Integrating Vision-Based AI and Language Models for Real-Time Water Pollution Surveillance

Dinesh Jackson Samuel[1], Yusuf Sermet[1], David Cwiertny[1,2,4,5], Ibrahim Demir[1,2,3]

[1] IIHR Hydroscience and Engineering, University of Iowa
[2] Department of Civil and Environmental Engineering, University of Iowa
[3] Department of Electrical Computer Engineering, University of Iowa
[4] Department of Chemistry, University of Iowa
[5] Center for Health Effects of Environmental Contamination, University of Iowa

Abstract

Water pollution has become a major concern in recent years, affecting over 2 billion people worldwide, according to UNESCO. This pollution can occur naturally, such as through algal blooms, or it can be man-made when toxic substances are released into water bodies like lakes, rivers, springs, and oceans. To address this issue and monitor surface-level water pollution in local water bodies, an informative real-time vision-based surveillance system has been developed in conjunction with Large Language Models (LLMs). This system has an integrated camera connected to a Raspberry Pi for processing input frames and is further linked to LLMs for generating contextual information regarding the type, causes, and impact of pollutants on both human health and the environment. This multi-model setup enables local authorities to monitor water pollution and take necessary steps to mitigate it. To train the vision model, seven major types of pollutants found in water bodies like algal bloom, synthetic foams, dead fishes, oil spills, wooden logs, industrial waste run-offs and trashes were used for achieving accurate detection. ChatGPT API has been integrated with the model to generate contextual information about pollution detected. Thus, the multi-model system can conduct surveillance over water bodies and autonomously alert local authorities to take immediate action, eliminating the need for human intervention.

Keywords: Water Pollution Monitoring, Vision-Based Surveillance System, Large Language Models, YOLOv5 Object Detection, Real-Time Contextual Information, Environmental Monitoring Technology

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1. Introduction

Water is undeniably vital for the survival of all living organisms on Earth. However, in recent years, our water resources, including rivers, lakes, and oceans, have suffered from the consequences of poor human choices. The escalating pace of industrialization and the ever-increasing standards of living have led to the discharge of pollutants into these water bodies [Jones et al., 2018]. Moreover, water pollution is not solely a result of human activity; it is worsened by natural phenomena such as soil erosion, agricultural runoff, and harmful algal blooms [Mount et al., 2023]. As a result, surface waters, in particular, have become increasingly susceptible to contamination when compared to groundwater sources [Sit et al., 2021].

Surface water pollution manifests in various ways, from the thoughtless dumping of garbage to the unfortunate mixing of pollutants caused by natural disasters [Feng et al., 2017; Perera et al., 2019]. It includes events like death of fishes due to oxygen depletion, devastating oil spills, and the runoff of industrial waste, which can result in the creation of harmful synthetic foams and explosive algal blooms. These contaminants pose not only immediate threats to aquatic ecosystems but also long-term dangers to human health. Drinking water sources are often compromised, leading to waterborne diseases and chronic health issues.

The gravity of the situation is evident in statistics provided by UNESCO in 2023, revealing that a staggering 2 billion people, constituting 26% of the global population, lack access to safe drinking water [Bonazzi et al., 2023]. Equally concerning is the fact that 3.6 billion people, or 46% of the world's population, are without access to properly managed sanitation systems. To combat water pollution effectively, a multi-faceted approach is imperative. This includes regular monitoring of water bodies for visible pollutants, an in-depth understanding of the causes and consequences of pollution, the development of comprehensive action plans to prevent and mitigate pollution, and the implementation of stringent water quality control measures by governmental and local authorities. Only through concerted efforts supported by community we can safeguard our precious water resources for generations to come [Weber et al., 2018].

1.1. Evolution of Vision-Based Detection in Pollution Management

Traditional pollution and waste management methods heavily rely on human observation, which is susceptible to errors and time-consuming. However, the emergence of artificial intelligence and deep learning has brought about significant advancements in image-based object detection and remote sensing techniques [Krizhevsky et al., 2017; Li and Demir, 2023; 2024]. Traditional object detection models have a history, with significant advancements over the years. Felzenszwalb et al. [2008] introduced the Deformable Part Models (DPM), which were subsequently improved upon in cascade objection detection in deformable part models [Felzenszwalb et al., 2010, Felzenszwalb et al., 2010]. In 2016, Girshick et al. introduced the Region Convolutional Neural Network (R-CNN) model, marking a pivotal moment in object detection. This R-CNN model served as the foundation for subsequent object detection algorithms [He et al., 2015], including Fast R-CNN [Girshick et al., 2015]. Another noteworthy development came in 2015 when Liu et al. proposed the Single Shot MultiBox Detector (SSD) [Liu et al., 2016], which introduced multi-reference and multi-detection techniques. Around the same time, in 2015, the "You Only Look Once" (YOLO) model was introduced. YOLO represented a breakthrough with its single-stage detection approach, leading in the era of deep learning for object detection [Redmon et al., 2016].

To address the issue of water pollution monitoring, cameras combined with computer vision algorithms have become instrumental. Zhao et al. introduced an intelligent lightweight system designed for the detection of dead fish, utilizing YOLOv4 as the backbone with the efficient MobileNetV3 [Zhao et al., 2022]. Aria et al. proposed a smart trash bin capable of sorting recyclable materials using Yolov5-based object detection. This system is integrated into a Raspberry Pi, enabling the detection and classification of recyclable trash items [Wahyutama et al., 2022]. Hrushikesh et al. in his work, waste object detection and classification use a Gaussian-Poisson Generative Adversarial Network (GP-GAN), with joint optimization between the gradient and image color information. Transfer learning with finetuned Faster R-CNN achieves good results in classification of waste objects [Kulkarni et al., 2019].

Although the surface level pollution in water bodies is a serious issue, only few works has been taken with cutting-edge of AI to combat it. Although deep learning-based approaches for object detection has been used for visual pollution detection, but not for contextual text generation. The end user did not have any contextual information of the detected pollutant. In order to have the contextual information from the image, we propose a multi-modal vision-based system which uses the Large Language Models (LLMs) to generate the information about the detected pollutant.

In this study, we have developed a multi-modal surveillance system using vision-based computational algorithms based on Deep Learning to detect specific pollutants and generate contextual information related to pollution. While surface-level visual pollutants in water bodies may appear similar, their composition can vary from one location to another. Moreover, detecting these pollutants in plain view can pose challenges for the system. To address these issues, we have implemented a robust computer vision model using YOLOv5, for pollutant detection. To train the object detection model effectively, we have gathered comprehensive data on pollution in water bodies. This step is pivotal in the development of a vision-based system for the continuous monitoring of water pollution, all without the need for human intervention.

Our contributions can be summarized as follows: (1) conducted experiments with the YOLOv5 object detection model to effectively identify various types of potential water pollution; (2) designed and implemented a dedicated system where our trained models, in conjunction with LLMs, are deployed for both detection and the generation of information pertaining to pollution; (3) gathered and utilized region-specific data from the Iowa River, enhancing the system's effectiveness and offering a real-world use-case scenario; (4) customized prompts were developed, playing a pivotal role in connecting the vision-based component with the LLMs; (6) implemented active incremental learning techniques to continuously update and manage data, ensuring efficient and ongoing monitoring of pollution levels. Thus, using the proposed multi-modal monitoring system, the water pollution can be monitored without human intervention in real-time.

The remainder of this article is organized as follows. Section 2 delves into the evolution of vision-based detection technology and its application in pollution management. Section 3 describes the design and development of the Raspberry Pi-based intelligent system for real-time monitoring. Section 4 presents the pollution detection systems and their integration with artificial intelligence, introduces the LLMs and their role in generating contextual information, and details the methodology, including system architecture and YOLOv5 integration. Section 4 outlines the system implementation, including hardware deployment and YOLO model training. The results and discussion of the system's performance are provided in Section 5. Finally, Section 6 concludes the paper with a summary of the findings and potential future directions for this research.

2. Background

In the era of artificial intelligence, researchers have a profound interest in applying it to real-world use cases, such as the detection and monitoring of pollution in local water bodies. Our approach involves real-time monitoring and contextual information generation, representing an improvement over the system proposed by Sermet et al. [2023]. Sermet proposed an intelligent system for decentralized environmental monitoring. The author introduced an intelligent stream stage methodology for measuring water levels and sharing reports to support environmental monitoring in rivers. This system relies on Raspberry Pi and a motorized camera for automated measurements, incorporating deep learning techniques for water level segmentation and Point of Interest (POI) computations. In addition to this system, we have seamlessly integrated our real-time pollution monitoring capabilities in Raspberry-Pi computer.

Pollution Detection Systems: In recent times, many authors have introduced pollution detection systems harnessing artificial intelligence to address real-world challenges. Hoang et al. have provided an overview of the use of Artificial Intelligence in pollution control and management [Hoang et al., 2022]. Additionally, the author categorizes AI's applications in wastewater management and the monitoring of water quality parameters [Fijani et al., 2019]. In a similar vein, other researchers have discussed the application of AI and hybrid AI methods in mitigating environmental pollution and emphasize the outcomes achieved. Notably, a machine learning-based approach has been employed to forecast arsenic contamination in groundwater [Bindal et al., 2019]. In this study, data from India was collected and machine learning techniques were applied to identify areas with high arsenic groundwater contamination using maps. This research serves as a valuable resource for policymakers, enabling them to take proactive measures in contaminated areas.

Kumar et al. introduced a deep learning-based approach for smart waste management [Kumar et al., 2020]. Their system performs waste segregation utilizing a trained YOLOv3 model, distinguishing between six different classes of trash. This model facilitates the separation of recyclable waste, enhancing waste management practices. Meanwhile, Tian et al. employed deep learning networks to predict water pollution resulting from rainfall-runoff [Tian et al., 2022]. The authors discovered that significant river water pollution occurs during the summer/dry period, intensifying when there is rainfall within a ten-minute window. Their models establish a connection between rainfall characteristics and the mean concentration of chemicals in rivers through artificial neural networks, enabling the prediction of chemical concentrations in rivers.

Further, Hossain et al. proposed an automated system for detecting pollution using object detection algorithms. The authors developed an Android application that utilizes images along with Global Positioning System (GPS) coordinates to locate and analyze visual pollutants, with the results visualized through generated heat maps [Hossain et al., 2023].

Large Language Models: LLMs like ChatGPT have indeed found applications in various fields, including education and the medical field. They are leveraged for their natural language processing capabilities to enhance and streamline processes in these domains. LLMs enable personalized learning experiences by generating tailored educational content, quizzes, and assessments based on individual student needs [Bernacki et al., 2021; Sajja et al., 2023a]. Matthew et al. defines the theory-guided method for personalized learning experience. Further Language tutoring serve as virtual language tutors, providing instant feedback and support in language acquisition. Meyer et al. investigates the potential use of LLM based chatbots in academic works and ethical implication [Meyer et al., 2023; Sajja et al., 2023b].

Also, educators use the LLM models to create engaging educational materials, including textbooks and interactive lessons [Dai et al., 2023; Sajja et al., 2023c]. Recently, LLMs are also used in various medical fields. LLMs assist in diagnosing diseases by analyzing medical records and reports, offering valuable insights to healthcare professionals [Sermet and Demir, 2021]. The LLMs like ChatGPT assists the medical technicians in generating the reports based on patients' laboratory results [Zhou et al., 2023]. Further the LLMs facilitate patient-doctor communication through chatbots and virtual assistants, improving accessibility and health monitoring. This paves way to tele medicine during the pandemic like Covid-19 [Jadczyk et al., 2021]. It also aids in literature reviews, summarizing vast amounts of scientific literature, training for engineering exams [Pursnani et al., 2023] and identifying relevant research assistance [Kitsios et al., 2023].

In the above-mentioned studies, the authors followed a similar approach of collecting data, annotating objects, and employed the annotated data to train their models. Once the model was trained, the authors used them for detecting pollution. In contrast, our work introduces a real-time monitoring system with contextual information about the water pollution in local bodies. This system not only detects pollutants but also generates contextual information about them as they occur in real-time.

3. Methodology

The system architecture of the proposed multi-modal system is structured into two primary phases: the hardware framework and software development as illustrated in Figure 1. The hardware framework involves the integration of a Raspberry Pi with a camera for monitoring purposes. The camera captures frames, which are then transmitted to the Raspberry Pi for processing. The Raspberry Pi is a small computer which is easier, affordable, and sufficient for computation. Subsequently, a multi-modal computer vision software, in conjunction with LLMs, is developed and integrated on the Raspberry Pi. This software aids in generating contextual information from the captured frames.

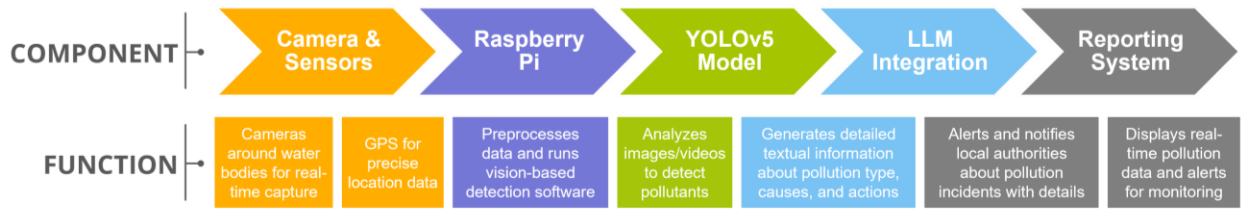

Figure 1: System architecture for real-time water pollution surveillance system.

3.1. Design and Development of Raspberry Pi-Based Intelligent System

Sermet et al. proposed five geometry-based approaches for measuring water levels using cost-effective sensors. Among these methods, the 3-cone intersection method, as utilized in this work, stands out for its high flexibility and independence from specific site locations [Sermet et al., 2020]. However, it is important to note that human errors can introduce non-negligible margins of error when predicting floods and managing reservoirs. Building upon this previous work, Sermet et al. introduced an intelligent stage stream monitoring system in 2022. The system integrates sensors, maintains a Point of Interest (POI) registry, and operates on the Raspberry Pi end device. This comprehensive system includes a camera, a servomotor, an Inertial Measurement Unit (IMU), and a GPS receiver attached to the computer. The POI registry's primary objective is to determine the water level by creating a structure between the camera and the water intersection on the opposite side of the river. Subsequently, water segmentation using U-Net is employed to detect the intersection of water with the structure. Geometrical calculations are then performed based on Cartesian coordinates. Image-based visual servoing is utilized to automate the camera's movement, allowing it to track the water intersection with the structure.

3.1.1 Conceptual Framework

The underlying conceptual framework of our system is designed to facilitate real-time monitoring of pollution levels in local aquatic ecosystems. At the heart of the hardware setup is the Raspberry Pi, a single-board computer, which is paired with a servo motorized camera to continually surveil the water bodies. To provide geolocation data and enhance its precision in monitoring, a GPS module is seamlessly integrated into the system. Additionally, the architecture is versatile, accommodating supplementary modules such as a WiFi modem for data transmission. This ensures sustainability and broadens the system's applicability, making it adaptable for environmental monitoring scenarios. The conceptual framework of the system is represented as a flowchart in Figure 2.

The camera's primary function is to capture the field of view necessary for pollutant detection. To set up the camera, it is securely positioned at the monitoring location, ensuring that its field of view covers the majority of the water in that specific area. The camera's orientation is adjustable with the assistance of a servo motor, enabling it to rotate as needed. Additionally, the camera's focal length is fine-tuned for optimal focus. It records video at a rate of 30/60 frames per second (fps) with a resolution of 1280 x 920. It also has night vision capabilities, providing extensive coverage of up to 240 feet and remaining robust in various external temperature conditions.

The Raspberry Pi hosts the computer vision algorithm and integrates with the LLM for creating information to monitor the situation in real time. The computer vision model is trained to detect common surface-level pollutants, such as algal blooms, synthetic foams, dead fish, oil spills, wooden debris, industrial waste runoff, and trash. In this context, the YOLOv5 model is utilized for pollutant detection from the input frames. Once a pollutant is identified within an input frame, the information is relayed to the LLM. The LLM is configured with prompt engineering to generate queries. A semantic role identification prompt extracts pollutant details and forwards them to the LLM. Based on the queries generated by the prompt, the LLM generates contextual information about the pollutants.

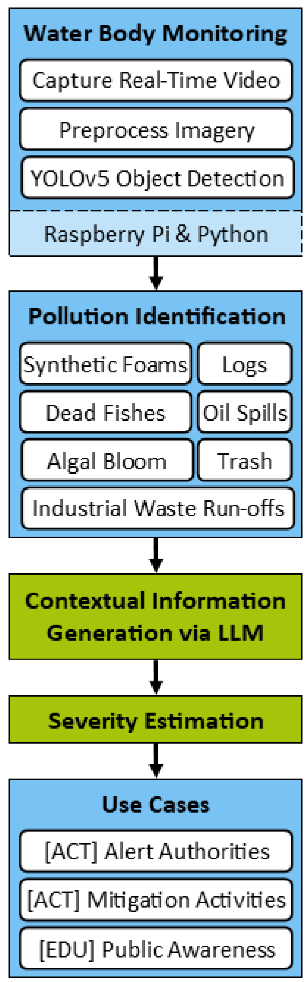

Figure 2: Workflow of the proposed multimodal vision based LLM for contextual information generation.

3.2. Integration of the YOLOv5 Model

The YOLO ("You Only Look Once") model is a widely recognized object detection model renowned for its speed and accuracy [Redmon et al., 2016]. YOLO tackles object detection as a regression problem using a single Convolutional Neural Network (CNN) model, unlike the Fast

R-CNN approach. YOLO employs a single-pass detection strategy and uses CSPDarknet53 as its backbone, which splits the feature map and merges it through cross-stage hierarchy, aiding in efficient training and better performance as illustrated in Figure 3. Instead of scanning the image with multiple filters at various sizes, as traditional sliding window and region proposal-based methods, YOLOv5 divides the image into an A x A grid. Within each grid cell, YOLO predicts bounding boxes, their associated confidences, and class probabilities.

The model also leverages multi-scale predictions, where it predicts objects at three different scales, which is advantageous for detecting objects of various sizes. This is achieved by employing three different sizes of anchor boxes for each scale, which are defined based on the object sizes in the training dataset. Each grid cell predicts multiple bounding boxes, and for each bounding box, the cell predicts the box's center coordinates, dimensions, a score indicating the likelihood of the box containing an object, and class probabilities specifying the object's class. The bounding box coordinates are determined using the values of x, y, w, and h. Here, x and y denote the coordinates of the bounding box's center within an image, while w and h represent the width and height of the bounding box relative to the image.

Following the raw predictions, YOLOv5 undergoes several post-processing steps: (1) thresholding is applied to discard boxes with low objectness scores; and (2) non-maximum suppression (NMS) is employed to remove overlapping boxes, retaining only the boxes with the highest objectness score among overlapping candidates. YOLOv5 utilizes anchor boxes, predefined boxes based on common object shapes in the training data. During training, the model learns to adjust these anchor boxes to better fit the true object dimensions, enhancing detection accuracy. The training process also incorporates data augmentation strategies. This technique combines four training images into one composite image, increasing input data diversity and improving the model's ability to detect objects in various scenarios.

The training loss for YOLOv5 is a combination of mean squared error for bounding box predictions, binary cross-entropy for objectness prediction, and categorical cross-entropy for class predictions. The model also employs the Complete Intersection over Union (CIoU) loss, which focuses on shape, overlap, and central point distance between predicted and ground truth boxes. Unlike two-stage detectors that first propose regions and then classify them, YOLOv5 operates in an end-to-end fashion, predicting bounding boxes and their corresponding classes simultaneously. This design choice makes YOLOv5 faster and enables real-time object detection across various applications.

3.2.1. YOLOv5 Implementation in the System

The system employs YOLO for the detection and estimation of surface-level pollutants, including algal bloom, synthetic foams, dead fish, oil spills, wooden logs, industrial waste run-offs, and trash. Specifically, YOLO version 5 architecture is utilized, which incorporates various components to enhance detection accuracy. The YOLO version 5 architecture includes a backbone which uses the Cross-Stage Partial (CSP) network from Darknet, along with Spatial Pyramid Pooling (SPP) layers as the backbone for feature extraction. The neck of the architecture incorporates a Path

Aggregation Network (PANet) as the neck to further refine features. And the head detectors are responsible for finalizing the object detection process. Different versions of YOLO vary based on the number of feature extraction modules and convolution kernels they employ. One notable feature of the YOLO architecture is its adaptive anchor frame calculation on input images to extract deep feature maps, contributing to accurate detection.

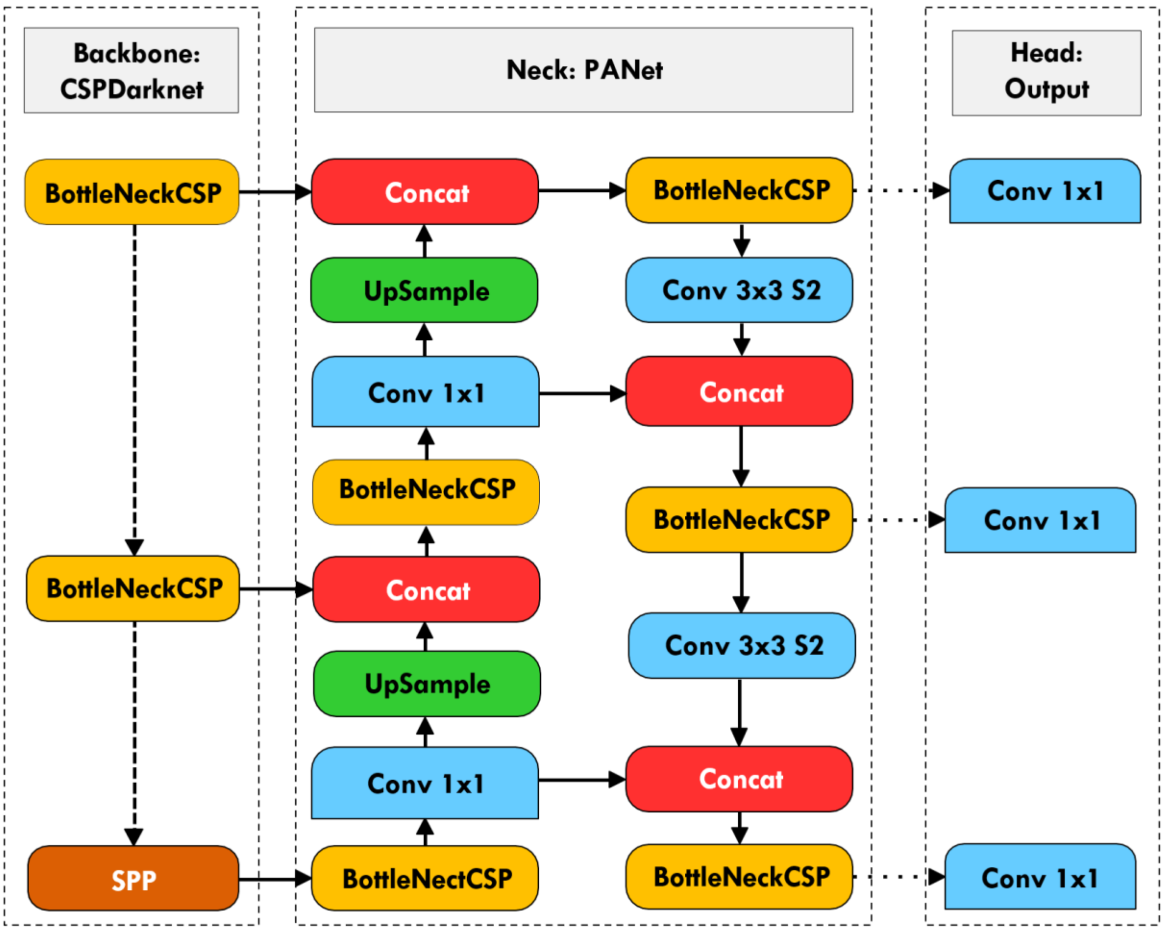

Figure 3: Architecture of YOLOv5 model

3.2.2. Dataset Preparation and Training of the YOLOv5 Model

The YOLO model is trained to detect seven common surface-level pollutants: algal bloom, synthetic foams, dead fish, oil spills, wooden logs, industrial waste run-offs, and trash. To train the model, a dataset of pollutant images is compiled from various sources, including images acquired from the Iowa river, datasets downloaded from Kaggle, images found through search engines, and web crawling. While the data collection process can be tedious, it is necessary to ensure a diverse set of images for training. In total, the pollutant dataset comprises approximately 840 images, with approximately 120 images available for each type of pollutant. The total number of annotated instances is around 3000 which is shown in Figure 4. Once the dataset is collected, the images are manually annotated with bounding boxes in YOLO format to prepare them for model training.

This comprehensive approach enables the YOLO model to accurately detect and estimate surface-level pollutants in real-world scenarios.

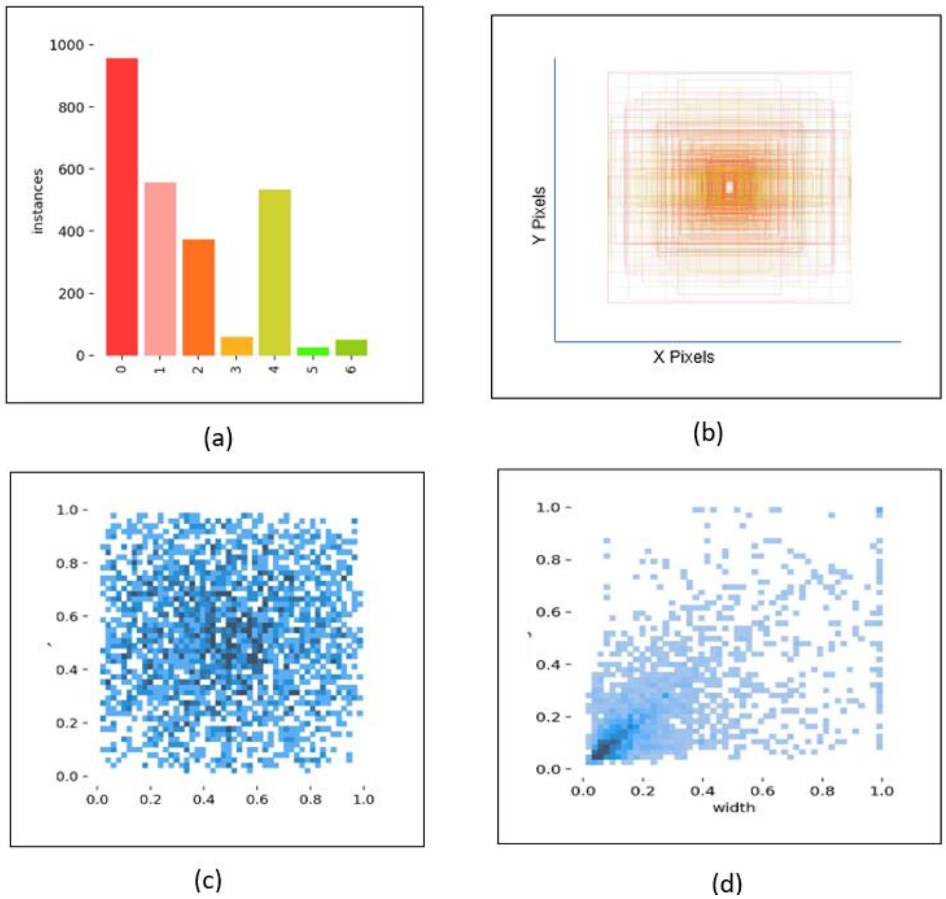

Figure 4: Distribution of training data (a) Shows the number of annotated instances for classes (b) Visualizes the annotated bounding box size (c) Distribution of annotated classes (d) Coordinates of annotated bounding boxes for surface level pollution dataset in each image.

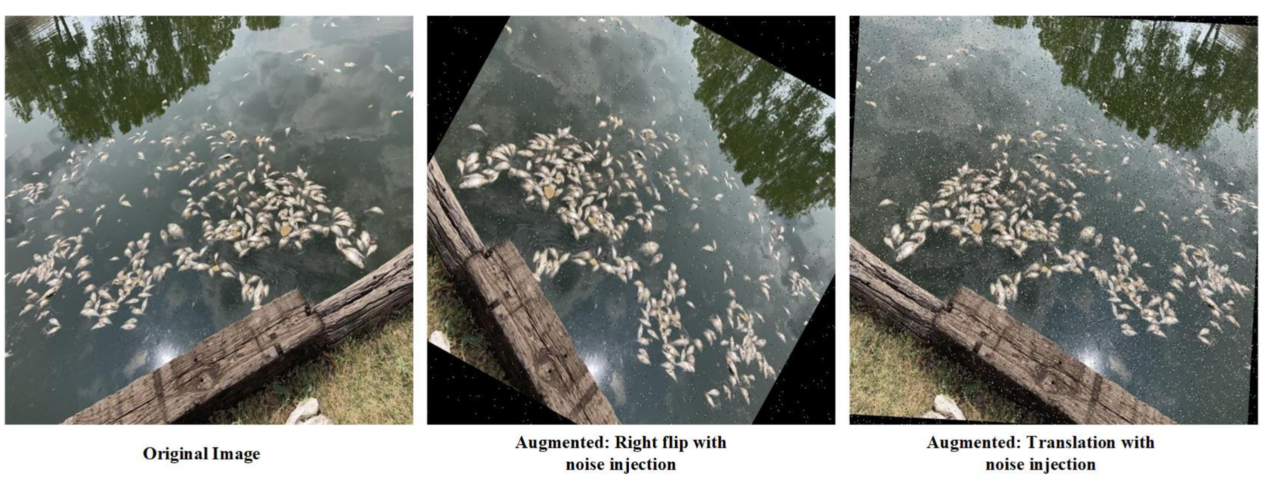

Figure 5: Image augmentation techniques applied to enhance model robustness.

To enhance the training dataset's size and diversity, image augmentation techniques are employed. These techniques introduce variations to the existing images, creating additional training examples. These techniques involve operations such as horizontal or vertical flipping, random cropping, rotation augmentation, translation to shift images in various directions, and noise injection, as shown in Figure 5. By applying these image augmentation techniques, the training dataset becomes more diverse, allowing the model to generalize better and perform well on a wider range of real-world scenarios. This is especially important in tasks like pollution detection, where environmental conditions and object positions can vary significantly. Image augmentation helps the model become more resilient and accurate in detecting pollutants under different circumstances.

3.3. Integration of Vision Model with Large Language Models

The integration of the vision-based model with the LLM constitutes a critical aspect of system development, and this integration is accomplished through semantic role identification prompts. In this architecture, the vision-based model employs the YOLO architecture, while the ChatGPT API is utilized for generating information. The YOLO architecture receives input frames from the camera and endeavors to detect pollutants within those frames. During the training phase of the YOLO model, pollutants are annotated with their respective names to recognize them accurately. In real-time operation, the YOLO model identifies pollutants within the frames and passes the details of these pollutants to the LLM. The customized prompts are a powerful tool for bridging the gap between the vision and language models. These prompts are designed to guide the system in generating well-structured queries based on the detected pollutants. Once the detected pollutant details are received, the customized prompts instruct the system to generate well-structured queries. These queries are then passed to the ChatGPT, which utilizes its natural language processing capabilities to generate context-specific information pertaining to the detected pollutants. As a result, the system is capable of generating contextual information from real-time videos that is specific to the pollutants it identifies, enhancing its capabilities for pollution monitoring and reporting.

3.3.1. Prompt Engineering for Contextual Information Generation

Prompts play a pivotal role in shaping the outputs of LLMs such as those based on the GPT architecture. It acts as a bridge, translating user intentions into specific tasks that the model should perform. These tasks can range from translating vision computations to generating contextual information, as is the case in our system. The formulation of a prompt can significantly influence the style, length, and format of the system's response.

For instance, when a pollutant is detected by the YOLO model, a prompt is constructed to generate a query about the detected pollution. This query is then passed on to the LLM, such as ChatGPT, for the generation of contextual information. The prompt used in this context is designed to inquire about several aspects of the pollution, including what it is, causes, its impact, and the actions that should be taken to mitigate it. The choice of prompt can yield different outcomes. A concise prompt may result in a brief summary of information, while a more detailed and descriptive prompt may lead to a more comprehensive analysis in the model's response. Furthermore, prompts enable on-the-fly task adaptation, allowing ChatGPT to handle a wide range of tasks without the need for task-specific parameters. This flexibility makes prompts a valuable tool in directing the capabilities of LLMs to meet specific user needs and objectives.

4. Results and Discussion

This section presents the results and discussion of our proposed method for surface level pollution detection. We evaluate the performance of our method on various metrics, such as precision, recall, F1-score, mean average precision (mAP), and intersection over union (IoU). We also compare our method with several state-of-the-art methods and demonstrate its superiority. Furthermore, we conduct an ablation study to analyze the impact of different components of our method on the final results. Finally, we provide qualitative results and discuss the limitations and future directions of our work.

4.1. Experimental settings

The comprehensive experimental study was conducted using a PC with the following specifications: an Intel(R) Core (TM) i7-10700KF CPU @ 3.80GHz, 16.0 GB of RAM, and one NVIDIA GeForce GTX 1070 GPU. In the training process, the training data consists of images with varying resolutions. Before being input into the model, these images are resized to a consistent resolution of *640 x 640* pixels. The training process is configured with the following parameters:

The batch size is set to 64, indicating that 64 images are processed in each training iteration. The total number of training epochs is set to 600. One epoch represents one complete pass through the entire training dataset. A training cut-off mechanism is used to stop training if there is no improvement in loss for approximately 100 epochs. This early stopping technique helps prevent overfitting. Stochastic Gradient Descent (SGD) optimizer is utilized for model optimization. The learning rate is set to 0.001, the momentum is set to 0.845, and there is weight decay of $4\ x\ 10^{-4}$. These parameters govern how the optimizer updates the model's weights during training.

The Intersection over Union (IoU) threshold for bounding box anchors is adjusted to fall between 0.2 and 0.6. The IoU threshold is a critical parameter for evaluating the overlap between predicted bounding boxes and ground truth bounding boxes. It plays a key role in determining whether a predicted object is considered a true positive or a false positive. These training configurations ensure that the model is trained effectively and efficiently to detect surface-level pollutants in a wide range of scenarios, while also incorporating techniques like early stopping and dynamic IoU thresholds to enhance training stability and accuracy.

4.2. Implementation and Evaluation

The YOLOv5 model is trained using the pollution dataset with the hyperparameters defined above. The dataset was split into three sets: training, testing, and validation, with a ratio of 80:10:10, respectively. The evaluation of the model's pollution detection accuracy is based on the mean

Average Precision (mAP) metric, which considers both the precision and recall of the detected objects as well as the model's confidence in generating bounding boxes. During the validation phase, the mAP at an IoU threshold of 0.5, which means that the detected and predicted bounding boxes should have at least 50 percent overlap, was found to be 95 percent. Figure 6 shows the training loss, validation loss and the mAP for the model. The high mAP score indicates that the YOLOv5 model is 95 percent accurate in detecting pollution in water bodies. This level of accuracy is considered acceptable when deploying the model on the Raspberry Pi, ensuring reliable pollution detection in real-time scenarios.

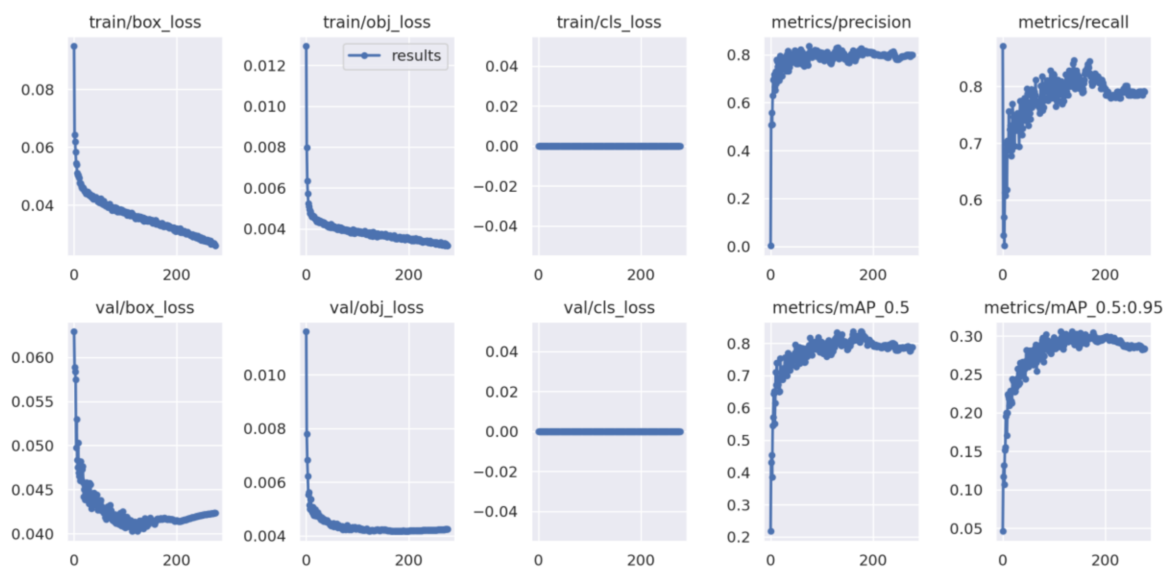

Figure 6: Training loss, validation loss and accuracy of YOLOv5 model

Figure 7 shows the sample contextual information generated for the real-world scenarios. The overall accuracy of the generated information is qualitatively evaluated by domain experts based on the considerations of accuracy, completeness, and relevance, and deemed appropriate. The real-time monitoring system operates efficiently, taking only approximately 12.3 milliseconds to process each frame. The processing time demonstrates the system's robust computational capabilities, enabling it to function effectively in real-time for monitoring and promptly alerting authorities about water pollution incidents [Demir et al., 2009]. Moreover, the system not only detects pollutants but also provides estimation values to gauge the severity of the pollution detected. This additional information equips local authorities with critical data to assess the gravity of the situation and take necessary actions accordingly.

4.3. Discussion

The development and implementation of our proposed system, integrating vision-based AI and language models for real-time water pollution surveillance, represents a noteworthy contribution to the field of environmental monitoring. The system's capacity to identify various pollutants and generate contextual information concerning their characteristics, sources, and potential impacts offers a multifaceted approach to water quality assessment.

The proposed system brings several advantages to environmental monitoring efforts. By combining YOLOv5 object detection with LLMs for contextual analysis, it transforms raw data into insightful information, enabling more informed decision-making processes regarding pollution management. This integration not only enhances the accuracy of pollutant detection but also enriches the data with valuable context. Another significant benefit is the system's flexibility and scalability, allowing for deployment across diverse platforms and environments. Whether through drone technology for expansive aerial surveillance or mobile applications for community-led monitoring initiatives, the system facilitates broad participation in and access to environmental conservation efforts.

Figure 7: Samples of contextual information generated by ChatGPT from the video/image data.

The system further executes several critical functions that extend its utility beyond initial identification. Utilizing the contextual information and any supplemental data collected, the system is capable of assessing the severity of detected pollution. This assessment is crucial for deciding on the appropriate course of action, whether it involves immediate intervention or long-term monitoring. The ability to prioritize responses based on the severity of pollution events ensures that resources are allocated effectively, enhancing the overall efficiency of environmental management efforts. Relevant use cases are described below.

Education: Public Awareness via Technology Solutions: The system's capability to engage in public education and awareness campaigns is an invaluable asset. By disseminating information about less severe pollution incidents or general environmental health through technology, it fosters community involvement and promotes a culture of sustainability. This proactive approach to environmental education can lead to more informed communities and encourage individual and collective actions towards pollution prevention.

Action: Alerting Authorities (Based on LLM-Inferred Severity): In instances of severe pollution, the system's ability to automatically alert local authorities with comprehensive reports is particularly advantageous. This rapid communication ensures that critical information reaches decision-makers promptly, facilitating swift action to mitigate the impact of pollution. The detailed reports generated by the system provide authorities with the necessary insights to implement effective response strategies.

Action: Mitigation Activities: Based on the evaluated severity and type of pollution, the system can recommend or initiate specific mitigation activities. These might include clean-up operations, restrictions on certain activities, or targeted conservation efforts. The system's guidance on action steps is instrumental in addressing pollution efficiently, minimizing environmental damage, and safeguarding public health.

4.3.1. Limitations

While the proposed system showcases a promising approach to tackling water pollution through advanced AI technologies, it does inherently possess limitations that warrant acknowledgment and consideration for future enhancements. Addressing these limitations presents a rich avenue for future work aimed at refining and enhancing the proposed system.

A primary constraint lies in the system's reliance on the quality and diversity of its training dataset. The accuracy of pollutant detection and the subsequent generation of contextual information are heavily dependent on the representativeness of the dataset. Pollutants with subtle visual signatures or those not adequately represented may not be accurately identified, leading to potential gaps in monitoring. This limitation underscores the necessity for continuous expansion and diversification of the training dataset to encompass a wider variety of pollution scenarios. Additionally, the system's focus on visual data processing means that it may overlook pollutants that do not have a significant visual footprint, particularly certain chemical pollutants that may be colorless or dissolved in water. This limitation highlights the potential need for integrating additional sensory inputs, such as chemical sensors, to detect a broader range of pollutants and ensure a more comprehensive assessment of water quality.

Another significant limitation of the proposed system is the absence of a case study and formal evaluation focusing on the accuracy, completeness, and performance of the contextual information generation and severity assessment components. Without empirical validation through a case study, the system's effectiveness in real-world scenarios remains speculative. This gap in the research presents a substantial limitation, as it leaves unanswered questions regarding the system's practical applicability and reliability in accurately assessing pollution events and guiding appropriate responses. The lack of formal evaluation also extends to the system's ability to dynamically determine the severity of pollution and recommend suitable actions. Without rigorous testing and validation, the precision of these assessments and the efficacy of the recommended interventions cannot be confidently asserted. This limitation not only affects the credibility of the system's outputs but also its utility as a decision-support tool for environmental management and conservation efforts.

5. Conclusion and Future Work

The proposed multi-modal vision based LLM system for real-time monitoring of water pollution represents a significant advancement in environmental monitoring technology. Its high efficiency and accuracy in detecting a broad spectrum of surface-level pollutants, coupled with the capability to generate detailed contextual information, substantially elevate the efficacy of real-time water quality assessment in local water bodies.

Integration of this system into the Raspberry Pi platform demonstrates its versatility and potential for diverse applications. The system's adaptability to drones and mobile applications promises to extend the reach of environmental monitoring, offering more flexible and accessible solutions. The system's extension to monitor additional environmental factors beyond pollution, such as water discharge, movement patterns, and overall water quality, will offer a holistic view of water ecosystem health and assist in more informed environmental management and conservation practices.

The potential application of our system extends far beyond the mere identification of various pollution types. The capacity of our system to classify additional relevant entities or conditions illuminates its versatility and underscores the breadth of its application in environmental monitoring and conservation efforts. The identification of clean water areas, for instance, serves as a pivotal benchmark within our surveillance system. It not only demonstrates the system’s adeptness at detecting pollution but also at recognizing signs of environmental health, providing a comprehensive view of water body conditions. This dual capability is essential for ongoing water quality assessments and for validating the effectiveness of pollution mitigation strategies. Moreover, the ability to distinguish between harmful algal blooms and beneficial aquatic vegetation is critical for understanding ecosystem health. This distinction aids in identifying areas that may benefit from conservation efforts and in preventing unnecessary alarm or action in regions where aquatic plant life is thriving and contributing positively to the ecosystem.

The potential recognition of wildlife, particularly species that are vulnerable to pollution or indicative of a healthy ecosystem, adds another layer of environmental monitoring. This capability could offer valuable insights into the biodiversity of water bodies and the ecological impacts of pollution, guiding conservation priorities and actions. Additionally, recognizing human activities that might contribute to pollution, such as recreational boating or industrial operations, can inform more targeted regulatory and educational initiatives aimed at mitigating human-induced water pollution. This aspect of the system could play a crucial role in developing community-based strategies for reducing pollution and promoting sustainable practices.

Integrating weather data into our system can enhance its predictive capabilities, allowing for the inference of potential pollutant spread based on weather conditions. Similarly, understanding water flow patterns can aid in predicting the movement of pollutants and identifying contamination sources, which is crucial for timely and effective pollution response strategies. Lastly, the detection of sediment plumes could serve as an early warning system for soil erosion or other forms of land-based pollution entering water bodies. This capability underscores the importance of integrating a holistic view of environmental factors into our system, enhancing its utility as a comprehensive tool for water pollution surveillance.

The integration of these additional classes into our system not only showcases its current potential but also highlights the interconnectedness of environmental factors. This approach enables a more informed and nuanced understanding of water body health, laying the groundwork for more effective decision-making and action planning in environmental protection and sustainability efforts. Through this comprehensive monitoring solution, we aim to contribute significantly to the advancement of environmental monitoring technologies and to the protection of our vital water resources.

Future work will focus on expanding the system's sensory array, incorporating advanced chemical sensors capable of detecting molecular-level pollutants that evade visual detection. The synergy with Internet of Things (IoT) devices will broaden the scope of data collection and enhance automation, facilitating a more interconnected and responsive monitoring network. Furthermore, the development of predictive machine learning algorithms based on historical and real-time data will enable the forecasting of pollution trends and potential ecological impacts. Such advancements will pave the way for proactive environmental strategies, mitigating the risks associated with water pollution and ensuring the sustainability of vital water resources.

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