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Underwater Image Enhancement & Restoration Using Deep Learning

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Abstract— Deep underwater exploration is greatly aided by underwater photography. The image quality deteriorates due to a variety of environmental conditions, such as light scattering and absorption. Even with numerous efforts made in the field of picture restoration and enhancement, improving distorted and degraded images remains a difficult task. When employed at deep depths underwater, image capturing systems are unable to provide high-resolution photographs, and the necessary equipment is costly. Rebuilding and improving image quality is achievable with image processing techniques, without the need for dependable and expensive image acquisition software. By applying deep learning models for fine-tuning, sharpening, and grain removal, the goal is to produce better underwater photographs.

Keywords—*Underwater image, CNN, GAN*

I. INTRODUCTION

In modern world, the ability to capture crystal-clear underwater images has been the subject of research by academics worldwide in recent years. In addition, the entire process of recovering the acquired photos is a laborious undertaking. A few flaws can be found in the underwater photographs that were obtained because of the scientific phenomena of absorption and scattering. Three prominent issues with these photos are low contrast, blurriness, and an original colour distortion. For researchers in the field of image processing, overcoming these shortcomings is an enormous undertaking. While light passes through water, its path is narrowed. Pictures become submerged and turn greenish blue when they fall short on specific frequency portions because the larger frequencies in this case are more affected than the smaller ones. Because the longer frequency segments of the apparent range are weakened first, an image taken, for instance, at a depth of about 4-5 metres underwater, will require red frequency. Other frequency segments will also start to lose significance with further increase. Therefore, the images suffer from the negative impacts of a narrow range of perception, uneven illumination, and the presence of magnificent antiques. The suggested research project enhances the underwater photos using a deep learning model in order to get around it..To explore sea underwater images are required to capture, but underwater images are distorted. In other images are not clear enough for research deep under sea. Images captured under sea has low contrast, hue of underwater images tends to be close to green and blue. In this paper, we will discuss how underwater image enhancement is carried out with the help of algorithm based on deep learning. The result of this experiment shows that the advantages of the algorithm and it eliminates the influence of environmental factors, enriches the colour, enhances the detail.

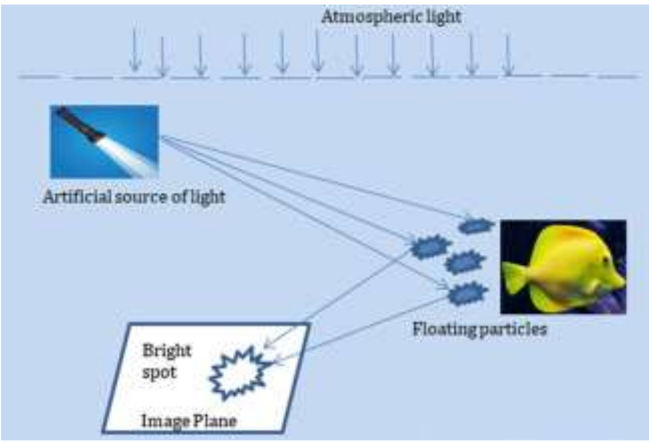
Images captured underwater are fuzzy, diminished have non-uniform illumination and it is not possible to use to this image for various purposes such as exploring natural resources, creatures living under sea, under-sea pipeline and cables. Blur images are not useful until it is being deblurred. There are various algorithms have been proposed for enhancement of underwater images such as CNN, generative adversial networks (GANs), LSTM etc.

1.1 Description of Underwater Environment

The region which is completely immersed is water such as natural or artificial water bodies like reservoirs, ocean, lakes, rivers is called the underwater environment. Most living organisms live in their natural habitat. For example, Sea organisms live inside water because aquatic creatures can't survive anywhere else. The origin of life on earth mainly depends on environment underwater because it is vital part of life on earth. Human interference in underwater environment are carried out in certain regions so it our prime duty to understand the environment under sea surface. To explore undersea it is required to understand how image formation is carried out undersea .

1.2 *Image Formation Model*

Underwater image is formed by either scattering of light directly from object itself or from natural light present in the environment. If artificial source of light is reflected from the object then due to floating particles bright spots is being created. This is called non-unform illumination. So images captured underwater are not clear. So to clear it needs to be processed.



Source: UIE, A comprehensive Review 2021[1]

Challenges faced in Underwater Imaging

Light absorption is a major problem in underwater imaging. Color of every object turns to be red or bluish because of shorter wavelength. Light gets absorbed as we go deeper and deeper undersea. Suspended particles also effects image quality. Fluorescence makes it difficult to capture good quality images. Scattering of light from the object effects the Picture quality. To overcome these challenges, various models have been proposed. We will discuss various methods applied for underwater enhancement.

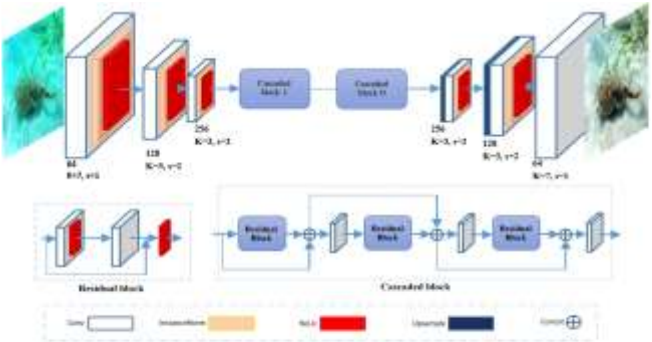
2.1 Image Enhancement Techniques

Convolutional neural networks allow to apply certain techniques for improving quality of images. MCycleGAN and DCP are applied to enhance the image quality (Smitha Raveendran 2021). Generative adversial networks are used for dehazing and color correction. The framework(GAN) is divide into two parts, haze detector and a sub-network of color correction. Dehazing is caused due to refraction of light and degradation of contrast. A residual Convolutional neural network estimates transmission map as discussed in Smitha Raveendran [1]. Residual based network is effective for removing the hazy effect and helps in illumination balance. This can be achieved by Underwater residual convolutional neural networks(URCNN).

In deep learning, CNNs use a variation of multilayer perceptron designed for minimal pre-processing. Traditional filters that were used before were hand-engineered. Another method for image enhancement comprises of RGB to grayscale conversion, applying histogram equalization and convert grayscale image into RGB image. The benefit of using conversion method is to reduce calculation size. Grayscale image have a single channel to execute but RGB image have three channels. Calculation of three channels become complex while applying Convolution neural networks. After converting RGB image into grayscale image, contrast adjustment process is applied using histogram equalization technique. Throughout this adjustment, global contrast of images increases by effectively spreading out the most frequent intensity values as discussed in UIEB, A. Yadav [2]. After histogram equalization, grayscale image is again converted into RGB image using convolutional neural networks to get the output image. This method generates less mean square error, better entropy and low peak signal to noise ratio.

2.2Image Enhancement through GANs

In this technique image-to-image translation from one domain to another is used. Conditional GANs can be used in aerial photograph to map, edges to photo, etc. GANs can be trained in a supervised manner on trained data or unsupervised manner if paired data is unavailable. GANs accelerate the performance by providing more detailed images for a better result. Generated realistic pairings can be done by using CycleGAN which generates the perceptual quality of images based on local and global style information. For underwater image due to inherent distortions, the quality of image gets affected. To overcome this, a new method is proposed for underwater image enhancement called CRN-UIE Model which is an improved GAN model for detailed clearance and enhancement as discussed in Karen Panetta, [3].



Source: CUOTB, Karen Panetta, 2021[3]

Color correction can be performed by method under CycleGAN as discussed in Xuelei Chen [4]. In this paper, the image formation model is combined with deep learning method in order to achieve enhanced clear image. In this method input image is processed in three modules namely backscatter estimation module, direct-transmission estimation module and reconstruction calculation.

2.3 Backscatter Estimation Module

Input image is processed into the backscatter estimation module which includes two groups of 3x3 convolution kernels, one global mean pooling layer and two groups of 1x1 convolution kernels. The activation function, parametric rectified linear unit is used for the convolution operation. On comparing with the normal rectified linear unit(ReLU), the parametric rectified linear unit(PReLU) avoid the phenomenon when gradient becomes zero and weights can't be updated later.

2.4 Direct Transmission Estimation Module

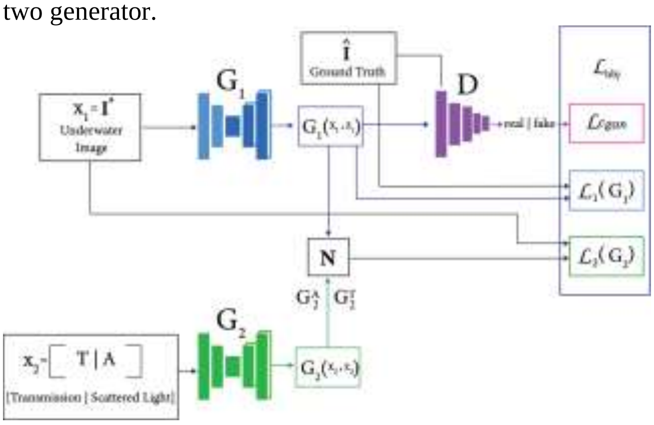
The DTE module first combines backscatter estimation with the input image and then continuous operation performed via three groups of 3x3 dilated convolution kernels and one group of 3x3 convolutional kernels(normal). The total no. of dilated convolution kernels is 8 and that of normal convolution kernels is 3. Dilated convolution fills extra zeros in the convolution kernel without adding extra parameter. In this process each input image has a corresponding reference image as target.

3.1 UOD2021 Datasets

For monitoring performance of image enhancement and restoration UIEB, RUIE, SQUID datasets are constructed for studying state-of-the-art (SOTA) UIER algorithms. 3D TURBID dataset, UID-LEIA dataset, UIDD dataset and SUID dataset are several synthetic underwater image datasets Contain reference images, which can be further proceeded for FR evaluation of UIER technologies. These datasets contain a very limited number of images and only cover a few challenging scenes which causes using this application for huge amount. UID2021 overcomes all the drawbacks of the above datasets as discussed in Guojia Hou [5]. UID2021 is a large-scale underwater image enhancement dataset which establishes 900 improved quality images from 60 degraded underwater images. It is an appropriate dataset for applying image enhancement algorithms for evaluating results so that it can suggest a new research direction. It also contains mean opinion scores(MOS) from 52 observers and nine NR quality assessment metrics for evaluation. It can set as a benchmark for optimization process for underwater image enhancement ad restoration algorithms. On applying this dataset over image enhancement algorithms and to analyze the performance, average MOS value is calculated. By comparing the average MOS value of different UIER algorithms performance is being find out.

II. DGD-cGAN

Underwater imaging biggest challenges are depth acquisition, scattering and measurement. Datasets in underwater lacks ground truth, depth information. We aim at estimating the transmission and veiling light, including the diffuse attenuation coefficient set to zero. We will design a model using conditional generative adversial networks(cGAN) that trains two generators and one discriminator. We will implement a CNN model based on U-Net for the two generators G_1 and G_2 and a discriminator based on PatchGAN. U-Net is widely used by researchers because both input and output have similar structure as well as high resolution. U-Net preserves the image resolution by applying an encoder-decoder architecture with mirrored layers and output of encoder combines with the decoder. Salma Gonzalez-Sabbagh [6] tells that DGD-cGAN modularity is BatchNorm-ReLU-Convolution-ResU. PatchGAN employs two generator.



Source: DGD-CGAN Salma Gonzalez [6]

III.UIE-NET FRAMEWORK

Deep Learning models are based Convolutional neural networks usedfor low-level vision tasks, low-light image enhancement, de-hazing, de-blurring, de-raining and enhancing noisy images. There are many researchers who proposed an Underwater enhancement method which trains an end-to-end transformation model between degraded or hazed images and clear images. Similarly, Underwater Image Enhancment-net (UIE-net) is a CNN based underwater image enhancement framework used for color correction and haze removal. It uses a pixel disrupting strategy for extraction of of inherent features of local patches of the image and it fastens convergence of the model and improves accuracy. In

Yan Wang [7] proposed a synthetic underwater image database that were generated in indoor environment for training UWCNN and it was used to clear real image and synthetic image to prove is generosity.

IV. CNN Based Image Restoration

CNN-based image restoration used depth maps through feature learning. The performance of methods depends on the training data and network architecture. Because of the use of synthetic images and potential defect architecture, it can perform well on all type images. The effectiveness of this model restrict its application for limited underwater images types. As compared to other restoration methods, deep learning methods are time consuming because rior knowledge and data segregation are used to investigate the color correction of underlying image. To be specific a multi-variable convolution model learns the composition of underwater image including the clean image, transmission map and background light. The meat learning used to capture knowledge-prior and then learning the underwater environment by fine tuning on real underwater image dataset. The state-of-the-art(SOTA) enhancement methods performed on UIEB dataset for image quality and robustness.

V.IMAGE EVALUATION METRICS

In the realm of underwater photography and imaging, the evaluation of image quality presents unique challenges and considerations compared to terrestrial photography. Underwater environments introduce variables such as light absorption, color distortion, and particulate interference that necessitate specialized metrics for assessing image quality. This article delves into the key metrics used to evaluate underwater images, their importance, and how they are applied in practice.

5.1. *Color Accuracy*

Underwater images are significantly impacted by the absorption and scattering of light in water. As depth increases, colors shift, with reds and yellows becoming less visible while blues and greens dominate. To evaluate color accuracy, metrics such as the Delta E (ΔE) can be used. ΔE measures the difference between the colors in the image and the true colors, which are often derived from standard reference images or color charts.Accurate color reproduction is crucial for scientific documentation, artistic purposes, and ecological studies. For instance, researchers might need to identify specific coral species or track changes in marine biodiversity, where accurate color representation is critical.

5.2. Contrast and Sharpness

Contrast measures the difference in luminance or color that makes objects distinguishable from each other. Sharpness pertains to the level of detail and the clarity of edges within the image. In underwater imagery, both contrast and sharpness can be affected by water turbidity, camera settings, and lighting conditions.

5.3.Techniques for Evaluation

Contrast Ratios: Evaluated through histograms or contrast stretch techniques that enhance the distinction between the foreground and background.Edge Detection Algorithms: These algorithms help quantify sharpness by measuring the clarity of edges and fine details.Importance: High contrast and sharpness are essential for clear visual representation, especially in applications like underwater navigation, marine biology research, and recreational diving. Resolution and Image Quality.Resolution is a measure of the detail an image holds and is typically quantified by the number of pixels. In underwater imaging, resolution can be influenced by factors like water clarity, camera optics, and distance to the subject.

5.4.Evaluation Methods

Pixel Count: The number of pixels can directly affect the level of detail in an image.modulation Transfer Function (MTF): This metric assesses how well the imaging system can reproduce fine details, providing insights into both resolution and lens performance..Importance of Higher resolution allows for more detailed analysis and better visualization, which is vital for documenting marine life, underwater structures, and conducting scientific research. Dynamic range refers to the range of light intensities from the darkest to the brightest parts of an image. Underwater environments often present challenging lighting conditions, from brightly lit surfaces to deep shadows, making dynamic range a critical factor.Histograms can show how well an image captures the full range of light intensities.High Dynamic Range (HDR) Imaging: Combining multiple exposures to enhance the dynamic range.Importance of Effective dynamic range ensures that both bright and dark areas are captured with detail, which is crucial for capturing the full spectrum of underwater scenes.Noise in underwater images can result from various sources, including low light conditions and camera sensor limitations. Noise manifests as random variations in brightness or color and can obscure important details.Signal-to-Noise Ratio (SNR): A higher SNR indicates less noise and better image quality.Noise Reduction Algorithms: These techniques help in reducing the noise while preserving image details.Importance of Minimizing noise is essential for maintaining clarity and ensuring accurate visual representation, particularly in low-light underwater scenarios. Water Clarity and Distortion Water clarity impacts how light travels and thus how well the image represents the underwater environment. Metrics for evaluating clarity include:Turbidity Measurements: Assessing the amount of particulate matter in the water.Optical Distortion Metrics: Evaluating the impact of water on image distortion, such as refraction and lens aberrations.

VI. COLORIZATION OF IMAGE

Colorization in underwater image enhancement is a crucial technique due to the unique challenges posed by underwater environments. Water absorbs and scatters light differently than air, leading to color distortion and loss of contrast in underwater images. Colorization helps restore the natural appearance of underwater scenes, making them more visually accurate and useful for scientific, artistic, or recreational purposes.

6.1.Challenges in Underwater Colorization

Color Loss is Red, orange, and yellow wavelengths are absorbed more quickly by water, leading to a predominantly blue or green tint in deeper images.Turbidity includes Suspended particles and plankton can scatter light, affecting color accuracy and image clarity. Lighting Conditions: Variable lighting conditions can further complicate color reproduction.

6.2.Colorization Technique

Color Correction Algorithms includes White Balance Adjustment: Adjusts the colors to compensate for the color temperature of the water. By setting a reference white point, the colors in the image can be adjusted to appear more natural.Color Transfer Uses reference images or known color charts to transfer accurate colors to the underwater image. This method maps the color distribution of the underwater image to the color distribution of the reference image. Machine Learning Approaches like Convolutional Neural Networks (CNNs) can be trained on large datasets of underwater images to learn how to restore natural colors. Models like U-Net or ResNet can be adapted for colorization tasks.GANs can be employed to generate realistic colorizations by learning from pairs of grayscale and color images.

6.3.Color Enhancement Filters

CLAHE (Contrast Limited Adaptive Histogram Equalization): Enhances local contrast, making colors appear more vivid. Applied after initial color correction to fine-tune the image. Color Mapping applies a predefined color map to the grayscale or color-corrected image to simulate realistic underwater colors.Post-Processing Techniques like Image Fusion Combines multiple images taken at different depths or times to enhance color accuracy. This can be useful in scenarios where multiple exposures capture different color ranges.Manual Adjustment after automated colorization, manual tweaks can be made using image editing software to refine colors and contrast.

6.4.Colorization Workflow for Underwater Images

Preprocessing Noise Reduction Remove noise that may interfere with color correction.Image Enhancement Apply initial enhancements like sharpening and contrast adjustment to improve image quality before colorization. Color Correction Apply White Balance Adjust the image’s white balance to correct for color temperature issues. Perform Color Transfer Use reference images or color charts to correct the color distortions.Colorization. Apply Machine Learning Models Use pre-trained models or train a model to predict and restore natural colors based on learned patterns. Enhance with Filters Apply CLAHE or other enhancement filters to further improve the color representation. Post-Processing Refine Colors Make manual adjustments as needed to correct any remaining color inaccuracies. Finalize Image to Ensure the final image meets the desired quality standards for the intended application.

VII. HISTOGRAM EQUALIZATION

Histogram Equalization is a method of adjusting the contrast of an image by modifying its histogram. The histogram of an image represents the distribution of pixel intensities (brightness levels) from black to white. HE aims to spread out the most frequent intensity values, effectively increasing the global contrast of the image.Compute the Histogram: Calculate the histogram of the image, which is a graph showing the number of pixels at each intensity level. For grayscale images, this is a plot of pixel intensity values (0-255) versus the frequency of these values. Calculate the Cumulative Distribution Function (CDF): The CDF is a cumulative sum of the histogram values, normalized by the total number of pixels. It represents the probability distribution of pixel intensities.Normalize the CDF: Scale the CDF so that it ranges from 0 to 1. This normalization is done by dividing the CDF by the total number of pixels. Map the Old Intensity Values to New Values: Create a mapping function based on the normalized CDF. Each pixel intensity in the original image is mapped to a new intensity value according to this function. Generate the Equalized Image: Apply the mapping function to the original image to produce the histogram-equalized image.

7.1.Steps in Histogram Equalization

Compute the Histogram: If an image has pixel values ranging from 0 to 255, create a histogram representing the count of pixels for each value.

Compute the CDF: For each intensity level iii, the CDF is calculated as:

CDF(i)=j=0∑iHistogram(j)

Normalize the CDF by dividing by the total number of pixels N:

Normalized CDF(i)= CDF(i)/N

Normalize the CDF:

Scale to fit the range of the image's intensity values:

New Value=round(Normalized CDF(i)×(L−1))

Where LLL is the number of intensity levels (typically 256 for an 8-bit grayscale image).

Apply the Mapping Function: Replace each pixel's intensity with the new value derived from the mapping function.

Generate the Equalized Image: Create the final image with the adjusted pixel values.

Suppose an image has poor contrast with pixel intensities concentrated around certain values. The histogram might show peaks at a few intensity levels. Histogram Equalization redistributes these intensities more evenly across the full range, enhancing the contrast and making details that were previously hidden in shadows or highlights more visible.

7.2.Applications of Histogram Equalization

Medical Imaging: Enhances the visibility of features in X-rays, MRI scans, and other medical images. Astronomy: Improves the visibility of celestial objects in astrophotography.

Remote Sensing: Enhances satellite and aerial imagery to reveal more details. General Photography**:** Improves the overall contrast and detail in photographs.

7.3.Advantages and Limitations

Advantages: Improves Contrast Enhances details and features in low-contrast images. Simple and Effective: Computationally straightforward and easy to implement.

Limitations: Over-enhancement Can cause artifacts or exaggerate noise in some images.Loss of Detail: In some cases, it may lead to a loss of detail in highly uniform areas of the image.Advanced Variations Adaptive Histogram Equalization (AHE): Divides the image into tiles and performs HE on each tile to enhance local contrast. AHE can be used to avoid the global contrast issues that can arise with standard HE.Contrast Limited Adaptive Histogram Equalization (CLAHE): A variant of AHE that limits the amplification to reduce noise and over-enhancement, making it suitable for practical applications.

VIII. LAPLACIAN FILTER

The Laplacian filter is a fundamental image processing tool used primarily for edge detection and image sharpening. By highlighting regions of rapid intensity change, it helps in enhancing the edges and fine details within an image. This filter is particularly useful in applications where precise edge detection is critical, such as in computer vision, medical imaging, and image analysis.

The Laplacian filter is a second-order derivative filter that calculates the second derivative of the image intensity function. It is designed to highlight areas where the intensity changes rapidly, such as edges and corners. Unlike first-order derivative filters (like the Sobel or Prewitt filters), which detect edges based on gradients, the Laplacian filter directly measures the rate of change in intensity, providing a more direct method for detecting sharp transitions.

In mathematical terms, the Laplacian of an image I(x,y)I(x, y)I(x,y) is defined as:

Laplacian(I)= $\partial x2/\partial 2I+\partial y2/\partial 2I$

where $\partial x2\partial 2I$ and $\partial y2\partial 2I$ are the second partial derivatives of the image with respect to the xxx and yyy coordinates, respectively.

IX.HIGH BOOST FILTER

The High Boost Filter is an advanced image enhancement technique used to improve the sharpness and detail of images. It builds upon the concept of image sharpening by amplifying high-frequency components, which enhances the edges and fine details in an image. This filter is particularly useful in applications where clarity and detail are crucial, such as in medical imaging, satellite imagery, and digital photography.The High Boost Filter is a refinement of the basic sharpening filters, such as the Laplacian or Sobel filters. It works by applying a high-pass filter to emphasize the high-frequency components (edges and details) of an image and then combining the result with the original image. This process effectively boosts the image's sharpness while preserving its overall structure.

The High Boost Filtering process involves the following steps:

High-Pass Filter Application:First, a high-pass filter (like the Laplacian filter) is applied to the image to isolate the high-frequency components.Amplification: The high-frequency components are then amplified by a scaling factor kkk, which controls the degree of enhancement. Combining with the Original Image: The amplified high-frequency components are added back to the original image to produce the final high-boosted image. Mathematically, the high boost filtering operation can be described as:

High Boost Filtered Image=Original Image+k×High Pass Filtered Image

where kkk is the boost factor, typically greater than 1.

Steps in High Boost Filtering

Apply a Low-Pass Filter: Smooth the original image using a low-pass filter (like a Gaussian filter) to obtain a blurred version of the image.Compute the High-Pass Filtered Image: Subtract the low-pass filtered image from the original image to obtain the high-frequency components.

High-Pass Filtered Image=Original Image−Low Pass Filtered Image

High-Frequency Components:Multiply the high-frequency components by a boost factor kkk.

Combine with the Original Image:

- Add the amplified high-frequency components to the original image.

High Boost Filtered Image=Original Image+k×(Original Image−Low-Pass Filtered Image)

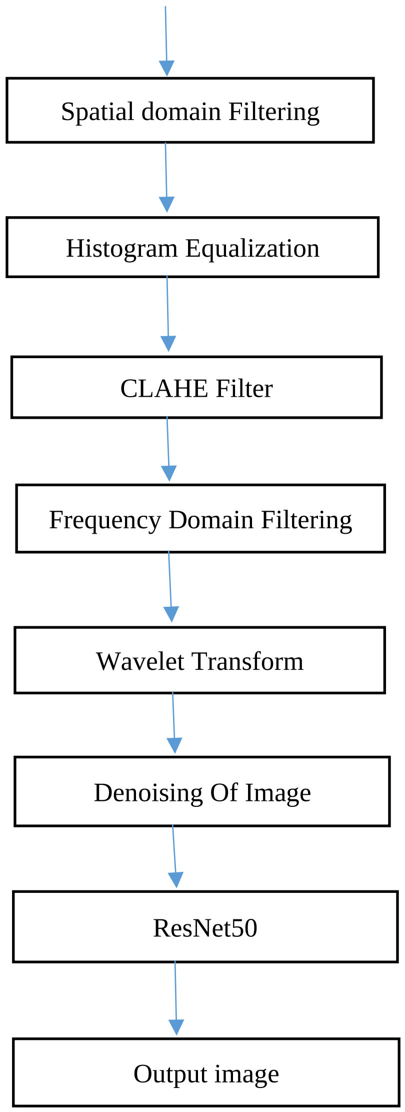
Applications are Image Sharpening: Enhances the edges and fine details, making the image appear clearer and more defined. Medical Imaging: Improves the visibility of structures and anomalies in diagnostic images. Satellite and Aerial Imagery: Enhances details and boundaries in geographic and environmental analysis. Photography: Refines image details and improves the visual quality of digital photos..Advantages and Limitations Advantages are Enhanced Detail: Effectively increases the sharpness and detail of images, making features more prominent.Customizable: The boost factor kkk allows for control over the degree of sharpening, enabling fine-tuning of results.Limitations: Noise Amplification: May amplify noise along with the edges, which can reduce image quality if not properly managed. Over-Sharpening: Excessive boosting can lead to artifacts such as haloing or ringing around edges. Consider an image of a landscape that appears somewhat blurred or lacks detail. Applying a High Boost Filter with a suitable boost factor kkk would enhance the edges of mountains, trees, and other features, making them more distinct and sharper. This results in a clearer, more detailed image, improving the overall visual quality.

Comparison with Other Filters like Unsharp Masking: Similar to High Boost Filtering, Unsharp Masking also enhances image sharpness but uses a slightly different approach. It involves subtracting a blurred version of the image from the original image, typically using a Gaussian blur. Laplacian Filter: While both Laplacian and High Boost Filters enhance edges, the High Boost Filter allows for more control over the amount of enhancement through the boost factor.

X.PROPOSED METHODOLOGY

First of all we will input the source image into the spatial domain filters.Further histogram equalization is applied and then Contrast limited adaptive histogram equalization (CLAHE) then frequency domain filtering.After that wavelet transform followed by denoising of Image and finally neural network ResNet50 is applied to get clear image.

Input Image



Frequency domain filtering is a powerful technique used in image processing that involves analyzing and modifying images based on their frequency components. Unlike spatial domain filtering, which operates directly on pixel values, frequency domain filtering works with the frequency representation of the image. This method can be particularly useful for tasks such as noise reduction, image enhancement, and compression. Concept of Frequency Domain **is** Spatial Domain: Refers to the direct representation of an image in terms of pixel values. Operations like convolution and filtering are performed directly on these pixel values.Frequency Domain Refers to the representation of an image in terms of its frequency components. Frequencies correspond to patterns and variations in pixel intensity. High frequencies represent rapid changes (edges and fine details), while low frequencies represent slow changes (smooth areas). Fourier Transform The Fourier Transform is a mathematical tool used to convert an image from the spatial domain to the frequency domain. It decomposes an image into its sinusoidal frequency components.Discrete Fourier Transform (DFT): The DFT is used for digital images, providing a matrix of complex numbers representing the magnitude and phase of different frequencies.Fast Fourier Transform (FFT): An efficient algorithm for computing the DFT, making frequency domain operations faster and more practical for real-time applications. Frequency domain filtering involves applying a filter in the frequency domain and then transforming the image back to the spatial domain. The steps are:Transform the Image.Convert the image from the spatial domain to the frequency domain using the Fourier Transform.Apply the Filter:Design a filter that operates in the frequency domain. Common filters include low-pass filters, high-pass filters, and band-pass filters. Multiply the image's frequency representation by the filter's frequency response.Inverse Transform:Convert the filtered frequency domain image back to the spatial domain using the Inverse Fourier Transform.Analyze the Result:Examine the filtered image for the desired enhancement or modification.Types of Frequency Domain Filters Low-Pass Filters Allow low frequencies (smooth regions) to pass through while attenuating high frequencies (edges and noise)Gaussian Low-Pass Filter, Ideal Low-Pass Filter Used for blurring and noise reduction. High-Pass Filters Allow high frequencies (edges and fine details) to pass through while attenuating low frequencies (smooth areas)Gaussian High-Pass Filter, Laplacian Filter.Used for edge enhancement and sharpening. Band-Pass Filters Allow a specific range of frequencies to pass through while attenuating frequencies outside this range.Band-Stop Filter (notch filter), Butterworth Band-Pass Filter Used for feature enhancement and noise removal within specific frequency bands. Blurring an Image:Objective: To reduce high-frequency noise and achieve a smooth effect.Apply the Fourier Transform to the image to get its frequency representation.Multiply the frequency representation by a Gaussian Low-Pass Filter to attenuate high frequencies. Apply the Inverse Fourier Transform to get the blurred image in the spatial domain.Edge Detection: To enhance the edges in an image.Apply the Fourier Transform to the image. Multiply the frequency representation by a High-Pass Filter to enhance high frequencies.Apply the Inverse Fourier Transform to get the sharpened image with enhanced edges.

Advantages are Effective for Complex Operations: Frequency domain filtering can efficiently handle complex operations like blurring and sharpening. Handling Noise allows for precise control over noise and detail enhancement by manipulating specific frequency components. Limitations are Computational Complexity: Performing Fourier Transforms and their inverses can be computationally expensive, especially for large images.Artifacts: Frequency domain filtering may introduce artifacts such as ringing or aliasing if not properly managed. Applications are Image Compression The frequency domain is used in image compression algorithms (e.g., JPEG) to reduce image size while preserving important details. Enhances and processes images for better visualization of medical conditions. Processes astronomical images to reveal more details and reduce noise.

Wavelet transform is a mathematical tool used in signal processing and image compression to analyze and process signals at different scales. It offers advantages over traditional Fourier analysis by providing localized information in both time and frequency domains simultaneously. Wavelet transforms are particularly useful in handling non-stationary signals and images with varying levels of detail. Wavelet transform decomposes a signal or an image into a set of basis functions called wavelets, which are scaled and translated versions of a mother wavelet function. This decomposition allows for the analysis of signal characteristics at different resolutions or scales.Types of Wavelet Transform Continuous Wavelet Transform (CWT): The CWT operates over a continuous range of scales and provides a continuous representation of the signal. It uses a continuous mother wavelet function and translates and dilates it across the signal.Discrete Wavelet Transform (DWT). The DWT operates at discrete scales and positions. It decomposes the signal into a set of discrete wavelet coefficients, capturing both high-frequency and low-frequency components of the signal at different levels of resolution. Localization: Wavelets are localized in both time and frequency domains, allowing for the analysis of transient signals and localized features in an image. Multi-resolution Analysis: Wavelet transform provides a multi-resolution representation of the signal, capturing details at different scales. Orthogonality and Bi-orthogonality: Wavelets can be orthogonal or bi-orthogonal, which aids in efficient signal decomposition and reconstruction.

Wavelet transform is widely used in image compression algorithms (such as JPEG2000) to achieve high compression ratios with minimal loss of image quality. Wavelet transform is effective in separating noise from signal components and denoising signals by thresholding wavelet coefficients. In image processing, wavelet coefficients can be used as features for pattern recognition and image analysis tasks. Wavelet transform allows for the simultaneous analysis of signal characteristics in both time and frequency domains, making it useful in analyzing non-stationary signals. Haar Wavelet The simplest wavelet function, characterized by its step-like shape. Daubechies Wavelets: A family of wavelets with compact support & good frequency localization.Symlet Wavelets: Similar to Daubechies wavelets but with more symmetric properties. Biorthogonal Wavelets: Wavelets that have different functions for decomposition and reconstruction, allowing for more flexible signal representation.

Denoising of images is a crucial task in image processing aimed at removing noise while preserving important image features. Noise in images can degrade image quality, making it difficult to analyze or interpret them accurately. There are various methods and techniques used for denoising images, ranging from simple spatial domain filters to sophisticated algorithms based on statistical models or machine learning approaches. Methods for Denoising Images is Spatial Domain Filters. These filters operate directly on the pixel values of the image without transforming it into another domain. Gaussian Blur applies a Gaussian kernel to blur the image, averaging nearby pixel values to smooth out noise. This filter is effective for Gaussian noise but may blur edges and details. Median Filter replaces each pixel with the median value in its neighbourhood. It is particularly effective in preserving edges while reducing impulse noise (salt-and-pepper noise). Mean Filter similar to Gaussian blur but uses a simple averaging kernel. It is less effective for preserving image details compared to median filters. Frequency Domain Filters. These filters operate in the frequency domain after transforming the image using Fourier or Wavelet transforms. Wiener Filter A statistical filter that estimates the original signal from a noisy image by taking into account both the noise and the signal characteristics .Wavelet-Based Denoising: Uses wavelet transform to decompose the image into different frequency components. Thresholding techniques are applied to wavelet coefficients to suppress noise components. Non-Local Means (NLM) Denoising
NLM denoising compares patches of pixels across the image and averages similar patches to preserve image details while reducing noise. It exploits the redundancy in natural images where similar structures and textures appear frequently. Deep Learning-Based Approaches Convolutional Neural Networks (CNNs) are trained to learn filters that automatically denoise images. They can effectively handle complex noise patterns and preserve fine details. Autoencoders belongs to Variational autoencoders (VAEs) and other autoencoder architectures can be trained to reconstruct clean images from noisy inputs, effectively denoising images in the process. Patch-Based Methods These methods divide the image into overlapping patches, denoise each patch independently, and then reconstruct the image. Block Matching 3D (BM3D)A popular patch-based method that first groups similar patches together and then applies a collaborative filtering technique to denoise each group. Considerations and Challenges Trade-off Between Denoising and Detail Preservation: Most denoising methods aim to find a balance between reducing noise and preserving important image features and details.
Noise Characteristics such as Different types of noise (e.g., Gaussian, salt-and-pepper) require different denoising strategies. Some methods may be more effective for specific noise types than others. Computational Complexity: Some advanced denoising techniques, especially those involving deep learning, can be computationally intensive and require substantial computational resources. Applications are Medical Imaging in which Denoising is critical for improving the accuracy of diagnostic images such as MRI, CT scans, and ultrasound images. In digital photography, denoising enhances image quality by reducing noise that often appears in low-light or high ISO settings. Denoising techniques are applied to satellite images and aerial photographs to improve the clarity and accuracy of geographic information.

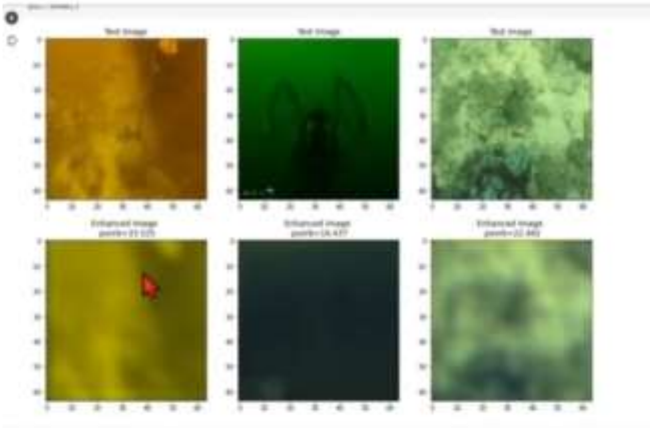
ResNet50 is a deep convolutional neural network architecture that belongs to the family of Residual Networks (ResNets). It was introduced by Microsoft Research in their paper titled "Deep Residual Learning for Image Recognition" in 2015. ResNet50 is specifically known for its depth, featuring 50 layers, which allows it to learn more complex features compared to earlier models. Residual Learning includes
the core innovation of ResNet architectures, including ResNet50, is the use of residual learning blocks. These blocks enable training of very deep neural networks (up to hundreds of layers) by addressing the vanishing gradient problem. The residual blocks are designed to learn residual mappings instead of directly fitting to a desired output. This is achieved by introducing skip connections, or shortcuts, that skip one or more layers:

$$F(x)=H(x)-x$$

where $H(x)$ represents the desired mapping, and $F(x)$is learned as the residual.

Architecture includes Layers: ResNet50 consists of 50 layers, including convolutional layers, pooling layers, fully connected layers, and residual blocks. Convolutional Layers: These layers extract features from input images using convolution operations with learnable filters. Pooling Layers: Used for down sampling feature maps to reduce spatial dimensions and computational load. Fully Connected Layers: These layers at the end of the network perform classification based on the extracted features. Prevalence of Skip Connections Identity Shortcut Connections: These connections allow gradients to flow directly through the network, mitigating the vanishing gradient problem encountered in training very deep networks. Performance and Applications are Image Classification. ResNet50 has been primarily used for tasks such as image classification in computer vision. It has achieved state-of-the-art results on various benchmark datasets such as ImageNet. Transfer Learning is Due to its effectiveness and pre-trained models available, ResNet50 is often used in transfer learning scenarios where it serves as a starting point for training on other datasets or tasks with limited data.Object Detection and Segmentation: ResNet50 has also been adapted and used as a backbone network in object detection and segmentation tasks, providing robust feature extraction capabilities. Limitations and Considerations such as Computational Complexity in which Training ResNet50 from scratch requires significant computational resources and time due to its depth and the number of parameters.Overfitting: Deep networks like ResNet50 are prone to overfitting if not properly regularized or trained with sufficient data.

ResNet50 is available as part of several deep learning frameworks such as TensorFlow, PyTorch, and Keras. Pre-trained models are often provided, allowing users to perform transfer learning or use the model directly for various image recognition tasks without training from scratch. In this methodology both keras and tensorflow are used to get the desired clear underwater image. Residual Networks (ResNets) are a class of deep neural network architectures that were introduced to address the challenge of training very deep neural networks effectively. They were proposed by Kaiming. in their seminal paper titled "Deep Residual Learning for Image Recognition" Residual networks revolutionized deep learning by introducing the concept of residual blocks, which enable the training of networks with hundreds or even thousands of layers. Residual Networks (ResNets) have had a profound impact on deep learning, enabling the training of extremely deep neural networks that were previously challenging to optimize. By introducing residual blocks and skip connections, ResNets have significantly advanced the state-of-the-art in tasks such as image classification, object detection, and segmentation. Their success underscores the importance of architectural innovations in deep learning and continues to inspire further developments in neural network design and optimization.



XI.RESULTS AND DISCUSSION

The experiments used to assess the accuracy of neural network estimates. In the first case, all the datasets were used for training and evaluation using the test images. Nevertheless, this is not really a real scenario because training images are usually not available at the treatment site. This is why the current study approximates the above circumstance preparing for only yet another dataset used for system validation. In order to assess the accuracy of the neural network predictions, the images are improved by two common techniques and compared to the approach proposed. The first, contrast enhancement, investigates the processed image histogram and moves it to adopt the optimal material. The contrast enhancement most frequently used in this paper changes the image features to a normal distribution of each channel. The second algorithm to be compared is an Automatic Color Enhancement, as mentioned in literatures and also shown in underwater environments. This technique improves the image on the basis of a Convolutional Neural Network model, inspired by specific methodologies such as grey world evolution, white picking, transverse inactivation and application based adaptation. The proposed model shows the effective results mainly 50 epochs, accuracy 83 percent which makes this model a pioneer in the world of Underwater image enhancement more accurate and clear to explore underwater environment.

CONCLUSION

Based on all the image enhancement and restoration algorithms, more deep learning techniques are applied including Generative Adversial Networks to regulate the white balance and Recurrent Neural Networks to de-noise and gather more detailed images which requires a great number of paired original and reference images. ResNet50 represents a significant advancement in deep learning architecture, particularly in addressing the challenges of training very deep neural networks. Its innovative use of residual blocks and skip connections has made it a cornerstone in modern computer vision applications, demonstrating superior performance on tasks ranging from image classification to object detection and segmentation. As deep learning continues to evolve, architectures like ResNet50 continue to serve as foundational models, pushing the boundaries of what is possible in visual recognition tasks. Synthetic Datasets are often used to train deep neural networks which are obtained from complex underwater environments. Therefore it is essential to construct a benchmark dataset foe testing the accuracy and efficiency of the model. In this review UIEB datasets are used for qualitative evaluation and to compare the model with other used algorithms on metrics so that if the model does not performs up to the mark then major changes can be carried out for the enhancement of the used model. The evaluation favors over enhanced colorful image which are subjective to naturalness. Current image enhancement methods focus on perpetual effect of images bot ignore the high-level features and accuracy of the image. Light attenuation and scattering of light affects the quality of image so we need to focus on new deep image enhancement measures to be carried out in future.

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