Smart Floating Waste Collector

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Abstract— Water pollution due to floating solid waste in rivers, lakes, and coastal areas has become a significant environmental concern. This paper presents an experimental smart floating waste collector that integrates deep learning–based object detection with an automated collection mechanism. A USB camera captures images of the water surface, which are processed using the YOLO (You Only Look Once) algorithm to detect waste materials such as plastic bottles, polythene bags, and aluminium cans. Upon detection, the output is transmitted to an Arduino Uno microcontroller, which activates a DC motor–driven conveyor system and a servo mechanism for waste collection. Additional sensors, including ultrasonic and inductive proximity sensors, enhance obstacle detection and system awareness. The system is powered by solar energy unit with a battery, enabling continuous operation in outdoor environments.

Experimental evaluation shows effective real-time detection and reliable mechanical operation. As a prototype model, the system demonstrates the feasibility of combining deep learning with automated waste collection for sustainable aquatic waste management.

Keywords— Deep Learning, YOLO, Object Detection, Floating Waste Detection, Arduino, Solar-Powered System, Computer Vision, Smart Waste Management

1. INTRODUCTION

Water pollution caused by floating debris has become a growing environmental concern in rivers, lakes, and coastal areas. Everyday items such as plastic bottles, polythene bags, and aluminum cans often accumulate on the surface of water bodies, affecting aquatic life and degrading the natural ecosystem. Conventional methods of cleaning these wastes usually involve manual labor or large mechanical equipment, which can be costly and inefficient. Because of these limitations, there is a growing need for intelligent and automated systems that can monitor and remove floating waste more effectively. In recent years, developments in deep learning and computer vision have made it possible for machines to detect objects in images with high accuracy and speed. One such approach is the YOLO. object detection algorithm, which can identify and locate objects in an image in real time using a single processing step [1]. Other single-stage detection models, such as SSD, have also demonstrated effective performance for real-time object detection tasks [2]. On the other hand, two-stage detection models like Faster R-CNN provide higher detection accuracy but generally require greater computational resources [3]. The success of these detection models is largely due to the advancement of deep convolutional neural networks (CNNs). CNN-based image classification techniques have achieved remarkable results on large image datasets such as ImageNet, forming the basis for many modern object detection methods [4]. Further studies in deep learning have shown that neural networks are capable of automatically learning hierarchical features from images, enabling them to recognize complex visual patterns and objects [7]. At the same time, the growth of Internet of Things (IoT) technologies has encouraged the development of smart environmental monitoring systems. IoT-based architectures enable the integration of sensors, data processing, and embedded control mechanisms for real-time monitoring in smart city environments [5], [6]. Researchers have also explored the use of deep learning models for environmental monitoring and real-time detection applications, demonstrating promising results in identifying objects in dynamic outdoor environments [8], [10]. In addition, several studies have proposed automated waste collection systems that use embedded controllers and sensors to improve waste management efficiency [9]. However, many existing systems either focus mainly on detection or on mechanical waste collection, with limited integration between intelligent vision systems and automated collection mechanisms. To address this limitation, this paper proposes a smart floating waste collector that integrates deep learning–based YOLO object detection with an Arduino-controlled mechanical collection system powered by solar energy. The proposed system detects floating waste using computer vision and automatically activates a motor-driven mechanism to collect the waste. The use of solar power enables the system to operate in outdoor water environments without relying on external electrical supply, making it suitable for sustainable environmental monitoring**.**

2. SYSTEM ARCHITECTUTE

The proposed smart floating waste collector integrates computer vision, embedded control, sensors, and solar power to detect and remove floating things from water. A USB camera is positioned above the water surface to capture real-time images of the surrounding area. These images are processed on a host computer using the YOLO deep learning model, which detects floating waste such as plastic bottles, polythene bags, and aluminium cans. Once waste is detected, the detection output is transmitted to an Arduino Uno microcontroller through serial communication. The Arduino acts as the control unit and activates the waste collection mechanism. A DC motor drives the conveyor system that gathers floating debris, while a servo motor controls the gate mechanism used to guide the collected waste into a storage container.

To enhance system functionality, ultrasonic sensors are used for obstacle detection and distance measurement, while an inductive proximity sensor identifies metallic

Fig.1 shows the system consists of a USB camera for image acquisition, a YOLO-based deep learning model for waste detection, and an Arduino Uno for control. Based on detection results, the Arduino activates the motor-driven waste collection mechanism. Sensors assist in obstacle detection, while a solar power unit provides energy for continuous operation.

3. HARDWARE COMPONENTS

The proposed smart floating waste collector integrates multiple hardware components that work together to detect and collect floating waste from the water surface. These components include a camera for image acquisition, a microcontroller for system control, motors for mechanical actuation, sensors for environmental awareness, and a solar power unit for energy supply.

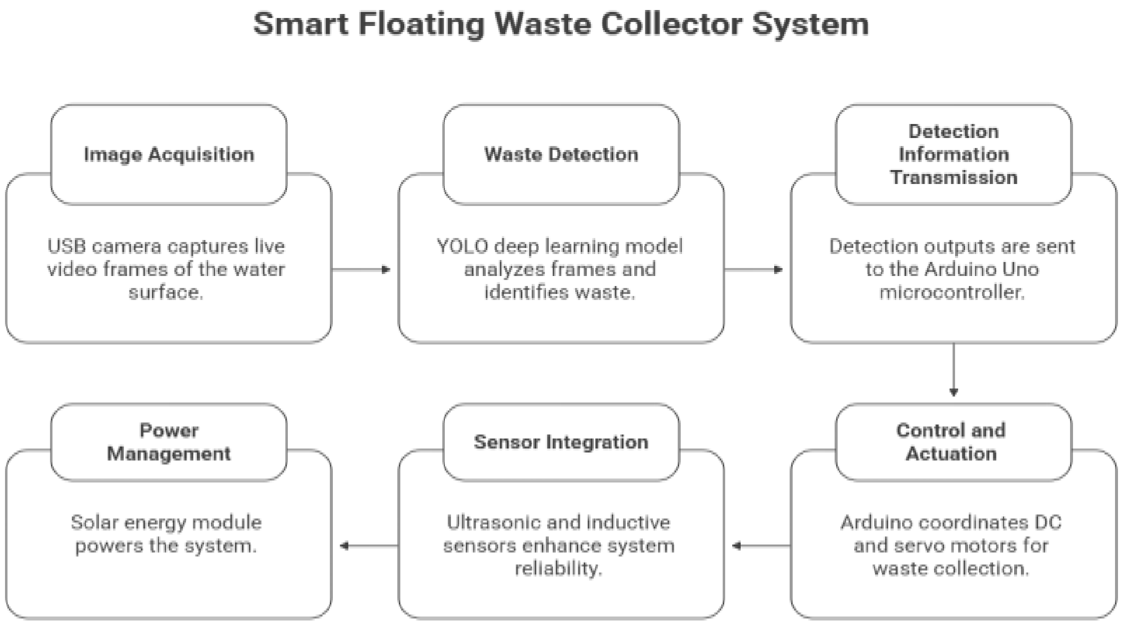

Fig.1. System architecture of floating waste collector.

A) USB Camera: A USB camera is used to capture real-time images other water surface. It continuously monitors the surrounding area and sends image frames to the host computer for processing. These frames are analyzed using the YOLO deep learning model to detect floating waste such as plastic bottles, polythene bags, and aluminum cans.

B) Arduino UNO: The Arduino Uno works as main control unit of the prototype. It receives detection signals from the host computer through serial communication and controls the operation of the motors and sensors. Based on the detection output, the Arduino activates the mechanical waste collection mechanism.

DC Motor: A DC motor is used to drive the conveyor mechanism responsible for collecting floating waste from the water surface. When the Arduino receives a detection signal, the DC motor is activated to move the conveyor and gather the detected debris.

E) Servo Motor: A servo motor is used to control the directional movement of the waste collection mechanism. It operates a gate or guiding structure that directs the collected waste into a storage container.

F) Ultrasonic Sensor: Ultrasonic sensors are integrated into the system to measure the distance between the device and surrounding objects. These sensors help detect obstacles in the operating area and improve the safety and reliability of the system.

G) Inductive Proximity Sensor: An inductive proximity sensor is used for detecting metal objects among the floating debris. This allows the system to identify waste materials such as aluminum cans that may not always be easily recognized visually.

H) Solar Panel and Rechargeable Battery: To support outdoor deployment, the system is powered using a solar panel connected to a battery. The solar panel converts sunrays into electrical energy, which is stored in the battery and used to power the Arduino, sensors, and motor-driven mechanisms. This renewable source enables the system to operate independently without requiring external electrical connections.

4. DEEP LEARNING – WASTE DETECTION

Deep learning has become a powerful approach for image recognition and object detection tasks. In this work, a deep learning–based detection model is used to identify floating waste materials on the water surface. The proposed system utilizes the YOLO algorithm due to its ability to perform fast and accurate object detection in real-time environments.

YOLO is a single-stage object detection framework that processes the entire image in one pass through a convolutional neural network (CNN). Instead of analysing different parts of image separately, the model predict object locations and class labels simultaneously. This approach significantly reduces processing time and makes YOLO suitable for real-time monitoring applications.

In the proposed system, the YOLO model analyses frames captured by the USB camera and detects floating waste objects such as plastic bottles, polythene bags, and aluminium cans. For each detected object, the model generates a bounding boxes, which represents the location of the object in the image, along with a class label indicating the type of waste.

The trained detection model runs on a host computer that processes the incoming camera frames. When floating waste is detected, the system generates a detection output that includes object location and classification information. This detection result is then transmitted to the Arduino microcontroller, which activates the waste collection mechanism.

By combining deep learning–based visual recognition with an embedded control system, the proposed approach enables automated detection and collection of floating waste in real-time environments.

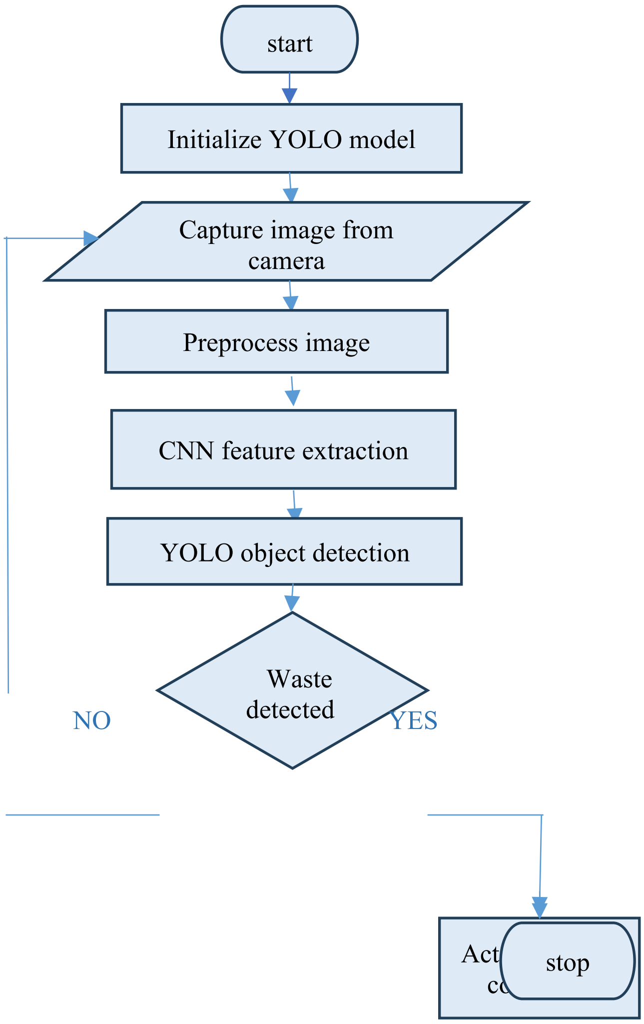

Fig. 2. Flowchart of deep learning–based waste detection process.

Fig.2 shows the process begins with capturing images from the camera, followed by preprocessing and feature extraction using a convolutional neural network. The YOLO model then detects waste objects and generates bounding boxes and class labels. If waste is detected, a control signal is sent to the Arduino to activate the collection mechanism.

This training involves feeding labeled images into the model, where the network learns to associate visual features with specific waste categories. During training, the model optimizes its parameters by minimizing loss functions related to bounding box accuracy and classification. Data augmentation techniques such as image flipping, scaling, and brightness adjustment can be used to improve model robustness. This training process enables the model to perform accurate and efficient detection in real-world environments.

5. SYSTEM IMPLEMENTATION AND RESULTS

System performance can also be affected by the environmental conditions like water currents, humidity and floating debris. Reflections of water can cause sensors to give inaccurate readings and mechanical parts can wear and tear as time goes. Electronic components will have to be waterproofed and insulated to avoid damage and provide long life. Also, the coordinate between the detection system and hardware reaction should be thoroughly sustained to prevent the delays in collecting wastes. These challenges notwithstanding, the effective system design, testing and optimization guarantee smooth and stable work under the real-life conditions.

The developed prototype integrates computer vision, embedded control, and a mechanical collection unit to create an automated floating waste removal system. The system consists of a USB camera for image acquisition, a host computer running the YOLO object detection model, and an Arduino Uno microcontroller for controlling the mechanical components.

Real-time images of the water surface are captured using the USB camera and transmitted to the host system. These images has processed by a trained YOLO model, which detects floating debris such as plastic bottles, polythene bags, and aluminium cans by generating bounding boxes and class labels. Based on the results, control signals are sent to the Arduino, which activates the DC motor–driven conveyor and servo mechanism for waste collection.

To enable continuous outdoor operation, the system is powered by a solar connected to a rechargeable battery, for energy-efficient and autonomous functioning in remote environments.

Experimental testing of the prototype demonstrates effective real-time detection and collection of floating waste. The model shows consistent reduction in training and validation Average Precision (mAP), indicating reliable detection performance. The coordination between the detection module and the control system enables smooth and timely operation of the collection mechanism.

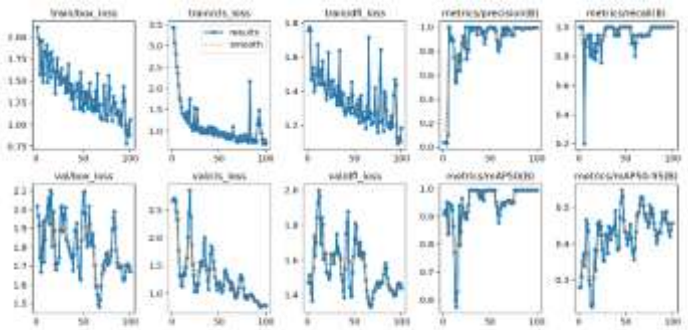

Fig. 4. YOLO model training performance

From Fig.4 it explains about each and every graph and its performance like:

Training Graphs -

1. train/box_loss:
   Shows the reduction in bounding box prediction error, indicating improved object localization.

2. train/cls_loss:
   Represents classification error, which decreases as the model learns to correctly identify waste types.

3. train/dfl_loss:
   Indicates improvement in fine-grained object detection accuracy over training.

Precision and Recall –

1. metrics/precision(B):
   Precision increases over epochs, showing that the model makes fewer false detections.

2. metrics/recall(B):
   Recall improves, indicating that the model detects more actual waste objects correctly.

Validation Graphs -

1. val/box_loss:
   Shows bounding box error on unseen data, indicating generalization performance.

2. val/cls_loss:
   Represents classification performance on validation data, improving over time.

3. val/dfl_loss:
   Indicates stable detection performance on validation dataset.

Accuracy Metrics -

1. metrics/mAP50(B):
   Shows high detection accuracy at IoU 0.5, indicating strong overall performance.

2. metrics/mAP50-95(B):
   Represents stricter accuracy across multiple IoU

thresholds, showing moderate but consistent performance.

Fig. 5. Sample output of the proposed YOLO-based system detecting a floating plastic bottle with bounding box and class label.

The Fig.5 illustrates a sample detection result obtained from the proposed system. The YOLO model successfully identifies a floating plastic bottle in real-time and highlights it using a bounding box along with the corresponding class label.

The model demonstrates stable convergence as observed from the smooth decrease in loss curves and consistent improvement in performance metrics. The high precision indicates fewer false detections, while improved recall ensures most waste objects are detected. These characteristics are essential for real-time environmental monitoring applications.

The system has tested under different conditions to evaluate its performance. The model was able to detect multiple objects simultaneously and maintain consistent detection accuracy. The integration between the detection module and the control system ensured timely activation of the waste collection mechanism. The solar power system provided stable energy supply during operation, demonstrating the feasibility of long-term deployment in outdoor environments.

6. CONCLUSION

This paper presented a smart floating waste collector that integrates deep learning–based object detection with an automated waste collection mechanism. The system uses a USB camera and the YOLO algorithm to identify floating waste in real time, while an Arduino-based control unit activates the conveyor and collection mechanism. Additional sensors improve obstacle detection and system awareness. The usage of solar energy allow the system to operate in thr outdoor environments without relying on external power sources. Experimental testing shows that the proposed system can effectively detect and collect floating waste. Overall, the approach offers a practical and sustainable solution for improving water pollution management.

7. FUTURE SCOPE

Although the developed prototype demonstrates effective detection and collection of floating waste, several improvements can further enhance the system. Future work may focus on expanding the training sets so that the deep learning model can recognize a wider variety of waste materials under different environmental conditions. The detection model can also be deployed on embedded edge devices, allowing the system to operate independently without requiring a host computer. Improvements in the mechanical design of the collection mechanism could increase the efficiency and capacity of waste collection. In addition, integrating IoT communication modules and GPS tracking can enable real-time monitoring of the system's location and operational status. Such enhancements would make the system more suitable in large-scale deployment in rivers, lakes, and coastal areas.

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