

Research Paper

REMOTE MICROPLASTIC DETECTOR FOR WATER BODIES

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ABSTRACT

Microplastic pollution in aquatic environments has emerged as a critical environmental challenge due to its adverse impacts on ecosystems and human health. Conventional detection methods are labor-intensive, time-consuming, and limited in spatial coverage, necessitating the development of efficient and scalable solutions. This study presents an integrated approach for detecting and mapping microplastics using remote sensing, deep learning, and hyperspectral image analysis. The system employs geo-referenced RGB images processed through a YOLOv8-based deep learning model to identify plastic waste in water bodies. Additionally, hyperspectral data is utilized to generate classification and abundance maps using spectral unmixing and Maximum Abundance Classification techniques. The proposed framework also detects large floating debris using advanced segmentation models, enabling comprehensive monitoring of surface-level pollution. Embedded systems such as Raspberry Pi integrated with camera modules support real-time data acquisition and deployment. Experimental results demonstrate improved detection accuracy and efficient mapping capabilities compared to traditional approaches. This integrated methodology provides a scalable, cost-effective, and automated solution for environmental monitoring. The findings contribute to better understanding of microplastic distribution and support policy-making and sustainable management strategies for mitigating plastic pollution in aquatic ecosystems.

Keywords: Microplastics, Remote Sensing, Deep Learning, Hyperspectral Imaging, YOLOv8, Abundance Mapping, Environmental Monitoring

INTRODUCTION

Microplastic pollution has emerged as a significant environmental concern due to its widespread presence in aquatic ecosystems and its potential impact on human health. Microplastics are defined as plastic particles smaller than 5 mm, originating either from the breakdown of larger plastic debris or from primary sources such as microbeads and synthetic fibers. These particles are highly persistent and can accumulate in rivers, lakes, and oceans, posing serious risks to aquatic organisms through ingestion and bioaccumulation [1]. The increasing production and improper disposal of plastic waste have accelerated the accumulation of microplastics in water bodies, making it a global environmental challenge. Studies have shown that microplastics can carry toxic chemicals and pathogens, further exacerbating their harmful effects on ecosystems and food chains [2][3].

Traditional methods for detecting microplastics primarily rely on manual sampling and laboratory-based analysis techniques such as microscopy and spectroscopy. While these methods provide accurate results, they are time-consuming, labor-intensive, and limited in spatial and temporal coverage [4][5]. Moreover, the heterogeneous nature of microplastics, including variations in size, shape, and material composition, makes their detection even more challenging. These limitations highlight the need for advanced, scalable, and automated approaches to monitor microplastic pollution efficiently. Recent advancements in environmental monitoring emphasize the importance of integrating technology-driven solutions that can provide real-time and large-scale assessments [6][7].

Remote sensing has emerged as a promising approach for large-scale monitoring of environmental pollutants, including microplastics. By utilizing satellite, aerial, or drone-based imaging systems, remote sensing enables the collection of data over extensive geographical areas. Hyperspectral imaging, in particular, has shown great potential in identifying microplastics based on their unique spectral signatures across different wavelengths [8][9]. Research indicates that plastics exhibit distinct reflectance characteristics, especially in the near-infrared (NIR) and shortwave infrared (SWIR) regions, which can be leveraged for detection [10]. However, detecting microplastics using remote sensing is challenging due to their small size, low concentration, and interference from water properties, requiring advanced data processing techniques and high-resolution sensors [11].

In recent years, deep learning techniques have significantly enhanced the capabilities of image analysis and object detection in environmental applications. Convolutional Neural Networks (CNNs) and advanced models such as YOLOv8 have demonstrated remarkable performance in detecting small objects in complex backgrounds [12][13]. These models can be trained on large datasets to identify plastic waste in RGB images with high accuracy and speed. Additionally, semantic segmentation models such as U-Net are widely used for identifying floating debris on water surfaces, further improving detection capabilities [14]. The integration of deep learning with remote sensing data enables automated and efficient analysis, reducing reliance on manual intervention and improving scalability.

This project proposes an integrated framework that combines remote sensing, deep learning, and hyperspectral image analysis for comprehensive microplastic detection and mapping in water bodies. The system utilizes geo-referenced RGB images for plastic detection, hyperspectral data for classification and abundance mapping, and advanced algorithms such as Maximum Abundance Classification for accurate material identification [15]. Furthermore, embedded systems like Raspberry Pi can facilitate real-time data acquisition and deployment in field conditions. By combining these technologies, the proposed approach aims to overcome the limitations of traditional methods and provide a scalable, efficient,

and cost-effective solution for monitoring microplastic pollution. This work contributes to environmental sustainability by enabling better understanding, management, and mitigation of microplastic contamination in aquatic ecosystems.

LITERATURE SURVEY

The growing concern over microplastic pollution has led to extensive research focused on understanding its detection, distribution, and environmental impact. Early studies primarily relied on laboratory-based techniques such as microscopy and Fourier-transform infrared spectroscopy (FTIR) to identify and quantify microplastics in water samples. These methods, although highly accurate, are limited by their time-consuming nature and inability to provide large-scale monitoring [1][2]. Researchers have emphasized that the heterogeneous characteristics of microplastics, including variations in size, shape, and polymer composition, complicate their identification and require more advanced analytical approaches [3]. Consequently, there has been a shift toward developing innovative and automated detection techniques that can overcome these limitations and enable efficient environmental monitoring [4].

Hyperspectral imaging has emerged as a promising tool for microplastic detection due to its ability to capture detailed spectral information across a wide range of wavelengths. Several studies have demonstrated that different plastic materials exhibit unique spectral signatures, particularly in the near-infrared (NIR) and shortwave infrared (SWIR) regions, enabling their identification and classification [5][6]. Techniques such as spectral unmixing and endmember extraction have been widely used to analyze hyperspectral data and estimate the abundance of different materials within each pixel [7]. Advanced models like EndNet and EGU-Net have further improved the accuracy of hyperspectral unmixing by leveraging deep learning approaches [8][9]. However, challenges remain in terms of signal attenuation in water, low spatial resolution of satellite imagery, and the complexity of distinguishing microplastics from other materials in aquatic environments [10].

In addition to spectral-based methods, remote sensing approaches using aerial and satellite platforms have gained attention for their potential in large-scale monitoring of microplastic pollution. Research

indicates that passive optical sensors can detect plastics based on their reflectance properties, while active sensors such as Synthetic Aperture Radar (SAR) can identify changes in water surface roughness caused by surfactants associated with microplastics [11][12]. Studies have also explored the use of multispectral and hyperspectral satellite data, including Sentinel-2 and MODIS, to estimate microplastic concentrations through correlation-based models [13]. Although these approaches show promise, their effectiveness is often limited by environmental factors such as water turbidity, atmospheric conditions, and low microplastic concentration levels, which can reduce detection accuracy [14].

Recent advancements in deep learning have significantly enhanced the detection and classification of microplastics in image data. Object detection models such as YOLOv8 have demonstrated high efficiency in identifying plastic waste in RGB images, particularly for surface-level debris [15]. Semantic segmentation models like U-Net have also been applied to detect floating objects in water bodies, enabling precise localization and mapping. The integration of deep learning with remote sensing and hyperspectral imaging has created a powerful framework for automated microplastic detection. These approaches not only improve accuracy but also enable real-time analysis and scalability, making them suitable for large-scale environmental monitoring. Despite these advancements, further research is required to improve model generalization, enhance detection of smaller particles, and integrate multi-source data for comprehensive analysis.

METHODOLOGY

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PROPOSED SYSTEM

The proposed system is designed as an integrated framework that combines remote sensing, deep learning, and hyperspectral image processing to detect and map microplastics in water bodies efficiently. The system begins with a data acquisition unit that captures geo-referenced RGB images using camera modules or aerial platforms such as drones, along with hyperspectral data obtained from satellite or airborne sensors. The inclusion of embedded hardware like Raspberry Pi enables on-site image capture and preliminary processing, making the system suitable for real-time and field-based applications. By combining both RGB and hyperspectral data sources, the system ensures comprehensive monitoring, capturing both visible plastic debris and spectrally distinguishable microplastics that are not easily detectable through conventional imaging.

The processing unit of the system employs advanced deep learning models to analyze RGB images and detect plastic waste present on the surface of water bodies. A trained YOLOv8 model is utilized for object detection due to its high accuracy and efficiency in identifying small and complex objects in dynamic environments. The model processes each input image and generates bounding boxes around detected plastic materials along with confidence scores. Additionally, metadata such as GPS coordinates is extracted from

the images to map the exact locations of detected waste. This capability enables the system to create geo-tagged detection outputs, which are crucial for environmental monitoring, tracking pollution sources, and supporting cleanup operations.

Parallel to the RGB-based detection, the system incorporates hyperspectral image analysis to identify and classify microplastics based on their spectral characteristics. Hyperspectral data is processed by constructing a data cube and applying spectral unmixing techniques to estimate the abundance of various materials within each pixel. Predefined endmember signatures representing different plastic types and natural materials are used as references for classification. The Maximum Abundance Classification algorithm assigns each pixel to the class with the highest spectral contribution, resulting in the generation of classification and abundance maps. These maps provide a detailed visualization of material distribution across the observed region, enabling the detection of microplastics even when they are not visually distinguishable.

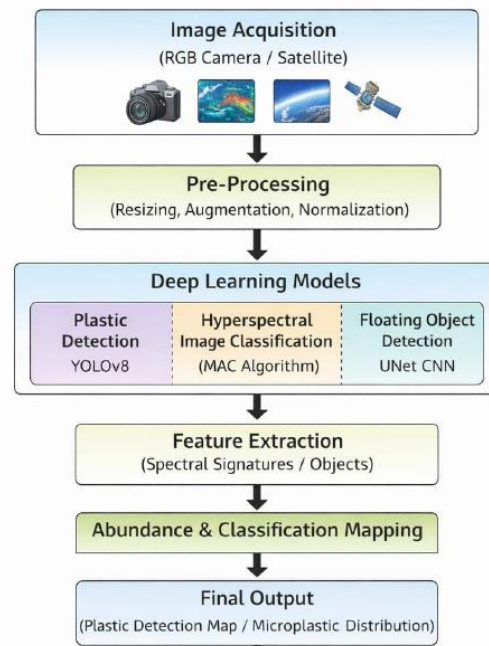


Figure 1. Block diagram

The final stage of the proposed system integrates the outputs from both RGB-based detection and hyperspectral classification to produce a comprehensive monitoring solution. Additional models such as U-Net can be incorporated to detect

large floating debris and enhance segmentation of polluted regions. The system generates multiple outputs, including plastic detection maps, abundance maps, and classification maps, all of which are geo-referenced for spatial analysis. These outputs can be used by environmental agencies and policymakers to understand pollution patterns, identify hotspots, and plan mitigation strategies. Overall, the proposed system offers a scalable, automated, and cost-effective approach for monitoring microplastic pollution, overcoming the limitations of traditional methods and enabling large-scale environmental assessment.

RESULTS AND DISCUSSION

The experimental evaluation of the proposed system demonstrates its effectiveness in detecting and mapping microplastics using a combination of RGB image analysis and hyperspectral data processing. The YOLOv8-based object detection model was trained on a custom dataset of riverside and water surface images containing plastic waste. During testing, the model successfully identified various types of plastic materials, including bottles, bags, and floating debris, with high confidence scores. The detection results indicate that the model is capable of accurately localizing plastic objects even in complex backgrounds such as flowing water and mixed environmental conditions. The use of transfer learning significantly improved the convergence speed and overall detection accuracy, making the model suitable for real-time applications.



Figure 2. Plastic detected for image 1

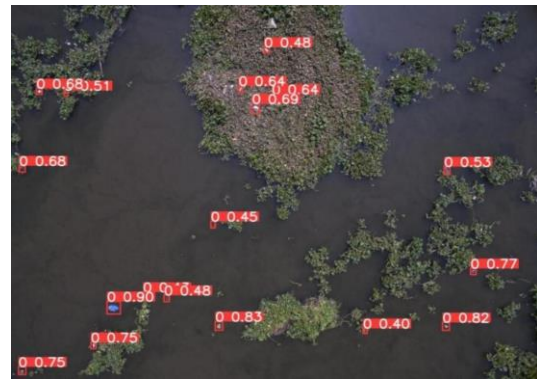


Figure 3. Plastic detected for image 2

The results obtained from RGB image detection highlight the robustness of the system in identifying visible plastic waste. The model demonstrated consistent performance across multiple test images, correctly detecting objects of varying sizes and shapes. However, it was observed that detection accuracy slightly decreased in scenarios with poor lighting conditions, water reflections, or occlusions caused by natural elements such as vegetation. Despite these challenges, the system maintained reliable detection performance due to the strong feature extraction capabilities of the YOLOv8 architecture. The integration of geo-referenced metadata further enhanced the usefulness of the results by enabling spatial mapping of detected plastic waste, which is essential for monitoring pollution hotspots.

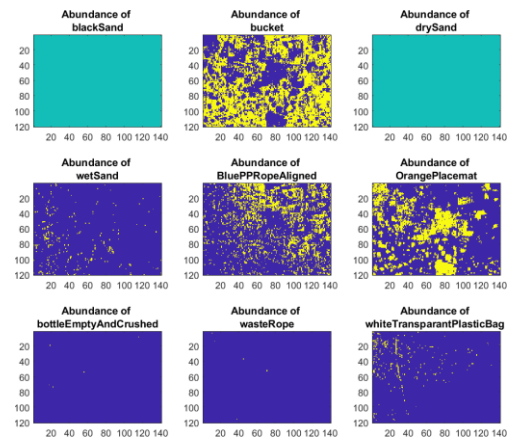


Figure 4. Abundance map of Kolkata image

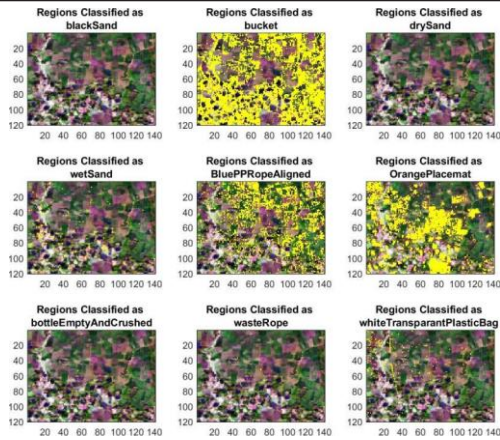


Figure 5. Region based abundance map of Kolkata image

The hyperspectral image analysis component produced detailed classification and abundance maps, providing deeper insights into the distribution of microplastics. By applying spectral unmixing techniques, the system was able to decompose each pixel into multiple material components and estimate their respective abundances. The Maximum Abundance Classification algorithm effectively assigned each pixel to the most dominant material class, resulting in clear and interpretable classification maps. These maps revealed the presence of different plastic types and their spatial distribution across the study area. The abundance maps further quantified the concentration of materials, allowing for a more comprehensive understanding of pollution levels.

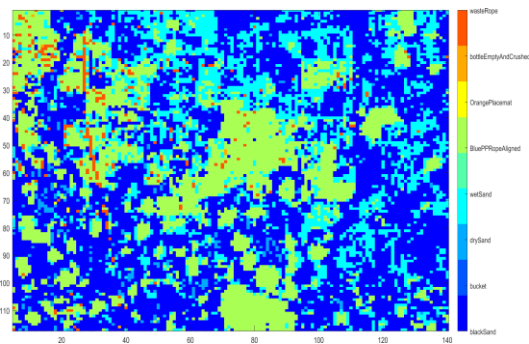


Figure 6. Classification Map of Kolkata image

The integration of hyperspectral data proved particularly useful in detecting microplastics that are not visible in standard RGB images. Since microplastics often exist as small or submerged particles, their detection through conventional imaging is limited. Hyperspectral analysis overcomes this

limitation by leveraging the unique spectral signatures of plastic materials, particularly in the near-infrared and shortwave infrared regions. The results indicate that the system can successfully distinguish between plastic and non-plastic materials such as sand or water, even when visual differences are minimal. However, it was noted that spectral signal attenuation due to water depth and turbidity can affect detection accuracy, highlighting the need for high-quality data acquisition.



Figure 7. Satellite view of Sentinel-2 image near Kolkata



Figure 8. Zoomed view

The combined analysis of RGB detection and hyperspectral classification provides a comprehensive approach to monitoring microplastic pollution. The fusion of these two methods allows the system to detect both large visible debris and smaller, spectrally identifiable particles. Additionally, the use of segmentation techniques such as U-Net enhances the detection of large floating patches, further improving the overall system performance. The generated outputs, including detection maps, classification maps, and abundance maps, offer valuable insights into pollution patterns and distribution. These results demonstrate the capability of the proposed system to support environmental monitoring and decision-making processes effectively.



Figure 9. Floating objects detected in Hooghly River using UNet

Despite the promising results, certain limitations were identified during the study. The performance of the system is dependent on the quality and diversity of the training dataset, which can influence detection accuracy in real-world conditions. Environmental factors such as lighting variations, water turbidity, and atmospheric interference can also impact both RGB and hyperspectral analysis. Additionally, processing hyperspectral data requires significant computational resources, which may limit real-time implementation in some scenarios. Nevertheless, the overall findings indicate that the proposed system provides a scalable, efficient, and accurate solution for microplastic detection and mapping. Future improvements in sensor technology, data processing techniques, and model optimization are expected to further enhance system performance and applicability.

CONCLUSION

The proposed system presents an effective and innovative approach for detecting and mapping microplastic pollution in aquatic environments by integrating remote sensing, deep learning, and hyperspectral image analysis. By combining RGB-based object detection using YOLOv8 with hyperspectral classification and abundance mapping, the system successfully identifies both visible plastic debris and spectrally distinguishable microplastics. The use of embedded systems further enhances its applicability for real-time and field-based monitoring. Experimental results demonstrate improved accuracy, scalability, and efficiency compared to traditional manual methods. Although certain challenges such as environmental variability and computational requirements exist, the system provides a strong foundation for large-scale environmental monitoring. Overall, this work contributes to advancing sustainable solutions for microplastic pollution management and supports informed decision-making for environmental protection and policy development.

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