International Journal of Research Publication and Reviews

Journal homepage: www.ijrpr.com ISSN 2582-7421

Underwater Image Dehazing Using Deep Learning

Dr. (Mrs.) S. K. Wagh[1], Vinit Patil[2], Sahil Anil Sathe[3], Sanket Krishnat Suryavanshi[4], Yashraj Rajput[5]

[1]Modern Education Societys's Wadia College of engineering, Savitribai Phule Pune University, Pune, India
skwaghnba@gmail.com[1], vinitdpatil15@gmail.com[2], sahilsathe83788@gmail.com[3], sanket20020312@gmail.com[4], yashrajput3589@gmail.com[5]

ABSTRACT—

The Attenuation and dispersion of light in the underwater environment will cause blurring or deterioration of image quality, which will cause serious problems in photographic equipment. In this work, we propose a reliable, revolutionary, deep learning-based underwater image removal system with advanced post-processing methods. We offer methods that can increase the effectiveness of underwater applications, including oceanography, exploration and evaluation, and increase the visibility and clarity of underwater images. The deep learning we use in the plan is specifically designed to deblur underwater images. The architecture uses the power of convolutional neural networks (CNN) to learn the art of blurry and clear underwater images. Additionally, we also use a new post-processing technique to further enhance the deblurred image. Together, these techniques improve visual quality and reduce artifacts during deblurring, as well as noise removal, contrast and colour correction. We provide detailed experimental results to verify the effectiveness of our method. Our evaluation evaluated image quality metrics such as System Similarity Index (SSIM) and Peak Signal-to-Noise Ratio (PSNR). Additionally, qualitative analysis was performed to determine the optimality of deblurred images. As a proof of the effectiveness of our proposed method to solve the underwater fog problem, the results show a significant improvement in image quality.

Key Words— Underwater Image Dehazing, Convolutional Neural Networks (CNNs), Deep Learning, Dehazing, Neural Network.

1. INTRODUCTION

Underwater videography is a treasured device in many subjects consisting of marine biology and underwater archeology and has practical packages within the maritime region. The underwater world's enigmatic and uncharted geography makes it significant from a systematic and business point of view; however, the underwater surroundings nevertheless pose sizeable hurdles to getting clear, accurate pictures. Even with advancements in photography, underwater images would possibly appear unprofessional due to the impact of light pollution and water debris. Light interacts with water through some tactics, such as absorption scattering and reflection fog, which is a phenomenon wherein photograph comparison and visibility overlap. Consequentially, underwater images are often blurred and lacking in elements, hindering accurate interpretation and evaluation. Awful underwater pictures may have serious results. Marine biologists use underwater imaging to study ocean strategies, study the conduct of marine life, and monitor environmental adjustments. Desirable images are crucial for underwater exploration to capture landscapes, hold cultures, and discover historic mysteries in industries that include oil and gas manufacturing. Smooth underwater photos are necessary to inspect underwater infrastructure, examine environmental effects, and ensure operational safety. The issues created by the underwater atmosphere ought to be solved by increasing the visibility and intelligibility of underwater photographs. Scientists, researchers, and commercial enterprise experts could make better selections. Better understand methods in water for our bodies and assist in new traits in many fields. With this in mind, the improvement of effective strategies for underwater photo maintenance is a critical area of research that promises to overcome the shortcomings of currently used imaging structures. Our goal is to exchange the underwater surroundings, encourage deep learning, and provide new possibilities for getting to know and exploring the underwater world. The ocean floor is a big and enigmatic place.

1.1 Motivation

The growing interest in underwater exploration and research projects has increased demand for efficient underwater photography solutions. Clear and comprehensive underwater imaging is essential for solving problems related to marine ecosystems and for locating lost archeological treasures. On the other hand, traditional techniques for improving the quality of underwater images primarily rely on tedious manual adjustments or specially designed algorithms. Even while these methods are useful, they frequently fail to tackle the complexity of underwater settings, especially in difficult circumstances where there is a great deal of haze and light attenuation. Driven by the swift progress in deep learning and computer vision, there is a strong chance to transform underwater imaging methods Deep learning techniques present a viable path toward creating more reliable and effective underwater image dehazing solutions because of their capacity to extract intricate patterns and relationships from data. Deep learning models can be trained to successfully detect and reduce the effects of hazing, hence improving visibility and image quality, by utilizing massive datasets of matched hazy and clear underwater photographs. We are driven by the realization that deep learning methods can revolutionize the way that persistent problems in underwater imagery are resolved. We hope to advance the field of underwater exploration and study by utilizing artificial intelligence to enable fresh discoveries and insights into the unseen kingdoms beneath the waters.

1.2 Problem Definition

Numerous fields, such as marine biology, underwater archeology, and offshore engineering, depend on underwater imaging. Unfortunately, light is absorbed and scattered by water molecules and suspended particles in underwater photographs, degrading them and producing low contrast, color distortion, and poor visibility. Because of the special qualities and difficulties presented by the underwater environment, traditional image enhancing techniques are frequently useless for underwater pictures. The objective of this research is to develop efficient and accurate deep learning-based techniques for underwater image dehazing. Given an input underwater image I and associated natural language description, the problem involves designing a computational system capable of A generating clear and visually appealing images that accurately correspond to the visual content and the textual query. Formally, let I denote the input underwater image with dimensions H x W x C, where H, W, and C represent the height, width, and number of color channels, respectively. Additionally, let Q represent the associated natural language description. The goal is to predict the most appropriate dehazed image *I* dehazed, where *I* dehazed ∈ R H x W x C, effectively removing the underwater haze while preserving visual fidelity and semantic content. Dehazing underwater images involves a number of challenges, such as identifying the complex optical features of underwater environments, such as light absorption, scattering, and depth-dependent effects; adjusting for variations in underwater sceneries, such as different lighting, water turbidity levels, and scene arrangement; and resolving the inconsistencies and complexity in the natural language descriptions of underwater photos.

1.3 Dataset

The EUVP (Enhancing Underwater Visual Perception) Dataset is used by us. This dataset, which comprises three separate subsets, tries to enhance underwater visual perception:

1. Underwater Dark: - Contains 5550 training pairs and 570 validation pairs, a total of 11,670 images. Designed to focus on underwater images of poor perceived quality, which may be characterized by low brightness, low contrast or poor visibility.
2. Underwater ImageNet: - Includes 3700 schooling pairs and 1270 validation pairs, generating 8670 images. Likely inspired by the popular ImageNet dataset, this subset aims to provide a larger-scale dataset for training and validation, which can cover a variety of underwater scenes and qualities than.
3. Underwater scene: - Includes 2185 education pairs and a hundred thirty validation pairs, general 4500 images.. This subset appears to be focused on capturing a variety of underwater scenes, which can include a variety of environments, lighting conditions, and image qualities.

Overall, the dataset provides a comprehensive collection of paired and unpaired underwater imaging samples, providing rich training and validation data for developing and evaluating models monitored to improve underwater imaging. It addresses various aspects of underwater imagery, including scenes with low perceived quality, large-scale ImageNet-like datasets, and various underwater scenes.

1.4 Contributions

In the proposed system, we make several contributions to the field of Underwater Image Dehazing by proposing a novel approach that leverages Convolutional Neural Net- works (CNNs) for efficient images and the contributions can be summarized as follows:

1) 1) Deep Learning-Based Dehazing Framework: We present a novel method for enhancing clarity in underwater photographs by removing haze using Convolutional Neural Networks (CNNs). Our system delivers better dehazing performance than conventional techniques by utilizing deep learning, allowing for clearer and more aesthetically pleasing underwater pictures.
2) CNN Architecture Integration: We use cutting-edge CNN architectures designed especially for picture dehazing tasks in our methodology. We improve our framework's capacity to recognize intricate patterns and characteristics present in underwater sceneries by incorporating these structures, which produces more reliable and accurate dehazing outcomes.
3) Sturdy Haze Removal: We tackle the difficulties in removing haze from underwater images by creating sturdy algorithms that can efficiently reduce several kinds of haze, such as color distortion and light scattering. We accomplish amazing dehazing performance across a wide range of underwater situations and habitats through significant experimentation and adjustment.
4) Preservation of Visual elements: In addition to eliminating haze from underwater photos, our method also works to maintain significant visual elements and structures. We guarantee that crucial information is preserved during the dehazing process by meticulously crafting our CNN-based dehazing model, producing picture that is crisper and more informative.
5) Thorough Evaluation and Benchmarking: To determine the efficacy and generalizability of our suggested method, we perform exhaustive tests using industry-standard underwater image dehazing benchmarks. We highlight the effectiveness of our CNN-based dehazing approach by

demonstrating notable improvements in both qualitative visual quality and quantitative performance indicators through thorough experimentation and comparison with existing methods.

2. LITERATURE SURVEY

The challenges faced by Unmanned Underwater Vehicles (UUVs) in effectively performing undersea monitoring tasks due to distorted target objects caused by light absorption and scattering, as well as limited power supply constraints. The proposed two-stage framework employs a deep neural network for underwater object detection and an efficient restoration method to improve visual quality. Objective and subjective evaluations demonstrate superior performance, surpassing state-of-the-art methods for object detection with a mean Average Precision (mAP) of 94.35% and an Underwater Color Image Quality Evaluation (UCIQE) score of 3.09. With an execution time of 0.550 seconds, the proposed approach enables UUVs to autonomously detect objects and dehaze images within operational running requirements, offering a promising solution for efficient underwater monitoring tasks [1].The challenge of enhancing underwater images captured by underwater vehicles, which often suffer from low visibility and color distortion. Through a framework based on transfer learning, it introduces a domain transformation module for color correction and an image enhancement module. By embedding a physical model into the domain transformation module and incorporating coarse-grained similarity calculation, the proposed method effectively transfers in-air image dehazing techniques to underwater image enhancement while maintaining physical properties. Experimental results demonstrate the superiority of the method over existing algorithms in both qualitative and quantitative evaluations on real-world underwater images. Additionally, ablation experiments highlight the contributions of individual components, further validating the effectiveness of the proposed approach. This research contributes to advancing underwater image enhancement techniques for applications in ocean exploration and marine research [2].Digital image processing has growing significance, particularly in fields like robotics and underwater network formation. Underwater image processing, in particular, is crucial due to light wave distortion. While existing image restoration methods are effective, they often require multiple images, hindering real-time application. To address this, a deep learning approach is proposed, leveraging CNNs to dehaze individual underwater images. The study draws on successful applications of deep learning in various image analysis tasks like colorization and object identification. The proposed method aims to enhance image restoration quality by training the CNN model on standard image inputs. Evaluation demonstrates the approach's efficiency and generalization capability, validated through separate area training. This research contributes to advancing underwater image processing, emphasizing the potential of deep learning algorithms for real-time enhancement in diverse underwater environments [3].The significance of underwater image processing in various fields like underwater microscopy, terrain scanning, mine detection, and autonomous underwater vehicles. It identifies the challenges associated with underwater imagery, such as absorption, scattering, color distortion, and artificial light noise, leading to image degradation. The paper proposes two main approaches for enhancing underwater imagery: image dehazing and color restoration. It reviews state-of-the-art intelligence algorithms, particularly deep learning methods, for underwater image dehazing and restoration. Comparative evaluations of different dehazing and restoration methods are presented to assess their performance. Additionally, an underwater image color evaluation metric is introduced to quantitatively evaluate the quality of restored images. The paper concludes by providing an overview of major underwater image applications and emphasizes the importance of underwater image processing in exploring and understanding the underwater environment [4].It presents a novel approach to underwater image dehazing by learning the transmission map directly using color features of hazed images as input to a deep learning network. Traditional methods relying on the Atmospheric Scattering Model (ASM) face challenges in accurately estimating the transmission parameter due to varying scene depths and light absorption in underwater environments. The proposed method trains a neural network to predict the transmission map from hazed images, achieving superior results compared to existing fusion-based, Retinex-based, and deep learning-based methods in terms of contrast, sharpness, and overall restoration appearance. The paper highlights the effectiveness of the approach in addressing the unique challenges of underwater image restoration and demonstrates significant improvements over traditional methods.[5].The application of visualization techniques to convolutional neural networks (CNNs) focusing on networks handling image transformation tasks. While CNNs are widely used in computer vision and image processing, understanding their inner workings remains limited. Visualization methods, commonly applied to classification models, are evaluated in the context of networks where input and output are images. Results demonstrate that visualization provides insights into how these systems operate, aiding comprehension and enhancement. The study specifically utilizes visualization of an image restoration CNN to optimize its architecture for improved efficiency without compromising performance. By shedding light on the internal mechanisms of CNNs handling image transformation, the paper contributes to advancing the understanding and optimization of these powerful machine learning models [6].The novel dark channel prior dehazing method aimed at addressing low visibility and poor contrast in underwater images. By considering the characteristics of the light source, the image is partitioned into light and non-light source regions. The proposed approach utilizes mixed precision operation for subsampling the dark channel image and employs deep learning networks along with GPU acceleration to enhance algorithm speed for real-time application. Experimental results demonstrate that the new algorithm achieves a balance between image quality indicators and underwater image metrics, meeting the requirements of underwater vehicles. Additionally, the algorithm exhibits superior real-time performance compared to similar methods, achieving an average frame rate of 29.4 when processing 950x550 pixel images, which is 2.46 times faster than the dark channel prior approach. This advancement lays a foundation for more efficient underwater operations conducted by underwater robots [7].The challenges of haze and color distortion in underwater images captured by optical cameras. Leveraging the similarity between underwater and atmospheric models, the dehazing algorithm is commonly employed for image enhancement. This paper introduces a novel background light estimation method crucial for dehazing model effectiveness, particularly applicable in depths of 30-60m with artificial light. The proposed method combines deep learning to extract red channel information from the underwater image's dark channel for background light estimation. Experimental results demonstrate the efficacy of the method in improving image blur and color deviation, outperforming other approaches in multiple non-reference image evaluation metrics. By integrating adaptive background light estimation with the dark channel prior algorithm, the proposed method contributes to enhancing underwater image quality, paving the way for improved visual perception and analysis in underwater environments [8].The significance of Unmanned Underwater Vehicles (UUVs) in undersea monitoring tasks, emphasizing their limitations in complex environments due to distorted object appearances caused by light absorption and scattering. It addresses the challenges of limited power supply and motion resistance of water, proposing a two-stage framework combining deep neural networks for object detection and efficient restoration methods for improved visual quality. The survey underscores the objective and subjective assessments conducted using nine evaluation metrics, achieving a high mean Average Precision (mAP) of 94.35% and a notable Underwater Color Image Quality Evaluation (UCIQE) score of 3.09. Additionally, the proposed method demonstrates fast execution time, making it suitable for automatic undersea object detection and dehazing within operational constraints of UUVs [9].A growing interest in addressing the challenges of underwater image enhancement. Previous studies have highlighted issues such as low visibility, blurred details, and color distortion in underwater imagery captured by visual systems of underwater vehicles. To tackle these challenges, the paper proposes a novel underwater image enhancement framework based on transfer learning. By incorporating a domain transformation module and an image enhancement module, the framework aims to effectively transfer in-air image dehazing techniques to the underwater domain. The study emphasizes the importance of maintaining physical properties of underwater images and introduces a coarse-grained similarity calculation to improve color correction. Experimental results demonstrate the superiority of the proposed method over existing algorithms, both qualitatively and quantitatively, across various underwater scenes. Ablation experiments further validate the effectiveness of each component, providing insights for practical application [10]. Combines Simplest Color Balance and Contrast Limited Adaptive Histogram Equalization for underwater photograph re-enhancement.[11].Proposes a method using Dark Channel Prior and Super Resolution GAN for improving resolution of dehazed images[12].Introduces UW-CycleGAN for underwater image restoration, leveraging cycle-consistent adversarial learning.[13].Proposes a deep unfolding network with physics-based priors for underwater image enhancement.[14].Introduces a self-supervised transmission-guided network for underwater image enhancement, including color restoration.[15].Proposes a deep learning method for underwater image color correction and contrast enhancement based on hue preservation.[16].Introduces latent low-rank decomposition and image fusion for enhancing underwater imagery.[17].Proposes AquaGAN for the restoration of underwater images using computational modeling.[18]. Introduces a new degradation model for imaging in natural water and validates it through image recovery.[19].Compares visualization of vision transformers and convolutional neural networks for feature representation optimization[20]

3. METHODOLOGY

In this section, we present a detailed methodology for developing a Underwater Image Dehazing model using CNN. The methodology encompasses data collection, model architecture design, training procedure, and evaluation metrics.

3.1 Model Architecture Design

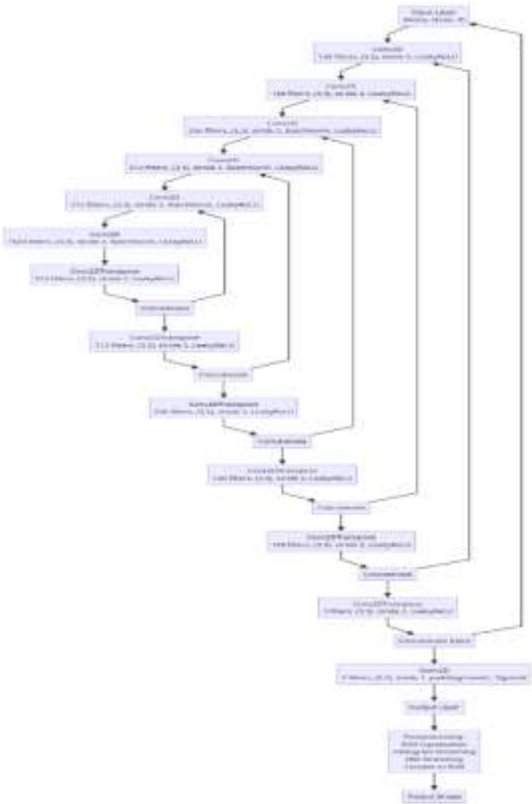


Fig 1 - Model Architecture Diagram

The proposed model architecture represents a convolutional neural network (CNN) tailored for image enhancement applications. Commencing with an input layer configured to accommodate images of variable dimensions and three color channels (RGB), the architecture progresses through an encoding phase, characterized by multiple convolutional layers. These layers, equipped with progressively increasing filter counts and striding operations, systematically distill hierarchical features from the input image while reducing its spatial dimensions. Activation functions like LeakyReLU are judiciously applied to introduce non-linearity and enhance feature extraction capabilities. Subsequently, a bottleneck layer serves as a pivotal intermediary, housing a greater number of filters to capture more abstract image characteristics. Transitioning into the decoding phase, the architecture employs transposed convolutional layers to facilitate upsampling and reconstruct the original image dimensions.

Through concatenation operations between corresponding encoder and decoder layers, feature maps from disparate resolutions are seamlessly integrated, enabling comprehensive image reconstruction. The final output layer, employing a convolutional operation with a small kernel size and stride 1, refines the reconstructed features, while activation functions such as Sigmoid ensure output pixel intensities remain within a valid range. Post processing steps, including RGB Equalization, Histogram Stretching, HSV Stretching, and Convert to RGB, further refine the enhanced image quality, underscoring the comprehensive nature of the proposed architecture's approach to image enhancement.

3.2 Training Procedure

Creates a new model instance. Compiles the model by specifying the optimizer (Adam optimizer used here) and the loss function (mean squared error (MSE) used here to minimize the difference between the predicted dehazed images and the ground truth).Trains the model by fitting it on the preprocessed underwater images (input) and their corresponding ground truth images (target).It iterates through the data in batches of a 8 size .During each iteration, the model updates its internal weights to minimize the loss between the predicted dehazed images and the ground truth. Also applied post processing to enhance the output.

3.3 Evaluation Metrics

1) Peak Signal-to-Noise Ratio (PSNR: PSNR measures the ratio between the maximum possible signal (pixel value) in the dehazed image and the background noise introduced during the dehazing process. Higher PSNR values indicate better dehazing quality, with restored underwater images closer to the original scene without haze.
2) Structural Similarity Index (SSIM): SSIM goes beyond just measuring noise levels. It compares the image structures (textures) between the original and dehazed images. Higher SSIM values indicate better preservation of image details during dehazing, ensuring the recovered image reflects the underlying scene accurately.

By following this detailed methodology, we aim to develop a robust Underwater Image Dehazing model capable of dehazing underwater images.

4. EXPERIMENTAL ANALYSIS

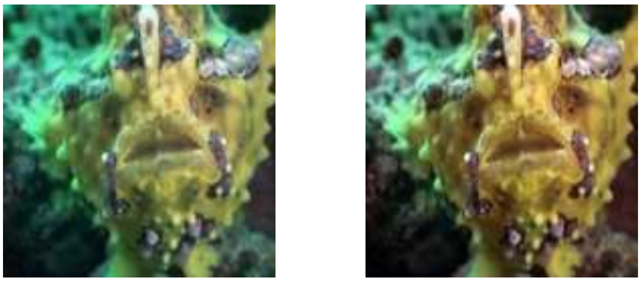
4.1 Results

(a) (b)

Fig. 2 - (a) Input Image1 ; (b) Output Image1

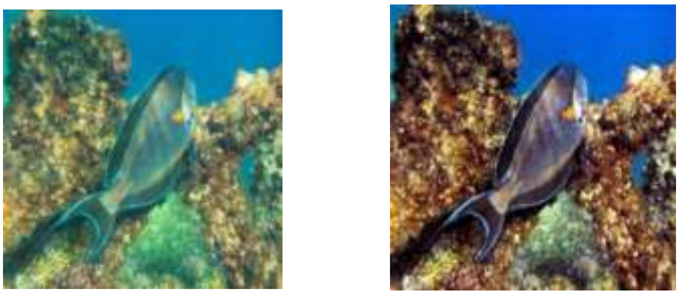
(a) (b)

Fig. 3 - (a) Input Image2 ; (b) Output Image2



(a) (b)

Fig. 4 - (a) Input Image3 ; (b) Output Image3



(a) (b)

Fig. 5 - (a) Input Image4 ; (b) Output Image4

(a) (b)

Fig. 6 - (a) Input Image5 ; (b) Output Image5

4.2 Graphs

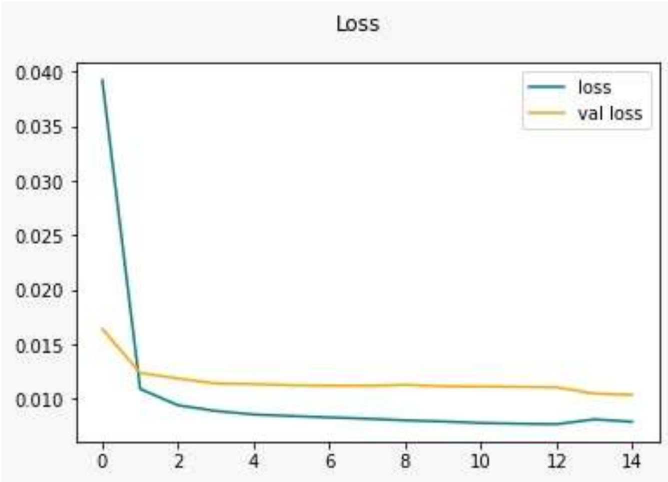


Fig 7 - Loss v/s Epochs

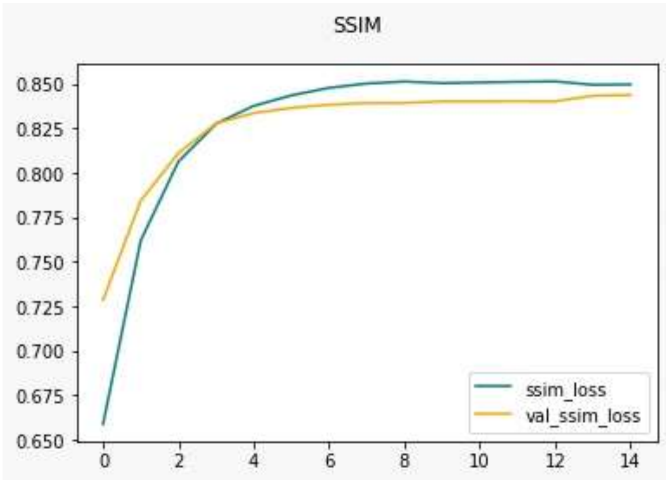


Fig 8 - SSIM v/s Epochs

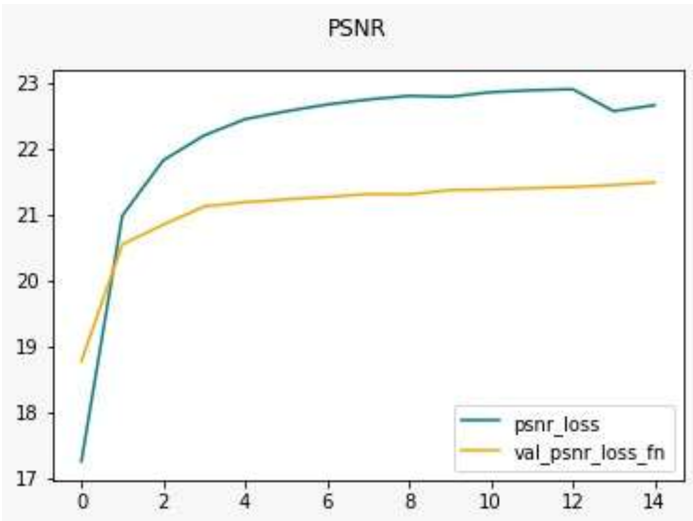


Fig 9 - PSNR v/s Epoch

5. CONCLUSION

The deep learning model for de-hazing underwater images utilizes CNNs, ensuring haze removal while preserving image details. Its adaptability and integration with existing systems make it valuable for research and commercial use. Rigorous evaluation showcases its superior performance, underscoring its significance in advancing underwater imaging technology. Its seamless implementation and computational efficiency further enhance its appeal for practical applications in underwater exploration and environmental monitoring.

ACKNOWLEDGMENT

It gives us great pleasure in presenting the preliminary project report on "Underwater Image Dehazing using Deep Learning". We would like to express my deep sense of gratitude towards my Internal Guide Dr. (Mrs.) S.K. Wagh for their support, continuous guidance, and for being so understanding and helpful throughout the project. We am also grateful to Dr. (Mrs.) N. F. Shaikh, Head of Computer Engineering Department, and MESWCOE for her indispensable support and suggestions.

REFERENCES

[1] S. Fayaz, S. A. Parah, G. J. Qureshi, J. Lloret, J. D. Ser and K. Muhammad, "Intelligent Underwater Object Detection and Image Restoration for Autonomous Underwater Vehicles," in IEEE Transactions on Vehicular Technology, vol. 73, no. 2, pp. 1726-1735, Feb. 2024, doi: 10.1109/TVT.2023.3318629.

[2] Y. Zhang, Q. Jiang, P. Liu, S. Gao, X. Pan and C. Zhang, "Underwater Image Enhancement Using Deep Transfer Learning Based on a Color Restoration Model," in IEEE Journal of Oceanic Engineering, vol. 48, no. 2, pp. 489-514, April 2023, doi: 10.1109/JOE.2022.3227393.

[3] G. Ramkumar, A. G, S. K. M, M. Ayyadurai and S. C, "An Effectual Underwater Image Enhancement using Deep Learning Algorithm," 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2021, pp. 1507-1511, doi: 10.1109/ICICCS51141.2021.9432116.

[4] M. Han, Z. Lyu, T. Qiu and M. Xu, "A Review on Intelligence Dehazing and Color Restoration for Underwater Images," in IEEE Transactions on Systems, Man, and Cybernetics: Systems, vol. 50, no. 5, pp. 1820-1832, May 2020, doi: 10.1109/TSMC.2017.2788902.

[5] J. -H. Wang, K. -E. Lin, S. -K. Lee and Y. -C. Lai, "Underwater Image Restoration via Machine Learning Transmission Map of Atmospheric Scattering Model," OCEANS 2023 - Limerick, Limerick, Ireland, 2023, pp. 1-4, doi: 10.1109/OCEANSLimerick52467.2023.10244677.

[6] É. Protas, J. D. Bratti, J. F. O. Gaya, P. Drews and S. S. C. Botelho, "Visualization Methods for Image Transformation Convolutional Neural Networks," in IEEE Transactions on Neural Networks and Learning Systems, vol. 30, no. 7, pp. 2231-2243, July 2019, doi: 10.1109/TNNLS.2018.2881194.

[7] S. Yang, Z. Chen, Z. Feng and X. Ma, "Underwater Image Enhancement Using Scene Depth-Based Adaptive Background Light Estimation and Dark Channel Prior Algorithms," in IEEE Access, vol. 7, pp. 165318-165327, 2019, doi: 10.1109/ACCESS.2019.2953463.

[8] R. Hu and Y. Li, "Underwater Image Processing with New Dark Channel Prior Dehazing," 2023 5th International Conference on Communications, Information System and Computer Engineering (CISCE), Guangzhou, China, 2023, pp. 438-442, doi: 10.1109/CISCE58541.2023.10142806.

[9] A. R. Espinosa, D. McIntosh and A. B. Albu, "An Efficient Approach for Underwater Image Improvement: Deblurring, Dehazing, and Color Correction," *2023 IEEE/CVF Winter Conference on Applications of Computer Vision Workshops (WACVW)*, Waikoloa, HI, USA, 2023, pp. 206-215, doi: 10.1109/WACVW58289.2023.00026.

[10] H. Liu, Z. Wu, L. Li, S. Salehkalaibar, J. Chen and K. Wang, "Towards Multi-domain Single Image Dehazing via Test-time Training," *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, New Orleans, LA, USA, 2022, pp. 5821-5830, doi: 10.1109/CVPR52688.2022.00574.

[11] W. Zhang, H. Wang, P. Ren and W. Zhang, "Underwater Image Color Correction via Color Channel Transfer," in *IEEE Geoscience and Remote Sensing Letters*, vol. 21, pp. 1-5, 2024, Art no. 1500805, doi: 10.1109/LGRS.2023.3344630.

[12] P. K. Singh, B. Sharan, V. K. Kushwaha, S. P. Yadav and S. Vats, "Underwater Image Denoising Using Adaptive Retinal Processes and Smoothening Filters," *2023 3rd International Conference on Advancement in Electronics & Communication Engineering (AECE)*, GHAZIABAD, India, 2023, pp. 329-334, doi: 10.1109/AECE59614.2023.10428533.

[13] G. Mageshwari, M. Chandralekha and D. Chaudhary, "Underwater image re-enhancement with blend of Simplest Colour Balance and Contrast Limited Adaptive Histogram Equalization Algorithm," *2023 International Conference on Advancement in Computation & Computer Technologies (InCACCT)*, Gharuan, India, 2023, pp. 501-508, doi: 10.1109/InCACCT57535.2023.10141807.

[14] S. Shubham, S. Deb and R. Chaudhuri, "Improved Resolution of Dehazed Images with Dark Channel Prior and Super Resolution GAN," *2022 IEEE International Conference on Distributed Computing and Electrical Circuits and Electronics (ICDCECE)*, Ballari, India, 2022, pp. 1-6, doi: 10.1109/ICDCECE53908.2022.9793249.

[15] C. -H. He, C. -H. Yeh and C. Lo, "Self-Supervised Transmission-Guided Network for Underwater Image Enhancement," *2024 International Conference on Electronics, Information, and Communication (ICEIC)*, Taipei, Taiwan, 2024, pp. 1-4, doi: 10.1109/ICEIC61013.2024.10457154.

[16] C. -H. Yeh, C. -H. Huang and C. -H. Lin, "Deep Learning Underwater Image Color Correction and Contrast Enhancement Based on Hue Preservation," *2019 IEEE Underwater Technology (UT)*, Kaohsiung, Taiwan, 2019, pp. 1-6, doi: 10.1109/UT.2019.8734469.

[17] W. Zhao, S. Rong, T. Li, J. Feng and B. He, "Enhancing Underwater Imagery via Latent Low-Rank Decomposition and Image Fusion," in *IEEE Journal of Oceanic Engineering*, vol. 48, no. 1, pp. 147-159, Jan. 2023, doi: 10.1109/JOE.2022.3192089.

[18] C. Desai, B. S. S. Reddy, R. A. Tabib, U. Patil and U. Mudenagudi, "AquaGAN: Restoration of Underwater Images," *2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW)*, New Orleans, LA, USA, 2022, pp. 295-303, doi: 10.1109/CVPRW56347.2022.00044.

[19] Y. Chen, Z. Zeng and Y. Pan, "A New Degradation Model for Imaging in Natural Water and Validation Through Image Recovery," in *IEEE Access*, vol. 7, pp. 123244-123254, 2019, doi: 10.1109/ACCESS.2019.2938981.

[20] R. Shi, T. Li, L. Zhang and Y. Yamaguchi, "Visualization Comparison of Vision Transformers and Convolutional Neural Networks," in *IEEE Transactions on Multimedia*, vol. 26, pp. 2327-2339, 2024, doi: 10.1109/TMM.2023.3294805.

[21] Zhu, Shidong, Weilin Luo, and Shunqiang Duan. 2022. "Enhancement of Underwater Images by CNN-Based Color Balance and Dehazing" *Electronics* 11, no. 16: 2537. https://doi.org/10.3390/electronics11162537.