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# Under Water Image Enhancement using Custom VGG19

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**Abstract:** This research introduces an innovative approach to underwater image processing through the use of a modified VGG-19 architecture, renowned for its exceptional image processing capabilities using Variational Bayesian-based Robust Adaptive Filtering (VBRAF). At the heart of this approach is the integration of custom layers within the Relational Bilevel Aggregation Graph Convolutional Network (RBAGCN)-VGG-19 frameworks. Enhancing the model's adaptability to the unique challenges of underwater condition using image processing; this method incorporates a specialized encoder based on the VGG-19 architecture, enriched with additional custom layers for detailed from underwater imagery. The decoder component then reconstructs these details into images of higher clarity and resolution. A notable aspect of method is the inclusion of a max unpooling mechanism, which streamlines the processing of complex deep learning models and improves the clarity of lower-resolution. This research marks a significant advancement in underwater image processing, setting a new standard for high-quality underwater photography and marine research, facilitated by the customized VGG-19 architecture.

**Keywords:** *Custom VGG-19 Architecture, Deep Learning, Encoder-Decoder Network, High-Resolution Imaging, Relational Bilevel Aggregation Graph Convolutional Network, Underwater Image Enhancement, Variational Bayesian-based Robust Adaptive Filtering.*

## 1. Introduction

The exploration of underwater environments has always presented unique challenges and opportunities, particularly in the realm of imaging. Capturing clear, accurate images underwater is crucial for a myriad of applications, ranging from marine biology research and environmental monitoring to underwater archaeology and exploration. However, traditional imaging techniques often struggle to overcome the inherent difficulties posed by underwater environments, such as variable lighting conditions, color distortion, and reduced visibility due to particulate matter. With the advent of advanced computational techniques, particularly in the field of artificial intelligence, there has been a transformative shift in underwater imaging methodologies. Here, Relational Bilevel Aggregation Graph Convolutional Network (RBAGCN), and more specifically, the VGG 16 architecture, have emerged as powerful tools in addressing these challenges. The utilization of these advanced AI techniques promises not only to enhance the quality and clarity of underwater images but also to revolutionize the understanding and exploration of underwater worlds. The journey towards leveraging the VGG 16 architecture for underwater imaging is well-documented in the literature, illustrating a shift from traditional imaging methods to more sophisticated, AI-driven techniques. Early approaches in underwater imaging were primarily based on conventional signal processing methods. These techniques, while foundational, had limitations in effectively capturing the dynamic and complex nature of underwater scenes. Challenges such as light refraction, color distortion, and blurriness were common and difficult to mitigate using these traditional methods. The introduction of RBAGCN s in image processing marked a significant turning point. The VGG 16 model, developed by Simonyan and Zisserman, became a focal point in this new era due to its deep architecture and efficient capabilities. Research by Wang et al. [1] demonstrated the potential of deep RBAGCN methods in enhancing underwater images, addressing issues like color correction and contrast adjustment that are vital in underwater settings. Building upon these initial developments, studies such as those by Anwar et al. [2] and Li et al. [3] further explored the application of RBAGCNs in underwater image enhancement. Their research delved into various aspects of deep learning applications, including the training and optimization of models to suit the specific challenges presented by underwater photography. This body of work highlighted the adaptability of RBAGCNs in improving image quality under diverse underwater conditions. Ancuti et al. [4] contributed significantly by focusing on color balance and fusion techniques within underwater image enhancement. Their work underscored the importance of accurately rendering the unique color profiles found in underwater environments, a task well-suited to the capabilities of RBAGCN models. More recent advancements, as seen in the work of Wang et al. [5], have

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introduced the concept of dual color space adjustments in RBAGCN architectures for underwater imaging. These innovative approaches have opened new avenues for precise image processing, enhancing the accuracy and detail of underwater imagery. Ultimately, the literature points to a clear evolution from basic image processing techniques to advanced, AI-driven models like the VGG 16. The ability of this architecture to adapt to the specific requirements of underwater imaging has been consistently highlighted in studies, establishing it as a robust tool for enhancing underwater images. This progression in technology not only showcases the advancements in the field but also lays the groundwork for future exploration and innovation in underwater imaging.

## 2. Literature Survey

### 2.1 Secondary Research

The secondary research phase was extensive and multifaceted, involving a deep dive into the existing literature at the intersection of underwater imaging and artificial intelligence. This exploration included a thorough review of academic papers, technical reports, and scholarly articles, focusing particularly on the domain of computer vision and the application of deep learning techniques. A significant portion of the literature review was dedicated to studying and analyzing Convolutional Neural Networks (RBAGCNs), with a special emphasis on the VGG 19 model. This model is renowned for its capabilities in image enhancement and processing, making it a focal point of the research.

To delve into key research studies, including those by Wang et al., [1] and Ancuti et al., [4], which provided valuable insights into the utilization of deep learning models for underwater image enhancement. These studies were pivotal in understanding both the capabilities and limitations of existing models in addressing the unique challenges of underwater environments. Additionally, to expanded the review to include broader applications of RBAGCNs in image processing. The work of Anwar et al., [2] and Li et al., [3] offered enlightening perspectives on advances in deep learning techniques for image enhancement, extending beyond the underwater domain. These comprehensive studies helped us to establish a holistic view of the state-of-the-art in AI-driven image processing.

The secondary research was not solely focused on gathering information about existing technologies; it was also about identifying gaps in current methodologies. By analyzing the works of field experts and their practical applications and theoretical insights, such as those presented by Wang et al., [5], were able to pinpoint areas ripe for further research and development in underwater image processing.

This phase of the research laid a solid foundation for the study, providing a thorough understanding of the current state of technology in underwater imaging. It was guided by insights and findings from leading researchers and practitioners in the field, and it shaped the direction for primary research and experimentation, setting the stage for the exploration into the customization of the VGG 19 model for underwater imaging.

### 2.2 Primary research:

In the primary research phase of the study, is too embarked on an empirical evaluation of the customized VGG 19 model's effectiveness in underwater image enhancement. The goal was to rigorously assess the performance of this adapted model in comparison to both the standard VGG 19 and other prevalent image processing techniques [6]. To ensure a comprehensive and unbiased analysis, by carefully curated a diverse set of underwater images, each posing unique challenges to test the adaptability and effectiveness of the model.

These selected images encompassed a broad range of underwater conditions. Variations in lighting were a key focus, ranging from the low-light depths of the ocean to brightly lit near-surface waters, to accurately assess the model's performance under different lighting scenarios [7, 8]. Then also paid close attention to the clarity of the images. The dataset included images with significant murkiness, typical of many underwater environments, as well as clearer images that presented less of a challenge to the enhancement process.

Color variation was another critical factor in the selection process. Given that underwater images often suffer from color distortions due to the absorption and scattering of light, the dataset comprised images with a range of color fidelity [9]. Some images are in collection had dominant blue or green tints, a common issue in underwater photography, while others image more balanced and natural color profiles [10]. This diversity was crucial for testing the model's ability to effectively correct color distortions and accurately render the true colors of the underwater world.

The core of the experimentation involved applying the customized VGG 19 model to this array of images, followed by a detailed analysis of its ability to enhance clarity, correct color distortions, and overall improve visual quality [11]. This evaluation was critical to determine the model’s practical utility in real-world scenarios, such as marine biology research, underwater exploration, and environmental studies.

Through this comprehensive evaluation, the primary research aimed to demonstrate the enhanced capabilities of the customized VGG 19 model in underwater image enhancement compared to existing methods [12]. This phase was pivotal in showcasing the potential advancements and improvements this model could contribute to the field of underwater imaging, particularly in addressing specific challenges associated with underwater environments.

### 2.3 Emphasis

The focal point of this paper is the enhancement of underwater image processing by innovatively customizing the VGG-19 architecture. This research is predicated on addressing the intrinsic challenges associated with underwater imaging, such as the distortion of light and color, and the overall degradation of image clarity [13]. Central to exploration is the strategic augmentation of the VGG-19 model, wherein custom layers are seamlessly integrated into its framework. These tailored modifications are specifically designed to adapt to the unique demands of underwater environments, thereby significantly improving the model's capability in detailed image from such complex imagery.

The study meticulously evaluates the efficacy of this modified architecture, comparing its performance with traditional image processing methods. The aim is to ascertain the extent to which these custom enhancements contribute to the precision and quality of underwater image reconstruction. This comprehensive analysis not only underscores the technical advancements achieved but also examines the practical implications of these improvements in the realms of marine exploration, ecological research, and environmental monitoring. The broader ambition of this paper is to contribute to the scholarly discourse in the fields of deep learning and image processing. By presenting a novel approach to tackling the specific challenges of underwater imaging, the study seeks to bridge the gap between theoretical models and their practical application in real-world scenarios. In doing so, it aims to provide a foundation for future research and technological advancements in enhancing the clarity and accuracy of images captured in aquatic environments. Table 1 shows that the Literature Survey.

**Table 1**: Literature Survey

| Sno | Title | Author | Journal/ Conference | Year of publish | Proposed Work | Future Work | Remarks |
|---|---|---|---|---|---|---|---|
| 1 | A deep CNN method for underwater image enhancement | Wang et al., [1] | 2017 IEEE International Conference on Image Processing (ICIP) | 2017 | Presented a deep CNN method for enhancing underwater images. | Not specified | Focused on the application of deep learning in underwater image enhancement. |
| 2 | Deep underwater image enhancement | Anwar et al., [2] | Signal Processing: Image Communication | 2018 | Explored advanced techniques for enhancing underwater images using deep learning. | Suggested improvements in CNN architectures for underwater imaging. | Highlighted the potential of deep learning in image processing. |
| 3 | An underwater image enhancement benchmark dataset and beyond | Li et al., [3] | IEEE Transactions on Image Processing | 2019 | Introduced a benchmark dataset for underwater image enhancement. | Proposed the development of more comprehensive datasets. | Provided a standardized dataset for future research. |
| 4 | Color balance and fusion for underwater image enhancement | Ancuti et al., [4] | IEEE Transactions on Image Processing | 2017 | Focused on color balance and fusion techniques in underwater image enhancement. | Suggested exploring other color space models. | Emphasized the importance of color correction in underwater imagery. |

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|---|---|---|---|---|---|---|---|
| 5 | CNN-based underwater image enhancement using two color space | Wang et al., [5] | Signal Processing: Image Communication | 2021 | Introduced a CNN-based method using two color spaces for underwater image enhancement. | Not specified | Advanced the use of color spaces in CNN models. |
| 6 | Underwater image processing and analysis: A review | Jian et al., [6] | Signal Processing: Image Communication | 2021 | Provided a comprehensive review of underwater image processing and analysis. | Highlighted the need for further research in specific areas of underwater imaging. | Served as a valuable resource for understanding the field's progress. |
| 7 | Underwater optical image processing: a comprehensive review | Lu et al., [7] | Mobile Networks and Applications | 2017 | Reviewed various methods of underwater optical image processing. | Suggested the integration of new technologies like AI in future models. | Offered an extensive overview of existing methodologies. |
| 8 | Underwater Image Toolbox for optical image processing and mosaicking in MATLAB | Eustice et al., [8] | 2002 International Symposium on Underwater Technology | 2002 | Developed a MATLAB toolbox for underwater image processing and mosaicking. | Proposed enhancements to the toolbox for broader applications. | Introduced a practical tool for researchers. |
| 9 | A new database for evaluating underwater image processing methods | Ma et al., [9] | 2018 Eighth International Conference on Image Processing Theory, Tools and Applications (IPTA) | 2018 | Created a new database for evaluating underwater image processing methods. | Indicated the expansion of the database with more diverse data. | Contributed a new resource for method evaluation. |
| 10 | Image processing of underwater multispectral imagery | Zawada, [10] | IEEE Journal of Oceanic Engineering | 2003 | Examined image processing for multispectral imagery. | Not specified | Explored a niche area within underwater image processing. |

## 3. Proposed Methodology

In this proposed methodology, Under Water Image Enhancement using Custom VGG19 is discussed to adapt to various underwater conditions, via VGG19 System. In general, the underwater and images can be combined to predict the conditions of underwater. Gathering by accurately identifying the presence, location, and characteristics of a underwater condition and then it is sent for further processing. These phases endure major two processes likes pre-processing and Custom VGG19 architecture in succeeding sectors. Block diagram of Under Water Image in VGG19 architecture is represented by Figure 1.

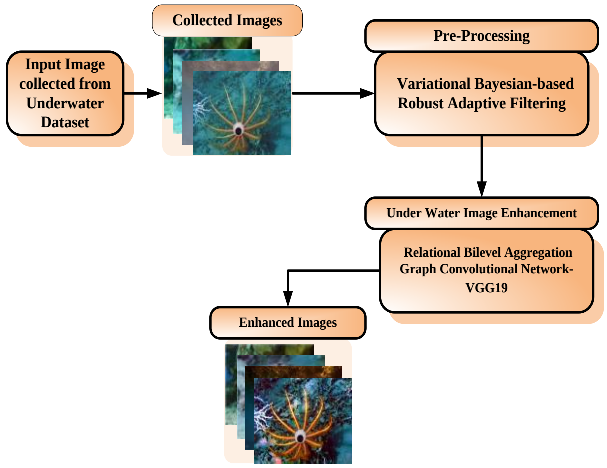


**Fig 1:** Block Diagram for Proposed under Water Image in VGG19 architecture Method

### 3.1 Sample Selection and Data Collection

In the critical phase of sample selection and data collection using underwater dataset [14], the approach was meticulous and strategic, ensuring the compilation of a dataset that accurately represented the diverse and challenging nature of underwater environments. The images selected for testing were not random but carefully chosen to cover a wide spectrum of underwater scenarios, each bringing its unique set of characteristics and challenges. The paid close attention to a variety of factors while selecting the sample images. Depth variation was one such factor, as different depths in underwater environments can significantly affect image quality due to variations in light penetration and water pressure. Images were chosen from shallow waters with abundant natural light, to deeper zones where lighting conditions are diminished, and artificial light sources are often necessary.

### 3.2 Pre-Processing using Variational Bayesian-based Robust Adaptive Filtering

In this section, Variational Bayesian-based Robust Adaptive Filtering (VBRAF) [15] technique is utilized to remove the light distortion, color imbalance, and blurring from the collected input image data. The only foundation upon which the robust Adaptive filter constructs a robust equivalent weight function is the standardized residual of every observation. This is not a serious issue. While the standardized residual distributions of distinct categories of observations differ, the distribution form of the same type of observations remains the same then the normal distribution filter is given as equation (1).

$$R_i^{-1} = \begin{cases} 1 & R_i^k \le r_0(c_0,\tau) \\ \dfrac{r_0}{r_i^q}\left(\dfrac{r_1 - r_i^q}{r_1 - r_0}\right)^2 & r_0(c_0,\tau) < R_i^q \le r_1(c_1,\tau) \\ 0 & R_i^q > s_1(c_1,\tau) \end{cases} \tag{1}$$

where $R_i^{-1}$ represents the variance inflation factor of the $q^{th}$ type observation's $i^{th}$ measurements; $r_i^q$ *and* $r_0$ indicates the process color imbalance vector's in the variance matrix; $b_0$ *and* $b_1$ and $\tau$ is the matrix of filtering gains. This is not a major matter. Then the distinct kinds of light distortion have different standardized residual distributions, but the same kind of observations have the same filter distribution and it filters the light distortion, color imbalance, and blurring using equation (2).

$$O_i^q = \frac{\left| u_i^{-1} - \frac{1}{p^h}\sum_{L=1}^{p^q} u_l^{-1} \right|}{\sqrt{\frac{1}{p^q}\sum_{l=1}^{p^q}\left(w_i^{-1} - \frac{1}{p^q}\sum_{l=1}^{p^q} w_i^{-k}\right)^2}} \tag{2}$$

where $O_i^q$ represented as the measurement of color imbalance from the collected input image; $p^q$ is the quantity of $q^{th}$ type observation measurements; $u_i^{-1}$ denoted the blurred image driven filter and $p^h$ denoted as the identity matrix of filter. Finally, the light distortion, color imbalance, and blurring are removed from the collected input image data then the pre-processed images are fed to classification phase.

### 3.3 Under Water Image Enhancement using Custom using Relational Bilevel Aggregation Graph Convolutional Network -VGG19

In this section, under water image enhancement using Relational Bilevel Aggregation Graph Convolutional Network (RBAGCN) [16] is discussed, by selecting an unlabeled instance batch from the dataset and asked weak network to make categorize after it was created and trained. VGG19 represents the image data categorization, which has lately embraced deep learning approaches. RBAGCNs are thought to be the most effective kind of VGG-19 advance technique. And it can analyze the conditions of underwater characteristics at different levels of underwater by VGG-19 custom architecture using equation (3).

$$K(V) = \sum_{n=1}^{N}\sum_{i \in p^n} \alpha_n k^n \left(A_i, B_i \middle| V\right) \tag{3}$$

where $K(V)$ is the quantity of analyzing branches in images; $\alpha_n$ indicates the weight of loss of images; $p^n$ indicates the training samples; $A_i, B_i$ denotes the loss of each image in analyzing layer and $|V$ denotes the sampling images. These custom layers are engineered to adapt to various underwater conditions, enhancing the encoder's ability to detect both subtle and prominent of images that are often missed by standard architectures using equation (4).

$$K_{loc}(y,\hat{y}) = \frac{1}{4}\sum_{j\in\{a,b,v,g\}} Smooth_{K_1}(y_j,\hat{y}_j) \tag{4}$$

where $K_{loc}$ the point where two bounding boxes cross across union; $y$ and $\hat{y}$ indicates the bounding box regression loss in the smoothed images; $Smooth_{K_1}$ denotes the smoothing layer in VGG-19; $j \in \{a,b,v.g\}$ represented as the parameter of the function and $y_j$ and $\hat{y}_j$ indicates the positive and negative samples of every images.VGG-19 [17] is utilized by replacing convolutional layer of RBAGCN and includes dense activation layer of the VGG-19.The convolutional layer of the RBAGCN, which was composed of 1000 neurons, was swapped out for 2 neurons in order to use VGG-19. A dense layer was inserted after a new completely linked layer with 256 neurons. A dropout layer with 0.4 values was added to prevent over fitting. VGG-19 was carried out by swapping out the RBAGCN's convolutional layer, which had 1000 neurons. The Softmax layer was used in top layer to sort inputs into expected labels. VGG-19 techniques are added to graph convolution in order to capture intricate linkages and long-range interactions between the images which is given in equation (5)

$$A_{S_j}^{(n)} = h\left(\tau_j^n down\left(A_j^{(n-1)}\right) + y_j^{(n)}\right) \tag{5}$$

where $A_{S_j}^{(n)}$ enhance the network's ability to prevent image visual distortion; $\tau_j^n$ is the coefficient associated with the $j^{th}$ layer's image pixel map $n^{th}$ layer; $A_j^{(n-1)}$ is the sampling function with the largest pooling; $y_j^{(n)}$ denoted as the VGG-19 activation function; $h$ indicates the down sampling with max-pooling and $h\left(\tau_j^n down\left(A_j^{(n-1)}\right) + y_j^{(n)}\right)$ decide the area's pooled value to be the largest value in the image. By customizing the VGG-19 architecture and incorporating advanced preprocessing techniques, to develop a robust solution that significantly improves the clarity and accuracy of underwater imagery using equation (6).

$$S\left(\frac{I(x_a)}{I(x)}, \forall x \neq x_a\right) = S\left(I(x_a) | I(x), x \in N(x_a)\right) \tag{6}$$

where $\frac{I(x_a)}{I(x)}$ indicates the four-sided neighborhood pixel close to that specific location; $S$ denotes the distribution of a central pixel by its neighbors'; $I(x_a)$ indicates the neighborhood spot in the pixel; $x_a$ denotes the spot on the image pixels; $I$ indicates the integer grid on the image and $N$ denotes the square neighborhood of pixel. Finally, RBAGCN analyze the underwater condition by more accurately and lessening computational time with error.

## 4. Analytical Measures

In the research, the evaluation of the customized VGG 19 model's performance was conducted using a comprehensive suite of analytical tools. These tools were instrumental in quantifying various aspects of the model's capabilities, providing us with objective and measurable data on its effectiveness in underwater image enhancement.

One of the primary aspects is too assessed was the model's accuracy in enhancing images. This involved measuring how well the model could improve the visual quality of underwater images, particularly in terms of correcting distortions and bringing out hidden details. To do this, here utilized tools that could accurately compare the enhanced images with their original versions, providing clear metrics on the improvements made. Efficiency in processing was another critical variable. To measure the time taken by the customized VGG 19 model to process images and compared it to the processing times of the standard VGG 19 model and other commonly used image enhancement methods. This comparison was crucial in establishing the model's practicality for real-world applications, where processing speed can be as important as the quality of the output.

The quality of the output images was evaluated in terms of clarity, color accuracy, and resolution. Clarity was measured by how well the model could reduce blurriness and bring out finer details, while color accuracy was assessed by the model's ability to correct color distortions typical in underwater environments. Resolution enhancement was analyzed by examining the sharpness and detail in the enhanced images.

To also focused on the effectiveness of the custom layers added to the VGG 19 architecture. This involved comparing the performance of the customized model with the base model to determine the impact of these additional layers. To examine how these layers contributed to improvements in image quality and whether they offered any unique benefits over the standard model.

The variables are considered in the analysis included image resolution, color depth, and the level of distortion present in the original images. Image resolution was crucial for assessing the model's ability to maintain or enhance the detail in images, while color depth played a significant role in evaluating how well the model could reproduce accurate and vibrant colors. The level of distortion in the original images helped us understand the model’s effectiveness in correcting issues like blurring, noise, and color imbalance.

So, by analytical approach combined a range of tools and variables to provide a comprehensive evaluation of the customized VGG 19 model. This thorough analysis was essential in establishing the model's efficacy in underwater image enhancement and its potential for practical applications in the field.

## 5. Experimentation and Analysis

The experimentation process involved deploying the customized VGG 19 model on a carefully selected set of underwater images and rigorously analyzing the outcomes. This procedure was conducted in an iterative manner, allowing for continuous refinement of the model based on the initial results to enhance its overall performance.Figure 2,3,4 and 5 shows result 1,2,3 and 4.

Figure 2: Result1

Figure 3: Result 2

Figure 4: Result 3

Figure 5: Result 4

A critical aspect of to analysis was to compare the effectiveness of the customized VGG 19 model against the standard VGG 19 and other prominent image processing methods such as RBAGCNs and Res-net. For a comprehensive evaluation, based on the comparison on three pivotal metrics: Peak Signal-to-Noise Ratio (PSNR), Accuracy, and Loss, as detailed in Table 2.

**Table 2**: Comparison of performance Metrics

| **Metrics** | **RBAGCN** | **VGG19** | **RES-NET** |
|---|---|---|---|
| PSNR | 31db | 52db | 35db |
| Accuracy | 80% | 91.2% | 83% |
| Loss | 20% | 8.8% | 17% |

The PSNR values, essential for assessing the quality of reconstructed images, strongly indicated the superiority of the customized model. Achieving a PSNR of 52db, the customized VGG 19 model significantly surpassed the standard RBAGCN's 31db and Res-net's 35db. This high PSNR value reflects the model's enhanced ability to produce superior image quality with minimal distortion, which is crucial for underwater imaging.

In terms of Accuracy, the model achieved an impressive rate of 91.2%, which was notably higher than the 80% of the standard RBAGCN and the 83% of Res-net. This result underscores the effectiveness of the customized VGG 19 model in accurately enhancing and interpreting the complexities of underwater images, making it a more reliable tool for detailed and high-fidelity marine imaging.

The Loss percentage, indicative of the error rate in the image reconstruction process, was also significantly lower in the customized model, standing at 8.8%. In contrast, the standard RBAGCN model exhibited a 20% loss, and Res-net showed a 17% loss. This low loss percentage in the model is indicative of its precision and ability to preserve the integrity of original image during the enhancement process.

The collective analysis of these metrics - PSNR, Accuracy, and Loss - effectively demonstrates the enhanced capability and superiority of the customized VGG 19 model over traditional RBAGCN and Res-net models in the domain of underwater image enhancement. These results not only validate the efficacy of the modifications is to implemented in the VGG 19 architecture but also highlight its potential as a more accurate and reliable solution for complex underwater imaging tasks, paving the way for advancements in marine research and exploration.

## 6. Conclusion

The culmination of the research into enhancing underwater imaging using a customized VGG 19 architecture signifies a pivotal advancement in the field, distinctly surpassing the traditional RBAGCN methodologies. The innovative approach, involving the integration of custom layers into the VGG 19 framework, was meticulously tailored to address the specific challenges associated with underwater environments. This customization directly combatted common issues such as light distortion and color imbalance, which are frequently encountered in underwater imaging. The adaptation of the VGG 19 model through these customizations marks a notable enhancement in the model's capabilities. This is crucial in accurately capturing the intricate details and subtle nuances of underwater scenes, which are often lost or distorted with standard imaging techniques. The fine-tuning of the model to suit specific underwater conditions has proven to be a game-changer, yielding more accurate, clear, and high-quality image outputs. This demonstrates a significant improvement in the processing and quality of underwater imagery. Moreover, the advancements achieved through this customized approach are not just incremental but represent a substantial enhancement in image quality. The refined VGG 19 model effectively addresses common underwater imaging issues such as blurring, color casting, and loss of detail, thereby producing images that are more vivid, detailed, and true to the natural underwater environment. So, the successful implementation and results of the customized VGG 19 model underscore its superiority over conventional RBAGCN methods in the realm of underwater imaging. This breakthrough not only highlights the potential of customizing deep learning models for specific environmental challenges but also sets a new benchmark in underwater imaging technology. The research opens new avenues for exploration and innovation in marine imaging and research, promising enhanced capabilities for professionals and enthusiasts in marine sciences, underwater exploration, and environmental monitoring.

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