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Detection of Plastic Debris in River Environments using Deep Learning

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ABSTARCT: Plastic pollution in rivers has become a critical environmental concern as rivers act as major pathways transporting plastic waste into oceans. Manual monitoring of river plastic pollution is labor-intensive, time-consuming, and limited in spatial coverage. Recent advances in remote sensing, image processing, and machine learning provide effective alternatives for large-scale environmental monitoring.

This project proposes an automated system for detecting river plastic pollution using image processing and machine learning techniques**.** Images of river surfaces are collected from cameras, drones, or publicly available datasets. The images undergo preprocessing steps such as noise removal, contrast enhancement, and segmentation to improve visibility of plastic objects. Feature extraction and machine learning models, including Convolutional Neural Networks (CNNs), are employed to distinguish plastic waste from natural elements such as water, vegetation, and reflections.
The proposed system aims to provide accurate identification and localization of plastic debris, supporting pollution assessment and cleanup planning. Compared to traditional manual methods, the system offers a cost-effective, scalable, and efficient solution for continuous river pollution monitoring, contributing to sustainable environmental management.

I. INTRODUCTION

Plastic pollution has emerged as one of the most serious environmental challenges of the modern era, with rivers acting as major pathways for transporting plastic waste into oceans. This project, titled **"**Detection of Plastic Debris in River Environments Using Deep Learning**"** aims to design and implement an automated system for detecting and classifying plastic waste in river environments using artificial intelligence. Machine learning models, including Convolutional Neural Networks (CNN), are trained to distinguish plastic materials from natural elements like water, vegetation, and reflections. River systems are particularly vulnerable to plastic pollution because they receive waste from urban runoff, industrial discharge, and improper solid waste disposal. Floating plastic debris not only affects water quality but also interferes with natural river flow, blocks drainage channels, and contributes to flooding during heavy rainfall. the proposed system lays the foundation for data-driven environmental monitoring and policy formulation. By continuously collecting and analyzing visual data over time, the system enables the generation of historical pollution trends and temporal patterns of plastic accumulation in river systems. Such insights can help authorities evaluate the effectiveness of waste management policies, identify recurring pollution sources, and implement targeted intervention strategies. In this context, the proposed river plastic pollution detection system contributes significantly to environmental sustainability

II.RELATED WORK

- **Satellite-based monitoring:**
- Uses Sentinel-2 multispectral images
- Detects large-scale plastic patches
- Limitation: cannot detect small objects due to low resolution
- High-resolution images
- Good for rivers and small debris
- Requires controlled conditions and labeled datasets
- CNN, YOLO, Faster R-CNN used for object detection
- High accuracy but need large training data
- Combination of preprocessing, segmentation, and ML

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- **UAV (Drone) based detection:**
- **Machine Learning & Deep Learning:**
- **Hybrid techniques:**
  - o Reduce false detection due to reflections and shadows

Research Gap Identified:

- Lack of cost-effective and scalable systems
- Need for lightweight, adaptable methods for river environments
- Limited real-world deployment in developing countries

Manual monitoring of plastic pollution in river environments is a slow, labor-intensive, and inconsistent process, especially when large river stretches must be observed regularly. Environmental authorities and researchers face challenges in accurately identifying and quantifying plastic debris using traditional methods. Existing monitoring approaches often lack automation, scalability, and real-time analysis, leading to delayed or incomplete assessments of river pollution. Therefore, there is a need for an automated deep learning–based system that can accurately detect plastic debris in river environments, enabling efficient, consistent, and scalable pollution monitoring.

III. RESEARCH FRAMEWORK AND OBJECTIVES

Framework includes:

1. Image collection from rivers
2. Image preprocessing
3. Feature extraction
4. Machine learning classification
5. Result visualization

Main Objectives:

- Develop an automated system for river plastic detection
- Reduce manual monitoring
- Provide accurate, low-cost, and scalable solution
- Use CNN-based models for classification

IV. METHODOLOGY

A. Data Acquisition

B. Image Preprocessing

C. Region of Interest (ROI) Selection

D. Feature Extraction

E. Plastic Detection Using Machine Learning

F. Result Visualization

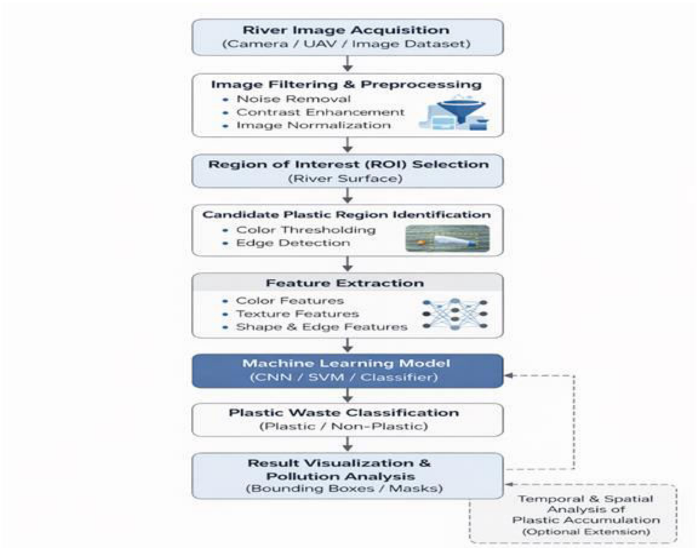

Fig. X. Workflow of the proposed river plastic pollution detection framework using image processing and machine learning.

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V. CASES OF STUDY

A. Study Area Description

The case study focuses on selected river segments where the accumulation of floating plastic waste is frequently observed due to urban runoff, improper solid waste disposal practices, and nearby human activities. These river sections typically exhibit slow to moderate water flow, making them prone to the accumulation of floating debris. Additionally, the presence of surface reflections, ripples, floating vegetation, and varying background elements such as riverbanks and nearby infrastructure creates visually complex conditions.To enable supervised learning and performance evaluation, the collected river images were manually annotated to label plastic and non-plastic regions. These labeled images serve as ground truth data for training, validation, and testing of the machine learning model. Accurate annotation ensures reliable learning of plastic-related visual patterns and enhances the overall credibility of the experimental results.

B. Dataset Description

A diverse dataset of river surface images was used to conduct the case study. The dataset includes images containing visible plastic waste such as plastic bottles, carry bags, wrappers, and other floating debris, along with images that do not contain plastic waste to ensure balanced classification. The dataset captures a wide range of real-world conditions, including variations in lighting intensity, water turbidity, surface ripples, reflections, shadows, and background complexity.This diversity ensures that the detection system is evaluated under realistic and challenging scenarios that closely resemble actual river environments. Prior to analysis, all images were resized to maintain uniform input dimensions required by the machine learning model.Pixel intensity normalization was also applied to reduce variations caused by changing illumination conditions. These preprocessing steps improve image quality, ensure dataset consistency, and facilitate more reliable feature extraction.

C. Experimental Setup

The experimental evaluation was carried out using a Python-based implementation incorporating standard image processing and machine learning libraries such as OpenCV, NumPy, and TensorFlow. The dataset was systematically divided into training and testing subsets to ensure unbiased and reliable performance assessment. All input images were subjected to the preprocessing steps described in the methodology section,. The detection process involved analyzing spatial and visual patterns to distinguish plastic objects from natural elements such as water reflections and vegetation. The experimental setup was designed to closely simulate real-world deployment conditions by evaluating the system under varying environmental scenarios, including changes in lighting, water flow, and background complexity. This setup enabled a comprehensive assessment of the robustness, generalization capability, and practical applicability of the proposed detection framework.

D. Detection Results

The proposed system successfully detected floating plastic debris in the test images. Detected plastic regions were highlighted using bounding boxes and visual overlays.allowing clear and intuitive identification of pollution-affected areas. The system demonstrated the ability to accurately distinguish plastic objects from natural river elements such as water surfaces, reflections, foam.

E. Performance Evaluation

The detection performance of the proposed framework was evaluated using standard classification metrics, including accuracy, precision, recall, and F1-score. The evaluation results indicate that the system achieves consistent and reliable detection performance across diverse environmental conditions. High precision values demonstrate the system's ability to minimize false detections, while strong recall values indicate effective identification of plastic debris.Although minor false detections were observed in scenarios involving strong water reflections or dense floating vegetation, these cases were limited and did not significantly impact overall system performance. The quantitative evaluation confirms the robustness and suitability of the proposed framework for practical river plastic pollution monitoring.

F. Discussion

The case study results demonstrate that the proposed river plastic pollution detection framework performs effectively in real-world river environments. The automated nature of the system significantly reduces the need for manual inspection and enables efficient analysis of large volumes of river surface images. The integration of image preprocessing, feature extraction, and machine learning–based classification allows the system to handle environmental variability and visual complexity.Furthermore, the results highlight the adaptability of the framework to different river conditions, making it

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suitable for deployment in both urban and semi-urban regions. The findings confirm that the proposed approach offers a cost-effective and scalable solution for continuous environmental monitoring and pollution assessment.

G. Practical Implications and Applications

The outcomes of the case study indicate that the proposed river plastic pollution detection framework has strong potential for practical deployment in real-world environmental monitoring applications. The automated detection capability can support environmental agencies and municipal authorities in conducting regular river inspections without extensive manpower. By enabling timely identification of plastic accumulation zones, the system can assist in prioritizing cleanup operations and optimizing resource allocation.Furthermore, the proposed framework can be integrated with existing monitoring infrastructures such as surveillance cameras, drone-based imaging systems, and smart environmental monitoring platforms. The generated detection results can also be combined with geospatial data to create pollution maps, facilitating long-term analysis of plastic pollution trends. These practical implications highlight the relevance of the proposed approach in supporting sustainable river management and environmental conservation initiatives.

H. Summary of Case Study

The conducted case study successfully validates the feasibility, robustness, and effectiveness of the proposed river plastic pollution detection framework. Through systematic experimentation on real river surface images, the system demonstrated its ability to accurately identify and localize floating plastic debris across a wide range of environmental conditions. The results confirm that the proposed approach can handle challenges such as varying illumination, surface reflections, water turbidity, and the presence of floating vegetation, which are commonly encountered in real-world river environments.

Overall, the case study highlights the practical applicability and real-world relevance of the proposed solution for river plastic pollution monitoring. The framework has the potential to support environmental authorities, researchers, and policymakers in assessing pollution levels, identifying critical plastic accumulation zones, and planning timely cleanup and mitigation strategies.

I. Future Scope Based on Case Study

Based on the outcomes of the conducted case study, the proposed river plastic pollution detection framework offers significant scope for future enhancements and broader deployment. The system can be extended to support real-time monitoring by processing continuous video streams obtained from surveillance cameras or drone-based platforms. Such extensions would enable continuous observation of river surfaces and early detection of plastic accumulation, allowing timely intervention.Furthermore, the integration of the proposed framework with geographic information systems (GIS) can facilitate spatial mapping and long-term analysis of plastic pollution patterns. Advanced deep learning models, transfer learning techniques, and larger annotated datasets can also be incorporated to further improve detection accuracy and adaptability under complex environmental conditions. These future enhancements would strengthen the practical applicability of the system and contribute to sustainable river management and environmental conservation efforts.

VI. RESULTS AND DISCUSSION

(a) Candidate search

Name	Runtime (s)	Area (Km^2)	Images
Potpecko dam	6	12100	6
Visegrad dam		12100	6
Hidrovacas dam	6.7	12100	4
Cairo, Egypt	3.22	12100	6

(b) Vectorization

Name	Runtime (s)	Area (Km^2)	Images
Potpecko dam	41	0.9	14
Visegrad dam		3	19
Hidrovacas dam	23.6	0.7	4
Cairo, Egypt	75.7	1.5	28

(c) SU

Name	Runtime (s)	Area (Km^2)	Images
Potpecko dam	32.3	12100	14
Visegrad dam		12100	19
Hidrovacas dam	16.4	12100	4
Cairo, Egypt	48.4	12100	28

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Fig1. Detection of floating plastic debris in 2020 at Hidrovacas Dam, Guatemala, over an area approximately 20 × 10 km. The image displays a true-color composite from Sentinel-2 data, using a median composite from spring 2020. Detected plastic areas are highlighted in red, located in the center of the image (circled in red), demonstrating how the analysis can be conducted at larger scales with no false alarms. The inset at the top left shows a PlanetScope image from 25 March 2020 (2020 Planet Labs), with the plastic extent outlined in red.

TEST SITES FOR THE SEARCH OF PLASTIC CANDIDATE AREAS

Name	Coordinates	Observation Period	N. of images
Potpecko dam, Serbia	N 43.52°, E 19.59°	1 February 2020–30 September 2020	6
Visegrad dam, Bosnia and Herzegovina	N 43.76°, E 19.29°	1 October 2020–30 August 2021	6
Hidrovacas, Guatemala	N 14.76°, E -90.50°	1 March 2020–30 September 2020	4
Cairo, Egypt	N 30.19°, E 31.29°	1 January 2020–30 September 2020	6

Fig2.Plastic detection for 2020 on Potpecko dam, Serbia, covering an approximate area of 30 × 15 km. The image shows a true color composite from the Sentinel-2 median image for spring 2020, with the plastic extent similarly outlined in red. No false alarms are present in the scene. The insert displays a PlanetScope image acquired on 20 March 2020, (2020 Planet Labs), with the plastic extent outlined in red. Further details on the multitemporal Sentinel-2 dataset and plastic detection results are provided in Fig. 3(a)–(g).

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Fig. 3. Plastic candidates identified at dam sites along the Lim river (Serbia). True-color composites of Sentinel-2 subsets from 2020 are shown (refer to Fig. 6 for the full view). Subimages (a)—(f) were captured on the same day as the higher resolution PlanetScope image in the insert of Fig. 6 [(a) 20th March, (b) 9th April,
(c) 10th July, (d) 28th July, (e) 22nd August, and (f) 6th September] and the plastic mask derived in (g) aligns with the plastic extent outlined in the PlanetScope image.

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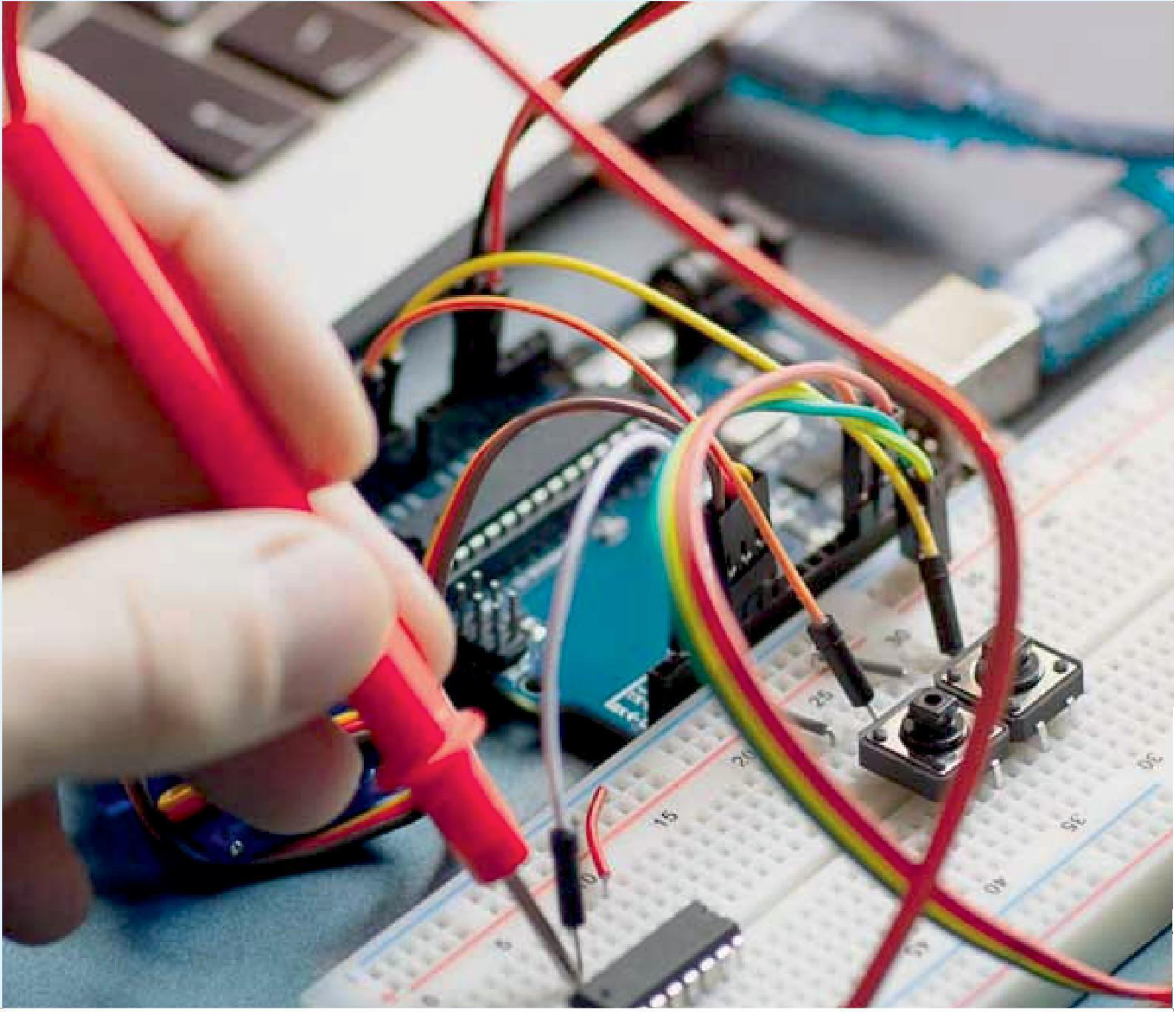

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