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Exploring Riverine Litter Detection by Developing Comprehensive Dataset and Deep Learning

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Abstract

With the rapid growth of the economy, the problem of plastic litter in rivers is becoming increasingly severe, particularly in key river basins such as the Taihu Basin. Plastic litter not only disrupts aquatic ecosystems but also poses a threat to human health and regional economic development. Therefore, it is imperative to take effective measures to reduce plastic litter in rivers in order to protect the environment and promote sustainable development. This study proposes an efficient river plastic litter detection method by combining unmanned equipment and deep learning. A dataset comprising 1,347 RGB images of river litter, captured under diverse environmental conditions, was developed to offer a wealth of diversity for model training. YOLOv10-N is employed for object detection and an mAP@0.5 of 94.4% on the dataset is achieved. The research results highlight the potential of applying deep learning in environmental monitoring. In addition, the contribution of this study's dataset provides valuable resources for future model training, with diverse types of images enhancing the model's generalization capabilities and offering possibilities for more effective litter collection.

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1 Introduction

As the economy continues to develop and grow rapidly, environmental issues have become increasingly prominent and are now a widespread concern globally. According to a World Bank report (Kaza et al., 2018), it is estimated that by 2050, 3.4 billion tons of waste will be generated per year, significantly impacting the natural environment. Plastic pollution has emerged as a significant concern for both public health and environmental sustainability. In particular, the presence of plastics in aquatic ecosystems has garnered considerable attention due to the economic losses and environmental risks it poses, as well as its potential effects on human health (González-Fernández et al., 2021; Van Calcar & Van Emmerik, 2020). The United Nations Environment Programme (UNEP) reports that marine debris is distributed as follows: 15% is found floating on the ocean surface, 15% is suspended within the water column, and 70% settles on the seabed (Jambeck et al., 2015). Rivers are identified as the primary contributors to marine plastic litter, with annual estimates of plastic discharged from rivers to the ocean ranging from 0.8 to 2.7 million tons (Meijer et al., 2021). Despite their vital role in the transport and accumulation of marine debris, research on river ecosystems remains limited (Jia et al., 2023). As litter in lakes, rivers, and oceans continues to rise, removing debris from the water's surface has become a crucial effort to enhance the ecological environment (Compa et al., 2019). The water quality of rivers can be partially assessed through the types and quantities of floating debris in the waterways, serving as a useful indicator for measuring water quality (Lin et al., 2021). However, conventional manual cleaning methods are often costly and inefficient. With advancements in unmanned equipment technology, utilizing such equipment to assist or even replace manual water purification has emerged as a viable solution (Kamarudin et al., 2021).

In recent years, convolutional neural networks (CNNs) have established themselves as the leading techniques in computer vision, largely owing to their remarkable accuracy and highly automated feature extraction capabilities (Ham et al., 2018; Dhillon and Verma, 2020; Esteva et al., 2021). In terms of object detection, YOLO accounts for more than 34% of the models used for object detection, followed by Faster R-CNN with 25% (Wu et al., 2023). Maharjan et al. (2022) found that the pre-trained YOLOv5s model was most useful for unclassified plastic detection in rivers from drone images. Van Lieshout et al. (2020) employed a visual method to estimate the flux of large plastic debris in rivers, identifying plastics within the dataset without categorizing them, with an accuracy of 68.7%. However, the application of these advanced techniques is limited by the lack of targeted and high-quality datasets, making model training and performance optimization challenging. In view of this, the objective of the study is to improve the performance of different types of river litter detection by developing a comprehensive self-made dataset combined with the latest deep learning techniques. This dataset not only covers multiple types of river litter, but also takes into account different environmental conditions and litter states, providing a rich and accurate data basis for model training.

The main contributions of this study include:

- Using RGB images of floating plastic litter in rivers acquired by drones and other equipment, a comprehensive multi-category dataset containing 1,347 images was developed (Zhang et al., 2024),and an object detection model, YOLOv10-N, was applied to achieve 94.4% mAP@0.5 on this dataset.

2 Method

2.1 Obeject Detection Algorithm

This study introduces a method for detecting riverine debris through the analysis of Unmanned Aerial Vehicle (UAV) imagery. The approach employs the YOLOv10 algorithm to facilitate the automatic identification and classification of self-classified plastic waste within river environments. The research workflow is shown in Figure 1. Five types of plastic litter are collected in the campus litter station, including plastic bottles, plastic bags, cans, plastic boxes, and plastic cups. The images are taken in the river using drones and other equipment, and the obtained images are classified and annotated. Then use the YOLOv10 algorithm as the base model. YOLOv10 achieves training and inference without non-maximum suppression (NMS) through consistent dual allocation, which significantly reduces inference latency and improves prediction efficiency (Wang et al., 2024). In addition, YOLOv10 also adopts an overall efficiency-accuracy driven model design strategy to optimize the various components of the model architecture to minimize computational overhead while improving performance (Sapkota et al., 2024). In term of performance, YOLOv10 outperforms previous versions and other state-of-the-art models on the COCO dataset (Wang et al., 2024). After the model training is completed, the prediction accuracy of the model is measured by calculating Intersection over Union (IoU) and mean Average Precision (mAP). This enables the model to predict the litter in the river and output the category and bounding box of each detected object. In this way, the method effectively detect and classify litter in the river, providing an efficient technical support for river litter management and environmental protection.

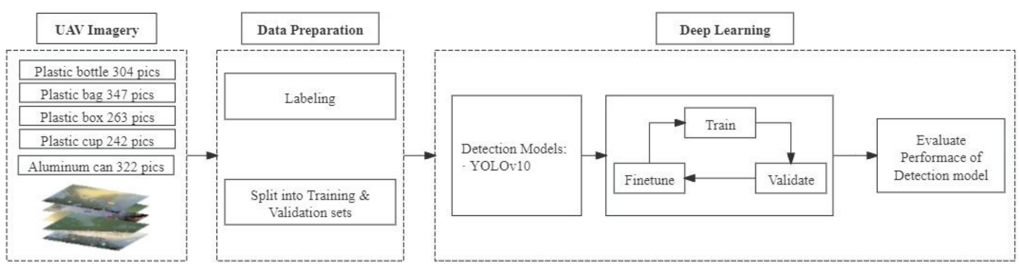

Figure 1: The research workflow for detecting plastic litters using the YOLO v10

2.2 Data Collection

As shown in Figure 2, data are collected from a representative water town in Suzhou, China. Aerial photography is performed using a DJI Phantom 4, which is equipped with a camera capable of 4K resolution. The drone is operated at a low altitude, ranging from 5 to 10 meters, to capture high-definition imagery. The camera is manually controlled and records images in the RGB spectrum during the daylight hours from 10:00 am to 5:00 pm. The native resolution of each photograph is an impressive 5472×3648 pixels. To evaluate the extent of plastic litter in the rivers, photographic surveys are also carried out at a closer altitude of 2 to 4 meters above the water's surface using an iPhone 13. Due to the insufficient number of images of floating plastic collected in field data. A variety of materials are utilized in creating a customized dataset for documenting riverine plastic waste. The materials include: (i) Fishing lines of two different diameters, 0.165 mm and 0.8 mm, which are employed to confine plastic debris within specific areas. (ii) Single-sided adhesive tape is used to secure the fishing line's other end to a hand or a vertical marker, thereby simplifying the manipulation of the waste. (iii) A variety of plastic items, including bottles, bags, cans, boxes, and cups, are included in the dataset. These items vary in size and color to represent the range of plastic litter found in the river. Specifically, the dataset encompasses various types of floating debris, ensuring a high level of diversity and representativeness among the samples. This diversity not only reflects the different types of waste present under various environmental conditions but also increases the variability during the model training process. As a result, the model's ability to generalize in complex scenarios is enhanced, thereby effectively improving detection precision and accuracy. Furthermore, the comprehensiveness of the dataset impacts the model's performance in real-world applications, as a rich and diverse dataset can better capture the various features and situations encountered in reality. Consequently, this comprehensiveness enhances the model's performance and further validates the reliability and effectiveness of the research findings, providing a solid foundation for future applications.

Figure 2: Location of study sites (Background map: OpenStreetMap, 2024)

2.3 Labeling

Tzutalin is credited with the development of LabelImg, a software tool that was made publicly available in 2018 (Tabassum et al. 2020). When integrated with the YOLO (You Only Look Once) object detection algorithm, LabelImg forms a formidable duo for the creation and training of high-performance object detection models, as highlighted by Varnima & Ramachandran (2020). LabelImg is emerged as a prevalent choice for image annotation in the field of object detection, as noted by Pande et al. (2022). The repository for LabelImg, which includes its source code and additional documentation, is hosted on GitHub (HumanSignal n.d.). As depicted in Figure 3, within the customized dataset crafted for river plastic litter, each item is assigned a distinct descriptor. The precise spatial orientation of each object within the photographic frame is delineated through an annotation file that specifies the object's coordinates and associated labels. This methodical annotation is crucial for the accurate training and evaluation of object detection models.

Figure 3: Image labeling steps for plastic bottles using LabelImg

3 Results

3.1 Experimental Environment and Evaluation Metrics

The data processing and analysis for this project were completed on a HP 8A17 (LPC Controller - 5172) motherboard system equipped with an Intel 12th-generation Core i7-12700H 14-core processor, 16GB of memory (4800MHz), a 1TB Western Digital WD PC SN810 SDCPNRY-1T00-1006 solid-state drive, and an NVIDIA GeForce RTX 3070 Ti Laptop GPU (8192 MB video memory). The operating environment is Windows 11 Home Edition (64-bit). The computational framework encompasses PyTorch version 2.1.1, Python version 3.9, and CUDA version 11.8. For the sake of maintaining uniformity and enabling the direct comparison of outcomes across different experiments, software milieu adhere to the specifications detailed in Table 1 for all subsequent trials.

Parameter	Value	Parameter	Value
Learning Rate	0.01	Weight Decay	0.0005
Batch Size	16	Momentum	0.937
Image Size	416x416	Epoch	200
Workers	8	Optimizer	Auto

Table 1: Training settings

In the domain of object detection, Intersection over Union (IoU) serves as a pivotal metric for assessing the accuracy of the detection model. IoU quantifies the extent to which the predicted bounding box aligns with the ground truth bounding box. The IoU is computed, as delineated in Equation (1), by taking the ratio of the area where the predicted box and the actual box overlap to the total area covered by both boxes combined (Maharjan et al., 2022). This calculation provides a measure of the model's precision in detecting objects within an image.

$$\mathrm{IoU} = \frac{\text{Area of Overlap}}{\text{Area of Union}} \tag{1}$$

The mean Average Precision (mAP), as described by Equation (2), is a critical metric for assessing the overall effectiveness of an object detection model. This metric calculates the average precision across various confidence thresholds, offering a holistic view of the model's performance (Jackovljevic et al., 2020). Furthermore, the model's performance is also gauged by two fundamental metrics: Precision, as defined by Equation (3), and Recall, outlined in Equation (4). The evaluation index is based on four key statistics: True Negative (TN), True Positive (TP), False Positive (FP) and False Negative (FN). These metrics are essential for understanding the model's ability to accurately identify objects without producing excessive false positives or missing true positives.

$$\mathrm{mAP} = \frac{1}{N}\sum_{i=1}^{N} \mathrm{AP}_i \tag{2}$$

$$\mathrm{Precision} = \frac{TP}{TP+FP} \tag{3}$$

$$\mathrm{Recall} = \frac{TP}{TP+FN} \tag{4}$$

3.2 Experimental Results

The experimental results presented in Table 2 demonstrate the remarkable detection performance of YOLOv10-N in identifying various types of riverine debris. For instance, plastic bottles and aluminum cans exhibit high precision and recall rates above 89%, suggesting that YOLOv10 is highly reliable in detecting these items. Notably, plastic boxes boast a near-perfect precision of 98%, with a commendable recall rate of 93.8%, indicating exceptional detection capabilities. As shown in figure 4a, the mAP at IoU thresholds of 0.5 and 0.5:0.95 further underscores the model's robustness, with mAP values exceeding 94.4% for all classes. This indicates that YOLOv10 not only detects debris with high accuracy but also does so consistently across different IoU thresholds.

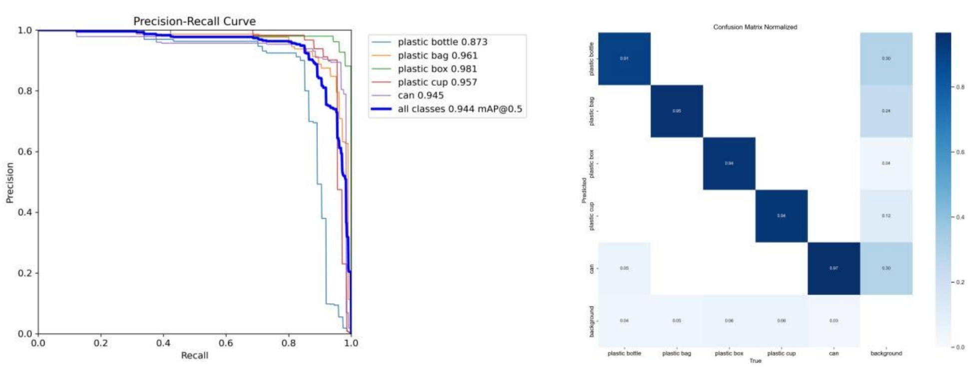

Figure 4: (a) Performance Evaluation of Object Detection Models

(b) Confusion Matrix Normalized for plastic litter Classification

Class	P /%	R /%	CMN/%	mAP $_{@0.5}$/%
Plastic bottle	89.9	85.1	91	87.3
Plastic bag	90.9	89.5	95	96.1
Plastic box	98	93.8	94	98.1
Plastic cup	93.7	89.2	94	95.7
Aluminum can	89.4	93.4	97	94.5
all	92.4	90.2	94.2	94.4

Table 2: Experimental results

For Confusion Matrix Normalized (CMN), the diagonal elements are as close to 1 as possible, and the off-diagonal elements are as close to 0 as possible. Such a matrix indicates that the model's predictions on all categories are very accurate, that is, the model has high precision and high recall. As shown in Figure 5, the classification of Aluminum cans performed best with an accuracy of 97%, which shows that the model is very effective in identifying cans. The model's performance on most categories is satisfactory, but there is room for improvement in distinguishing plastic bottles. The accuracy and robustness of the model can be further improved by increasing the training data, optimizing feature extraction, or adjusting the model parameters.

The performance of the YOLOv10-N model was evaluated in the task of identifying river litter in complex scenarios. As shown in Figure 4b, when high intersection-over-union (IOU) conditions and target confidence thresholds (not less than 0.6) are set, YOLOv10-N demonstrates its excellent processing capabilities, especially in the case of target overlap and occlusion. Encouragingly, the YOLOv10-N model has demonstrated the capability to accurately detect plastic bottles in imagery captured within natural river settings, including areas with dense vegetation. The model exhibits a confidence threshold for object detection that averages approximately 66%.In addition, when the image contains multiple categories of litter and presents various morphological changes, YOLOv10-N can still effectively detect targets, showing its excellent adaptability.

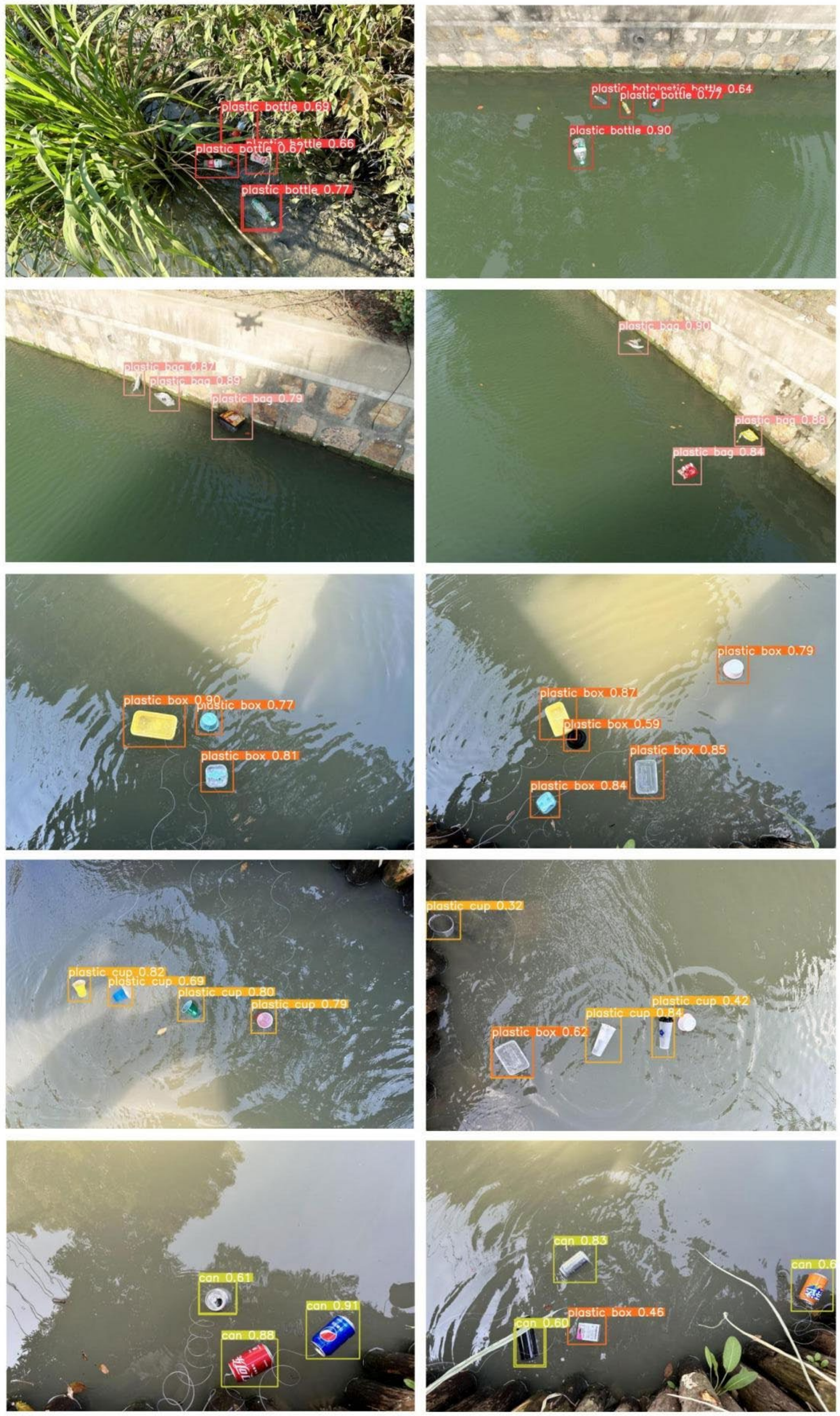

Figure 5: The datasets image samples about successful prediction of YOLOv10-N

4 Discussion

4.1 Analysis of Datasets

This research endeavors to create a specialized classification dataset specifically tailored for the identification of riverine plastic waste, a pressing environmental issue that necessitates effective monitoring and management strategies. Recognizing the urgency of addressing plastic litter in aquatic ecosystems, the dataset has been validated within the YOLOv10-N object detection algorithm, achieving both the high efficiency and precision of waste recognition processes. The dataset’s quality and diversity are paramount, providing the algorithm with robust training and validation information essential for its performance. The dataset encompasses a wide variety of floating plastic waste typically found in riverine environments, including items such as plastic bottles, plastic bags, plastic boxes, plastic cups, and aluminum cans. Each category is represented with multiple examples, reflecting the real-world conditions where these items are often encountered. During the prediction phase, although the overall performance of the model was satisfactory, some aluminum cans were misidentified or missed due to their similarity to the background, indicating that the algorithm still needs to be further optimized in distinguishing objects similar to the background. Notably, the dataset includes various shapes of crushed cans and a range of forms for plastic boxes and cups, such as open cups and specialized containers like milk tea cups. This attention to detail in capturing different variations of plastic waste contributes to the dataset's representativeness and practicality, allowing for more accurate modeling of the complexities associated with plastic waste in aquatic settings. The diversity embedded within the dataset not only enhances its robustness but also ensures the model's wide applicability in real-world scenarios. By training the YOLOv10-N algorithm on a comprehensive set of plastic waste examples, the model is better equipped to handle the multifaceted challenges posed by varied environmental conditions. The scale and quality of the dataset play a crucial role in the effective training of deep learning models, as highlighted by Xiao et al. (2021), emphasizing the importance of high-quality inputs in achieving reliable outputs.

4.2 Limitation and future work

The research conducted in this study reveals several limitations that warrant further discussion and exploration. A primary challenge has been the difficulty in gathering comprehensive data from riverbanks that are densely populated with vegetation. This limitation has led to a focused study on a single river channel, which may restrict the broader applicability of the findings. To enhance the generalizability of this research, future studies should consider expanding data collection to include a variety of river environments. Such diversity in the study locations would allow researchers to draw more robust conclusions that can be applied to different ecological contexts. Additionally, the current focus has predominantly been on floating objects within the river channel. However, it is crucial to expand this focus to include aquatic plants, such as cyanobacteria and water hyacinth, which play significant roles in the river ecosystem. These organisms not only contribute to the ecological balance but also influence water quality and habitat dynamics. By incorporating the monitoring of these aquatic plants, future research can provide a more comprehensive understanding of the river's health and the factors affecting its biodiversity.

Moreover, the limitations associated with drone flight capabilities and monitoring in densely vegetated environments suggest the need for innovative technological solutions. Future studies should explore the integration of mast mounted cameras with drones to enhance data collection efficiency and coverage. Mast mounted cameras can operate effectively in shallow water areas along riverbanks, enabling researchers to access regions that drones alone might not effectively survey. Conversely, drones can cover a broader area from the air, providing valuable aerial perspectives and data. The collaborative operation of mast mounted cameras and drones presents an exciting opportunity for comprehensive monitoring of river environments. By leveraging the strengths of both technologies, researchers can achieve a more thorough and nuanced understanding of river ecosystems. This combined approach could facilitate the collection of a diverse array of data points, including water quality metrics, vegetation mapping, and assessments of aquatic species distribution.

In future research, an in-depth exploration of the performance of various deep learning models in river litter detection tasks is planned. Specifically, comparisons will be made between YOLOv10-N and other advanced object detection models, such as YOLO-world and the Segment Anything model, to evaluate their differences in detection accuracy, speed, and robustness. This comparison will aid in understanding the advantages and limitations of each model, facilitating the selection of the most appropriate model framework for future research and applications. Additionally, the quality and diversity of the dataset are recognized as essential for training efficient and accurate detection models. Therefore, incorporating data augmentation techniques to balance data distribution will be a part of the research, addressing the issue of class imbalance and enhancing the model's ability to recognize various types of litter. A variety of data augmentation methods will be explored, including image rotation, scaling, and color adjustment, to generate a more diverse set of training samples. Through these future research efforts, it is anticipated that the performance of river litter detection technology will be significantly enhanced, providing more reliable technical support for practical applications.

5 Conclusions

The focus of this study is on improving the performance of river litter detection by developing a comprehensive dataset of floating litter in rivers and applying it to deep learning models. The dataset covers 5 litter types and diferent morphologies, and is tested on the YOLOv10-N object detection algorithm. Experimental results show that the YOLOv10-N algorithm achieves 92.4% precision, 90.2% recall, and 94.4% at 0.5 IoU, respectively. By incorporating a diverse range of litter types, such as plastic bottles, bags, boxes, cups, and aluminum cans, the dataset provides a solid foundation for training deep learning models to recognize and classify plastic waste accurately. These remarkable results not only demonstrate the quality of the dataset itself, but also its key role in improving model performance. The dataset ensures high annotation accuracy and abundant sample size through a carefully designed collection and annotation process, providing the necessary training and validation information for deep learning models. This diversity and meticulous annotations enable the model to capture the subtle features of plastic litter, thereby achieving high accuracy in the detection process. Future work will further explore how to expand the diversity of the dataset to optimize other deep learning models and how to apply it to a wider range of environmental monitoring tasks.

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