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Underwater Image Enhancement and Object Detection

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Abstract : **This paper proposes a model for the enhancement of underwater images and is further the images are classified into 2 classes of fish and trash. It involves improving the quality of images using NUCE (Natural-based underwater image color enhancement). NUCE is a four-step strategy process involving color cast neutralization on underwater images, a fusion of dual-intensity images, and then an unsharp masking algorithm to sharpen the high frequencies. YOLO is used to classify objects into 2 categories: fish and trash. The paper covers a variety of enhancement techniques to get results with very high accuracy. The model gives satisfying results with high precision and accuracy**

IndexTerms - Neutralization, masking, equalization, YOLO, classifiers.

I. Introduction

Oceans occupy approximately 70% of the planet and contain abundant natural resources, which has long been a cause of concern for human growth. Exploring this mysterious region of the ocean is becoming more popular as marine observation and exploitation advance quickly. Due to the increased use of marine resources, underwater image processing is now seen as crucial [15]. Physical properties existing in the underwater environment make underwater imaging very challenging.

Underwater image quality is a natural phenomenon and is caused by scattering, absorption, and color distortion [9]. The rays of light are absorbed when passed through the ocean based on the wavelength of light. The large particles suspended underwater are caused by scattering. Underwater images have low contrast and are dominated by blue color because of color distortion [7]. The wavelength of light is inversely proportional to the attenuation thus when rays of light pass-through unit water it adversely affects the quality of the image. Also, parameters that affect underwater image processing are light attenuation, water density, absorption, short range, and scattering which causes blurring effects, low contrast, non-uniform illumination, diminished colors, and prominent blue or green hues [3] [9]. The high-dimensional images are affected by the sediments in the water. Light attenuation diminishes the visibility in clear water by 20m and < 2m in turbid water [8]. Light attenuation does not provide sufficient light, so an additional resource of light is required but this causes a [8] large bright spot in the center of the image and affects the edges of dark areas. The distance between the scene and the camera results in color attenuation. Although the previously mentioned Range Gated System captures images that are always smoothened, it eliminates noise caused by backscattering efficiently [2].This paper presents a model that significantly enhances the image and is used to classify fish and trash. Enhancement is performed using Natural-based underwater image color enhancement through fusion of swarm intelligence algorithms.The paper is organized as follows: In Section 2 the Literature Survey is discussed, Section 3 includes the methodology of the proposed model, Section 4 discusses various results obtained and Section 5 gives the conclusion.

II. Literature Rivew

Image enhancement aims to enhance the visual appearance of the restored image i.e., enhance the quality and characteristics of an image. The quality and details are refined using image enhancement techniques. Yujie Li et al [11] suggested improved methods of non-Local mean denoising, classical median filtering, and dark channel prior as important steps for underwater image enhancement. The NLM(Non-Linear Median) denoising method searches a similar image block from the full spectrum of images to the central neighborhood window. The value of center pixel value for all similar blocks is based on average weight. But it fails when the complexity computationally is very high causing loss of edges and other details of the information. The improved NLM works on segmentation superpixel segmentation. A region with a flat structure can be thought of as having more similarities in the search window and the largest number of comparable blocks discovered by translating a similar window indicates the window has high similarity. The dark channel prior technique [12] helps to get an image with better contrast, non-blurred effect, and color correction which is affected by light attenuation.Although the basic idea of the dark channel prior algorithm is to fill the scattered light by increasing the dark pixels in the underwater image's intensity values which helps to develop a true undisturbed underwater image. The improved dark channel algorithm uses histogram equalization to improve the underwater image pixels' dynamic range and then the resultant image is converted to YUV space to equalize the brightness which enhances the contrast of the image.

Also, the image preprocessing includes classical median algorithms (non-linear filter) which preserve the edges of the signal and works excellently on impulse noise. Thus, the quality of the image is enhanced using median algorithms. The improved classical median filtering is an improved median filtering method that incorporates voting statistics and noise detection techniques.[9] By recognizing noise picture blocks based on the number of pixels in noise image block filter windows, the dual-platform histogram equalization improves the image. It has straightforward logic with high efficiency of filtering. However, these improved techniques lack accuracy causing texture smoothness.

Image restoration techniques aim to recover the details of images degraded because of dynamic objects. The images captured successively include dynamic objects which lead to distortions. Image restoration algorithms are used to eliminate these dynamic objects. In the Image restoration method, dynamic objects are recognized and removed by comparing two successively captured frames and subtracting them from each other. The algorithm follows the step: convert the image to grayscale then select points where there is a difference between two images that is greater than the threshold used to estimate the motion of an item. The dynamic object is eliminated after calculating its area. To fill the patch, an upgraded total variation model is used which reduces the resolution. For restoring (super-resolution) some detail the s in image e the BP network is upgraded and then applied to the BP network which is trained The image restoration techniques are complicated because of the less knowledge about degraded images. The image enhancement techniques such as improved NLM, dark channel prior, and classical median filtering optimize the underwater image processing and the bastille algorithm improves the image contrasts and edges of objects. The brightness of a dull image and clarity of the image can be enhanced, and the complexity of computation can be reduced using The dark channel prior method. The underwater noise is also reduced using linear and non-linear filters, guided filters, and adaptive filters. The algorithm uses residual skip connection and up-sampling. [20] In this approach, three-step detection is performed by applying a 1x1 kernel on the feature vector. For training YOLO with custom objects, the anchor boxes need to be arranged in the decreasing order of their dimension. The nine anchors of YOLO are assigned as the biggest anchor for the first scale, the next set of three for the second and third. [10] The YOLO algorithm is used in this approach, and it outperforms the sliding window algorithm. YOLO predicts the size, position, and class probability of an object and hence this algorithm has good accuracy.

III. METHODOLOGY

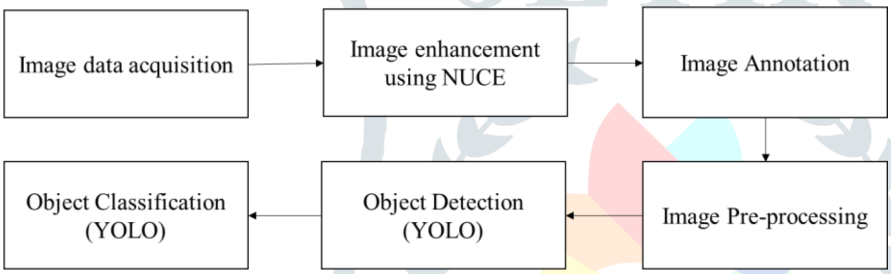

Fig 1. *Generic Block Diagram of the System*

Fig.1 describes the generalized algorithm of the proposed model.
First, an underwater image is taken as input. This image is enhanced using NUCE and further image annotation is performed to train the model using labeled images. The images are preprocessed by resizing and augmentation of images. The Object detection algorithm and the class of the object are predicted using YOLO v8.

A. Data Acquisition

The dataset of underwater images of two classes, fish and trash is obtained from Kaggle. It consists of a total of 1761 images. The data was split into 70-10-20 percent for training, validating, and testing respectively.

TABLE I. DATASET COMPOSITION

	Class	Number of Images
1	Fish	1600
2	Trash	800
	Total	2400

The distribution of the dataset across the classes can be learned from Table I.

B. Enhancement

Underwater Image Enhancement is performed using NUCE and is as follows

Algorithm: Natural-based underwater image color enhancement through fusion of swarm intelligence
1. **for** each class in the data
2. **for** each image in the dataset
3. Color Cast Neutralization based on superior channel
4. Dual Intensity Image Fusion
5. Histogram Equalization on swarm intelligence
6. Unsharp Masking using high pass filter
7. **for** end
8. **for** end

Natural-based underwater image color enhancement through fusion of swarm intelligence algorithm includes 4 major steps: Color cast neutralization, Dual-intensity image fusion, Mean equalization, and unsharp masking.

1. The inferior color channels are enhanced using gain factors. The inferior channels are those with low intensity and Those with high intensities are superior channels.
2. Image contrast is improved using mean and median values. The average value is calculated and chosen to produce lower-stretched and upper-stretched histograms.
3. Naturalness of the output image can be improved using Histogram equalization. The swarm intelligence algorithm adjusts the mean values of inferior color channels equivalent to the mean value of the superior color channel.
4. The high-frequency elements in images are enhanced by masking the low-frequency elements. This is performed using a High pass filter.

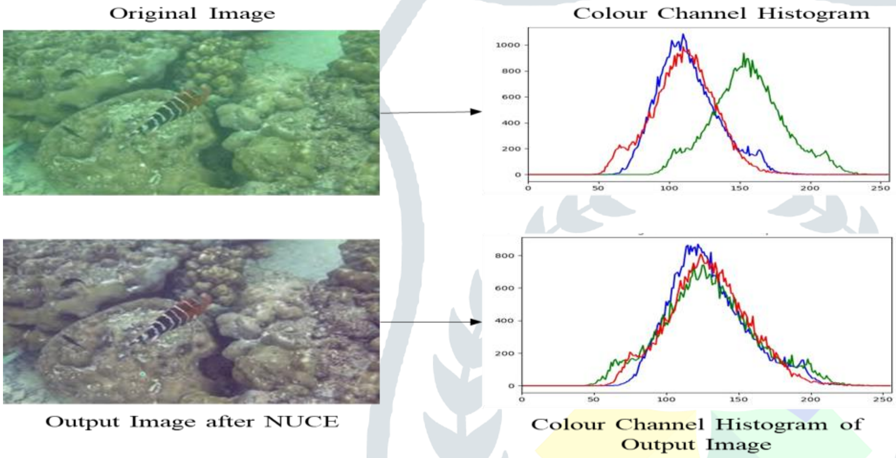

Fig.2. *Underwater Image Enhancement*

Fig.2. describes the color histogram of the original underwater image and the histogram of the enhanced image obtained after applying NUCE on it. NUCE improves the contrast and color of the underwater image.

C. Image Annotation

Image annotation is performed on the platform of Roboflow. This helps to train the model using labeled images. Images are divided in fish and trash classes.

Algorithm for image annotation
1. **for** every image in the dataset
2. define class labels of objects to detect
3. crop the object by dragging a box around the object
4. choose the class label (fish or trash) for every box
5. **for end**

D. Processing

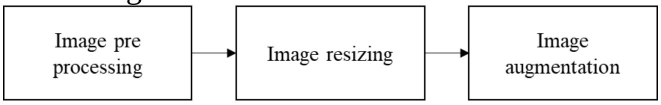

Fig. 3. *Image preprocessing block diagram*

Fig.3. describes the steps involved in image preprocessing. The dataset of all images is preprocessed. All the images are resized to 350x350 size for easy processing and to tackle the problem of irregular data in case images of different dimensions are present in the dataset.

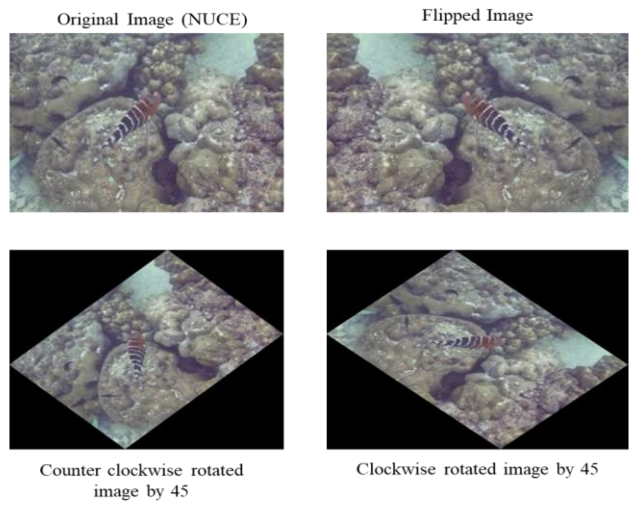

Fig.4. *Augmentation results*

Fig.4. shows the results of augmentation on the image enhanced using NUCE.
Image augmentation is performed to artificially increase the dataset by adding minor alterations in the enhanced data images. Hence, the accuracy of the model is increased. The resized image is flipped and rotated 45 degrees clockwise and counterclockwise. The augmentation of images increased the dataset by three times.

E. Object detection and classification

Classification of fish and trash is performed using YOLO v8.YOLO (You Only Look Once) is an efficient algorithm for object-detection tasks. Its fast inference speed made possible the processing of real-time images.

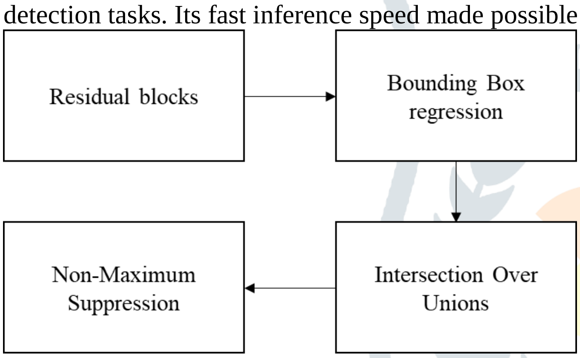

Fig.5. Generic Block diagram of YOLO v8

As shown in Fig. 5, YOLO first starts with residual blocks i.e. dividing the image into nxn grid cells of equal size. Every cell is responsible for predicting the class of the object it covers, along with its probability value. Secondly, in bounding box regression, only cells with probability > 0 are selected and the attributes of these bounding boxes are determined by YOLO. Thirdly, the IOU value is calculated (0 to 1), that is for each grid cell, the intersection ais rea divided by union area. A threshold value is then selected and only cells with IOU>threshold is considered and others are supposedly irrelevant. Lastly, NMS is used to keep only those boxes that have the highest probability score of detection.
YOLOv8 is the latest version of YOLO for object detection. It is a faster and more accurate training model than the previous versions. It has a very user-friendly API. It not only supports object detection but also instance segmentation and image classification. It is highly efficient and flexible, and supports numerous export formats to be used.

IV. RESULTS

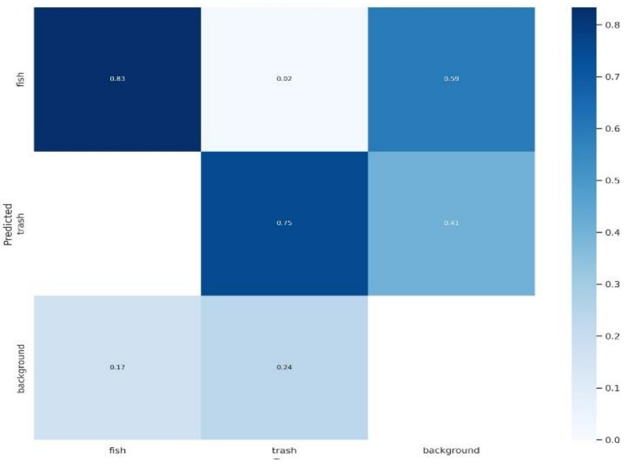

Fig.6. Confusion Matrix

Above Fig.6. shows the performance of the classification algorithm. The accuracy of predicted values and actual values, i.e., true positives of fish and trash is 83% and 75% respectively.

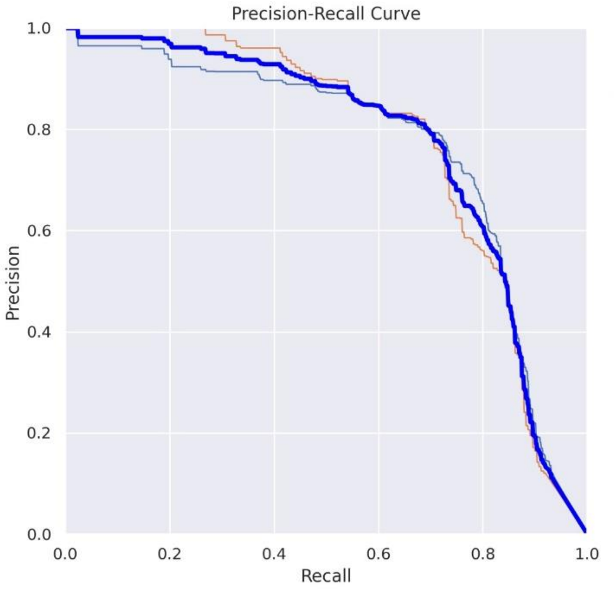

Fig. 7. Precision-Recall Curve

Fig. 7 is a plotting of precision-recall curve (PR curve). A good tradeoff is done between precision and recall as shown in the figure. The area under curve for precision-recall curve can be used as a single metric to determine the overall accuracy of the model. Another standard metric for the model analysis is mAP. It is calculated by calculating precision at every recall value with a step size of 0.01 and then it is repeated for IoU thresholds of 0.50, 0.55,…,0.95. At last, the average is taken over all the thresholds as the mAP.The overall mAP of the model was found out to be 76%. This was obtained with a high precision of 79.6% precision score and 72.2% recall score.

CONCLUSION

The underwater images are first enhanced for the sake of quality using Natural-based Underwater Color Enhancement. The processed images are used in training the YOLO model for fish and trash detection. After training and testing, it was found that an overall precision of 79.6% and a recall score of 72.2% were obtained from the model. At the same time mean Average Precision is 76%. It can be concluded that the results obtained are at par. However, it should be noted that the results will get better with more underwater image data.

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