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Detection of Submerged Objects With Machine Learning

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Abstract*:* The precision of underwater target recognition by autonomous underwater vehicles is a crucial guarantee for submerged object detection, rescue, and security. Object detection is time-consuming when investigating important regions of underwater surveillance, much as resource exploration or investigation. This paper provides solutions that are computer vision-based, automated, and based on machine learning. The purpose of this paper is to provide an ideal solution for underwater item identification that leverages the YOLOv3 architecture, an upgraded version of YOLO, and deep learning to automatically recognize underwater things. The goal behind this research is to search for the most efficient and accurate solutions for the detection, identification and classification of submerged objects and to design a fast operating system to detect object in the system and optimization for parallel computations, rather than the low computation volume theoretical indicator. We tried that the given object can be easily trained and used. In our system it gives the accuracy of 75% when the input data or image is clear aur noise reduced. But when the images are very diverse then the system gives the accuracy near 67 to 70 % .

Keywords: YOLOv3, Underwater image detection.

I. INTRODUCTION

As the maritime trade and number of submarines are increasing day-by-day, it is not only creating enormous threat to the subaquatic ecological environment but also to the safety and security of the trade and submarines. Multiple solutions have been proposed to the issue till date, but the optimal solution does not exist. The prominent challenges presented to the submerged object detection include scattering of light and absorption of light. With the advent of deep learning we can solve problems like submerged target detection and recognition, emergency rescue, chances of underwater disaster and its prevention.

Counting and tracking various items are other applications for object detection. It differs significantly from recognition in that object detection first creates a bounding box around the object before labelling it, unlike recognition, which applies a label to a picture. Currently, underwater object detection is crucial for researching climatic factors, port security, resource exploration, etc. Previously employed manual methods for analysis were labor- and time-intensive; as a result, they were replaced by automatic Remotely Operated Vehicles (ROV), which allow for a reduction in manpower. These vehicles' primary goals include automatic identification of man-made structures, off- shore structures, object detection, obstacle avoidance, etc.

The accuracy with which autonomous underwater vehicles (AUV) recognize aquatic life is a precise assurance for aquatic and marine life detection, rescue, and security. Deep learning has recently achieved considerable advances in digital image processing for target recognition, life detection, and classification, making aquatic target recognition research a popular investigation subject [1].

This paper consistently describes the applying of deep learning in underwater image analysis within the past few years and in that brief period of time that, expounds on the fundamental principles of varied underwater target recognition and life detection. Meanwhile the applicable conditions, pros and cons of varied in a different ways of detection. The technical issues of AUV underwater dangerous target recognition ways are analyzed, and corresponding results are given. At an equal time, we tend to outlook the longer-term development trend of AUV aquatic target recognition.

Object detection is a critical activity that is widely utilized in a variety of sectors for monitoring, inspection, sorting, and so on. It is a technology that recognizes and localizes the needed targets from video frames in real time, and it may

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also be taken from photos for study and under water life preservation. Object detection can also be used to count and monitor the location of various things. It differs from recognition in that image recognition provides a label to a picture, whereas object detection creates a bounding box and then labels the item.[2] This is used in a variety of domains such as automated vehicle frameworks, movement recognition, object verification, and so on.

Traditional methodologies as well as learning approaches can be used to accomplish object detection. Deep neural network architectures are employed in learning methodologies for the end-to- end process of feature extraction and object detection. Nowadays, underwater object detection is used to research climatic aspects, port safety, resource exploitation, under water life investigation, and other topics. Formerly employed manual techniques for analysis are labor-intensive and time- consuming; as a result, we prefer to replace them with autonomous ROVs that require less manpower.

The video data collected from the ROV is quite huge, and it is capable of automatically processing enormous volumes of video information, which would make the procedure tiresome. The primary goals of this paper is to demonstrate that they should conduct automated identification of man-made structures, offshore structures, marine life, object detection and/or obstacle avoidance, and so on.

The YOLOv3 (You Only Look Once version 3) is an improved version of the YOLO detection model which is a fast-performing object detection algorithm. It is a real-time object detection algorithm which identifies specific objects in images, videos or live feeds. Enhancing the previous models enables to extend the detection model to multi-scale with stronger feature extraction, and uses cross-entropy error functions, hence can be applied for multiple object tracking. In YOLO, the information in image pixels is directly used to predict bounding boxes and the probability of being a particular object class.[3]

II. RELATED WORK:

In the past, we discussed some research on machine-learning techniques for image detection. Feature selection, data reduction, and classification model improvement are a few examples of the difficulties that each study focuses on. The relevant literature on underwater image processing and enhancement methods is presented in this area. Wn. R. Schneider advocated using colored filters in black-and- white photography in 1990 to alter how a scene's tones were captured on film. Yellow filters are typically used. White light from clouds is not filtered like light from a blue sky since it does not come from a blue sky. A yellow filter makes clouds appear more noticeable than usual. The image's quality is impacted. There was a desire to examine the undersea environment as well, although this effort was mostly for photographs that were in the presence of air.

In their research, Yang, H. et al. used YOLOv3 to recognize underwater objects. 2021, Microsystem Technologies, 27(4), p. 1837–1844. Using two current popular techniques, this research examines a collection of underwater image data. According to the research's outcomes, the mean Average Precision (mAP) and recall rate (Recall) of the YOLOv3 algorithm are both 6.4% and 13.9% higher than those of the Faster R-CNN, respectively. The YOLOv3 algorithm's detection speed is also 20 FPS, which is 12 FPS quicker than the Faster R- CNN's. The research's demands for real-time detection are met by the YOLOv3 algorithm's detection speed.

K. Iqbal et at. They done a research on "Enhancing the low-quality photos using Unsupervised Color Correction Algorithm." That gave the underwater photographs were affected. There is less contrast and an uneven color cast because of the water environment's light absorption and dispersion. They proposed an Unsupervised Color Correction Method (UCM) in response to enhance the quality of underwater photographs. Color matching, contrast enhancement of the RGB color model, and contrast enhancement of the HSI color model form the basis of UCM. The color cast is first concentrated when the color values are equalized.

Second, a more effective contrast adjustment approach may be utilized to emphasize the blue hue while intensifying the red color by stretching the blue histogram to the minimum. Also, by expanding true color with Saturation and resolving the lighting issue with Intensity, the Saturation and Intensity components of the HSI color model have demonstrated their value for contrast correction.

Ali-Gombe, et al. have proposed research on “Fish classification in the context of noisy images,” This research examines the performance of deep convolutional neural networks on noisy fish species photos. Four different noisy and difficult dataset variations were used in thorough studies. Many deep convolutional models were tested. Secondly, we used a noisy dataset of fishing boat photos to train our models. The models were trained using our second method, which only annotated fish instances from the initial batch of photos. Last but not least, we used affine transformations and random noise to create new data to synthesize the models' training data. The results show that deep convolutional networks' performance suffers when their training data is poorly annotated. Future research in automatically annotating images has a new path thanks to this. The new way of removing noisy images or removing noise from the images to clear the dataset. Whenever the clear dataset is used the accuracy of the system increases.

Jalal, A., proposed research on Fish detection and species classification in underwater environments using deep learning with temporal information. An integrated method to detect and categorize fish in unrestricted underwater films uses a hybrid solution that combines optical flow and Gaussian mixture models with YOLO deep neural network. YOLO-based object detection techniques were first used to only record occurrences of fish that were stationary and easily observable. Using temporal data obtained from Gaussian mixture models and optical flow, we remove this restriction from YOLO so that it may detect freely swimming fish that are hidden in the backdrop. For both datasets, we achieve fish detection F-scores of 95.47% and 91.2%, as well as fish species classification accuracies of 91.64% and 79.8%. These results, which demonstrate the efficacy of our suggested strategy, are, to our knowledge, the best ones that have been reported on these datasets.

Akkaynak D., et. al. They proposed a theory in their paper on Sea-Thru: A method for removing water from underwater images. The sea-thru approach tries to reliably eliminate water from underwater photos, enabling more efficient analysis of vast datasets. It functions as follows: given an RGBD picture, it calculates backscatter using the known range map and drawing inspiration from the Dark Channel Prior (DCP) created for the haze. The range-dependent attenuation coefficient is then estimated using an optimization framework with a local space average color illumination map as input. From there research it shown that the images can be optimize and can be classified in multiple colors according to the need of the user. The color selection can be fixed or it may be according the user based on their needs of classification. Based on these the popularity of these system got increased. Because it uses the RGB form of colors that can be assign to various object under water.

In 2011 the completion on "Low Complexity Underwater Image Improvement Based on Dark Channel Prior" by Hung-Yu Yang, et. al. [16]. They show the deep-sea engineering; a blurred underwater vision is a constant source of irritation. They suggested a reliable and simple dark channel-based underwater picture-enhancing approach. To estimate the depth map of an image, our method substitutes the median filter for the soft matting method. Furthermore, a technique for color correction is used to maximize the color contrast for underwater images. The first findings show that the recommended strategy can substantially improve the underwater image and reducing the implementation period. This method is also well suited for real-time supervision and underwater navigation implementation on real-time supervision and underwater navigation and requires less computational reserve. They proved that the enhancement of the underwater images is need in order to improve the accuracy of the algorithm as well as the system is very much dependent on that.

Enhancement of the Canny Edge Detection Algorithm by Jun Li and Sheng Ding. Sows the conventional Canny edge method and makes several enhancements to the smoothing filter selection, point amplitude computation, and high or low threshold selection processes. The enhanced Canny algorithm estimates gradient amplitude in 3*3 neighborhoods, switches to the B-spline function from the Gaussian function, and bases threshold selection on the gradient

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histogram. The experiment shows that the new algorithm enhances positioning accuracy and offers a stronger and more pronounced de-noising effect. Edge detection, improved Canny method, B-spline function, and threshold select are some of the terms used. The Canny Edge Detection algorithm is very improved and also has the highest level of accuracy on enhancing the images.

III. WHAT IS SUBMERGED OBJECT DETECTION ? :

Image preprocessing is the most critical step for object detection in underwater computer vision. Due of the effects of light dispersion and absorption in water, the pictures acquired by the underwater vision system have uneven lighting, low contrast, and significant noise.

A typical submerged computer-based vision system consists of lighting, a camera or sensor, and application software. As illustrated in Fig. 1, the software process of the underwater object detection and recognition system normally contains multiple aspects, such as light scattering, image preprocessing, convolution neural network, and target recognition.[4]

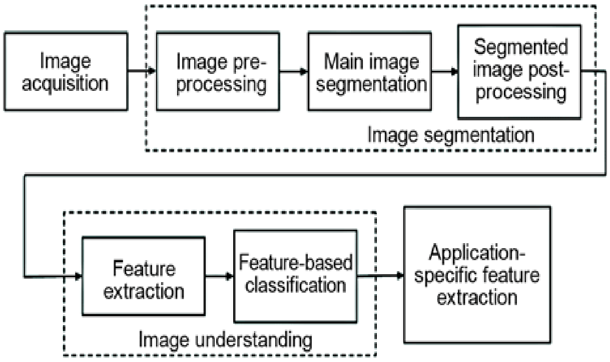

Fig: 1 Image Acquisition

Image preprocessing is used to boost picture contrast and maintain valuable features during the image enhancement and filtering processes. Object detection and classification are founded on feature extraction, which aims to extract the most effective fundamental elements that reflect the target. This paper focuses mostly on image preprocessing and target detection from underwater vision.

In many different study disciplines, the Convolution Neural Network (CNN) is acknowledged as the quickest detection method. In this paper, we used a novel CNN approach to tackle the problem of submerged object identification. Given the uniqueness of underwater vision, the image is validated using the RCNN and YOLOv3 algorithms.[5]

IV. PROPOSED SOLUTIONS :

We occasionally desire underwater shots that are not simply obvious and regular, but also have a lot of richness and gloss to them. These high- differentiation submerged images are also important for submerged question identification, angle order, and so on. The recommended estimate of distinction improvement is founded on distribution insights of outwardly appealing common scene images.

DATASETS : Because underwater image processing is a relatively young field of research, there are only a limited amount of datasets accessible for use in underwater computer vision. The following are some of the most important reasons for the small number:

1. Owing to a late start in the sector, the required underwater picture collections have not received adequate attention.
2. Although academic researchers have lately begun to appreciate the benefits of an underwater image collection, producing such a dataset is time-consuming and labor-intensive due to the specific constraints given by the ocean environment.
3. The underwater world is incredibly diverse, making manual collection and classification of ground truths for a wide range of underwater images difficult.
4. The semantic-segmentation-of- underwater-imagery dataset is also used to investigate the possibilities of

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custom training YOLOv3-based underwater object identification models.

Data set	Train Data set	Valid Data Set	Test Data Set
Number of images	1350	899	252

Image Pre-processing :

Pre-processing refers to activities with pictures at the most basic level of abstraction, where both input and output are intensity images. These iconic pictures are the same as the original sensor data, with an intensity image often represented by a matrix of image function values (brightness). Although geometric changes of pictures (e.g. rotation, scaling, translation) are categorised as pre-processing methods, the goal of pre-processing is an upgrade of the image data that suppresses unwanted distortions or boosts particular image attributes useful for future processing. Xiangwei Lu, Muwei Jian, Hanjiang Luo, Hui Yu, and Junyu Dong,"Underwater Image processing,"[6] The study of complex and effective underwater image processing (UIP) models has been the main focus of underwater vision research in recent years.

W. Zhang, X. Pan, X. Xie, L. Li, Z. Wang, and C Han proposed the Color correction and adaptive contrast enhancement for underwater picture improvement. [7]

Figures 2.1 and 2.2 show the picture before and after pre-processing.

Fig: 2.1

Fig: 2.2

Image Segmentation :

Image segmentation is a method used in digital image processing and analysis to divide an image into several portions or areas, frequently depending on the properties of the pixels in the picture. Image segmentation might entail separating foreground and background pixels or grouping groups of pixels based on color or form similarity [9]. Picture division is commonly employed in photos to find objects and limitations (lines, bends, and so on). More specifically, picture division is the process of assigning a mark to each pixel in an image such that pixels with similar names proportion certain qualities. Image division produces an arrangement of numbers that cover the full image or an association of forms isolated from the image. For segmentation, we use the K-means clustering method. Nassir Hussen Dar, from their research concluded Image segmentation techniques the processes of splitting the image into many segmentation afterword's splitting the image make it easy for further process thus after completing the operation image will be re-joined.[10]

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Image Enhancement :

One of the most crucial methods in image research is said to be picture enhancement. The primary goal of image enhancement is to improve the image's quality and aesthetic appeal or to give a better transform representation for automated image processing in the future. Depending on the goal, the enhancing approach varies from one field to another. P. Janani*, J Premaladha and K.S. Ravichandran Image Enhancement Techniques" It improves the clarity of images for human viewing, removing blurring and noise, increasing contrast, and revealing details [8].

Iqbal K. Odetayo, et. al. from their research concluded that low quality image can be enhanced using Unsupervised Color Correction method. Hung-Yu Yang et. al. saw the completion of "Low Complexity Underwater Image Improvement Based on Dark Channel Prior"[9]. Background subtraction techniques: thorough assessment and comparative analysis, Clara Shanthi, G., and Saravanan, E.

Image Edge Detection:

Canny introduced three edge detection criteria in 1986, which are widely accepted as the most tightly stated criteria to date [4]. Signal-to-noise ratio (SNR), location accuracy criterion, and single-edge response criterion are the three criteria. Using numerical optimization approaches, he developed the best edge detection operator. With strong SNR and edge localization performance, a clever operator may create information from two aspects: edge gradient direction and strength. Because the technique is reasonably simple to implement in a short period of time, it becomes the benchmark for other edge algorithms.

Canny has improved the Canny operator in various ways. It has accomplished picture edge detection precision and accuracy by adding the B-spline function to replace the Gaussian function, 3*3 neighborhoods of the gradient magnitude computation, and the gradient histogram based thresholding.

Canny edge detection criteria :

Jun Li and Sheng Ding have improved the Canny Edge Detection Algorithm. The techniques for choosing a smoothing filter, calculating point amplitudes, and choosing a high or low threshold are all improved over the traditional Canny edge approach.[11]

1. Excellent detection. There should be a low likelihood of missing actual edge locations and a low probability of labelling nonedging points incorrectly. The maximum signal-to- noise ratio should be used.
2. Good localization. The operator's designated edge points should be as close to the center of the real edge as practicable.
3. Low erroneous response. A single edge generates fewer multiple answers, and erroneous boundary responses are reduced to the greatest extent possible.

Classification:

Classification is a general

process related to categorization, the process in which ideas and objects are recognized, differentiated and understood. Here we are using YOLOv3. i.e. YOLOv3 improved version of the YOLO detection model which is a fast-performing object detection algorithm. The distinction is between continuous and discontinuous sampling. Their application varies according on the problem. To classify a particular set of data, for example, Fish classification in the context of noisy images. it is helpful to first define a few key terms, such as "Classifiers," "Classification Model," "Feature," and "Labels.". The classifier is an algorithm that maps an input to a given class, and the classification model predicts the class based on the input. The feature is a measurable trait, and the labels are data points that have been classified. Classification techniques may be broken down into two basic parts. The first is to accurately categorize novel patterns using a dataset acquired from a large randomly selected population. Each case's mistake rate may be calculated. The semination is mostly determined by statistical pattern recognition. Jalal A. Salman et. al. gave fish species classification in an underwater environment using deep learning. The leaving- one-out resampling approach is employed for this reason. The sea thru method is used for removing water from an underwater image.[12]

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Canny Theory and Its Limitations

A. Canny Edge Detection Criteria

The following are Canny's three edge detection criteria..

1) Accurate detection. Low probabilities of both marking non-edge points incorrectly and failing to indicate real edge points are expected. A maximum signal-to-noise ratio ought to be achieved.

2. Effective localization. The operator's designated edge points should be as close as feasible to the center of the actual edge.

3) Minimal false reaction. Less multiple answers are produced by a single edge, and spurious boundary responses are reduced to the greatest extent possible.

The coordinate conversion formula that converts polar coordinates from Cartesian coordinates yields the pixel gradient's magnitude and gradient direction. The gradient amplitude determined using the second-order norm is

$$(i,j) = \sqrt{F_X(i,j)^2 + F_Y(i,j)^2}$$

Formula for : Canny Edge Detection Criteria

Machine Algorithms :

From 2015 till the present, several efforts at recognizing fish pictures have been made. To identify fish successfully underwater, Spampinato et al. used the moving average algorithm. Ravanbakhsh et al. employed the Haar Classification to integrate face recognition and image processing. Although both systems were excellent at the time, they had a significant drawback: the inability to handle enormous volumes of underwater imagery.

Some photographs in the database illustrate which method of image detection is used for each category. Specific information on image processing and the database is among the features employed. It is clear in the classifier category how all results are summed.

Deep Learning :

Object detection is a computer vision-based activity which refers to the process of identifying and locating features of an object in an image. Most prominent algorithms which detect objects in an image are YOLO, RCNN, etc. using deep convolutional neural networks.

1. Deep CNN
2. YOLOv3
3. Accuracy

Deep CNN :

Algorithm of underwater target recognition based on CNN features by QUAN Wenwen et al. Image Classification is a broad area with several solutions. A region-based Convolutional Neural Network is one such solution (R- CNN).[13] Neural networks and neural computing are relatively new advances in the information sciences, emerging from 1950s and 1960s artificial intelligence research. Neural networks are so termed because they have some superficial similarities to how arrays of neurons apparently function in biological learning and memory. 2019 Jesper Haahr Christen, Roberto Galeazzi. Detecting objects Finding fish CNN deep learning. This is the Deep CNN OFDNet. Visual data collected from cameras is used for fish detection, localization, and classification.[14]

YOLOv3 :

The CNN structure is made up of five layers: the Convolutional Layer detects specification, the Non-Linearity Layer detects system nonlinearity, the Pooling or Down sampling Layer reduces the weight number and controls suitability, the Flattening Layer prepares data for classical neural networks, and the Fully-Connected Layer performs CNN standard classification.

Regional CNN is superior to the Classical CNN algorithm. It initially finds the region's extraction proposal among 2000 possible regions, reducing the operation time. But, any decent solution may be improved to make it even better. Fast R-CNN and Faster R-CNN have various advantages for speeding up image categorization systems.

The most often used deep learning methods for object detection are Deep Convolutional Neural Networks. Large datasets are used to train deep convolutional networks. These networks are far more efficient and accurate than previous approaches in detecting objects.

Some algorithms, such as YOLO (You Only Look Once), divide the captured image into a MxM grid. A bounding box is constructed for each grid. It is quicker than the quickest R- CNN algorithm when using a probability offset value scheme. Nevertheless, the disadvantage is that it may have trouble with little things.

IV. CONCLUSION :

This study proposes to analyses several YOLOv3 models by concentrating on object detection architecture configurations that incorporate the original YOLOv3. Substantial evidence that YOLOv3 may be used to locate submerged items in specific circumstances such as haze/cloudy and occasionally mild conditions. This paper addressed contemporary deep learning algorithms for identifying and categorizing diverse underwater marine items. Approaches are classified based on their detection targets. The characteristics and deep learning architectures that were used have been summarized. It was vital to showcase all methods to marine data analysis in a single study so that future studies based on the deep neural network method could be easily focused on.

It was observed that while efforts were made for coral recognition and classification using the deep learning approach, no work was completed for the case of seagrass, which is equally important for a balanced oceanic environment. When color and texture-based information are merged, the efficacy, accuracy, and resilience of any detection and classification system are considerably boosted. The combination of hand-crafted characteristics and a neural network may yield improved results for seagrass detection and classification. As a result, there is a chance to create an efficient and effective deep learning solution for underwater seagrass imaging, which will be the focus of our future research

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