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Marine Plastic Detection Using Deep Learning

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Abstract. Ocean Pollution is one of the alarming environmental concerns where studies reveal that the biggest reason for ocean pollution is caused by the plastic debris discarded from the land. These plastics pose a threat to the coastal wildlife, marine ecosystem balance, and the economic health of the coastal communities. Inevitably this would result in affecting both human and aquatic living. The most commonly used methods, though effective, pose certain disadvantages when it comes to detecting and quantifying plastics. Thus, it is important to adopt alternative methods involving the latest technologies that would easily help us to identify the plastics and aid in their removal. In this paper, we have investigated the YOLO v4 and YOLO v5 deep learning object detection algorithms for detecting and identifying the marine plastics in the epipelagic layers of the water bodies. Ocean plastic images available on the internet are used to create the datasets. Image augmentation helps in increasing the number of images in the dataset. The Mean Average Precision of YOLO v4 and YOLO v5 are studied and the algorithm performance is explained with the results concluded.

Keyword. Deep Learning, YOLO v5

1. Introduction

Studies show that the major contributors to ocean pollution are the types of plastic wastes discarded from the land that either float or submerge in the various layers of the ocean. These plastics from the surface lands can directly kill and harm the metabolism of marine organisms either through ingestion or entanglement. Apart from aquatic wildlife, the imbalance in the marine ecosystem due to plastics will adversely affect the humans and the economy of coastal communities. Humans who consume seafood can be affected by marine plastic pollution due to the small plastic pieces found in the organs of aquatic living organisms.Thus, it is essential to quantify the positively buoyant marine plastics from the epipelagic layers of the oceans as in the regions the organisms can come up for oxygen and sunlight. The quantification will help us in identifying the high concentrated

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zones across the world's oceans and help in the removal of plastics. The most common monitoring methods include the use of devices such as the manta trawl and oceanic vehicles such as interceptors which function on open waterways, collecting the plastics on the surfaces. These processes are labour-intensive and expensive and can cause harm to the aquatic living. This paper aims at utilising an automated approach by using deep learning algorithms to identify ocean plastics. Object Detection algorithms will assist in identifying marine plastics and debris. They are a widely studied problem and developments in machine learning have contributed to achieving the results even with large datasets. With the advances and popularity of deep learning, the common object detection algorithms such as CNN, R-CNN, Fast R-CNN, SSD, YOLO will aid in identifying the marine plastics in real-time.In this study, the YOLO object detection algorithm is used and it is effective as an image identification algorithm.

This algorithm will be trained with datasets containing marine plastic images, that would help in identifying the plastics. To ease the magnitude of study and training of the model, the plastics and debris are limited to those that can be potentially found floating in the epipelagic layers of the ocean.

2. Prior Work:

Popular deep learning algorithms such as convolutional neural networks are used in computer vision tasks[3]. CNN immensely finds itself employed in healthcare. Heart diseases are easily predicted with higher accuracy using CNN[5]. CNN works best in case of image classification. The extension of CNN is the RCNN which aids in object detection. The latest addition to the CNN based object detection would include Fast RCNN and Faster RCNN [4]. The RCNN and Faster RCNN have two- stage networks [6]. RCNN have a computational time of about forty to fifty seconds and they follow the process of selective search[9]. In order to overcome the drawbacks of selective search, the Faster RCNN was proposed[4].The YOLO - You Only Work Once algorithm[8], was proposed just to increase the performance and speed when it comes to object detection. YOLO combines the multi step process of classification and prediction with a single neural network instead of running the processes separately. Key difference between YOLO and CNN is that YOLO sees the complete image only once. The research on the development of underwater robots for object detection[1] used transfer learning along with the YOLOv3 algorithm. The YOLOv3 algorithm helped in improving the difficulty in detecting small objects as in YOLOv2.

Even though the accuracy was greatly improved, the speed was not as fast as YOLOv2.YOLOv3 has been used for underwater custom training for detecting fishes and the training is done using the Fish 4 Knowledge dataset[2]. The labelling is done in YOLO format such that it contains the details of the object class, the bounding box coordinates and the height and width of the image. The much simplified version of YOLOv3 which is the YOLOv3-Tiny is used in the one stage improved model[8]. YOLOv3-Tiny when compared to YOLOv3, has a much smaller number of convolutional layers avoiding the model to occupy a large memory space. This reduces the need for a large hardware space and thus increases the speed of detection. There were researches carried out for deep-sea debris identification where they have done two different studies based on using deep neural networks such as YOLOv3 for the identification and the other one being deep convolutional neural networks (CNN) [3,6]. The article[3] proposed a new convolutional neural network termed as Shufflfle-Xception based on Xception to attain the maximum accuracy in identifying the deep sea debris. In order to extract more advanced features from the data, the network adopts separable convolution operations. The same study for the identification of deep-sea debris was done using the YOLOv3 architecture[6].

The study used the ResNet50-YOLOV3 model and compared its performance with eight other advanced detection models. The comparative study showed that, ResNet50-YOLOV3 did not only have a good ability in identifying the deep-sa garbage from the 3D dataset it was trained from, it was also able to do the same with a faster detection speed. The change of the backbone architecture also significantly affects the performance of the model. ResNet50 was more suitable compared to other backbone. For object detection in the underwater environment, they have used a deep learning algorithm, and specifically, they have employed YOLO-v3. In this study, the new weights were obtained by retaining the old weights. The model was trained to detect fish but showed poor performance when multiple fish appeared in a single frame.

3. Algorithm

This paper discusses the implementation of YOLOv4 and YOLOv5 algorithms for the purpose of identifying the ocean plastics in the epipelagic layers. The YOLO algorithm is known for its Speed, High Accuracy and Learning Capabilities. The extended developed version of YOLOv3 is the YOLOv4 algorithm which showed significant improvement in the characteristics when compared with YOLOv3. YOLOv5 is different from the prior releases as it utilisesPyTorch implementation. YOLOv4 had major improvements such as the algorithm is based on the state of art BoF(bag of freebies) and BoS(bag of specials). BoF has the tendency to increase the accuracy of the detector without increasing the inference time. The backbone structure of YOLOv4 is the CSPDarknet-53[10] which is compatible with input images of any size.

In order to prevent the loss of effective information during training, YOLOv4 utilises the GPU to call the CUDA library which increases the computational power during training[10]. YOLOv5 has the same CSP as v4. The structure and the weights file for YOLOv5 is comparatively small thus making it extremely fast and lightweight. But a study on comparing the performance of YOLOv3, YOLOv4 and YOLOv5 for Autonomous Landing Spot Detection in Faulty UAVs[7] shows that the accuracy of YOLOv5I was higher than YOLOv4 and YOLOv3 but there was a significant drop in the speed. Certain other research articles say the opposite. Both YOLOv4 and YOLOv5 have similar accuracy with minor changes seen either in the mAP or FPS covered[9]. For real-time object detection, studies conclude it is best to go for YOLOv5 but for custom configurations, YOLOv4 would be the most feasible algorithm.

4. Dataset

Finding a dataset that contained annotated images of marine plastics was hard. Thus, we surfed the internet and scrapped some marine and ocean plastic images from Kaggle, Shutterstock, and other sources. Since for training and increasing the accuracy, more images were required. For this purpose, Data Augmentation procedures were implemented to increase the already existing image library. The images were flipped, rotated, colour corrected to mimic marine plastics images. In the end, the dataset used consisted of 4000 images with them divided to form the train and test data. The division is done in the general ratio of 80 percent images for training and 20 percent images for testing. **Figure 1** shows some of the images from the marine plastics dataset.

Figure 1. Dataset containing Marine Plastic Images

5. Data Augmentation:

For augmentation of the dataset in order to increase the number of images, TensorFlow was used to perform the different augmentation methods. The augmentation was done and tested in two ways. The first method used the Keras Processing Layers to perform the annotation operations. Keras Processing Layers helped in resizing of the images and to resize the pixel values using tf.keras.layers.Resizing and tf.keras.layers.Rescaling, RandomFlip and RandomRotation..The second method consisted of using the tf.image methods which functions to flip the images left or right and to change the colour saturation. Tf.image.rgb_to_greyscale changed the coloured images to grayscale. The brightness of the images is adjusted using the tf.image.adjust_brightness. **Figure 2** shows the augmented images.

Figure 2. Augmented images with change in size, brightness and colour.

6. Data Labelling

The collected images are augmented and labelled using the labelling open source software[1].The dataset is uploaded and the places containing the marine plastics are marked using the software. The tool then saves the image along with the coordinates text file which denotes the position of the plastics in the image. The annotated images are labelled within a single class which identifies whether it is plastic or not. This labelled data is used to train the YOLOv4 and YOLOv5 algorithms.

7. Implementation

The YOLOv4 and YOLOv5 algorithms are implemented separately to understand and conclude which algorithm worked the best for real-time plastic detection in epipelagic layers of the water bodies. **Figure 3** shows the building of the algorithm with the functional tools required.

The YOLOv4 algorithm runs on the CSPDarknet-53[10], the project folder is created with the darknet framework installed. The system is entirely trained and implemented using the Google Colab Pro GPU. For training large datasets, the YOLO algorithm works effectively with a GPU based system[10]. The labelled custom dataset containing the both input image files and their corresponding YOLO format labelled ".txt" files are uploaded to the project directory. Process.py python script is used in this model to separate the dataset into train and test data. To specify the batch size, number of classes and the max iterations to training the data, the specifications are added to the custom configuration file. The configuration file for the YOLOv4 present in the Darknet/cfg folder is edited and has some of the following parameter specifications: Batch, Subdivisions, height, width, max_batches, saturation, exposure, learning_rate, steps. The max_batches specify the number of iterations to train the testing dataset. The dataset is classified under one class on whether it is a marine plastic or not. The number of classes are specified in the obj.names file. The obj.data file specifies the path to the train and test data and to the backup files. The YOLOv4-Tiny model is used for the implementation.

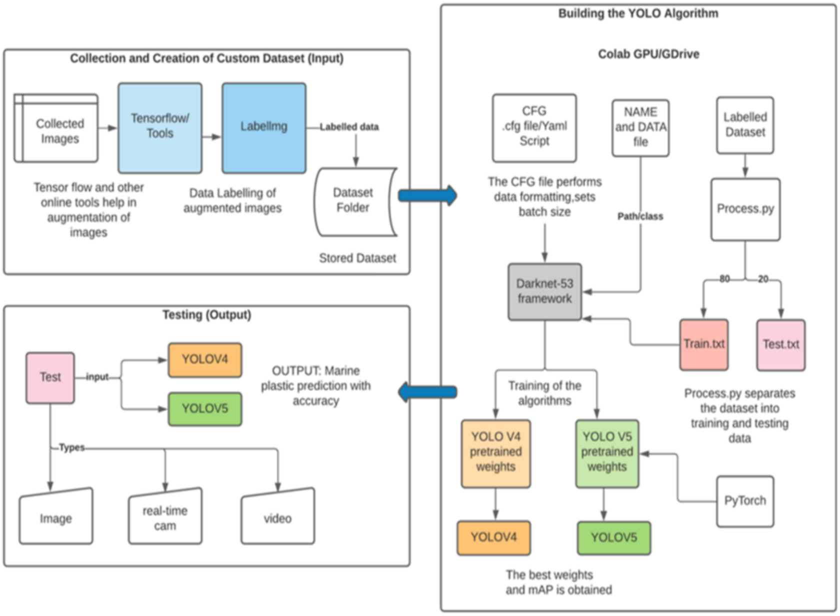

Figure 3. Building the YOLOv4 and YOLOv5 algorithm

In the case of the YOLOv5 algorithm, the dependencies and PyTorch are installed[10]. YOLOv5 requires a yaml script to define the parameters such as number of classes, layers, anchors etc. There are several different models in YOLOv5 such as v5s, v5m, v5l, v5x depending upon their accuracy and speed. We have used the v5S which relatively has a higher accuracy due to its small size. During the training of YOLOv5, parameters such as number of epochs, image size, batch size are edited to suit the number of images in our dataset. Pre-trained weights are used to train the algorithm with the training dataset. Best weights, Last weights and weights after every set of 1000 iterations are stored. These weights are then later used to identify the best weights in order to attain the maximum mean average precision. The performance of both YOLOv4 and YOLOv5 algorithms are compared using the mAP and the training chart. The Tensor Board helps in understanding the training samples and their average precision scores.

8. Results

The YOLOv4 and YOLOv5 algorithms have been trained on several other datasets such as the COCO dataset but had to be retrained for marine plastic images in the epipelagic zone of the oceans. Due to the lack of enough images, the dataset was successfully created using image augmentation techniques. The datasets required fine tuning hyper parameters and repeated iterations with best weight produced in order to increase the mAP of the algorithms. The weights were stored for every 1000 epochs, and compared to produce the best weights for both YOLOv4 and YOLOv5. The algorithm was first tested with marine plastic images and videos. This helped in identifying the best weights and increasing the precision metrics.

The models were tested real-time by creating ocean epipelagic layer scenarios. The live camera feed was fed to the system as input and it was able to predict the plastics at about a minimum 40 percent to a maximum of 80 percent accuracy. Real-time predictions of the algorithm can have increased accuracy by including more marine plastic images in the dataset consisting of all environmental factors that would affect the clarity of the image and nature of the plastic. The performances of YOLOv4 and YOLO v5 were compared. The YOLOv4 model was about to achieve 80-82 percent of mean average precision. The average precision and frames per second computed by YOLOv4 was 8-10 percent higher than YOLOv3. The algorithm had effective accuracy and speed for video inputs and was able to identify almost all the marine plastics in real time camera feed.

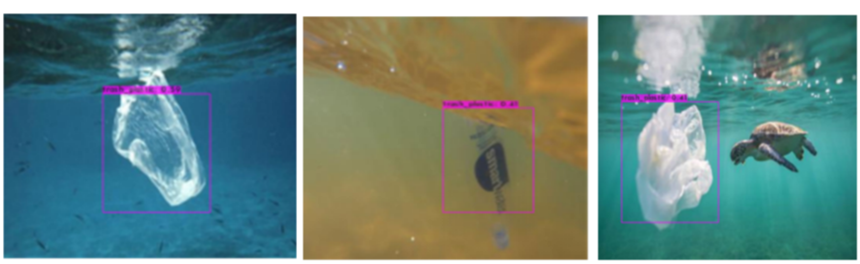

Figure 4. Output images of marine plastic predictions

In case of YOLOv5 algorithm, it showed similar results to that of YOLOv4, but using YOLOv5-S showed significant high in precision, mAP,F1-score and inference speed when compared to YOLOv4. The algorithm produced 85 percent mAP for image inputs. Addition of more dataset images of all types of marine plastics would increase their accuracy in real-time inputs. Best Performing Model: YOLOv5 with 96 percent precision, 85 percent mean average precision, 0.89 F1-score and inference speed of 2.1 milliseconds/img. **Figure 4** shows the produced output.

9. Conclusion And Future Work

This paper experimented with YOLOv4 and YOLOv5 algorithms to identify and detect the marine plastics in the epipelagic layers of the ocean. The results of the experiment show that the recent versions of the YOLO algorithm were able to efficiently predict the ocean plastics with increased speed and accuracy compared to other algorithms when given the image and video feed as input. Both YOLOv4 and YOLOv5 algorithms showed similar results in accuracy and speed with the YOLOv5-s showing a significant edge in performance over YOLOv4-Tiny. The real-time results of both the algorithms can be improved by increasing the dataset and parameter tuning while training the algorithms. In the future, the YOLOv4 and YOLOv5 algorithms can be integrated into Deep Learning apps to test the performance, and integrate it with underwater robots or vehicles, aiding them to identify and remove the ocean plastics. This study is just a small part of the task, the improvised algorithm can be implemented along with other technologies to effectively remove marine plastics across the world.

References

[1] C. -C. Wang and H. Samani, "Object Detection using Transfer Learning for Underwater Robot," 2020 International Conference on Advanced Robotics and Intelligent Systems (ARIS), 2020, pp. 1-4, doi: 10.1109/ARIS50834.2020.9205774.

[2] P. Athira., T. P. MithunHaridas and M. H. Supriya, "Underwater Object Detection model based on YOLOv3 architecture using Deep Neural Networks," 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS), 2021, pp. 40-45, doi: 10.1109/ICACCS51430.2021.9441905.

[3] B. Xue, B. Huang, G. Chen, H. Li and W. Wei, "Deep-Sea Debris Identification Using Deep Convolutional Neural Networks," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 8909-8921, 2021, doi: 10.1109/JSTARS.2021.3107853.

[4] M. Moniruzzaman, S. M. S. Islam, P. Lavery and M. Bennamoun, "Faster R-CNN Based Deep Learning for Seagrass Detection from Underwater Digital Images," 2019 Digital Image Computing: Techniques and Applications (DICTA), 2019, pp. 1-7, doi: 10.1109/DICTA47822.2019.8946048.

[5] M.Bhanumathi, R. S. Gautham Kumar, M KarthikaHemaManasa, R Aravindh, "Heart Disease Prediction Using Convolutional Neural Network," in Advances in Parallel Computing Technologies and Applications, 2021, pp. 1-6, doi:10.3233/APC210161.

[6] B. Xue et al., "An Efficient Deep-Sea Debris Detection Method Using Deep Neural Networks," in IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 14, pp. 12348-12360, 2021, doi: 10.1109/JSTARS.2021.3130238.

[7] Nepal, U. Eslamiat, H. Comparing YOLOv3, YOLOv4 and YOLOv5 for Autonomous Landing Spot Detection in Faulty UAVs. Sensors 2022, 22, 464. https:// doi.org/10.3390/s22020464

[8] P. Adarsh, P. Rathi and M. Kumar, "YOLO v3-Tiny: Object Detection and Recognition using one stage improved model," 2020 6th International Conference on Advanced Computing and Communication Systems (ICACCS), 2020, pp. 687-694, doi: 10.1109/ICACCS48705.2020.9074315.

[9] Z. Wu et al., "Using YOLOv5 for Garbage Classification," 2021 4th International Conference on Pattern Recognition and Artificial Intelligence (PRAI), 2021, pp. 35-38, doi: 10.1109/PRAI53619.2021.9550790.

[10] Z. Qiang, W. Yuanyu, Z. Liang, Z. Jin, L. Yu and L. Dandan, "Research on Real-Time Reasoning Based on JetSon TX2 Heterogeneous Acceleration YOLOv4," 2021 IEEE 6th International Conference on Cloud Computing and Big Data Analytics (ICCCBDA), 2021, pp. 455-459, doi: 10.1109/ICCCBDA51879.2021.9442515.

[11] M.Bhanumathi, R. S. Gautham Kumar, M KarthikaHemaManasa, R Aravindh, "A New Approach for Security in Cloud Data Storage for IOT Applications Using Hybrid Cryptography Techniques," in Advances in Parallel Computing Technologies and Applications, 2021, pp. 1-8, doi:10.3233/APC210138.