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Water Guardian : Intelligent Underwater Waste Detection

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***Abstract*—Underwater waste is a serious problem caused by human activities like fishing, shipping, tourism and dumping of garbage and plastics into rivers and oceans. Detecting underwater waste is difficult because of low visibility and deep or hidden locations. Unmanned Underwater Vehicles (UUVs) are cost-effective solutions for undersea monitoring but face significant challenges due to visual distortions caused by light absorption and scattering as well as limited onboard power resources.**

To overcome these issues, an intelligent two-stage framework has been developed that first employs an efficient deep learning model for detecting underwater objects and regions of interest (ROIs) such as fish, divers and submarines. The detected ROIs are then processed through an advanced image restoration algorithm that enhances visual quality supporting more reliable navigation and monitoring for resource-constrained UUVs.

Building upon this foundation, the proposed system extends its capabilities by incorporating an underwater waste detection module designed to identify and classify non-biodegradable waste materials such as plastic bottles, tyres, face masks, gloves and selected categories of electronic waste (E-waste) including mobile adapters, mouse, keyboard, smartphones and TV remotes. The system supports image and video uploads as well as real-time inputs and integrates underwater image preprocessing techniques with specialized object detection algorithms to enable accurate recognition of waste objects, thereby enhancing underwater environmental monitoring and contributing to marine ecosystem protection. This integrated framework allows consistent detection performance across different input formats while maintaining reliable identification of non-biodegradable waste materials. As a result, the system provides a comprehensive solution for continuous and effective underwater waste monitoring.

***Index Terms*—— Underwater Trash, Waste Detection, Machine learning, E-waste, Image Processing.**

I. Introduction

Marine and underwater ecosystems are important for maintaining ecological balance and supporting life on Earth. However increasing industrial growth urbanization and human activities have led to a significant rise in underwater pollution. Large amounts of waste enter oceans rivers and coastal areas due to improper waste disposal and poor waste management. This underwater debris reduces water quality harms marine life and disturbs aquatic ecosystems. Traditional monitoring methods rely on divers and manual inspection which are time-consuming expensive and sometimes unsafe. Therefore there is a need for automated systems that can efficiently detect underwater waste.

Underwater waste includes materials such as plastic bottles fishing gear tyres masks gloves and other non-biodegradable items. These materials remain in water for long periods because they decompose very slowly. They can harm marine animals through ingestion or entanglement and may also damage underwater habitats. Plastic waste can break down into microplastics that enter the food chain and cause environmental and health problems. Detecting such waste is challenging because underwater images often suffer from low visibility color distortion and complex backgrounds.

Recent research in underwater computer vision mainly focuses on detecting marine animals divers or general trash. However less attention has been given to detecting underwater electronic waste. Items such as mobile phones keyboards remote controls and adapters contain harmful chemicals and heavy metals that can leak into water and damage marine ecosystems. The lack of systems designed specifically to detect underwater e-waste creates an important research gap.

To address this issue this study proposes an AI-based underwater waste detection system with a focus on identifying electronic waste. The system can detect different types of underwater waste such as plastic bottles tyres masks gloves and e-waste items like mobile phones keyboards adapters and remotes. Using deep learning–based object detection the system can work with both real-time camera input and stored images or videos. It can also integrate location tracking to record where waste is found helping environmental teams plan efficient cleanup activities. Overall the proposed system supports better underwater monitoring and contributes to reducing marine pollution.

A. Problem Statement

The rapid accumulation of debris in underwater environments has become a growing environmental challenge yet reliable detection and monitoring of submerged waste continue to be difficult. A considerable portion of discarded materials, including plastic bottles, tyres, face masks, gloves and electronic components, eventually sinks beneath the water surface where detection becomes difficult due to poor illumination, light absorption and visually complex underwater surroundings. Traditional monitoring approaches, such as diver-based inspections and sonar surveys are expensive, time-intensive, restricted in spatial coverage and often insufficient for distinguishing between different categories of waste materials.

Current underwater object detection research has largely emphasized the identification of marine organisms, divers, underwater vehicles or generic debris while limited attention has been directed toward detecting underwater electronic waste. Items such as discarded mobile phones, keyboards, mobile adapters and remote control devices are increasingly present in aquatic environments as a result of improper disposal or accidental loss. These electronic materials often contain hazardous substances that gradually contaminate water bodies, posing long-term ecological risks to marine habitats. Despite this growing concern, existing detection frameworks lack dedicated datasets and specialized models for reliable underwater e-waste identification.

In addition, underwater image acquisition is inherently affected by factors including color attenuation, scattering effects, low contrast and background interference, which significantly reduce detection performance when conventional vision models trained on terrestrial imagery are applied directly. The absence of an integrated automated framework capable of simultaneously detecting multiple underwater waste categories particularly electronic waste, restricts effective monitoring and limits targeted cleanup operations.

II. LITERATURE SURVEY

A literature review helps in understanding existing research by analyzing previously published studies. It summarizes current knowledge evaluates different research methods and identifies areas that need further study. By reviewing earlier work researchers can avoid repeating the same efforts and find new opportunities for improvement. In underwater waste detection many studies have explored methods to monitor aquatic environments and detect pollution using image processing and intelligent systems.

For the Water Guardian system reviewing previous research provides a strong foundation for system development and helps identify existing challenges. Detecting underwater waste is difficult due to problems such as water turbidity poor lighting and the presence of natural underwater objects which can reduce detection accuracy. Therefore more robust detection techniques are needed to work effectively under different underwater conditions.

A. Intelligent Underwater Object Detection and Image Restoration for Autonomous Underwater Vehicles

Underwater monitoring using Unmanned Autonomous Underwater Vehicles (UUVs or AUVs) is difficult because underwater images often have low contrast color distortion haze and blur caused by light absorption and scattering. These problems reduce object visibility and make navigation and object detection challenging especially because underwater vehicles have limited power and processing capability. To address this issue the system combines deep learning based object detection with underwater image restoration so that important objects can be detected clearly while reducing computational load [2][6].

The system works in two stages. In the first stage underwater images captured by cameras on the vehicles are processed using a deep learning object detection model such as YOLO. The model scans the image and identifies important objects like fish divers submarines or waste materials. Instead of processing the entire image the system extracts only the Region of Interest (ROI) where objects are detected which removes unnecessary background information and reduces memory usage and processing time [9][10][12].

The system can detect underwater objects such as fish divers submarines and other targets even when images are unclear due to light absorption and scattering. The image restoration stage improves contrast sharpness brightness and color balance which makes underwater scenes clearer and easier to analyze. The results show that the restored images maintain important details without producing unnatural colors or excessive brightness [3][4]. Another advantage of the system is reduced processing time because it analyzes only the Region of Interest (ROI) instead of the entire image. This reduces computational load storage and energy usage. As a result the system is suitable for real time use in autonomous underwater vehicles which have limited power and processing capacity. Faster processing also helps vehicles make quick navigation decisions detect objects efficiently and perform monitoring tasks more effectively [2][10][11] .

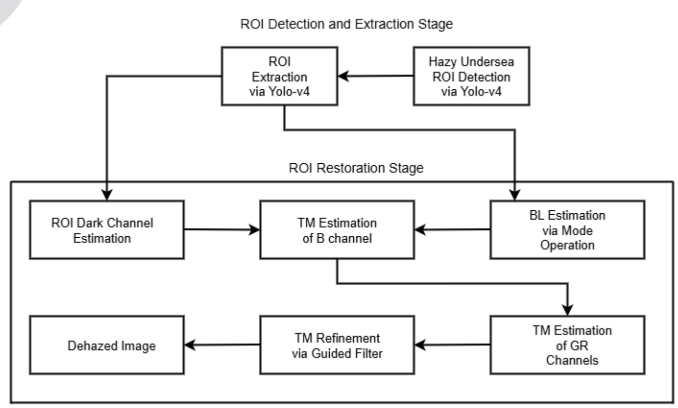

Fig. 1. General process flow of method

Artificial intelligence has improved the way visual data is analyzed. Deep learning is widely used in computer vision because it can automatically learn patterns from large datasets. These models use neural networks to learn features from images and videos, starting with simple patterns such as edges and textures and later identifying complex objects. This ability helps models work effectively in different environments.

To address this issue, this work proposes a deep learn- ing–based underwater waste detection system. The system uses convolutional neural networks to detect and classify marine debris from underwater images. It is designed to work in difficult conditions such as low visibility, color distortion and image noise, allowing real-time detection and monitoring of underwater waste.

The system processes images captured by an autonomous underwater vehicle. First, the images are resized to 416 × 416 pixels and augmented to simulate underwater conditions like lighting changes and water turbidity. This improves the model's ability to handle different environments.

The processed images are then analyzed using object detection models. Single-stage YOLO models such as YOLOv5, YOLOv6, YOLOv7 and YOLOv8 are used for fast real-time detection. Two-stage models like Faster R-CNN and Mask R-CNN are also used to improve detection accuracy, with Mask R-CNN providing object segmentation.

B. Deep Learning Approaches for Underwater Waste Detection

Deep learning is a branch of artificial intelligence that uses multilayer neural networks to learn features directly from images. Unlike traditional methods that require manual feature design, deep learning automatically learns patterns from simple features like edges to complex objects, which improves performance on different datasets [9][12].

Underwater debris is a serious environmental issue caused by pollution and poor waste management. It harms aquatic life and damages marine ecosystems. Detecting waste underwater is difficult due to low visibility and challenging conditions. This work proposes a deep learning based underwater waste detection system using Convolutional Neural Networks (CNN) [5]. The system detects and classifies marine debris such as plastics and metals, helping in real time monitoring and environmental protection [5][8][9].

A custom dataset of about 10,000 underwater images was created from sources such as Autonomous Underwater Vehicles (AUVs), Remotely Operated Vehicles (ROVs) and online marine repositories [6]. The images represent different underwater conditions. Each image was annotated with bounding boxes and labeled into categories such as underwater trash, rover and biological life [8][9].The dataset was divided into training (70%), validation (20%) and testing (10%). Data augmentation techniques like rotation, flipping, scaling and brightness adjustment were used to improve the model's performance [2][10].

TABLE I
COMPARISON OF CLASSES PRESENT IN DIFFERENT DATASETS

Dataset	Classes	Bio	Paper Glass	Metal Plastic	Others	Unknown	Images
Trash ICRA 19	3	1966	0	5051	0	0	6148
TrashCan 1.0	3	1009	0	2163	0	180	7212
TrashNet	6	0	1300	0	0	0	2527
Google search	1001	92	250	0	0	366	1320
Extended TACO	28	70	1190	6060	2800	150	1500
Drinking waste	4	0	1160	3600	0	0	9640
Classify waste	3	160	3900	9660	2800	520	27500

C. E-Waste Management Challenges in India From the Perspective of Producer Responsibility Organizations

Electronic waste (e-waste) is one of the fastest growing waste streams in the world because of rapid technological development, short product life cycles and increasing use of electronic devices. Improper disposal of e-waste can cause serious environmental and health problems since it contains harmful materials such as lead mercury and arsenic. At the same time valuable metals like gold and copper are often lost when recycling is not properly managed [1][7].

In India e-waste management is challenging due to low public awareness the dominance of informal recycling sectors and limited collection and treatment facilities. To address this issue the government introduced Extended Producer Responsibility (EPR) which makes manufacturers responsible for managing end of life electronic products. Producer Responsibility Organizations (PROs) were created to help producers collect and process e-waste. However PROs still face several operational and coordination challenges [8].

To study these issues researchers reviewed 131 research articles and selected 63 relevant studies. Experts from four PRO organizations were also consulted and nine major challenges were identified. These challenges occur at different stages of the e-waste management process such as collection transportation segregation dismantling recycling and disposal. The study found that waste segregation is the most critical challenge because mixed electronic waste is difficult and expensive to separate. Other important problems include lack of collection centers and transportation limited recycling technology poor knowledge sharing weak collaboration among stakeholders and high operational costs. The study suggests improving cooperation among stakeholders promoting eco friendly product design using tracking technologies and providing better policy and financial support to improve e-waste management [1][2][8].

III. METHODOLOGY

The proposed Underwater AI Waste Detection System follows a structured and systematic pipeline comprising dataset creation, preprocessing, model training, real time deployment and communication architecture design. The methodology is formulated to ensure reliable detection of underwater waste objects under practical operational constraints, particularly limited wireless communication capability in underwater environments. This approach improves detection efficiency and enables effective monitoring of underwater pollution in real-world conditions.

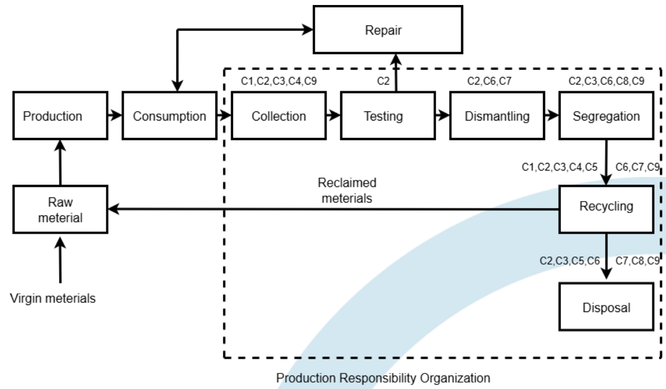

Fig. 2. Mapping challenges in the E-waste management process

A. Underwater Dataset Creation

A custom underwater dataset was developed using an underwater camera system to capture realistic waste disposal scenarios typically observed in aquatic environments. Various commonly encountered waste materials such as surgical masks, gloves, mobile adapters, mobile phones, keyboards and related debris were intentionally introduced into underwater scenes to create representative training samples.

Data collection was conducted across diverse environmental conditions in order to simulate real-world underwater variability. Images and video frames were captured under different lighting conditions, water clarity levels and scene compositions. Recordings were taken from multiple viewpoints and distances to capture objects at different scales and perspectives, thereby improving dataset diversity.

Special attention was given to incorporating natural underwater challenges such as water turbidity, illumination changes, object orientation differences, partial occlusions caused by sediments or aquatic plants, and cluttered backgrounds. These variations are essential to enable the detection model to generalize effectively and maintain detection accuracy in practical deployment conditions where environmental factors are unpredictable.

B. Data Preprocessing and Annotation

Before initiating model training, the collected dataset underwent several preprocessing operations to ensure quality, consistency and suitability for deep learning training requirements.

All waste objects present in the collected images were manually annotated using the LabelImg annotation tool. Bounding boxes were drawn precisely around each visible waste object and the annotations were saved in YOLO format to ensure compatibility with the training framework. Careful annotation ensures accurate object localization during model learning.

To maintain uniform input dimensions and stabilize training performance, all images were resized to a consistent resolution using IrfanView. Standardizing image resolution also reduces computational requirements during training while ensuring efficient memory usage on GPU hardware.

Dataset cleaning procedures were also performed to remove duplicate images, severely blurred frames and samples with extremely poor lighting conditions that could negatively influence model convergence.

C. Model Training Using YOLOv11

After preprocessing, the dataset was organized into a YOLO-compatible directory structure containing separate training and validation subsets. Class configuration files were created to include all underwater waste categories considered in the study, enabling the detection model to recognize multiple object classes.

Model training was conducted in a GPU-enabled computing environment to accelerate training iterations and reduce overall training time. During the training process, key performance metrics such as loss values and validation accuracy were continuously monitored to detect potential overfitting or instability in model convergence.

Hyperparameters and training parameters were tuned to achieve balanced performance between detection accuracy and generalization capability. The final trained model weights were selected based on validation performance to ensure reliable detection performance on previously unseen underwater scenes.

D. Deployment in Real-Time Detection Application

Following training, the optimized YOLOv11 detection model was integrated into a real-time detection application capable of running on both mobile and desktop platforms.

The deployed application processes live video streams obtained from an underwater camera system. Each captured video frame is passed through the trained detection model, which identifies waste objects and displays bounding boxes along with corresponding class labels in real time.

This immediate visual feedback allows operators or monitoring systems to identify underwater waste objects instantly, facilitating rapid decision-making and enabling real-time monitoring of polluted underwater environments.

E. Communication Architecture for Underwater Operation

Wireless communication is highly unreliable underwater due to rapid signal attenuation, making direct wireless data transmission impractical for long-distance underwater monitoring. To overcome this limitation, a surface-assisted communication architecture was designed.

A floating surface unit positioned above the water surface houses processing hardware and a Wi-Fi transmission module. The underwater camera is connected to this floating unit through a wired communication link, ensuring stable and high-quality data transfer without signal degradation.

Captured underwater video is first transmitted via the wired connection to the surface unit, where data processing and forwarding occur. The surface unit then transmits the video feed wirelessly using Wi-Fi to the monitoring application, enabling real-time observation and detection without communication interruptions.

This architecture ensures reliable data flow while maintaining practical deployment feasibility in real-world underwater environments.

F. System Outcome

The developed system successfully performs real-time underwater waste detection using a custom-trained YOLOv11 model integrated with live camera input. By combining carefully designed dataset creation, systematic preprocessing, deep learning-based object detection and a surface-assisted communication infrastructure, the methodology provides a practical and deployable solution for underwater debris monitoring.

The integrated pipeline ensures accurate detection, stable data transmission and real-time operational capability, making the system suitable for environmental monitoring, pollution assessment and cleanup support activities. The methodology demonstrates the feasibility of deploying AI-based underwater monitoring systems in real operational environments for effective identification and management of underwater waste.

IV. PROPOSED SYSTEM

The proposed framework, Water Guardian: Intelligent Underwater Waste Detection, introduces an automated solution for identifying and monitoring waste materials present in underwater environments. The system employs modern deep learning–based object detection techniques to recognize submerged waste items such as plastic bottles, tyres, masks, gloves, and selected electronic waste materials. The goal of the system is to minimize manual inspection efforts, enhance monitoring efficiency, and support faster cleanup operations to preserve marine ecosystems. The overall functioning of the system is organized into several major components.

A. Image Acquisition and Preprocessing

The system first gathers underwater visual data in the form of images or video frames captured using underwater cameras, remotely operated vehicles, or publicly available marine datasets. Underwater imagery typically suffers from challenges such as color distortion, scattering effects, noise and low contrast due to light absorption in water.

To address these issues, preprocessing operations are applied before performing detection. Input images are resized to match the resolution required by the YOLOv11 detection model to ensure consistent processing. Pixel normalization is applied to stabilize training and improve detection performance. Additional enhancement and noise reduction techniques are used to improve visibility, enabling the model to capture meaningful features even in low-quality underwater scenes.

B. Deep Learning–Based Waste Detection

Waste identification in the proposed system is carried out using the YOLOv11 object detection network, which is selected because it provides a good balance between high detection accuracy and fast processing speed. YOLO (You Only Look Once) performs object detection by analyzing the entire image in a single pass, making it highly efficient compared to traditional multi-stage detection methods. This capability makes the model well suited for applications that require near real-time detection, such as underwater monitoring and robotic inspection systems.

Once trained, the YOLOv11 model can process incoming frames from underwater cameras and quickly detect the presence of waste objects. This enables reliable monitoring of underwater environments and supports automated systems designed for environmental observation and pollution management.

C. Waste Classification

After detection, identified objects are categorized into predefined waste groups. Common underwater pollutants such as bottles, tyres, masks, and gloves are recognized, along with finer classification of electronic waste components such as mobile phones, adapters, keyboards, computer mice, and remote controls. Such classification assists in understanding pollution patterns and supports decision-making processes for targeted cleanup operations.

D. Localization and Visualization

For each detected object, the system generates bounding boxes and assigns corresponding class labels with associated confidence scores. These results are overlaid on images or video frames to visually indicate waste presence and location. The framework can also incorporate GPS information from supporting surface systems to help map waste distribution zones, thereby assisting authorities in organizing efficient cleanup missions.

E. Real-Time and Offline Analysis

The detection framework operates in both real-time and offline modes. Live underwater video feeds can be analyzed continuously, while previously captured data can also be processed for post-mission evaluation. This dual operational capability enables both continuous environmental monitoring and later analysis, significantly reducing manual labor while improving detection consistency and reliability.

F. Location Tracking

Beyond detecting waste, the system also records the geographical position of detected objects, enabling effective planning of cleanup activities. When waste items are identified from live camera feeds or uploaded visual data, the corresponding location details are stored and presented. This functionality allows cleanup teams to directly target polluted zones instead of manually searching large underwater regions. The architecture of the system outlines the workflow followed in underwater waste monitoring. Initially, underwater visual datasets containing waste objects are collected and annotated with bounding boxes and labels. The dataset is then divided into training and testing subsets. The training data is used to train the YOLO detection network composed of backbone, neck, and head components responsible for feature extraction, fusion, and object prediction.

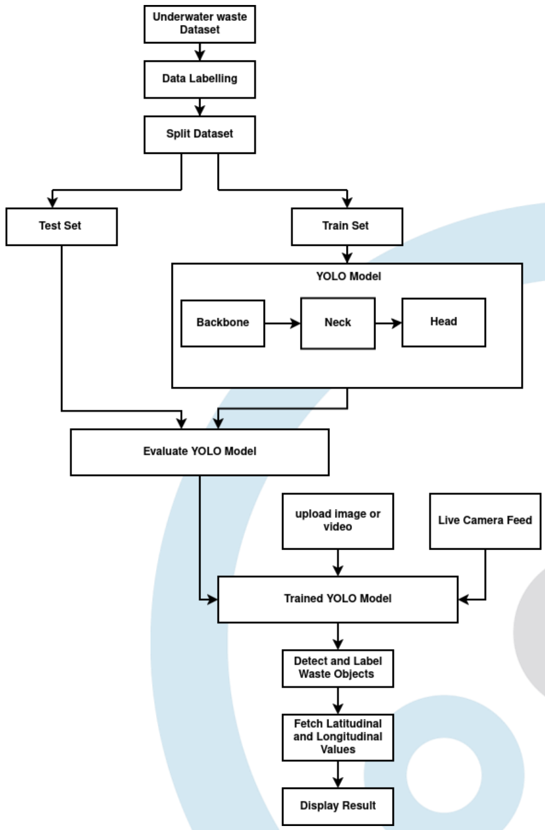

Fig. 3. Architecture Diagram

V. RESULT

The project results show that the proposed Underwater Waste Detection System can effectively detect and classify different types of underwater waste from both real-time camera input and stored images. The system is capable of identifying several common waste materials found in aquatic environments such as plastic bottles, gloves, masks and tyres. In addition to these general waste items, the system can also detect electronic waste objects including mobile phones, mobile adapters, keyboards, mouse and remote devices. This ability to recognize multiple categories of waste helps in monitoring and analyzing underwater pollution more efficiently.

For every detected object, the system provides a confidence score which represents the reliability of the prediction made by the model. A higher confidence score indicates that the model is more certain about the detected object and its classification. This helps users evaluate the accuracy of the detection results and ensures that the system provides dependable information during monitoring.By displaying these scores along with the detected objects, the system allows users to easily evaluate the reliability of each detection and make better decisions during underwater monitoring and analysis.

Each waste item in the dataset is carefully annotated using bounding boxes that mark the exact location of the object within the image. These bounding boxes help the detection model learn where objects appear in the scene and allow the system to highlight detected waste clearly during prediction.

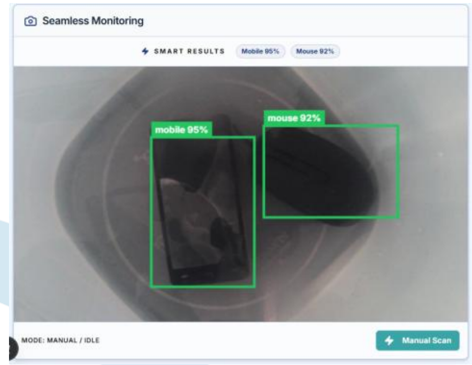

Fig. 4. Mobile and Mouse

This image presents the manual scan result of the monitoring system. When the user triggers a manual scan, the system processes the captured image and detects objects such as a mobile phone and mouse with high confidence levels.

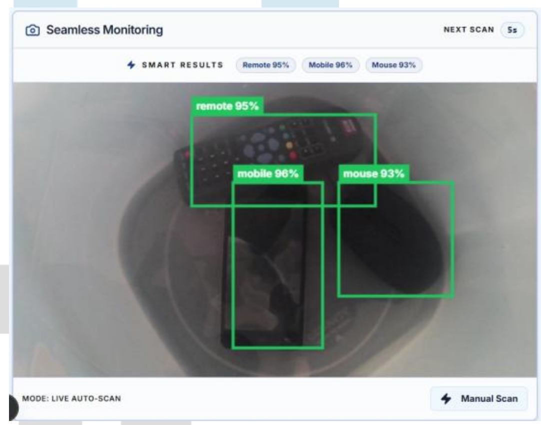

Fig. 5. Remote, Mobile and Mouse

This image demonstrates the live monitoring interface where the system automatically scans and detects multiple electronic waste objects in real time.

Fig. 6. Live Location of detected underwater waste

This image shows the GPS Heatmap interface used to visualize the location where electronic waste is detected. The system records the geographic coordinates of the detection and marks the position on the map using a red indicator.

A. Model Training Performance

The underwater waste detection model was trained using the YOLOv11 architecture on a custom underwater dataset created for this project. The dataset included different types of waste such as plastic bottles, gloves, keyboards, surgical masks, mobile phones, chargers, mouse, remotes and tyres, which represent common waste found in marine environments. The trained model contains 126 layers and about 2,036,971 parameters, allowing efficient object detection while keeping the model relatively lightweight. The model was evaluated using a validation dataset of 161 images with 166 labeled objects, which helped test its performance on different underwater scenes and object variations.

B. Overall Model Performance

The overall evaluation results show that the model has strong detection performance. It achieved a precision of 0.951, recall of 0.944, mAP@0.50 of 0.964, and mAP@0.50–0.95 of 0.841. The high precision indicates that most predicted objects are correct with very few false detections, while the recall shows that the model can detect most objects present in the images. The high mAP scores also confirm that the system can accurately detect and precisely locate underwater waste objects in the images.

C. Class-wise Detection Performance

The model showed good detection performance for most waste categories in the dataset. Objects such as plastic bottles, keyboards, masks, mobile adapters, and mouse achieved very high accuracy with mAP values close to 0.995. However, some classes like gloves, mobile phones and tyres had slightly lower performance. This may be due to underwater lighting conditions, partial visibility of objects or fewer training samples.The remote class had slightly lower precision but a recall of 1.0, meaning the model detected all remote objects but sometimes produced extra detections.

VI. CONCLUSION

This study presents an intelligent underwater pollution detection system that uses deep learning to automatically detect and classify underwater waste, with special focus on electronic waste (e-waste). A custom underwater dataset containing different waste categories was created and annotated to train the model. The system is based on the YOLO architecture, which enables fast and accurate detection from both real-time camera feeds and stored images or videos. The model shows strong detection performance across various waste types commonly found in aquatic environments. In addition, the system includes location tracking and mapping features that record where waste is detected, helping environmental agencies plan efficient cleanup operations.

VII. FUTURE SCOPE

The proposed underwater waste detection system can be further improved by enhancing the accuracy and reliability of the location tracking mechanism. In the current implementation, the detected waste location is estimated using the geographical position of the mobile device connected to the detection unit. Future work can incorporate dedicated positioning modules and advanced localization techniques to provide more precise geo-tagging of detected waste. Accurate location information will help environmental agencies and cleanup teams efficiently identify pollution hotspots and plan targeted waste removal operations.

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