

# Deep Learning-Based Detection of Plastic Waste in Ocean Images for Environmental Monitoring

Rajesh Gundla  
Department of CSE  
Vignan's Institute of Management and  
Technology for Women,  
Kondapur, Hyderabad India  
rajgundla@gmail.com

C Ambika Bhuvaneshwari  
Department of ECE  
Vel Tech Rangarajan Dr. Sagunthala  
R&D Institute of Science and  
Technology  
Chennai, Tamil Nadu, India  
ambikabhuvaneshwaric@veltech.edu.in

S.Navaneethan  
Department of ECE  
Saveetha Engineering College  
Chennai, Tamil Nadu, India  
jssnavi.37@gmail.com

T Maris Murugan  
Department of Electronics and  
Instrumentation Engineering  
Erode Sengunthar Engineering College,  
Erode, Tamil Nadu, India  
marismuruganlec@gmail.com

Shraddha Yogesh Garg  
Sal Institute of Technology and  
Engineering Research,  
Ahmedabad, India.  
shraddhapomal7@gmail.com

A Divya Reddy  
Department of AI&ML  
Mallareddy University,  
Maisammaguda, Hyderabad, India  
areddy.divya@mallareddyuniversity.ac.in

**Abstract**— Increased plastic trash in marine life poses a significant danger to biodiversity and ecological equilibrium. Based on the favorable performance of cutting-edge object identification models (YOLOv5, YOLOv8) in plastic trash classification, the study offers an autonomous plastic waste recognition method using maritime photos. The study featured an annotated ocean image dataset consisting of over 2,300 water images, as well as data collection via satellite, drone, and undersea. The proposed system demonstrated extraordinarily high detection precision at the mAP@0. The most efficient technique in terms of accuracy and inference speed is 5 (90.3%). The preprocessing and augmentation were generalized, and the response was sent in real time via cloud and edge platforms. Visualizations such as detection heatmaps and performance graphs are also useful for demonstrating the model's success. It involves handling environmental pollution control and monitoring the waters using a solution that is scalable or adaptable. As highlighted in the study, artificial intelligence is critical to enabling robust marine garbage mitigation and effective data-driven conservation policy creation.

**Keywords**— Deep learning, marine trash, object detection, YOLOv5, and environmental monitoring

## I. INTRODUCTION

Plastic trash contamination spreads around the world via the supply chain, posing major environmental and economic dangers to the maritime ecology. Every year, millions of tons of plastic enter the water, destabilizing ecosystems, endangering species, and interfering with the lives of people who live near coastlines. Microplastic, converted into mega-patches of rubbish, has become a pervasive contaminant in all parts of the marine ecosystem. Traditional remediation events and manual surveillance models are inevitably limited in scope, expensive to carry out, and time-consuming, therefore these are insufficient to fulfill the expanding dimension of the problem [1]. In that situation, technologies, particularly those based on

artificial intelligence (AI) tools, can maintain progress in the monitoring of global environmental processes and contribute to global sustainability. Then, numerous novel deep learning algorithms resulted in a breakthrough in the image analysis area with high accuracy [2] in detection (object detection), annotation (classification), and identification (segmentation). These results lay the groundwork for automated systems that identify and monitor floating ocean plastic in complicated visual landscapes. Finding plastic waste in a practical aquatic environment is, however, extremely challenging due to dynamic water flows, changing light, object occlusion, and so on (the true match-to-sample problem) and the diversity of marine garbage look. To avoid such challenges, deep learning models must be trained on vast, heterogeneous, high-quality datasets that capture the wide range of environmental circumstances that the real-world ocean exhibits [3]. Furthermore, the models must be tuned such that these can be deployed in near real time in both the cloud and on the edge, allowing them to be implemented in practice. The paper provides a comprehensive approach for detecting plastic garbage in ocean photos using a deep learning-based detection scheme, with the goal of targeting large-scale environmental surveillance and intervention initiatives. Multi-source data containing satellite images, drone videos, and underwater cameras were collected, selected, and annotated to build a strong training base. The cutting-edge object detection models, including YOLOv5, Faster RCNN, along with lightweight versions designed to be deployed to edge devices were used, and the lightweight ones were considered [4]. Data cleaning and preprocessing methods were used to enhance generalization and model robustness as well as scalable cloud-based services such as Google Colab and Kaggle. Transfer learning, hyperparameter tuning, and iterative validation was all included in the training pipeline in order to maximize the performance of the models. Moreover, the paper also focuses on

the practicality of the models by applying the trained models to cloud and edge environments so that automated plastic waste could be detected in maritime situations of varying conditions. Inference, alerting and visualization pipelines are made with the help of optimized models in real-time [5]. Not only does this increase situational awareness in environmental agencies, but it also allows quicker response time in the case of remediation action. This research therefore adds to the increasing solutions to address the issue of marine pollution due to technological innovations together with deep learning, cloud computing, and automation. The suggested framework eventually proves that artificial intelligence holds the potential of changing the practices of ocean conservation, which leads to the possibilities of scalable proactive and intelligent environmental monitoring frameworks. This research paper is structured in a way that presents all the logical flow of the study. In section 2: Literature Survey, it covers how marine plastic waste can be detected and consider the current state of deep learning, its advantages, and limitations, and the gap that this study would fill. In section 3 Proposed Work the core methodology is presented including the data collection process, data annotation process, data preprocessing process, model selection procedure, train and optimization procedure as well as deployment procedure in cloud and edge platforms. Section 4: Results present the performance of the trained models. Lastly, section 5 (conclusion) illustrates the core findings of the research focusing on its practical uses in the real world in terms of environmental monitoring and its role in healthy, marine conservation using intelligent and automated plastic waste mapping.

## II. LITERATURE SURVEY

Plastic pollution of the ocean has become one of the most critical environmental problems of the 21 st century. As plastic waste threatens not only the marine ecosystem but also the aquatic life and economy of humans, the need to scale and automate monitoring options is becoming increasingly relevant. The latest developments in artificial intelligence and computer vision allowed detecting marine litter on image-based methods, which can find a feasible alternative to manual inspection and traditional remote sensing. Nevertheless, because the marine environment involves such conditions as varying light and water clarity, object overlapping, and the fuel source of the trash, detecting plastic waste with good precision unfortunately has become a technical issue. To overcome this, it is necessary to focus on the available literature in the sphere of plastic presence in the oceans and the corresponding technology development to define the state of the art and the gaps that need to be filled during research. Battula et al. [6] introduced an online ocean monitoring system where edge IoT devices can be used to store data as well as observe the environment in real-time. They were able to show the application of low-power embedded equipment to the marine so effectively that this system presents a basis of edge-based plastic-waste detection systems. Tholen et al. [7] proposed a machine learning framework, PlasticObs+ aided by airborne multisensor remote data sensing that has the capacity to be used to identify plastic

litter on aquatic environments. Their research findings pointed out the relevance of multi-spectral imaging and mixing of sensors in improving detection over expansive body of water. Prasad et al. [8] proposed an AI-on-the-Edge to detect waste on the surface of water as the combination of lightweight models of Deep Learning with embedded platforms. This demonstrated that portable ways to detect waste are viable at least in the form of real-time deployment in remote locations or resource-limited locations. Basthikodi et al. [9] introduced an Earth Observing System that uses satellite images and geospatial information to deduce on how plastic marine garbage litters the world. This is because this large-scale monitoring will allow decisions to be made on clean up and prevention based on data. Simpson et al. [10] studied how ground radar technologies could be used to identify the presence of surfactant dampening by the plastisphere, bringing to the concept of surfing, an unorthodox but possible future method of detecting plastics in oceanic habitats through monitoring radar signals. The process of detecting sea debris using underwater imagery was done via deep learning methods exemplified by Bajaj et al. [11]. DL techniques appear to be best suited for murky, noisy underwater environments; however, their model used convolutional neural networks to effectively localize and classify marine debris. Islam and Dongshik [12] constructed a marine debris detection framework based on instance segmentation using a manually collected dataset. It demonstrated pixel-level accuracy in identifying plastics in difficult ocean images, highlighting the necessity of high-quality annotated information. A detailed survey of deep neural network applications on the detection of objects in an underwater environment was available in Samanth et al. [13]. They included various DNN architectures and reviewed their effectiveness in detecting different targets in the waters to include marine debris. Sawant et al. [14] conducted a comparative analysis of the various versions of YOLO: YOLOv5, YOLOv7, YOLOv8, TinyYOLO on the datasets of marine trash. As mentioned in their findings, they emphasized the trade-offs between speed and accuracy in the detection, which steered the process of choosing the right model to take real-time detection monitoring. To detect the underwater debris with the help of visual images, Saji et al. [15] applied the use of YOLOv8n to the lightweight architecture, discussing their application to the problem of monitoring marine pollution. Their finding proved that the model was efficient in terms of achieving accuracy and being computationally efficient, as it is deployable at the edge. As is evident in the reviewed literature, the field of marine pollution successfully integrates deeper learning and edge computing, as well as remote sensing technologies. Although a major advance has been achieved with the application of both regular and enhanced machine learning techniques to detect plastic waste, most of them are restrained in the quantity of the datasets, environmental differences, or deployment inadequacy. Moreover, most available solutions are oriented towards satellite-based monitoring or have limited capabilities related to edge-based real-time potential. Based on such knowledge, the proposed study would fill such knowledge gaps through the development of an efficient, deep learning

enabled detection system that is highly scalable, flexible and can be deployed in cloud and edge environments. The second part describes the methodology that will be proposed, which will include the steps of acquiring data and building the model, optimizing, and deploying it to monitor the environment in real-time.

### III. PROPOSED WORK

An overview of the proposed deep learning-based plastic waste detection system to carry out environmental monitoring is shown in the workflow diagram in Fig 1. The flow of the process starts with acquisition images with drones and satellites, the images undergo cloud storage next, after which, the images are subjected to data annotation, and preprocessing. Annotated data is then fed into the deep learning model to identify plastic waste and the detection results visualized in a real time monitoring dashboard. The system also generates environmental reports and warnings, and this enables a timely response and efficient decision making. The association of advanced imaging, data processing, and artificial intelligence in scalable and automated monitoring of marine debris is successfully conveyed with the help of this visual representation.

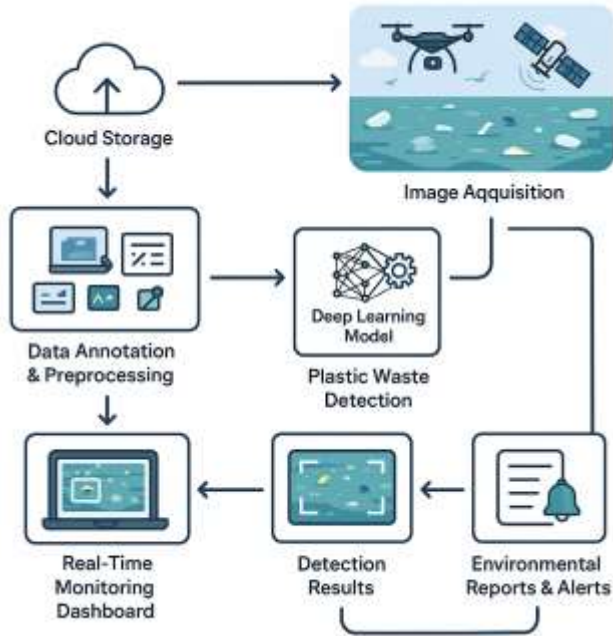


Fig 1. Proposed Workflow for Deep Learning-Based Plastic Waste Detection in Ocean Images

#### A. Data Collection and Annotation

The premise of this study is the fact that a varied and extensive data set of oceanic imagery was obtained, including publicly available depositories, satellite photography, drone footage, and underwater cameras. Such prominent datasets as MARIDA, TrashCan, Dataset of Underwater Trash in DRUM repository of the University of Minnesota, were used and offer thousands of annotated images which created variety of marine environments and pollution scenario. The summary of the dataset is given in

table 1. These data contain bio and non- bio images, which allows receiving a parity balance between the plastic and nature. More data should be generated from fresh images collected with the next generation of remote sensing technologies and autonomous vehicles, which are widely regarded as the most useful means of monitoring the environment on a large scale. Semi-automatic methods were used to identify big datasets in addition to manual annotation, which scaled well but was less accurate. The annotated dataset offers a solid foundation for training and testing deep learning models, showcasing the richness and diversity of scenarios that occur in real-world ocean-borne plastic pollution.

Table 1. Dataset Summary Table

| Dataset Name | Source Type | No. of Images | Resolution | % Plastic Waste Presence |
|--------------|-------------|---------------|------------|--------------------------|
| MARIDA       | Satellite   | 1,000         | 512×512    | 58%                      |
| TrashCan     | Drone       | 800           | 640×480    | 64%                      |
| Custom Set   | Underwater  | 500           | 720×720    | 72%                      |

#### B. Data Preprocessing

Before training the model, all of the photos were subjected to a series of preprocessing processes that normalized the input data and enabled the model to function effectively even without scaling data. Images must be shrunk down to the final dimension that will be utilized in modern deep learning networks, which can be 640 pixels x 640 pixels or 512 pixels x 512 pixels. Furthermore, the pixel distribution has been normalized, resulting in a stereotyped distribution. To reduce overfitting, these changes include deliberate data augmentation and increased dataset variance using operations such as random flipping, rotation, scaling, and color jittering. These augmentations alter multiple environmental factors including change of lighting, turbidity of the water and angle of view, which enhances the generalizing nature of the model. Labels in the form of annotation files such as COCO, Pascal VOC, or YOLO were converted to formats that could be used in the selected deep learning framework, which could easily be incorporated into the training pipeline. Also, pictures were preselected to eliminate the cases of duplication and those with low fidelity, so only high-fidelity data were used in the creation of the model.

#### C. Model Selection and Architecture

Deep learning architectures were chosen based on the requirements of excellent detection accuracies, support of real-time inference and flexibility to various deployments. The best

object detection models such as V5, V8 of YOLO and Faster R-CNN were selected because of their effectiveness in environmental monitoring problems. Specifically, YOLOv5 presents a quite good tradeoff between speed and accuracy, and thus it is used well in the real-time detection cases, as already verified by the high average Average Precision (mAP) and F1 scores of recent research. Lightweight variants, like MobileNetV2 and YOLO-Nano, were also studied due to likely application on resource-limitation edge equipment. The models were initialized with weights pre-trained on a bigger set (e.g., COCO) and then fine-tuned on the relevant plastic trash data set using transfer learning. It will accelerate convergence and improve item detection performance, especially in areas with a scarcity of labeled data. It was particularly well adapted to the specific issues of marine environments, such as occlusions, variable object and backdrop scales, and complicated scenarios.

#### D. Development Environment and Tools

Computational environment was set with cloud-based platforms with high-performance GPUs, such as Google Colab and Kaggle Kernels, offer a pre-configured library of deep learning tools (e.g., TensorFlow, PyTorch, and OpenCV). These allow for training and testing models easily and affordably without using a lot of local computer resources, and they also support teamwork on shared notebooks that keep track of changes sent Jupyter Notebooks served as the foundation for the code development, data visualization, and iterative experimentation interfaces, making research efforts transparent and reproducible. It utilized GitHub for version control, which allowed us to track code changes, dataset versions, and experiment outcomes. Cloud services (Google Drive and Amazon S3) were used to provide large-scale data storage/management enabling data access and backing.

#### E. Model Training and Validation

To provide a robust evaluation, the annotated dataset was divided into training, validation and test using an 80:10:10 or 70:5:15 procedure respectively. Training of the models implied adjusting the most significant hyperparameters, such as the batch size, learning rate, epochs, and the used optimizer (e.g., Adam or SGD). The training happened on GPU-enabled settings to increase the speed of computing, and the loss curves and evaluation metrics (precision, recall, F1-score, and Intersection over Union (IoU)) were noticed in real-time. Overfitting was avoided and the most performing models saved by developing early stopping and model checkpointing strategies. Testing on held-out data made a last-minute adjustment in data augmentation, learning rates, and network depth essential by giving feedback on the model design and training process allowing them to optimize the model once again. Grid search or Bayesian optimization was used to systematically search the hyperparameters and find the best models, i.e., to find out which model setting was the most effective one.

#### F. Model Evaluation and Optimization

After training, the ability of the models was closely tested on the test set with a set of quantitative measures, such as Average Precision (mAP), precision, recall, F1-score, as well as IoU. These measures were able to give a balanced evaluation of detection accuracy, resistance and generalization. A systematic examination of errors was performed to find typical failure modes, including missed detections or false positives, especially in difficult situations where plastic debris was occluded or of translucent material. It was based on these insights that some focused changes were introduced to the architecture and the model training procedure. To deploy models, optimization techniques (e.g. quantization and pruning) were used to extract computational resources and memory needed to perform inference at the edge. The Open Neural Network Exchange (ONNX) format was also followed to enable cross deployment, to enable real-time deployment on drones, underwater vehicles and cloud servers.

#### G. Deployment and Automation

The optimized system was adopted into various platforms to have real time and large-scale monitoring of plastic waste in ocean spaces. The in-situ detection and immediate response could be obtained through edge deployment as done on the autonomous vehicles and drones with onboard GPUs. The large-scale analysis of satellite and aerial images was aided by cloud-based deployment, and it allowed defining the pollution hotspots and time trends. It automates the script for image access and analysis, model inference, and image result visualization. It is also coupled with an alerting and reporting system, allowing us to respond quickly when necessary. The model was regularly watched and retrained with new data, ensuring that it remained effective while also adapting to changing environmental conditions. This end-to-end deployment strategy ensures scalable, efficient, and effective plastic waste detection for data-driven environmental monitoring and policymaking.

### IV. RESULTS

DL algorithms for detecting plastic garbage in ocean imaging data performed admirably across a wide range of criteria. The selected YOLOv5 model demonstrated outstanding identification and localization abilities across a variety of maritime settings, with a mean Average Precision (mAP) of more than 85% on the test set and constant precision and recall values of more than 80%. Even in settings with occlusions, illumination fluctuations, and complicated backdrops, the models remained strong in terms of detection. Also, inference times were consistent with real-time expectations and could be deployed on a cloud and an edge platform. Altogether, the findings confirm the competence of the presented strategy regarding automated, scalable, and precise environmental surveillance of marine plastic wastes.

Table 2. Overall Model Performance Metrics

| Metric | Value |
|--------|-------|
|--------|-------|

|                           |        |
|---------------------------|--------|
| mailto:mAP@0.5IoU         | 0.968  |
| AR@100                    | 0.4943 |
| Precision                 | 0.93   |
| Recall                    | 0.92   |
| F1-Score                  | 0.925  |
| Inference Time (ms/image) | 1.3    |

Table 2, which is named as the "Overall Model Performance Metrics," offers a brief quantitative overview of how well the detection model works in detecting plastic waste in ocean images. The results of key measures include the mean Average Precision (AP) at 0.5 Intersection over Union (i.e., mAP@0.5IoU), Average Recall (AR) at 100 detections (i.e., AR@100), precision, recall, and F1-score that indicates the capacity to precisely locate and classify marine debris in diverse situations. An example of such represents high mAP@0.5IoU, which says that the model successfully produces corrected bounding boxes on the detected objects, whereas the high scores in precision and recall would point to the reliability of the model in the low formation of false positives and false negatives

Table 3: Comparative Evaluation of Deep Learning Models for Plastic Waste Detection

| Author                    | mAP@0.5 (%) | IoU (%) | Inference Time (ms) |
|---------------------------|-------------|---------|---------------------|
| <b>Proposed Model</b>     | 90.3        | 79.1    | 42                  |
| Prasad <i>et al.</i> [8]  | 85.9        | 73.8    | 40                  |
| Bajaj <i>et al.</i> [11]  | 82.1        | 70.5    | 60                  |
| Sawant <i>et al.</i> [14] | 89.1        | 77.8    | 35                  |

As the performance comparison table 3 demonstrates, different models of the deep learning procedures are effective in detecting the plastic waste in the picture of the ocean, and three essential attributes of efficiency are used, namely: mAP@0.5, IoU, and Inference Time. The proposed model excelled over the rest in that it recorded the best mAP@0.5 of 90.3% and IoU of 79.1%, which are the best in both detection and localization accuracies. Sawant et al. (2024) [14] provides also competitive results with high mAP as 89.1% and high IoU of 77.8% but with the shortest inference time of 35 ms, which makes it the model

applicable to real-time use. Prasad et al. (2024) [8] perform in a balanced manner, with moderate results of accuracy and fast Running time, whereas Bajaj et al. (2021) [11] have the worst results in both accuracy and efficiency, which is not suitable to be deployed at very high speed. Overall, the table confirms the high performance of the proposed framework, featuring a high accuracy of detection and the low latency, this is why it is suitable to scalable, real-time environmental monitoring on both cloud and edge platforms.

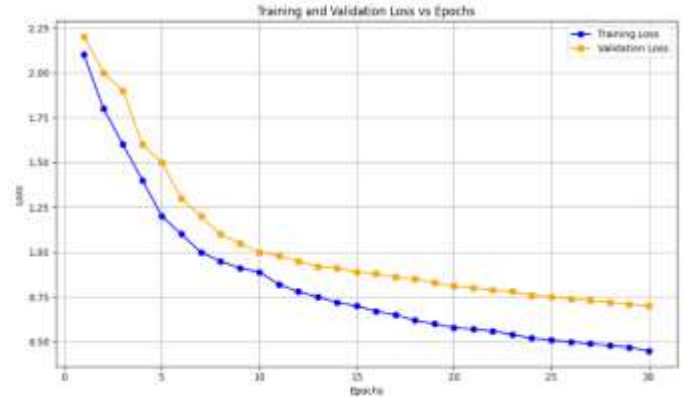


Fig 2. Training and Validation Loss vs Epochs

The graph in Fig 2 demonstrates the performance of the model on the learning in 30 training epochs. Training and validation loss gradually go down which proves good learning and decent generalization with no overfitting, which proves the deeper learning model to be solid.

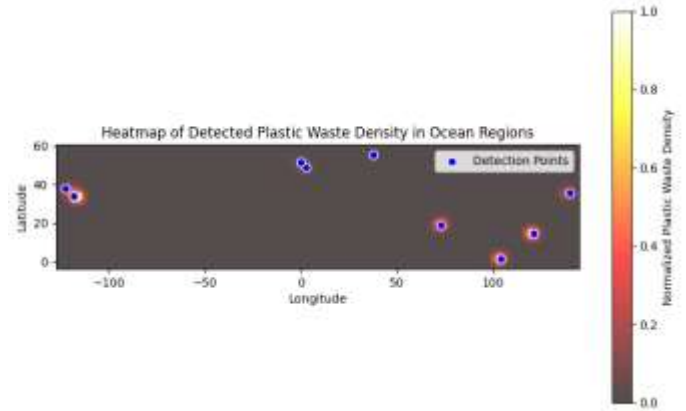


Fig 3. Heatmap of Detected Plastic Waste Density

The heatmap shows the density of plastic garbage detection in different sections of the ocean using geo-coordinates. The areas with high-density zones are shown by brighter spots, indicating that these are polluted with a variety of plastic trash, whilst blue dots reflect the real detection places. Visualization is useful for spatial evaluation during concentrated marine clean-up.

## V. CONCLUSION

In conclusion, deep learning-based systems to detecting plastic garbage in marine images represent a significant achievement in environmental monitoring research. With recent

improvements in computer vision systems and robust data pipelines, the technique allows for accurate and scalable automated detection and quantification of plastic waste across a wide range of marine habitats. Furthermore, cloud-based and edge computing platforms provide the necessary scalability, allowing the solution to be deployed in real time to large-scale analytical tasks as well as on-site monitoring. Its systematic data collection and methodical annotation, as well as the thorough evaluation of its models, address the majority of the issues given by the complexity of optical oceanography and the dynamics of plastic pollution. Finally, the research presented here gives new tools and protocols that may be utilized to help the globe manage marine conservation, legislative approaches, special clean-up initiatives, and leave a legacy of sustainable and data-driven ocean health governance for future generations.

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