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LAKE POLLUTION DETECTION FOR SAVINGBOITIC LIFE

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Abstract: This paper introduces an integrated system designed to combat plastic pollution in lakes This paper provides solution for controlling the lake pollution without the human intervention. The data from the sensors and images from the camera module are being captured and yolo algorithm is used to detect the plastic. Then the predicted results are used to calculate the density and this density is compared to a predetermined threshold. If the density exceeds the threshold an email is sent to the authorities with the density values. In conjunction with plastic detection, system contains the water quality sensors to continuously monitor the lake's environmental conditions. Regular updates about the lake ensures the controlling and prevention of the plastic pollution in lakes. This initiative signifies a significant stride in leveraging advanced technology to tackle environmental issues and safeguard the well-being of aquatic ecosystems.

***Index Terms* - Computer Vison, YOLO V5, Coordinate attention, Raspberry pi OS, LabelImg, Sensors.**

I. INTRODUCTION

1.1 Background

In the phase of uncontrollable industrialization and urban expansion, our nature escalated so many changes in the environment, more on freshwater ecosystems such as lakes, rivers which are getting polluted day by day. The unintended pollution on biotic life within these aquatic animals has a greater impact, this needs to be taken care of as soon as possible. Our project, called "Lake Pollution Detection for Saving Biotic Life" becomes the solution to these greater crises, as we are part of the growing technology, we focus on using most modern methods to detect and mitigate the lake pollution.

This prioritizes the new revolution for the essential water resources and keeps the wellbeing environment clean and safe. As we dive into our complexity approach, the project looks to blend technological advancements with environmental protection, by attempting innovative techniques, we don't only aim on identifying the hotspots of polluted lakes but also to notify the respective superiors to take measures. Our main motive is to rebuild the polluted water bodies to newer and fresh of these ecosystems. Throughour concerted efforts, we threw to pave the way for a sustainable future where these water bodies flourish as vibrant.

1.2 YOLO Algorithm

The YOLO (You Only Look Once) algorithm is a real-time object detection system that gained popularity for its efficiency and accuracy. Developed by Joseph Redmon and Santosh Divvala, YOLO takes a novel approach by dividing an input image into a gridand simultaneously predicting bounding boxes and class probabilities for each grid cell. Unlike traditional object detection methodsthat rely on region proposals, YOLO processes the entire image in one forward pass, making it extremely fast. The algorithm is capable of detecting multiple objects within a single frame and assigning them to corresponding classes. YOLO has undergone several iterations, with YOLOv4 being one of the latest versions, incorporating advancements such as feature pyramid networks and darknet- 53 architecture to enhance its detection performance. YOLO's speed and accuracy make it well-suited for real-time applications, including autonomous vehicles, surveillance systems, and various other computer vision tasks.

YOLO operates by dividing an input image into a grid and predicting bounding boxes, along with class probabilities, for each grid cell in a single pass. This unique approach distinguishes YOLO from traditional object detection methods, as it eliminates the need for multiple passes and region proposals, resulting in faster inference times. YOLO's ability to detect and classify multiple objects in real-time has made it a popular choice for applications such as video surveillance, robotics, and image analysis in variousindustries. The algorithm has undergone several iterations, each introducing improvements to enhance its overall performance, withYOLOv4 being one of the latest and most advanced versions available.

II. LITERATURE REVIEW

[1] This" Plastic Waste Detection on Rivers Using YOLOv5 Algorithm" study develops an automated river plastic detection system by training a YOLOv5 model on custom debris imagery. Raspberry Pi integration enables a compact edge device to identify floatingbottles through USB cameras with 84% accuracy, providing portable analytics. [7] Despite live challenges in complex water environments, the prototype cascade shows promise for combatting waste through localized AI assistance. Further dataset enrichment and model optimization can strengthen sustainability contributions to neighborhoods via reasonably precise smart plastic quantification.[2] This "Real-Time Military Tank Detection Using YOLOv5 Implemented on Raspberry Pi "research develops a real-time military tank detection system using a customized YOLOv5 model trained on expert-annotated image data augmented through transfer learning. Among detection architectures, YOLOv5l achieves over 98% accuracy for classifying tanks under diverse operational conditions. Raspberry Pi deployment enables rugged embedded application, allowing 7.9ms inference times on 614x614 test frames. The proposed analytics pipeline sets a new benchmark for AI-assisted battlefield awareness to informtime-critical combat decisions based on automated visual intelligence. Further operational datasets can solidify generalizability before field deployment to units worldwide, aiding strategically pivotal and lifesaving detection capabilities.[3] This "A Waste Management Technique to detect and separate Non-Biodegradable Waste using Machine Learning and YOLO algorithm" originalresearch develops a machine learning system leveraging YOLO object detection to automatically classify non-biodegradable wasteinto metallic, plastic and glass categories from bin imagery. A customized model trained on [5] manually annotated debris data demonstrates reliable multi-material waste discrimination capabilities. Deployment on a Raspberry Pi camera allows low-cost edgeintegration into smart bin prototypes aimed at assisting waste segregation to further sustainability. The promising automated wasteanalytics pave the way for streamlined recycling initiatives and responsible consumption at scale. [4] This "Low-cost Sensor Systemfor on-the-field Water Quality Analysis" study develops an original low-cost water quality sensor system to economically facilitateclean water source identification in sub-Saharan Africa, where only 24% have access currently. By [9] determining general potability indications plus possible dissolved contaminants for each new source probed, exploitation costs can be cut from 30$ to under 5$ per sample. The frugal analyzer aims to accelerate access expansion for the 50% without clean water by enabling affordable large-scale surveys, driving equity in line with UN Sustainability Goals. Field trials pending in target communities would validatefeasibility before scaling to life-saving application across resource-poor regions worldwide.

III. SYSTEM OVERVIEW

In the system, data is acquired from the camera and processed using the YOLO algorithm model. The primary objective is to detect the presence of plastic in the captured image. If the calculated area occupied by the detected plastic surpasses a predefined threshold value, an automated email notification is triggered and sent to the relevant authorities. This mechanism ensures a proactive response in situations where a significant amount of plastic is identified, allowing for timely intervention and appropriate actions to address environmental concerns.

The Water Quality Monitoring system utilizes four sensors, namely pH, turbidity, ultrasonic, and temperature/humidity. Connected to the Raspberry Pi [14]through an ADC (ADS1115), these sensors play a crucial role in assessing the water quality. ThepH sensor measures the acidity or alkalinity of the solution in a logarithmic scale, while the turbidity sensor detects suspended particles in the water using light. The ultrasonic sensor provides distance measurement, helping to gauge water level or other relevant spatial information. Additionally, a temperature and humidity sensor contribute valuable environmental data. The system processes data from these four sensors, calculates the average values over a two-hour period, and compares them against predefined standard values. If the comparison reveals values exceeding the set standards, an email notification is triggered, providing a proactive alert mechanism.

Sr.No	Component	Use
1	Raspberry Pi	For interfacing Sensors
2	Ph Sensor	To gauge pH value of water sample
3	Turbidity Sensor	To gauge turbidity of water sample
4	Temperature and Humidity Sensor	To monitor and provide real-time data on temperature and humidity levels.
5	Ultra Sonic Sensor	For distance measurement or obstacle detection
6	9v Battery	To power the pH sensor module

Tabel 1: List of Components

IV. METHODOLOGY

The proposed application workflow begins with the collection of a diverse set of images representing various material categories such as glass, metal, and plastic. These images are then labeled using the LabelImg software, employing the YOLO format for object detection algorithm training. Subsequently, a convolutional neural network model is trained over 14 hours usinga Python script, enabling the model to learn visual features and patterns for material classification. The training process producesessential output files, including trained network weights and architecture configuration files required for predictions. Before finaldeployment, real-world performance is evaluated through webcam testing, ensuring the effectiveness of the model.

Following successful testing, the model is optimized and deployed on a Raspberry Pi, utilizing the Pi camera for video input.The embedded computer vision model outputs rectangular bounding boxes around detected objects in the camera image feed. Thetotal area of these bounding boxes is then calculated, and a density metric is derived by dividing the total summed bounding boxarea by the total image area, providing valuable insights into material presence.

In equation form, the area is calculated as the product of width and height, while the density is determined by the total area ofthe bounding boxes divided by the total image area. The workflow also includes a flow diagram (Fig 2) illustrating the step-by-step process.

In a separate application scenario, water analyzers such as pH and Turbidity sensors are strategically placed, continuously transmitting readings to a central Raspberry Pi controller. The Pi calculates two-hour rolling averages of key indicators and compares them to established quality thresholds. Any exceedances automatically trigger email alerts to environmental authorities,[13]providing crucial information like sensor ID, current averaged value, timestamp, threshold exceeded, and supporting content forinvestigation. Scientists can periodically adjust sensor routines, averaging windows, baseline standards, and alert targets to adaptto evolving water knowledge. By constructing an IoT network with embedded intelligence, potential issues can be detected early,offering decision-makers accurate signals about aquatic health. The cost-effectiveness and flexibility of the Raspberry Pi enabledense, customized deployments not practical with traditional monitoring techniques.

Hardware Tools:

- Raspberry Pi: Microcontroller functioning as core embedded processor to coordinate system modules[14].
- Camera Module: Integrated additional hardware unit to capture imagery for analysis.
- Power Supply: Regulated 5V DC power delivery to Raspberry Pi via micro-USB port. Enables stable power for smooth videoand data analysis.
- Sensors: Modular inputs for monitoring environmental signals like temperature, pH, vibration that can be analysed by the Raspberry Pi locally [12].

Software Tools:

- Python: General purpose programming language used to write custom software code for model training and deployment.Includes extensive machine learning libraries.
- YOLO Framework: "You Only Look Once" - specialized deep learning algorithm targeted for fast object detection suited for embedded use.
- LabelImg: Opensource image annotation tool used to map object boundaries in images to establish ground truth for training.
- JupyterNotebook: Development environment to run Python data transformation and modeling pipelines. Providesdocumentation and visualization.
- Raspberry Pi OS: Lightweight Linux distribution for Raspberry Pi devices. Optimized for machine learning with Python integration. Enables edge deployment of custom analytics solutions [12].

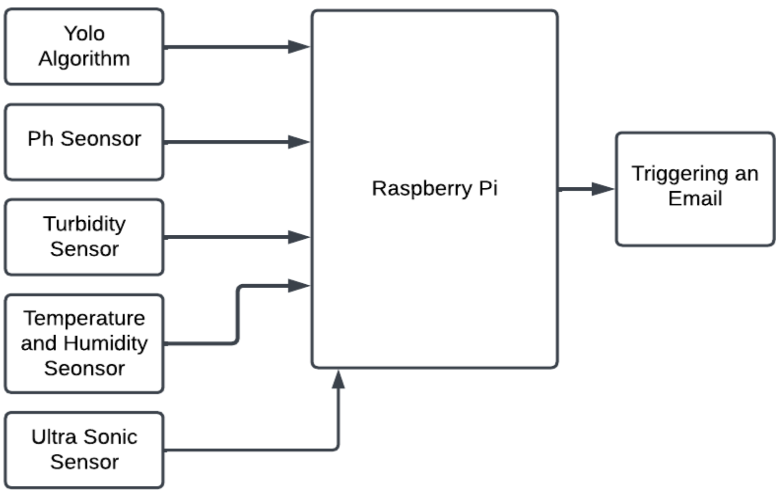

Fig 1: Block Diagram

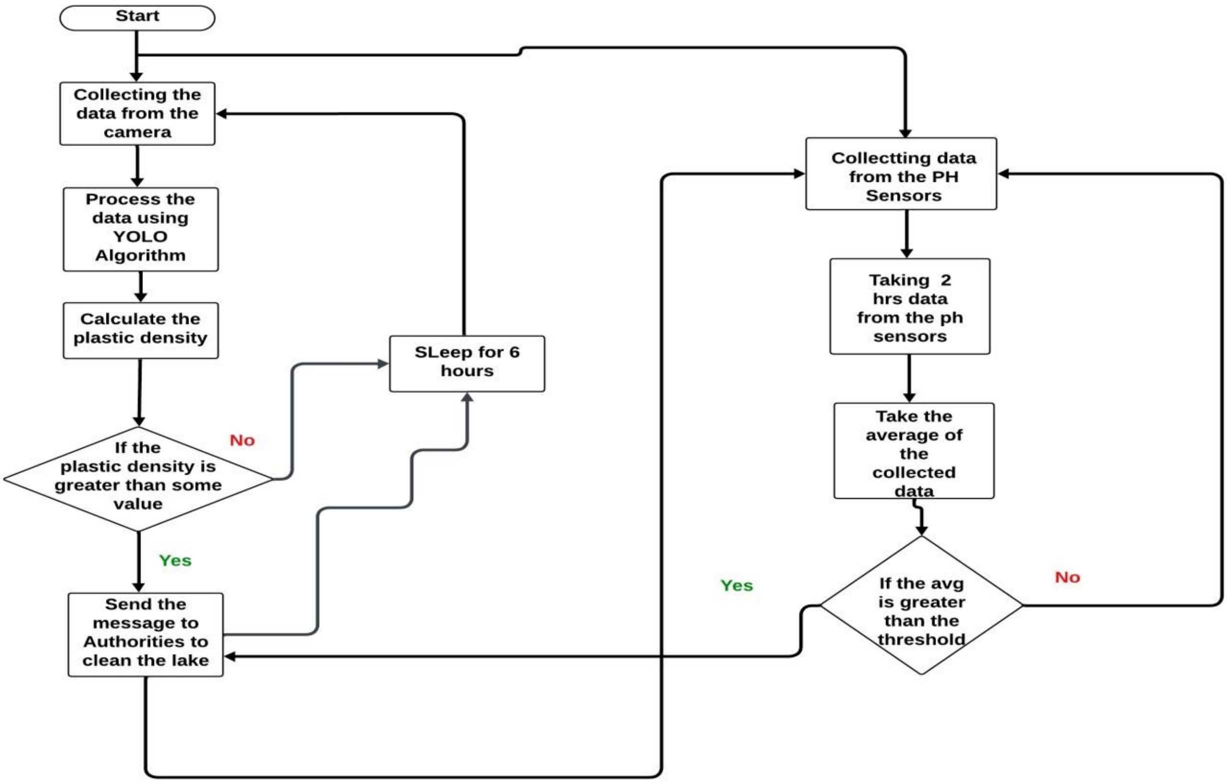

Fig 2: Flow Chart

YOLOv5, the fifth iteration of the You Only Look Once (YOLO) series, signifies a significant advancement in object detection algorithms within the field of computer vision. Built on the custom architecture of CSPDarknet53, a refined variant of the Darknet architecture, YOLOv5 prioritizes enhanced efficiency and speed. Notable for its competitive performance in both accuracy and real-time processing, YOLOv5 employs a grid-based approach to divide input images, predicting bounding boxes and class probabilities for simultaneous detection of multiple objects. Leveraging the PyTorch deep learning framework, YOLOv5 is accessible to a wide range of researchers and developers. The model's training involves optimizing parameters on large datasets, and it offers various versions such as YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x, each presenting a trade-off between speed and accuracy. With an active community supporting its development, YOLOv5 continues to evolve, making it a versatile and impactful solution for real-time object detection tasks. For the latest updates and details, it is advisable to refer to the official YOLOv5 repository and relevant publications[11].

V. APPLICATIONS

By integrating machine learning for visual detection of plastic debris with sensors monitoring water quality and plastic density calculations, the proposed system enables continuous pollution oversight and conservation support for lake ecosystems. When densities exceed preset thresholds, a direct notification system alerts authorities to retrieve accumulating plastics before wildlife impacts emerge and microplastic proliferation worsens. Beyond spurring timely clean-up of high debris areas, the quantifiable pollution data from this automated monitoring allows policymakers to measure plastic mitigation success, supports citizen science through model training, and promotes broader sustainability goals of reducing anthropogenic waste in natural waterways. Throughthis combination of real-time alert capabilities and rich longitudinal Analytics, the system offers an innovative tool to aid preservation, restoration and responsible oversight of fragile freshwater habitats.

VI. CONCLUSIONS

This automated monitoring system leverages the power of technology to aid freshwater conservation efforts. Integrating real-time detection of plastic buildup with proactive alerts enables targeted mitigation before substantial ecological impacts occur. Rich longitudinal data on pollution densities empowers both reactive clean-ups when thresholds are exceeded, as well as informed policy decisions to curb plastic infiltration long-term. Connecting authorities directly to visual and sensor intelligence on plasticaccumulation facilitates sustainable preservation of vital water bodies facing infiltration threats. By quantifying and alerting basedon science-based debris levels, the solution can pinpoint developing issues early while collecting actionable data to guide practical habitat restoration over time. Harnessing leading machine learning innovations thus propels an actionable system for stewards tocounter contamination, preserve cherished inland ecosystems, and take tangible steps toward a cleaner, more responsible future.

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