Supplementary Information

Accuracy and CPU speed gains across lightweight YOLO generations under downstream uncertainty

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Contents: documentary audit and source records (Table S1); comparison practices (Table S2); supplementary figures S1–S5; scope of the retained reproduction records.

Retained evidence and reproduction scope

Supplementary Data 1 (a ZIP archive uploaded with the article) provides the per-run metrics and stored bootstrap outputs underlying the accuracy comparisons. The floating-debris and VOC arrays contain matched resample scores for the observed runs. Confidence-filtered detection records are a separate evaluation pass and are identified as such. VisDrone is represented by the recorded per-run and bootstrap summaries. Platform A and C latency files retain round-level values; platform B provides summary statistics. The reproduce_key_numbers.py script recomputes values from the retained arrays and records; it does not retrain models or regenerate the missing per-image matching matrices.

The validation scripts set no head override. In Ultralytics 8.4.106 the YOLO26 configuration enables the end-to-end head (end2end: True), and the validator evaluates that head unless an override is given, so the downstream YOLO26n scores correspond to the 40.1 reference. Both published COCO scores are retained for reference sensitivity. Changing the YOLO26 COCO value from 40.9 to 40.1 changes six-model Kendall τ from −0.33 to −0.20 on floating debris and from 0.73 to 0.60 on VOC, while preserving the COCO order of YOLOv8n, YOLO11n and YOLO26n. The timed ONNX export uses the same end-to-end head, with 300 detections per image.

Supplementary Table S1 Documentary audit

The retained search yielded 2,444 unique Crossref records and 130 title-screened records; 53 eligible papers plus seven earlier scoping-search papers give 60. Full-text extraction is retained for 42 records, abstract-only information for 16, and readable text is unavailable for two. Repetition counts require an explicit source statement: the retained evidence establishes three runs for P5 and five for P12; other counts are unknown. A single score or a stated seed does not establish a single run. Module gains are the smallest non-negative contrasts between ablation rows differing by one module; negative steps are separately marked. Derived evaluation sizes and validation sets remain labelled in the machine-readable audit. A second language-model extraction for 23 records serves as a consistency check; its quoted table rows are in Supplementary Data 1.

ID	DOI	Access	Baseline	Runs explicitly supported	Evaluation images	Metric	Min. non-negative gain	Negative step
P1	10.1038/s41598-025-32817-x	full	YOLOv8n	Unknown	2800 (derived)	mAP50	0.19	—
P2	10.1038/s41598-025-10163-2	full	YOLOv8s	Unknown	136 (derived)	mAP50	0.3	—
P3	10.1038/s41598-026-40688-z	full	YOLOv7	Unknown	697	mAP	1.9	—
P4	10.3389/fmars.2026.1914553	full	YOLO11n	Unknown	375	mAP50	0.9	—
P5	10.3390/su18105083	full	YOLO11n	3	581	mAP50	1.4	—
P6	10.1371/journal.pone.0340822	full	YOLOv8n	Unknown	993 (derived)	mAP50	0.3	—
P7	10.1038/s41598-026-53751-6	full	YOLOv8n	Unknown	Unknown	mAP50	0.1	—
P8	10.1038/s41598-025-31043-9	full	YOLOv8n	Unknown	Unknown	mAP50	0.6	Yes
P9	10.1038/s41598-024-55051-3	full	YOLOv5s	Unknown	Unknown	mAP50	1.5	—
P10	10.3390/s24010050	full	YOLOv7	Unknown	381	mAP50	0.48	—
P11	10.3390/s25061938	full	YOLOv8n	Unknown	Unknown	mAP50	0.3	—
P12	10.3390/math10224366	full	YOLOv5	5	Unknown	none	—	—
P13	10.3390/s24155059	full	YOLOv8n	Unknown	600	mAP50	0.2	Yes
P14	10.3390/electronics14183615	full	YOLOv8n	Unknown	360 (derived)	mAP50	0	Yes
P15	10.3390/jmse11122234	full	YOLOv5-X	Unknown	Unknown	mAP50-95	0.4	—
P16	10.32604/cmc.2024.054188	full	YOLOv8n	Unknown	130 (validation)	mAP50	0.2	—
P17	10.5755/j01.itc.54.3.38966	full	YOLOv8s	Unknown	2160	mAP50	0.2	Yes
P18	10.19693/j.issn.1673-3185.03689	full	YOLOv5s	Unknown	740 (derived)	mAP50	0.2	—

ID	DOI	Access	Baseline	Runs explicitly supported	Evaluation images	Metric	Min. non-negative gain	Negative step
P19	10.1038/s41598-026-53167-2	full	YOLOv7	Unknown	481	mAP50	1.4	—
P20	10.3390/rs14174161	full	YOLOv5s	Unknown	Unknown	mAP50-95	0.5	Yes
P21	10.3390/rs18050736	full	YOLO11s	Unknown	459 (derived)	mAP50	0.24	Yes
P22	10.1088/1402-4896/ad5657	abstract	YOLOv8	Unknown	Unknown	—	—	—
P23	10.1049/ipr2.70248	abstract	YOLOv8n	Unknown	Unknown	—	—	—
P24	10.1002/rob.70039	abstract	YOLO11	Unknown	Unknown	—	—	—
P25	10.1051/wujns/2024294338	abstract	YOLOv7	Unknown	Unknown	—	—	—
P26	10.1007/s11760-026-05181-0	none	Unknown	Unknown	Unknown	—	—	—
P27	10.3390/e23091111	full	YOLOv5s	Unknown	480	mAP50	0.29	—
S4	10.11113/elektrika.v25n1.708	full	YOLOv5s	Unknown	400	none	—	—
S35	10.1016/j.eswa.2026.131552	abstract	YOLOv13n	Unknown	Unknown	—	—	—
S58	10.1007/s11554-025-01806-8	abstract	YOLOv8n	Unknown	Unknown	—	—	—
S90	10.1007/s00371-024-03709-4	abstract	YOLOv8s	Unknown	Unknown	—	—	—
S115	10.1007/s11554-023-01265-z	abstract	YOLOv5 (likely YOLOv5n; abstract compares YOLOv5n/s/m)	Unknown	Unknown	—	—	—
S7	10.1088/2631-8695/ae9c99	abstract	YOLOv12n	Unknown	Unknown	—	—	—
S59	10.24003/emitter.v13i2.978	full	YOLOv5s	Unknown	73	none	—	—
S97	10.12677/mos.2024.133273	full	YOLOv5m (ablation baseline; the main comparison table is against rotated detectors Gliding-Vertex, R3Det, S2A-Net)	Unknown	869	mAP50	1.3	—

ID	DOI	Access	Baseline	Runs explicitly supported	Evaluation images	Metric	Min. non-negative gain	Negative step
S117	10.3390/app13137367	full	YOLOv5s	Unknown	624 (derived)	mAP	—	—
S25	10.1109/tim.2025.3617393	abstract	YOLOv8n	Unknown	Unknown	—	—	—
S43	10.1016/j.jenvman.2025.125154	abstract	YOLOv8 (variant not stated in abstract; 'original model')	Unknown	Unknown	—	—	—
S56	10.1109/les.2025.3544623	abstract	YOLOv4-based baseline (exact variant, e.g. YOLOv4-tiny, not stated in abstract)	Unknown	Unknown	—	—	—
S12	10.1109/lgrs.2025.3636279	abstract	YOLOv8n	Unknown	Unknown	—	—	—
S38	10.37385/dpqnng18	full	YOLOv11s (Ultralytics YOLO11s)	Unknown	Unknown	mAP50	0.1	Yes
S67	10.1007/s12145-024-01679-8	none	Unknown	Unknown	Unknown	—	—	—
S99	10.3233/jifs-234222	abstract	YOLOv5n	Unknown	Unknown	—	—	—
S27	10.47297/taposatwsp2633-456920.20260705	full	YOLOv8 ("traditional YOLOv8"; model size not specified)	Unknown	300	none	—	—
S14	10.3390/wevj17030156	full	YOLOv11 (scale not stated; Table 3 lists 30 M params / 6.9 GFLOPs)	Unknown	300 (derived)	AP75	0.4	—
S39	10.3390/eng7070315	full	YOLOv11n	Unknown	800	mAP50	0.1	Yes
S73	10.54097/t1napg15	full	YOLOv8s	Unknown	600 (derived)	none	—	—
S109	10.3390/w16010086	full	YOLOv5s	Unknown	1010 (derived)	mAP50-95	0.47	—
S2	10.3389/fcomp.2026.1859574	full	YOLOv11s	Unknown	2047 (derived)	mAP50	0.4	—

ID	DOI	Access	Baseline	Runs explicitly supported	Evaluation images	Metric	Min. non-negative gain	Negative step
S28	10.7837/kosomes.2026.32.2.203	full	YOLO26-Seg (n scale)	Unknown	114	mask mAP50-95	0.7	Yes
S71	10.1016/j.marpolbul.2025.118189	full	YOLOv8n (main comparison); ablation baseline = DSFLDNet without ASF/PFEM	Unknown	435	mAP50	0.6	—
S87	10.3390/w16111633	full	YOLOv5s	Unknown	800 (derived)	mAP50	0.3	Yes
S19	10.1088/1361-6501/ae5de8	abstract	YOLOv8s	Unknown	Unknown	—	—	—
S40	10.3390/app16020651	full	YOLOv11 (nano-size: 2,590,425 params, 6.44 GFLOPs; paper just says 'YOLOv11')	Unknown	2400	mAP50	0.96	—
S84	10.12677/csa.2024.144092	full	YOLOv5s	Unknown	1064	mAP50	0	—
S111	10.3390/app13042303	full	YOLOv3	Unknown	1296 (derived)	mAP	1.6	—
S9	10.2166/hydro.2026.072	abstract	Unknown	Unknown	Unknown	—	—	—
S33	10.63313/jcsft.9046	full	YOLOv11s	Unknown	800	mAP50	0.4	—
S41	10.3390/photonics12060620	full	YOLOv8 (Table 3); ablation figure caption specifies YOLOv8n	Unknown	3000	mAP50	0	—
S88	10.1109/jstars.2024.3367713	full	YOLOX (model size not stated)	Unknown	240 (derived)	mAP	2.1	—

Source titles for Table S1

P1. Enhanced YOLOv8 for accurate and efficient floating object detection on water surfaces. Scientific Reports 16:2907 2026. https://doi.org/10.1038/s41598-025-32817-x

P2. An enhanced YOLOv8 model for accurate detection of solid floating waste. Scientific Reports 2025. https://doi.org/10.1038/s41598-025-10163-2

P3. Small target detection of floating objects in river channels based on improved YOLOv7. Scientific Reports 16:11423 2026. https://doi.org/10.1038/s41598-026-40688-z

P4. CEC-YOLO: a floating-debris detection algorithm for complex water-surface environments. Frontiers in Marine Science 2026. https://doi.org/10.3389/fmars.2026.1914553

P5. Real-Time Small Floating Object Detection from Dynamic Water Surfaces Using YOLO11-MCN for Sustainable Aquatic Monitoring. Sustainability 18(10):5083 2026. https://doi.org/10.3390/su18105083

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P7. Research on the intelligent detection and analysis of floating debris in polluted water. Scientific Reports 2026. https://doi.org/10.1038/s41598-026-53751-6

P8. Lightweight robust detection of anthropogenic floating debris in turbid and dynamic aquatic environments via enhanced feature fusion. Scientific Reports 2025. https://doi.org/10.1038/s41598-025-31043-9

P9. Water surface garbage detection based on lightweight YOLOv5. Scientific Reports 2024. https://doi.org/10.1038/s41598-024-55051-3

P10. APM-YOLOv7 for Small-Target Water-Floating Garbage Detection Based on Multi-Scale Feature Adaptive Weighted Fusion. Sensors 2023. https://doi.org/10.3390/s24010050

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P15. A Floating-Waste-Detection Method for Unmanned Surface Vehicle Based on Feature Fusion and Enhancement. Journal of Marine Science and Engineering 2023. https://doi.org/10.3390/jmse11122234

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P19. ESAK-YOLO: multi-scale attention enhanced object detection for floating waste in complex water scenes. Scientific Reports 2026. https://doi.org/10.1038/s41598-026-53167-2

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S97. Rotating Target Detection Model of Water Surface Garbage Based on YOLOv5. Modeling and Simulation 2024. https://doi.org/10.12677/mos.2024.133273

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S109. Detection of Floating Objects on Water Surface Using YOLOv5s in an Edge Computing Environment. Water 2023. https://doi.org/10.3390/w16010086

S2. A feature-enhanced and attention-focused intelligent detection method for water-floating garbage. Frontiers in Computer Science 2026. https://doi.org/10.3389/fcomp.2026.1859574

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S9. Deep learning-based floating garbage detection for unmanned surface vehicles in complex water environments. Journal of Hydroinformatics 2026. https://doi.org/10.2166/hydro.2026.072

S33. TECI-YOLO: An Efficient, Lightweight Model for Detecting Small Floating Objects on Water Surfaces. Journal of Computer Science and Frontier Technologies 2026. https://doi.org/10.63313/jcsft.9046

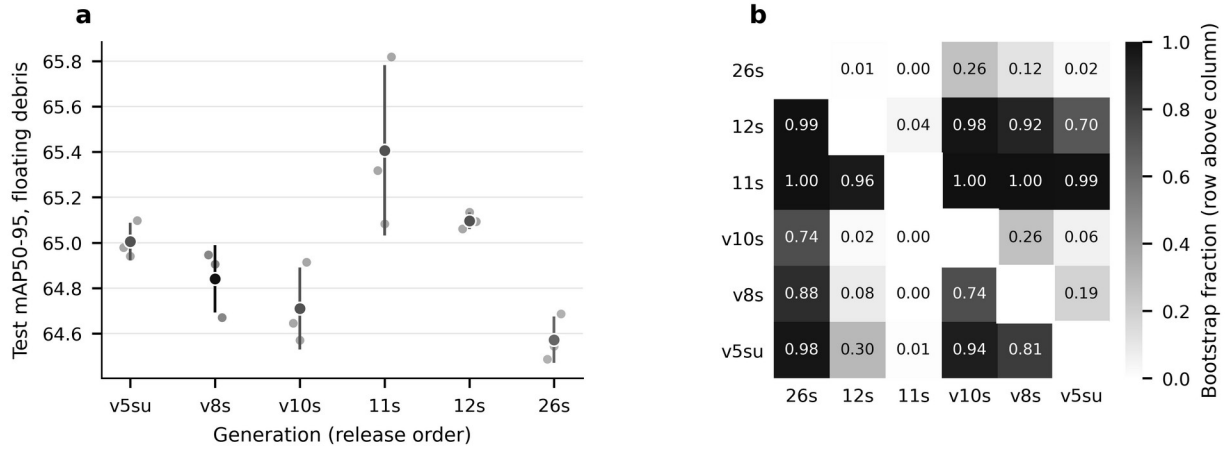
S41. A Novel Method for Water Surface Debris Detection Based on YOLOV8 with Polarization Interference Suppression. Photonics 2025. https://doi.org/10.3390/photonics12060620

S88. EC-YOLOX: A Deep-Learning Algorithm for Floating Objects Detection in Ground Images of Complex Water Environments. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing 2024. https://doi.org/10.1109/jstars.2024.3367713

Supplementary Table S2 Comparison practices

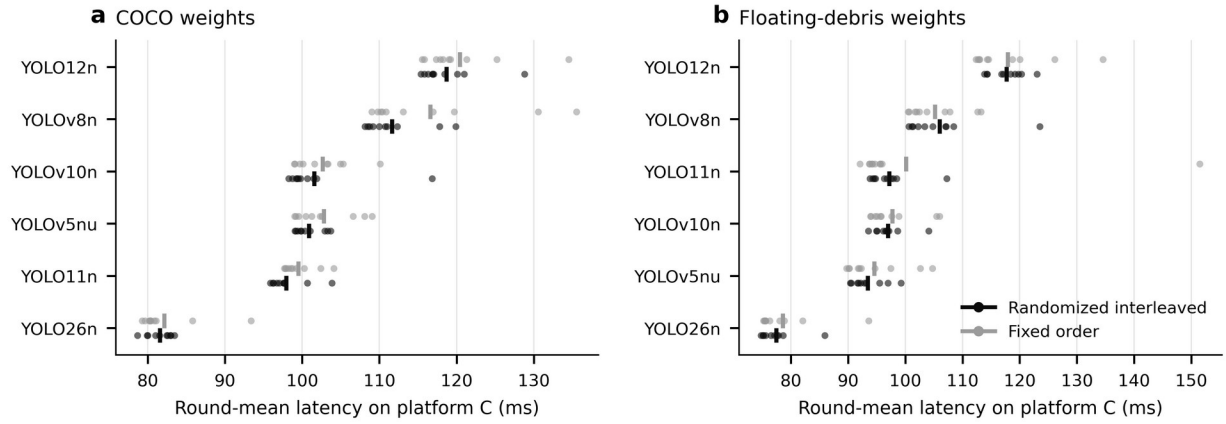
Decision	Evidence in this study	Useful reporting practice
Upgrade or baseline selection	Stable YOLOv8n–YOLO26n contrasts differ by task; complete rankings change under image resampling.	Report the target-task gap, seed spread and paired image interval; combine accuracy with operational costs.
CPU deployment	Measured relative reductions are smaller than the published-table reductions.	Measure candidates in randomized interleaved rounds and report hardware, runtime, threads and end-to-end costs.
Module-gain interpretation	23/36 retained ablation tables have a smallest non-negative increment below 0.5 points.	State repetition count and estimate uncertainty on the study's own evaluation data.
Benchmark documentation	YOLO26 has two head-specific COCO scores.	Identify the evaluated head, export output and post-processing configuration.

Supplementary Figure S1 Small-scale comparison on floating debris



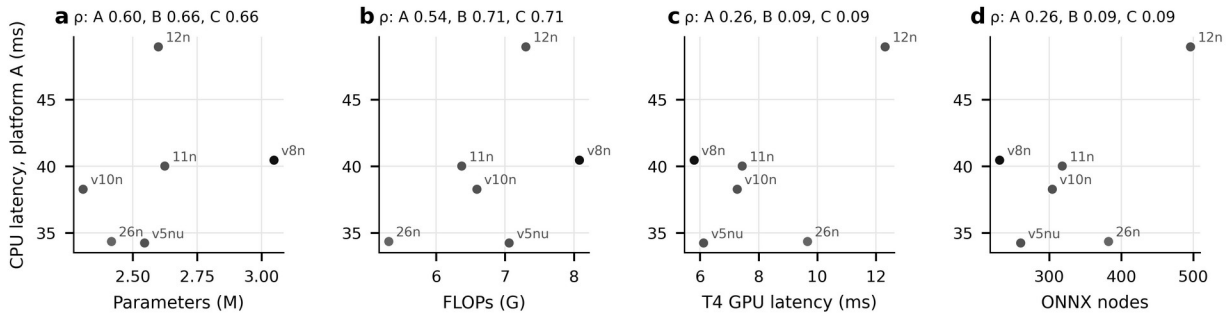
Three seeds are shown with their mean and standard deviation. The paired image-bootstrap panel reports the fraction in which the row model's seed-mean score exceeds the column model's score. YOLO26s has the lowest mean; the v8s–26s and v10s–26s ordering frequencies are 0.88 and 0.74.

Supplementary Figure S2 Fixed-order and randomized measurements on platform C



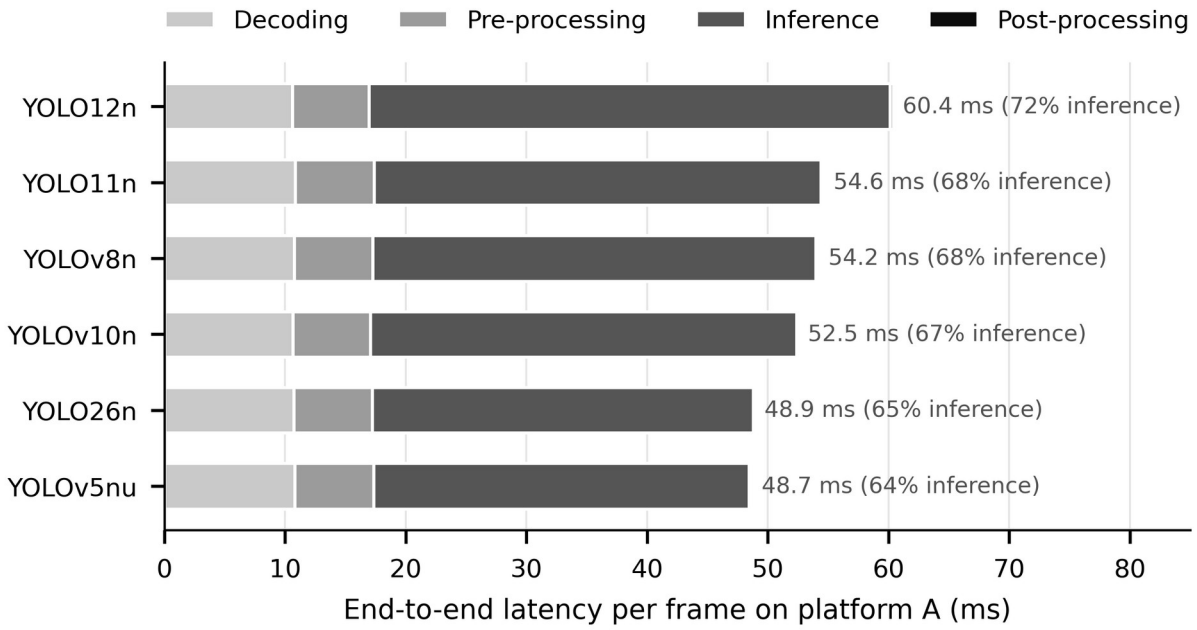
Each point is a round mean of 100 inferences. Short vertical lines mark the mean of ten rounds. Panels show COCO and floating-debris weights. Both protocols can contain slow rounds; their observed mean latencies differ by less than 5%.

Supplementary Figure S3 Static efficiency descriptors and measured CPU latency



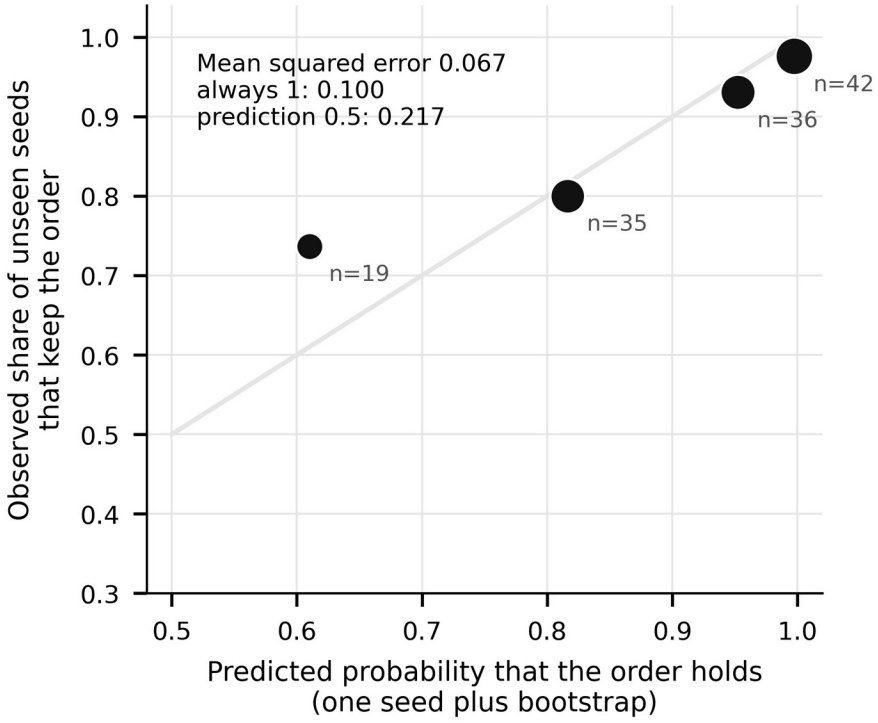
Platform A latency is plotted against parameter count, FLOPs, measured T4 GPU latency and ONNX node count. Titles list Spearman correlations for platforms A, B and C. The six-model correlations describe these comparisons.

Supplementary Figure S4 End-to-end latency on platform A



Stage means cover decoding, pre-processing, inference and post-processing over 100 floating-debris images under the interleaved protocol. Inference accounts for 64–72% of total latency.

Supplementary Figure S5 Leave-one-seed-out ordering check



For each pair-by-seed case, the bootstrap frequency from one seed is compared with the fraction of the other two seeds retaining its observed order. Points are bin means, sized by their case count. The 135 cases reuse the same model runs. This internal check describes correspondence with observed held-out seeds.