Detecting Marine Waste and Classifying it into Recyclable and Non-recyclable Using YOLOv3

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MSc Data Analytics

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Detecting Marine Waste and Classifying it into Recyclable and Non-recyclable Using YOLOv3

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Abstract

There has been a substantial amount of increase in environmental pollution all around the world since the birth of Industrial Revolution which is now unstoppable. The pollution that was harming the environment has found its way into the water bodies and has degraded the marine life as well. The man-made pollution such as Plastic, Metal and Rubber reach the water bodies and remain in there for years to come and are sometimes consumed by marine life such as fishes which leads to choking and sever injuries. This study is intended to deal with this issue by detection marine waste and also classifying it into Recyclable and Non-Recyclable waste using YOLOv3 object detection algorithm. There are 3 datasets namely Plastic, Metal and Rubber from JAMSTEC Deep-sea Debris Database that is used in this research. In this study, ParseHub is used for web scrapping and LabelImg tool is used for annotations. There are 3 experiments carried out, Experiment 1: Rubber, Experiment 2: Plastic and Experiment 3: Metal. For all the three experiments YOLOv3 object detection algorithm was used with IoU as an evaluation method. 5 samples from each dataset was chosen for evaluation and out of which 4 of the sample had an IoU > 0.75. With the evaluation and results of all the three experiments it was quite evident that using YOLOv3 gave the desired results.

Keywords: Marine Debris Detection, YOLOv3, Recyclable and Non-Recyclable Waste

1 Introduction

From the time Industrial Revolution took place, the increase in environmental pollution has been unstoppable. Human made pollution such as plastic, metal, rubber etc. find their way into the environment and harm not only the animals but also humans. There have been so many efforts made in order to control this negative impact that human made pollution is having on the environment such as, trying to control the amount of waste that is being produced and use of recycling. Although not much has been done to deal with the waste that is already present in the environment. Robots were normally a choice that has been used to getting rid of litter which was also shown in the fictional movie WALL-E. But the real problem which has not been much explored is marine pollution, that consists of marine debris. The human made pollution like plastic, rubber etc. have found their way into the water bodies, hence destroying the marine life. Dealing with marine debris was usually ignored due to factors such as debris getting submerged deep into the water and hence being difficult to be found (Valdenegro-Toro, 2019).

To monitor the environment globally, satellite remote sensing was commonly used. Using this enabled collection of information regarding the atmosphere as well as the ocean surfaces. Few special types of satellites such as WorldView-3 and WorldView-4 could capture pictures with the help of some spatial resolutions where the image was reconstructed into a three-dimensional image. This spatial resolution couldn’t be trusted much because of lack of precision and it was also quite expensive and couldn’t be of must use as it was unable to gather information from underwater and also in dense forests where the amount of light was as close to complete darkness. UAV’s came into picture to capture images with high resolution and this was specifically for observation of land and drones were used for agricultural purposes. To observe the underwater and seabed exploration autonomous underwater vehicles and remotely operated vehicles have been developed. We are well aware about how important and critical it is to conserve the marine environment. Many fishing industries and tourism have great potential; however, utilization of oceans has delayed due to lack of technology. Marine life is mainly explored by divers and the state-of-the-art object detection algorithm, YOLO v3 came into picture to deal with more complex background in the underwater sea and detecting underwater sea life, detecting debris on beaches as well as on sea surfaces (Watanabe, et al., 2019).

There are many deep learning algorithms that are gaining popularity, one of which is proposed by (Erhan, et al., 2014) which is used for training the detector DeepMultiBox. This detector is able to generate the bounding boxes around the object in an image. (Wang, et al., 2016) designed SOAR robot which was basically a vision surveillance that connected with the android smartphone and a robotic fish to monitor the underwater debris. The features of SOAR is real time detection and it was specially design keeping in mind the unique environment underwater. The SOAR design was successful in capturing the marine debris.

(1) Plastic – Non – Recyclable (2) Rubber – Recyclable (3)Metal – Recyclable

Figure1: Three different classes used in detecting marine debris along with their labels

In the above **Figure1**, there are three images, **(1), (2)** and **(3)** which are the sample images of the three datasets that has been used in this research.

The goal of this project is finding solution for the following research question:

"*Using YOLOv3 object detection algorithm for detecting the debris found underwater and also being able to classify it. The two-classifications used here is Recyclable and Non-Recyclable".*

The contribution of this research work is - saving the environment from trash deposit which is submerged deep into water. A lot of degradation of eco-system takes place due to the trash deposit which is why it has become quite needful to come up with a solution. This research work would play a vital role as it would not only detect the debris but will also classify it into Recyclable and Non-Recyclable

The study on above research question illuminates different parts beginning with literature review in section 2 which sheds light on different studies that have been performed on object detection of marine debris and the technology used to do so. Section 3 refers to the Methodology that has been used in order to describe the various steps that has been followed to execute the project. Structural design architecture is an important aspect in any research project which has been presented well in Section 4. Additionally, in detail Implementation of training the images and application of YOLO v3 model is described in section 5. Evaluation of the model to measure the accuracy is explained in section 6. Conclusion and Future work of the research is explained in the last section 7.

2 Related Work

This section includes critical analysis beginning from history of marine debris and all of the models used in all the research work which was used to detect marine debris and possible methods that were used to do so.

2.1 Marine Debris

A lot of literature survey is present in the research world when it comes to marine debris. Beginning with how the marine debris enters the water bodies and pollutes the environment. There are reports addressing about how break down of plastic reaches into the internal bodies of marine animals, marine life getting trapped in fishing nets, ingestion of plastic straws etc. (W.Laist, 1987).

A survey was carried out by (Derraik, 2002) regarding the pollution of plastic and how it is affecting the marine environment. It was found that around 60-80% of the total waste found was plastic. This included everything from fishing nets, other fishing equipment's, leftovers of the beach that reach the waterbodies, also the litter that was carried by the rivers into the ocean. Information about the very first survey of the debris in California coast was shared by (L.Watters, et al., 2010) where, round 365 meters below the surface debris like Glass, Metal and Plastic were found. 22 years old optical images were used by (Schlining, et al., 2013) that were captured with the help of ROV and marine debris was manually found by the researchers. Around 33% of Plastic, 23% of Metal, 14% of Rope, 6% of Glass, 7% of unknown debris and around 17% in total was of Rubber, Cloth and Paper. Though such debris were identified successfully by the researchers, yet due to the use of optical imaging which had its own limitations such as poor visibility and low absorption of light due to the scattering of water.

2.2 Object Detection techniques used to detect objects underwater

Initially the marine divers were the only source to depend upon to observe the underwater life. These marine divers made observation regarding the marine life as well as the debris that is found underwater. Satellite remote sensing technique was addressed by (Watanabe, et al., 2019) that was then used in order to detect land as well the floating debris. Yet, it was quite difficult to search for small floating objects and next to impossible to search for marine debris underwater due to the environmental conditions such as, unreachability of light underwater which made detecting debris difficult. Sonar sensing along with AUV's was proposed by (Valdenegro-Toro, 2019) to detect the debris that is submerged deep into water with the help of FLS which stands for Forward-Looking Sonar. With the help of this detector it was precisely possible to separate the debris from the background as it produces very high resolution with high frame rate images. Convolutional Neural Network (CNN) architecture was used along with FLS which together formed a very strong object detection system focussing on the small sized debris which was considered quite ideal keeping in mind the conditions underwater. In the research which consisted of the common marine debris that is usually found in the household that was captured with the help of ARIS Explorer 3000 FLS, obtained accuracy of around 80.8% correct detection while using binary detector. When using multiclass detector around 70.8% correct detection was carried out. The system proved to have an excellent capability of generalization as it could detect untrained objects as well. CNN was used for classification as well as it gave the output in probability distribution where it was used to classification of the debris. It derived 97.1% of mean accuracy and only 4.1% of the background was detected as debris which is comparatively low. This researcher was confident enough that FLS and Neural Network together is quite robust. Plethora of deep learning algorithms were addressed by (Fulton, et al., 2019) to detect trash in the realistic environment underwater. The ultimate goal was to use AUV's for exploring as well as removing the debris from underwater. A very unique datatset which is publicly available was used which is the actual debris that is found underwater. This object detection research used three classes – Plastic, ROV (man made objects found underwater) and Bio (natural materials found underwater). A system was developed by (Walther, et al., 2004) that was able to detect the objects underwater and also track these objects in real time which were of particular interests to the human annotators. The salient targets were selected prior to the tracking. This was done using selective attention algorithm.

When it comes to detecting the debris which usually floats on the surface of the water, it's not such an easy task. Previously floating debris were detected using satellite and there were boat expeditions that took place to find such debris. An aquatic sensor node was used by (Wang, et al., 2015) for detecting the floating debris but it did have few limitations due to environmenatl difficulties such as high waves where, the object detector in few instances was detecting the waves in the water as a debris. This showed that it couldn't really differentiate much between the background and the actual debris due to which it was difficult to detect images in real life. Plastic was one of the main debris that was usually found floating on the surface of the waterbodies which is why (Kyriaki, et al., 2019) research work discusses about the detection of 3 different plastics namely, bottle, bucket and straws using deep learning. VGG-16 model was used on ImageNet dataset inorder to train the model. The results achieved were quite remarkable where, the accuracy of training was 100%, accuracy of test accuracy was 99% and accuracy of validation was 86%. This research was performed not performed on real time, which is why there could be some difference in the accuracy when performed on real life marine debris found floating in ocean.

A unique design was presented by (Wang, et al., 2014) where SOAR was introduced and presented. SOAR is survelience based vision robot that was designed using a smart phone and a robotic fish that could glide. Though the smart phone that was used had few angular issue with the view from the camera but the use of rotation scheduling algorithm made it quite feasible. The fish robo that is used in this research has a tail like feature whoch has a motor embedded into it like any other motor boat that enables this robo fish to move easily in the water like a real fish. The mobile phone used was an android phone that was embedded with an app that runs CV. On the other when it comes to detecting objects underwater (Xu, et al., 2018) research of detecting underwater seafood creatures such as sea cucumber etc. in real time was considered quite remarkable. This study used the CNN object detection algorithm Faster R-CNN. Once the object was detected, underwater robot were used in order to fetch these creatures in real time.

Another similar reseach was studied by (Suxia Cui, 2020) where deep learning method CNN was used in order to detect fishes underwater. This really saved time effort of sea divers that would manually go underwater and fetch these sea creatures. This study showed that object detection not only works well with detecting marine debris but also works wonder with detecting different other objects found inside the waterbodies.

2.3 Analysis and Limitations of Related Work

After performing analysis on all of the conference papers, there were few challenges that were identified. There were challenges faced by (Girshick, et al., 2014) with the dataset where, there were redundancy issue on the auxiliary dataset which occurred between training and testing dataset. Few challenges were faced by (Valdenegro-Toro, 2019) as well where, even with good detection accuracy, the system was unable to tell the type of debris although it could detect the debris in the image. The training dataset used in this research does not consists of the actual debris which is usually found a bit deformed when found in the marine but the researcher believes that training of such datasets would surely give required results.

The challenges faced by these researchers can be studied deeply to avoid happening the same in further researches.

3 Research Methodology

For the study of this research work, there were various methodologies that were studied to understand which methodology would suite best for this research focussing more on the type of dataset being used. Section 3.1 discusses about in detail description of the dataset including the type of data and the source of data. Section 3.2 includes the steps considered in preparation of the dataset to make it aligned with the research. Section 3.3 is modelling, which discusses about the object detection algorithm that is used for generating the required outputs and also discusses about the alternate methodology considered in section 3.3.1 and section 3.4 respectively. Section 3.5 discusses about the evaluation method used in this research.

3.1 Data Understanding

The dataset used in this research is JAMSTEC Deep-sea Debris Database. The dataset used here consists of real-life videos as well captured images of trash that is found underwater. The image quality may vary due to the obvious environmental conditions underwater like the light not reaching all the parts underwater making it difficult to have a clear view of the image. Following **Figure2** shows a snapshot of the JAMSTEC Deep-sea Debris.

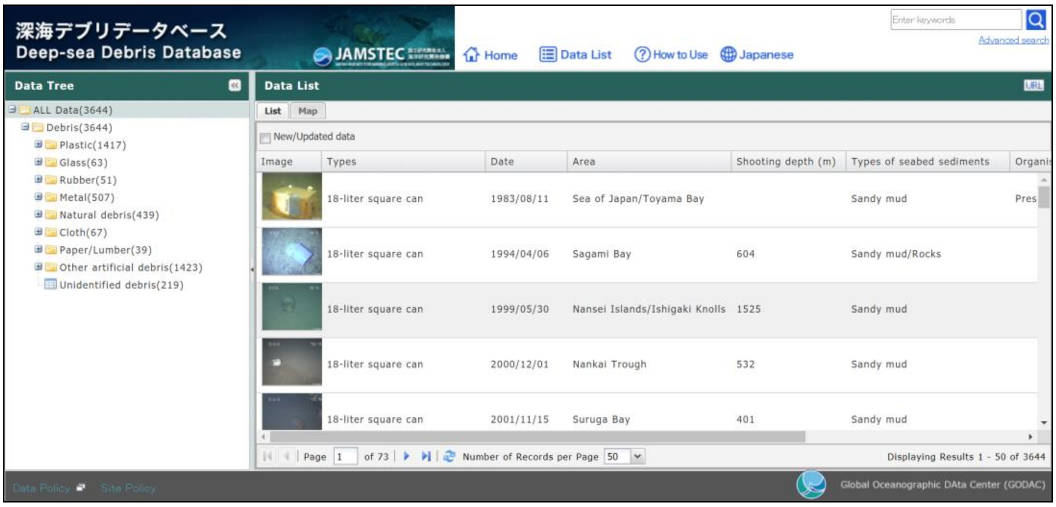

Figure2: Snapshot of JAMSTEC Deep-sea Debris

The three databases used in this research is explained as follows –

<u>Plastic Dataset:</u> This dataset includes all kind of plastic debris including plastic bottles, plastic bags etc.

<u>Metal Dataset:</u> This dataset includes all kind of metal debris found underwater such as metal cans, metal cord/string, metal sheets etc.

<u>Rubber Dataset:</u> This dataset includes all kind of rubber debris found underwater such as tire.

3.2 Data Preparation

Data preparation is the most vital part of any research. The data in JAMSTEC Deep-sea Debris is in the form of data list and we wanted it to be in the form of images which is why web scrapping was used using ParseHub. In detail description on how ParseHub was used in web scrapping is explained in Section 5 Implementation.

3.3 Modelling

Modelling is a fundamental step that consists of creation of deep learning model, it's application and the research evaluation method used to evaluate the results. Below explained is deep learning's object detection algorithm YOLO along with Darknet which is basically a Neural Network Framework which used to train the detector. The combination of both is used in this research work for detection of object and in classification as well.

3.3.1 YOLOv3 - You Only Look Once with Darknet-53

One of the new approaches called YOLO was presented in the research work of object detection by (Redmon, et al., 2016). This framework is one of a kind object detection pipelines in a single network which is capable to be quite efficient and provide end to end performance in detection. The researcher claims that their architecture is quite fast and YOLO model does the processing of images at 45 frames per second in real-time which is quite appreciable. When the comparison is made to the other object detection algorithms, it was quite evident that yolo has more localization errors on the contrary probability of it to predict false positives on background was also very low.

YOLOv3 was introduced by (Redmon & Farhadi, 2018) with small changes. Beginning with predicting objectness score using Logistic Regression for each of the bounding box. The objectness score should be 1 if ground truth is overlapped by bounding box. In terms of feature extraction, a new network is used which is Darknet-53 with 53 convolutional Networks. Darknet is basically framework which is written in C language or CUDA language and is used to train Neural Networks. Darknet is the base of YOLO.

3.4 Alternative Methodology Considered

Fast R-CNN is considered very sucessful and top object detection algorithm (Girshick, 2015), and yet it mistakens the patches that are present in the background for objects. This was because it was unable to see huge contexts. When the comparison is made based on generalization error YOLO outperforms R-CNN where YOLOY has less amount of generalization error compared to R-CNN. YOLO outperforms DPM and R-CNN when it comes to generalizing natural images from other domains. There are various benefits of using YOLO over other traditional object detection methods. Starting with its speed, YOLO is fast. Second, compared to other real-time systems YOLO has twice the precision of mean average and the latency is under 25 milliseconds. During the training and testing time, YOLO does something different compared to the normal sliding window and the region proposal techniques, which is, it sees entire image at a time due to which it is able to encode all the information including the classes. YOLO definitely outperforms other object detection algorithms considering the advantages it has over other algorithms.

3.5 Evaluation Methodology

Once the results are derived, it is important to evaluate those results. IoU also known as Intersection Over Union is a similar evaluation method which is used to determine how accurate the results of an object detection are. As the output that is provided by our object detection consists of the bounding box, I have used IoU for this research work.

3.5.1 Intersection Over Union

IoU is a very popular object detection evaluation method (Rezatofighi, et al., 2019). There are two main important prerequisites that needs to be followed to apply IoU:

1. The bounding boxes which are labelled manually also known as the ground truth bounding box. This is derived in the form of coordinates of the bounding boxes and can be XML, CSV or TXT format.

2. The bounding boxes that are predicted by the model.

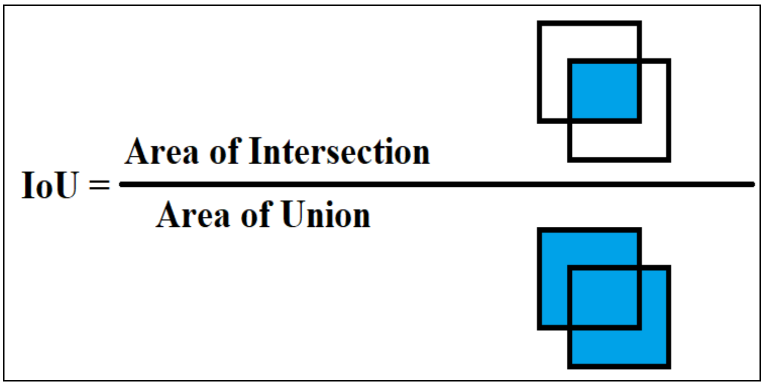

Figure3: Formula for IoU

Above **Figure3** shows the formula that is followed to achieve IoU (Majumder, 2020).
There is plethora of tools available in the market using which we can manually draw the annotations, also known as the bounding boxes. LabelImg being one of the most popular one.

4 Design Specification

A designed architecture is very important when it comes to implement any research project. Below **Figure4** shows an overall architecture of the marine debris object detection system. This architecture is very useful in terms of carrying out the specified tasks of research question and objective as mentioned in section 1. As per below **Figure4**, the system will work from initially loading of dataset followed by training the images using darknet framework and object detection using YOLOv3 algorithm and finally the evaluation and the results.

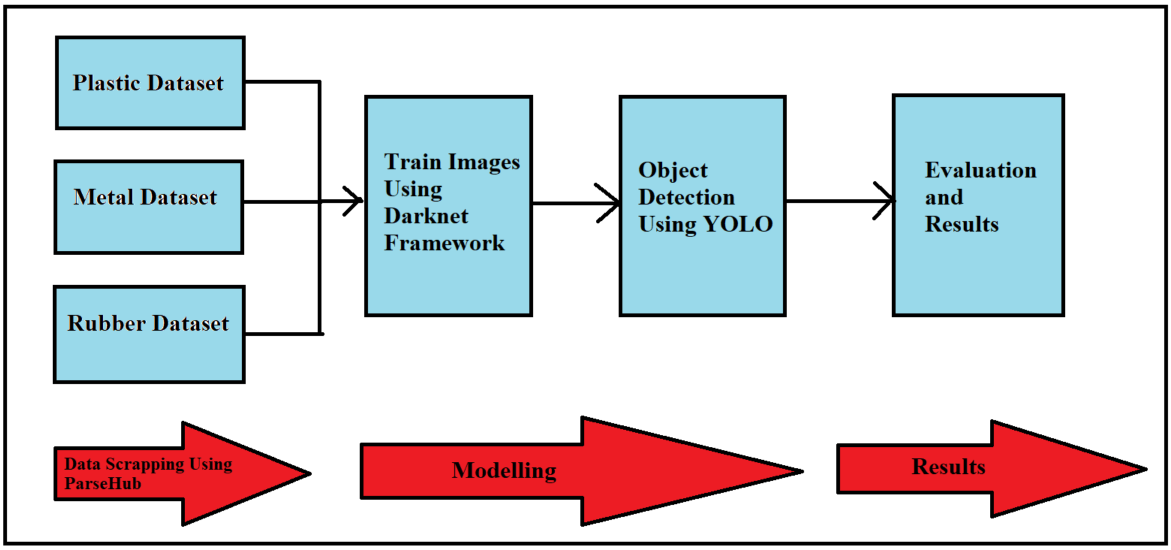

Figure4: Designed Architecture of Detecting Marine Waste

The 3 datasets that are being used is derived from performing web scrapping using ParseHub. Once I have the images, I have trained the images using Darknet-53 Neural Network Framework and YOLOv3 object detection algorithm. After performing this we derive YOLOv3 weights.

Using these training weights and predefined testing weights, we successfully detected objects and classified them into recyclable and non-recyclable. Further using IoU – Intersection Over Union, evaluation of results was performed which is used to determine the accuracy of the detection.

5 Implementation

The below **Figure5** shows an overall process that has been followed in this research for carrying out the implementation. In detail discussion of the same is discussed further below.

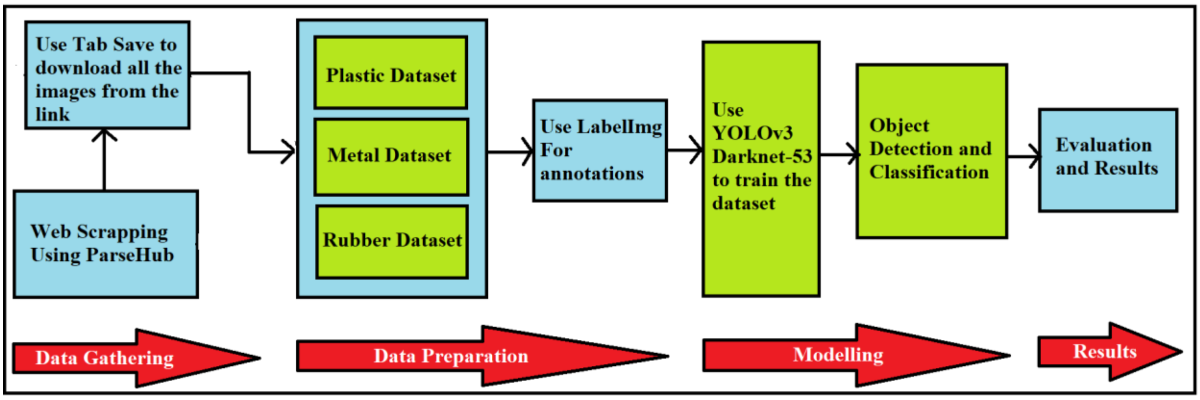

Figure5: Research Implementation Process

5.1 Data Gathering

ParseHub is a very powerful and free tool which is basically used for web scrapping. Once the required scrapping of images is performed, the link to each of the image is stored in an excel file. Tab save extension is used to download all the images by providing it with the links that were stored in the excel file. All the images are downloaded in the downloads section of the machine. In this way we derive our dataset and proceed further for training of the dataset. Below **Figure6** shows the snapshot of ParseHub tool.

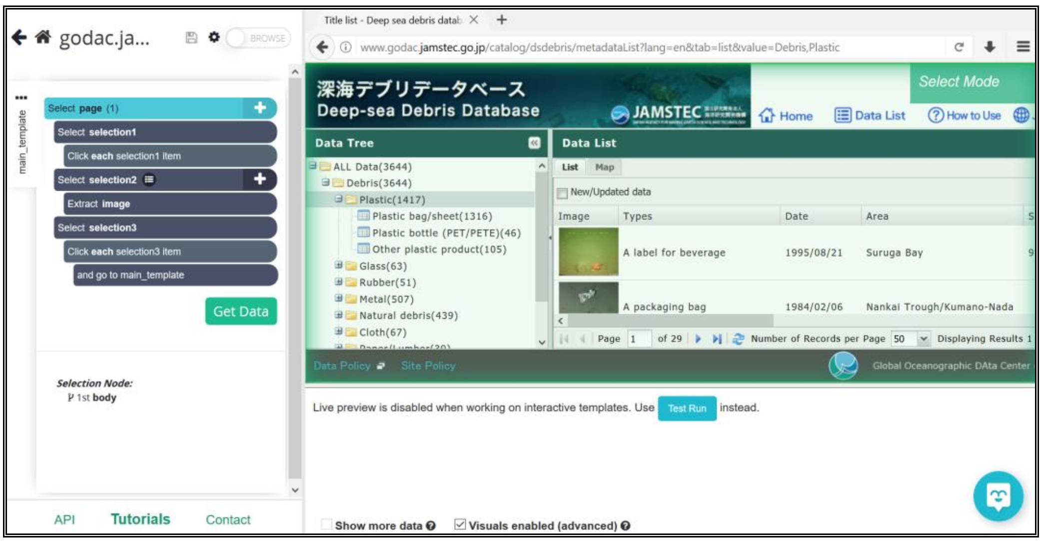

Figure6: Snapshot of ParseHub tool

5.2 Data Preparation

LabelImg tool was used further, which is a tool used for annotation of images and labelling of bounding box. As we are using YOLOv3 algorithm for object detection, we used .txt format to save the co-ordinates of bounding box that supports YOLO. There are other formats available as well such as PASCAL VOC format where XML files are saved. These formats are usually used by ImageNet. Now that I have the images as well as it's bounding box co-ordinates we move further.

5.3 YOLOv3 with Darknet-53

The dataset, which is stored in Google Drive is mounted to Google Colaboratory and then I have loaded it. Then I have used Darknet-53, I cloned the GitHub available at [1]. After cloning you will see something like below **Figure7:**

```
[ ]  !git clone https://github.com/AlexeyAB/darknet

     Cloning into 'darknet'...
     remote: Enumerating objects: 14078, done.
     remote: Total 14078 (delta 0), reused 0 (delta 0), pack-reused 14078
     Receiving objects: 100% (14078/14078), 12.72 MiB | 6.91 MiB/s, done.
     Resolving deltas: 100% (9580/9580), done.
```

Figure7: Cloning of Darknet

All the images stored in the dataset are in .jpg format which is why we are using "glob"- a package which is used to find all the files in a given format. Following **Figure8** shows the output presented.

```
[ ]  import glob
     images_list = glob.glob("data/obj/*.jpg")
     print(images_list )

     ['data/obj/6K0322C2SV3014 (2).jpg', 'data/obj/6K1008C2DV3012.jpg', 'data/obj/6K0322C2SV3014.jpg'
```

Figure8: Using glob

Then we run the detector and run Darknet which is basically used to print the output. After all the images are trained we will derive the YOLOv3 weights which basically consists of the co-ordinates of the bounding boxes. Following **Figure9** shows the snapshot of the images getting trained and weights getting generated.

[1] https://github.com/AlexeyAB/darknet

```
[ ] !./darknet detector train data/obj.data cfg/yolov3_training.cfg darknet53.conv.74 -dont_show

 total_bbox = 8744, rewritten_bbox = 0.000000 %
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 82 Avg (IOU: 0.773537, GIOU: 0.765755), Class: 0.385197, Obj: 0.318768,
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 94 Avg (IOU: 0.682385, GIOU: 0.666807), Class: 0.413965, Obj: 0.149970,
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 106 Avg (IOU: 0.000000, GIOU: 0.000000), Class: 0.000000, Obj: 0.000000,
 total_bbox = 8749, rewritten_bbox = 0.000000 %
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 82 Avg (IOU: 0.393993, GIOU: 0.301871), Class: 0.503531, Obj: 0.279866,
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 94 Avg (IOU: 0.000000, GIOU: 0.000000), Class: 0.000000, Obj: 0.000000,
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 106 Avg (IOU: 0.000000, GIOU: 0.000000), Class: 0.000000, Obj: 0.000000,
 total_bbox = 8753, rewritten_bbox = 0.000000 %
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 82 Avg (IOU: 0.439550, GIOU: 0.388723), Class: 0.456934, Obj: 0.339107,
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 94 Avg (IOU: 0.000000, GIOU: 0.000000), Class: 0.000000, Obj: 0.000000,
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 106 Avg (IOU: 0.000000, GIOU: 0.000000), Class: 0.000000, Obj: 0.000000,
 total_bbox = 8757, rewritten_bbox = 0.000000 %
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 82 Avg (IOU: 0.469614, GIOU: 0.417922), Class: 0.470273, Obj: 0.403026,
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 94 Avg (IOU: 0.218838, GIOU: 0.218838), Class: 0.862388, Obj: 0.402000,
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 106 Avg (IOU: 0.000000, GIOU: 0.000000), Class: 0.000000, Obj: 0.000000,
 total_bbox = 8761, rewritten_bbox = 0.000000 %
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 82 Avg (IOU: 0.348981, GIOU: 0.189708), Class: 0.502424, Obj: 0.205182,
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 94 Avg (IOU: 0.000000, GIOU: 0.000000), Class: 0.000000, Obj: 0.000000,
v3 (mse loss, Normalizer: (iou: 0.75, cls: 1.00) Region 106 Avg (IOU: 0.000000, GIOU: 0.000000), Class: 0.000000, Obj: 0.000000,
 total_bbox = 8765, rewritten_bbox = 0.000000 %
```

Figure9: Using YOLOv3 and Darknet to Train the images

We then move on to Jupyter where we will load the Dataset, training YOLOv3 weights and Config file. Once we run the Object Detection we see the required output where the object is detected with rectangle boxes known as bounding boxes allong with the label – **"R" – Recyclable or "N" – Non-Recyclable**. The bounding boxes are nothing but the rectangular boxe that surrounds the object detected in an image. The results are further explained in Section 6 Evaluation.

5.4 Technical Configurations Used

Following **Table1** shows the basic hardware and software configurations that are used in this research work.

System RAM	8 GB
Processor	Intel(R) Core(TM) i5-8265U
Speed	CPU @ 1.60GHz 1.80 GHz
Programming Tool Used	Google Coloboratory, Jupyter
Programming Language Used	Python
Library Used	cv2, glob, NumPy, random
Additional Tools Used	ParseHub, Tab Save, LabelImg

Table1: Shows the Basic Technical Configurations Used

6 Evaluation

The datasets used in this research are images of underwater marine debris that includes Plastics with 1350 images, Metal with 1358 and Rubber with 1086 images and in total 3794 images. Following **Figure10** is 2d graph that shows the distribution of the 3 databases used in this research.

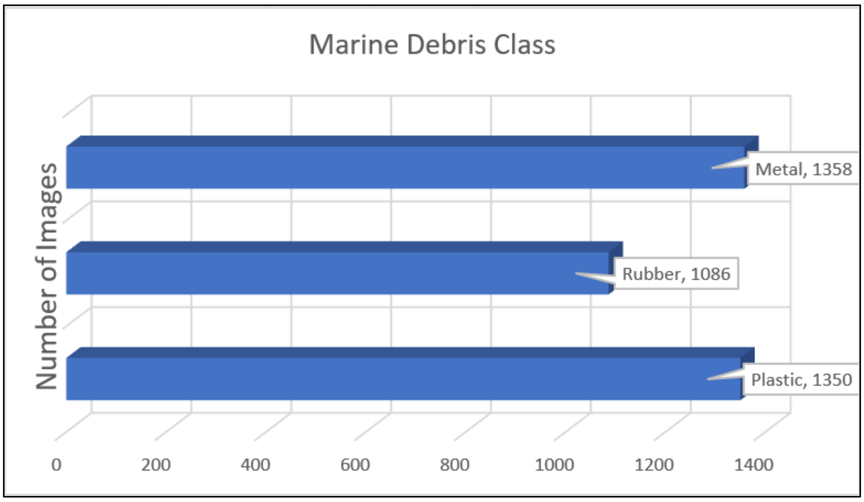

Figure10: Data Distribution of each class

After training all the 3 datasets, I have run the YOLOv3 object detection algorithm and derived results which is discussed in section 6.4 Results and Discussion.

Once I have achieved the required results, it is important to evaluate them to know till what extent the results are accurate. Following 3 experiments were carried out on 3 different datasets. To evaluate the results IoU (Intersection Over Union) which is an evaluation metric used to measure how accurate the detection of object has been is used. Keeping in mind the threshold value = 0.75 where, the value more that 0.75 is considered as a good prediction. As we are using YOLOv3 as an object detection algorithm the threshold value considered is 0.75 which is different from previous threshold value of YOLO and YOLOv2 where the threshold value considered is 0.5. The experiments carried out below shows in detail explanation about the IoU score generated by the images of three different datasets. 5 samples from each dataset has been considered here.

6.1 Experiment 1: Rubber

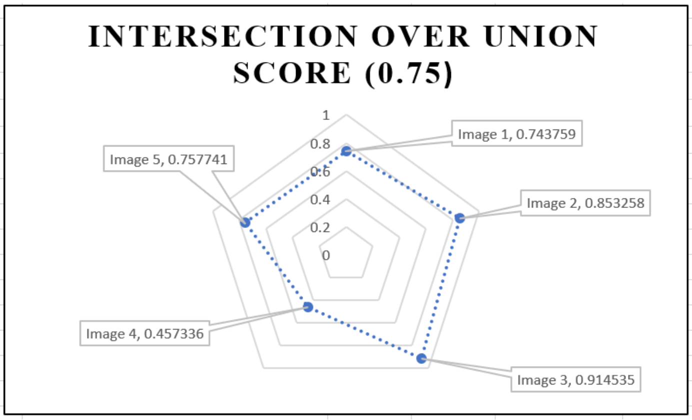

Figure (11) Radar Graph

Class-Rubber	Intersection over Union score (0.75)
Image 1	0.743759
Image 2	0.853258
Image 3	0.914535
Image 4	0.457336
Image 5	0.757741

Table2: IoU values for 5 Sample Images

Figure(11) Shows Intersection over union (IoU) value with the help of Radar Graph and Table2 indicates the IoU values in a tabular format where, IoU > 0.75 is considered a "good" prediction.

In **Figure(11)** shows a radar graph. A radar graph is basically used when we need to show multiple values starting from the same point. In above **Figure(11)**, the start point is at the centre which is 0. The five blue points show the IoU value of the 5 images of dataset Rubber and class Recyclable. As the threshold value for IoU is 0.75, the value which is as far as possible from 0.75 is considered as a good prediction score and the value as close to 0.75 and even less than it is considered as bad prediction. In the table2, image1, image2, image3 and image 5 has a IoU score > than 0.75, which means it is a good prediction. Image4 on the other hand has value < than 0.75 which proves it's a bad prediction.

6.2 Experiment 2: Plastic

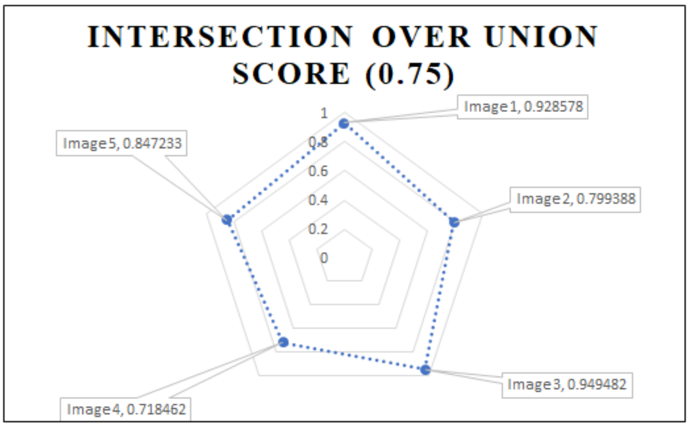

Figure (12) Radar Graph

Class-Plastic	Intersection over Union score (0.75)
Image 1	0.928578
Image 2	0.799388
Image 3	0.949482
Image 4	0.718462
Image 5	0.847233

Table3: IoU values for 5 Sample Images

Figure(12) Shows Intersection over union (IoU) value with the help of Radar Graph and Table3 indicates the IoU values in a tabular format where, IoU > 0.75 is considered a "good" prediction.

Figure(12) shows a radar graph. In above **Figure(12)**, the start point is at the centre which is 0. The five blue points show the IoU value of the 5 images of dataset Plastic and class Non-Recyclable. As the threshold value for IoU is 0.75, the value which is as far as possible from 0.75 is considered as a good prediction score and the value as close to 0.75 and even less than it is considered as bad prediction. In the table3, image1, image2, image3 and image 5 has a IoU score > than 0.75, which means it is a good prediction. Image4 on the other hand has value < than 0.75 which proves it's a bad prediction.

6.3 Experiment 3: Metal

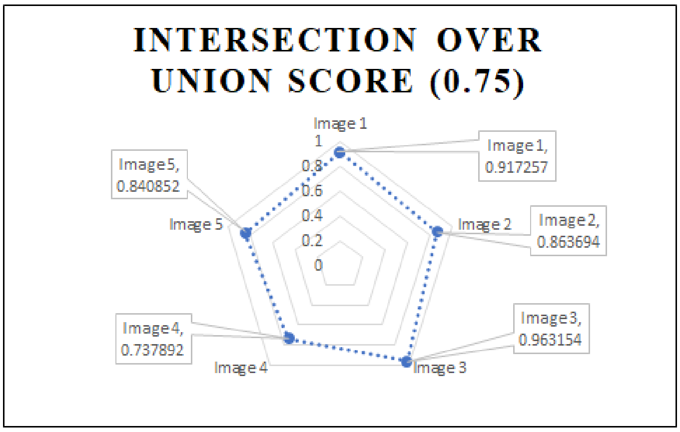

Figure (13) Radar Graph

Class-Metal	Intersection over Union score (0.75)
Image 1	0.917257
Image 2	0.863694
Image 3	0.963154
Image 4	0.737892
Image 5	0.840852

Table4: IoU values for 5 Sample Images

Figure(13) Shows Intersection over union (IoU) value with the help of Radar Graph and Table4 indicates the IoU values in a tabular format where, IoU > 0.75 is considered a "good" prediction.

Figure(13) shows a radar graph. In above **Figure(13)** the start point is at the centre which is 0. The five blue points show the IoU value of the 5 images of dataset Metal and class Recyclable. As the threshold value for IoU is 0.75, the value which is as far as possible from 0.75 is considered as a good prediction score and the value as close to 0.75 and even less than it is considered as bad prediction. In the table4, image1, image2, image3 and image 5 has a IoU score > than 0.75, which means it is a good prediction. Image4 on the other hand has value < than 0.75 which proves it's a bad prediction.

Class Label	Intersection over Union score (0.75)	Average Accuracy
Recyclable	0.743759	0.74
Recyclable	0.853258	
Recyclable	0.914535	
Recyclable	0.457336	
Recyclable	0.757741	
Non-Recyclable	0.928578	0.84
Non-Recyclable	0.799388	
Non-Recyclable	0.949482	
Non-Recyclable	0.718462	
Non-Recyclable	0.847233	
Recyclable	0.917257	0.86
Recyclable	0.863694	
Recyclable	0.963154	
Recyclable	0.737892	
Recyclable	0.840852	

Table5: Shows a Summary Table of the Evaluation

Table5 above shows a brief summary of the findings and shows an average accuracy of all the five images sample of three classes namely, Plastic, Metal, Rubber and the two labels that they are classified into which is Recyclable and Non-Recyclable. Considering the average accuracy, it can be seen in **Table5** that the first 5 records of class label recyclable has average accuracy of 0.74. The next 5 records of class label Non-recyclable have average accuracy of 0.84 and the last 5 records of class label recyclable has average accuracy of 0.86. These results shown in the Table5 is quite evident that my marine debris detection system did work successfully for all the 3 classes and the 2 labels.

6.4 Results and Discussion

This research paper, is well designed to detect the marine debris that is found underwater such as- Plastic, Rubber, Metal and also performing the classification on the same by labelling it into Recyclable and Non-Recyclable. There have been research done on detecting the debris underwater and to classify them into their labels such as Plastic, Metal etc. There were plethora of object detection algorithm that were compared and considered to choose the appropriate and the best one such as Fast R-CNN, Faster R-CNN etc, YOLO, YOLOv2 and YOLOv3. The decision to go ahead with YOLOv3 was done considering the great advantages and features it composis of compared to other algorithms. YOLOv3 also uses a framework called Darknet-53 with 53 convolutional layers.

Three experiments were performed in this research. First experiment was on Dataset Rubber which belongs to class Recyclable. Following **Figure(14)** and **Figure(15)** show the results.

Figure (14)

Figure (15)

Figure (14) Shows Recyclable Debris Before Detection and Figure (15) Shows Recyclable Debris After Detection.

The **Figure (14)** above is one of the samples from Rubber dataset that was used in object detection. Once the detection is completed using YOLOv3 algorithm, the resultant image can be seen in **Figure (15)** where it can be clearly seen that this debris detection was successful in locating the object that we required and it has marked it with a bounding box. The letter "R" in **Figure (15)** denotes for Recyclable, which shows that the debris that has been detected is a Recyclable debris. We took a sample of 5 images and out of those 5, there were 4 images whose IoU score was greater than the threshold value 0.75 which is considered as a good prediction. Our object detection system was successful in detection as well as in classification.

Second experiment was on Dataset Plastic which belongs to class Non- Recyclable where IoU was used to detect how accurately was YOLOv3 algorithm was able to detect the object and classify it. We took a sample of 5 images and out of those 5, there were 4 images whose IoU score was greater than the threshold value 0.75 which is considered as a good prediction.

Figure (16)

Figure (17)

Figure (16) Shows Non-Recyclable Debris Before Detection and Figure (17) Shows Non-Recyclable Debris After Detection.

The **Figure (16)** above is one of the samples from Plastic dataset that was used in object detection. The numbers written on the left corner of the figure is basically the dates. Once the detection is completed using YOLOv3 algorithm, the resultant image can be seen in **Figure (17)** where it can be clearly seen that this debris detection was successful in locating the object that we required and it has marked it with a bounding box. The letter "N" in **Figure (17)** denotes for Non-Recyclable, which shows that the debris that has been detected is a Non- Recyclable debris. Our object detection system was successful in detection as well as in classification.

The third and the final experiment was on Dataset Metal which belongs to class Recyclable where IoU was used to detect how accurately was YOLOv3 algorithm was able to detect the object and classify it. We took a sample of 5 images and out of those 5, there were 4 images whose IoU score was greater than the threshold value 0.75 which is considered as a good prediction.

Figure (18)

Figure (19)

Figure (18) Shows Recyclable Debris Before Detection and Figure (19) Shows Recyclable Debris After Detection.

The **Figure (18)** above is one of the samples from Metal dataset that was used in object detection. Once the detection is completed using YOLOv3 algorithm, the resultant image can be seen in **Figure (19)** where it can be clearly seen that this debris detection was successful in locating the object that we required and it has marked it with a bounding box. The letter "R" in **Figure (19)** denotes for Recyclable, which shows that the debris that has been detected is a Recyclable debris. Our object detection system was successful in detection as well as in classification.

After all the analysis of the experiments, it is evident that YOLOv3 algorithm worked quite effeciently in detection object and classifying them. There were few limitations though that were observed during the analysis of the entire result and evaluation phase. It is known that YOLOv3 algorithm has a drawback of not detecting smaller objects in an image with a very less generalization error compared to other object detection algorithms and same was noticed in this research work as well. The overall performance of the object detection and classification was quite impressive.

7 Conclusion and Future Work

The main objective of this research work is being able to detect the trash that is submerged deep into water and also classifying it by labelling it whether it is recyclable or non-recyclable which was done sucessfully. To do this, object detection algorithm YOLOv3 was used. This work would do wonders when it comes to resusability of trash. The main objective is to save the environment from trash deposit which is already present in the underwater. It has become really very important to stop the degradation of the eco-system and this solution for the same has been very useful. The three experiments performed namely, Experiment 1: Rubber, Experiment 2: Plastic and Experiment 3: Metal. For all the three experiments YOLOv3 object detection algorithm was used with IoU as an evaluation method. With the evaluation and results of all the three experiments it was quite evident that we successfully detected the marine debris using the object detection algorithm and even were able to classify it.

This study has a limitation, currently this model classifies plastic as non-recyclable, but there are various types of plastics that are recyclable and the same could be applied in further research work. **In future** I can train different types of recyclable and non-recyclable plastics and then perform object detection and classification to derive the recyclable plastics as well. Further, this marine debris detection and classification system can be used along with AUV's - Autonomous Underwatar Vehicles.

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