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Research on Real-Time Detection Method for River Floating Objects Using UAVs Based on Lightweight YOLOv8s Model

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Abstract: To address the challenge of identifying small floating objects in river debris detection, this study proposes an enhanced model that integrates YOLOv8s with Large Separable Kernel Attention (LSKA) and Asymmetric Kernel Convolution (AKConv). The optimized architecture reduces the parameter count of YOLOv8s from 11.1M to 8.3M while improving mAP50 from 68.0% to 77.9% on the "Water Surface Floating Object Dataset" developed by the China Institute of Water Resources and Hydropower Research. Experimental results demonstrate that the proposed method significantly enhances detection accuracy, strengthens occlusion recognition capability, and improves network adaptability to complex river environments. This advancement effectively upgrades the real-time monitoring performance of UAVs in riverine applications, providing an efficient solution for water resource management.

Keywords: Floating object recognition; UAV; Lightweight; Real-time detection; YOLOv8s.

1. Introduction

Floating debris in rivers—such as aquatic plants, branches, and plastic waste—can quickly accumulate, causing pollution, obstructing water flow, degrading quality, and harming ecosystems. Debris can also strain hydraulic equipment, reducing efficiency and causing failures. Timely detection and removal are crucial but manual inspection is challenging and slow due to complex environments and limited access[1]. Therefore, automated detection technologies, particularly advances in UAVs and intelligent sensing, offer promising solutions to improve the efficiency and effectiveness of river debris management.

2. Research Status and Significance

Current river debris detection relies on costly sensor-equipped buoys and satellite remote sensing, limiting large-scale use. UAV imaging offers a cost-effective alternative but faces challenges from small debris, reflections, and complex backgrounds. This study presents a lightweight YOLOv8s model enhanced with LSKA, AKConv, and BSFPN to improve small debris detection while reducing computation [2]. The UAV-based method effectively addresses multi-scale detection, occlusion, and background complexity, advancing automated river monitoring with strong academic and practical significance.

3. Lightweight YOLOv8s Model

The study proposes an improved lightweight version of the YOLOv8s model, in which several advanced modules are integrated to enhance the network's adaptability and detection performance under challenging conditions. Specifically, the model incorporates the Large Selective Kernel Attention (LSKA) mechanism to expand the receptive field and improve the ability to capture discriminative features from multi-scale objects. In addition, the Adaptive Kernel Convolution (AKConv) module is introduced to dynamically adjust the convolutional kernels according to the spatial and contextual information of the input, thereby enabling the network to better extract fine-grained features of small and densely distributed targets. Furthermore, a Bi-directional Scaled Feature Pyramid Network (BSFPN) is employed to strengthen multi-level feature interaction and fusion. This design not only preserves spatial detail information during downsampling but also effectively enhances semantic representation at different feature scales. By integrating these modules into the YOLOv8s framework, the proposed lightweight model achieves a better balance between computational efficiency and detection accuracy. As a result, it demonstrates a stronger capability in detecting tiny objects under complex backgrounds, occlusions, and scale variations, while maintaining the real-time inference speed required for practical applications.

3.1. LSKA technology.

LSKA overcomes traditional convolution's limits in capturing long-range dependencies by combining large-scale separable convolutions with attention [3]. It decomposes large kernels into deep, dilated, and 1×1 convolutions, then splits 2D kernels into 1D horizontal and vertical ones connected in series. This design efficiently captures long-range features with low computational cost, making it ideal for small target detection in complex river environments.

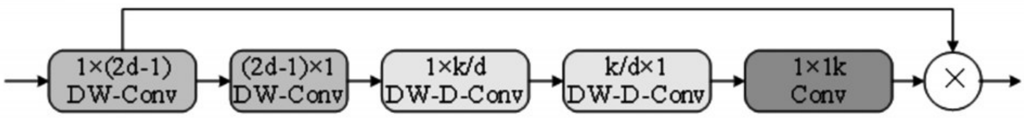

Figure 1. Large Separable Kernel Attention (LSKA) network architecture

3.2. BSFPN Technology.

To enhance the model's performance on the river floating object dataset, this study introduces the SCDown module built upon the Bi-Directional Feature Pyramid Network (Bi-FPN) framework, resulting in the novel BSFPN feature pyramid network. The SCDown module specifically improves the recognition of small targets by employing scaled convolution downsampling, which effectively preserves important spatial details while reducing feature map resolution. When combined with multi-level feature fusion, this approach enables the network to better capture and discriminate challenging targets embedded within complex and cluttered backgrounds commonly found in river environments. Furthermore, the YOLOv8s model is comprehensively optimized through the integration of advanced techniques including Large Spatial Kernel Attention (LSKA), the C2FAKConv module, and the newly developed BSFPN. These enhancements work synergistically to improve feature representation and detection accuracy across multiple scales [4]. The overall optimized network architecture is illustrated in the accompanying figure, demonstrating the structural modifications that contribute to improved detection performance on small and occluded floating objects in riverine scenes.

Beyond structural improvements, the proposed strategy enhances robustness to challenges such as illumination changes, water reflections, and background interference. SCDown and BSFPN strengthen small and occluded target detection, while LSKA and C2FAKConv improve long-range dependency modeling and fine-grained feature extraction. These optimizations together ensure efficient and accurate performance, supporting practical drone-based monitoring of riverine debris.

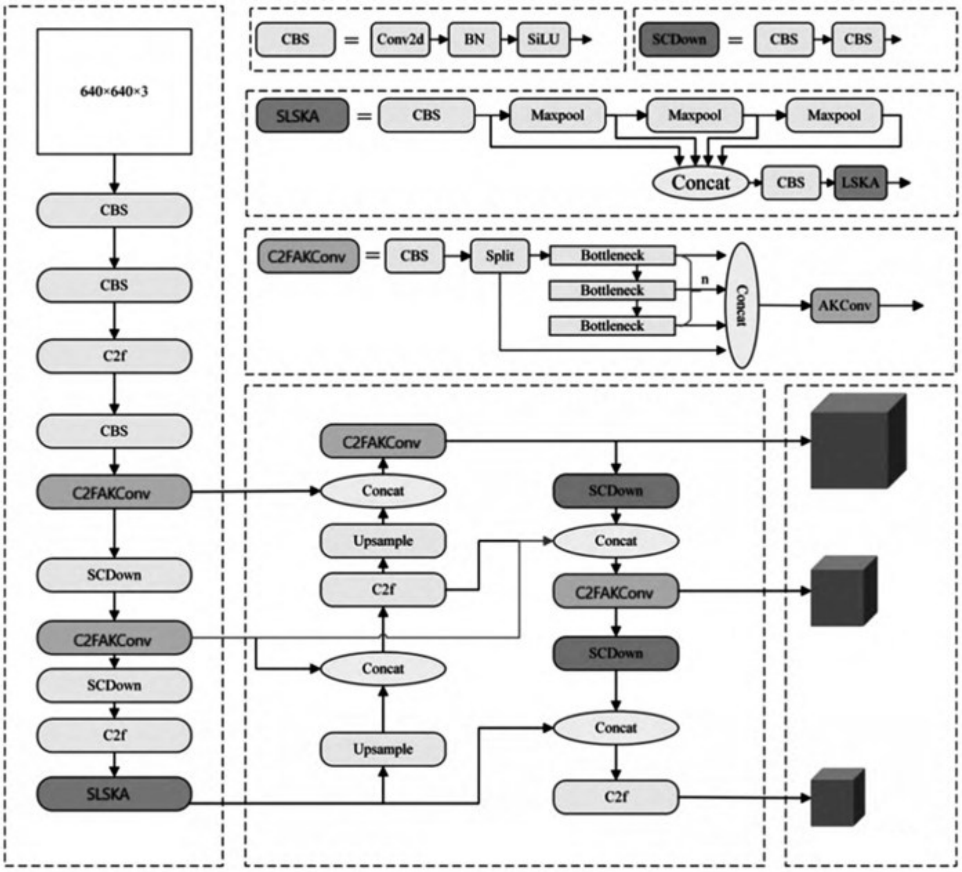

Figure 2. The lightweight architecture of the YOLOv8s object detection network

4. Experiments

4.1. Dataset

The study used the "Floating Objects Dataset" developed by the China Institute of Water Resources and Hydropower Research to evaluate the accuracy and performance of the algorithm [5]. The dataset is 2.09GB in size, contains 3,000 images, and has 23,692 labeled objects, including common floating objects such as plastic bottles, foam boards, aquatic plants, and algae. The images taken by surveillance cameras and drones are relatively similar.

4.2. Experimental Results

To comprehensively evaluate both detection accuracy and computational efficiency, mean average precision (mAP), frames per second (FPS), and the number of model parameters are selected as the primary performance metrics. The training process is conducted using stochastic gradient descent (SGD) optimization, with the initial learning rate set to 0.01. A cosine annealing strategy is employed to gradually adjust the learning rate down to 0.01, ensuring smoother convergence. To further enhance generalization capability and prevent overfitting, a weight decay coefficient of 0.0005 is applied, together with a momentum parameter of 0.937 to stabilize gradient updates. The experimental dataset is partitioned into training and testing sets at a ratio of 4:1, ensuring a balanced evaluation. All experiments are initialized with pre-trained weights, allowing the model to leverage prior knowledge and accelerate convergence.

The experimental results demonstrate that the proposed lightweight YOLOv8s model achieves a mean average precision of 77.9%, while maintaining only 8.3M parameters and delivering an average inference time of 3.1 ms per frame. Compared with other detection algorithms, the model exhibits superior performance in balancing detection accuracy and computational efficiency. This optimization not only reduces the complexity of computation but also enables real-time object detection in river monitoring scenarios. The achieved performance makes the model particularly suitable for deployment on resource-constrained UAV platforms, thereby supporting efficient, reliable, and scalable monitoring of riverine environments.

Table 1. Testing performance of different object detection algorithms on the dataset

Model	Input size/ px	mAPtest 50-95 / %	Frame speed/ms	Parameters/ M
Faster R-CNN	600	52.7	142.9	86.3
RetinaNet	640	66.3	51.4	145.7
SSD	300	62.9	26.0	95.0
CenterNet2	640	59.3	140.0	570.9
YOLOv5s	640	67.1	4.5	7.0
YOLOv6s	640	65.2	2.7	18.5
YOLOv7	640	66.3	6.7	6.2
YOLOv8s	640	68.0	4.5	11.1
YOLOv9	640	69.1	6.3	252.2
Lightweight YOLOv8s	640	77.9	3.1	8.3

4.3. Algorithm Application

The optimized lightweight YOLOv8s model effectively reduces the total number of parameters to 8.3M while maintaining robust detection performance, thereby achieving an inference speed of 3.1 ms per frame. This balance between accuracy and efficiency highlights the model's strong potential for deployment on drone-embedded platforms that are inherently constrained by limited computational and storage resources. In practical UAV-based river monitoring scenarios, the drone is typically equipped with a high-resolution wide-angle camera, enabling wide-area coverage of riverine environments within a single flight mission. Continuous video stream acquisition ensures comprehensive observation of surface conditions. Leveraging the optimized detection model, these streams can be processed in real time, enabling the rapid and precise identification of a variety of floating objects, including common pollutants such as plastic bottles, discarded packaging materials, aquatic vegetation, and other debris. By ensuring reliable detection under dynamic and complex conditions, the system supports effective target tracking and localization across extensive and heterogeneous river environments.

Following the successful detection of floating objects, the UAV system transmits critical information—including spatial coordinates, object category, and estimated quantity—via wireless communication links to a ground control station. This mechanism enables operators to respond promptly to emerging pollution incidents or environmental hazards, thereby improving the timeliness of ecological management and intervention. Simultaneously, the drone stores both raw image data and detection outputs locally, which not only ensures data availability for post-mission verification but also provides valuable datasets for long-term analysis of pollution dynamics and trend prediction. This dual strategy of real-time communication combined with on-board storage reduces redundant data transmission, optimizes bandwidth usage, and lowers overall system overhead, ultimately improving operational efficiency.

By integrating high detection accuracy with efficient data management and communication strategies, the proposed lightweight YOLOv8s model demonstrates its capacity to achieve real-time, reliable, and scalable monitoring of river debris using UAV platforms. The research findings suggest that such a system can provide strong technical support for environmental governance, pollution control, and sustainable water resource management. Furthermore, its adaptability and efficiency position it as a practical solution for future applications in intelligent environmental monitoring systems, with significant potential for extension to other ecological domains beyond riverine debris detection

5. Conclusion

To address the challenges posed by multi-scale targets, small object sizes, complex backgrounds, and frequent occlusions in UAV-based river floating object detection, this study develops a lightweight YOLOv8s model that integrates vertical one-dimensional convolutions, variable kernel convolutions, and bidirectional feature fusion mechanisms. Through these architectural enhancements, the proposed model achieves notable improvements in detection accuracy and inference speed, while also reducing computational complexity, thereby demonstrating its suitability for real-time applications in river monitoring scenarios. Despite these encouraging results, the current model's recognition accuracy still falls short compared with more computationally intensive high-precision detectors, particularly in environments characterized by higher variability and greater complexity, where detection performance tends to decline.

Building upon these findings, future research will focus on refining the model's generalization capacity by investigating more advanced convolutional operators, adaptive feature representation mechanisms, and enhanced multi-scale fusion strategies. These improvements are expected to further strengthen the robustness of the model in handling diverse and challenging environments. By integrating such innovations, subsequent models are anticipated to provide more reliable, efficient, and intelligent solutions for UAV-based real-time river monitoring, thereby contributing to improved environmental management and more effective protection of water resources.

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