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RESEARCH ARTICLE

Real-Time Monitoring For Detecting Lake Pollution And Biotic Conservation

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Abstract

This research unveils a comprehensive system designed to tackle plastic pollution in lakes autonomously, eliminating the necessity for human intervention. By harnessing sensor data and camera imagery processed through the YOLO algorithm, the system identifies plastic debris. It then calculates the debris density and compares it against a preset threshold. Once the threshold is exceeded, an automated email alert containing the density data is sent to relevant authorities. Additionally, water quality sensors are integrated to continuously monitor environmental conditions. Regular updates are provided to enable proactive measures in pollution prevention. This endeavor showcases the utilization of advanced technology to address environmental challenges and safeguard aquatic ecosystems' health. By employing automated detection and monitoring mechanisms, the system offers a sustainable approach to combat plastic pollution in lakes, fostering environmental conservation endeavors.

Keyword: Computer Vison, YOLO V5, Coordinate attention, Raspberry pi OS, LabelImg

Introduction

Amidst an era marked by rampant industrialization and sprawling urbanization, nature faces significant environmental alterations, particularly in freshwater ecosystems like lakes and rivers, which bear the burden ofescalating pollution. The inadvertent contamination impacting aquatic life carries far-reaching consequences, demanding immediate action. In response to this urgent crisis, we introduce the initiative"Lake Pollution Detection for Preserving Aquatic Biodiversity." Embracing the evolving technological landscape, this endeavor employs state-of-the-art methodologies to detect and address lake pollution effectively. It emphasizes the crucial shift needed to safeguard vital water resources, ensuring environmental cleanliness and safety. As we delve into the intricacies of our approach, this initiative aims to blend technological advancements with environmental conservation by implementing innovative techniques. It not only targets pollution hotspots in lakes but also promptly alerts relevant authorities to take necessary actions. Our primary goal is to rehabilitate polluted water bodies, restoring these ecosystems to their original state of purity. Through our collective efforts, we aspire to pave the way for a sustainable future where aquatic habitats flourish as vibrant ecosystems, fostering biodiversity and ecological equilibrium.

Literature Survey

[1] explores the creation of an automated system for detecting river plastic using the YOLOv5 algorithm. It achieves an 84% accuracy rate in identifying floating bottles, aiding efforts to combat plastic pollution through localized AI assistance. [2] delves into the development ofa real-time military tank detection system using YOLOv5 on Raspberry Pi. The system boasts a remarkable 98% accuracy in classifying tanks across diverse operational scenarios, offering valuable visual intelligence for time- sensitive combat decisions. [3] introduces a waste management technique leveraging machine learning and the YOLO algorithm to detect and sort non-biodegradable waste from bin imagery into metallic, plastic, and glass categories. The aim is to enhance waste segregation in smart bin prototypes, contributing to sustainability initiatives. [4] presents an innovative study on a low-cost sensor system for on-the-field water quality analysis, with a focus on identifying clean water sources in sub-Saharan Africa. The system aims to significantly reduce operationalcosts, enabling large-scale surveys to address the issue of clean water scarcity. [5] provides a comprehensive reviewof methodologies and challenges in deep multi-modal object detection and semantic segmentation for autonomous driving. It discusses sensor fusion techniques and surveys current research in the domain. [6] discusses the integration of image processing techniques to detect and quantify red blood cells in human urine, aiming to streamline manual counting processes and reduce errors. The study achieves automated counting with a percent error of 9.561% and an average counting time of 0.4561 seconds per sample. [7] analyzes global data on plastic debris in rivers, emphasizing the correlation between plastic waste loads and mismanaged plastic waste generated in river catchments. The study underscores the significant contribution of rivers to marine plastic pollution. [8] presents a vision-based water surface garbage capture robot equipped with a modified YOLOv3-based garbage detection method. It demonstrates real-time and

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high- precision object detection in dynamic aquatic environments, contributing to efforts to mitigate water surface pollution. [9] proposes an efficient YOLO-compact network tailored for single-category real-time objectdetection. The network achieves high performance with a smaller model size compared to existing YOLO models, making it suitable for practical applications such as pedestrian detection. [10] offers a review of methodologies and challenges in deep multi-modal perception for autonomous driving, focusing on sensor modality fusion and network architecture design. [11] introduces a modeling approach to quantify and predict riverine plastic waste emissions into the ocean. By integrating data on plastic waste, land use, weather conditions, and river characteristics, the model estimates global plastic emissions, identifying regions with high pollution levels and suggesting targeted mitigation strategies. [12] describes the development of a vision-based

water surface garbage capture robot equipped with a modified YOLOv3- based garbage detection method. The approach enhances real-time object detection in dynamic aquatic environments through simplified detection scales and re-clustered anchor boxes for improved accuracy. [13] proposes an efficient YOLO-compact network optimized for single-category real-time object detection. The paper discusses methods for transforming large and deep networks into compact and efficient ones, resulting in a significantly reduced model size while maintaining high performance.

SYSTEM ARCHITECTURE

The The proposed system employs a range of hardware components for gathering and analyzing environmentaldata. At its heart lies a Raspberry Pi microcontroller, managing system operations and data analysis. Incorporating a camera module enables the capture of localenvironmental images, while a pH sensor gathers readingsfrom water sources to monitor acidity and alkalinity levels.

The Raspberry Pi consolidates and processes the various sensor data streams. Tailored software algorithms analyze the images to identify pertinent objects and events, whereaspH data facilitates ongoing tracking of water quality. Localstorage of analyzed data is facilitated by the Raspberry Pi,with the option of wireless transmission to the cloud or a local server for further examination and long-term retention.

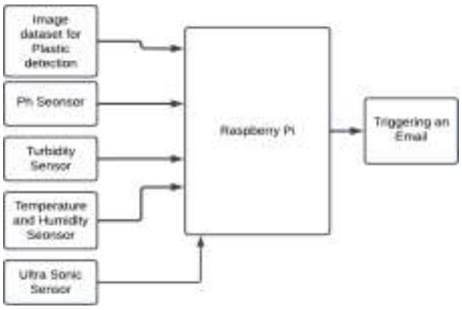

Fig 1. Block Diagram

Configurable alerts and notifications can be set up for the detection of critical events, such as sudden shifts in water pH or the presence of unwanted objects in the camera's view. The system's modular and expandable design allows for seamless integration of additional sensors and functionalities as monitoring requirements evolve.

Integration of a USB webcam with the microcontroller is proposed to enable seamless image capture. Both devices possess high-definition image capturing capabilities, ensuring compatibility and minimizing potential issues. This integration with the Raspberry Pi offers a reliable solution for capturing images, facilitating the detection of plastic in rivers.

In addition to plastic detection, sensors are incorporated to monitor the water quality of the river. These include a turbidity sensor, designed to measure light scattering caused by solid particles suspended in water. This measurement indicates turbidity, which correlates with the concentration of Total Suspended Solids (TSS) and is commonly used in wastewater examination processes.

Furthermore, pH sensors are employed to quantify the acidity or alkalinity level within the water. These sensors operate by assessing the concentration of hydrogen ions present, providing precise pH readings.

An ultrasonic sensor is also utilized to determine the distance to an object by emitting sound waves and analyzing their return time. This sensor emits pulses and receives their reflections, thereby providing information on the proximity of objects based on the time taken for the sound waves to return.

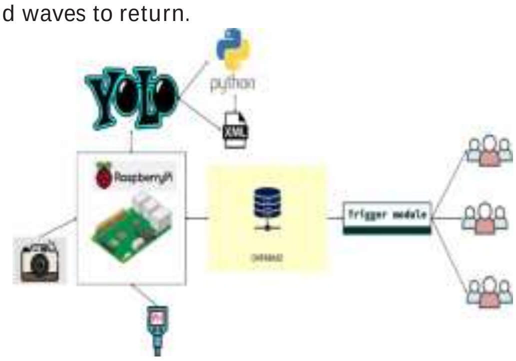

Fig 2. System architecture

METHODOLOGY

Collection of Dataset:

The dataset consists of a series of images taken by acamera positioned at various points surrounding the lake.These images show different aspects of the lake's surfaceand may vary in terms of lighting, weather, and time of day to ensure the models trained on them are robust and versatile. Each image is annotated to indicate where plastic debris is present, either through bounding boxes or segmentation masks outlining the detected plastic objects. The dataset covers a wide range of scenarios andenvironments to effectively train computer vision algorithms. Alongside the image data, the dataset also includes environmental information gathered by sensors placed in and around the lake. This environmental data includes factors such as water quality indicators (pH, turbidity) and meteorological data (temperature, humidity), providing context to understand the relationship between environmental conditions and theoccurrence of plastic pollution in the lake.

Water analyzers such as pH and oxygen sensors are strategically positioned at key locations to continuously transmit data to a central Raspberry Pi controller. The Pi calculates rolling averages of key parameters every two hours and compares them against predefined quality thresholds specific to each location. Whenever these thresholds are exceeded, the system automatically sends email notifications to the relevant environmental authorities. These notifications include details such as sensor identification, current average readings, timestamp,exceeded threshold, and additional contextual informationto facilitate prompt investigation. Scientists periodically adjust sensor configurations, averaging intervals, baseline standards, and alert criteria inresponse to advancements in water science. By deploying this IoT network with embedded intelligence, potential issues can be detected early, providing decision-makers with accurate and timely information to safeguard aquatic ecosystems. Furthermore, the affordability and versatility of the Raspberry Pi allow for cost-effective and tailored deployments that are not feasible with traditional monitoring methods.

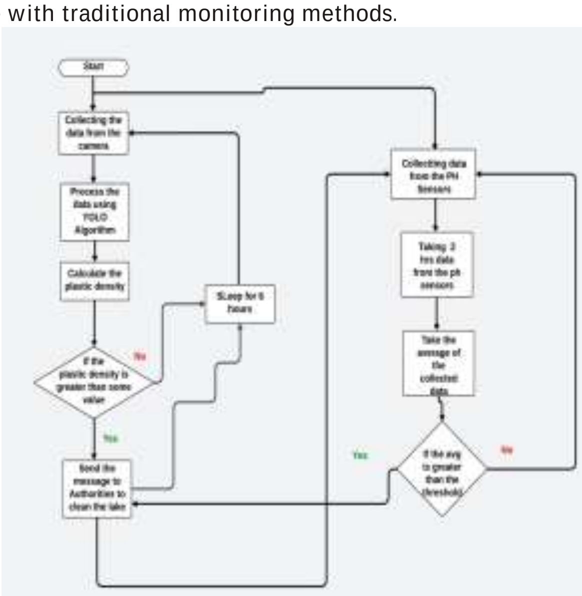

Fig 3. Flow Chart

Result and Discussion

Suggested Application Workflow:

Step 1: Image Collection

Numerous images representing different material categories such as glass, metal, and plastic were gathered. This collection comprised a mix of sourced images and custom photographs, captured from varied angles to ensure diversity.

Step 2: Image Labeling

Utilizing LabelImg, a labeling software, images were tagged with appropriate labels in YOLO (You Only Look Once) format. This format aids in identifying object locations crucial for training detection algorithms.

Step 3: Algorithm Training

A Python script was developed to train a convolutional neural network model. This script utilized the entire labelled image dataset and underwent approximately 14 hours of training. Through this process, the model learned to recognize visual features and patterns for material classification.

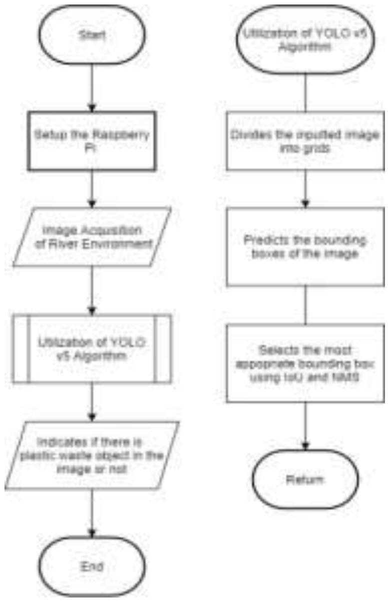

Fig 4. Working of Plastic Detection Module

Step 4: Model Outputs

The training procedure resulted in the generation of trained network weights and architecture configuration files. These files are essential for executing predictions using the trained model.

Step 5: Webcam Testing

Prior to final deployment, preliminary testing was conducted by running predictions on a live webcam feed. This step aimed to assess the model's real-world performance in practical settings.

Step 6: Raspberry Pi Deployment

Efforts were made to optimize and adapt the model for deployment on a Raspberry Pi. Special attention was givento ensuring efficient utilization of resources while maintaining performance. The Pi camera was utilized for video input during this process.

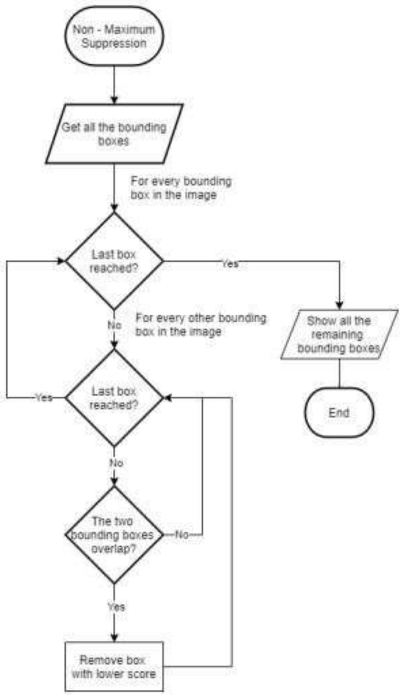

Fig 5. Working of Non-Maximum Suppression

RESULT

The practical application of the suggested blueprint showedencouraging outcomes, affirming its efficacy. The provided illustration illustrates the successful detection of plastic bottles within the specified image dataset. The model, aftertraining, accurately identifies the presence of floating plastic bottles in the river.

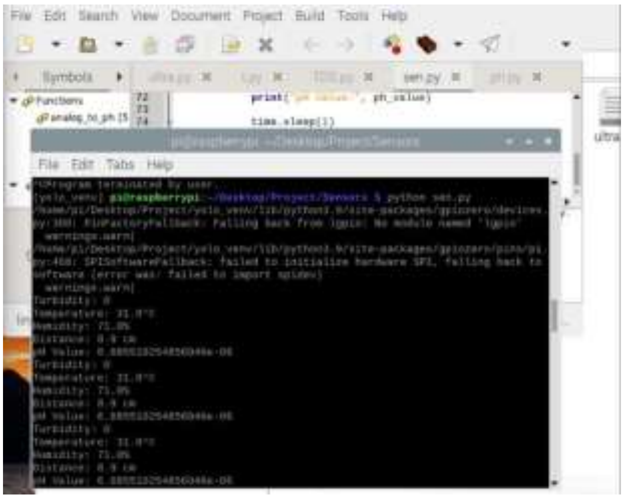

Fig 6. Plastic Detection Results

The model encounters difficulties in distinguishing between compacted plastic bottles and intact ones. Additionally, it struggles to reliably identify plastic bottles,especially when they are situated at a distance from the camera. Improvement in model performance is noticeable when images are taken without reflections from surrounding surfaces or landscapes. Furthermore, using higher-resolution images enhances the model's accuracy. During real-time inference or detection tasks, the model operates at a rate of approximately 1 frame per 3 seconds due to the processing limitations of the Raspberry Pi's CPU.However, when provided with pre-recorded images, the processing speed increases to around 1 frame per second. In this investigation, the primary goals were achieved through the development of a YOLOv5-based system incorporating both hardware and software components.The system underwent rigorous training and testing phasesutilizing a tailored dataset, with accuracy evaluations conducted using a confusion matrix. The findings unveiledan impressive accuracy rate of 89.928%. Analysis of the prototype's metrics confirms its proficiency and efficacy in identifying plastic bottles within river environments.

APPLICATIONS

By seamlessly integrating machine learning methods for visually identifying plastic waste with sensors that monitorwater quality parameters and algorithms for calculating plastic density, the proposed system offers continuous monitoring of pollution levels in lakes. When the detected densities exceed predetermined thresholds, a direct notification system alerts relevant authorities to swiftly remove accumulating plastics, preventing harm to wildlifeand the spread of microplastics. Apart from facilitating timely clean-up efforts in areas with high debris concentrations, the quantifiable pollution data produced by this automated monitoring system enables policymakers toevaluate the effectiveness of plastic reduction strategies. Additionally, it supports citizen science initiatives by providing data for model training and contributes to broader sustainability goals by promoting the reduction ofhuman-made waste in natural water bodies. Through this combined approach of real-time alerts and comprehensive analytics, the system serves as an innovative tool for preserving and responsibly managing fragile freshwater ecosystems, ensuring their protection forfuture generations.

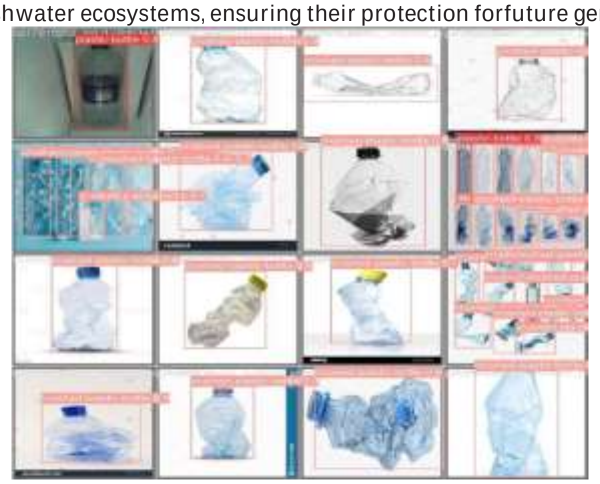

Fig 7. Values of Hardware Sensors

CONCLUSIONS

This groundbreaking system leverages cutting-edge technologies to address freshwater pollution and advance conservation efforts. By combining machine learning algorithms for identifying visual plastic debris with water quality sensors and density calculations, it enables ongoingmonitoring of contamination levels in lake ecosystems. When plastic buildup surpasses predefined thresholds, the system automatically alerts relevant authorities, facilitating prompt intervention before significant harm to aquatic ecosystems occurs. In addition to facilitating targeted clean-up efforts, the system's pollution data allows forevaluating the effectiveness of mitigation strategies,supporting community-led science initiatives throughmodel training, and contributing to broader sustainability objectives of minimizing human-generated waste in naturalwater bodies. This holistic approach, which integrates real-time alerts with thorough analytics, offers an inventive solution to support the preservation, rehabilitation, andresponsible stewardship of vulnerable freshwater habitats, promoting a cleaner and more sustainable future.

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