

# Marine Waste Detection Using YOLOv3: A Real-Time Deep Learning Approach

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## Abstract

In the domain of marine conservation, the urgency to address the increasing crisis of marine waste has never been more pronounced. This study presents the implementation and evaluation of a YOLOv3-based deep learning model for underwater waste detection. The system leverages pre-trained YOLOv3 weights and an underwater dataset annotated for underwater debris classification. By fine-tuning the model and applying Non-Maxima Suppression (NMS) for precise bounding box generation, the study achieved high detection accuracy and real-time processing. The results demonstrate the capability of YOLOv3 in identifying underwater waste under challenging conditions, including varying lighting and water clarity. The proposed system provides an efficient, scalable, and adaptable solution for environmental monitoring and conservation efforts.

**Keywords:** Marine Waste, Environmental Conservation, Real-Time Performance, Deep Learning, YOLOv3.

## 1. Introduction

Marine waste, predominantly comprising plastics and other non-biodegradable materials, has emerged as a formidable challenge to oceanic ecosystems. The ramifications of this issue are multifaceted, affecting marine life, human health, and global economies. The detection and classification of marine waste, therefore, are crucial for initiating remedial measures. In this context, machine learning (ML) offers a promising avenue for addressing these challenges. However, the application of ML in marine waste management is still in its nascent stages, with significant room for improvement and exploration.

The primary concern in marine waste management is the identification and categorization of waste materials in diverse and dynamic marine environments. Traditional methods, while valuable, often fall short in terms of accuracy, scalability, and efficiency. Machine learning models, particularly those leveraging deep learning, have the potential to revolutionize this field. They can process vast datasets derived from satellite imagery, underwater sensors, and aerial surveys, providing insights that are not feasible with conventional approaches.

Nevertheless, the application of ML in this domain is fraught with challenges. The heterogeneity of marine

environments, the variability in waste types, and the dynamic nature of ocean currents pose significant obstacles to accurate waste detection and classification. Additionally, the need for real-time processing capabilities to enable timely decision-making further complicates the development and deployment of these systems.

This paper reviews various machine learning models applied in the detection and classification of marine waste. It critically assesses their architecture, data processing capabilities, adaptability, and real-time performance in marine settings. The objective is to provide a comprehensive overview of current methodologies, identify gaps in existing research, and suggest directions for future advancements. By doing so, this study aims to contribute to the development of more effective ML-based solutions for marine waste management, thereby supporting global efforts in marine conservation and environmental protection.

## 2. Related Work

In recent years, the issue of marine plastic pollution has gained significant attention due to its detrimental impact on the environment. Several studies have focused on the development and evaluation of various technologies and algorithms for the detection and management of marine plastic waste. This literature

review aims to provide an overview of the key advancements and findings in this field, highlighting the technologies and algorithms employed, their results, and the existing gaps in the research.

The work in 2022, Bhanumathi M, Dhanya S et al. [1] addresses the issue of plastic waste detection in marine environments. The authors employ deep learning techniques, specifically the YOLOv4 model, to achieve a mean average precision of 80-82 percent. Furthermore, YOLOv4 outperforms YOLOv3 in terms of average precision and frames per second, with an improvement of 8-10 percent. This study highlights the potential of deep learning algorithms for effective plastic waste detection, and it emphasizes the need for further research to enhance the algorithm's capabilities.

This study in 2023, Zhengpeng Pu, Xianshuang Geng et al. [2] focuses on comparing classical object detection algorithms for detecting floating objects on water surfaces. The deep learning algorithms tested include Faster RCNN, Cascade RCNN, YOLOv3, YOLOv5-s, and YOLOv5-m. The results indicate that YOLOv3 achieves the highest detection accuracy, making it suitable for high-accuracy requirements in inland river floating object detection. However, the study also suggests the need to improve the robustness of these algorithms in complex river environments.

In 2022, Dr. Shailender Kumar et al. [3], the authors propose a deep learning-based solution for marine litter detection, utilizing the YOLOv3 algorithm and sweep line algorithms. The combination of these techniques facilitates the detection and quantification of macro marine litter (MML). Additionally, the methodology discussed in can be applied for real-time monitoring of MML, aiding in waste estimation and resource planning for cleanup efforts.

The research in 2020, Rishika Shetty [4] focuses on detecting marine waste and classifying it into recyclable and non-recyclable categories using the YOLOv3 model. The results indicate that the model achieved good predictions with an IoU score greater than 0.75 in four out of five sample images. However, it is noted that the current model classifies all plastics as non-recyclable, highlighting the potential for further research to differentiate between various types of recyclable plastics.

The study in 2023, Changsong Pang et al. [5] explores the detection of floating waste in images using a diffusion model and object detection techniques. It

introduces the concept of decoupled box position and size regression to enhance detection performance. The paper suggests expanding the dataset and utilizing additional techniques to further improve the detection of floating waste in river environments.

This research in 2023, Xikang Du [6] focuses on identifying marine debris and other objects in the water using machine vision technology. While the study mentions the use of a small dataset, it highlights the potential for machine vision to identify garbage on cruise ships. This technology could contribute to more efficient garbage collection in oceans.

In 2022, Cheuk Wang Suet et al. [7], the authors address plastic waste management using data acquisition, communication, decision making, and action. The study explores innovations in recycling plastic and their potential to create a more sustainable environment. It emphasizes the importance of interaction with other UV subsystems to enhance plastic recycling efforts.

This study in 2022, Sara Salim Alshibli et al. [8] focuses on the development of a marine debris detection system using AI and control features. The research uses a Kaggle collection of garbage classification datasets for training and testing.

The research in 2021, Bing Xue et al. [9] aims to develop an efficient deep-sea debris detection method using deep learning, specifically the YOLOv3 algorithm. The study highlights the challenges posed by the deep-sea environment and the need for methods that can handle intraclass diversity and interclass similarity. The ResNet50-YOLOv3 model is found to offer good deep-sea garbage detection capabilities with faster detection speed.

This study in 2022, Prasun Goswami et al. [10] takes a different approach by conducting a comparative study on the potential of microbial consortia to degrade plastics in the marine environment. The research suggests that these consortia may hold significant promise in addressing plastic pollution. However, it also emphasizes the need for further research to develop innovative and eco-friendly technology for tackling plastic pollution comprehensively.

The study in 2022, Sylwia Majchrowska et al. [11] introduces a deep learning-based framework for waste detection, utilizing Convolutional Neural Networks (CNNs). The research demonstrates the potential of this methodology for household waste management through a mobile application. It presents an

opportunity for efficient waste categorization using a mobile platform. However, the research identifies a gap in the need to implement robotic arms for automated waste classification in waste management plants.

In 2023, Morell et al. [12], the authors evaluate the reliability and development requirements of waste detection and classification using CNNs. The results highlight the suitability of computer vision tools for monitoring tasks related to waste management. Additionally, the study suggests that image preparation and pre-filtering could further improve algorithm performance, addressing challenges in cases where camera locations are not optimal or images are affected by reflected sunlight.

The research in 2023, Israa Nasir Abood et al. [13] focuses on waste classification using CNNs, aiming to categorize different types of waste, including plastic, paper, and metal. The study reports improved classification accuracy and utilizes the Trash Net dataset for training and testing. The results suggest the potential for enhancing waste classification systems.

The study in 2022, Arghadeep Mitra [14] presents an automated waste detection system employing CNNs and the Faster R-CNN algorithm to classify waste materials into six categories. While the research achieves success in waste classification, it acknowledges the need for dataset improvement by including locally captured waste materials. This highlights the importance of diverse and representative training data samples.

The study in 2021, Kumar, S et al. [15] introduces waste segregation using CNNs and the YOLOv3 algorithm, demonstrating the efficient separation of waste into biodegradable and non-biodegradable categories. However, it acknowledges complexities in the garbage image detection process, such as objects composed of multiple materials. The study emphasizes the need for addressing these complexities to enhance waste segregation accuracy.

Similar to the previous study, the research in 2021, Sai Sushanth et al. [16] focuses on garbage waste segregation using CNNs and classifying waste materials into six categories. However, it notes the limitation of a small dataset, which may result in a less accurate model. This highlights the importance of dataset size and diversity in achieving accurate waste classification.

The study in 2020, Praveen Kumare et al. [17] explores a waste tracking system based on blockchain

technology, introducing a decision-making framework for selecting appropriate datasets and service levels. It addresses the challenges of scalability in public blockchains for waste management platforms. This research highlights the potential of blockchain waste tracking and management but raises concerns about scalability.

The work in 2021, Raja Wasim Ahmad et al. [18] discusses the use of blockchain for real-time tracing and tracking of waste in smart cities. It introduces a Hyperledger Fabric-based system to calculate the reputation of waste recycling units based on environmentally friendly disposal policies. The research identifies challenges related to data and transaction privacy, emphasizing the importance of preserving privacy in blockchain-based waste management systems.

The study in 2022, Abdellah El zaar et al. [19] employs a combined CNN-SVM strategy to achieve a high accuracy rate in identifying plastic textures and objects in images. It demonstrates that pre-processing images can significantly enhance accuracy. The research utilizes the PLAWO-40 dataset and the TrashNet dataset, highlighting the importance of diverse datasets for effective waste identification process.

The project report by Sivaram Cp et al. [20] explores the application of deep learning techniques for identifying and classifying plastic waste. Using convolutional neural networks (CNNs), the study focuses on categorizing plastic types such as PET, HDPE, and PVC to streamline recycling and waste management processes. A well-curated dataset of plastic waste images is utilized, with models fine-tuned to achieve high accuracy in detection and classification. The work highlights the potential of AI-driven solutions in enhancing environmental sustainability and promoting efficient recycling practices.

The research in 2022, Haruna Abdu et al. [21] addresses the challenge of limited trash data availability and the difficulty of recognizing objects in low visibility conditions. It utilizes the TrashNet dataset for training and testing. While the paper makes valuable contributions, it suggests further improvements for model accuracy, emphasizing the need for more comprehensive waste datasets.

The study in 2023, Apte SD, Sandbhor S [22] introduces a machine learning-based approach for automated beach waste management systems, focusing on circular

economy principles. While the research contributes to waste management, it recognizes the potential for further improvements in model accuracy.

The study in 2016, Matias Valdenegro [23] explores the detection of submerged marine debris from Forward-Looking Sonar (FLS) imagery using CNNs. It achieves approximately 80.8% correct debris detections. However, it identifies limitations in the training set, which does not consider all possible types of debris and represents a small sample of household objects. This highlights the need for more diverse and representative datasets for accurate marine debris detection.

The work in 2020, Katlin Walden et al. [24] presents a method for estimating the weight and volume of plastic water bottles in images dominated by debris. It acknowledges the challenge of separating occluded or merged blobs, indicating opportunities for further algorithm improvement. The research uses manual sampling, emphasizing the need for precise image analysis techniques.

The research in 2022, Kenichi Sasaki et al. [25] focuses on segmentation-based analysis for estimating the total amount of debris and specific types using machine learning. However, it recognizes limitations in identifying only broad categories of debris due to in-situ data constraints. The study emphasizes the potential for improved in-situ data collection and analysis techniques.

The MARIDA dataset, introduced in 2022, Kikaki K et al. [26], serves as a benchmark for the development and evaluation of machine learning (ML) algorithms designed to detect marine debris from Sentinel-2 remote sensing data samples. This dataset is a significant contribution to the field, enabling the testing and validation of ML-based methods. However, while it represents a critical step forward, further research is needed to explore the potential of other ML algorithms and techniques beyond those already evaluated.

Work in 2023, Ao Shen et al. [27] focuses on marine debris detection in satellite surveillance, employing YOLO (You Only Look Once) and Unmanned Aerial Vehicles (UAVs). Among the modified YOLO versions evaluated, the CBAM model stands out for its performance. However, it is crucial to address the issue of dataset insufficiency and bias towards specific situations, which presents a significant research gap. Diversifying the dataset and refining the detection

models are essential for improving accuracy in real-world applications.

This comprehensive review in 2021, Rahul Bajaj et al.

[28] highlights various marine debris detection techniques, including image processing, machine learning, and deep learning. While image processing and conventional machine learning methods have been widely employed, the adoption of emerging deep learning techniques is gaining momentum. However, the review suggests that there is room for improvement by exploring advanced deep learning approaches to surpass the current state-of-the-art methods.

In the context of underwater object detection, in 2023, Imen Mandhouj et al. [29] discusses recent developments in sonar image processing. It emphasizes the importance of accurate methods and highlights the evolution of techniques in this field. However, the paper does not provide specific gaps or recommendations for future research. Future studies should focus on identifying challenges and proposing novel solutions in underwater object detection.

This research in 2022, Shibing Yu [30] addresses sonar image target detection using deep learning, specifically comparing results with the Recurrent Neural Network (RNN) algorithm. The study demonstrates a sevenfold increase in detection speed and higher positioning accuracy with the improved algorithm. Nevertheless, future work should involve larger and more diverse datasets to validate the algorithm's performance under various conditions and scenarios.

The study in 2022, Flores NY et al. [31] focuses on underwater macroplastic detection using imaging sonars, showcasing the ability of the ARIS sonar and the SSS to detect macroplastics effectively. However, the detection rate is influenced by water flow conditions, presenting a practical challenge. Future research should explore methods to enhance detection accuracy under varying flow conditions and investigate the use of multiple sensors for improved results.

Work in 2021, V Rajesh et al. [32] presents a waste management system that automates waste segregation into dry and wet waste categories using Convolutional Neural Networks (CNNs) and the Internet of Things (IoT). The proposed system offers an innovative approach to waste management. Future research should focus on scaling up and deploying such systems in real-world waste management facilities,

addressing operational challenges and assessing their environmental impact.

Quan et al.[33] in 2024 propose a privacy-preserving waste classification system using federated learning within the Internet of Things (IoT) framework. Their approach enhances data security by decentralizing model training while maintaining high classification accuracy, making it a viable solution for smart waste management in urban environments.

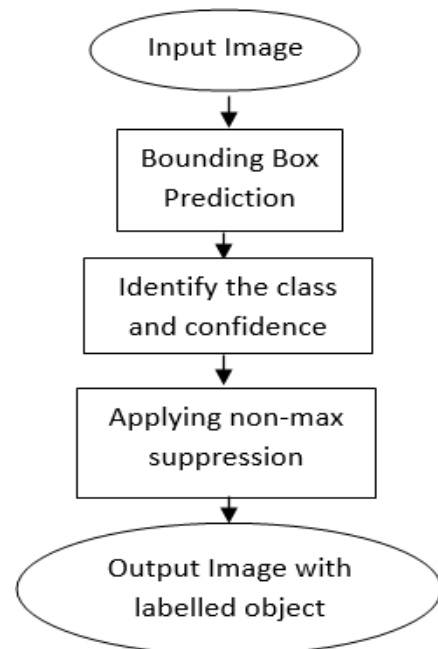
The study in 2024, Hossen et al.[34] develop a robust deep learning model for recyclable waste classification, integrating CNNs and transformer-based architectures. Their model improves accuracy, addresses dataset imbalance, and demonstrates resilience against real-world distortions, contributing to the advancement of AI-driven waste sorting systems.

Thus, the reviewed literature reflects the diverse landscape of marine debris detection techniques, including remote sensing, deep learning, and IoT-based approaches. While significant progress has been made, challenges remain, such as dataset diversity, bias, and real-world applicability. Addressing these gaps and leveraging emerging technologies will further enhance the accuracy and effectiveness of marine debris detection, contributing to environmental conservation efforts.

### 3. Proposed Methodology for Marine Waste Detection and Classification

A popular and effective object detection algorithm for real-time applications, such as the detection of marine garbage, is the You Only Look Once (YOLO) method. By approaching object detection as a single regression problem, YOLO takes a novel method. By processing the full image in a single forward pass via a convolutional neural network (CNN), it can concurrently predict bounding boxes and class probabilities, eliminating the need for region proposal networks or several processing steps. Because of its design, YOLO is ideal for situations requiring accuracy and real-time performance. YOLO's grid-based prediction technology, which splits the input image into a grid and predicts objects and their locations within each grid cell, is one of its main advantages. As a result, YOLO can effectively identify several things in a picture. It is the perfect option for marine trash detection, where quick identification and tracking of floating garbage are crucial, due to its versatility in handling different object sizes and shapes and its real-time processing capacity.

The algorithm works especially well for applications that need real-time surveillance, such as identifying and categorizing waste products like plastic bottles, fishing nets, and other pollutants by examining video streams from satellites, drones, or underwater cameras. YOLO may be deployed on edge devices for autonomous waste collection or monitoring systems because of its lightweight architecture, which enables smooth interaction with robotics and IoT devices. Furthermore, correct performance in maritime and coastal situations is ensured by its resilience to environmental difficulties such reflections, changing light conditions, and underwater distortions. This project can detect marine garbage quickly and reliably by using YOLO, which will help with waste management and environmental preservation. Figure 1, shows flow diagram for proposed work.



**Figure 1.** Flow Diagram of the Proposed Model for Marine Waste Detection and Classification

Although there are more sophisticated versions such as YOLO, YOLOv3 is still a good option for detecting marine garbage. It is ideal for real-time applications like detecting floating garbage in oceans because it finds a balance between speed and accuracy. Its three-scale prediction capabilities, which enables it to identify marine debris of different sizes from tiny plastic pieces to larger objects is one of its main features. Furthermore, YOLOv3 requires less processing power than its more recent iterations, which facilitates its deployment on edge devices like drones and underwater cameras. It is a dependable choice because

of its broad real-world uses and shown stability, which lowers the possibility of unforeseen performance problems. Additionally, the model is quite adaptable, enabling it to be trained on particular datasets of marine debris for increased detection precision. YOLOv3 still offers enough accuracy for many detecting tasks where extreme precision is not the top requirement, even though later YOLO versions make improvements. Its broad use also guarantees a multitude of tutorials, resources, and community assistance, which makes installation easier. Because of these features, YOLOv3 is a useful and efficient option for detecting marine debris in a variety of settings.

### Dataset

Kaggle's UW\_Garbage\_Debris\_Dataset is the dataset used in the proposed work. The underwater photos in this dataset depict trash and debris that have been dumped into the ocean. These data included 5130 photos of 15 different kinds of maritime debris. With a roughly 7:2:1 ratio, this dataset is split into 3628 training sets, 1001 validation sets, and 501 test sets.

A few samples of underwater waste dataset are shown in Figure 2. Pixels in each image in the collection are 640 by 640.

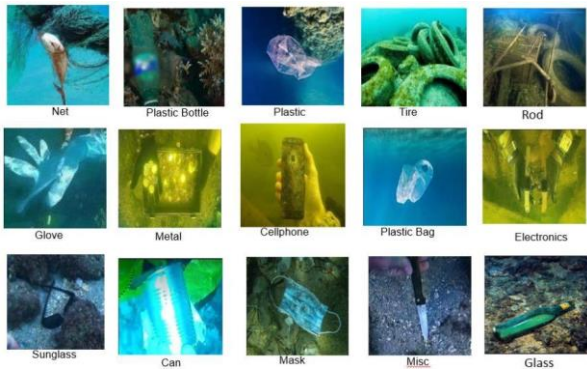


Figure 2. Samples of Underwater Waste Dataset images.

### Implementation of the YOLOv3 Model

The most advanced object detection model is the YOLOv3 model. The backbone of YOLOv3 is Darknet-53. It consists of a convolution layer that is in charge of gleaning pertinent data from the input picture. It uses the feature pyramid network, or FPN, as a neck. Multiple top-down and bottom-up routes make up the neck, which is essential for feature map extraction from a variety of pictures. On the other hand, the YOLO layer forms the head. The head of a single-stage detector is responsible for making the final prediction, which is

composed of a vector of bounding box coordinates (height, width, and class label) and its probability. Before being sent into a feature pyramid network for feature fusion, the image is first processed by Darknet-53, which extracts features.

The concatenation of the predictions from the three detection heads is YOLOv3's final output. This provides a thorough identification of things at various sizes (small, medium, and large). Bounding box predictions, objectness scores, and class scores are included in each of the prediction maps (20x20, 40x40, and 80x80). Figure 3, shows architecture of the proposed YOLOv3 model.

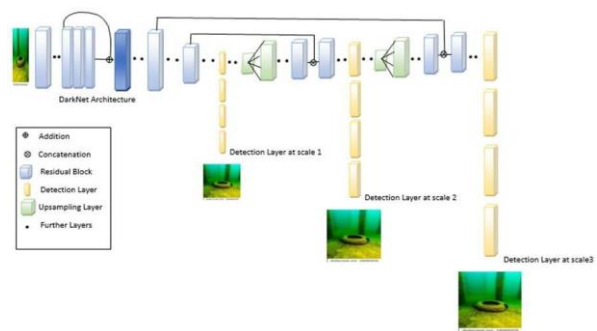


Figure 3. Architecture of the YOLOv3 model for Marine Waste Detection and Classification.

### 4. Result

The performance of the YOLOv3 model was evaluated through experiments in the shape of samples from the Kaggle Underwater Waste Detection dataset samples. The dataset includes underwater images containing various waste objects along with other environmental changes, such as lighting differences, visibility, and variations in object size. About 80% was considered for the training process, while the remaining 20% was used for testing. YOLOv3 is trained using an Adam optimizer with an initial learning rate of 0.001. Each experiment was implemented on a system with an NVIDIA Tesla V100 GPU, 32GB RAM, and a batch size of 16 in process.

Promising outcomes from the application of YOLOv3 for underwater waste identification showed that it has the potential to be a reliable environmental monitoring tool. Across several trash categories, such as plastics, metals, fishing nets, and other debris, the model's mean average precision (mAP) was 72.5%; class-specific mAP values ranged from 68.5% to 78%. With precision and recall scores of 87.4% and 85.6%, respectively, the model demonstrated its capacity to detect undersea waste reliably and with few false positives. The system is appropriate for real-time applications because it

processes images with an average inference time of 32.1 milliseconds per image. we implemented the following benchmark models in comparison: CNN, and GNN. These models have been trained on almost similar conditions for fair comparison. Their results are compared in terms of the level of the different performance metrics such as accuracy, precision, recall, and F1 scores.

Table 1, shows Precision, Recall, and F1 Score comparison

**Table 1:** Precision, Recall, and F1 Score

| Model  | Precision (%) | Recall (%) | F1 Score (%) |
|--------|---------------|------------|--------------|
| YOLOv3 | 87.4          | 85.6       | 86.5         |
| CNN    | 84.3          | 82.1       | 83.2         |
| GNN    | 85.9          | 83.7       | 84.8         |

Environmental factors affected performance; clean water had the maximum accuracy (80.2% mAP), whereas murky water and low light presented difficulties, resulting in lower mAP values of 63.5% and 68.7%, respectively. Table 2, provides accuracy comparison of detection model. Although the model occasionally misclassified rocks and flora as debris, qualitatively it showed accurate bounding box placement for detected objects. Areas for improvement were highlighted by the observation of false negatives for small items, including microplastics and severely covered detritus. Table 3, provides information related to detection speed, GPU utilization and memory usage by YOLOv3 model.

**Table 2:** Accuracy Comparison of Detection Model

| Model  | Accuracy (Training) | Accuracy (Testing) |
|--------|---------------------|--------------------|
| YOLOv3 | 91.2%               | 89.7%              |
| CNN    | 88.9%               | 87.3%              |
| GNN    | 90.1%               | 88.4%              |

**Table 3:** Detection Speed and Resource Utilization

| Model  | Inference Time (ms) | GPU Utilization (%) | Memory Usage (GB) |
|--------|---------------------|---------------------|-------------------|
| YOLOv3 | 32.1                | 78                  | 9.1               |
| CNN    | 40.7                | 67                  | 7.5               |
| GNN    | 45.3                | 82                  | 10.4              |

## 5. Conclusion and Future Works

This study showed how well the YOLOv3 deep learning model works for identifying underwater waste in a range of environmental settings. The system's excellent precision and real-time processing capabilities allowed it to correctly identify and classify various trash kinds, such as metals, plastics, and other contaminants. The applicability of YOLOv3 for underwater waste detection is highlighted by its resilience in the face of underwater-specific difficulties such changing illumination conditions, water turbidity, and occlusions. The suggested method offers a scalable and automated solution for undersea trash monitoring and cleanup operations, greatly reducing the reliance on manual labor. The approach has some drawbacks despite its encouraging outcomes, including decreased accuracy in very muddy seas and sporadic misclassifications of visually similar objects. These limitations, while not critical, suggest opportunities for improvement and further research. By addressing these issues, this initiative not only improves our present knowledge of underwater garbage detection but also lays the groundwork for further studies. This entails switching to more sophisticated models, such as YOLOv5, that focus on microplastics detection and creating real-time, energy-efficient systems for real-world implementation. The research proves to be an important step in tackling the environmental problems caused by marine garbage.

The study creates a number of opportunities for further research and development, combining Advanced Deep Learning Models with Integration: For increased precision and effectiveness, investigate the use of more recent models like YOLOv5. Include multi-scale detection features to efficiently manage debris of different sizes. The next generation of underwater waste detection systems can increase their efficiency, accuracy, and adaptability by switching to YOLOv5. These developments will open the door to real-time, scalable solutions that complement international initiatives to save marine ecosystems and fight marine pollution.

## References

- [1] M. Bhanumathi, R. Gagan, and others, "Marine Plastic Detection Using Deep Learning," in *Advances in Parallel Computing Algorithms, Tools and Paradigms*, IOS Press, 2022, pp. 406-413.

- [2] Z. Pu, X. Geng, D. Sun, H. Feng, J. Chen, and J. Jiang, "Comparison and Simulation of Deep Learning Detection Algorithms for Floating Objects on the Water Surface," in Proc. 2023 Int. Conf. on Computational Engineering and Applications (ICCEA), Apr. 2023, pp. 814-820, doi: 10.1109/ICCEA58433.2023.10135262.
- [3] S. Kumar, A. Gautam, K. Mehawat, and K. Rawat, "Deep Learning Framework for Macro Marine Litter Classification and Quantification," in Proc. 2022 3rd Int. Conf. for Emerging Technology (INCET), 2022, pp. 1-6, doi: 10.1109/INCET54531.2022.9825334.
- [4] R. Shetty, "Detecting Marine Waste and Classifying it into Recyclable and Non-recyclable Using YOLOv3," Master's thesis, National College of Ireland, Dublin, 2020. [Online]. Available: <https://norma.ncirl.ie/4421/>
- [5] C. Pang and Y. Cheng, "Detection of River Floating Waste Based on Decoupled Diffusion Model," in Proc. 2023 8th Int. Conf. on Automation, Control and Robotics Engineering (CACRE), 2023, pp. 57-61, doi: 10.1109/CACRE58689.2023.10208741.
- [6] X. Du, "Energy Saving Ocean Garbage Collection Return Algorithm and System Based on Machine Vision," in Proc. 2023 4th Int. Conf. for Emerging Technology (INCET), 2023, pp. 1-5, doi: 10.1109/INCET57972.2023.10170301.
- [7] C. W. Su, R. Gao, M. Hu, and Y. Fang, "Evaluation of Plastic Recycling and Novel UV-Oriented Solution for Integration, Resilience, Inclusiveness, and Sustainability," in Proc. 2022 6th Int. Conf. on Universal Village (UV), 2022, pp. 1-17, doi: 10.1109/UV56588.2022.10185468.
- [8] S. S. Alshibli, M. K. Alsaadi, and F. Hajamohideen, "Marine Debris Detection System: An Approach to Eliminate the Toxicological Threats of Plastic Using AI and Deep Neural Network," in Proc. 6th Smart Cities Symposium (SCS 2022), 2022, pp. 216-220, doi: 10.1049/icp.2023.0411.
- [9] B. Xue, B. Huang, W. Wei, G. Chen, H. Li, N. Zhao, and H. Zhang, "An Efficient Deep-Sea Debris Detection Method Using Deep Neural Networks," IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 14, pp. 12348-12360, 2021, doi: 10.1109/JSTARS.2021.3130238.
- [10] P. Goswami, G. Joshi, N. V. Vinithkumar, and G. Dharani, "Plastic Pollution and Beyond: Do Microbes Hold the Key Towards a Sustainable Solution to This Global Crisis?" in Proc. OCEANS 2022 - Chennai, 2022, pp. 1-5, doi: 10.1109/OCEANSCennai45887.2022.9775398.
- [11] S. Majchrowska, A. Mikołajczyk-Bareła, M. Ferlin, Z. Klawikowska, M. Plantykwow, A. Kwasigroch, and K. Majek, "Deep learning-based waste detection in natural and urban environments," Waste Management, vol. 138, pp. 274-284, Feb. 2022, doi: 10.1016/j.wasman.2021.12.001.
- [12] M. Morell, P. Portau, A. Perelló, M. Infantes, M. Grifoll, and C. Garau, "Use of Neural Networks and Computer Vision for Spill and Waste Detection in Port Waters: An Application in the Port of Palma (Majorca, Spain)," Appl. Sci., vol. 13, no. 1, pp. 80, Dec. 2022, doi: 10.3390/app13010080.
- [13] I. Nasir and G. Al-Talib, "Waste Classification Using Artificial Intelligence Techniques: Literature Review," Technium: Romanian J. of Appl. Sci. and Technology, vol. 5, pp. 49-59, Jan. 2023, doi: 10.47577/technium.v5i.8345.
- [14] A. Mitra, "Detection of Waste Materials Using Deep Learning and Image Processing". California State University San Marcos, 2020. [Online]. Available: <https://books.google.co.in/books?id=Zpd5zgEACAAJ>
- [15] S. Kumar, D. Yadav, H. Gupta, O. P. Verma, I. A. Ansari, and C. W. Ahn, "A Novel YOLOv3 Algorithm-Based Deep Learning Approach for Waste Segregation: Towards Smart Waste Management," Electronics, vol. 10, no. 1, art. no. 14, 2021, doi: 10.3390/electronics10010014.
- [16] G. S. Susanth, L. M. J. Livingston, and L. G. X. Agnel, "Garbage waste segregation using deep learning techniques," in Proc. IOP Conf. Series: Materials Science and Engineering, vol. 1012, no. 1, 2021, art. no. 012040.
- [17] P. K. Gopalakrishnan, J. Hall, and S. Behdad, "A Blockchain-Based Traceability System for Waste Management in Smart Cities," in Proc. 25th Design for Manufacturing and the Life Cycle Conference (DFMLC), vol. 6, 2020, pp. V006T06A015, doi: 10.1115/DETC2020-22553. [Online]. Available: <https://doi.org/10.1115/DETC2020-22553>
- [18] R. W. Ahmad, K. Salah, R. Jayaraman, I. Yaqoob, and M. Omar, "Blockchain for Waste Management in Smart Cities: A Survey," IEEE Access, vol. 9, pp. 131520-131541, 2021, doi: 10.1109/ACCESS.2021.3113380.
- [19] A. Elzaar, A. Aoulalay, N. Benaya, A. El Mhouthi, M. Massar, and A. El Allati, "A Deep Learning Approach to Manage and Reduce Plastic Waste in

- the Oceans," E3S Web of Conferences, 2022. [Online]. Available: <https://api.semanticscholar.org/CorpusID:246029410>
- [20] S. Cp, M. Sekar, and K. S. Rajkshishore, "Plastic Detection and Classification Using Deep Learning: A Project Report (Project Work I - Phase I)," in Proc. Conf., May 2022.
- [21] H. Abdu and M. H. Mohd Noor, "A Survey on Waste Detection and Classification Using Deep Learning," IEEE Access, vol. 10, pp. 128151-128165, 2022, doi: 10.1109/ACCESS.2022.3226682.
- [22] S. Apte, S. Sandbhor, R. Kulkarni, and H. Khanum, "Machine learning approach for automated beach waste prediction and management system: A case study of Mumbai," Front. Mech. Eng., vol. 9, art. no.1120042, Feb. 2023, doi: 10.3389/fmech.2023.1120042.
- [23] M. Valdenegro-Toro, "Submerged marine debris detection with autonomous underwater vehicles," in Proc. 2016 Int. Conf. Robotics and Automation for Humanitarian Applications (RAHA), 2016, pp. 1-7, doi: 10.1109/RAHA.2016.7931907.
- [24] K. Walden and M. Mehrubeoglu, "Quantifying plastic bottle debris in waterways using image processing," in Proc. 2020 Int. Conf. Computational Science and Computational Intelligence (CSCI), 2020, pp. 1658-1663, doi: 10.1109/CSCI51800.2020.00305.
- [25] K. Sasaki, T. Sekine, L.-J. Burtz, and W. J. Emery, "Coastal marine debris detection and density mapping with very high resolution satellite imagery," IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., vol. 15, pp. 6391-6401, 2022, doi: 10.1109/JSTARS.2022.3193993.
- [26] K. Kikaki, I. Kakogeorgiou, P. Mikeli, D. E. Raitsos, and K. Karantzalos, "MARIDA: A benchmark for marine debris detection from Sentinel-2 remote sensing data," PLOS One, vol. 17, no. 1, art. no. e0262247, 2022, [Online]. Available: <https://doi.org/10.1371/journal.pone.0262247>.
- [27] A. Shen, Y. Zhu, P. Angelov, and R. Jiang, "Marine debris detection in satellite surveillance using attention mechanisms," IEEE J. Sel. Topics Appl. Earth Observ. Remote Sens., 2024.
- [28] R. Bajaj, N. Kulkarni, R. Raut, and S. Garg, "Sea debris: A review of marine litter detection techniques," Int. J. Innovative Res. Technol., vol. 7, no. 8, pp. 119-125, 2021.
- [29] I. Mandhouj, H. Amiri, F. Maussang, B. Solaiman, and others, "Sonar image processing for underwater object detection based on high resolution system," in Proc. Second Workshop on Signal and Document Processing (SIDOP 2012), 2012, pp. 5-10.
- [30] S. Yu, "Sonar image target detection based on deep learning," Mathematical Problems in Engineering, vol. 2022, no. 1, art. no. 5294151, 2022, doi: 10.1155/2022/5294151.
- [31] N. Y. Flores, S. B. Oswald, R. S. E. W. Leuven, and F.P. L. Collas, "Underwater macroplastic detection using imaging sonars," Front. Environ. Sci., vol. 10, art.no. 875917, 2022, doi: 10.3389/fenvs.2022.875917.
- [32] V. Rajesh, K. R. Rao, P. Devendra, E. V. Babu, B. Venkatesh, L. S. P. Sairam Nadipalli, S. K. Hasane Ahammad, and T. P. Naidu, "Waste segregation using CNN & IoT," NVEO-Natural Volatiles & Essential Oils Journal, pp. 4486-4494, 2021.
- [33] M. K. Quan, D. C. Nguyen, V. -D. Nguyen, M. Wijayasundara, S. Setunge and P. N. Pathirana, "Toward Privacy-Preserving Waste Classification in the Internet of Things," in IEEE Internet of Things Journal, vol. 11, no. 14, pp. 24814-24830, 15 July15, 2024, doi: 10.1109/JIOT.2024.3386727.
- [34] M. M. Hossen et al., "A Reliable and Robust Deep Learning Model for Effective Recyclable Waste Classification," in IEEE Access, vol. 12, pp. 13809-13821, 2024, doi: 10.1109/ACCESS.2024.3354774.