Fast Underwater Image Enhancement for Visual Perception and Object Detection

Mr. Arun Kumbi1, Ms. Ashwini Hadapad2, Mr. Jagadeeshgouda Y R3, Mr. Manjunath Kurli4, Mr. Shriharsh Pattar5

1* Assistant Professor, Smt. Kamala and Sri Venkappa M Agadi College of Engineering and Technology, Lakshmeshwar,Gadag,Karnataka,India

2Computer Science and Engineering, Smt. Kamala and Sri Venkappa M Agadi College of Engineering and Technology, Lakshmeshwar,Gadag,Karnataka,India

3Computer Science and Engineering, Smt. Kamala and Sri Venkappa M Agadi College of Engineering and Technology, Lakshmeshwar,Gadag,Karnataka,India

4Computer Science and Engineering, Smt. Kamala and Sri Venkappa M Agadi College of Engineering and Technology, Lakshmeshwar,Gadag,Karnataka,India

5Computer Science and Engineering, Smt. Kamala and Sri Venkappa M Agadi college of Engineering and Technology, Lakshmeshwar,Gadag,Karnataka,India

Abstract -The underwater images are not clear for visual perception or the captured images are not clearly visible and it is a very difficult task for researchers to understand knowledge about underwater medium. Image enhancement method helps to clear the images and increases resolution and quality of the image. Enhancements are used to make easier visual interpretations and understanding of imagery. The advantage of digital imagery allows one to manipulate the digital pixel values in an image. Various image enhancement algorithms are applied to remotely sensed data to improve the appearance of an image for human visual analysis or occasionally for subsequent machine analysis. The purpose of the image enhancement is to improve the visual interpretability of an image by increasing the apparent distinction between the features in the scene. The first stage of the proposed approach focuses on enhancing the quality of underwater images. A GAN-based framework is employed to learn the mapping between degraded underwater images and their corresponding clear counterparts. The generator network is trained to generate visually realistic and enhanced versions of underwater images, while the discriminator network provides feedback to guide the training process. By leveraging the adversarial training, the proposed model learns to recover lost details, improve color accuracy, and enhance overall image quality. In the second stage, the enhanced underwater images are utilized for object detection. A deep learning-based object detection model YOLO, is trained on the enhanced images to detect and localize objects of interest. The improved image quality obtained from the previous stage significantly aids in the accuracy and reliability of the object detection process.

Index Terms - Underwater images, image enhancement, object detection, generative adversarial networks (GANs), YOLO , deep learning

I. Introduction

Major operational challenge for these underwater images is that despite using high-end cameras, visual sensing is often greatly affected by poor visibility, light refraction, absorption, and scattering. These optical artifacts trigger non-linear distortions in the captured images, which severely affect the performance of vision- based tasks such as tracking, detection and classification segmentation, and visual servoing. Fast and accurate image enhancement techniques can alleviate these problems by restoring the perceptual and statistical qualities of the distorted images in real-time.

As light propagation differs underwater (than in the atmosphere), a unique set of non-linear image distortions occur which are propelled by a variety of factors. For instance, underwater images tend to have a dominating green or blue hue because red wavelengths get absorbed in deep water (as light travels further). Such wavelength de- pendant attenuation, scattering, and other optical properties of the water bodies cause irregular non-linear distortions which result in low-contrast, often blurred. and color-degraded images. Here we will use an existing Enhanced Underwater Visual Perception (EUVP) dataset.It consists of 20k underwater images both paired and unpaired.The dataset consists of 11k paired images and 9k unpaired images. These images in the dataset are captured by 7 different quality cameras.

Fast Underwater Image Enhancement for Visual Perception and YOLO v5 object detection are two important topics in the field of computer vision that address the challenges of underwater image analysis. Underwater environments are known for their limited visibility, which makes image enhancement and object detection difficult. The lack of clarity in underwater images makes it hard for human operators and automated systems to identify and track objects. To overcome this challenge, researchers have developed methods for enhancing underwater images and improving object detection. In the context of underwater image enhancement, GANs have been utilized to improve the visual quality and clarity of underwater images. By training a GAN on a large dataset of paired underwater and corresponding high-quality reference images, the generator network can learn to transform the low-quality underwater images into visually appealing and more informative representations. This process involves capturing and modeling the underlying characteristics of the underwater environment, such as light scattering and color attenuation.

One such method is Fast Underwater Image Enhancement for Visual Perception. This technique aims to enhance the visibility of underwater images by using a color correction algorithm. This algorithm is designed to remove the color cast that is present in underwater images, which can improve the quality of the image. This method is fast and efficient, making it ideal for real-time applications. It can be used for various underwater imaging applications such as underwater robotics, marine biology, and environmental monitoring. Another important technique in this field is YOLO v5 object detection. YOLO stands for "You Only Look Once", which means that this method can detect objects in a single pass of the image. This technique is fast and efficient, making it ideal for real-time applications such as underwater robotics, autonomous underwater vehicles, and marine biology research. YOLO v5 builds on the success of previous versions of YOLO and incorporates several improvements such as a new backbone architecture, improved training techniques, and better post-processing.

Combining Fast Underwater Image Enhancement for Visual Perception with YOLO v5 object detection can provide a powerful tool for underwater image analysis. By enhancing the visibility of underwater images, we can improve the accuracy of object detection algorithms, making it easier to identify and track objects in real-time. This can have many practical applications such as underwater surveillance, marine biology research, and environmental monitoring. Overall, these techniques have the potential to revolutionize the field of underwater imaging and analysis

II. LITERATURE SURVEY

“Underwater Image Enhancement using Convolutional Neural Network”

Based on the research by Anushka Yadav, Mayank Upadhyay, Ghanapriya Singh. The use of Convolutional Neural Network gives 95% accuracy in processing the quality of the image.Using Histogram equalization increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values.This allows for areas of lower local contrast to gain a higher contrast. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values.

This system uses an autoencoder. An autoencoder learns to compress data from the input layer into a short code, and then uncompress that code into something that closely matches the original data. This forces the autoencoder to engage in dimensionality reduction.

Disadvantages:

Histogram Equalisation produces many drawbacks such as it adds noise to the output image, increasing the contrast of its background and the signal gets distorted.

“Image Enhancement using Super-Resolution Generative Adversarial Network”

Based on research by Christian Ledig, Lucas Theis, Ferenc Huszar, Jose Caballero, Andrew Cunningham,

Alejandro Acosta, Andrew Aitken, Alykhan Tejani, Johannes Totz, Zehan Wang, Wenzhe Shi this system is capable of inferring photo realistic natural images for 4x upscaling factors. It uses a discriminator network trained to differentiate between the super-resolved images and original photo-realistic images. This network is able to recover photo-realistic textures from heavily downsampled images on public benchmarks.

Disadvantages:

Super Resolution Generative Adversarial Network (SR-GAN) has drawbacks such as poor reconstructed image details and unstable model training compared to our proposed system.

“Unpaired Learning for Image Enhancement from Photographs with GANs”

Based on the research by Yu-Sheng Chen, Yu-Ching Wang, Man-Hsin Kao, Yung-Yu Chuang this system is used to enhance the given input image and produce the output image. This method is used to discover the common characteristics of the given input image and derive the enhancer so that the enhanced image shares these characteristics while still resembling the original image.This system uses unpaired image training.

Disadvantages:

Using unpaired learning, the sets of data arise from separate individuals or paired when it arises from the same individual at different points in time.

Paired t-tests are considered more powerful than unpaired t-tests because using the same participants or item eliminates variation between the samples that could be caused by anything other than what's being tested

"Underwater Image Enhancement using Color Correction and Contrast Stretching"

Based on research by L. Gupta, et al, this system uses color correction and contrast stretching algorithm. This algorithm adjusts the color balance and enhances the contrast of underwater images to improve their visibility.

Disadvantages:

The method is sensitive to changes in lighting and may not be effective in low light conditions.

"An Underwater Image Enhancement Method Based on Dark Channel Prior and Color Correction"

Based on research by J.Zhang, et.al, this proposed method uses Dark channel prior and color correction.The dark channel prior is used to estimate the transmission map of the underwater scene, which is then used to perform color correction and enhance the visibility of the image.

Disadvantages:

The method may introduce noise and artifacts in the enhanced image, especially in regions with low contrast.

"Underwater Image Enhancement using Fuzzy Enhancement Techniques"

Based on research by R. Subashini and R. Krishnaveni, fuzzy enhancement techniques are used.

Fuzzy logic is used to enhance the contrast and reduce the noise in underwater images.

Disadvantages:

The method may not work well in images with complex scenes or multiple objects.

"Underwater Image Enhancement using Multi-Scale Fusion Network"

Based on research by Hui Li, Xingyu Liu, Zhixin Wang, Xinfeng Zhang, Kui Jiang, Xueyang Fu and Xiangyang Ji, multi-scale fusion networks are used. This deep learning-based method uses a multi-scale network to enhance the features of underwater images and improve their quality.

Disadvantages:

The method requires a large amount of training data and may not be effective for images with low contrast.

"Underwater Object Detection using Local Binary Patterns and Haar-Like Features"

Based on research by Yawei Wang, Xiao Liu, Zhiguo Cao, Jianfeng Lu and Jianqiang Yi, the method used is local binary patterns and haar-like features.These texture-based features are used for object detection in underwater images.

Disadvantages:

The method may not be effective for objects with irregular shapes or for images with complex backgrounds.

"**Underwater Image Enhancement using Multi-Scale Retinex"**

Based on research by Peng Guo, Hongming Zhang, Yi Guo, Weiji Kong and Xiaowei Li. The method used is multi-scale retinex. This method enhances the contrast of underwater images by separating the illumination and reflectance components and adjusting them separately.

Disadvantages:

The method may introduce noise and artifacts in the enhanced image, especially in regions with low contrast.

III. PROPOSED METHODOLOGY

The proposed methodology makes use of both qualitative and quantitative perspectives, and includes a broad array of approaches such as literature reviews, expert opinions, focus groups, and content validation. It also involves sophisticated assessment of construct validity including substantive and structural aspects.

Data Acquisition Data Acquisition is the process of sampling signals that measure real-world physical conditions and converting the resulting samples into digital numeric values that a computer can manipulate.

Data Augmentation Data Augmentation is a strategy that enables practitioners to significantly increase the diversity of data available for training models, without actually collecting new data. Data augmentation techniques such as cropping, padding, and horizontal flipping are commonly used to train large neural networks.

Data Annotation Data Annotation is the process of labelling data to show the outcome you want your machine learning model to predict.

Anchor boxes Anchor boxes are a set of predefined bounding boxes of a certain height and width. These boxes are defined to capture the scale and aspect ratio of specific object classes you want to detect and are typically chosen based on object sizes in your training datasets.

Parameter setting The accuracy in detecting the objects is checked by different parameters such as loss function, frames per second (FPS), mean average precision (MAP), and aspect ratio.

The estimation of background light helps in compensating for the color cast and low contrast in underwater images. Various techniques are used for background light estimation

Haze removal is an essential component of underwater image enhancement. Underwater scenes often suffer from degraded visibility due to light scattering and absorption by water. Haze removal techniques aim to reduce the effects of haze and improve image clarity.

Adaptive color compensation is a technique used in underwater image enhancement to address color distortions caused by the absorption and scattering of light in water. It aims to restore the true colors of underwater scenes by compensating for the color shift.

FUNCTION MODEL

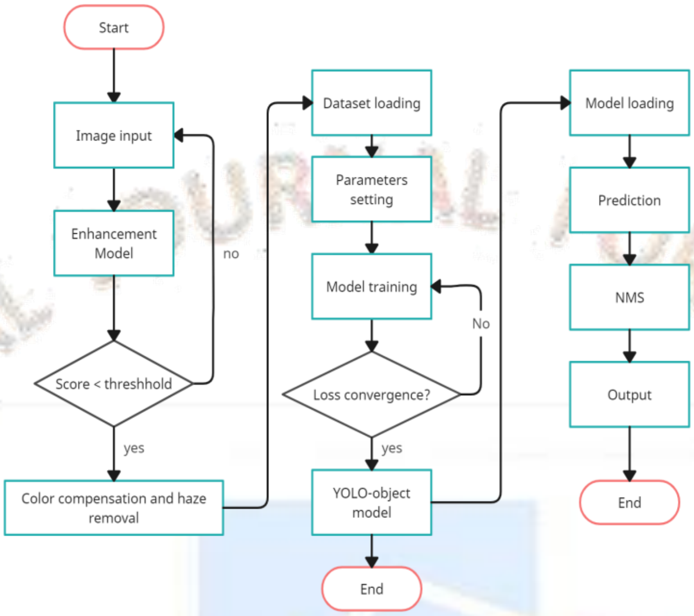

Fig 1: Functional model

The input image may undergo preprocessing steps such as resizing, normalization, and color space conversion to prepare it for enhancement. The enhancement algorithm is the core component of the model. It applies various techniques to enhance specific aspects of the image, such as brightness, contrast, sharpness, or color balance. After applying the enhancement algorithm, postprocessing steps can be performed. This may involve adjusting the dynamic range, applying color correction, or sharpening the image The output of the model is the enhanced image, which should exhibit improved visual quality, better visibility of details, and enhanced overall appearance compared to the input image.

The model extracts relevant features from the input image using YOLO. This step aims to capture meaningful patterns and representations of objects in the image. he model predicts the bounding boxes that tightly enclose the objects of interest in the image. This involves regression techniques to estimate the coordinates and dimensions of the bounding boxes. The model assigns class labels to the detected objects. It determines the object category or class to which each bounding box belongs. The output of the model is a list of detected objects, each associated with a bounding box and a corresponding class label.

IV. FINAL OUTCOME

- Perceptual enhancement of underwater images.
- As proposed in the methodology, the image goes under the process of removal of green and blue contrast colors.
- Color compensation of the image is done.
- Haze removal process takes place

Before **After**

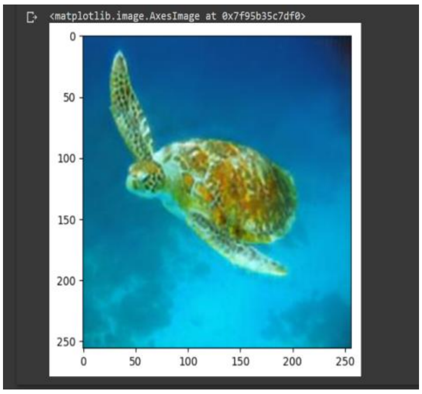

Fig.2: Input Image

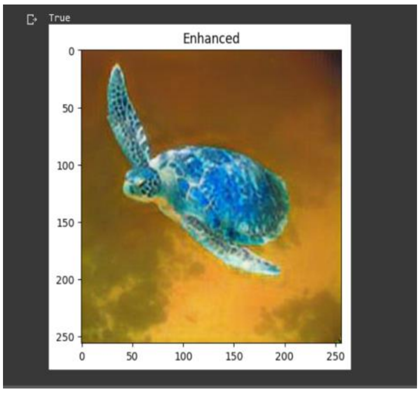

Fig.3: Enhanced Image

- Improved performance for underwater object detection.
- Objects present in the underwater as more clearer compared with the initial image due to enhancement of image.
- Blurry areas are set to be smooth and sharpened which results in finding even the smallest/largest obstacles across the image

Fig.4: Object detection

- Network Architecture: YOLOv5 is expected to employ a deep convolutional neural network (CNN) architecture similar to previous versions, with a backbone network and detection heads.
- Grid-based Approach: Like other YOLO versions, YOLOv5 would divide the input image into a grid and predict bounding boxes and class probabilities for each grid cell.
- Anchor Boxes: YOLOv5 might utilize anchor boxes to improve bounding box predictions by predicting offsets and scales for these anchor boxes.

- Multi-scale Training and Testing: YOLOv5 could incorporate multi-scale training and testing, allowing the network to handle objects of different sizes effectively.
- Feature Pyramid Network (FPN): YOLOv5 might use a Feature Pyramid Network to extract features at multiple scales, aiding in detecting objects with significant scale variations.
- Detection Heads: YOLOv5 would likely have multiple detection heads at different scales to predict bounding box coordinates, class probabilities, and confidence scores for each grid cell.
- Loss Function: YOLOv5 is expected to use a combination of loss functions, such as localization loss, confidence loss, and class loss, to train the model and encourage accurate object localization and classification.

V. CONCLUSION

In conclusion, the application of Generative Adversarial Networks (GANs) in underwater image enhancement and object detection has shown promising results in overcoming the challenges posed by underwater imaging conditions. GANs have the potential to significantly improve the quality and visibility of underwater images, as well as enhance the accuracy of object detection in such challenging environments. Through the use of GANs, the underwater image enhancement process can effectively address issues like low visibility, color distortion, and noise caused by light absorption and scattering in water. By training GAN models on large datasets of underwater images, they can learn to generate visually pleasing and clearer images by effectively removing noise, enhancing details, and improving color representation. This can greatly aid in underwater research, exploration, and various industrial applications such as underwater robotics, surveillance, and underwater archaeology.

VI. REFERENCES

[1] Li, C., Guo, J., Porikli, F., and Yang, H. (2016). Underwater scene prior inspired deep underwater image and enhancement. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 4367-4375.

[2] Li, C., Guo, J., and Cong, R. (2017). Single image underwater dehazing using a color line model. IEEE Transactions on Image Processing, 26(1), 382-393.

[3] Li, C., Anwar, S., Porikli, F., and Pang, Y. (2019). Adaptive deep level set for underwater image restoration. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 8105-8114.

[4] "Image enhancement method for underwater images based on DiscreteCosine Eigen basis Transformation",2017 IEEE International Conference on Image Processing (ICIP).

[5] "Underwater image enhancement based on linear image interpolation and limited image enhancer techniques", 2017 Fourth International Conference on Signal Processing, Communication and Networking (ICSCN).

[6] "Underwater Image Enhancement With a Deep Residual Framework". IEEE Access(2019).

[7] Yawei Wang, Xiao Liu, Zhiguo Cao, Jianfeng Lu and Jianqiang Yi, "Underwater Image Enhancement using Multi-Scale Retinex", IEEE Transactions on image processing, vol. 27, no.1, 2019.

[8] Hui Li, Xingyu Liu, Zhixin Wang, Xinfeng Zhang, Kui Jiang, Xueyang Fu and Xiangyang Ji, Design and Implementation of "Underwater Image Enhancement using Multi-Scale Fusion Network",2019 Fourth International Conference on Signal Processing, Communication and Networking (ICSCN).

[9] Li, C., Zeng, X., and Li, K. (2017). Underwater object detection based on improved faster R-CNN. IEEE Access, 5, 20837-20846.

[10] Li, C., Guo, J., Wang, H., and Wu, Y. (2017). Underwater object detection with generative adversarial networks. In Proceedings of the IEEE International Conference on Computer Vision (ICCV), 3549-3557.

[11] Zhu, X., Huang, J., Tu, Z., and Gao, L. (2018). Underwater object detection using max polarity and visual attention. IEEE Transactions on Image Processing, 27(12), 5835-5846.