

1 **Supplementary Information for: Real-Time Water Surface Garbage**  
2 **Detection with Bi-directional Re-calibration and Structural Re-**  
3 **parameterization**

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6 **Supplementary Note 1: Detailed Experimental Configuration**

7 All intensive model training tasks were accelerated using an NVIDIA L20 Server  
8 GPU cluster. To evaluate the engineering practicability for USVs and drones, all  
9 inference benchmarks were conducted on the NVIDIA Jetson Orin Nano edge  
10 computing module. This platform operates within a 15W power envelope,  
11 representing the typical hardware constraints in autonomous aquatic monitoring.

12 **Supplementary Table S1. Hardware Configuration Details.**

<b>Hardware Type</b>	<b>Version Details</b>
Training Server Resources	NVIDIA L20
Test Platform GPU	NVIDIA Jetson Orin Nano
Test Platform CPU	Arm® Cortex®-A78AE
Test Platform Memory	8GB

13 **Supplementary Table S2. Experimental Software Environment.**

<b>Software Type</b>	<b>Version Details</b>
Operating System	Ubuntu 22.04 LTS
Deep Learning Framework	PyTorch 2.1.0; TorchVision 0.16.0
Inference Engine	NVIDIA TensorRT 8.6.1

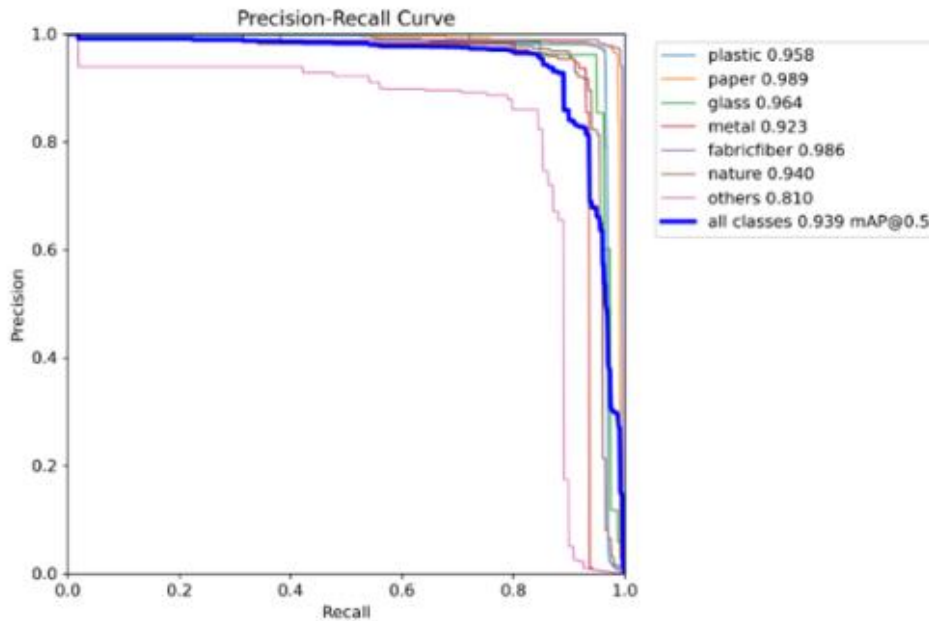
14 **Supplementary Table S3. Training Hyperparameters for Experimental Models.**

<b>Parameter Name</b>	<b>Data</b>
epochs	200
Batch	16
imgsz	640
workers	4
optimizer	AdamW

15 **Supplementary Note 2: Extended Evaluation Metrics (Precision-Recall Curve)**

16 To further evaluate the robustness of the BR-Trans model across different categories

17 of complex aquatic environments, we analyzed the Precision-Recall (P-R) curve on  
18 the YRDG test set.



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20 **Supplementary Fig. S1. Precision-Recall Curve of the BR-Trans model on the**  
21 **YRDG test set.** The thick blue line represents the average performance across all  
22 categories (mAP@0.5 = 0.939). The curve is highly convex toward the upper-right  
23 corner, indicating a strong balance between high precision and high recall. Among the  
24 subcategories, *paper* (0.989), *fabric/fiber* (0.986), and *glass* (0.964) exhibit the  
25 highest detection efficiency, demonstrating the StarBlock backbone's exceptional  
26 capability to extract distinct textural and reflective properties. The *others* category  
27 achieved a precision of 0.810, which still meets practical engineering deployment  
28 requirements despite consisting of highly irregular shapes and undefined textures.

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### 30 **Supplementary Note 3: Cross-Dataset Generalization Analysis (FloW Dataset)**

31 To verify the generalization ability and engineering practicability of BR-Trans in  
32 diverse unseen aquatic scenarios, we conducted cross-domain validation experiments  
33 on the public FloW floating debris detection dataset. This dataset exhibits significant  
34 domain differences from our YRDG training set in terms of lighting, water turbidity,

35 and target distributions. The experimental configuration was kept completely  
36 consistent with the main comparative experiments.

37 **Supplementary Table S4.** Comprehensive performance comparison of detection  
38 models on the FloW dataset.

Model name	mAP@0.5 (%)	mAP@0.5: 0.95 (%)	Precision (%)	Recall (%)	F1-Score	Params	GFLOPs
YOLO11	0.8891	0.4541	0.8975	0.8423	0.869	42.0M	67.8
YOLO26	0.8852	0.466	0.8936	0.8381	0.865	38.7M	67.6
RT-DETR	0.8837	0.4669	0.895	0.8603	0.8668	76.9M	56.9
Our	0.91.08	0.4716	0.9055	0.8312	0.8773	71.7M	61.2

### 39 **Analysis of Generalization Results:**

40 As shown in Supplementary Table S4, BR-Trans maintains optimal comprehensive  
41 performance on the unseen FloW dataset, achieving 91.08% mAP@0.5. This  
42 represents a significant margin of 2.17 percentage points over YOLOv11 and 2.71  
43 percentage points over the baseline RT-DETR.

44 The high cross-domain performance validates the targeted architectural design. Rather  
45 than overfitting the specific background features of the YRDG dataset, the high-  
46 dimensional implicit mapping of the StarBlock and the Bidirectional Re-calibration  
47 Module (BRM) successfully learn generalizable feature representations of floating  
48 debris. The dual-stream BRM consistently suppresses domain-specific background  
49 interferences (e.g., novel ripple patterns and reflections in the FloW dataset) while the  
50 SimFusion global alignment efficiently handles multi-scale targets in unseen  
51 scenarios. These results confirm that BR-Trans possesses robust domain adaptability  
52 suitable for practical deployment across diverse river basins.