



**UNDER WATER PLASTIC DETECTION USING YOLO**

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**ABSTRACT**

With short average usage times, limited alternatives for reuse and recycling, and widespread use of plastics, modern society is facing a crisis that could have catastrophic effects on both human and non-human life. The magnitude of the risk humanity is taking is highlighted by the fast expanding body of knowledge regarding the effects of plastics in all forms on the planetary life-support system. Aquatic ecosystems are destroyed by waste in aquatic areas, which poses a serious environmental and financial concern. Understanding how plastic waste builds up throughout the world's oceans and locating hotspots for concentrated cleanup efforts depend on marine plastic debris. Currently, using manta trawls for hand sampling is the most used technique for quantifying marine plastic. However, this approach is expensive. And demands labour from people. By employing an autonomous technique that uses neural networks and computer vision models trained on photos collected from various layers of the ocean column to do real-time plastic quantification, this approach eliminates the requirement for manual sampling. YOLOv5 deep-learning system is trained to visually recognise debris (waste/garbage/bottles) in realistic underwater situations using a "Deep-sea Debris Database" of underwater plastic waste.

**1.INTRODUCTION**

According to studies, the sorts of plastic wastes thrown from the land that either float or submerge in the different layers of the water are the main causes of ocean pollution. Through ingestion or entanglement, these plastics from the surface lands can directly kill and impair the metabolism of marine species. The imbalance in the marine ecosystem caused by plastics will have a negative impact on humans as well as the local economies of coastal communities, in addition to aquatic creatures. The tiny plastic fragments discovered in the organs of aquatic living species can cause marine plastic pollution to have an impact on people who eat seafood. As a result, it is crucial to measure the positively buoyant marine plastics from the ocean's pipe logic levels since in those areas, creatures can become harmed. can appear for sunlight and oxygen. We can remove plastic by detecting high concentration zones across the waters of the world with the aid of measurement. The devices like the manta trawl and maritime vehicles like interceptors that operate in open waterways and gather the plastics on the surfaces are the most widely used monitoring techniques. These procedures are labour- and money-intensive, and they risk harming aquatic life. Plastics are used in almost every product we make, trade, and use, from the clothes we wear to the homes and workplaces we inhabit. They also protect our food and online orders, as well as the systems that provide us with services like water, power, sewage, communication, and transportation.the numerous electrical devices we use. A total of 448 million tonnes of plastics were manufactured in 2015, of which 161 million tonnes had a lifespan of less six months. A continuous and potentially catastrophic burden of plastics has built up in all flows in the Earth's life-support system as a result of this vast plastics manufacturing and an estimated average usage period of 5 years compared to a plastics life-span of between 500 and 5000 years. Additionally, a lot of these air and water fluxes send trash into the ocean. In actuality, 10% to 12% of all created plastics are thought to find their way into the ocean. By 2050, there will be more plastic in the oceans than fish if the current trajectory holds. Polymers have been discovered in the tissues of fish as well as in the stomachs of marine megafauna and humans. The marine environment and food web are being impacted by the growing global problem of plastic pollution. Plastics in the environment degrade into tiny fragments over time. The effects of plastics on the biosphere, including people, depend on the additives used in production as well as the particle size. If swallowed, macro plastics (those larger than 5 mm) can physically harm animals and obstruct the digestive tracts. Less than 5 mm microplastics can build up in organisms across the food chain, with unknown effects on human health. Some creatures have cellular integration of nanoplastics (less than 1 m in size), and they can pass the blood-brain barrier. Rivers are mostly to blame for the plastic waste that now enters the ocean. Estimates of the river contribution varied widely, with the 20



top-ranking rivers providing 67% to the worldwide river-borne load and the ten top-ranking rivers accounting for almost 90% of the burden. The urgent need for better observations is highlighted by this significant uncertainty. The majority of the best rivers are found in Asia and Africa. Recognising that a significant portion of this load is caused by the export of plastics that are difficult to recycle from richer to poorer nations, the United Nations enhanced the Basel Convention on May 10, 2019, adding a legally binding framework to significantly reduce this export and making trade between Convention members and other nations illegal. The quickly evolving commercial and regulatory environment has a significant impact on the flow of plastics entering the ocean as well as their trajectory. The United States substantially cut back on the amount of plastic garbage that may be exported to China in 2017 after China. As a result of this adjustment, the USA is exporting significantly more to Malaysia, Thailand, and Vietnam, countries with very subpar processing. The Basel Convention's amendments will make it illegal for member (Thailand, Vietnam, and Malaysia) and non-member (USA) nations to trade in plastic trash, which will once again drastically alter the worldwide trajectory of plastic garbage. However, there aren't enough data to allow for an evaluation of how these changes would affect the fluxes of plastics into the ocean.

A more comprehensive accord is required to address plastic pollution. The formulation of such an agreement must take into account in-depth studies of plastics' sources, applications, and trajectories into the environment. Although the amounts removed are currently only a proverbial drop in the bucket, new initiatives to remove plastic from the ocean for economic use are arising at various levels. All of these activities require information on where to locate plastics in quantities that would make this extraction economically viable. Quantitative information on plastics in the water is needed for risk evaluations and cost-benefit analyses, as well as a better understanding of the entire effects of plastics on the marine ecology at all scales. Impact analyses currently only cover a tiny subset of spatial regions and have a very narrow reach.

The primary goals are to identify ocean plastics using an automated method employing deep learning algorithms. The identification of marine plastics and detritus will be aided by object detection algorithms. They have been extensively investigated, and advances in machine learning have made it possible to get the results even with big datasets. The common object detection algorithms like CNN, R-CNN, Fast R-CNN, SSD, and YOLO will help in the real-time identification of marine plastics due to the development and popularity of deep learning. The YOLO object detection algorithm is utilized in this study and it is efficient as an algorithm for picture recognition. This algorithm will be trained using datasets that include pictures of marine plastic that may be used to identify the plastics. Plastics and other garbage are only included in the model for training and study if they are likely to be discovered floating in the ocean's pipe logic layers.

## 2.LITERATURE SURVEY AND RELATED WORK

Computer vision challenges use well-liked deep learning technologies like convolutional neural networks. CNN is heavily involved in the medical industry. Using CNN, heart problems can be predicted more accurately and with ease. In terms of picture classification, CNN performs best. The RCNN is a CNN extension that helps with object detection.

FastRCNN and Faster RCNN are the newest additions to CNN-based object detection. The two-stage networks used by the RCNN and Faster RCNN. The computing duration of RCNN is between 40 and 50 seconds, and they use the method of selective search. The Faster RCNN was suggested as a solution to selective search's disadvantages.

The You Only Work Once algorithm (YOLO) was developed only to improve performance and speed. In terms of object recognition. Instead of executing the multi-step classification and prediction processes independently, YOLO combines them using a single neural network. The primary distinction between YOLO and CNN is that YOLO only shows the entire image once. Transfer learning and the YOLOv3 algorithm were both employed in the research on the creation of underwater robots for item detection.

The YOLOv3 algorithm assisted in easing the YOLOv2 algorithm's difficulty in detecting small items. Although the accuracy had significantly increased, the speed was still slower than with YOLOv2. The Fish 4 Knowledge dataset has been used to train YOLOv3 specifically for underwater fish detection tasks. The tagging is completed using the YOLO format, which includes the information about the image's height and width, as well as the object class and bounding box coordinates.

The one stage enhanced model uses the YOLOv3-Tiny, a much simplified version of YOLOv3. When compared to YOLOv3, YOLOv3-Tiny contains a significantly lower number of convolutional layers, preventing the model from



taking up a lot of memory. This decreases the requirement for substantial hardware space and speeds up detection. Researchers have conducted two separate experiments for the identification of deep-sea debris, one utilising deep convolutional neural networks (CNN) and the other employing deep neural networks, such as YOLOv3 for the identification.

### 3. PROPOSED WORK AND ALGORITHM

A system's structure, behaviour, and other aspects are all defined by its system architecture, a conceptual model. A formal description and representation of a system that facilitates inferences about its behaviour and structure is called an architecture description. A system representation that incorporates the functional mapping of hardware and software components, the software architecture mapping to the hardware architecture, and the interaction of humans with these components.

To accomplish real-time plastic measurement, neural networks and computer vision models that were trained on photos taken from different strata of the ocean column. YOLOv5 deep-learning system is trained to visually recognise trash (waste/garbage) in realistic underwater environments using a "Deep-sea Debris Database" of underwater plastic waste as dataset.

#### APPLICATIONS OF PROPOSED SYSTEM

- Detecting sub surface plastic on seas and oceans
- Satellite monitoring of plastic litter

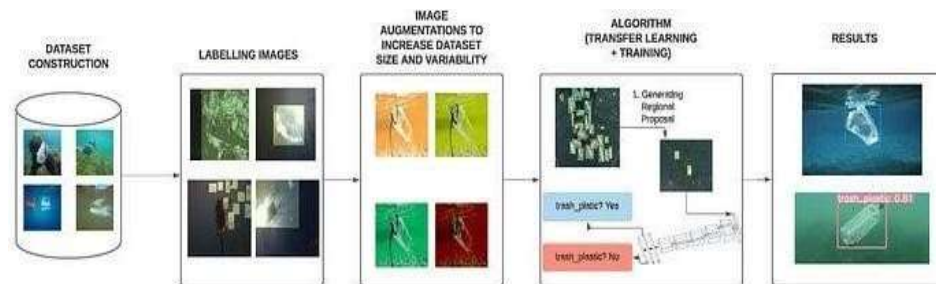


Fig 1: System architecture

### 4. METHODOLOGIES

Datasets are groups of data. The contents of a single database table or statistical data matrix, where each column of the table represents a specific variable and each row represents a specific member of the dataset in question, serve as the most popular examples of datasets. The data set includes values for each variable, such as an object's height or weight, for each dataset participant. A data set is put into a certain kind of data structure. A data set in a database, for instance, can include a selection of company data (names, salary, contact details, sales numbers, etc.). As well as the data sets included within it, the database itself can be regarded as a data set. tied to a certain type of data, such sales statistics for a specific corporate division.

The phrase "data set" was first used by IBM, where it had a similar definition to the word "file." A data set is a named collection of data in an IBM mainframe operating system that includes individual data units organised (formatted) in a particular, ibm-prescribed way and is accessed using a particular access method depending on the data set organisation. Sequential, relative sequential, indexed sequential, and partitioned data set organisation types are included. The indexed sequential access method (isam) and the virtual sequential access method (vsam) are examples of access methods.

#### 4.1 DETAILS OF THE DATABASE

JAMSTEC's Deep-Sea Debris Database offers information on marine debris gathered from deep-sea images and videos. They have already taken during research surveys by the Japan Agency for Marine-Earth Science and



Technology (JAMSTEC) submersibles "SHINKAI6500", "HYPER-DOLPHIN", etc.

You may view lists of debris that have been categorised based on their videos and images and are arranged by forms and materials. Additionally, by looking at the areas where the films and photographs were taken, you can learn more about the trash that has been buried to great depths.

In this research, images of 3131 plastic bags and sheets were taken from underwater detritus.

#### 4.2 PRE-PROCESSING OF DATA

Data pre-processing and data mining techniques are employed to transform the raw data into a format that is both practical and effective. Before using machine learning techniques, this step is taken. It changes the original data into a format that a specific algorithm can utilize. Various jobs are involved in data pre-processing, such as data transformation, feature selection, and data cleaning.

#### 4.3 CLEANING OF DATA

Data cleaning is the process of eliminating or changing data that is inaccurate, lacking, unnecessary, duplicated, or formatted incorrectly in order to prepare it for analysis. When it comes to data analysis, this information is typically not required or useful because it could impede the process or produce unreliable results. Depending on how the data is stored and the questions that need to be answered, there are many techniques for cleaning the data. Data cleaning is not just about deleting data to create room for new data; rather, it is about figuring out how to increase a data set's accuracy without necessarily deleting data. For starters, data cleaning goes beyond simply eliminating data; it also involves correcting grammar and syntax issues, standardising data sets, and fixing errors including missing codes, empty fields, and duplicate data point detection.

#### 4.4 TRANSFORMATION OF DATA

The process of changing data from one format to another, usually from that of a source system into that needed by a destination system, is known as data transformation. Most data integration and management operations, including data wrangling and data warehousing, include some type of data transformation. Data transformation, a phase in the elt/etl process, can be categorised as either "simple" or "complex," based on the kinds of modifications that must be made to the data before it is sent to its intended destination.

### 5.RESULTS AND DISCUSSION SCREENSHOTS

YOLOv5-S: Precision: 96%, Mean-Average-Precision: 85%, F1-Score: 0.89

Upload an image to your google drive to test, thresh flag sets accuracy that detection must be in order to show it

```
[ ] * custom detector with this command (upload an image to your google drive to test, thresh flag sets accuracy that detection must be in order to show it)
t detector test data/obj.data cfg/custom-yolov4-tiny-detector.cfg /content/darknet/backup/custom-yolov4-tiny-detector_best.weights /ydrive/OceanPlastic
redictions.jpg')
ms_kind: greedynms (1), beta = 0.600000
31 route 27 -> 13 x 13 x 256
32 conv 128 1 x 1/ 1 13 x 13 x 256 -> 13 x 13 x 128 0.011 Bf
33 upsample 2x 13 x 13 x 128 -> 26 x 26 x 128
34 route 33 23 -> 26 x 26 x 384
35 conv 256 3 x 3/ 1 26 x 26 x 384 -> 26 x 26 x 256 1.198 Bf
36 conv 18 1 x 1/ 1 26 x 26 x 256 -> 26 x 26 x 18 0.006 Bf
37 yolo
[yolo] params: low_loss: clsu (4), low_norm: 0.07, obj_norm: 1.00, cls_norm: 1.00, delta_norm: 1.00, scale_x_y: 1.05
ms_kind: greedynms (1), beta = 0.600000
Total #flops: 6.787
avg_outputs = 299663
Allocate additional workspace size = 26.22 MB
Loading weights from /content/darknet/backup/custom-yolov4-tiny-detector_best.weights...
seen 64, trained: 105 k-Images (1 kilo-batches 64)
Done! Loaded 38 layers from weights-file
Detection layer: 38 - type = 28
Detection layer: 37 - type = 28
/ydrive/OceanPlastic/internet_validation/plastic2.jpg: Predicted in 2.165000 milli-seconds.
trash_plastic: 42%
trash_plastic: 39%
trash_plastic: 32%
```

Fig 2: train and Test model of trash



Fig 3: Detected plastic from image

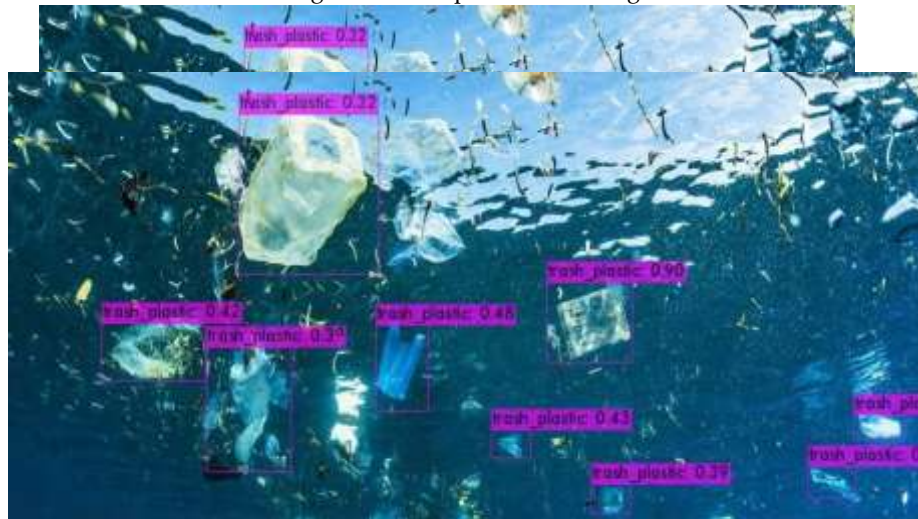


Fig 4: detected plastic from image



Fig 5: detected plastic from image



Fig 6: detected plastic from image



## 6. CONCLUSION

The marine plastics in the ocean are to be recognised and detected by the YOLOv5 algorithm. The experiment's findings demonstrate that, when given an image and video feed as input, recent iterations of the YOLO algorithm were able to predict ocean plastics with greater efficiency and speed than previous algorithms. The accuracy and speed of the YOLOv5 algorithms were comparable to those of the YOLOv5. By expanding the dataset and fine-tuning the parameters while the algorithms are being trained, the real-time outcomes of the algorithms can be enhanced. In the future, the YOLOv5 algorithm can be connected with underwater robots or vehicles to help them detect and remove ocean trash, as well as with Deep Learning apps to test the performance. This research is only a modest The adapted algorithm can be used in conjunction with other technologies to successfully remove marine trash from oceans around the world.

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