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Underwater Image Recognition using Machine Learning

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Abstract

Machine Learning is the branch of Artificial Intelligence in which a computer is fed with data and based on that data it tries to find out solution on its own. It encompasses the procedure for feeding algorithms information to create the algorithms realize patterns in the data and then increase the performance of the algorithms. A Convolutional Neural Network (CNN) is a type of a deep learned an algorithm that has been created for image processing when using convolutional layers to automatically and in a hierarchical way learn features from the input images. Computers can perform well when it comes to image recognition and classification because of its capacity to detect and record such features as edges, or texture, and shapes among others. A rise in focusing on processing underwater images is essential for various research purposes necessary in marine biology, economy as well as in the management of species' biodiversity. Observance of such organisms as plankton and Posidonia Oceanic allows determining environmental shifts, global warming, and impact of people on sea creatures. These include respectively planktons that are fundamental for oxygen generation, climatic events and the Posidonia Oceanic, which helps improve the sea Biodiversity and water quality. In the organisation study, image processing supplement the physio-chemical analysis and the sonar detection system. The performances of deep learning models, especially the CNNs, in underwater image processing are significantly better than the conventional methodologies. Pre-processing is important because images are often low-quality; data augmentation and transfer learning tackle the problems of a small dataset and class imbalance, which allow you to save computations during training. Through human activities, marine trash remains a menace to deep sea ecosystems and marine organisms calling for proper debris control.

Keywords

Convolutional Neural Networks (CNN), Image Preprocessing, Object Detection, Underwater Image Recognition, White Balance Techniques

Introduction

Imagining the underwater environment is not easy because water and its conditions are often tough and sometimes unfriendly to the obtained pictures. Some of the barriers include light absorption of water, scattering and change in color that affects the images that are required to capture objects for recognition. "Aquatic Vision: Underwater Image Recognition" is a proposed research study, which is estimated to overcome and address these challenges with the help of image processing and Machine Learning algorithms.

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The research objective is to determine the successful and sustainable model for the acknowledgement of objects in the underwater image. This system includes the HOG features and the classifier that is known by the KNN name that works along with the CNN characteristics. Thus, researchers find that HOG feature is appropriate to explain the object shapes and edge and KNN classifier is admirable way of classifying the objects as it tests the simplest hypothesis first. On the same note, CNNs provide a new technique of feature extraction through use of deep learning patterns and texture in the images.

The strategy that is used comprises some basic steps and these are as follows; Firstly, the images are undergoes pre-processing to remove noises and to enhance the picture that was taken under water. This entails adjusting the images to the novel size and turn them to images in black and white using the white balance methods that remove distortion of the colours. These gives the pre-processing stage some benefits as it leads to making the extraction of features and classification of the images easier as the images shall have already been standardized. Therefore, the increase in the picture quality, the system will to a greater extent be able to identify objects in the underwater environment.

It adopts data representation with a CNN that is intended to learn aspects of the images since they have been pre-processed. Convolution, pooling, dropout, and dense layers used in the CNN architecture utilized in this work and all of them assist in feature extraction. Image pre-processing is a part of feature extraction, which is done utilizing deep learning via CNN, aimed to extract the necessary features from the given image. Thus, the CNN architecture in this project comprises several layers of convolution, pooling, dropout, and dense that all contribute to the enhancement of feature extraction. After then, these attributes are transferred to the KNN classifier which sorts the images into the given classes of classification. CNN as extraction of feature and KNN as classification methods remain compelling due to novelty with the intention to increase the overall recognition of images.

Problem Statement

It is difficult to understand that the underwater environment proved to be problematic in terms of image recognition because of problems like light absorption, distortion, and a difference in visibility. The conventional methods of image recognition fail to seize the essence of distinguishing the objects in these complex scenarios of the real environment. This brings the team to the problem that this research seeks to solve, which is to create an underwater image recognition system i.e., efficient in the face of the mentioned difficulties. The purpose is to create a solid structure that permits the use of enhanced image pre-processing approaches, feature extraction strategies, and Machine Learning methodologies enhancing the outcomes of object identification and categorization within underwater images. This work seeks to increase the effectiveness of such underwater vision systems hence more efficiency in marine life monitoring, environmental surveys, and underwater navigation.

Literature Review

The target of this research work is to investigate the use of deep learning and Machine Learning for the classification of Posidonia meadows in the underwater images. When defining the ways of identifying these critical marine habitats, they tried various algorithms and when controlling the ways of their use, they substantiated that as an approach. (Li et al., 2016). The author focuses on the technique of recovering the blurred and light absorbed underwater image, a paper has been submitted. To tackle these problems, they use a two-step approach whose goal enhances not just the previously proposed deblurring algorithms (Martija et al., 2020).

The author focuses on analysing and explaining how single underwater image can be enhanced using two methods to be presented on intelligent signal processing and communication systems at ISPAc in 2017. The latter is a description of a process and the pre-processing steps plus the most advanced post-processing image enhancement techniques (Peng et al., 2017).

The author emphasized the underwater object identification using deep residual neural network structures to identify sea cucumbers. This discovered that deep residual networks could improve the identification rate of images captured underwater that will aid to assessing the creatures and environment (Riabchenkoet al., 2016). The author used a novel deep learning framework DRFN was introduced as a method of reconstructing super-high-resolution images from a single low-resolution picture. It employs new continuous fusion networks with large receptive fields to enhance the picture's details and create larger, higher-quality images (Xiamen, 2017).

The authors of the document outline the method of approaching the recognition of underwater gesture regarding employing the CMV and DL. In detail, they proved that the integrated system which combines the vision approaches used in classical vision systems with the new deep learning methods provides better effectiveness and robustness (Yang et al., 2019).

Methodology

The efficiency of current systems is assessed according to the deep learning approaches surveyed in the context of underwater image classification and the procedure of contrast between the methods employed. Consequently, deep learning strategies' suitability regarding underwater image categorization is an interesting concept to consider. Although this survey has revealed the state-of-the-art of profound learning for underwater images and new directions for advancing this type of research are recommended. This paper provides a deep learning survey methods, significant aspects of comparison, datasets for deep learning, training methodologies, and CNN designing and improving. The proposed system starts by defining an underwater image dataset in a reputable data archive. The pre-processing phase involves several key steps: focusing based on the dimensions of the images and making the images all of same size, quantizing the images to grayscale as that will minimize the data, and last applying white balance as that will help in dealing with colour distortion and thereby enhancing the images. The processed images are then divided into two sets: It includes the training set to train the CNN and testing set for proving the efficiency of the CNN model. CNN model is used for high accuracy image classification, and it is instructed using the help of the training set to learn various features and patterns of different underwater scenes. The outcomes depict that CNN has considerably high accuracies in identifying the various types of underwater images, and segment objects by outlining accurate bounding boxes around them. Furthermore, this advances image classification result and shows a utilization of deep learning in underwater image processing.

Results and Discussions

In this research work, the strategy for image preprocessing and object detection is built and tested using Convolutional neural network for classification and objects detection as shown in figure 1. The preprocessing steps of the data entails resizing of the image as in figure 2 and reduction of the image color to the grayscale as in figure 3 as well as the white balance in figure 4. which is important in cases where the data must be standardized before feeding into the system. The white balance correction was performed using two methods: the Lab color space correction and the average channel correction both quantified that color correction improves image resolution that is essential for further analysis as in figure 5. The test of the model's generic performance was done by observing the position of the bounding box surrounding the detected objects as in figure 6 which were correct according to the XML-annotations of the images. It also proves the approach that integrates the state-of-art deep learning architectures with the conventional image preprocessing methods for real-world image recognition and object detection problems. Using a simple CNN architecture for the chosen task, the code works, possessing a satisfactory result, which indicates the prospects for improving the preprocessing stage and the use of more intricate CNN deep learning models.

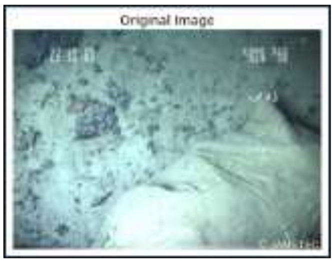

Figure 1. Original Image

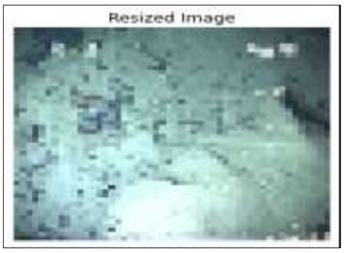

Figure 2. Resized image

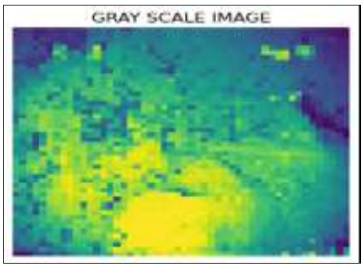

Figure 3. Grayscale image

Figure 4. White balance image

Figure 5. Balanced image

Figure 7. Object Image

Conclusion

This work concludes and provides a comprehensive solution approach that integrates conventional image processing with complex state-of-art deep learning. The inception begins with the idea of loading an image file and reducing the image dimension of the file to one of 300 x 300, to ensure compatibility across intermediate procedures. The image is then converted to intensity only information which is then followed by white balancing to rectify the image quality issues. After these pre-processing steps of code, it further builds and trains a CNN that is an efficient Machine Learning model to handle visual data. The design of the CNN model entails using of the layers of convolution to detect features from the images, pooling layers to minimize on the dimensionality of feature maps, and dropout layers to avoid overfitting when training the CNN model. The network is worked on a set of pictures that are divided into two classes, and its effectiveness is quantitatively measured using accuracy. Once after training, the model and tested, the code takes an XML annotation file to parse object detection data such as bounding box. These coordinates help to frame rectangles around of objects detected in the original image to visually check the correctness of the model's outcomes. As a comprehensive approach, this workflow clearly demonstrates one profound strategy of the picture pre-processing, deep learning for classification, and even the object detection with real data annotation and visualization.

References

Dong, L., Zhang, W., & Xu, W. (2022). Underwater image enhancement via integrated RGB and LAB color models. *Signal Processing: Image Communication*, *104*, 116684. https://doi.org/10.1016/j.image.2022.116684

Lee, H. S., Moon, S. W., & Eom, I. K. (2020). Underwater image enhancement using successive color correction and superpixel dark channel prior. *Symmetry*, *12*(8), 1220. https://doi.org/10.3390/sym12081220

Li, C. Y., Guo, J. C., Cong, R. M., Pang, Y. W., & Wang, B. (2016). Underwater image enhancement by dehazing with lowest information loss and histogram distribution prior. Paper presented at IEEE Transactions on Image Processing, 25(12), 5664–5677. https://doi.org/10.1109/TIP.2016.2612882

Martija, M. A. M., Dumbrique, J. I. S., & Naval Jr, P. C. (2020). Underwater gesture recognition using classical computer vision and deep learning techniques, Journal of Image and Graphics, 8(1). https://www.researchgate.net/publication/339497444_Underwater_Gesture_Recognition_Using_Classical_Computer_Vision_and_Deep_Learning_Techniques

Moghimi, M. K., & Mohanna, F. (2021). Real-time underwater image enhancement: a systematic review. *Journal of Real-Time Image Processing*, *18*(5), 1509-1525. https://doi.org/10.1007/s11554-020-01052-0

Peng, Y. T., & Cosman, P. C. (2017). Underwater image restoration utilizing image blurriness and light absorption. Paper presented at IEEE Transactions on Image Processing, 26(4), 1579–1594. https://doi.org/10.1109/TIP.2017.2663846

Riabchenko, E., Meissner, K., Ahmad, I., Iosifidis, A., Tirronen, V., Gabbouj, M., & Kiranyaz, S. (2016). Learned vs. engineered features for fine-grained classification of aquatic macroinvertebrates. Paper presented at ICPR, pp. 2276–2281. https://doi.org/10.1109/ICPR.2016.7899975

Xiamen, (2017). Two-step approach for single underwater picture enhancement. Paper presented at Proceedings of the International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS), China, pp. 789–794. https://doi.org/10.1109/ISPACS.2017.8266583

Yang, X., Mei, H., Zhang, J., Xu, K., Yin, B., Zhang, Q., & Wei, X. (2019b). DRFN: Deep Recurrent Fusion Network for Single-Image Super-Resolution with Large Factors. *IEEE Transactions on Multimedia*, *21*(2), 328–337. https://doi.org/10.1109/tmm.2018.2863602

Zhang, W., Pan, X., Xie, X., Li, L., Wang, Z., & Han, C. (2021). Color correction and adaptive contrast enhancement for underwater image enhancement. *Computers & Electrical Engineering*, *91*, 106981. https://doi.org/10.1016/j.compeleceng.2021.106981