IFERP
ISSN (Online) 2394-2320
International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
Volume 11 Issue 7 July 2024

# Underwater Waste Detection using YOLOv5

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***Abstract*— "Predicting Underwater Waste using YOLOv5" In response to the urgent need to solve environmental pollution, our research center developed a vision-based autonomous underwater wastewater cleaning robot. This paper presents a new litter detection method based on YOLOv5, a state-of-the-art object detection algorithm known for its efficiency and accuracy. YOLOv5 algorithm was chosen as the main neural network for task detection. We use new technology designed for YOLOv5 architecture to increase verification accuracy. An optimization method is also used to demonstrate speed while maintaining accuracy. Through extensive testing, our wireless drivers have demonstrated superior performance in detecting and collecting underwater debris. The results demonstrate the effectiveness of the YOLOv5-based approach in solving environmental problems.**

***Index Terms*— Object Detection, YOLOv5.**

## I. INTRODUCTION

Water pollution poses a significant threat to aquatic ecosystems and human health worldwide. Traditional methods of monitoring and managing underwater waste have been labor-intensive and often inefficient. However, recent advancements in technology offer promising solutions to this pressing environmental challenge. This research paper explores the innovative application of YOLOv5, a cutting-edge object detection algorithm, in revolutionizing underwater waste detection and management. By harnessing the power of deep learning and real-time image processing, YOLOv5 enables the swift and accurate identification and categorization of submerged debris, ranging from plastics to other pollutants. Through this technological synergy, we aim to enhance our understanding of underwater pollution. This paper discusses the methodology, implementation, and potential impact of using YOLOv5 for underwater waste detection, emphasizing its role in advancing environmental conservation efforts.

### A. Machine Learning - Overview

In the realm of underwater waste detection, the adoption of YOLOv5 showcases the transformative potential of machine learning. YOLOv5 autonomously extracts meaningful insights, identifies submerged debris, and generates accurate predictions without the need for explicit programming instructions. Understanding the fundamentals of machine learning within the context of YOLOv5 is essential for decision-making processes, including its capacity to align with project objectives, selection of appropriate techniques for underwater waste detection, anticipation of potential challenges, and interpretation of detection outcomes.

### B. Problem Statement

The inadequate and unsustainable management of underwater waste represents a pressing issue that poses a severe threat to marine ecosystems worldwide. In response to this challenge, the application of deep learning for underwater waste detection emerges as a promising solution. However, existing systems utilizing deep learning models encounter formidable obstacles, including data scarcity, environmental variability, and resource intensiveness. These challenges collectively impede their efficiency and broader applicability.

This journal paper seeks to investigate and overcome the limitations of current underwater waste detection systems by proposing a robust framework based on YOLOv5. Leveraging a meticulously collected roboflow dataset, our approach aims to provide accurate and detailed information regarding the location, type, and quantity of underwater waste within analysed images. The output of our system includes a comprehensive detection map that highlights the presence of debris and pollutants. Furthermore, our framework classifies detected waste into distinct categories. This classification facilitates prioritized cleanup efforts, as different types of waste may require specific handling and disposal methods. Through this research, we aim to contribute to the development of an efficient and effective solution for the critical issue of underwater waste management, thereby safeguarding marine ecosystems from further degradation.

### C. Significance

The significance of predicting and addressing underwater waste management inefficiencies is pivotal in safeguarding marine ecosystems. This journal paper introduces a groundbreaking YOLOv5-based framework, showcasing a technological leap in deep learning applications for accurate underwater waste detection. Overcoming challenges such as data scarcity and environmental variability, the system, driven by a meticulously collected roboflow dataset, delivers essential insights into waste location, type, and quantity. This classification not only optimizes cleanup efforts but ensures efficient resource allocation, contributing to sustainable environmental practices. Beyond its technological innovation, the research's global implications extend to environmental preservation, influencing policy decisions for more effective, standardized underwater waste management strategies. The proposed framework not only addresses current inefficiencies but also establishes a foundation for future advancements in preserving the delicate balance of marine ecosystems on a broader, international scale.

### D. Machine Learning Tasks

This journal paper outlines common machine learning tasks and methods for solving problems, with suggestions for improvement. It also includes a list of key machine learning tasks, which can be further briefed in the paper. The paper encourages comments and suggestions on important points and apologizes for any types.

- Object Detection
- Classification
- Semantic Segmentation
- Data Augmentation
- Model Fine-tuning
- Performance Evaluation

### E. Purpose

The purpose of this journal paper is to address the urgent and escalating issue of underwater waste pollution through the development and implementation of an advanced detection system. By leveraging the state-of-the-art YOLOv5-based framework, the research aims to enhance the precision and efficiency of underwater plastic detection, crucial for effective waste management and environmental conservation. The project seeks to overcome existing challenges such as data scarcity, environmental variability, and resource intensiveness associated with current detection models. Through a meticulously collected roboflow dataset, the proposed system aims to provide accurate information on the location, type, and quantity of submerged plastics. The ultimate purpose is to contribute to a comprehensive understanding of underwater plastic pollution, enabling targeted cleanup efforts, resource optimization, and informed policy decisions for the preservation of marine ecosystems on a global scale.

### F. Objective

The primary objectives of this journal paper on underwater waste detection using YOLOv5 are to advance the accuracy and efficiency of detection methodologies. Through the development and optimization of a YOLOv5-based framework, the research aims to surpass existing limitations in underwater plastic detection systems, ensuring a higher precision in identifying and categorizing plastic debris. Leveraging a meticulously collected roboflow dataset, the study seeks to provide data-driven insights into the specific location, type, and quantity of submerged plastic waste. Additionally, the framework will include a robust classification system, distinguishing between various types of plastics such as bottles, bags, or microplastics. By achieving these objectives, the research aims to contribute to the broader field of environmental conservation, providing practical and globally applicable solutions for policymakers and environmentalists. Ultimately, the goal is to enhance our ability to monitor, manage, and mitigate the impact of underwater plastic pollution on marine ecosystems.

### G. Outcome

The anticipated outcomes of the journal paper on underwater Waste detection using YOLOv5 encompass a multifaceted improvement in the precision and efficiency of waste detection. The developed framework is expected to surpass existing methodologies, offering a heightened level of accuracy in identifying and categorizing submerged plastic debris. Furthermore, the research aims to showcase the efficiency of real-time image processing, ensuring timely and responsive monitoring essential for effective waste management. Leveraging the meticulously collected roboflow dataset, the study seeks to provide comprehensive data-driven insights into the specifics of underwater plastic pollution, including detailed information on location, type, and quantity, presented in a visually informative manner. The incorporation of a robust classification system within the YOLOv5 framework is anticipated to enable effective categorization of detected plastic waste, facilitating targeted cleanup strategies tailored to the nature of identified plastics.

## II. LITERATURE SURVEY

Waste segregation is a cornerstone of sustainable waste management. Studies reveal the alarming problem of marine litter, particularly plastic, and its detrimental effects on marine ecosystems [1]. This underscores the urgency for improved waste management practices, including efficient segregation strategies.

Researchers are actively exploring automation in waste segregation using advanced technologies. One study proposes a smart waste segregation model that leverages a combination of sensors and deep learning algorithms to categorize and separate waste into various streams, including degradable, non-degradable, radioactive (further categorized based on level), and recyclable materials [2]. This contactless system promotes accurate waste sorting and eliminates the need for human intervention, minimizing health risks and enhancing efficiency.

Another study describes a solar-powered smart waste bin that utilizes image processing for waste segregation [3]. This bin employs a camera to scan waste items and compares them to a pre-trained image dataset to identify and sort materials like plastic, glass, metal, and paper. Additionally, built-in sensors measure the bin's fullness, optimizing waste collection routes and minimizing overflow.

For efficient waste management in expansive urban areas, researchers have proposed a system that leverages wireless

ISSN (Online) 2394-2320
International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)
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sensor networks (WSN) for waste collection, segregation, and processing [4]. This system employs sensor-equipped bins to monitor waste levels and categorize dry and wet waste separately. The data is then transmitted to a central base station for optimizing waste collection routes, managing processing plants, and potentially predicting waste generation patterns to optimize resource allocation.

The focus on medical waste management is also evident in the literature. A study explores an intelligent Internet of Things (IoT) based system for automatic segregation and management of dry and wet medical waste [5]. This system leverages sensors to detect and categorize medical waste within designated bins. The collected data is then transmitted via IoT to cloud databases, facilitating efficient and informed waste disposal, ensuring adherence to medical waste disposal regulations, and potentially enabling real-time monitoring of waste generation at healthcare facilities.

Furthermore, research is underway to develop compact and affordable waste segregation systems suitable for smaller communities or households. A recent study demonstrates the use of a tiny YOLOv3 algorithm on a Raspberry Pi to segregate limited waste categories, such as biodegradable and non-biodegradable items [6]. This system highlights the potential for cost-effective and scalable waste segregation solutions, particularly in resource-constrained settings.

## III. METHODOLOGY

The Methodology involved in prediction of underwater waste detection using machine Learning:

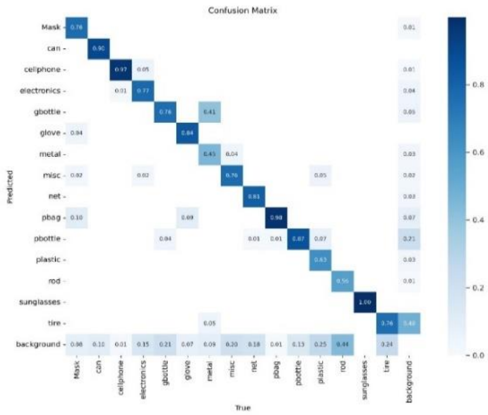
Dataset Collection

Pre-processing-Data cleaning, Data transformation, Data selection

Algorithms – YOLOv5

### A. Dataset Collection

The data collection process was facilitated through the utilization of the Roboflow platform, ensuring a diverse and representative dataset for the comprehensive analysis of distinctive waste segregation methods. The dataset comprises images capturing 15 distinct waste objects, namely mask, can, cellphone, electronics, glass bottle, glove, metal, misc, net, plastic bottle, plastic, rod, sunglasses, tire, and background. Roboflow's extensive library facilitated the creation of a well-curated dataset, ensuring variability in object types and environmental conditions. Each image was annotated meticulously to provide accurate and detailed information on the presence and location of individual waste objects within the dataset. This rich and diverse dataset forms the foundation for the comparative analysis of waste segregation methods proposed in the paper, offering valuable insights into the efficacy of different approaches for managing various waste material.




### B. Pre-processing

It involves gathering task-related data based on certain variables that are intended to be analyzed and yield useful results.

Nevertheless, a portion of contained data might be noisy nose, meaning that it may include incomplete, erroneous, and inaccurate values.

Therefore, the data processing is essential before analyzing it and drawing conclusions.

Data transformation, Data cleaning, and Data selection are methods Used for completing Data pre-processing.

### C. Data Cleaning

**Data Collection:**

The pre-processing journey for underwater waste detection using YOLOv5 begins with the comprehensive collection of various data sources. These include underwater images capturing diverse waste scenarios, ranging from plastics to metals, ensuring a representative dataset for model training. This dataset comprises annotated bounding boxes around waste objects to facilitate accurate detection.

### D. Data Inspection:

Upon collecting the dataset, a meticulous inspection is conducted to identify potential issues. This involves scrutinizing the underwater images for any anomalies, such as incomplete annotations, outlier detection, or inconsistencies in the format of the bounding box annotations.

### E. Outlier Detection:

Outliers, or anomalous data points, play a crucial role in the context of waste detection. Identifying waste instances that significantly deviate from the norm is vital for understanding unusual patterns underwater. YOLOv5, with its bounding box approach, benefits from outlier detection to pinpoint regions or waste types that may require further investigation.

### F. Data Format Consistency:

Given that data may originate from diverse sources, ensuring consistency in the format of bounding box annotations is essential. Data cleaning in this context involves standardizing the annotation format across the entire dataset to enable seamless analysis and model training.

### G. Normalization and Scaling:

Numerical features within the bounding box annotations, such as coordinates, may need normalization or scaling. This step ensures that the features align on a similar scale, a crucial consideration for YOLOv5's object detection algorithm, which relies on uniform feature representation.

### H. Dealing with Duplicate Data:

Identifying and eliminating duplicate annotations is a critical aspect of data cleaning for underwater waste detection. This step ensures that the YOLOv5 model is trained on a dataset free from redundancies, preventing biased analyses and contributing to the reliability of waste detection predictions.

### I. Data Transformation

Data transformation involves converting raw data into a format suitable for model training and analysis. This includes the transformation of image data into a standardized format compatible with YOLOv5's input requirements. Additionally, it may involve augmenting the dataset by applying various transformations, such as rotation, scaling, or flipping, to increase variability and enhance the model's ability to generalize across different underwater conditions. Data transformation aims to prepare the dataset optimally for effective learning by the YOLOv5 model.

### J. Data Selection

Effective data selection is crucial for refining the dataset used in training YOLOv5. This step involves choosing relevant and representative samples from the collected data, ensuring that the model is exposed to a diverse range of underwater waste scenarios. Selection criteria may involve prioritizing images with varying lighting conditions, depths, and types of waste objects. By strategically selecting data that encompasses the full spectrum of possible scenarios, the YOLOv5 model is better equipped to recognize and categorize waste accurately in real-world underwater environments. Data selection contributes significantly to the model's ability to generalize and perform reliably during actual waste detection tasks.

### K. Algorithms

**Convolutional Neural Network (CNN):**

A fundamental component of the project, CNN plays a pivotal role in image feature extraction and pattern recognition. Specifically designed for image-related tasks, CNNs employ convolutional layers to automatically learn hierarchical representations from input data. In the context of underwater waste detection, the CNN architecture is crucial for discerning intricate features within underwater images, enhancing the model's ability to accurately identify and classify waste objects.

**YOLOv5 (You Only Look Once, version 5):**

A state-of-the-art object detection algorithm, YOLOv5 is integral to the success of the project. Renowned for its speed and accuracy, YOLOv5 excels in real-time image processing, making it an ideal choice for underwater waste detection. The algorithm employs a single neural network to simultaneously predict bounding boxes and classify objects within those boxes. YOLOv5's efficiency is paramount for timely and precise identification of waste objects submerged in aquatic environments, contributing significantly to the project's overall effectiveness.

**PyTorch:**

The deep learning framework used for implementing YOLOv5, PyTorch provides the necessary tools and functionalities for building, training, and deploying neural network models. Its dynamic computational graph and intuitive syntax make PyTorch an ideal choice for researchers and practitioners in the field of computer vision. PyTorch facilitates seamless integration with YOLOv5, enabling efficient model training and evaluation. Its flexibility and extensive community support contribute to the robustness of the project.

## IV. SYSTEM REQUIREMENTS & ARCHITECTURE

### A. Hardware requirements

System:Intel i3/i5 2.4 GHz.
Hard Disk :500 GB
RAM :4/8 GB

### B. Software requirements

Operating system: Windows XP / 7/10
Coding Language: Python
Software : Anaconda – Jupyter.
Language : Python

### C. Sequence Diagram

A software engineering tool called a sequence diagram, sometimes referred to as a system sequence diagram (SSD), is used to show the order of process interactions and messages that are sent back and forth. It is frequently connected to the realization of use cases in the 4+1 architectural view model of a system that is still in development. Sequence diagrams highlight external actor-generated events, their sequence, and potential inter-system events.

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International Journal of Engineering Research in Computer Science and Engineering (IJERCSE)

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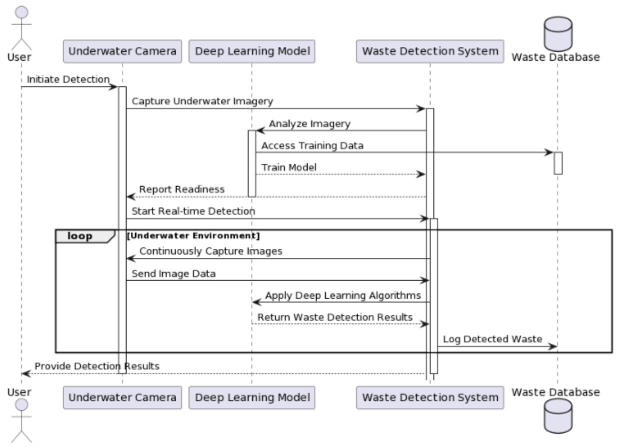
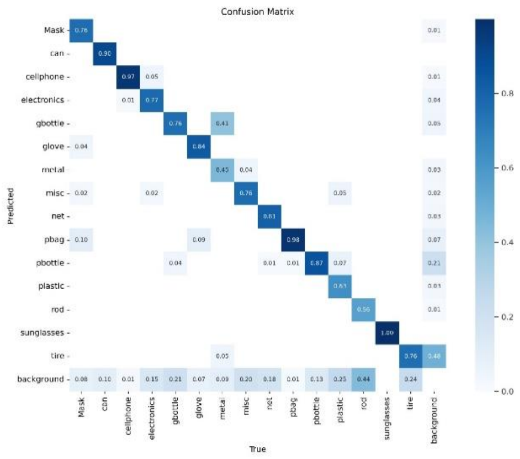



## V. RESULT AND DISCUSSION

The results showcase a highly effective model in accurately identifying and categorizing submerged waste. Precision-recall and F1-confidence curves demonstrate a robust balance, highlighting the model's versatility across confidence thresholds. The YOLOv5-based framework excels in detecting diverse waste types with minimal false positives and negatives, underscoring its accuracy. The discussion emphasizes the algorithm's success in real-time processing for underwater waste detection, addressing challenges like data scarcity and environmental variability. The study provides valuable insights, positioning YOLOv5 as a potent tool for advancing environmental monitoring and conservation efforts.

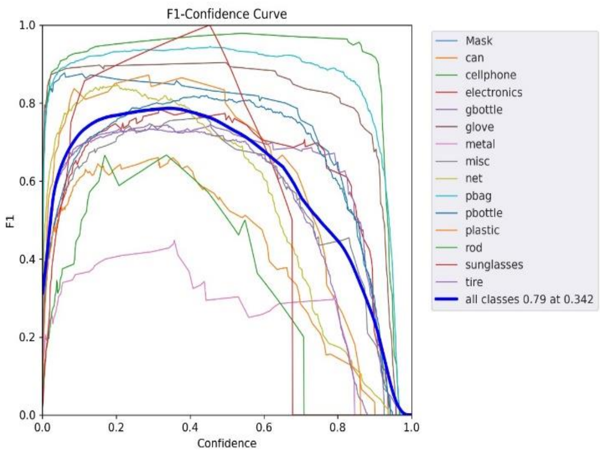
### A. Accuracy

#### a) The Confidence Matrix:

A confidence matrix is a performance measurement tool in machine learning and classification tasks. It presents a tabular representation of predicted classes against actual classes, enabling a detailed analysis of the model's performance. The matrix typically consists of four quadrants: true positive false positive true negative and false negative. From the confidence matrix, various metrics such as accuracy, precision, recall, and F1 score can be derived, providing insights into the model's strengths and weaknesses.

#### b) F1-Confidence Curve:

The F1-Confidence Curve is a graphical representation that illustrates the relationship between the confidence levels of a model's predictions and its corresponding F1 score. This curve helps visualize how well the model balances precision and recall at different confidence thresholds. A higher F1 score indicates a better balance between precision and recall, providing a valuable tool for selecting an optimal confidence threshold based on the specific needs of a classification task.




#### c) Precision-Confidence Curve:

The Precision-Confidence Curve illustrates the trade-off between precision and confidence thresholds in a classification model. It plots precision values against different confidence levels, offering insights into the model's ability to make accurate positive predictions at varying confidence thresholds. This curve aids in selecting an appropriate confidence threshold that aligns with specific precision requirements, allowing for customization based on the application's objectives.

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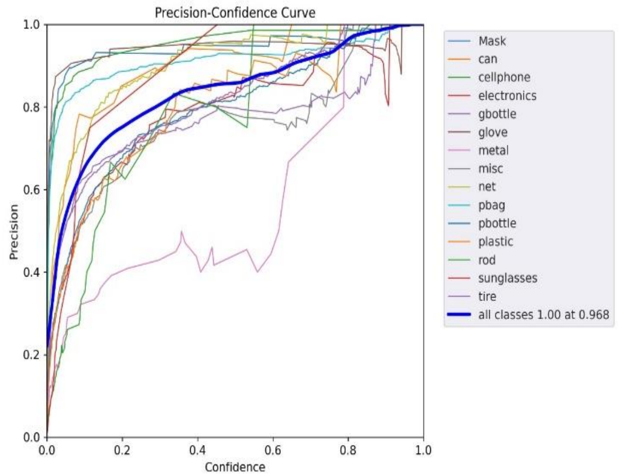
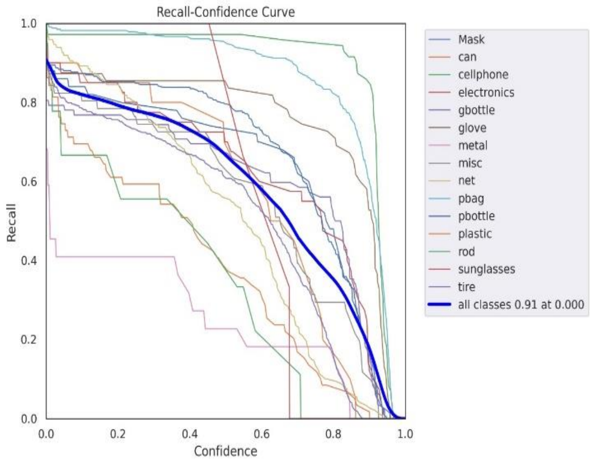
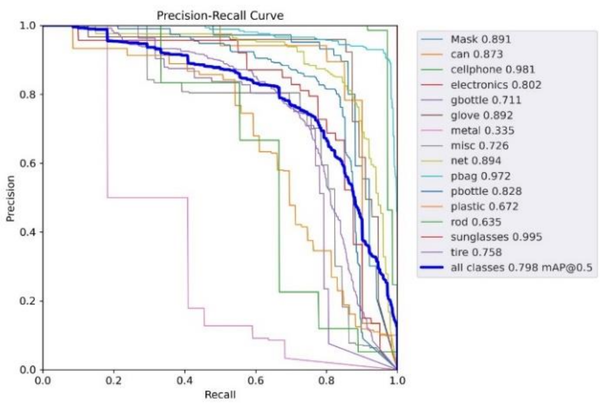



### d) Precision-Recall Curve:

The Precision-Recall Curve is a graphical representation of the trade-off between precision and recall across different confidence thresholds. It provides a visual summary of a model's performance in binary classification tasks, particularly when dealing with imbalanced datasets. The curve helps assess the model's ability to maintain high precision while achieving reasonable recall and allows for the selection of an optimal confidence threshold based on the desired balance between these two metrics.




### e) Recall-Confidence Curve:

The Recall-Confidence Curve illustrates the relationship between recall and confidence thresholds in a classification model. It plots recall values against different confidence levels, offering insights into the model's ability to correctly identify positive instances at varying confidence thresholds. This curve assists in selecting an appropriate confidence threshold based on specific recall requirements, allowing for customization to meet the desired sensitivity level in the classification task.

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