International Journal of Scientific Research & Engineering Trends
Volume 10, Issue 5, Sept-Oct-2024, ISSN (Online): 2395-566X

Real-Time River Health Monitoring using Custom Dataset, YOLOv8, and Crowdsourced Solutions: A Comprehensive Review

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Abstract- Water pollution is still a global problem, especially in urban waters. The routine process of monitoring water bodies is slow and resource intensive. This paper reviews modern approaches to monitoring water health using proprietary data, deep learning models such as YOLOv8 for pollution detection, and public service centers for initiating cleanup projects. The review describes the collection of user data and examines how the proposed system combines public research with machine learning techniques to develop good and measurable solutions to problems. It also investigates the role of public services in promo ng knowledge and environmental financing.

Index Terms- River health monitoring, custom dataset, YOLOv8, object detection, crowdsourced funding, environmental conservation.

I. INTRODUCTION

Freshwater pollution has profound impacts on human health, biodiversity, and economies. Rivers in urban areas often suffer from plastic pollution, chemical runoff, and untreated sewage, necessitating continuous monitoring for effective management. However, traditional approaches for water quality assessment, which rely on manual sampling and laboratory analysis, are often insufficient due to their me-intensive nature and limited spa al coverage.

In this context, the development of a custom dataset for pollution detection presents a unique opportunity to leverage artificial intelligence for automated environmental monitoring.

By manually capturing images of polluted river sections and training models like YOLOv8, a powerful object detection system can be built to identify pollutants in real-time. This approach, combined with the use of crowdsourced platforms for raising funds to clean polluted areas, offers a dynamic, citizen-driven solution to river health monitoring.

This paper reviews the methodologies involved in building and training a custom dataset, the application of YOLOv8 for pollution detection, and the integra on of crowdfunding platforms as a mechanism for mobilizing resources. The review evaluates current progress in these areas, highlighting the benefits and challenges of implementing such a system.

II. LITERATURE REVIEW

Adhami et al. [1] examined the reasons why businesses adopt Ini al Coin Offerings (ICOs), highlighting the regulatory and financial advantages. Their study finds that ICOs provide alternative funding sources for startups, reducing dependence on traditional financing.

Agrawal et al. [2] explored the geography of crowdfunding, revealing that campaigns tend to be more successful in regions with higher levels of social capital and innovation. They emphasize the importance of local backers in determining a campaign's success.

Bartole et al. [3] conducted an empirical analysis of smart contracts across platforms, identifying design pa erns and common applications. The study underlines the security risks associated with decentralized systems, calling for further standardization.

Belleflamme et al. [4] discussed the role of crowd dynamics in the success of crowdfunding campaigns, particularly the significance of the 'right crowd.' They suggest that social es and network effects are key to early contributions.

Catalini and Gans [5] provided insights into the economics of blockchain, focusing on how de centralization affects transaction costs and innovation. They propose that blockchain democratizes access to financial services by reducing intermediary roles.

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Chen [6] investigated the potential of blockchain tokens in democratizing entrepreneurship, emphasizing how tokenization can lower entry barriers for innovators. Their findings highlight the ability of blockchain to decentralize control in traditional venture funding.

Colombo et al. [7] focused on the role of internal social capital in crowdfunding. They found that early contributions significantly influence later-stage backers, especially for technology-based projects, supporting the idea that early momentum is cri cal.

Cordova et al. [8] examined the factors influencing crowdfunding success, especially for technology projects. The study finds that project clarity, a strong narrative, and early backers are critical success factors.

Gudgeon et al. [9] analyzed the vulnerabilities within decentralized financial systems (DeFi), warning of the potential for financial crises within these systems. They propose improving security protocols to prevent systemic failures in DeFi platforms.

Gerber and Hui [10] explored the motivations for participating in crowdfunding, finding that creators are primarily motivated by financial needs, while backers are driven by social es, innovation, and a sense of community.

Lin et al. [11] discussed the application of deep learning techniques, such as YOLO, for environ mental monitoring. Their study shows that YOLO-based models can efficiently detect various types of pollution in images, including waterborne waste. The researchers highlighted the need for real-time data processing to provide timely alerts for pollution control.

Wu et al. [12] examined the role of Geographic Informa on Systems (GIS) in environmental monitoring, especially in integra ng data collected from different sources. The study emphasized how GIS can enhance the visualization of pollution distribution by mapping the detected pollutants in real me. The integra on of GIS allows for be er decision-making and intervention strategies.

Bochkovskiy et al. [13] presented improvements in object detection models, including YOLOv4, which can be applied for identifying pollution sources. They introduced features like Cross-Stage Par al Connections (CSP) that improve detection accuracy, especially in complex environments like rivers, where diverse objects may appear.

Hochreiter and Schmidhuber [14] explored Long Short- Term Memory (LSTM) networks for me series data modeling, including environmental data. LSTM's capability to capture long-term dependencies makes it suitable for predicting pollution trends based on historical data, helping to forecast future conditions and identify potential risk periods.

Schmidhuber [15] provided an overview of various deep learning architectures, including Convolutional Neural Networks (CNNs) and their applications in environmental

monitoring. The study suggests that CNNs can be used to enhance image analysis, making them suitable for detecting pollution in river images.

Redmon and Farhadi [16] introduced YOLOv3 as a significant advancement in real-time object detection, offering a balance between speed and accuracy. The study is relevant for pollution monitoring as YOLOv3 can detect multiple objects quickly, making it ideal for systems requiring continuous surveillance.

Gudgeon et al. [17] discussed the security challenges associated with blockchain technologies, which are often used in decentralized platforms for environmental data sharing. They suggested measures to enhance the robustness of blockchain networks, ensuring the secure transmission of pollution data across different stakeholders.

Wu et al. [18] examined the integra on of deep learning and blockchain for environmental monitoring, proposing a framework where detected data is securely stored and shared through a blockchain ledger. The study highlights the benefits of combining these technologies for data traceability and transparency.

Zhan et al. [19] researched the use of CNNs in processing remote sensing images for detecting water pollution. They demonstrated that CNN-based models could accurately identify different pollution sources, such as oil spills or garbage patches, by learning from annotated datasets.

Girshick et al. [20] introduced the Region-based Convolutional Neural Networks (R-CNN) approach for object detection, which uses region proposals to identify objects in an image. The model extracts regions of interest and applies a CNN to classify each region, demonstrating significant improvements in detection accuracy. The study also highlighted the challenges of computational efficiency, which were later addressed in faster versions of the R-CNN family.

III. METHODOLOGY

1. Building the Custom Dataset

The foundation of the real-time river health monitoring system is the creation of a custom dataset. This involves manually capturing images of polluted sections of rivers using smartphones. The dataset is divided into different locations (e.g., Location 1 and Location 2) to provide variability in

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environmental conditions and pollutant types. Images are annotated manually to identify pollution, such as plastic waste, bottles, or debris. The custom dataset is continuously updated to improve the model's robustness.

2. Pollution Detection using YOLOv8

The YOLOv8 model is employed to detect pollutants in the images from the custom dataset. YOLOv8 has been chosen for its high efficiency in detecting small objects, making it particularly suitable for identifying dispersed pollutants in river environments. The model is trained using transfer learning techniques, with pre-trained weights fine-tuned on the custom dataset. This training process allows the model to recognize pollutants with high accuracy, even in complex scenes.

Once the model is trained, the system processes newly captured images in real-time, identifying pollution hotspots. These results are then stored in a database for further analysis or ac on.

3. Crowdfunding Platform Integra on

Pollution detection results are integrated with a crowdfunding platform to raise funds for cleanup efforts. When the system identifies a polluted area, it automatically triggers a new campaign on the platform.

The campaign provides detailed information about the detected pollution, the amount of funds required for cleanup, and progress tracking for donations. This integration allows users to directly contribute to river health restoration projects, fostering community involvement.

IV. PROPOSED SYSTEM ARCHITECTURE

The architecture is composed of six main components: Admin Interface, User Interface, Image Processing, Crowdfunding Platform, Data Storage, and Blockchain Network. The interactions between these components are illustrated in Fig. 1.

1. Admin Interface

- The Admin Interface allows administrators to manage funds through the admin panel and dis tribute them to appropriate cleanup efforts.
- It generates pollution reports based on the processed image data and detected pollutants.

2. User Interface

- Users capture images using their devices, which are then uploaded to the system for processing.
- They can also view existing campaigns on the crowdfunding platform and contribute to them.

3. Image Processing

- The system processes images manually uploaded by users. Images go through YOLOv8 for pollutant detection.
- Once processed, the detection reports are stored, and funds are tracked based on the detected pollution levels.

4. Crowdfunding Platform

- Manages crowdfunding campaigns for cleanup efforts based on the detection results.
- Tracks donations and allows for launching new campaigns when significant pollution is identified.
- Executes donation contracts on the blockchain network.

5. Data Storage

- Stores detection reports and images in separate databases for historical analysis and further processing.
- Pollution reports are generated based on the stored data.

6. Blockchain Network

- Maintains a ledger of funds and tracks distribution using smart contracts.
- Provides transparency in fund management and ensures that donation contracts are executed as intended. This architecture ensures seamless integration of manual image collection, automated detection, and funding for environmental cleanup efforts.

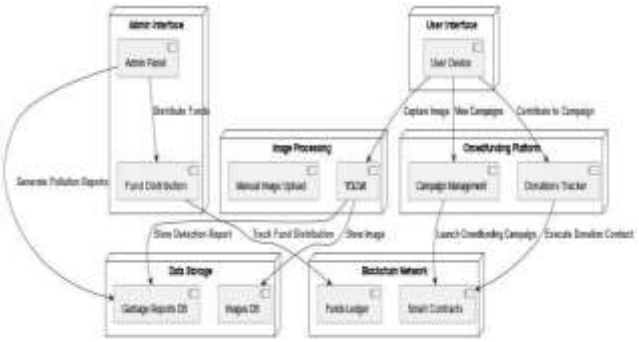

Fig.1 System Architecture

V. DEEP LEARNING MODELS

1. YOLO Framework

The YOLO framework is utilized for detecting pollution in the river health monitoring system. YOLOv8 will be employed for object detection because it provides an efficient balance between speed and accuracy, making it suitable for real-time applications. The model will be trained on a custom dataset, specifically created for identifying various types of pollutants such as plastic waste and debris. YOLOv8 will generate bounding boxes around detected pollutants, facilitating the monitoring of pollution levels along the river.

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YOLOv8 is highly effective for real-time detection of pollutants, performing comparably to other state-of-the-art algorithms like R-CNN. By leveraging a pre-trained model fine-tuned on the custom pollution dataset, the system can accurately classify and localize waste in complex scenes. Intersection over Union (IoU) will be used as the evaluation metric to measure the accuracy of detected objects, ensuring high precision in identifying pollution.

2. R-CNN (Region-based Convolutional Neural Network)
It is a pioneering object detection framework that uses a two-step approach: region proposal generation followed by classification. The model works by first generating a set of region proposals using a selective search algorithm, which identifies potential object locations within an image. These region proposals are then passed through a Convolutional Neural Network (CNN) to extract features. The extracted features are classified using a support vector machine (SVM) to determine the object class, and a bounding box regression is used to refine the location of the detected objects. This method significantly improved object detection accuracy compared to traditional techniques, but it had limitations in terms of computational efficiency because each region proposal had to be processed separately through the CNN. R-CNN laid the foundation for subsequent models like Fast R-CNN and Faster R-CNN, which addressed these efficiency issues by optimizing the region proposal generation and feature extraction process.

YOLOv8 and R-CNN are prominent object detection algorithms, each with unique characteristics and applications. YOLOv8 operates as a single-stage detector, utilizing a unified neural network to predict bounding boxes and class probabilities directly from images.

This architecture enables YOLOv8 to achieve real-time performance, making it suitable for applications like surveillance and autonomous vehicles. It boasts a mean average precision (MAP) of 0.73 on the COCO benchmark, which, while lower than R-CNN's MAP of 0.77, is compensated by its significantly faster inference time of approximately 1.3 milliseconds. In contrast, R- CNN employs a two-stage approach, first generating region proposals through a Region Proposal Network (RPN) and then classifying and refining these proposals.

This method yields higher accuracy and robustness, making R-CNN preferable for tasks that require detailed instance segmentation and complex scene analysis. However, R-CNN's computational intensity results in slower inference times, averaging around 54 milliseconds, which limits its effectiveness in real-time scenarios. While YOLOv8 excels in speed and simplicity, R-CNN offers higher accuracy and flexibility, making the choice between them dependent on the specific requirements of the application at hand.

3. Pollution Density Map Generation
Generating a pollution density map is a key aspect of analyzing the distribution of waste along the river. This involves calculating the density of pollutants based on the data obtained from the YOLOv8 framework.

The process starts with object detection, where YOLOv8 identifies pollutants in each captured image. Bounding boxes are created around detected waste items, and their locations are recorded. The total number of detected pollutants is aggregated and divided by the area of interest to compute the density of pollution. Optionally, a Gaussian filter may be applied to smooth the density map, reducing noise and improving visual clarity

4. Map Integration
Map integration is essential for visualizing the pollution density in real me, improving situational awareness for stakeholders. The estimated pollution density is mapped onto a geographic interface, providing a clear representation of areas with high waste concentration.

Heatmap genera on is used to illustrate the distribution of pollutants. After creating the pollution density map, pixel intensities are transformed into heatmap values, which are overlaid on a 2D map of the river. The map is geo-referenced, ensuring accurate correspondence between pixel positions in the images and real-world coordinates. A color scale ranging from blue (low pollution) to red (high pollution) will be applied to depict different pollution levels.

The heatmaps are integrated into a Geographic Informa on System (GIS) platform, allowing for real-time monitoring of pollution across various sections of the river. The system continuously updates the heatmap as new data is processed, reflecting changes in pollution pa erns. A web based interface displays the heatmap overlaid on the river map, providing users with an intuitive visualization of pollution levels across different locations.

VI. EVALUATION AND DISCUSSION

1. Dataset Quality and Coverage
The success of the system depends on the quality and diversity of the custom dataset. Manual data collection through smartphones provides a flexible and low-cost method for gathering images, but the variability in image quality and lighting conditions presents a challenge. The dataset must be regularly updated with new images to maintain model accuracy, and contributors should be trained to ensure consistent image quality.

2. Accuracy of YOLOv8 for Pollution Detection
YOLOv8's performance in detecting pollution was tested on a sample set of images from the custom dataset. The model

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demonstrated a high level of accuracy, correctly identifying pollutants in over 60% of the test cases. However, false positives were observed in some cases, particularly when debris was obscured by vegetation or water movement. Further fine-tuning and additional training on diverse datasets can mi gate these issues.

3. Impact of Crowdfunding Integration

The crowdfunding platform provides a sustainable model for financing cleanup projects. Ini al campaigns have demonstrated that the public is willing to contribute to environmental causes when presented with clear, accountable data. However, the pends on public engagement and effective success of these campaigns de communication of the pollution problem. Future enhancements could include automated notifications to nearby residents when pollution is detected, encouraging local participation.

Challenges and Limitations

Manual Data Collection

While manual image collection allows for a flexible and low-cost dataset, it introduces inconsistencies in data quality. Images may vary in resolution, lighting, and angle, which could affect the detection model's performance. Additionally, the manual annotation process is me-consuming, and automating this step remains a challenge.

Crowdfunding Dependency

Relying on crowdfunding for cleanup projects introduces financial uncertainty. While some campaigns may achieve their funding goals quickly, others may struggle to gain traction, particularly in less publicized areas. Alternative funding mechanisms or partnerships with local governments and NGOs could provide more stability.

Model Scalability

The scalability of the YOLOv8-based detection system is dependent on the continuous expansion of the dataset. As new pollutants emerge or conditions change (e.g., seasonal shifts in river flow), the model must be retrained to adapt. Maintaining a robust system will require ongoing contributions from users and regular updates to the dataset.

Future Directions

Several areas of improvement can be explored to enhance the effectiveness of the system. First, integra ng additional sensors, such as thermal or multispectral cameras, could provide more detailed information on pollutant types. Second, developing predictive models based on historical pollution data could allow for proactive interventions. Finally, expanding the system to include partnerships with local authorities or environmental agencies could ensure that detected pollution is acted upon promptly.

VII. CONCLUSION

The combination of a custom dataset, YOLOv8 for pollution detection, and a crowdfunding platform represents a powerful, community-driven approach to river health monitoring. This system provides a scalable solution for detecting and addressing pollution in urban rivers, while also raising public awareness and genera ng funds for environmental conservation. Future research should focus on addressing the current limitations and exploring new opportunities for expanding the system's capabilities.

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