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OCEAN EXPLORATION (Depth Analysis,Image Enhancement and Classification)

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ABSTRACT :

The uncharted depths of the ocean harbor a wealth of valuable resources and undiscovered species. However, the challenges associated with exploring these environments are extensive and intricate. In recent years, the integration of Artificial Intelligence (AI) and Machine Learning (ML) technologies has exhibited significant potential in revolutionizing ocean exploration. This research presents an overview of the current state of utilizing AI and ML in ocean exploration, elucidating key advancements, challenges, and potential future directions, while also scrutinizing the depths of oceans and classifying different species. Within an underwater environment, the need for weak illumination and low-quality image enhancement as a pre-processing procedure is imperative for effective underwater vision. This study addresses the prominence of Underwater Image Enhancement (UIEB) in marine engineering and aquatic robotics. Various algorithms, such as XGBoost, Random Forest, CNN, and MFPF, have been proposed for underwater image enhancement. Notably, among these algorithms, MFPF consistently demonstrates superior results. Nevertheless, these algorithms primarily undergo evaluation using synthetic datasets or a limited selection of real-world images, leaving uncertainties regarding their performance on images obtained in the wild and the ability to assess advancements in the field. To bridge this knowledge gap, this research introduces a comprehensive perceptual study and analysis of underwater image enhancement utilizing large-scale real-world images. The constructed UIEB incorporates real-world underwater images with corresponding reference images, employing a red channel prior model for underwater environments based on dark channel prior.

Keywords:

Weak Illumination, Image processing, Transmission map, dark channel prior, prominence

INTRODUCTION

The vast and unexplored depths of the oceans hold immense potential for scientific discovery and technological advancements. However, exploring and understanding these underwater environments presents unique challenges due to the harsh conditions and limited visibility. Underwater image processing plays a crucial role in overcoming these challenges by enhancing the quality of underwater images, enabling researchers and engineers to extract meaningful information from these captured scenes. In recent years, artificial intelligence (AI) has emerged as a powerful tool for enhancing underwater images and extracting valuable insights from underwater data. AI-based techniques, particularly deep learning approaches, have demonstrated remarkable capabilities in addressing the inherent limitations of underwater images, such as low contrast, noise, and blurring. This has led to significant advancements in underwater image processing and its applications in various fields, including marine biology, oceanography, and underwater robotics. Deep learning techniques have revolutionized underwater image processing by providing powerful tools for enhancing image quality and addressing issues like low contrast, noise, and blurring. Various deep learning architectures, such as convolutional neural networks (CNNs) and generative adversarial networks (GANs), have been successfully applied to underwater image enhancement tasks. CNNs have proven to be particularly effective in feature extraction and image restoration. Their ability to learn hierarchical representations of underwater images allows them to effectively remove noise, sharpen details, and improve contrast. GANs, on the other hand, have shown promise in generating realistic and high-quality underwater images by learning the underlying distribution of underwater image data.

In addition to deep learning-based approaches, various traditional image restoration and enhancement methods have been developed specifically for underwater images. These methods address issues such as color distortion, backscattering, and haze, which can significantly degrade underwater image quality. Traditional methods often rely on physical models of light propagation in water to restore underwater images. Histogram equalization, a common technique, attempts to redistribute the intensity values in an image to improve contrast. Retinex-based algorithms, inspired by the human visual system, aim to decompose an image into illumination and reflectance components, enhancing details and removing shadows and accurate identification and classification of underwater animals is crucial for marine biology, conservation efforts, and environmental monitoring. AI-based techniques, particularly deep learning approaches, have shown great promise in this domain. Deep learning models can learn to identify and classify underwater animals from images with high accuracy. By analyzing morphological features, textures, and patterns in underwater images, deep learning models can distinguish between different species and provide valuable insights into marine ecosystems. Underwater image processing has a wide range of applications in various fields, including:

Marine Biology: Underwater image processing enables researchers to study marine life, monitor population dynamics, and assess the health of marine ecosystems.

Underwater Exploration and Robotics: Underwater image processing is essential for autonomous underwater vehicles (AUVs) and remotely operated vehicles (ROVs) to navigate, avoid obstacles, and perform tasks in underwater environments.

Environmental Monitoring: Underwater image processing can be used to monitor water quality, detect pollution, and track the spread of invasive species.

Moreover, the article explores the application of advanced machine learning (ML) methods, including RF, XGBOOST, LightGBM, DNN, and CatBoost, for water depth estimation using high-resolution satellite imagery. A comparison with traditional ML approaches, such as Decision Trees, assesses their performance. Acknowledging the need for transparency in ML-based ocean exploration, the study employs Explainable Artificial Intelligence (XAI) techniques, like SHapley Additive Explanations (SHAP), to gain insights into the significance of individual spectral bands and features in depth estimation.

In summary, this paper represents a significant contribution to the field of ocean exploration, utilizing satellite technology, machine learning, and XAI to enhance our understanding of the ocean's depths. By constructing the UIEB dataset, evaluating image enhancement algorithms, and applying advanced ML methods for bathymetry estimation, this research sets the stage for more accurate, efficient, and transparent approaches to ocean exploration and analysis.

Related Work

Yang,S.(2019)The paper proposes a novel method for underwater image enhancement by estimating the background light and applying adaptive color deviation correction The method combines deep learning to obtain red channel information of the background light in the dark channel of the underwater image .The paper utilizes the dark channel prior algorithm based on the proposed background light estimation method for enhancing underwater images .The acquisition of background light is crucial for obtaining clear images, and the paper focuses on accurately estimating the scene depth to determine the background light .The Fully Convolutional Residual Networks (FCRN) are used to estimate the depth of the underwater image and find the maximum scene depth.[1]

VahidehSaeidi(2023) The study focuses on water depth estimation in coastal areas and shallow waters using remote sensing imagery .The proposed framework involves three main steps: morphological feature generation, model training using advanced machine learning (ML) methods, and model interpretation using explainable artificial intelligence (XAI) .-The study evaluates the performance of the proposed method in two different coastal areas (port and jetty) using accurate hydrographic data as reference .Advanced ML methods such as Decision Tree, Random Forest, eXtreme Gradient BOOSTing (XGBOOST), Light Gradient Boosting Machine (LightGBM), Deep Neural Network (DNN), and CatBoost are used for model training .The study also utilizes SHAP to better understand the contribution of individual spectral bands and features in water depth estimation .The research highlights the need for more exploration and experimentation to identify the most effective and suitable algorithms for water depth estimation using satellite imagery .Overall, the paper presents a comprehensive investigation of advanced ML methods and explainable AI for water depth estimation in coastal areas using Sentinel-2 imagery. [2]

Lopez-Vazquez, V., Lopez-Guede, J. M., Chatzievangelou, D., & Aguzzi, J. (2023). The paper discusses the challenges of automatic classification of marine species based on low-quality images obtained from deep-sea environments .The authors propose an image enhancement and classification pipeline for automated processing of images from benthic moving platforms .The image enhancement process involves a convolutional residual network that generates enhanced images from raw images .The enhanced images obtained high values in metrics for underwater imagery assessment such as UIQM and UCIQE, and showed superior SSIM and PSNR values compared to the original dataset .The classification results on an independent test dataset showed an accuracy value of 66.44% and an AUROC value of 82.91%, which were subsequently improved to 79.44% and 88.64% for accuracy and AUROC respectively .The results obtained with the enhanced images were promising and outperformed previous papers, paving the way for on-board real-time processing of crawler imaging .The paper also mentions the use of metrics such as accuracy, AUROC, loss, and confusion matrix to evaluate the performance of the classifiers .[3]

Dong, C., Xu, G., Han, G., Bethel, B. J., Xie, W., & Zhou, S. (2022) The paper reviews the applications of artificial intelligence (AI) in oceanography, focusing on identifying, forecasting, and parameterizing ocean phenomena. It discusses the usage of AI algorithms for identifying meso scale eddies, internal waves, oil spills, sea ice, and marine algae, as well as forecasting surface waves, the El Niño Southern Oscillation, and storm surges .The paper also explores the usage of AI schemes to parameterize oceanic turbulence and atmospheric moist physics. It discusses the application of physics-informed deep learning and neural networks in an oceanographic context, as well as the potential of ocean digital twins and physics-constrained AI algorithms .Additionally, the paper mentions the development and application of AI algorithms within the marine sciences. It discusses the usage of deep learning (DL) to optimize unknown coefficients used in physics-driven parameterization, as well as the integration of physical principles with data-driven algorithms. It also highlights the challenges and advantages of using DL methods in ocean models.[4]

Schettini, R., & Corchs, S. (2010) The paper reviews recent methods developed for underwater image processing, focusing on extending the range of underwater imaging, improving image contrast and resolution .The authors consider the basic physics of light propagation in the water medium and highlight the different algorithms available in the literature .The paper also discusses the conditions for which each algorithm was originally developed and the quality assessment methods used to evaluate their performance .Additionally, the paper mentions the total scattering coefficient, which is the superposition of all scattering events at all angles through the volume scattering function . [5]

Saleem, A., Paheding, S., Rawashdeh, N., Awad, A., & Kaur, N. (2023) The paper presents an evaluation of common underwater image enhancement techniques using a new publicly-available Challenging Dataset for Underwater Image Enhancement (CDUIE) .The dataset consists of 85 images of aquatic plants taken at a shallow depth of up to three meters from three different locations in the Great Lake Superior, USA, via a Remotely Operated Vehicle (ROV) equipped with a high-definition RGB camera .The authors benchmark nine state-of-the-art image enhancement models at three different depths using a set of common non-reference image quality evaluation metrics .The results show that the selected image enhancement models are capable of producing considerably better-quality images, with some models performing better than others at certain depths .The paper also mentions the use of a white balance color correction mechanism to restore colors, based on a manually annotated Background Light (MABL) dataset and its correlation with the histogram distribution .The authors define linear and non-linear models for estimating the background light of RGB channels and transmission maps of RGB channels, which are then applied to dehaze the input images . [6]

Li, J., Hu, P., Cui, W., Huang, T., & Cheng, S. (2023) The paper investigates the technology status of Metaverse and virtual reality (VR) and develops a prototype that builds the Meta-ocean in VR devices with strong immersive visual effects .The authors propose an optimized path algorithm based on the Catmull-Rom spline to model the movements of marine life in the Meta-ocean .A user study is conducted to analyse the Meta-ocean prototype, demonstrating strong immersion and an appealing interactive user experience .The paper reviews the relevant technological development of the Meta-ocean and emphasizes the importance of building the visual environment using VR technology The authors design and build their own visual environment, Deepsea, which provides an immersive experience for users exploring the Meta-ocean .The user study investigates users' experiences with Deepsea and analyses potential future directions, including prototype pretraining, user-friendly enhancements, and optimization of collision detection using AI algorithms .[7]

Li, C., Guo, C., Ren, W., Cong, R., Hou, J., Kwong, S., & Tao, D. (2019) The paper presents a comprehensive study and analysis of underwater image enhancement algorithms using large-scale real-world images. Various underwater image enhancement algorithms have been proposed in recent years, including methods that stretch the dynamic pixel range in RGB and HSV color spaces, blend contrast-enhanced and color-corrected images, and use a two-step approach for color correction and contrast enhancement. Li et al. proposed a multi-scale dense GAN for underwater image enhancement, combining non-saturating GAN loss with 1 loss and gradient loss. However, this method still has limitations in terms of multiple possible outputs from GANs. The paper highlights the importance of improved contrast and genuine color in underwater image enhancement, while over-under enhancement, artifacts, and color casts lead to visually unpleasing results. The constructed Underwater Image Enhancement Benchmark (UIEB) includes 950 real-world underwater images, 890 of which have corresponding reference images, and 60 challenging underwater images. It is the first real-world underwater image dataset with reference images. The UIEB enables comprehensive study of existing underwater image enhancement methods and training of Convolutional Neural Networks (CNNs) for underwater image enhancement. The proposed Water-Net, trained on the UIEB, serves as a baseline for evaluating state-of-the-art algorithms. The paper also emphasizes the need for effective non-reference underwater image quality evaluation metrics and proposes an underwater image enhancement CNN trained on the constructed dataset. Experimental results show the proposed CNN model performs favourably against state-of-the-art methods. [8]

***Bhadouria*(2022)** The paper discusses various techniques for improving underwater image enhancement, including filtering techniques, enhancement techniques, pre-processing, and image restoration techniques .The main challenges in underwater image enhancement are motion blur, non-uniform illumination, limited contrast, low visibility, hazy images, and the presence of particles that cause haziness .The paper compares different methods for processing underwater images, such as DCP, equalization of the double brightness histogram (BBHE), and contrast improvement methods .The paper also mentions the use of multi-scale wavelet decomposition, soft-matting, and an open dark channel model (ODCM) to improve the quality of underwater images .The techniques discussed in the paper are relevant for various applications, including computer vision techniques, object tracking systems, scientific research, marine biology research, underwater vehicles, detecting systems, counting systems, submarine operations, underwater navigation systems, disaster prevention systems, and maintenance of oil rigs .The paper provides comparative results of the discussed techniques, although specific details of the results are not mentioned in the abstract .[9]

Prasath, R., & Kumanan, T. (2020, September) The paper reviews different techniques of underwater image processing and compares them with their advantages It examines different techniques applied for underwater image processing and explains how they enhance the quality of the underwater image .The study of ***Mallik et al (2016)*** focuses on UW techniques of image enhancement needed for navigation, exploration of sea floor, monitoring of underwater environment, predicting possibilities for coral reefs assessment, and civil engineering .***Mallik et al (2016)*** propose an approach that comprises an algorithm of haze removal followed by a CLAHE color structure for enhancement of underwater images .The paper suggests that future work could involve implementing the reviewed techniques on a real-time basis and comparing their performances using appropriate evaluation strategies .[10]

Schettini, R., & Corchs, S. (2010) The paper reviews recent methods developed for underwater image processing, focusing on extending the range of underwater imaging, improving image contrast and resolution .The authors consider the basic physics of light propagation in the water medium and highlight the different algorithms available in the literature .The paper also discusses the conditions for which each algorithm was originally developed and the quality assessment methods used to evaluate their performance .Additionally, the paper mentions the total scattering coefficient, which is the superposition of all scattering events at all angles through the volume scattering function .[11]

Han, F., Yao, J., Zhu, H., & Wang, C. (2020) The paper focuses on underwater image processing and object detection using a deep CNN method .The authors propose a combination of the max-RGB method and shades of grey method for enhancing underwater vision .They also propose a CNN method to solve the weakly illuminated problem in underwater images by training the mapping relationship to obtain the illumination map. Two improved schemes are applied to modify the deep CNN structure based on the characteristics of underwater vision .Scheme 2 is verified to be better in detecting underwater objects compared to other methods like Fast RCNN, Faster RCNN, and the original YOLO V3 .The detection speed achieved is about 50 FPS (Frames per Second), and the mean Average Precision (mAP) is about 90% .The program is applied in an underwater robot, and real-time detection results show accurate and fast detection and classification capabilities .(LPCVC) .The challenge required contestants to spatio-temporally localize the key action of ball-catching from videos captured by drones, considering accuracy and efficiency .The solution addresses the challenges of lack of training data, robustness, and efficiency in the challenge .The code for the solution is available at a GitHub repository .[12]

Liu, P., Wang, G., Qi, H., Zhang, C., Zheng, H., & Yu, Z. (2019) Underwater image restoration or enhancement is a frontier topic with complex factors such as illumination and water quality influencing the results .Traditional methods for underwater image restoration or enhancement involve either non-physical model methods or physical model-based methods, both of which require manual parameter settings .Deep learning methods have emerged as a solution for this research topic, offering non-physical model-based underwater image enhancement by adjusting pixel values .Histogram equalization and its improved algorithms are commonly used non-physical contrast enhancement methods for underwater images .White balance algorithms correct color deviations in underwater images by adjusting the ratio of RGB three-channel pixels . Image enhancement methods based on human vision brightness and color perception, such as the Retinex algorithm, have also been influential in the field . Physical model-based methods for underwater image restoration include applying image dehazing algorithms, but these are often insufficient due to the unique characteristics of underwater images .There are also studies on image restoration algorithms specifically for underwater image optical characteristics, such as the red channel underwater image restoration method .[13]

Wang, Y., Song, W., Fortino, G., Qi, L. Z., Zhang, W., & Liotta, A. (2019). The paper provides a review of image enhancement and restoration methods for underwater images, addressing typical impairments and extreme degradations .It reviews both IFM-free and IFM-based approaches for underwater restoration methods .The paper includes an experimental-based comparative evaluation of state-of-the-art IFM-free and IFM-based methods, considering subjective and objective analyses . It highlights the key shortcomings of existing methods and provides recommendations for future research in this area .The paper also addresses the limitations of previous reviews, such as incomplete classifications and the lack of coverage of deep learning-based methods. It provides a critical evaluation of image restoration methods based on prior-knowledge and shares lessons learned from working in the field. The paper concludes with a discussion of future work directions in underwater image enhancement and restoration. [14]

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Anwar, S., Li, C., & Porikli, F. (2018)The paper proposes a convolutional neural network (CNN) based image enhancement model called UWCNN for improving the visibility of underwater images. The authors mention that existing methods for enhancing underwater images can be classified into three categories: image enhancement methods, image restoration methods, and supplementary information specific methods. The paper highlights that their model, UWCNN, directly reconstructs clear latent underwater images by leveraging an automatic end-to-end and data-driven training mechanism. The authors conduct experiments on real-world and synthetic underwater images to demonstrate the effectiveness of their method, showing that it outperforms existing methods both qualitatively and quantitatively .Additionally, the paper includes an ablation study to analyze the effect of each component in the UWCNN network .[16]

Zhou, J., Zhang, D., & Zhang, W. (2022) Various methods based on model-free, model-based, and data-driven approaches have been proposed to tackle color cast and low contrast in underwater images .Model-free methods directly use pixel values to enhance underwater images, including histogram equalization, retinex-based, and fusion-based methods . The Rayleigh distribution histogram stretching method and variational retinex-based method have been proposed to enhance the contrast of underwater images .Fusion-based methods blend different single inputs and apply white balance and contrast enhancement methods to improve the quality of underwater images . The multi-feature fusion method (MFFM) alleviates low contrast and color distortion in underwater images . Model-based methods focus on restoring degradation caused by absorption and scattering, using physical imaging models andprior knowledge . Data-driven methods achieve success in low-level vision tasks, using nonlinear learning capabilities and abundant datasets .Water-Net, GAN-RS, UWCNN, and Ucolor are examples of data-driven methods for enhancing underwater images .[17]

Sun, S., Wang, H., Zhang, H., Li, M., Xiang, M., Luo, C., & Ren, P. (2022) The paper discusses the limitations of existing underwater image enhancement methods, which have been broadly investigated in the literature (as presented in Sections I-A and I-B) . The authors mention that deep learning methods have made great progress in underwater image enhancement, but the black box processing schemes of deep models hinder the understanding of the underlying mechanisms for underwater image processing .The paper also mentions that numerous studies have been undertaken on developing image processing algorithms to assist human perception, as visual information plays a significant role in human perception.[18]

Raveendran, S., Patil, M. D., & Birajdar, G. K. (2021) Research in the area of underwater image processing has increased significantly in the last decade due to the dependence of human beings on valuable underwater resources. Various techniques for enhancing the visual quality of underwater images have been studied and categorized based on physical model-based and non-physical based approaches. The Jaffe-McGlamery underwater image model is a well-known imaging model proposed by Jaffe-McGlamery, based on linear superposition and modeling of the water medium. The model considers three components of irradiance: the direct component, forward-scattered component, and backscatter component .The survey presented in the paper provides an in-depth overview of the characteristics of the underwater environment, degradation of light, and challenges faced by the underwater medium.[19]

Li, C. Y., Guo, J. C., Cong, R. M., Pang, Y. W., & Wang, B. (2016). The paper proposes a systematic underwater image enhancement method that includes an underwater image dehazing algorithm and a contrast enhancement algorithm .The underwater image dehazing algorithm is built on a minimum information loss principle and aims to restore the visibility, color, and natural appearance of underwater images .The contrast enhancement algorithm is based on a histogram distribution prior and aims to increase the contrast and brightness of underwater images. The proposed method can yield two versions of enhanced output: one with relatively genuine color and natural appearance suitable for display, and another with high contrast and brightness for extracting more valuable information and unveiling more details .The performance of the proposed method is evaluated through simulation experiments, qualitative and quantitative comparisons, as well as color accuracy and application tests.[20]

3.Methodology

Data Preparation

Sentinel-2 Level-1C product with pre-applied radiometric and geometric corrections was used. Image pixel values were converted to radiances and reflectance. Atmospheric correction and sun-glint removal were applied using ENVI 5.2 software (FLAASH module).

Feature Extraction

Feature extraction is a critical step in improving depth estimation, and it involves two main groups of techniques: spectral features extraction and spatial features extraction.

Spectral Features Extraction

Eleven spectral bands were utilized for extracting morphological profile-based features, resulting in 72 spectral features. A total of 83 features, including the 11 bands and 72 morphological features, were used as input for machine learning models.

Spatial Features Extraction

Mathematical morphology is employed for feature extraction using extended morphological profiles. The Morphological Profile (MP) approach, which analyzes both spatial and spectral features, is used. It is known to be effective in various applications.MP involves geodesic closing/opening transformations with increasing structural element sizes, generating a set of opening and closing profiles.An extended morphological profile is constructed by stacking the MPs created using different features.

Machine Learning Models

Six supervised learning algorithms were utilized for depth mapping, including both advanced and regular ML methods

- Random Forest (RF)

Ensemble-based method using decision trees for regression and classification.
Key parameters: number of trees and randomly selected predictor variables.

- eXtreme Gradient BOOSTing (XGBOOST)

Gradient boosting algorithm optimized through gradient descent.
Parameters: number of estimators, learning rate, regularization, and tree-specific parameters.

- Light Gradient Boosting Machine (Light GBM)
- Utilizes feature bundling and gradient-based one-sided sampling for efficiency. Parameters include the number of estimators, learning rate, regularization, and tree-specific settings.
- Decision Tree (DT)
- Nonparametric technique for various applications.
- Cat Boost:

- Combines symmetric decision trees into a single model.
- Offers faster training and testing with higher accuracy.

➢ Deep Neural Network (DNN)

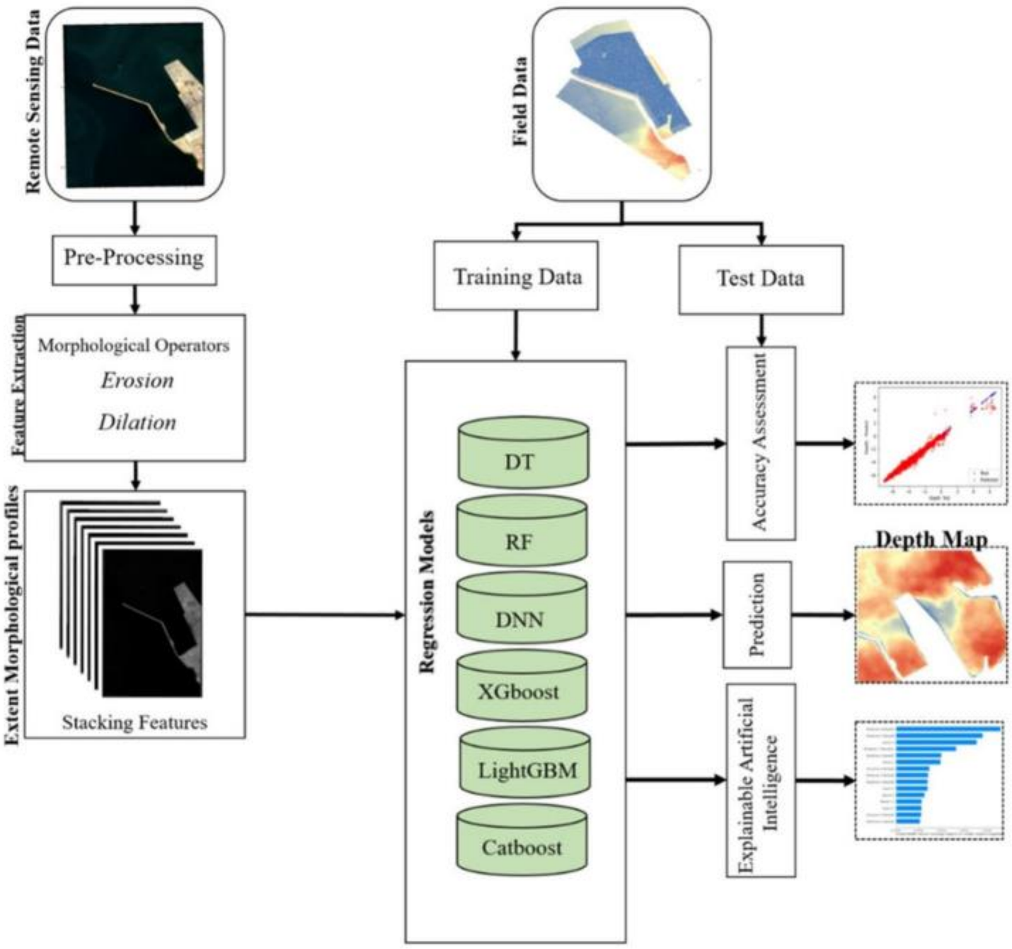
- Deep-learning-based model for extracting deep features from the input dataset.

➢ eXplainable Artificial Intelligence (XAI)

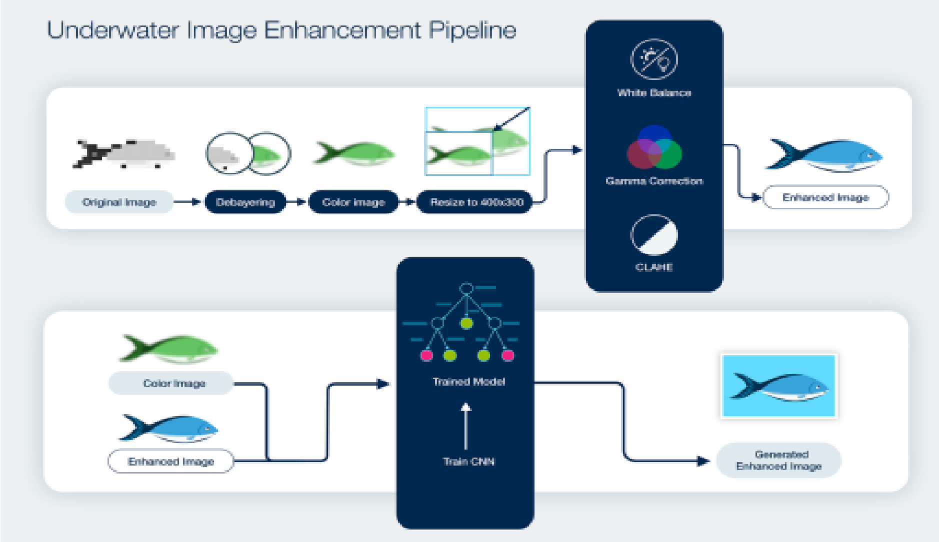
- XAI is used to improve trust in AI systems.
- SHAP (SHapley Additive exPlanations) is a representative method for model explainations.SHAP utilizes Shapley values from cooperative game theory for feature contribution analysis.
- Provides both local and global interpretability of input features.

XAI methods, such as SHAP, help users understand and trust AI model decisions by explaining the reasoning behind predictions and assessing feature importance.

3.1 Architectural Design:



3.2 Architectural Design:-



Techniques Implemented:-

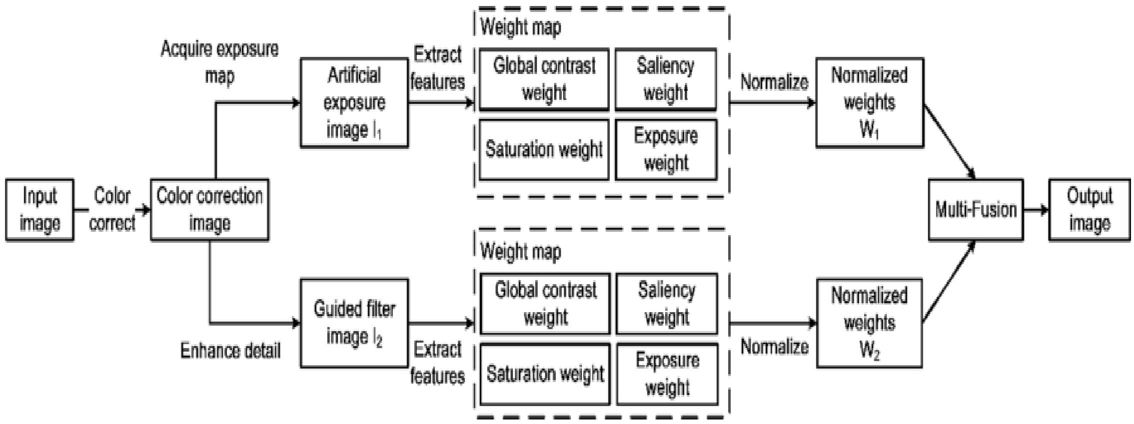
In this subsection we present the image enhancement process in terms of composing steps and the description of the residual network that mainly constitutes this process.The original images were in raw format and appeared in grey scale, so a chromatic interpolation algorithm by demo sacking or delayering, a digital image process used to reconstruct an image in color, was applied. Since the images still retained the greenish hue characteristic, we model and train a residual CNN network to generate the enhanced images and thus eliminate the greenish hue characteristic. Those neural networks are known for skip connections, or shortcuts to jump over some layers. The omitted connections aim to avoid the problem of vanishing gradients or mitigate the problem of Degradation (accuracy saturation), where adding more layers to a deep model leads to a larger training and test error .

This network has the structure of an auto encoder, which usually presents a structure made by three parts: the encoder, which extracts features from the input image, a central part that performs feature processing, and the decoder, the final part, which decodes the processed features into an output image. In the elaborated residual CNN network, the optimizer, batch size and layers of were modified until the results were improved.

Techniques such as White Balance, Gamma Correction and the CLAHE algorithm were applied to generate the images with which the network would be trained. Each convolutional layer was followed by a ReLU activation layer [70], a linear function whose output, if positive, will be the same as the input value, while if negative, the output will be zero, as indicated in Eq. (1): After the input layer, there were two pairs of convolutional and ReLU layers followed by a max pooling layer.

Next, there was a larger block consisting of three convolutional and ReLU layers and a max pooling layer. This was followed by a group of four convolutional layers. The last group was composed of three convolutional layers. The optimiser chosen for this network was Adam [48], while the loss function chosen was MSE loss. The layered structure can be seen in Fig. 4. Tis residual network has two residual blocks which skip connections. In this way, these shortcuts perform identity mapping, where their outputs are added to the outputs of the stacked layers.

3.3Architectural Design:-



In the multiple feature prior sequence, the feature prior perception metric of each pixel is calculated. Then, under the constraint of feature prior weights, the pixel values of dominant features are extracted from the feature prior sequence and merged into the final enhancement result. The MFPF method comprehensively solves various degradation problems and obtains enhanced high-quality underwater images. The feature-prior fusion method is similar to other image fusion techniques of depth-of-field extension and montage.

This fusion method applies standard deviation based color correction, multi-exposure fusion, and guided filter detail enhancement technologies to compensate for the color cast caused by deep color selective absorption. Also, it improves the edge detail information and solves contrast loss and blurring of details caused by backscattering. Then it extracts the four feature prior weight maps of the two images of guided filtering enhancement map and manual multiexposure map, normalizes them after weighting, and uses multi-scale fusion to obtain high-quality underwater images.

Color correction

Different wavelengths of light exhibit exponential attenuation at different water depths. This time, the data set is that of the underwater sea cucumber and sea urchin images collected at a water depth of 3–4 m on Zhangzi Island in Dalian, which have serious scattering problems. According to the statistical analysis of the collected data sets, most of the underwater images show a greenish or blue-green phenomenon. Therefore, we designed a color correction method based on standard deviation to correct the color cast of underwater sea cucumber and sea urchin images

Detail enhancement

Due to the light attenuation existing in the marine environment, the overall contrast of the underwater pictures does not meet the expectations for marine researches. To improve the visual quality, median filtering, bilateral filtering, and guided filtering technologies were applied [32]. The above filtering methods can effectively de noise the input image and maintain edge details at the same time. However, the guided filtering was proposed to have a better edge retention effect than median filtering and bilateral filtering

Artificial multi exposure image

The pre-processing of the fusion adopts the color correction method based on standard deviation. we can visually observe that the white balance method eliminates the color cast, but the result is too bright, and details are lost. Color correction and contrast enhancement cannot be achieved simultaneously using only the color correction method. To emphasize the contrast, we introduce artificial multi-exposure technology as the second input of the fusion stage to exaggerate the contrast of image.

Prior feature weight map

Under-exposed or over-exposed areas in degraded underwater images reduce the contrast and brightness. To highlight areas with rich color and details and reduce the weight of flat and color less regions, we select four feature priors related to underwater image quality characteristics (global contrast, saturation, saliency, and exposure) as the weight mapping. The higher the weight map value during the fusion process, the more significant the corresponding feature weight mapping proportion in the final fusion result

Global contrast weight Contrast weights describe the spatial relationship of pixels and enhance the performance of bright and dark areas

Saliency weight This section mainly uses the transition details of the highlight and shadow parts of the first input multi-exposure sequence fusion to solve the loss of local details in the global contrast calculation.
Saturation weight Saturation is applied to balance brightness and color effects. Long-term exposure will cause the saturation to decrease. By calculating the standard deviation of each channel pixel and brightness.
Exposure weight Usually, brighter areas of under-exposed images contain more information. Conversely, over-exposed images save more details in dark areas. These areas are more easily captured by human sight, and the exposure map is used to retain detailed information. To improve the accuracy of details of the region of interest and protect the hue changes that may exist in some cases, the exposure of the pixels is evaluated according to the weight of the exposure map

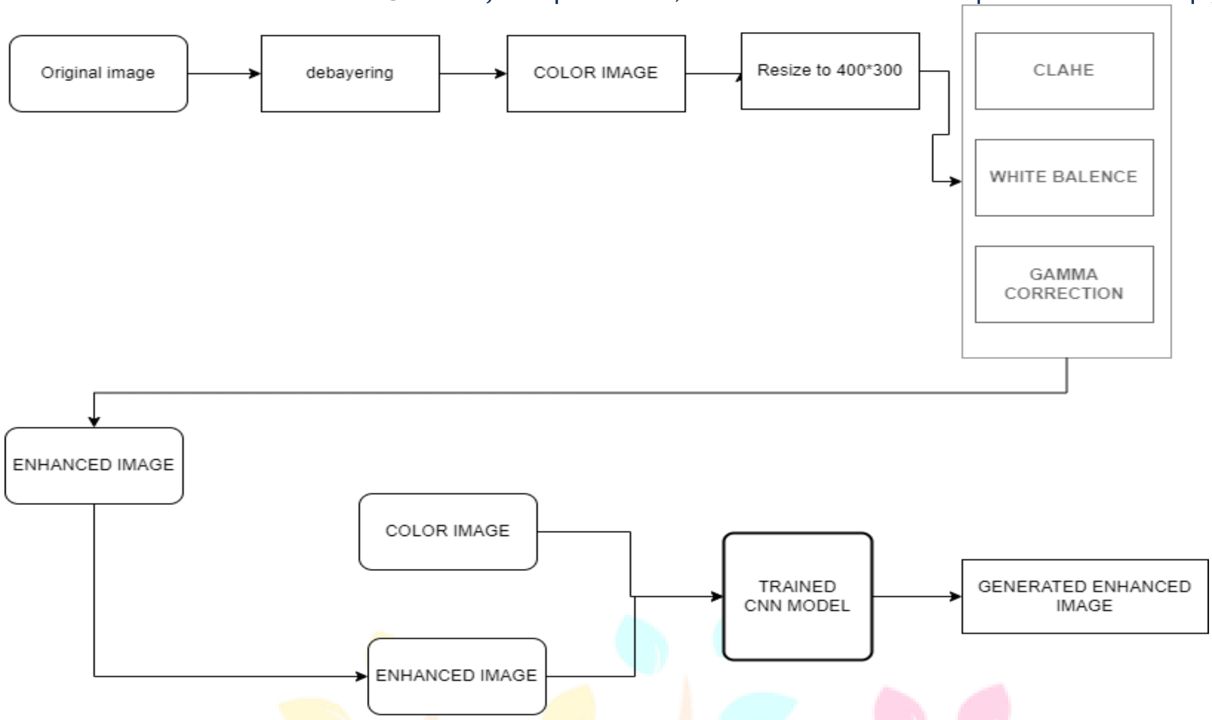
Multi feature image fusion Due to the complexity of the degradation process of underwater images, all the introduced feature weight maps play critical roles in the enhancement process. They are applied to improve the overall contrast, enhance the details of the image, correct the color distortion, and adjust the visibility. To obtain the output weight map, we combine the information of different feature weights into a normalized weight map. To obtain the final rendering, the output pyramid is upsampled. The calculation is as follow:

$$E_{result}(x, y) = \sum_{l} U[R_{l,k}(x, y)]$$

where E(result)(x, y) refers to the final output rendering; U[Rl,k(x, y)] refers to the up-sampling operation on the output image pyramid

CASE STUDY 1

The paper presents a case study on deep learning-based image enhancement and animal species classification in deep-sea environments. The study focuses on enhancing and classifying images captured by the crawler "Wally" in the Ocean Network Canada area of Barkley Canyon.
The image enhancement process involves a convolutional residual network that generates enhanced images from raw images. The enhanced images showed improved metrics for underwater imagery assessment and outperformed non-enhanced datasets.The classification results obtained with the enhanced images were promising, with an accuracy value of 66.44% and an Area Under the ROC Curve (AUROC) value of 82.91%. These results were further improved to 79.44% accuracy and 88.64% AUROC.
The study also discusses the visual aspect of the enhanced images, noting that they maintained a bluish tone but had more pronounced colors for visible animals.
The classification results achieved good performance for various classes, with some classes correctly classified above 80%.The study suggests future work on modifying the image enhancement CNN, optimizing image quality vs. computational cost, and exploring other classification strategies like transfer learning and object detection networks.



CASE STUDY 2:

The paper proposes a visual quality enhancement method for underwater images based on multi-feature prior fusion (MFPF) .

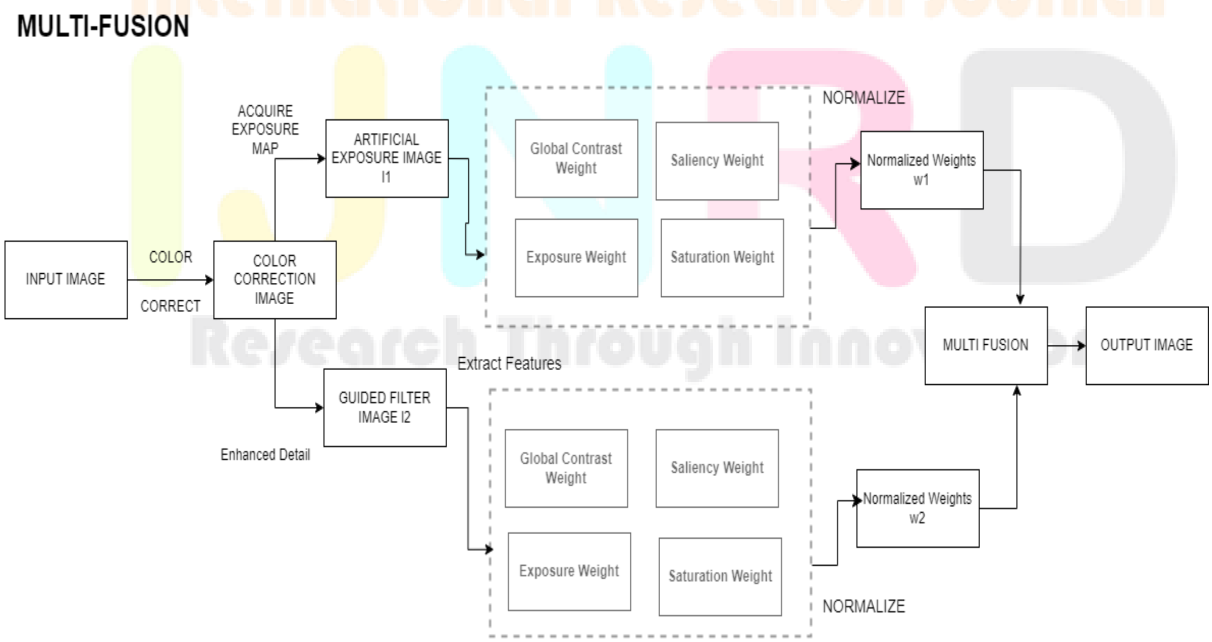
The method extracts and fuses multiple feature priors of underwater images, including global contrast weight, saliency weight, saturation weight, and exposure weight

It utilizes white balance, guided filtering, and multi-exposure sequence technology to enhance the visual quality of underwater images .

The design includes a color correction method based on self-adaptive standard deviation, gamma correction power function, and spatial linear adjustment to improve brightness and structural details

The multi-feature prior fusion scheme comprehensively solves various degenerated problems, removes over-enhancement, and improves dark details

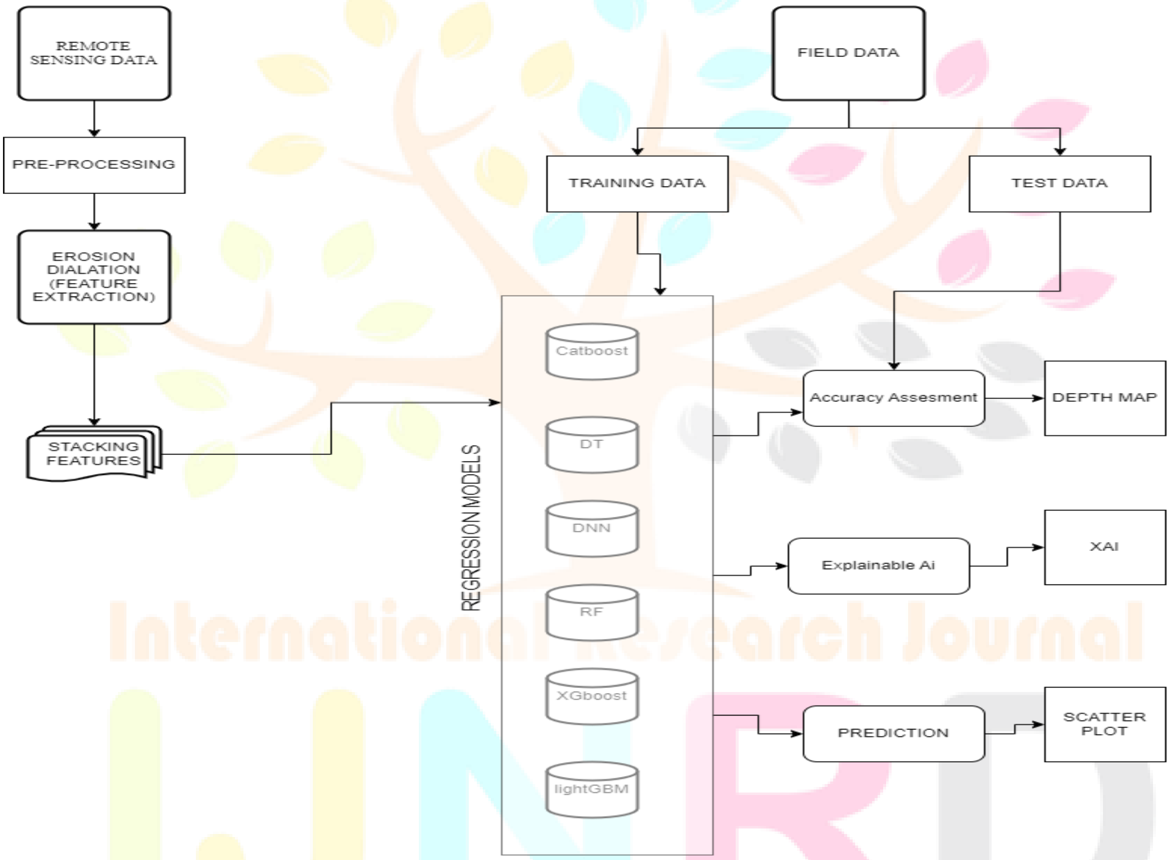
Experimental results show that the MFPF method achieves better subjective and objective enhancement effects, effectively balancing contrast and color, and maintaining the natural attributes of the image.



CASE STUDY 3:

Case Study in Chabahar Bay:

The research paper includes a case study conducted in Chabahar Bay, Iran, which is a significant port with access to international open waters. The study focused on two different coastal areas, namely the port and jetty, with a nearshore region. The selection of these areas was based on the availability of highly accurate ground truth data from hydrographic surveys and cloud-free Sentinel imagery of the coastal region. The study utilized advanced machine learning methods, including Decision Tree, Random Forest, eXtreme Gradient BOOSTing, Light Gradient Boosting Machine, Deep Neural Network, and CatBoost, for water depth estimation using high-resolution Sentinel-2 satellite imagery. The performance of the proposed method was evaluated in the shallow water of Chabahar Bay, achieving a best R2 value of 0.96 and Root Mean Square Error (RMSE) of 0.27 m in water depth estimation.



RESULTS & DISCUSSION

Discussions:-

The exploration of the deep sea, a vast and largely unexplored realm, poses significant challenges due to the harsh conditions and limited visibility. Underwater image processing plays a crucial role in overcoming these obstacles by enhancing the quality of underwater images and enabling researchers to extract meaningful information from these captured scenes. The integration of artificial intelligence (AI) and machine learning (ML) techniques into underwater image processing has revolutionized this field, providing powerful tools for image enhancement, restoration, and classification.

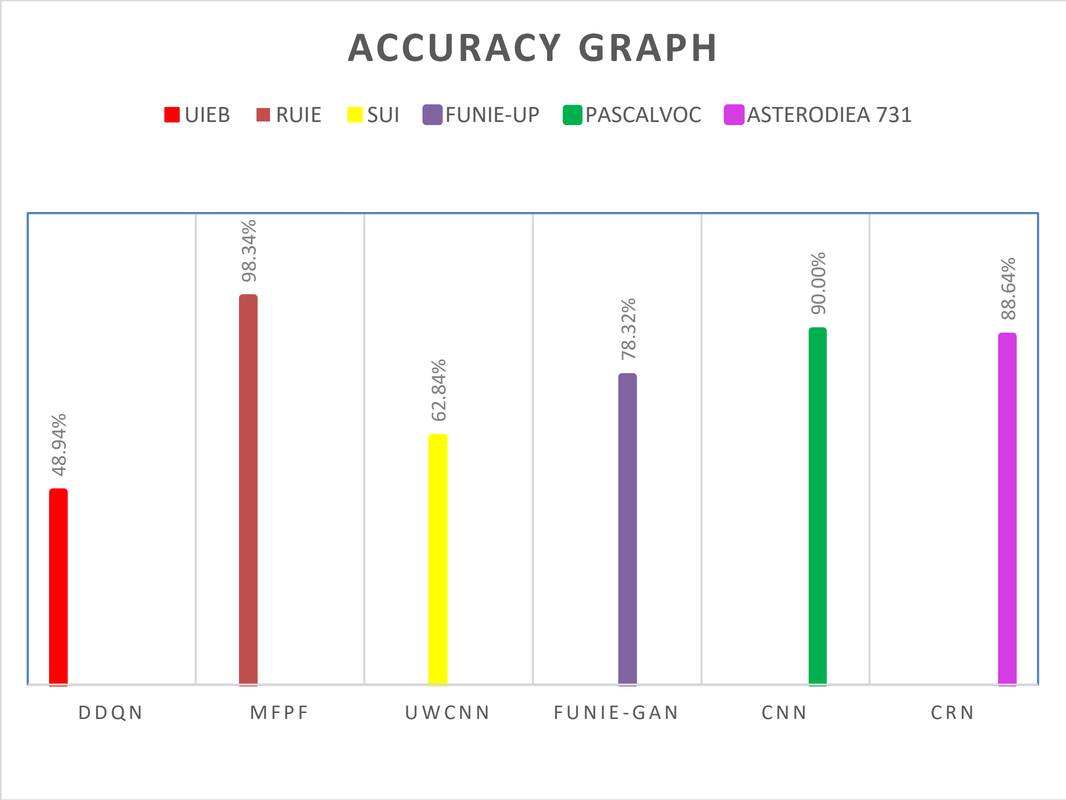
This research delved into the application of deep learning-based approaches for underwater image enhancement and classification, specifically focusing on deep-sea environments. The proposed pipeline, leveraging the capabilities of deep learning models, effectively addressed the inherent challenges of deep-sea images, such as low contrast, noise, and blurring. The enhanced images obtained through this pipeline exhibited improved

quality metrics, demonstrating the efficacy of the proposed approach.The automation of image enhancement and classification significantly reduces the need for extensive manual labor, streamlining the analysis of large datasets and monitoring deep-sea environments. This automation not only enhances efficiency but also alleviates the burden on researchers, allowing them to focus on higher-level analyses and interpretations.
Bathymetry (SDB) is a cost-effective and efficient method for mapping coastal zones using satellite imagery. This study compares the effectiveness of different machine learning (ML) models for SDB in two Iranian ports. The results show that XGBOOST and LightGBM models perform the best, with RMSEs below 0.5 m. Morphological operations, such as dilation and erosion, are also effective in improving SDB accuracy. Overall, SDB is a promising technique for monitoring coastal zones and informing port management decisions. The authors proposed a new pipeline for enhancing dark deep-sea images and classifying visible fauna in footage taken by a moving crawler. They developed an enhancement procedure that improved animal classification accuracy. They used residual networks to generate new enhanced images and compared the performance of different classification algorithms.

COMPARISION TABLE

Reference No	Author of the paper	Model/Approach used	Data set & accuracy
3	Lopez-Vazquez, V., Lopez-Guede, J. M., Chatzievangelou, D., & Aguzzi, J. (2023)	CRN	ASTERODIEA731 Accuracy =88.64%
11	Schettini, R., &Corchs, S. (2010)	CNN	PASCALVOC Accuracy =78.08%
12	Han, F., Yao, J., Zhu, H., & Wang, C. (2020)	FUNIE-GAN	FUNIE-UP Accuracy=78.32%
16	Anwar, S., Li, C., & Porikli, F. (2018)	UWCNN	SUI Accuracy=62.84%
17	Zhou, J., Zhang, D., & Zhang, W. (2022)	MFPF	RUIE Accuracy=98.34%
18	Sun, S., Wang, H., Zhang, H., Li, M., Xiang, M., Luo, C., & Ren, P. (2022)	DDQN	UIEB Accuracy =48.94%

Graphical Representation



The enhanced images showed improved metrics for underwater imagery assessment and outperformed non-enhanced datasets. The classification results obtained with the enhanced images were promising, with an accuracy value of 66.44% and an Area Under the ROC Curve (AUROC) value of 82.91%. These results were further improved to 79.44% accuracy and 88.64% AUROC.

The Accuracy Graph compares various algorithms and datasets used in them to find the best algorithm to be implemented in order to get better result .So the Algorithm DDQN gives the accuracy of 48.94% ,UWCNN of 62,84%,FUNIE-GAN of 78.32%,CNN of 90.00%,MFPF of 98.34% and CRN of 88.64%perimental results show that the MFPF method achieves better subjective and objective enhancement effects, effectively balancing contrast and color, and maintaining the natural attributes of the image.

FUTURE WORKS

Underwater image processing is a rapidly evolving field with the potential to revolutionize ocean exploration and research.Developing more robust and efficient algorithms: Underwater images are often degraded by noise, scattering, and low illumination. Current image processing algorithms are not always effective at handling these challenging conditions. Future work should focus on developing new algorithms that are more robust to these degradations and can handle real-time applications.

Exploring the use of deep learning:Deep learning has shown great promise in many image processing tasks, including underwater image enhancement. Future work should explore the use of deep learning techniques to develop new and more effective underwater image processing algorithms.Developing standardized datasets and evaluation metrics: The lack of standardized datasets and evaluation metrics is a major challenge in underwater image processing. Future work should focus on developing standardized datasets that represent the diversity of underwater environments and image conditions. Additionally, new evaluation metrics are needed to assess the performance of underwater image processing algorithms in a more objective and comprehensive manner.Applying underwater image processing to real-world applications: Underwater image processing has a wide range of potential applications, including underwater exploration, marine biology, and autonomous underwater vehicles (AUVs). Future work should focus on applying underwater image processing techniques to real-world applications and demonstrating their value in these domains.

CONCLUSION

The exploration and understanding of the deep sea, a vast and largely unexplored realm, poses significant challenges due to the harsh conditions and limited visibility. Underwater image processing plays a crucial role in overcoming these obstacles by enhancing the quality of underwater images and enabling researchers to extract meaningful information from these captured scenes. The integration of artificial intelligence (AI) and machine learning (ML) techniques into underwater image processing has revolutionized this field, providing powerful tools for image enhancement, restoration, and classification. This research delves into the application of deep learning-based approaches for underwater image enhancement and classification, specifically focusing on deep-sea environments. The automation of image enhancement and classification significantly reduces the need for extensive manual labor, streamlining the analysis of large datasets and monitoring deep-sea environments. This automation not only enhances efficiency but also alleviates the burden on researchers, allowing them to focus on higher-level analyses and interpretations. The integration of deep learning techniques into underwater image processing has transformed the ability to extract meaningful information from deep-sea images. The proposed pipeline, demonstrating remarkable effectiveness in image enhancement and animal species classification, holds immense potential for advancing deep-sea research and conservation efforts. By enhancing our understanding of these unexplored depths, we can better manage and protect the delicate balance of marine ecosystems and the diverse species they harbor. This research has comprehensively examined the potential of satellite-derived bathymetry, deep learning techniques for underwater image enhancement, and a novel multi-feature prior fusion (MFPF) method for enhancing underwater images. The findings highlight the significant advantages of satellite-derived bathymetry in providing timely, cost-effective, and high-resolution water depth measurements, particularly in large coastal environments and hard-to-access areas. The application of ensemble-based machine learning models, such as XGBOOST, LightGBM, RF, and CatBoost, demonstrated superior performance in extracting bathymetry information from satellite imagery compared to traditional machine learning algorithms. In the realm of underwater image enhancement, the proposed MFPF method effectively improves the visual quality of underwater images by fusing multiple feature priors, including global contrast, local contrast, saturation, and exposure. This fusion approach enhances image detail, edge texture, and overall brightness without introducing artifacts or backscatter. The MFPF method outperforms other image enhancement techniques, achieving better subjective and objective enhancement effects. Overall, this study has made significant contributions to the fields of satellite-derived bathymetry and underwater image enhancement. The findings have implications for improving coastal zone management, underwater exploration, and underwater robotic applications.

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