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Multiple Branch Deep Neural Network and Feature Fusion Model for Underwater Image Enhancement

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ABSTRACT

Underwater imaging faces formidable challenges due to light absorption, scattering, and restricted visibility, demanding sophisticated enhancement methods. This research presents a novel Multiple Branch Deep Neural Network and Feature Fusion (MB-DNN-FF) Model tailored specifically for Underwater Images Enhancement (UWIE), with a focus on its application to the UFO120 dataset. Driven by the limitations of existing techniques, our model harnesses the potential of Deep Learning (DL) and Feature Fusion (FF) to effectively address the intricate complexities present in underwater environments. The innovative architecture incorporates multiple branches, each strategically designed to tackle distinct challenges such as contrast degradation, limited visibility, and color distortion. Central to our model is feature fusion, a critical aspect that harmoniously integrates information from diverse branches, thereby enhancing overall image quality. The training and optimization processes are thoroughly detailed, encompassing unique strategies and loss functions fine-tuned for the nuances of UWIE, with emphasis on the characteristics of the UFO120 dataset. Experimental evaluations leverage the comprehensive UFO120 dataset, employing established performance metrics to quantitatively assess the efficacy of our model. Results exhibit substantial improvements over baseline models and state-of-the-art methods, showcasing the effectiveness and versatility of the proposed multiple branch model, particularly on the UFO120 dataset. The discussion interprets these findings in the context of underwater imaging challenges, highlighting the model's effectiveness and outlining potential applications. This research contributes a valuable asset to the area of UWIE, offering a nuanced and potent solution through the integration of multiple branches and feature fusion, validated on the UFO120 dataset. The conclusions underscore the significance of the MB-DNN-FF in advancing the state-of-the-art in UWIE, opening avenues for future research and practical applications in marine sciences, surveillance, and exploration.

1. Introduction

Underwater Image Enhancement (UWIE) is a crucial domain within image processing, intended at overcoming the inherent challenges associated with capturing clear and detailed images beneath

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the water's surface. Enhancing underwater images involves the development and application of advanced algorithms and techniques to mitigate the adverse effects of these challenges, restoring contrast, color fidelity, and overall visual clarity [1]. Researchers employ various approaches, ranging from traditional methods like color correction and contrast enhancement to cutting-edge techniques, including Deep Neural Network (DNN) -based models. The goal of UWIE extends beyond mere visual improvement; it plays a pivotal role in advancing scientific exploration, marine research and surveillance, where quality images are essential for UWIE. The degradation process of images in underwater photography is illustrated in Figure 1.

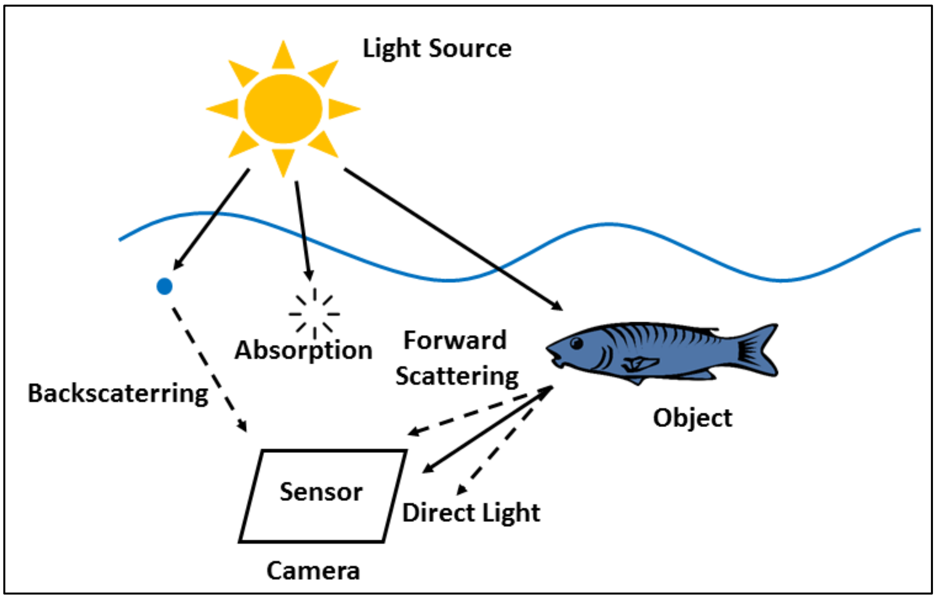

Fig. 1. Degradation of Underwater Images

The exploration of UWIE, with its profound mysteries and ecological significance, has long been hindered by the challenges of capturing clear and detailed images beneath the water's surface [2]. The attenuation of light, instigated by absorption and scattering, poses a significant hurdle in the field of underwater imaging. In recent years, the integration of DNN has emerged as a transformative paradigm, offering unprecedented potential for UWIE. This introduction delves into the fundamental motivations, challenges, and promises that underlie the utilization of deep neural networks in the context of UWIE.

The aquatic environment introduces a myriad of challenges for imaging systems. Light, which is the fundamental medium for visual information, behaves differently underwater, with varying degrees of absorption and scattering depending on water composition and depth. These phenomena result in a loss of contrast, color distortion, and reduced visibility, making it arduous to capture clear and meaningful images. Traditional image enhancement methods often fall short in addressing these challenges comprehensively, necessitating a paradigm shift towards more sophisticated and adaptive approaches. DNN, inspired by the human brain's structure, have demonstrated remarkable success in various domains of artificial intelligence, particularly in computer vision tasks [3]. Their ability to automatically learn hierarchical features from data makes them well-suited for complex tasks like image enhancement. In the realm of underwater imaging, DNNs offer the potential to adaptively learn and extract relevant features from degraded images, allowing for the restoration of details and improvement of overall visual quality. The non-linear nature of deep learning models enables them to capture intricate patterns and relationships that are challenging for traditional methods.

The motivation behind the exploration of DNN-based UWIE is rooted in the urgent need for improved imaging solutions that can unravel the mysteries concealed beneath the waves. From marine biology and environmental monitoring to underwater archaeology and defense applications, the potential impact of clearer and more detailed underwater images is far-reaching [4]. This research introduces a novel Multiple Branch Deep Neural Network and Feature Fusion (MB-DNN-FF) model, designed to specifically address the multifaceted challenges of underwater imaging. This research sets out to explore and advance the capabilities of DNN in the context of UWIE [5]. The subsequent sections will elucidate the intricacies of feature fusion, and present comprehensive experimental results. Furthermore, the evaluation will include the use of benchmark datasets such as UFO120, providing a rigorous assessment of the model's efficacy in diverse underwater conditions. Through this investigation, we aspire not only to contribute to the technical aspects of image enhancement but also to open new avenues for practical applications and scientific discoveries in the fascinating world beneath the surface.

Underwater imaging faces inherent challenges such as light absorption, scattering, and limited visibility, necessitating advanced image enhancement techniques. In recent years, DNN have emerged as a transformative tool for addressing these challenges. This literature survey explores key papers in the field of DNN-based UWIE, encompassing a range of methodologies and advancements.

Li *et al.,* [6] developed a dehazing approach for UWIE, minimizing information loss and incorporating a histogram distribution prior. By effectively addressing the impact of light absorption, this paper lays the foundation for nuanced UWIE. Iqbal *et al.,* [7] developed an integrated color model for UWIE, offering a comprehensive solution to address color distortion. This model combines color correction techniques, providing insights into the importance of color fidelity in UWIE. Perez *et al.,* [8] propose a DL approach for UWIE, showcasing the adaptability of DNNs to learn intricate patterns and features from degraded images. The study emphasizes the potential of deep learning in automatically restoring details and improving visual quality. Peng *et al.,* [9] focused on image restoration by considering both blurriness and light absorption, demonstrating the importance of addressing multiple aspects in UWIE. The paper contributes insights into optimizing image clarity in challenging underwater conditions.

Tang *et al.,* [10] introduced a multi-scale Retinex-based approach combined with color correction for UWIE. This paper highlights the significance of incorporating multi-scale processing to effectively handle diverse underwater scenes. Dong *et al.,* [11] introduced a hybrid color model for UWIE, emphasizing effectiveness in addressing challenges related to color correction. This model combines multiple color spaces, showcasing the potential of hybrid approaches in underwater imaging. Chiang *et al.,* [12] introduced a comprehensive method combining dehazing and wavelength modification for UWIE. By addressing the challenges posed by both absorption and scattering, the paper contributes to the holistic improvement of underwater image quality. Emberton *et al.,* [13] proposed fuzzy segmentation for underwater images and videos. This method demonstrates a nuanced understanding of haze regions, contributing to improved dehazing performance in underwater environments. Li *et al.,* [14] presented an UWIE method incorporating adaptive gamma correction. This approach effectively addresses contrast and brightness issues, showcasing the importance of adaptive adjustments for diverse underwater scenes.

Xu *et al.,* [15] introduced a deep Retinex decomposition approach to enhance low-light underwater images. By leveraging the Retinex theory, the model decomposes images into illumination and reflectance components, effectively mitigating the challenges posed by low-light conditions. This paper highlights the significance of combining classical theories with deep learning for improved underwater image quality. Han *et al.,* [16] presented an extended Generative Adversarial Network (GAN) approach for UWIE with perceptual quality awareness. The authors address the limitations of traditional GANs by incorporating perceptual quality metrics, resulting in more visually pleasing and perceptually accurate enhanced images. The work demonstrates the potential of GANs in capturing complex underwater scene characteristics. Guraksin *et al.,* [17] introduced a hue component merging approach for UWIE. By combining three orthogonal color components, the method effectively addresses color distortion. This work underscores the importance of leveraging color information in UWIE and contributes to the development of techniques rooted in color science.

This literature survey highlights the diverse approaches and methodologies employed in the realm of deep neural network-based UWIE. From dehazing techniques to color correction and multi-scale processing, these papers contribute to advancing our understanding of the complexities inherent in underwater imaging. The collective findings underscore the potential of DL models to meaningfully enhance the visual quality of underwater photographs, paving the way for further innovations in this critical field.

2. Methodology

The advent of sophisticated image enhancement techniques has paved the way for advanced models designed to elevate visual quality across diverse applications. Figure 2 unveils the architecture of the proposed MB-DNN-FF, an innovative system characterized by its integration of three pivotal modules: the Feature Extraction Module (FEM), the Enhancement Module (EM), and the Fusion Module (FM). These modules collectively orchestrate a holistic approach to image enhancement, each playing a specialized role in refining and amalgamating information. MB-DNN-FF's structured composition underscores its potential to address the intricate challenges associated with improving image quality, offering a promising avenue for enhanced visual perception and interpretation.

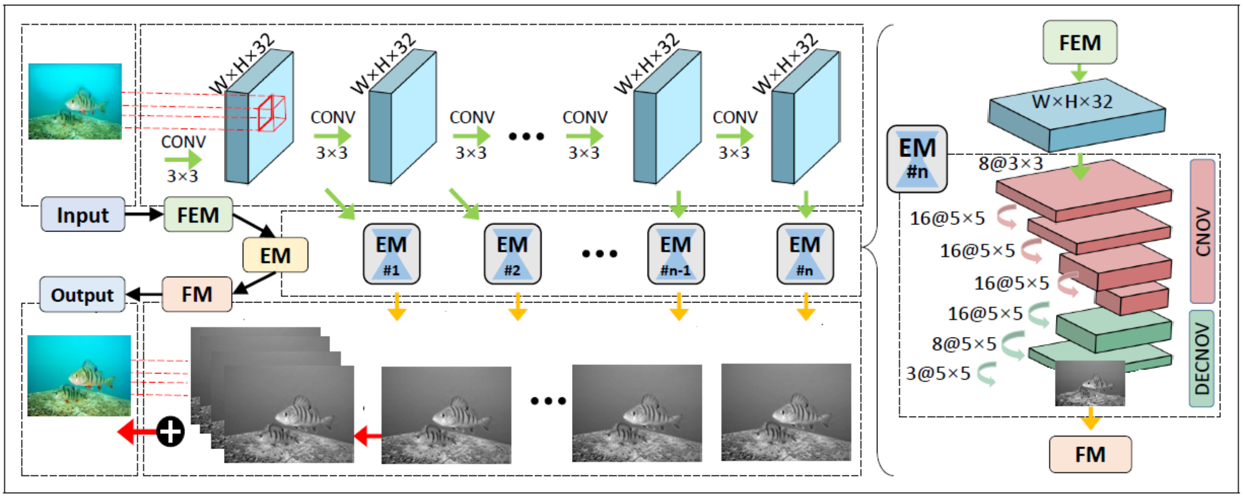

Fig. 2. Structure of proposed MB-DNN-FF model

FEM is structured as a singular stream network, comprising 10 convolutional layers. Each of these layers within FEM utilizes 3x3 kernels, stride of 1, and incorporates Rectified Linear Unit (ReLU) nonlinearity for UWIE model's capacity to capture complex patterns. The absence of a pooling operation in FEM underscores its focus on preserving spatial information, crucial for maintaining the details inherent in underwater color images. The initial layer of FEM receives the underwater color image as input, serving as the foundational step in the hierarchical feature extraction process. The output generated by each layer in FEM not only proceeds as input to the subsequent layer but also concurrently serves as input to the corresponding subnet within the EM. This intricate connectivity ensures a seamless flow of information through FEM, enabling the model to progressively extract hierarchical features from the underwater color image. The choice of 3x3 kernels in FEM's convolutional layers aligns with the model's objective to capture local patterns effectively, fostering a more comprehensive understanding of the input data. The ReLU nonlinearity introduces a critical element of non-linearity, allowing FEM to model complex relationships within the underwater color image data. FEM's design, with its reliance on 3x3 kernels and absence of pooling, emphasizes a meticulous approach to feature extraction, optimizing the model for the challenges posed by underwater environments. The interplay between FEM and EM begins with the interconnected outputs, setting the stage for subsequent modules to collectively contribute to the enhancement of the underwater color image. Let X_i represent the output of the i^{th} layer in FEM. Conv (·) is the convolution operation, W_i and b_i are the weight and bias for the i^{th} layer, and ReLU(·) is the ReLU activation function. The convolutional operation can be represented using Eq. (1).

$$X_{i+1} = \mathrm{Re}LU(Conv(X_i, W_i, b_i)) \tag{1}$$

EM introduces a sophisticated architecture with multiple sub-nets, corresponding in number to the layers within the FEM. Each sub-net within EM operates on the output of a specific layer from FEM, employing a symmetric structure that integrates both convolutional and deconvolutional operations. EM sub-net's input is the FEM output, and its ultimate output is a color image with dimensions identical to the original underwater image, emphasizing a meticulous preservation of spatial information. The first convolutional layer in each EM sub-net utilizes eight 3x3 kernels, stride of 1, and ReLU nonlinearity, setting the foundation for subsequent refinement. Following the initial layer, each EM sub-net features 3 convolutional and 3 deconvolutional layers, employing kernels of size 5x5, a stride of 1, and ReLU. The strategic use of convolutional and deconvolutional layers in EM sub-nets allows for the extraction of intricate features and subsequent enhancement, contributing to the model's capacity for nuanced image improvement. The varying kernel numbers, such as 16, 16, 16, 16, 8, and 3 in the convolutional and deconvolutional layers, underscore the adaptability of EM sub-nets in capturing diverse information and fine-tuning the enhancement process. Significantly, the sub-nets within EM are trained concurrently, but with an individual focus, ensuring a tailored learning process for each sub-net without the sharing of learned parameters. EM's symmetric structure, from convolution to deconvolution, reflects a careful design that aims to maintain coherence in the enhancement process while effectively addressing underwater image challenges. The meticulous configuration of EM, with its unique convolutional and deconvolutional layers and kernel specifications, positions it as a crucial element within the MB-DNN-FF architecture, contributing to the model's overall efficacy in UWIE. For the j^{th} sub-net in EM, let $Y_{i,j}$ represent the output of the i^{th} layer in that sub-net. The operations in an EM sub-net can be explained using Eq. (2) and Eq. (3).

$$Y_{i+1,j} = \mathrm{Re}LU(Conv(Y_{i,j}, W_{i,j}, b_{i,j})) \tag{2}$$

$$Y_{i-1,j} = \mathrm{Re}LU(Deconv(Y_{i,j}, W_{i,j}^{deconv}, b_{i,j}^{deconv})) \tag{3}$$

In FM, a crucial step involves the concatenation of all EM outputs along the color channel dimension, emphasizing a comprehensive integration of the diverse enhancements contributed by individual sub-nets. The concatenated outputs from EM serve as inputs to a 1x1 convolution kernel within the Fusion Module, strategically employed to merge the information effectively. This utilization of a 1x1 convolution kernel in FM signifies a weighted sum operation, where the learnable weights dynamically adjust the contribution of each EM sub-net to the final enhanced image. FM's approach of merging information through a 1x1 convolution kernel demonstrates its adaptability in adjusting the emphasis on different enhancement sub-nets, providing a mechanism for fine-tuning the overall enhancement process. The color channel dimension concatenation and subsequent convolutional merging in FM represent a sophisticated strategy within MB-DNN-FF, allowing for a holistic and dynamic integration of information from various sources. FM's capability to adjust the weights in the weighted sum operation highlights its role in achieving optimal enhancement by balancing the contributions of individual EM sub-nets in underwater image refinement. For the Fusion Module, let Z_j represent the output of the j^{th} EM sub-net. The fusion operation involves concatenation and a 1x1 convolution as explained in Eq. (4).

$$Z = Conv(Concat(Z_1, Z_2, ..., Z_n), W_{fusion}, b_{fusion}) \tag{4}$$

Recognizing the limitations of traditional metrics like Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), and Structural Similarity Index (SSIM) in fully assessing image quality, we introduce a novel loss function designed to address these shortcomings. Our proposed loss function goes beyond conventional measures by incorporating considerations for structural information, context information, and regional differences within the image, acknowledging the importance of these factors in enhancing both the qualitative and quantitative aspects of image quality. Figure 3 visually demonstrates the conceptual foundation of our novel loss function, showcasing how it captures intricate details related to the structure, context, and regional variations within an image.

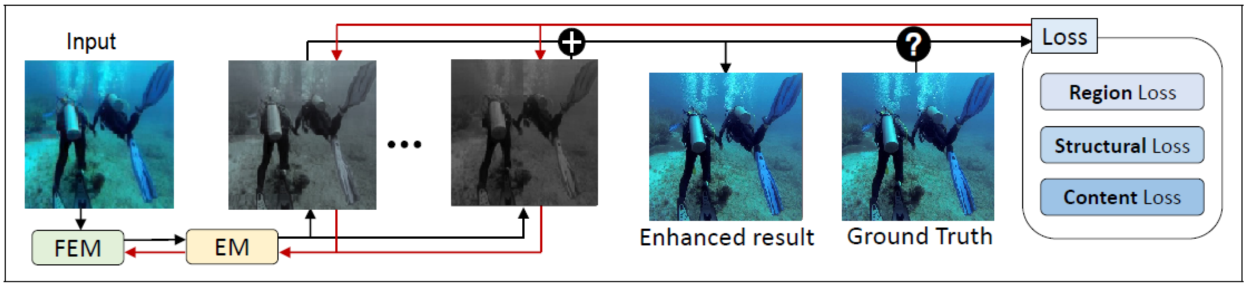

Fig. 3. Data flow of training process

The computation of our loss involves a comprehensive analysis of these factors, emphasizing a holistic approach to image quality improvement that extends beyond the constraints of traditional error metrics as explained in Eq. (5).

$$Loss = L_S + L_{vgg} + L_R \tag{5}$$

The Structure Loss (L_S) is a specialized loss function strategically crafted for UWIE, focusing on addressing issues arising from underwater image capture. Conventional metrics like Mean Squared Error (MSE) may fail to adequately handle structure distortions, but challenging for MSE to effectively address. Acknowledging the limitations of MSE in handling specific visual artifacts induced by underwater conditions, the L_S is introduced to quantify the disparity between ground truth and enhanced image, offering a more nuanced guide for the learning process. The primary objective of the L_S is to combat the distortions inherent in underwater captured images, providing a tailored measure that allows the learning algorithm to focus on mitigating specific structural anomalies for improved visual fidelity. By incorporating the L_S computed using Eq. (6), the learning process is sensitized to nuances that may be overlooked by traditional metrics, fostering a more precise and perceptually meaningful enhancement of underwater images.

$$L_S = \frac{1}{N}\sum_{x=y=0}^{N}\frac{2\mu_x\mu_y + A}{\mu_x^2+\mu_y^2+A} * \frac{2\sigma_{xy}+B}{\sigma_x^2+\sigma_y^2+B} \tag{6}$$

An effective content extractor for image processing often involves a neural network trained on extensive datasets, and we opt for the VGG network due to its well-structured and well-behaved characteristics. The choice of the VGG network in our method is motivated by its proven efficacy, and specifically, we utilize it as the content extractor to define the context loss, a key component in our image enhancement approach. The context loss, integral to our method, is constructed by employing a computational approach, calculating the sum of absolute differences, thereby facilitating a precise evaluation of contextual discrepancies. Leveraging the VGG network as a content extractor and employing the context loss (L_{vgg}) based on its activation layers, our method harnesses sophisticated neural network capabilities to enhance image content by minimizing discrepancies with ground truth representations.

$$L_{vgg} = \frac{1}{W\times H\times C}\sum_{x=1}^{W_{i,j}}\sum_{y=1}^{H_{i,j}}\sum_{z=1}^{C_{i,j}}\beta_{i,j}\left[(E)_{x,y,z}-(G)_{x,y,z}\right] \tag{7}$$

Where, W_i, H_i and C_i represent the dimensions of the feature map (i, j) for both ground truth (G) and enhanced (E). Region Loss (L_R) is introduced as a pivotal component in our UWIE strategy, departing from conventional approaches that consider the entire image as a single entity. In the context of underwater enhancement, the L_R is designed to address the specific challenge of low-light regions, acknowledging their significance in the overall visual quality of the image. Unlike global loss functions, L_R focuses on balancing the enhancement degree specifically for low-light regions, recognizing their unique importance in underwater scenes. L_R can be computed using Eq. (8).

$$L_R = \frac{1}{W\times H}\sum_{x=1}^{W_{i,j}}\sum_{y=1}^{H_{i,j}} w_L\left[(E)_{x,y,z}-(G)_{x,y,z}\right] + w_H\left[(E)_{x,y,z}-(G)_{x,y,z}\right] \tag{8}$$

In Figure 4, the layers and connections within the MB-DNN-FF are visualized, providing an overview of the neural network's structure. FEM, depicted in the initial layers, extracts essential features from the input underwater color image. These features are then fed into the EM, consisting of multiple sub-nets, each responsible for enhancing specific aspects of the image. Finally, the FM combines the EM outputs to create the output.

Algorithm 1: Proposed MB-DNN-FF Enhancement
Input: X=Test Underwater Image.
Output: Enhanced Underwater Image (Y)
Step 1: Initialize the input train images (D).
Step 2: Generate ImageNet input weights from VGG19.

Step 3: Extract features using FE.
Step 4: Enhance the Features separately using EM.
Step 5: Concatenate the enhanced features using FF.
Step 6: Train the proposed model using these features.
Step 7: Adjust and tune the hyperparameters.
Step 8: Save the MB-DNN-FF model.
Step 9: Test image (X) is given as input and obtain enhanced underwater image (Y).

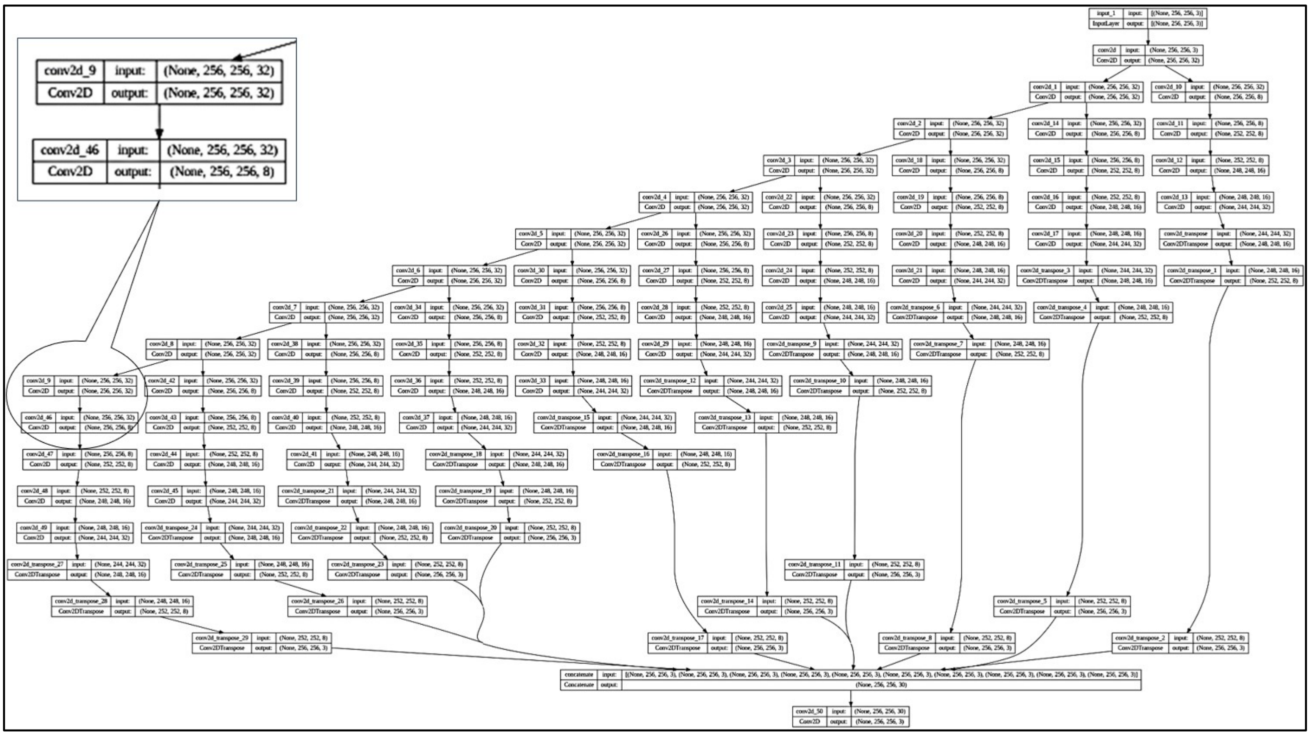

Fig. 4. Proposed MB-DNN-FF architecture

3. Results

In this work, we have chosen to implement our UWIE algorithm using the powerful combination of TensorFlow and DL models. TensorFlow, as the underlying open-source machine learning framework, offers flexibility and scalability, making it well-suited for the intricacies of our image enhancement task. Leveraging the collaborative benefits of Google Colab, we conduct our implementation in a cloud-based Python notebook environment. Colab's GPU acceleration enhances the efficiency of our model training and evaluation, allowing us to experiment with and fine-tune our algorithm in a collaborative and resource-efficient manner. The size of the underwater images is standardized to 640x480 for ground truth images and 320x240 for degraded images. This optimizes computational efficiency while retaining the essential information within the images. Sample images from the UFO20 dataset are displayed in Figure 5.

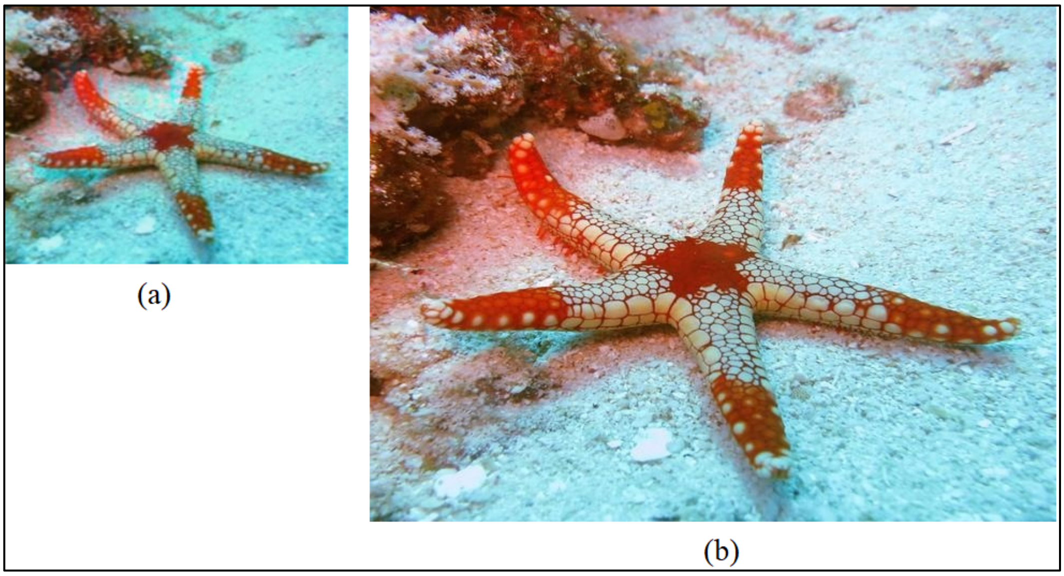

Fig. 5. Sample images from UFO120 Dataset (a) Degraded (b) Ground Truth

The UFO120 dataset comprises a diverse collection of underwater images, encompassing various environmental conditions and scenarios commonly encountered in underwater imaging. The dataset is meticulously curated to cover a broad spectrum of challenges, making it a comprehensive benchmark for assessing UWIE algorithms. The dataset consists of a substantial number of images, providing a sufficiently large sample for rigorous evaluation. Moreover, efforts have been made to maintain a balanced distribution across different categories, ensuring a representative assessment of algorithm performance for each class. The distribution of images in the UFO120 dataset is provided in Figure 6.

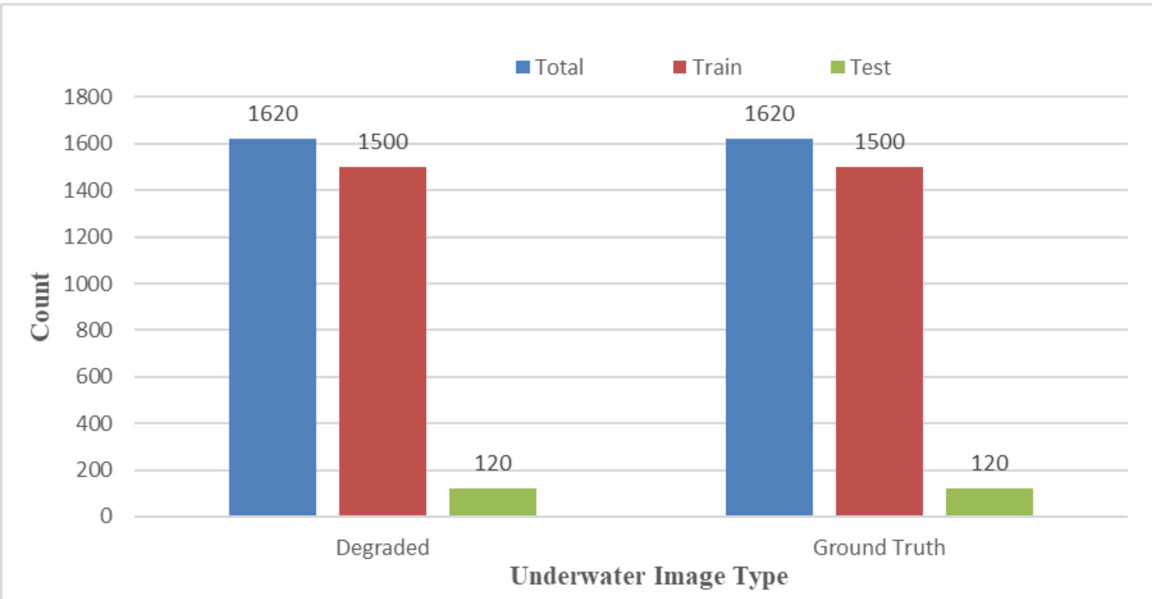

Fig. 6. Distribution of images in UFO120 dataset

The robustness of MB-DNN-FF is further demonstrated through quantitative evaluation on the UFO120 dataset, a challenging benchmark for UWIE. The model exhibits remarkable performance improvements, showcasing a substantial reduction in Mean Squared Error (MSE), an elevated Peak Signal-to-Noise Ratio (PSNR), and enhanced Structural Similarity Index (SSIM). This dataset-specific evaluation solidifies the versatility and effectiveness of MB-DNN-FF across diverse underwater scenarios. Figure 7 depicts the graphical representation of the training and validation performance of the proposed MB-DNN-FF model. The proposed model loss reduces throughout training and it remains constant after 10 epochs. The MSE of MB-DNN-FF reduces throughout the training process and it remains constant after 5 epochs. The PSNR of the MB-DNN-FF improves progressively and the value remains constant after 5 epochs. The SSIM value of MB-DNN-FF improves progressively and it remains constant after 5 epochs during the training process.

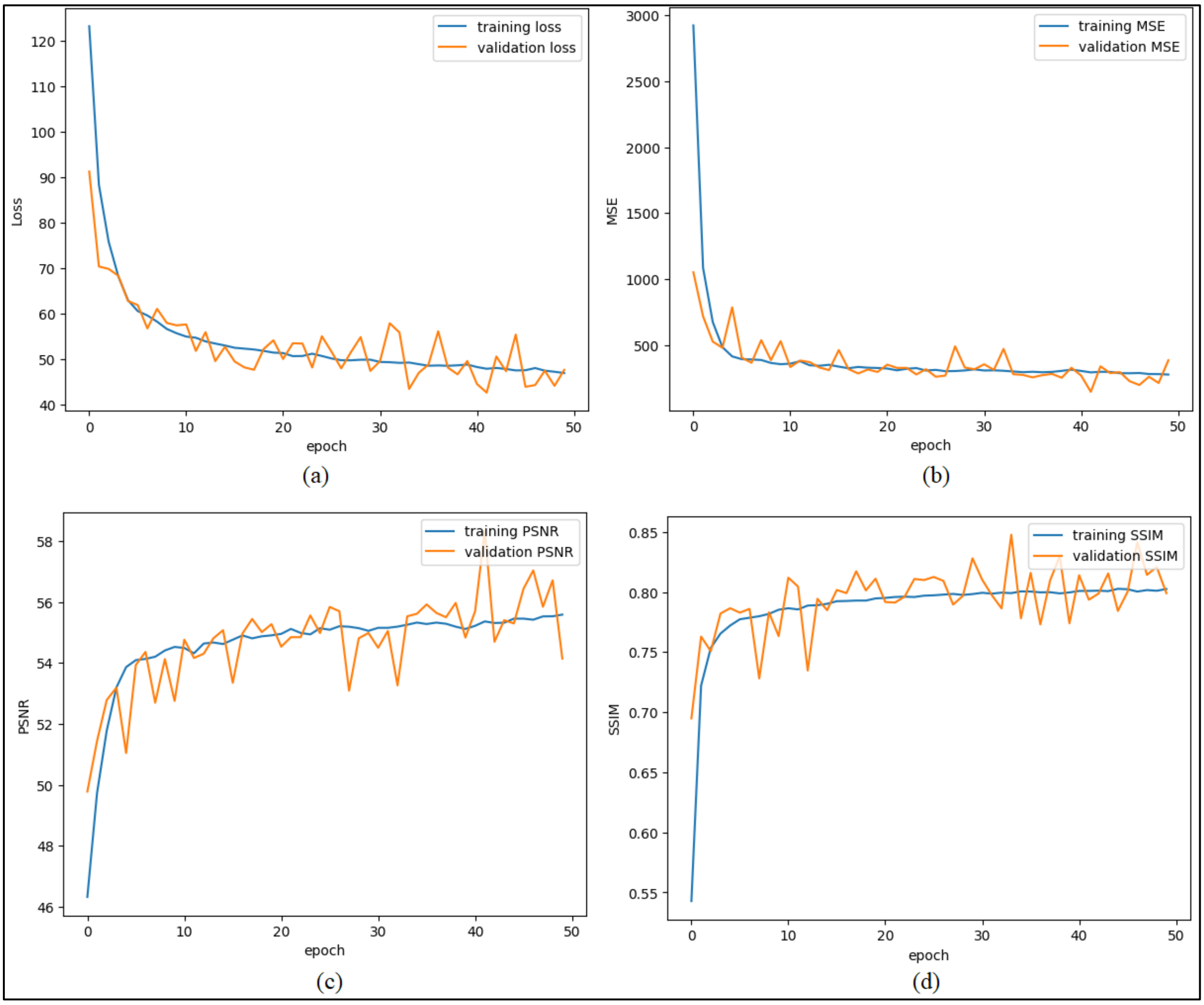

Fig. 7. Distribution of images in UFO120 dataset

The visual assessment of enhanced images provides valuable insights into the algorithm's performance across various underwater scenarios. One notable strength of MB-DNN-FF is its ability to preserve intricate details in underwater scenes. It is evident that the algorithm excels in enhancing the visibility of fine structures such as coral formations, marine life, and artificial structures. This is crucial in applications where maintaining the integrity of visual details is paramount. MB-DNN-FF demonstrates effectiveness in reducing artifacts commonly associated with underwater imaging, such as blurring and color distortions. The result images showcase a noticeable reduction in noise and unwanted distortions, contributing to the overall clarity and fidelity of the enhanced underwater scenes. The algorithm's performance in handling DEGRADATION is particularly noteworthy. In images where illumination is limited, MB-DNN-FF succeeds in enhancing visibility without introducing excessive noise or over-amplifying the existing degradation artifacts. This is crucial for applications requiring accurate interpretation of dimly lit underwater environments. From clear waters to turbid environments, the algorithm consistently improves image quality, showcasing its robustness across different underwater settings. The application of the MB-DNN-FF to the UFO120 dataset yields compelling results, as depicted in Figure 8.

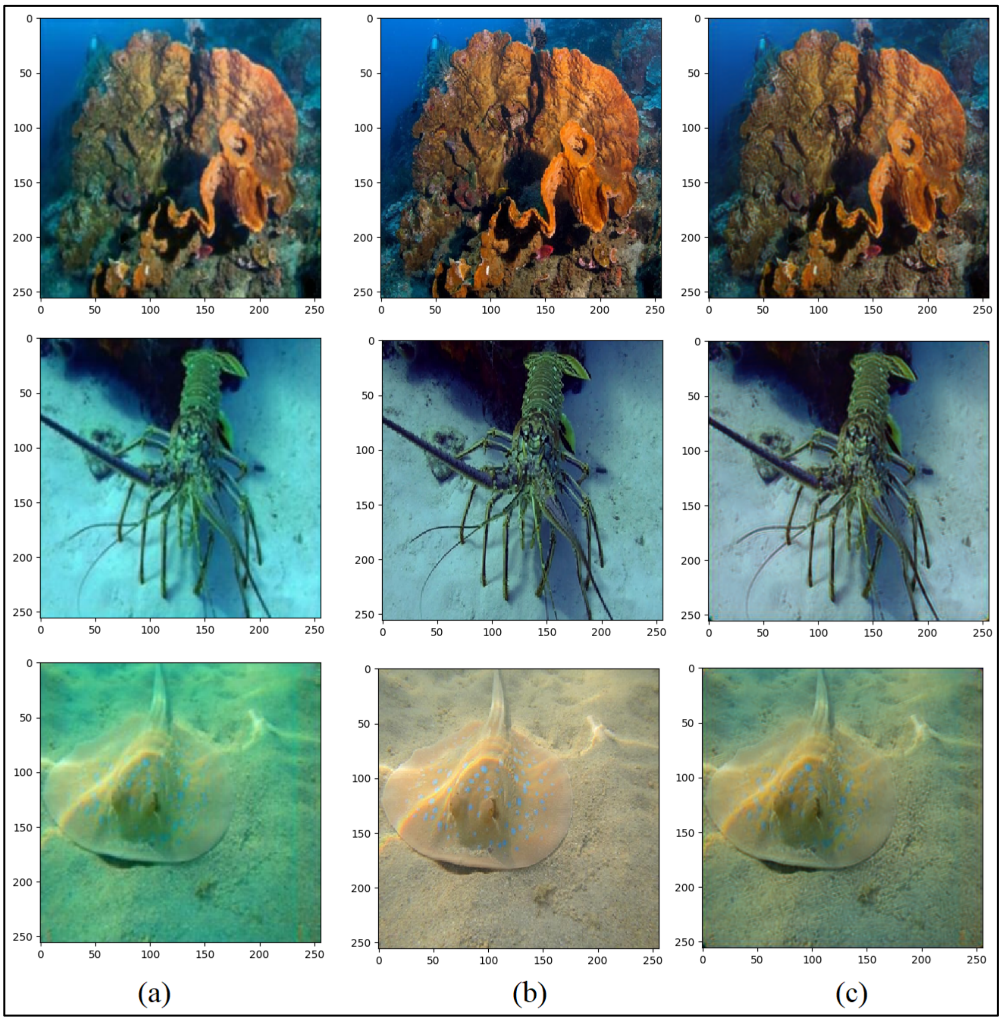

Fig. 8. Result images (a) Input degraded image (2) Ground Truth (3) Enhanced Image

To evaluate the effectiveness of the developed MB-DNN-FF approach, it is imperative to conduct a thorough assessment of its enhancement performance. In this regard, we carried out a comprehensive evaluation of the enhancement performance using the UFO120 dataset. Ten images (image 1 to image 10) are selected similar to those illustrated in Figure 8 and analyzed. The efficiency of MB-DNN-FF is evaluated using PSNR, MSE and SSIM. The results of this assessment are summarized in Table 1, which delivers an analysis of the efficiency of proposed model.

Table 1
Evaluation of Enhancement Performance

Image	PSNR (dB)	MSE	SSIM
Image 1	54.32	193	72.35
Image 2	51.18	245	70.87
Image 3	53.74	213	71.94
Image 4	55.87	189	74.66
Image 5	53.43	211	72.11
Image 6	54.11	197	72.03
Image 7	53.23	241	71.73
Image 8	52.45	223	71.25
Image 9	54.23	195	72.24
Image 10	54.58	190	73.01

The performance metrics consistently exhibit high values, indicating the effectiveness of the DNN and FF techniques in enhancing underwater images. Particularly remarkable achievement is the significantly low MSE achieved by the MB-DNN-FF model, which is recorded at an average of 209.7. Additionally, the PSNR reaches a notable average value of 53.74 dB, emphasizing the quality of the enhanced images. Moreover, SSIM values consistently measure high and provide an average value of 72.21, showcasing the ability of the MB-DNN-FF model to maintain structural characteristics during UWIE.

To assess the efficacy of the proposed MB-DNN-FF approach for UWIE, a rigorous evaluation of its performance is essential. To this end, a detailed assessment was conducted across various models using the UFO120 dataset. The outcomes of this evaluation are succinctly presented in Table 2, offering a comparative assessment of the efficiency of different methodologies based on selected image quality metrics.

Table 2
Comparison of Enhancement Performance

Model	PSNR (dB)	MSE	SSIM
UDCP [18]	20.23	456	47.53
IBLA [19]	27.18	245	50.27
GLNet [20]	31.44	223	61.54
UNet [21]	45.68	215	64.26
MB-DNN-FF (Proposed)	53.74	209	72.21

When assessing PSNR, the MB-DNN-FF model stands out with an impressive score of 53.74 dB. Among existing models, we observe admirable PSNR with UNet (45.68 dB), GLNet (31.44 dB), IBLA (27.18 dB) and UDCP (20.23 dB). It's noteworthy that the PSNR of the proposed MB-DNN-FF model surpasses that of UNet by a substantial margin of 8.06 dB. The comparison of PSNR is depicted in Figure 9.

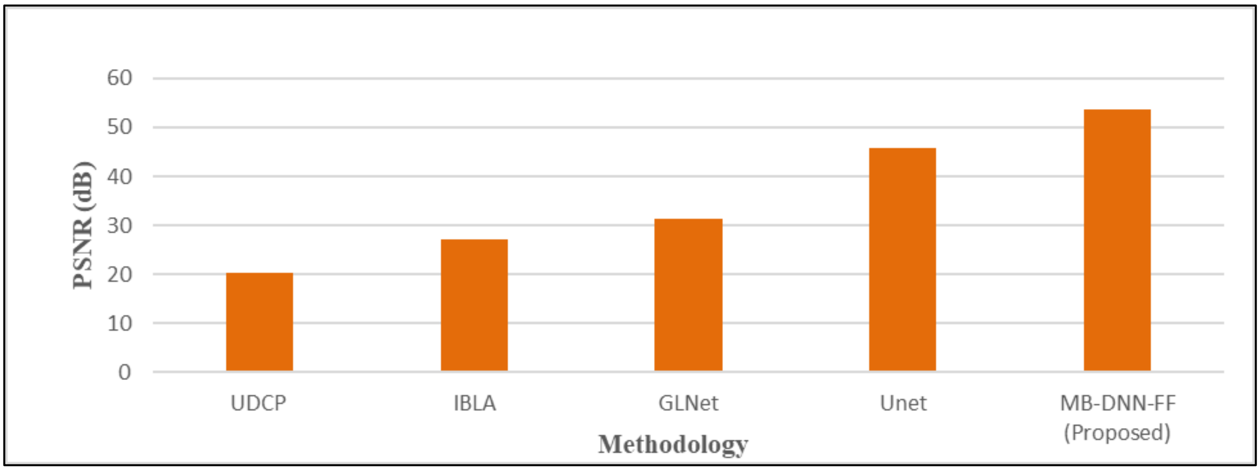

Fig. 9. Comparison of PSNR

The SSIM value for the MB-DNN-FF model is particularly noteworthy, standing at an impressive value of 72.21, marking it as the highest among all the models under consideration. Specifically, UNet exhibits a SSIM of 64.26, GLNet provide 61.54, IBLA provides 50.27 and UDCP also records 47.53. In comparison, the MB-DNN-FF model's SSIM significantly outperforms that of UNet by a notable 8.05. These findings underscore the exceptional performance of the MB-DNN-FF model in higher SSIM and higher PSNR, outperforming existing models. The comparison of SSIM is depicted in Figure 10.

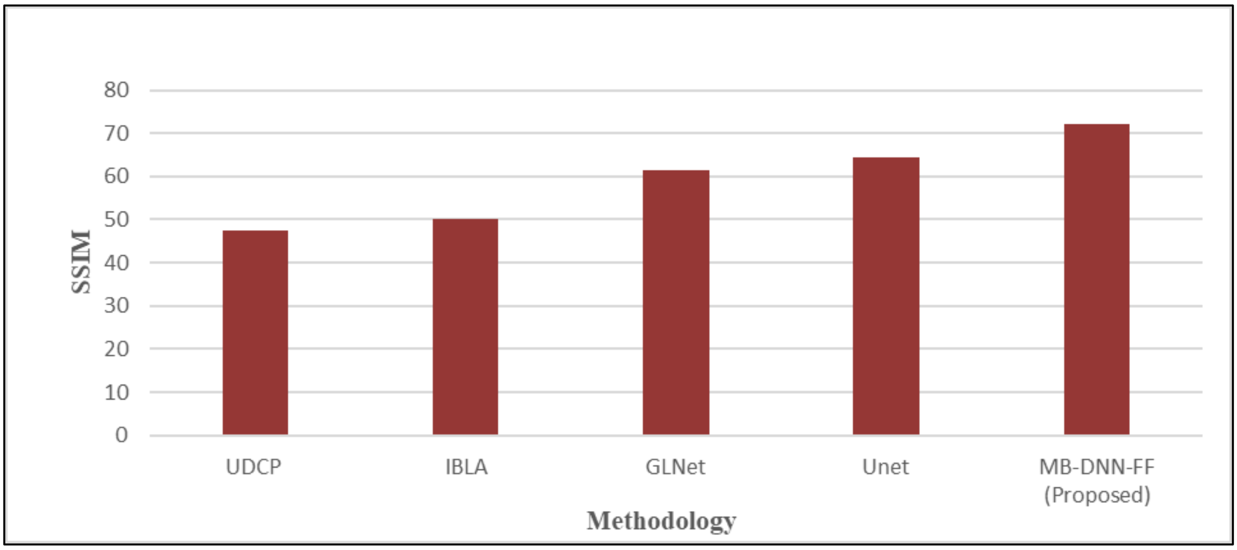

Fig. 10. Comparison of SSIM

While shifting our focus to MSE, the MB-DNN-FF model outperforms all other models by offering a remarkable MSE of 209. In comparison, UNet provides a MSE of 215, GLNet provides 223, and IBLA provides 245. The MSE of MB-DNN-FF is lower than that of UNet by 6. These findings highlight the exceptional recall and F1-score achieved by the MB-DNN-FF model, emphasizing the positive impact of its parameters and the contribution of DL in achieving superior performance. The comparison of MSE is depicted in Figure 11.

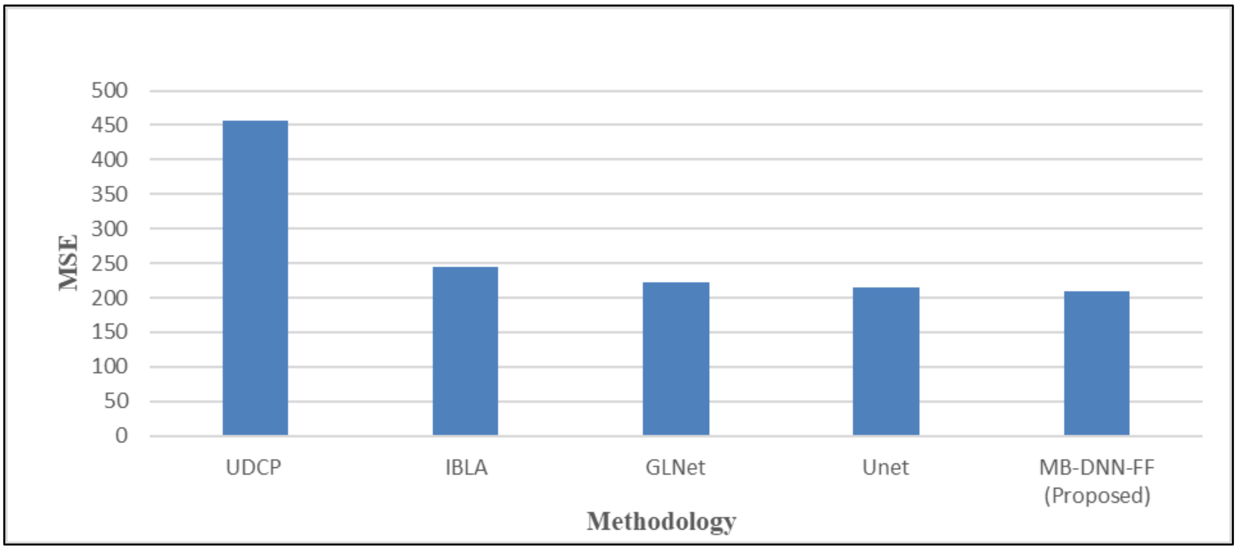

Fig. 11. Comparison of MSE

When these systems are employed in conjunction with large datasets for enhancement purposes, the entire enhancement workflow becomes automated. This removes the necessity for labor-intensive tasks such as feature extraction [22], noise filtering [23,24], delineation of regions of interest (ROI), or feature selection. Consequently, predictions generated by MB-DNN-FF models exhibit high reproducibility and are devoid of bias, signifying a notable progression from earlier DL methodologies. The integration of GPU resources within the Google Colab framework significantly mitigates computation time. For example, training the MB-DNN-FF on the UFO120 dataset required a mere 30 minutes and 25 seconds. Importantly, the performance metrics of the proposed enhancement algorithm surpass those of existing models.

4. Conclusions

This study investigated the exploration of MB-DNN-FF for enhancing underwater image data. The approach involves combining multiple branch structures with DNN and fusion to achieve peak enhancement performance. Incorporating transfer learning with ImageNet data and VGG19 improved the learning capability of the proposed model. Particularly, MB-DNN-FF stands out by surpassing other enhancement algorithms, showcasing an exceptional PSNR of 53.74 dB, SSIM of 72.21, and a lower MSE of 209 when applied to the UFO120 dataset. The remarkable enhancement capability of MB-DNN-FF serves as evidence of the effectiveness of the employed DL techniques. Notably, MB-DNN-FF reduces the necessity for pre-processing stages, outperforming established techniques in this regard. Looking ahead, future research endeavors will focus on integrating these models into mobile platforms to enhance accessibility, reducing computing complexity, and exploring advanced methods for fine-tuning the models. This work not only highlights the achievements of MB-DNN-FF but also paves the way for continued progress in UWIE.

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