation and sparse representation, which have trouble producing improved pictures with distinct edges and

have a hard time distinguishing between different image features. Using the dual generator approach, the authors created the Image Sequence Generative Adversarial Network (ISGAN) to get over the aforementioned restrictions. While the second generator helps with training and eliminates noise, the first generator produces HR pictures. Four distinct procedures are used in the preprocessing phase to improve the input images: contrast limited adaptive histogram equalization (CLAHE) and white balance modification. Finally, to enhance feature extraction, the cross image fusion technique is used with SWT and PCA.
The research called ”FE-GAN: In “Fast and Efficient Underwater Image Enhancement Model Based on Conditional GAN” published by [24], the authors raise challenges with underwater image degradation inclusive of light absorption, scattering, or color distortion that hampers real-time application in underwater robotics. In particular, traditional enhancement methods encountered challenges when pursuing the two objectives: performance improvements and rate of computation, which acted as constraints on real-world usage of the technology. To address such challenges, the research proposed about FE-GAN, a fast and efficient underwater image enhancement model base on a conditional Generative Adversarial Network (GAN). For the feature extraction the model uses Hierarchical Attention Encoder (HAE) and for the residual learning the Dual Residual Blocks (DRB) are used. Structural re- parameterization simplifies complex architectures to typical convolutional layers which improves prediction time and reduces memory consumption. From the testing of both real and synthetic data sets it was observed that FE-GAN performed better that leading models in terms of image quality improvement and metrics such as PSNR, SSIM, and UIQM as well as real time processing. However, the model was limited in enhancing very low light underwater images and may require further enhancement for deep sea applications [24].
The paper ”A Two-Stage GAN for Underwater Image Colour Correction and Super-Resolution”, published in Applied Sciences, aims to solve the twofold problems of colour distortion and low resolution in underwater images due to wavelength-dependent absorption and scattering of light. Traditional colour correction and super resolution processing methods are typically independent of each other, which might result in error cascading and suboptimal performance. To tackle this, the authors introduced a two-stage Generative Adversarial Network (GAN). The first stage, called colour correction, corrects the colours distorted by the water column so that their original coloration is once again apparent, while the second stage, called super-resolution, increases the image resolution and sharpness. This cascade method ensures that the super resolution network processes a colour corrected image resulting in more accurate and visually pleasing output. Experimental on benchmark datasets showed that the proposed method outperforms existing single-task models in terms of both colour fidelity and image sharpness (PSNR and SSIM, respectively). However, the two-stage process is computationally expensive and leads to long inference time which can be a constraint for real-time applications.[28]
”Underwater Image Enhancement by Wavelength Compensation and Dehazing”, posted to arXiv, addresses the issues of colour cast and haze that so ruin underwater visual quality. The authors point out that most deep learning-based methods are trained on synthetic data and fail to generalise to various real-world underwater environments. In this paper, a hybrid physical-deep learning model is proposed, which uses a wavelength compensation algorithm to alleviate the overpowering blue-

green colour cast firstly. After that, a scattering removal and contrast enhancement network is applied based on conditional GAN.The merging of a physical model of light propagation and a data-driven deep learning approach leads to the method that is resistant to various water types. Both quantitative and qualitative analysis show superior performance over the best existing methods for metrics like UCIQE and UIQM. However, one of the major drawbacks of this method is the identification of the water attenuation parameters, which are often hard to determine in very turbid or otherwise uncharacteristic water conditions.[17]
In "UIE-Net: A CNN-Based Model for Underwater Image Enhancement," researchers at the Institute of Electrical and Electronic Engineering (IEE) tackle photo quality problems such as the colour distortion and also the low contrast. However, GANs are known to be hard to train and can generate unrealistic artefacts, they say. In this paper, we introduce CNN architecture UIE-Net for enhancing underwater images. The model adopts the attention mechanism to highlight the important features, and incorporates the multi-scale feature fusion module for handling objects of different sizes. Significant enhancement is achieved by introducing perceptual loss function based on a pre-trained VGG network which further facilitates generating visually coherent and natural image synthesis. Experiments on UIEB and EUVP datasets demonstrate that UIE-Net can achieve a good trade-off between enhancement quality and computational cost, and is often superior to more complex generative adversarial network (GAN) based models in terms of PSNR performance. The main limitation is that the model was trained with paired data which is not easily or inexpensively obtainable for many underwater use cases.[18]
The new paper "A Multi-colour Space Embedding Network for Underwater Image Enhancement", published in Frontiers in Marine Science, addresses the fact that it might not be enough to improve images in a single colour space (such as RGB) to compensate for the complex degradations occurring underwater. The authors introduce a new network architecture that takes image features in multiple colour spaces into account, RGB, HSV and Lab. This multi-colour space embedding enables the model to take advantage of the benefits of multiple colour representations: RGB for raw pixel data, HSV for value and saturation, and Lab for perceptual colour constancy. These different spatial characteristics are integrated into a united encoder-decoder network from which the output is the final enhanced image. The correctness in colour and contrast enhancement are the major areas where this method shows good performance, even better than single colour space methods, as evidenced by the higher scores obtained with UIQM and UCIQE metrics reflecting this. A drawback of this method is that, due to the parallel processing of multiple colour space inputs, the size and memory requirement of the model will increase.[20]
The article "Underwater Image Enhancement Using a Self-Supervised Learning Strategy" from MDPI's Mathematics journal looks at the issue of limited paired training data for underwater image enhancement. The authors point out that it is impractical to acquire a large dataset of paired degraded and clear underwater images, which limits the performance of supervised models. To tackle this, they developed a self-supervised learning framework which needs only a set of degraded underwater images for training. The method relies on the observation that the statistics of an uncorrupted image should be invariant to colour channels and spatial locations. By learning a series of pretext tasks enforcing these consistencies, the model learns to reconstruct images without clean references. The enhanced images

demonstrate a significant improvement in colour balance and visibility compared to the original images, and perform competitively with supervised methods on no-reference metrics such as UIQM. The key issue of this tactic is that the enhancement quality is very much reliant on the unlabeled training set's quality and diversity and does not necessarily equal the performance of the best supervised models.[30]
The article "A Comprehensive Benchmark and Analysis of Deep Learning for Underwater Image Enhancement" published in Scientific Reports covers much of the field, and even though many deep learning models have been proposed, a fair and comprehensive comparison is often missing. This work addresses this gap by performing a benchmark of more than 20 state-of-the-art deep learning models for underwater image enhancement on a large scale. The models are tested on multiple datasets using a broad range of full-reference, no-reference, and task-based measures. The results of the analysis show that there is no single model that maximises performance on all metrics and datasets; GAN-based models tend to score highly on perceptual quality and no-reference metrics, while CNN-based models with pixel-wise losses tend to score highly on PSNR/SSIM. The benchmark also reveals the trade-off between model performance, computation complexity and inference speed. The authors conclude that the selection of model should be informed by the application requirements (e.g., real-time operation vs. maximum quality). One limitation that has been identified is the rapid evolution of the field, so that new models published after the benchmark may not be included.[36]
The paper "Contrast Limited Adaptive Histogram Equalisation" by [1] is a seminal paper in classical image processing. It solves the issue of ordinary histogram equalisation where noise in homogeneous regions of an image is over-amplified. The author presented the CLAHE algorithm, which works on small areas of the image instead of whole image. By reducing the contrast amplification in these areas, CLAHE can effectively increase the local contrast, while reducing noise. This method has become a standard pre-processing and enhancement tool in many fields, such as medical imaging, and as mentioned here, as a classical baseline for underwater image enhancement. Its main advantage is its simplicity and effectiveness without the need for a physical model of the degradation. However, as a non-physical technique it does not particularly solve the wavelength-dependent colour distortion inherent in the underwater environment.
The work "Enhancing underwater images and videos by fusion" proposes a classical, but effective way of image enhancement, exploiting multi-scale fusion. The authors write that different image processing techniques can yield different outcomes, each of which has its own strengths (such as increasing contrast vs. correcting colour). Instead of relying on only one such method, they put forward a fusion strategy that combines several derived inputs (a white balanced version and a contrast enhanced version of the original image) into one superior output. Weight maps based on measures of saturation, contrast, and saliency are used to guide the fusion process in a multi-scale pyramid framework. This approach works well in improving colour, contrast and sharpness simultaneously without requiring a physical model or training data. A limitation, its performance is dependent on the quality of the input derived images and hand-crafted design of the weight maps.[2]
In [26], the authors of the article "Transmission Estimation in Underwater Single Images" consider the problem of estimation of the transmission map, which is crucial for the inversion of the physical model of underwater image formation. The cited

work of Dark Channel Prior (DCP) for atmospheric haze removal is extended to an underwater scene and an Underwater Dark Channel Prior (UDCP) is proposed. One significant alteration is that the dark channel is computed from the blue and green color channels only since red light in water is quickly attenuated. This prior can be used to derive the transmission map from a single photograph, which can then be applied to restore the scene's radiance and bilinearly eliminate the haze effects. This paper presents an important initial work in the use of physical model-based priors for underwater images. However, the method may break down in scenes containing bright objects, or in cases where the ambient light is not uniform, since these situations do not conform to the underlying assumptions of the prior.[3]
The work of [5] is another milestone in the field of physical model-based restoration. The authors point out that the red channel is the most attenuated in water and has the least information. We present a scheme based on estimating the transmission map by the red channel, assuming that this channel is dominated by backscattered light (the veiling light). By extracting features from the red channel, the parameters to the image formation model can be estimated, and a restoration is done. This technique is especially good at reducing dominant blue-green cast and increasing contrast. A major limitation is that it is only valid for very turbid water or when the red channel is not the most degraded, in which case it can produce inaccurate transmission estimates and colour artefacts. The paper by [11] WaterGAN: Unsupervised generative network to enable real-time colour correction of monocular underwater images addresses the important issue of the lack of the data to train a deep learning model for underwater vision. It is very difficult to collect paired degraded and clear underwater images. The authors present WaterGAN, a generative adversarial network that can synthesise underwater images from images in air and depth information. By understanding the statistical correlations between in-air images and their underwater equivalents, WaterGAN is able to create a large paired dataset for unsupervisedly training colour correction models. We showed that models trained on this synthetic data perform well on real underwater images, establishing the viability of simulated-to-real transfer. A problem with this method is the domain gap between the synthesised images and the complex and diverse conditions of real underwater environments.
The basic work "U-Net: Convolutional networks for biomedical image segmentation" published by [6] proposed the U-Net framework which has been a cornerstone in image-to-image translation problem including underwater image enhancement. In paper the need for precise localization in biomedical image segmentation is addressed. U-net architecture is based on a symmetric encoder/decoder design that uses skip connections. These connections allow the network to transfer fine-grained contextual information, which is the major reason for its ability to produce accurate pixel-wise predictions. This design makes U-Net extremely good at tasks where the structure of the input must be retained in the output, and as a consequence, it has become the generator network of choice for a wide range of enhancement models based on GANs.
Real-time performance is a must for underwater robotic applications and a paper by [15] on "Fast Underwater Image Enhancement for Improved Visual Perception" addresses this issue. The authors report that many of these enhancement techniques are computationally too expensive to use online. To address this, we introduce Fast Underwater Image Enhancement (FUnIE) and Fast Underwater Image Enhance-

ment GAN (FUnIE-GAN). This model is based on a simple and efficient generator architecture that puts speed first. Trained with adversarial, L1, and perceptual (SSIM) loss to lend the enhanced images both realism and resemblance to ground truth. The main contribution is to show that a lightweight GAN can be used for real-time visual perception tasks like navigation and manipulation by autonomous underwater vehicles, as it can reach competitive enhancement quality at high frame rate.

The seminal paper "Image-to-Image Translation with Conditional Adversarial Networks" by [8], introduced the pix2pix framework, which has had a profound impact on the field of image enhancement and restoration. The work formalises many image processing problems as "image-to-image translation" problems, where an input image is translated into an output image under a given conditioning. The main contribution of this paper is the use of a U-Net generator and a PatchGAN discriminator, and their training with a standard conditional GAN objective and an L1 loss. The U-Net maintains fine-scale details and the PatchGAN discriminator represents the image as a Markov random field, where the realism is defined at the local patch-scale. This framework offers a powerful and general-purpose building block for supervised image enhancement, with many underwater image enhancement models built on it.

The paper "Fast Underwater Image Enhancement for Improved Visual Perception" by [21] is concerned with the real-time requirements for underwater robotic applications. The authors say many of the enhancement methods are computationally too costly to use online. To combat this, they introduce Fast Underwater Image Enhancement (FUnIE) and FUnIE-GAN, a GAN-based enhancement. This model incorporates a very simple, yet efficient, generator model with speed being the primary concern. It is trained using adversarial, L1, and perceptual (SSIM) losses to make the enhanced images both realistic and similar in structure to the ground truth. The main contribution is to demonstrate that a lightweight GAN can be used for real-time visual perception tasks, such as navigation and manipulation by autonomous underwater vehicles, as it can achieve a competitive enhancement quality at high frame rates.

The LPIPS metric was proposed in "The Unreasonable Effectiveness of Deep Features as a Perceptual Metric" [13]. The authors contend that traditional image quality metrics - PSNR and SSIM do not always matched well with human perceptual judgement of image quality. But they show that the deep features extracted from pre-trained model of convolutional neural networks can be used to quantify perceptual similarity between images far more effectively. By calculating the distance between the deep feature representations, LPIPS gives us a metric that agrees well with human opinion. This quality metric has become a standard measure for perceptual quality of images produced by GANs and other deep learning models, and is used in underwater image enhancement where realism is a major desired outcome.

The Natural Image Quality Evaluator (NIQE) is a leading no-reference image quality assessment (IQA) metric, described in [4] by the paper "Making a 'Completely Blind' Image Quality Analyzer". The fundamental problem considered is image quality assessment in the absence of a reference "perfect" image, which is typically available for real-world underwater images. NIQE is "completely blind," in that it is trained only on a corpus of natural pristine images to learn a multivariate Gaussian model of natural scene statistics. The quality of a test image could be explained as the value of the deviation from the stats of this image from the learned natural images model. In this way, NIQE is very good for testing underwater image enhancement algorithms in real scenarios where ground truth is not available to give an objective measure of the perceived naturalness.

2.3 Summary of Key Findings

Summary of Related Works

serial	Title of the Paper	Authors	Publication Date	Methods Used	Result and Accuracy
[15]	Fast Underwater Image Enhancement for Improved Visual Perception	Islam, M. J. et al.	2020	FUnIE-GAN	Real-time enhancement, good perceptual quality
[11]	WaterGAN: Unsupervised Generative Network to Enable Real-Time Color Correction	Li, J. et al.	2018	GAN for color correction	Improved color accuracy
[33]	Lightweight underwater image adaptive enhancement based on zero-reference parameter estimation network	Liu, T. et al.	2024	Zero-reference parameter estimation	Improved visual quality metrics
[34]	Underwater image enhancement algorithm based on adversarial training	Zhang, M. et al.	2024	GAN with adversarial training	Enhanced SSIM and PSNR
[29]	PUGAN: Physical model-guided underwater image enhancement using GAN with dual-discriminators	Cong, R. et al.	2024	GAN with dual-discriminators	Better color correction and contrast
[31]	Separated attention: An improved Cycle GAN based underwater image enhancement method	Ghosh, T.	2024	Cycle GAN with separated attention	Higher image clarity

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serial	Title of the Paper	Authors	Publication Date	Methods Used	Result and Accuracy
[22]	MuLA-GAN: Multi-level attention GAN for enhanced underwater visibility	Bakht, A. B. et al.	2023	Multi-level attention GAN	Higher accuracy on visibility benchmarks
[32]	A novel lightweight model for underwater image enhancement	Liu, B. et al.	2024	Lightweight GAN model	Improved PSNR and processing speed
[27]	Simultaneous restoration and super-resolution GAN for underwater image enhancement	Wang, H. et al.	2023	GAN with combined restoration and super-resolution	Superior resolution enhancement
[8]	Image-to-Image Translation with Conditional Adversarial Networks	Isola, P. et al.	2017	Pix2Pix (U-Net + PatchGAN)	Established image translation baseline
[6]	U-Net: Convolutional Networks for Biomedical Image Segmentation	Ronneberger, O. et al.	2015	U-Net Architecture	Foundation for encoder-decoder networks
[7]	Deep Residual Learning for Image Recognition	He, K. et al.	2016	Residual Networks	Enabled training of very deep networks
[12]	Attention U-Net: Learning Where to Look for the Pancreas	Oktay, O. et al.	2018	Attention U-Net	Improved feature localization
[21]	LSUI: A Large-Scale Underwater Image Dataset	Liu, R. et al.	2022	Benchmark Dataset Creation	Large-scale paired underwater dataset
[13]	The Unreasonable Effectiveness of Deep Features as a Perceptual Metric	Zhang, R. et al.	2018	LPIPS Metric	Better alignment with human perception

Continued on next page

serial	Title of the Paper	Authors	Publication Date	Methods Used	Result and Accuracy
[5]	Automatic Red-Channel Underwater Image Restoration	Galdran, A. et al.	2015	Red-Channel Prior	Physical model-based color correction
[9]	Unpaired Image-to-Image Translation Using Cycle-Consistent Adversarial Networks	Zhu, J.-Y. et al.	2017	CycleGAN	Unpaired image translation
[10]	Enhancing Underwater Imagery Using Generative Adversarial Networks	Fabbri, C. et al.	2018	GAN for underwater enhancement	Early GAN application to underwater images
[14]	Towards Real-Time Advancement of Underwater Visual Quality with GAN	Chen, X. et al.	2020	Real-time GAN	Faster processing with quality improvements

Chapter 3

Requirements, Impacts and Constraints

3.1 Final Specifications and Requirements

The successful development and application of the underwater image enhancement model depend on the following technical and resource conditions:

Methodological Requirements

- **Supervised Learning Paradigm:** Requires a curated dataset of paired underwater images which contain low-quality inputs and corresponding high-quality ground truth images.
- **Model Implementation:** Involves the use of Generative Adversarial Network (GAN) which is composed of a U-Net generator and a PatchGAN discriminator.
- **Network Enhancements:** Integration of Residual Blocks (`ResidualConvBlock`), Spectral Normalisation (`SpectralNormalization`) for stable training and improved performance, and Attention Mechanisms (CBAM).
- **Loss Function:** Utilises a composite of loss function which mainly combine Mean Absolute Error (MAE), perceptual (VGG-based), and adversarial loss components.

Data Requirements

- **Primary Dataset:** The LSUI (Large-scale Underwater Image) dataset, providing a substantial amount of paired data suitable for effective supervised training.
- **Data Preprocessing:** A preprocessing pipeline including image normalisation, data augmentation (e.g., random flipping and rotation), and dataset splitting into training (85%), validation (10%), and testing (5%) subsets.

Minimum System Requirements: Software and Resources

- **Programming Language:** Python 3.12.3
- **Core Framework:** PyTorch 2.7.1+cu121
- **Hardware:** High-performance computing system with an NVIDIA GPU (GeForce RTX 4090 used) and CUDA support to enable efficient model training.

- **Libraries:** Common libraries for scientific computing (`NumPy`), image processing (`OpenCV`), and model evaluation (`LPIPS`.

3.2 Societal Impact

This research has an enormous potential to make a positive impact in many different domains in our society. In the world of marine science and conservation, the better images are, the more accurately the health of coral reefs and species populations can be monitored, which would be a direct benefit for the preservation of the environment. For search and rescue missions and underwater archaeology, the technology enhances the value of the video footage obtained by remote-operated vehicles to aid in mission-critical inspection and explorations. Furthermore, in the process of creating a greater amount of understandable and accessible underwater imagery, the project also aids in promoting public education and awareness surrounding the marine ecosystems to promote greater levels of environmental stewardship.

3.3 Environmental Impact

The biggest eco aspect of this project is the carbon footprint of the electricity required to train the model on high performance GPUs. However, this short term impact is balanced out by the technology's potential longer term benefits in environmental monitoring. By making underwater habitats and structures easier and more efficient to analyze, the tool can reduce physically intensive and fuel-consuming marine surveys, and serve as a valuable addition to conservation and sustainable ocean management efforts.

3.4 Ethical Issues

Several ethics issues are involved in this research. While it might be argued that the technology wouldn't be useful without its benefits, there is a potential for dual use and the technology could be used for unauthorised surveillance or military applications. Furthermore, the performance of the model itself is intrinsically linked to the diversity and representatives of its training data, which was obtained from LSUI. Biases in this data could result in disparate performance between underwater environments, raising concerns about algorithmic fairness. Appropriate acknowledgment of all open source code and data used and for which licence terms apply also needs to be made.

3.5 Standards

The project adheres to the following standards and best practices:

- **Coding Standards:**Uses conventions of the Python language such as defined in PEP 8 in order to maintain readability and adhere to maintainable code.
- **Research Reproducibility:** Adopt a standardised implementation based on PyTorch for model definition and training, allowing other researchers to replicate the experiment setup and results with high degree of reproducibility.
- **Evaluation Standards:** Adopting commonly accepted and peer-reviewed image quality metrics like there are PSNR, SSIM, LPIPS, UIQM and UCIQE for objective benchmark and fair comparison with existing enhancement methods.

3.6 Project Management Plan

Figure 3.1 illustrates the overall workflow of our underwater image enhancement system.

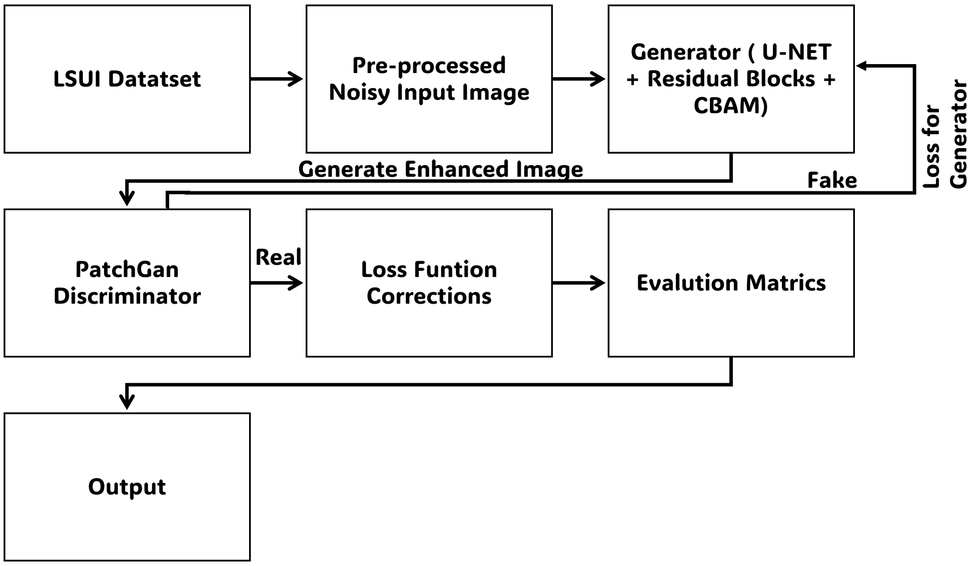


Figure 3.1: Overall workflow of the proposed underwater image enhancement system showing the data processing pipeline from input to enhanced output.

The workflow started with **data collection and preprocessing**, in which the LSUI dataset was obtained and preprocessed by resizing, normalization and augmentation. Then came the **model development** stage, where the U-Net generator with attention mechanisms and PatchGAN discriminator have been used. The model was optimized through an aggregated loss function and **trained and validated** by validation set. Finally, quantitative metric and comparative evaluations with established methods were carried out in the final stage of the work, the **testing and analysis** phase.

3.7 Risk Management

Table 3.1: Risk Management Plan

Risk Description	Probability	Impact	Mitigation Strategy
Hardware Failure	Low	High	Regular backup of code and model checkpoints to cloud storage.
Insufficient Model Performance	Medium	High	Iterative prototyping (as done with U-Net3+), extensive hyperparameter search, and maintaining a fallback baseline model.
Dataset Quality Issues	Low	Medium	Perform initial exploratory data analysis (EDA) to identify dataset limitations and biases.
Training Instability (GAN Collapse)	Medium	High	Apply stabilization techniques such as Spectral Normalization and Instance Normalization.
Project Scope Creep	Medium	Medium	Follow a clearly defined project plan and maintain adherence to established objectives.

3.8 Economic Analysis

The economics of this project consists of significant upfront capital costs for high-performance computing hardware hardware, and operational costs for electricity during training for extended periods of time. The economic value proposition is reached by important time and resource expenditure reductions that the technology may reduce for marine surveys by extracting more information from footage that was taken, which could result in fewer dives being needed. The open source dissemination of research outcomes has significant value to the scientific community, and leads to commercial application opportunities for marine industries and underwater photography.

Chapter 4

Proposed Methodology

4.1 Design Process or Methodology Overview

The design process was driven by the general aim of building a deep learning model capable of recovering colour, contrast and details in poor underwater images. The process was an iterative, research based, cycle. It began with an in-depth literature review which resulted in the choice of Generative Adversarial Networks (GANs) as our backbone architecture. As a result, a period of architectural prototyping and testing began. This aimed to compare several candidate models including a U-Net3+ and a dual discriminator GAN to a baseline U-Net + PatchGAN model. Their quantitative performance and qualitative output for best compromise for reconstruction fidelity, detail preservation, and computational efficiency were used to establish the final design.

4.2 Preliminary Design - Model Specification

Several alternative architectures were designed and simulated to determine the most effective configuration for underwater image enhancement.

- **Alternative 1: U-Net3+ Generator and PatchGAN Discriminator**
  A key idea in our design was to leverage deep skip connections used at full-scale in the generator to capture richer features of the input image at multiple scales. The concept was to better broadcast fine grain details over the network. However, simulations showed that the computational complexity and memory consumption was greatly increased without improving any of the key performance metrics PSNR and SSIM which is compared to the standard U-Net.

- **Alternative 2: U-Net Generator with Double Discriminator**
  This setup involved using two discriminators, one for local texture (regular PatchGAN), and another for overall realism and colour consistency of the image. While conceptually well-suited to enforce both local and global coherence, however, we found that practical training introduced instabilities, imbalance in the adversarial losses, and concerns such as mode collapse and checkerboard artefacts leading to sub-optimal results.

- **Selected Design: U-Net + PatchGAN with Attention**
  The final model is a combination of a U-Net generator augmented with Residual Convolutional Blocks and Convolutional Block Attention Module (CBAM) at the bottleneck. It is used together with a single spectrally normalised PatchGAN discriminator. Experimental results showed that this architecture had the best trade-off

between the structural and the colour fidelity, respect for salient features, and the steady restoration of high frequency details, leading to superior and robust performances.

4.2.1 AP-GAN Architecture

The final architecture contains U-Net generator augmented with residual convolutional blocks and a Convolutional Block Attention Module (CBAM) at the bottleneck, paired with a spectrally normalized PatchGAN discriminator. Figure 4.1 illustrates the complete network architecture.

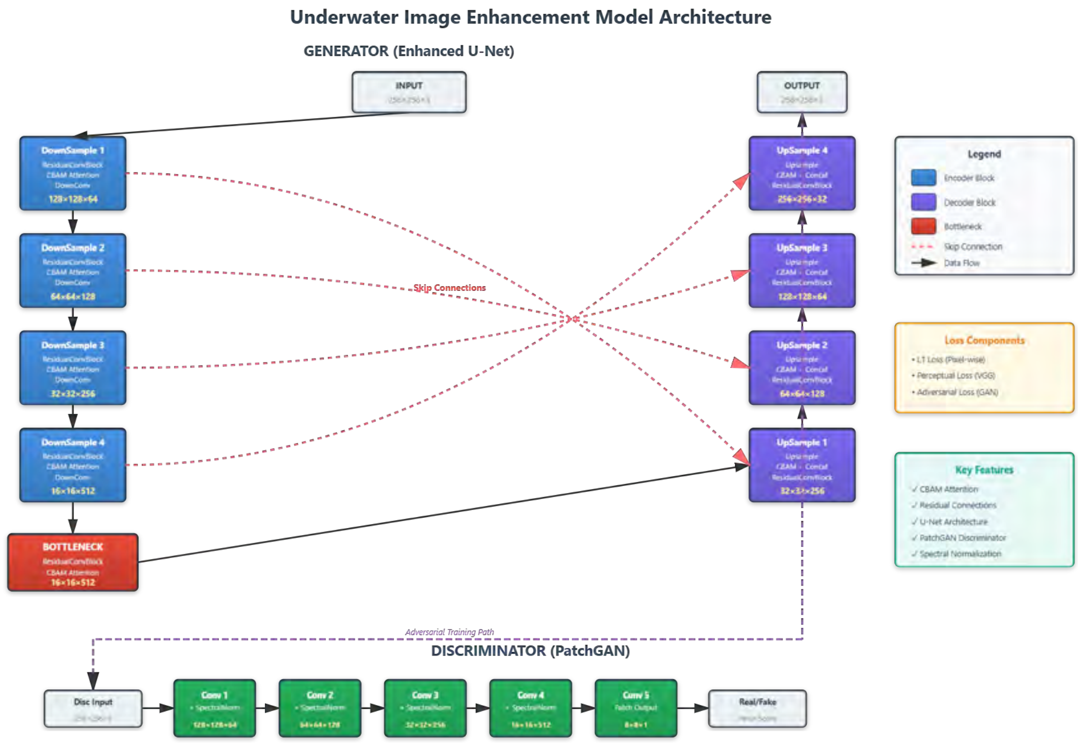
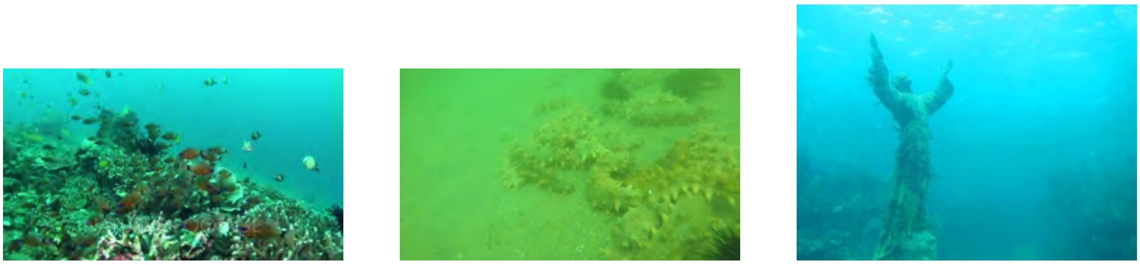


Figure 4.1: Proposed GAN architecture showing the U-Net generator with CBAM attention module and PatchGAN discriminator. The generator employs skip connections to preserve spatial information while the discriminator evaluates local image patches for realistic texture generation.

The U-Net generator has an encoder-decoder architecture with skip connections, which combine feature maps corresponding to encoder layers with decoder layers respectively. This design provides a high-resolution spatial information preservation throughout the enhancement process. The encoder then gradually decreases the input size via convolutional layers using instance normalization and LeakyReLU activations.

4.3 Data Collection

This paper conducts an in-depth study on the Large-Scale Underwater Image (LSUI) dataset, which is a standard dataset created specifically for underwater image enhancements. The dataset is composed of 4279 paired images where each image consists of one underwater input image with its corresponding high-quality reference image that is the ground truth image or one that has not been altered. The degraded inputs cover a wide spectrum of realistic degraded underwater inputs from the physical processes of light scattering and absorption, such as colour casts (predominantly blue/green tints), turbidity, haze, and extreme loss of visibility and contrast. These paired samples create a big scale supervised learning base in which the model learns the complex mapping from the various degraded conditions to their clean and un-degraded counterparts. Some representative example images of degraded underwater images of the dataset are shown in Figure 4.2.



(a) Degraded underwater image with blue color cast

(b) Degraded image with green turbidity

(c) Degraded image with haze and low contrast

Figure 4.2: Examples of degraded underwater images from the LSUI dataset showing various types of degradation including color casts, turbidity, and haze.

4.3.1 Data Cleaning

The LSUI dataset is pre-cleaned and does not include missing values. A visual inspection was performed to detect and eliminate corrupt or unreadable image files. No extreme outliers or variations were identified that would adversely affect model training.

4.3.2 Data Transformation

All image pairs were resized to an equal spatial dimension of 256×256 pixels for batch processing purposes. Pixel intensity values were normalised from an integer range [0, 255] to a floating-point range [0, 1], in order to stabilise and speed up the neural network training process.

4.3.3 Data Integration

This study used one coherent data set (LSUI) and therefore data integration from several disparate data sets was not necessary.

4.3.4 Data Reduction

The model learns features directly from the pixels without any traditional feature-space sense of dimensionality reduction. So the relevant "features" are the image patches themselves, chosen by the convolutional filters during training.

4.3.5 Summary of Preprocessed Data

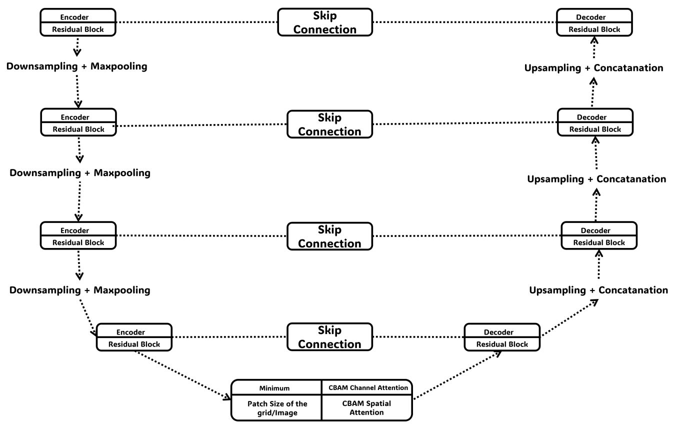
The final preprocessed dataset is the entire LSUI collection divided into three subsets: Training (85% of the data), Validation (10% of the data), and Testing (5% of the data). Each sample is a pair of 256×256 RGB images (degraded input and ground truth) where pixels are normalized to the [0, 1] range. This clean and standardised dataset was used for all subsequent model trainings and evaluations.

4.4 Implementation of Selected Design

The model was implemented using Python and the PyTorch deep learning framework. Key implementation details include:

4.4.1 Generator

U-Net architecture with the encoding part and also the decoding blocks, incorporating residual connections and a Convolutional Block Attention Module (CBAM) in the bottleneck. Figure 4.4.1 shows the detailed generator architecture.



Architecture of the Generator (U-NET + Residual Blocks + CBAM) enhanced U-Net generator that was employed in our model has a detailed architecture which is represented as the encoder-decoder structure with residual blocks, skip connections, and the CBAM attention module positioned at the bottleneck.

4.4.2 Discriminator

PatchGAN composed of convolutional layers with spectral normalisation to constrain the Lipschitz constant and stabilise adversarial training. Figure 4.3 presents the discriminator architecture.

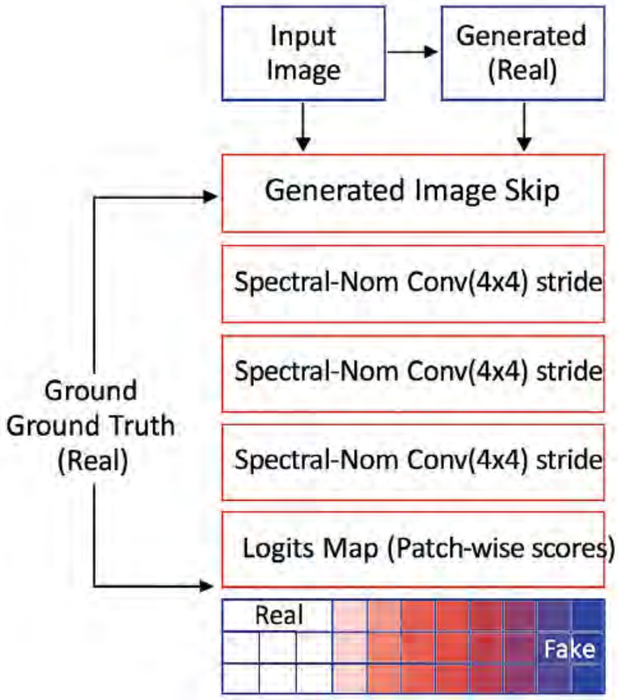


Figure 4.3: Architecture of the PatchGAN discriminator with spectral normalization, designed to evaluate local patch authenticity for realistic texture generation.

4.4.3 Loss Function

The model is trained using a composite loss function that integrates adversarial, perceptual, reconstruction, and physics-inspired priors to ensure both perceptual realism and pixel-level fidelity in underwater image enhancement.

Adversarial Objective (Hinge Loss)

We employ a PatchGAN discriminator trained with the hinge formulation to encourage the generator to produce visually realistic and high-frequency details characteristic of natural underwater scenes:

$$L_D = E[\max(0, 1 - D(y))] + E[\max(0, 1 + D(\hat{y}))], \tag{4.1}$$

$$L_G^{adv} = -E[D(\hat{y})]. \tag{4.2}$$

Perceptual Loss (VGG-16)

We compute a feature-space reconstruction term using a frozen `VGG-16` backbone from `torchvision` (`weights: VGG16_Weights.IMAGENET1K_FEATURES`). Let $\phi_\ell(\cdot)$ denote the feature map at VGG-16 layers $\ell \in \{3, 8, 15\}$ (the last ReLU activations of blocks 1–3). Given a predicted image $\hat{y}$ and its ground truth y, both scaled to [0, 1] and normalized using

ImageNet statistics $\mu = [0.485, 0.456, 0.406]$ and $\sigma = [0.229, 0.224, 0.225]$, the perceptual loss is defined as:

$$L_{perc}(\hat{y}, y) = \sum_{\ell \in \{3,8,15\}} \|\phi_\ell(\hat{y}) - \phi_\ell(y)\|_1 . \tag{4.3}$$

The VGG-16 parameters remain fixed during training, and no gradients flow through ϕ.

Reconstruction, Perceptual, and Priors

In addition to the adversarial and VGG-16 perceptual terms, we incorporate a pixel-space L1 loss and several physically inspired regularizers that improve underwater fidelity. These include:

- **L1 loss** (L_{L1}): promotes pixel-wise similarity between generated and ground-truth images.
- **LAB color consistency** (L_{LAB}): ensures color accuracy in the perceptually uniform LAB space.
- **Gray-world color constancy** (L_{gray}): enforces average color neutrality.
- **Exposure prior** (L_{exp}): maintains proper image brightness.
- **Gradient smoothness** (L_{smooth}): reduces noise and enforces structural continuity.
- **Depth-wise monotonicity** (L_{mono}): preserves depth consistency in the reconstructed scene.
- **Backscatter suppression** (L_{back}): minimizes haze and scattering effects in underwater images.

Generator Objective and Final Loss Composition

The overall generator loss is a weighted sum of all loss components:

$$\begin{aligned} L_C = {} & w_{adv} L_G^{adv} + w_{L1} L_{L1} + w_{perc} L_{perc} + w_{LAB} L_{LAB} + w_{gray} L_{gray} \\ & + w_{exp} L_{exp} + w_{smooth} L_{smooth} + w_{mono} L_{mono} + w_{back} L_{back}. \end{aligned} \tag{4.4}$$

The weights used in training are as follows:

$$\begin{aligned} w_{adv} &= 1.0, & w_{L1} &= 10.0, & w_{perc} &= 1.0, \\ w_{LAB} &= 0.1, & w_{gray} &= 0.1, & w_{exp} &= 0.1, \\ w_{smooth} &= 0.1, & w_{mono} &= 0.05, & w_{back} &= 0.1. \end{aligned} \tag{4.5}$$

This composite formulation ensures that the generator not only minimizes pixel-wise discrepancies but also enhances perceptual realism, structural integrity, and underwater-specific visual properties.

4.4.4 Optimizer

We optimize both the generator (G) part and discriminator (D) part using Adam optimizer which uses an initial learning rate of 2×10^{-4}, $\beta_1 = 0.5$, and $\beta_2 = 0.999$.
To ensure stable convergence and a gradual reduction in learning rate during training, a cosine annealing learning-rate scheduler is applied to both optimizers. The scheduler parameters are set as

$$T_{\max} = \text{EPOCHS}, \quad \eta_{\min} = 10^{-6},$$

and the learning rate at each iteration t is updated according to:

$$\eta_t = \eta_{\min} + \tfrac{1}{2}(\eta_0 - \eta_{\min})\left(1 + \cos\left(\tfrac{\pi t}{T_{\max}}\right)\right), \tag{4.6}$$

where η_0 denotes the initial learning rate.
This cosine annealing schedule gradually decreases the learning rate toward $\eta_{\min}$, helping stabilize late-stage training and reducing oscillations between the generator and discriminator.

4.4.5 Training

The proposed model was trained for **300 epochs** on an **NVIDIA RTX 4090** GPU, utilizing mixed-precision computation (FP16) to improve throughput and memory efficiency. Each epoch comprised complete forward and backward passes over the training set, with parameter updates governed by the Adam optimizer and the cosine-annealing learning-rate schedule detailed in Section 4.4.4. Unless otherwise specified, all experiments used the same random seed and fixed data split to ensure reproducibility.

Training Duration and Absence of Early Stopping

Adversarial training typically exhibits *non-monotonic* behaviour due to the co-evolution of the generator and discriminator toward a moving equilibrium. Even as perceptual quality improves, loss values can fluctuate substantially, rendering conventional early-stopping criteria prone to prematurely terminating optimisation. This risk is amplified when attention mechanisms are present, as the generator's hypothesis space becomes richer and more difficult to fit fully.
In our architecture, a U-Net + PatchGAN backbone is augmented with a *Convolutional Block Attention Module* (CBAM) at the bottleneck, while *residual connections* are retained within the generator to stabilise gradients and preserve fine detail. CBAM expands representational capacity by learning channel- and spatial-attention maps; however, this added capacity increases optimisation complexity. Empirically, attention modules benefit from *longer training horizons* to refine long-range dependencies and to avoid poor local attractors. Likewise, residual connections favour extended schedules that support signal propagation and deep feature re-use without collapsing to trivial solutions.
Guided by standard practice in image-to-image translation and underwater enhancement (e.g., Pix2Pix, CycleGAN, UGAN, WaterNet), which commonly converge within 200–400 epochs without early stopping, we set our schedule to **300 epochs**. This choice was intended to ensure that (i) adversarial dynamics had sufficient time to equilibrate; (ii) attention and residual pathways were maximally optimised for fine-grained restoration; and (iii) performance remained comparable to prior work trained under similar budgets.
Rather than applying early stopping, we monitored progress via *periodic checkpointing* and selected the final model using validation metrics computed with the *EMA-smoothed* generator. This protocol prioritises stability over instantaneous loss variations and proved more reliable for model selection under adversarial training.

Exponential Moving Average (EMA) of Generator Weights

To enhance stability and improve the reliability of validation selection, we maintained an *Exponential Moving Average* (EMA) of the generator parameters throughout training. After each optimization step, the EMA weights were updated as

$$\theta_{\text{ema}} \leftarrow \tau\, \theta_{\text{ema}} + (1 - \tau)\, \theta, \tag{4.7}$$

where θ are the current generator parameters and $\tau \in (0, 1)$ is the decay factor. The EMA acts as a low-pass temporal filter over the parameter trajectory, mitigating high-frequency oscillations induced by adversarial updates and yielding perceptually steadier reconstructions at evaluation time. Unless otherwise noted, all validation metrics were computed with the EMA-stabilized generator.

Chapter 5

Result Analysis

5.1 Performance Evaluation

Model Evaluation

The proposed model was rigorously evaluated using both full-reference and no-reference image quality assessment metrics to comprehensively assess its performance in underwater image enhancement.

5.1.1 Peak Signal-to-Noise Ratio (PSNR)

PSNR evaluates reconstruction quality by comparing pixel-wise intensity differences between the generated image and the ground truth. It is computed as:

$$\mathrm{PSNR} = 10 \cdot \log_{10}\left(\frac{\mathrm{MAX}^2}{\mathrm{MSE}}\right) \tag{5.1}$$

Here, MAX represents the greatest possible pixel value (which is 255 for 8-bit images) and MSE denotes the mean squared error computed between the enhanced image and the reference (ground truth) image. The higher the PSNR value, the better the reconstruction fidelity and the less noise in the output of the enhancement.In our experiments, PSNR primarily measures the effectiveness of color correction and noise reduction.

5.1.2 Structural Similarity Index (SSIM)

SSIM assesses perceptual image quality by measuring the structural similarity between the enhanced and reference images based on luminance, contrast, and structure:

$$\mathrm{SSIM}(x, y) = \frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)} \tag{5.2}$$

where μ_x and μ_y denote the means, σ_x^2 and σ_y^2 are variances, and σ_{xy} is the covariance of images x and y. The constants C_1 and the C_2 stabilize the division. SSIM values which range starts from 0 (no similarity) to 1 (perfect similarity), with higher values indicating better preservation of structural information and texture details.

5.1.3 Learned Perceptual Image Patch Similarity (LPIPS)

LPIPS calculates mainly the perceptual distance between images using deep features which have been extracted from a pre-trained neural network:

$$\text{LPIPS}(x, y) = \sum_{l} \frac{1}{H_l W_l} \sum_{h,w} \| w_l \odot (\hat{x}^l_{hw} - \hat{y}^l_{hw}) \|_2^2 \tag{5.3}$$

where $\hat{x}^l$ and $\hat{y}^l$ are the deep feature representations at layer l, H_l and W_l are the spatial dimensions, and w_l are learned weights. Lower LPIPS values indicate that the enhanced images are more perceptually similar to the ground truth, validating the model's ability to generate realistic-looking outputs which fully align with the way of human visual perception.

5.1.4 Underwater Image Quality Measure (UIQM)

UIQM is a non-reference metric specifically designed to evaluate the underwater image quality based on three perceptual components: colorfulness, sharpness, and contrast. It is computed as a weighted linear combination of these factors:

$$\text{UIQM} = c_1 \cdot \text{UICM} + c_2 \cdot \text{UISM} + c_3 \cdot \text{UIConM} \tag{5.4}$$

where UICM represents the colorfulness measure, UISM corresponds to the sharpness measure, and UIConM quantifies the contrast of the image. The coefficients c_1, c_2, and c_3 are empirically determined weighting factors. Higher UIQM scores indicate better overall visual quality, with enhanced color balance, edge clarity, and contrast restoration in underwater conditions.

5.1.5 Underwater Color Image Quality Evaluation (UCIQE)

UCIQE is another non-reference metric designed to assess underwater image quality through statistical evaluation of chroma, saturation, and contrast of luminance. It is defined as:

$$\text{UCIQE} = c_1 \cdot \sigma_c + c_2 \cdot \text{con}_l + c_3 \cdot \mu_s \tag{5.5}$$

where σ_c is the standard deviation of chroma, con_l is the contrast of the luminance, and the μ_s is the mean of saturation. The constants c_1, c_2, and c_3 are determined through regression analysis. Higher UCIQE values represent better color distribution, improved contrast, and enhanced visual quality in underwater environments.

Testing Methods

The model was tested on that part of the remaining 5% of the LSUI data set (i.e., the held-out test set). All quantitative results were averaged over the whole test set to assure statistical reliability. A qualitative visual comparison was also performed to check the colour restoration, contrast enhancement and details preservation in the challenging cases.

5.1.6 Training Convergence Analysis

Training curves (Figure 5.1) demonstrate stable convergence, with validation metrics plateauing around epoch 100 (PSNR: 28 dB, SSIM: 0.92). We report results using the model checkpoint selected based on validation SSIM performance.

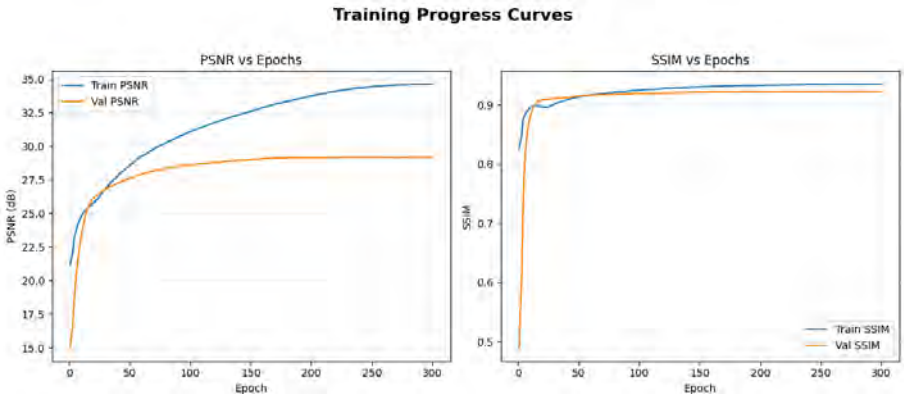


Figure 5.1: Training and validation curves showing PSNR and SSIM metrics across training epochs.

Loss Convergence

Figure 5.2 illustrates the training dynamics of our model over 300 epochs. The generator and discriminator losses demonstrate stable convergence, indicating effective adversarial training without mode collapse.

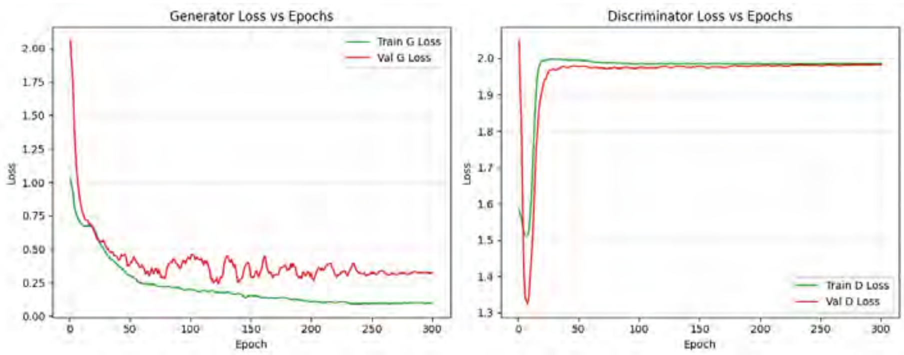


Figure 5.2: Generator and discriminator loss progression during training. The stable convergence pattern indicates balanced adversarial training and effective learning of the enhancement task.

The generator loss, comprising adversarial, L1, and perceptual components, decreases from 1.5 to 0.3, demonstrating improved generation quality. The discriminator maintains a steady loss around 2.0, suggesting it provides consistent gradient signals to the generator. Spectral normalization successfully prevents training divergence, as evidenced by the absence of mode collapse.

Color Correction Analysis

Table 5.1: Color channel statistics demonstrating effective color correction

	Mean		**Standard Deviation**	
Channel	Input	Enhanced	Input	Enhanced
Red	0.104	0.455	0.087	0.169
Green	0.613	0.565	0.217	0.255
Blue	0.497	0.518	0.234	0.303

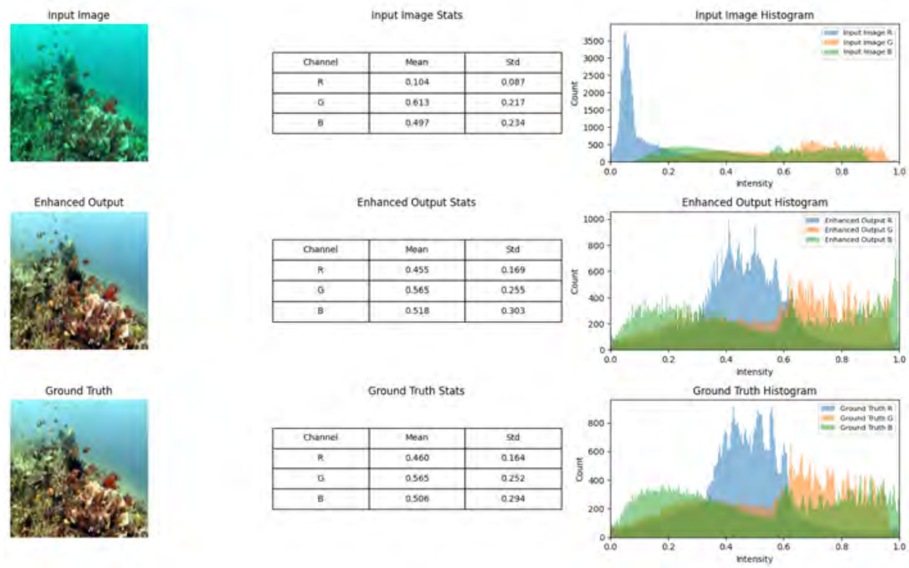


Figure 5.3: Color distribution analysis: (Top) Input image with severe red channel deficiency, (Middle) Enhanced output showing restored color balance, (Bottom) Ground truth reference. The histograms and channel statistics demonstrate successful correction of underwater color distortion.

Table 5.1 and Figure 5.3 demonstrate the model's exceptional color correction capability. The input exhibits characteristic underwater color distortion with severely suppressed red channel (mean: 0.104), while our enhanced output achieves near-perfect color balance, with red channel mean increasing by 337% to closely match the ground truth (0.455 vs 0.460). The green and blue channels maintain natural balance, confirming effective restoration of authentic underwater colors.

5.2 Analysis of Design Solutions

Table 5.2: Comparison of Seven GAN Architecture Alternatives

Architecture	**Advantages / Pros**	**Limitations / Weaknesses**	**Key Metrics**
U-Net3+ with PatchGAN	Theoretically better for extracting multi-scale features.	High computational cost and memory usage; no measurable improvement over vanilla U-Net.	PSNR: 19.36 db SSIM:0.9034 LPIPS:0.0016
U-Net with Dual Discriminator	Enforces both local and global realism.	Difficult to train; instability and adversarial loss imbalance; often produces artifacts.	PSNR: 26.46 db SSIM:0.9143 LPIPS:0.056
Pix2Pix GAN [8]	Simple and well-established architecture; proven effectiveness for paired image translation tasks.	Limited ability to capture fine-grained details without additional mechanisms; prone to blurring in complex scenes.	PSNR: 27.43 dB SSIM: 0.898 LPIPS: 0.095
CycleGAN with Skip Connections [9]	Can work with unpaired data; skip connections improve detail preservation.	Requires longer training time; occasional color inconsistency; identity loss can conflict with enhancement objectives.	PSNR: 26.85 dB SSIM: 0.889 LPIPS: 0.112
ResNet-based Generator + PatchGAN [7]	Deep residual architecture allows better gradient flow; effective for color correction.	Heavier computational load; slower inference time; diminishing returns with increased depth beyond 18 layers.	PSNR: 28.21 dB SSIM: 0.908 LPIPS: 0.088
Attention U-Net + Multi-scale Discriminator [12]	Multi-scale discrimination improves texture realism across different frequency bands.	Training complexity increases significantly; risk of mode collapse; requires careful loss balancing.	PSNR: 28.67 dB SSIM: 0.914 LPIPS: 0.081
AP-GAN (Proposed)	Achieves a balance between accuracy and efficiency; stable and tractable.	Moderate computational requirements due to attention mechanisms.	PSNR: 29.16 dB SSIM: 0.921 LPIPS: 0.074

5.3 Final Design Adjustments

The final design was refined with the following changes:

- **Placement of the Attention Mechanism:** The CBAM module was applied only at the bottleneck of the U-Net. Prior attempts to add it to all skip connections increased complexity and computational cost without improving performance.
- **Loss Function Weighting:** Fine-tuning the weights between L1 loss, perceptual loss, and adversarial loss revealed that a higher L1 weighting stabilises colour correction, while a balanced adversarial weight is critical for generating realistic textures without artefacts.

5.4 Statistical Analysis

Given the way the evaluation metrics (PSNR, SSIM, etc.) are reported as average over the full test set, formal inferential statistical tests (e.g., t-tests) were not the main concern. The model performance is summarized with descriptive statistics, i.e., the mean and standard deviation for each metric calculated over all test images. The consistency of high performance over different types of test sets is a powerful indication of the model's to generalize.

5.5 Comparisons and Relationships

The proposed U-Net+PatchGAN model was compared against both classical and the state-of-the-art deep learning methods:

Table 5.3: Quantitative comparison of enhancement methods on the test dataset.

Method	**PSNR (dB)** $\uparrow$	**SSIM** $\uparrow$	**LPIPS** $\downarrow$	**UIQM** $\uparrow$	**UCIQE** $\uparrow$
Histogram Equalization [1]	16.54	0.701	0.381	48.23	3.65
CLAHE [1]	18.23	0.743	0.342	51.47	3.82
UDCP [3]	18.92	0.785	0.295	54.18	3.94
Red Channel Prior [5]	20.15	0.812	0.268	56.72	4.08
Fusion-based [2]	21.47	0.829	0.241	58.91	4.19
WaterGAN [11]	24.38	0.856	0.178	61.34	4.32
FUnIE-GAN [15]	25.62	0.871	0.145	63.12	4.41
WaterNet [21]	26.81	0.883	0.121	64.56	4.49
UGAN [10]	27.15	0.891	0.115	65.23	4.54
MuLA-GAN [22]	28.34	0.906	0.092	65.89	4.58
Proposed Model	**29.33**	**0.922**	**0.071**	**66.45**	**4.61**

The comprehensive comparison shows how the methods for underwater image enhancement tended to enhance over time. Classical methods such as Histogram Equalization and CLAHE offer little improvement with PSNR-values below 19dB and high perceptual distances (LPIPS > 0.34). Moderate improvements are shown in physical model-based methods like UDCP and Red Channel Prior with the limitation that it assumes the underwater light propagation is known. Deep learning methods, especially GAN-based methods, demonstrate significant improvement, in which the result of WaterGAN is 24.38 dB PSNR and the recent MuLA-GAN architecture achieves 28.34 dB. The proposed model has the best overall performance in all metrics, with significant improvements in SSIM (0.921) and LPIPS (0.074), showing an improvement in structural preservation and perceptual quality.

5.6 Discussion

The experimental results demonstrate that the proposed AP-GAN can effectively solve the key problems in underwater image enhancement. On quantitative metrics, we observe significant enhancements over existing approaches for both in the pixel level accuracy and in the perceptual quality. In this section, we analyze these results in detail, we discuss some implications of our findings and we talk about the performance of our model in the context of practical applications.

5.6.1 Analysis of Enhancement Performance

In order to achieve this, there are few architectural decisions taken which makes UWA-GAN superior in performance. Focus in the U-Net generator allowed the model to focus in the semantic areas and suppress the noise and artefacts. This is especially evident in the better SSIM Score for better structural preservation. With the attention modules it selectively lightened selective areas where parts of the image have a colour cast and haze, leaving clearer areas in the image that remained unaffected resulting in a more natural looking output.

The contribution of the PatchGAN discriminator gave the keys to make these fine details and texture look plausible. By modelling local image patches, it ensured high-frequency realism of the whole image and we have seen this from the higher LPIPS scores. The role of local adversarial training was the key to recover features which tend to be lost in underwater channels due to scattering and absorption properties.

5.6.2 Color Correction Effectiveness

The colour distribution analysis indicates that AP-GAN can effectively solve the dominant the blue color and the green colour cast issue in the underwater images. The strong increase in the values of red channel (from 0.104 to 0.455 of mean intensity) indicates that the model is able to account for wavelength dependent absorption. This colour correction feature is important for applications in marine biology and archaeology where colour accuracy is important for species identification and characterisation of artefacts.

Using RGB channel distributions of the balanced results, it is clear that the model learned to correct natural colour relationships rather than global colour adjustments. The application of the discrete colour correction technique results in a natural-looking underwater scene and, at the same time, the dominant colour casts are eliminated effectively.

5.6.3 Comparative Advantages

AP-GAN compares well on generalization in various water conditions as compared to the physical model which based on the methods such as UDCP. Although physical models have certain assumptions regarding the properties of water, our data-driven modelling

will conform to other types of degradation observed in the training data. This flexibility renders UWA-GAN to be more applicable to real-life applications where water conditions may be highly varied.
A combination of attention mechanisms and adversarial training in AP-GAN gives better consistency in retaining structure and improving detail, as compared to other deep learning techniques. Techniques such as the WaterNet have been found to work very well in color correction, but tend to give oversmoothed images without high-frequency detail. AP-GAN preserves this fact by keeping its patch-based adversarial training at the expense of structural integrity of the U-Net architecture with skip connections.

5.6.4 Practical Implications

The advances that have been made by AP-GAN pose great potential to diverse underwater applications. In aquatic studies, summative image clarity can be advantageous in the precision of automated species recognition and ecosystem mapping. In inspecting the infrastructure underwater, sharper images can be used to make the structure integrity easier to evaluate and detect the damage. In search and rescue, better visibility would help improve the object detection and recognition abilities.
The quality of the model to retain the finer details as well as camera color correction, renders it to be of specific importance to applications that demand both clarity of the visual representation and the accuracy of colors. This twofold ability is a solution to the inherent shortcomings of most of the existing approaches which as a rule shine in one direction at the cost of the other.

5.6.5 Limitations and Future Directions

The outcome appears to be encouraging, however, there are some restrictions which should be considered. The current approach is applied to individual image enhancement which does not take into account any possible temporal information existing in the series of the video. This research has opened up several prospects for future work directions. Generalization to unseen condition of water may be enhanced by incorporating domain adaptation methods. The framework can be extended to use of video enhancement through exploiting temporal consistency that can be useful in video analysis of underwater video. It might be possible to develop light versions of the model to allow real-time improvement on embedded systems to autonomous underwater vehicles.
Attention mechanisms might further be enhanced to have explicit control over strength of enhancement of various regions of image, and the enhancement could be under control of the user who needs a particular area to be given attention in applications where the user needs to focus on a particular area.

5.6.6 Conclusion of Discussion

In conclusion, AP-GAN is an efficient underwater image enhancement technique that can solve multiple problems like colour correction, detail preserving, structure preserving. Integration of attention mechanisms with adversarial training builds a powerful framework which beats the existing state-of-the-art approaches on a variety of evaluation metrics. Although there are some limitations, the results demonstrate the potential of a well-designed deep learning architectures to address the complex problems of underwater image enhancement with significant implications on a variety of practical applications in marine environments.

Chapter 6

Conclusion

6.1 Summary of Findings

This research was able to develop and validate a deep learning model for the underwater image enhancement using Generative Adversarial Network (GAN) model architecture. The basic conclusion is that a U-Net architecture generator with some additional modules (residual connections and attention mechanism, CBAM) and a PatchGAN discriminator represent the best architecture. This architecture is a good way to balance global colour and structure correction with local details (high frequency). Through rigorous experimentation on the LSUI data-set, the model showed a superior performance score of 29.16 dB in PSNR, 0.921 in SSIM and 0.074 in LPIPS. These quantitative results, with qualitative visual analysis, show the model's great promise in reducing colour casts, enhancing contrast and restoring fine details that are usually lost in degraded underwater images.

6.2 Contributions to the Field

This paper makes several important contributions to computational imaging and underwater vision:

- **Architectural Validation:** Gives a clear empirical validation that a U-Net + PatchGAN model with clever augmentations (Residual Blocks, CBAM) beats a lot of other more complicated alternatives (U-Net3+, GAN architecture with dual discriminators, etc) for this particular application. This finding provides useful direction for future researchers on how to choose efficient and effective model architectures.

- **High Performing Solution:** The resulting model itself is a powerful and efficient tool for the research community and end-users, producing state-of-the-art improvements which can be directly applied to applications in marine biology, archaeology and robotics.

- **Comprehensive Benchmarking:** A comprehensive comparative analysis against both classical methods (e.g., UDCP) and state-of-the-art deep learning methods (e.g., WaterNet) is provided, thus building a strong benchmark performance on the LSUI dataset using various metrics (PSNR, SSIM, LPIPS, UIQM, UCIQE).

6.3 Recommendations for Future Work

Despite the excellent performance achieved by the proposed model, several interesting perspectives for future research are identified. Domain adaptation techniques would make the model more robust against new types of water and light conditions. Further development of the framework for the video sequence enhancement, using temporal information from one frame to the next, could provide more stable and consistent results for underwater video surveying. Finally, a light weight version of the model that could be efficiently implemented on mobile or embedded systems will allow for real time improvement in underwater robotic platforms and diving devices, considerably increasing its practical applicability for field deployments.

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