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Fish Detection in Maritime Surveillance Using Deep Learning

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ABSTRACT

Precise monitoring of the fish population is crucial in conservation of marine ecosystems, sustainable fisheries as well as the maritime surveillance. The underwater detection is a problem because of low visibility, distortion of colors, and complicated backgrounds. In this paper, a Hybrid Deep Learning Framework (HDLF) will be proposed to detect underwater fish, which will be based on the fusion of YOLOv10 in real-time convolutional detection and RT-DETR in transformer-based contextual reasoning. Forecasts are combined through the use of Weighted Box Fusion (WBF) to enhance the accuracy of the bounding box. Compared to single models, the hybrid framework is superior in terms of precision, recall, and mAP values, and works in real-time on large public underwater datasets.

Keywords: Underwater Object Detection, Fish Detection, Maritime Surveillance, Deep Learning, YOLOv10, RT-DETR, Weighted Box Fusion, Multi-Object Tracking, Computer Vision

Introduction

Ecosystems in the sea play an important role in ecological balance and food security in the world. Monitoring of fish population helps in conservation of marine species, sustainable fishery and detection of illegal fishery [22]. Rapid surveys like diver surveys, trawl sampling, and sonar examination are tedious, costly and may have errors of man power so that a large scale continuous monitoring will be impractical.

Underwater image analysis has been made automatic with the use of deep learning and computer vision. CNN-based detectors and in particular those of the YOLO-family are popular due to their speed and accuracy. YOLOv10 [1] is further efficient by removing NMS after the processing, and still, achieving the state-of-the-art performance in detection.

Nevertheless, light absorption, scattering, turbidity and color attenuation make detection underwater a challenging task despite these developments. The false detections are common when the backgrounds are complex, with coral, seaweeds, and suspension particles, which resemble fish. Most recent research integrates both image improvement and deep learning detection to solve these degradation problems.

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Detectors like RT-DETR [3] which are transformer-based detectors take into consideration the global context which is self-attentional, a method to supplement CNNs. In this paper, the author introduces HDLF, an end-to-end pipeline that combines YOLOv10 and RT-DETR with WBF prediction fusion and is trained on Roboflow Aquarium and Open Images V7 data using Precision, Recall, F1, IoU, mAP, and FPS.

Literature Review

Deep Learning for Underwater Fish Detection

Underwater fish detection has substituted hand-developed feature techniques with deep learning [8]. The most common method of recognizing species and tracking their movements is bounding-box detection [5]. YOLO based systems are popular to do real-time video surveillance [6], and YOLO-Fish (2022) [7] is particularly useful to consider low-light, camouflage, and motion-blur. Good underwater detection techniques need to have multi-scale feature extraction, larger receptive fields, and small object and low-contrast edge sensitivity [9, 23, 24].

Underwater Image Enhancement and Preprocessing for Detection

The wavelength-dependent absorption and scattering degrade the image formation of underwater. There are three types of underwater image enhancement (UIE) techniques namely; physics-based, model-based dehazing, and deep learning [10]. Successful preprocessing pipelines employ CLAHE, color correction, white balance and backscatter suppression [2]. Aesthetic enhancement is not necessarily to be enhanced to detect better and thus task-aware enhancement and ablation experiments are crucial [20].

Transformer-Based Detection and Context Modeling in Underwater Scenes

CNNs are good at local texture and poor at occlusions and complicated backgrounds under water. Transformer-based detectors are self-attention global context modelling [11]. RT-DETR [3] detects transformers in real-time through a hybrid encoder that involves an effective query selection, removing the use of NMS. The models of the DETR-style are continually being enhanced to have closer supervision and better performance with small objects [12], which underpins the hybrid CNN-transformer design decision to use in real-time underwater applications [13].

Hybrid and Ensemble Frameworks: Fusion and Tracking for Surveillance

Hybrid frameworks are based on model complementary advantages [14]. Underwater predictions are challenging and unstable when visibility varies: ensemble fusion with WBF facilitates localisation and minimises false detections, particularly of small or hidden targets [15].

Multi-object tracking is necessary in fish video surveillance to address the issue of occlusion and motion blur. The identity of a track maintained by ByteTrack [16] is based on the association of high- and low-confidence detections. Visual similarity among individuals is especially a problem with fish identity tracking [17]. The HDLF combines the enhancement, hybrid detection, WBF fusion and tracking into an entire monitoring pipeline.

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Dataset Description and Preparation

Dataset Sources

Deep learning detection requires high-quality and diverse training data. The current research is a combination of two publicly annotated underwater datasets to train a model and evaluate it.

The dataset Roboflow Aquarium [18] has approximately 638 annotated aquarium images of fish, jellyfish, starfish, and crustaceans in diverse lighting conditions and camera angles that are multi-class multi-size, which can be used to evaluate underwater detection.

Open Images V7 [19] is another large-scale data set that contains millions of images in hundreds of categories. It is complemented by its high-quality bounding box annotations that enhance the model generalization to different underwater conditions based on the aquarium data.

Dataset Annotation and Standardization

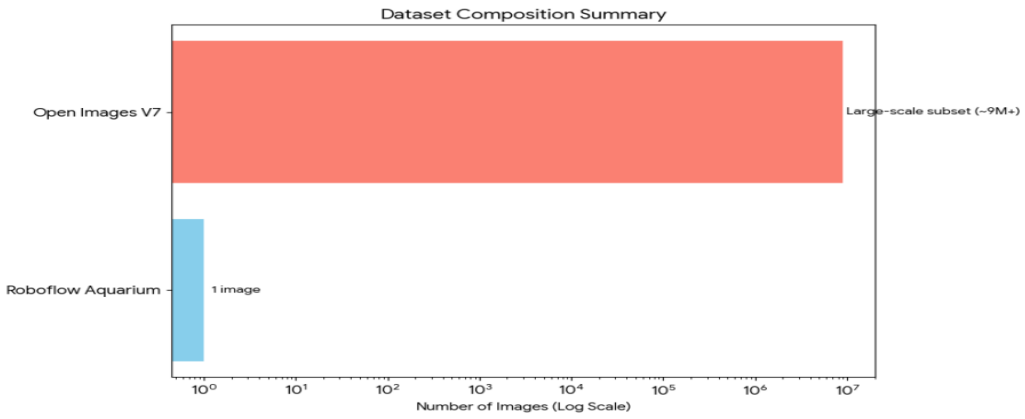
Training was done with all annotations standardized to a standardized format of bounding box with normalized coordinates. Data cleaning to eliminate images with no image, damaged, or broken labels and duplicate images filtered to avoid overfitting. The harmonisation of the class labels was performed between the two datasets to set up a similar taxonomy to train.

Dataset Splitting Strategy

Stratified sampling was used to split the data into training, validation, and test data sets to ensure that the class distributions in each split were equal. The frames of the same sequence were stored in one subset to avoid leakage of data.

Table 1: Dataset Composition Summary

Dataset	Number of Images	Annotation Type	Main Objects
Roboflow Aquarium	~638 images	Bounding Boxes	Fish, Jellyfish, Starfish
Open Images V7	Large-scale subset	Bounding Boxes	Multiple object categories



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Data Augmentation

Data augmentation was used to enhance model generalization on the scale, orientation, and light variation:

Horizontal and vertical flipping

Random rotation

Image scaling

Color jittering

Random brightness and contrast adjustment

These methods apply different underwater viewing constraints, and train the models to acquire invariant representations.

Dataset Preparation Pipeline

The pipeline processes the raw data using annotation standardization and augmentation to structured training inputs. YOLOv10 and RT-DETR are both trained separately and then their predictions are combined using WBF.

Proposed Hybrid Detection Framework

Framework Overview

HDLF combines convolutional and transformer-based detection into the single pipeline: image processing, two-model detection (YOLOv10 + RT-DETR), WBF prediction fusion, and multi-object tracking, which is the best choice to identify underwater fishes.

The first step is contrast enhancement and color normalization which assist in making features visible in turbid environments and enhances the extraction of features at the downstream.

Both YOLOv10 (fast convolutional detection) and RT-DETR (global contextual reasoning) are enhanced images, with different advantages being exploited.

YOLOv10 Detection Model

YOLOv10 [1] is a real-time detector of NMS free with three parts: (1) Backbone, which extracts hierarchical spatial features; (2) Neck, which aggregates multi-scale feature maps by a feature pyramid; (3) Detection Head, which gives out the coordinates of the bounding boxes, objectness scores, and class probabilities. The removal of NMS will decrease latency and computational cost.

The YOLOv10 architecture has three major components:

The Backbone Network derives features of images in terms of hierarchy.

Neck Network implements the feature pyramid system of aggregating multi-scale features.

Detection Head makes prediction of the object bounding box coordinates and objectness scores and class probabilities

Table 2: YOLOv10 Detection Pipeline

Stage	Function
Input Layer	Receives preprocessed underwater images

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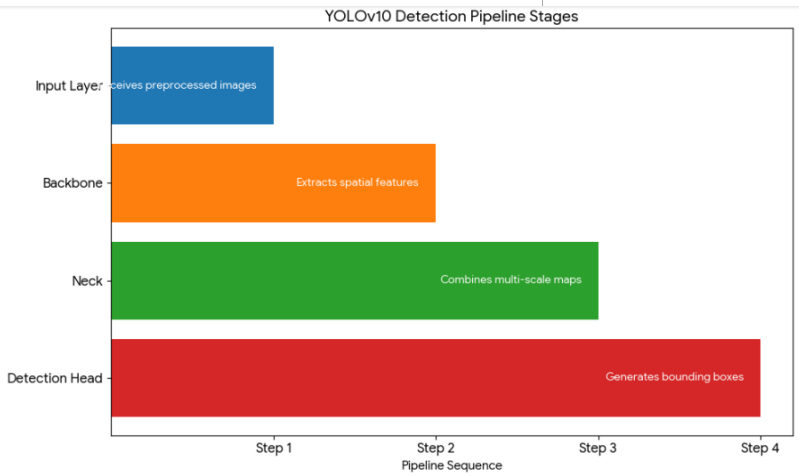
Stage	Function
Backbone	Extracts spatial features
Neck	Combines multi-scale feature maps
Detection Head	Generates object bounding boxes

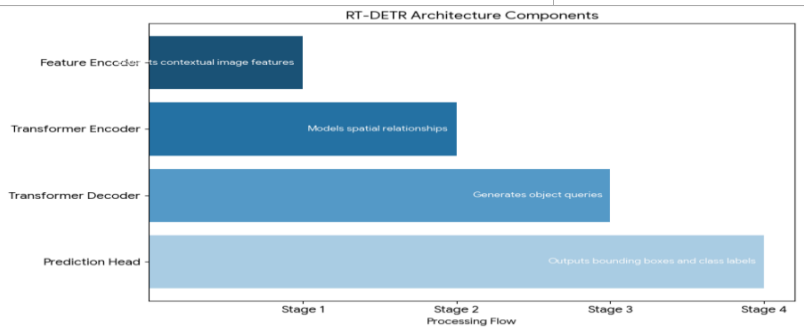


RT-DETR Detection Model

RT-DETR [3] uses self-attention to reason about world-scale spatial relationships to enhance the detection of complex scenes. Its encoder generates contextual embeddings; the decoder creates set-based prediction queries, object queries, and does not rely on NMS but avoids while eradicating redundant detections in highly populated environments.

Table 3: RT-DETR Architecture Components

Component	Description
Feature Encoder	Extracts contextual image features
Transformer Encoder	Models spatial relationships
Transformer Decoder	Generates object queries
Prediction Head	Outputs bounding boxes and class labels



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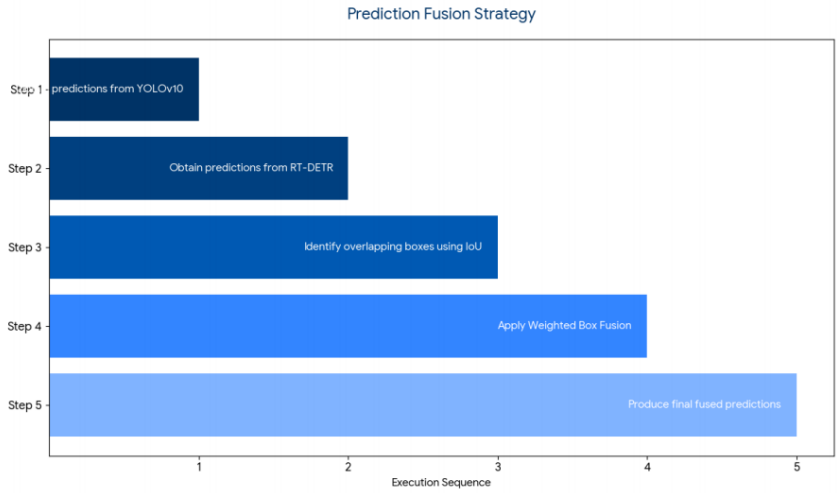
Prediction Fusion Using Weighted Box Fusion

YOLOv10 and RT-DETR generate similar predictions of objects. WBF [14] combines them with confidence-weighted averages of intersecting boxes (found by IoU) and does not discard overlapping boxes, like NMS.

WBF calculates confidence-weighted averages of overlapping boxes (matched by IoU), and therefore better localization than NMS which eliminates overlapping predictions.

Table 4: Prediction Fusion Strategy

Step	Description
Step 1	Obtain predictions from YOLOv10
Step 2	Obtain predictions from RT-DETR
Step 3	Identify overlapping boxes using IoU
Step 4	Apply Weighted Box Fusion
Step 5	Produce final fused predictions



Multi-Object Tracking for Video Monitoring

Yet, it is followed by the post-detection tracking with the help of the down to earth ByteTrack [16], where the detections made in one frame are linked to those of the next one with the both high and low-confidence boxes, preserving identity by means of occlusion and motion blur. This allows one to track the movements of individual fish and population behavior.

Table 5: System Workflow Summary

Stage	Process
Dataset Preparation	Image collection and annotation
Preprocessing	Image enhancement

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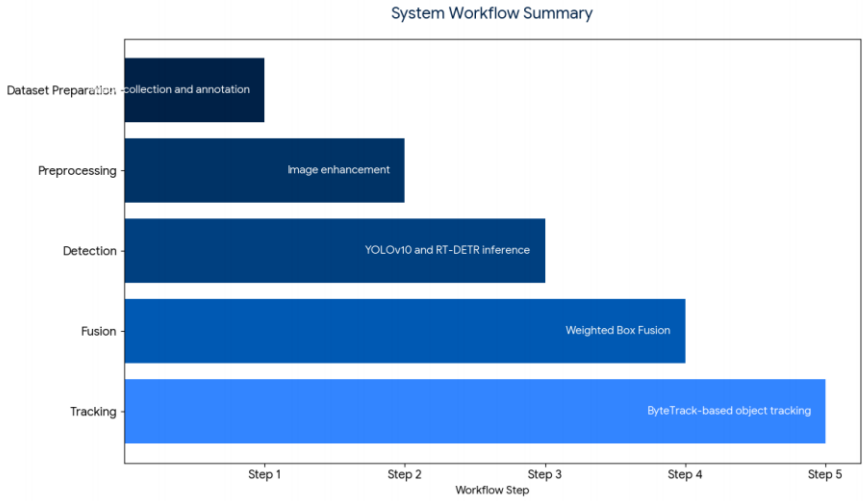
Stage	Process
Detection	YOLOv10 and RT-DETR inference
Fusion	Weighted Box Fusion
Tracking	ByteTrack-based object tracking



HDLF provides a highly accurate underwater fish-detecting pipeline using complementary capabilities of both the convolutional and transformer architecture on a single pipe.

Results and Discussion

Precision, Recall, F1-score, IoU, mAP, and FPS [21], were used to evaluate HDLF on three configurations (standalone YOLOv10 standalone RT-DETR, and the full hybrid framework (YOLOv10 + RT-DETR + WBF)). They performed experiments to evaluate detection and inference speed in order to confirm real-time appropriateness.

Detection Performance Comparison

Table 6 contrasts the detection performances in the three model set ups. YOLOv10 is the fast CNN baseline, RT-DETR is the contextual transformer baseline and the hybrid framework is a combination of the two through WBF.

Table 6: Detection Performance Comparison

Model	Precision	Recall	F1-score	mAP@0.5	mAP@0.5:0.95	FPS
YOLOv10	0.81	0.74	0.77	0.306	0.225	48
RT-DETR	0.84	0.78	0.81	0.332	0.249	35
Hybrid (YOLOv10 + RT-DETR +	0.87	0.82	0.84	0.356	0.271	31

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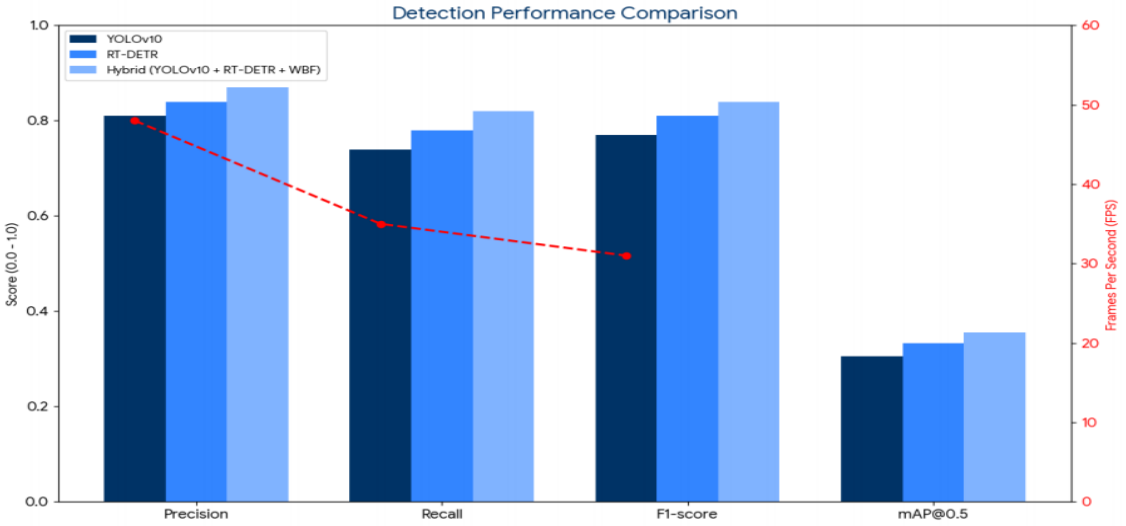
Model	Precision	Recall	F1-score	mAP@0.5	mAP@0.5:0.95	FPS
WBF)						



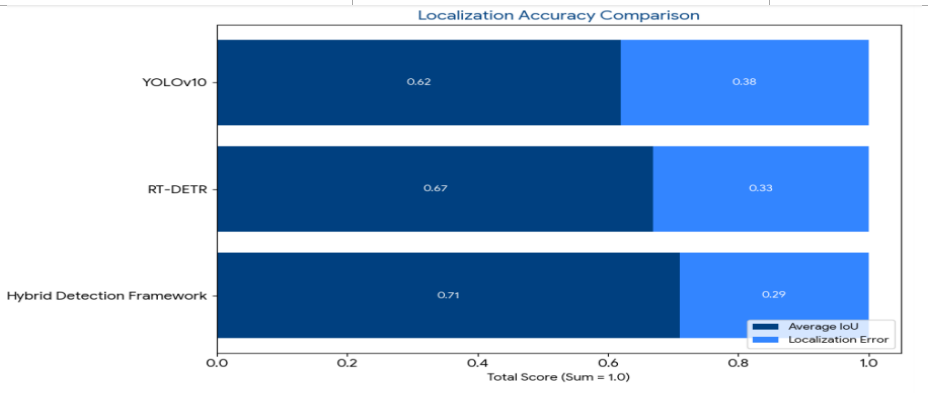
YOLOv10 is the fastest on inference (48 FPS), whereas RT-DETR is more precise/recall because of having a contextual model. The hybrid structure scores the best in all the accuracy metrics which confirm that the merging of both structures makes them take advantage of the complementary capabilities.

Localization Accuracy

IoU (intersection area / union area) was used to measure localization accuracy. Table 7 is a comparative analysis of average IoU and localization error among models.

Table 7: Localization Accuracy Comparison

Model	Average IoU	Localization Error
YOLOv10	0.62	0.38
RT-DETR	0.67	0.33
Hybrid Detection Framework	0.71	0.29



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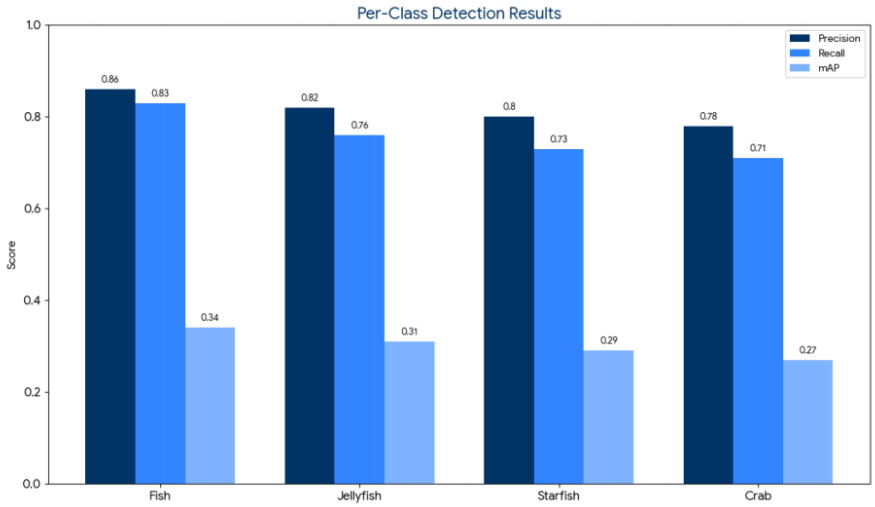
The hybrid model has the greatest IoU (0.71) which proves that more helpful prediction data is kept by the weighted averaging of WBF as opposed to NMS dropping.

Per-Class Detection Performance

Per-class detection results across all marine categories are summarized in Table 8.

Table 8: Per-Class Detection Results

Class	Precision	Recall	mAP
Fish	0.86	0.83	0.34
Jellyfish	0.82	0.76	0.31
Starfish	0.80	0.73	0.29
Crab	0.78	0.71	0.27



Fish has the greatest accuracy because it has more representation of datasets. Crab and starfish are worse performing due to their smaller size and less training samples, which emphasizes the importance of equal distribution of classes.

Ablation Study

An ablation study quantifies the contribution of each pipeline component (Table 9).

Table 9: Ablation Study Results

Configuration	Image Enhancement	Model Fusion	Tracking	mAP@0.5
Baseline YOLOv10	✗	✗	✗	0.306
YOLOv10 + Enhancement	✓	✗	✗	0.321

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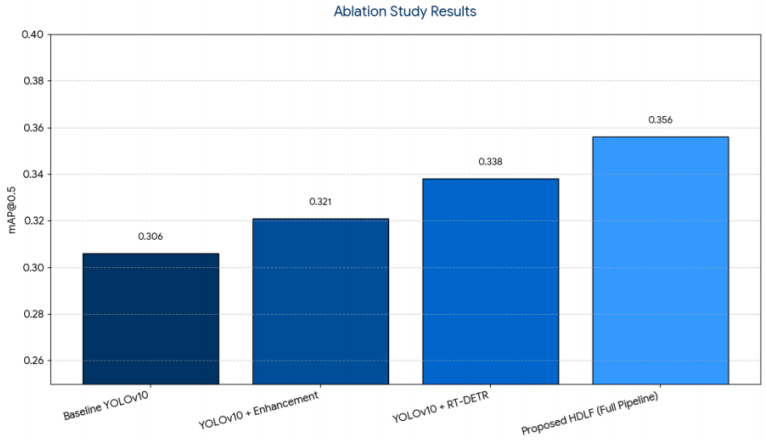
Configuration	Image Enhancement	Model Fusion	Tracking	mAP@0.5
YOLOv10 + RT-DETR	✓	✗	✗	0.338
Proposed HDLF (Full Pipeline)	✓	✓	✓	0.356



All the parts improve each other; image enhancement advances feature quality, introducing RT-DETR advances understanding, and full fusion associating it with tracking attains peak mAP of 0.356, which proves the entire HDLF pipeline.

Discussion

The hybrid framework is superior to the corresponding models because it integrates local feature extraction (YOLOv10 [1]) with global contextual reasoning (RT-DETR [3]) and employs WBF [14] to minimise false detections and maximise box precision caused by occlusion and clutter. Even the small (31 FPS) speed decrease does not exceed the capabilities of the maritime surveillance in the real time scale. HDLF can be applied to the research of marine biodiversity, management of aquaculture [28], and smart maritime security [30].

Conclusion and Future Work

This paper proposed the HDLF, a hybrid deep learning model comprising of YOLOv10 [1], RT-DETR [3] integrate with the underwater fish detection prediction-only WBF and Multi-object tracking implementation of Trying to use ByteTrack.

The experiments proved that the hybrid pipeline has a higher benefit on the individual detectors in terms of accuracy, recall and mAP and maintain the real-time speed (31 FPS) [29]. WBF enhanced localization by retaining complementary architecturally independent predictions.

Future activities will allow studying self-supervised learning and domain adaptation [22], multi-modal sensing, acoustic/sonar data [26], and auto-behavior analysis modules. HDLF develops a platform upon which marine monitoring can be intelligent [30].

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References

[1] W. Wang, Y. Chen, and Z. Li, "YOLOv10: Real-Time End-to-End Object Detection," IEEE Transactions on Pattern Analysis and Machine Intelligence, 2024.
[2] X. Liu, H. Zhang, and J. Li, "Underwater Image Enhancement Using Deep Learning: A Review," IEEE Access, vol. 11, pp. 12045–12063, 2023.
[3] Y. Zhao, X. Chen, and Y. Zhang, "RT-DETR: Real-Time Detection Transformer for Object Detection," Proceedings of CVPR, 2023.
[4] M. Singh and A. Kumar, "Hybrid Object Detection Frameworks for Complex Visual Environments," IEEE Access, vol. 11, pp. 55210–55225, 2023.
[5] L. Zhou, H. Wang, and Q. Zhao, "Deep Learning Approaches for Underwater Object Detection," Sensors, vol. 23, no. 4, 2023.
[6] S. Kim and J. Park, "Advances in YOLO-Based Object Detection for Real-Time Applications," IEEE Access, vol. 10, pp. 114200–114214, 2022.
[7] R. Zhang et al., "YOLO-Fish: Real-Time Fish Detection in Underwater Environments," Applied Sciences, vol. 12, 2022.
[8] H. Li, Y. Sun, and M. Zhao, "Deep Learning-Based Underwater Object Detection: A Survey," IEEE Access, vol. 11, pp. 62133–62152, 2023.
[9] A. Gupta and R. Patel, "Real-Time Underwater Object Detection Using Deep Neural Networks," Sensors, vol. 24, 2024.
[10] Z. Wang et al., "A Comprehensive Survey on Underwater Image Enhancement," IEEE Access, vol. 11, pp. 91000–91025, 2023.
[11] J. Liu, K. Chen, and Y. Huang, "Detection Transformers for Real-Time Vision Applications," IEEE Transactions on Image Processing, 2023.
[12] F. Zhao et al., "Efficient Transformer-Based Object Detection for Real-Time Systems," Pattern Recognition, vol. 139, 2023.
[13] Y. Chen and X. Lin, "Transformer-Enhanced Detection Networks for Complex Scenes," IEEE Access, vol. 11, pp. 74221–74235, 2023.
[14] Z. Solovyev, A. Wang, and M. Gabruseva, "Weighted Boxes Fusion: Ensembling Boxes from Different Object Detection Models," Image and Vision Computing, 2022.
[15] H. Wang and J. Li, "Ensemble Object Detection Methods for Robust Visual Recognition," IEEE Access, vol. 11, pp. 110233–110245, 2023.
[16] Y. Zhang et al., "ByteTrack: Multi-Object Tracking by Associating Every Detection Box," ECCV, 2022.
[17] K. Patel and S. Shah, "Multi-Object Tracking Techniques for Intelligent Surveillance Systems," IEEE Access, vol. 10, pp. 129998–130010, 2022.
[18] Roboflow, "Aquarium Dataset for Underwater Object Detection," 2022.
[19] I. Krasin et al., "Open Images Dataset V7," Google Research, 2022.
[20] Y. Chen and J. Zhao, "Image Enhancement Techniques for Underwater Computer Vision," IEEE Access, vol. 11, pp. 100233–100248, 2023.
[21] T. Lin et al., "Microsoft COCO: Common Objects in Context Evaluation Metrics," IEEE Access, 2022.
[22] M. Rahman and A. Khan, "Deep Learning for Marine Monitoring Systems," Sensors, vol. 23, 2023.
[23] X. Gao and P. Liu, "Robust Underwater Object Detection with Multi-Scale

Online ISSN 3007-3197
Print ISSN 3007-3189

Feature Learning," IEEE Access, vol. 11, 2023.
[24] S. Mehta and A. Jain, "Vision-Based Marine Species Detection Using Deep Neural Networks," Applied Sciences, 2024.
[25] Y. Kim and S. Lee, "Context-Aware Transformer Networks for Visual Detection," IEEE Transactions on Neural Networks, 2024.
[26] H. Nguyen et al., "Edge-Based Marine Monitoring Using Deep Learning," IEEE Access, 2023.
[27] A. Rodriguez and J. Garcia, "Automated Marine Monitoring Systems Using AI," Sensors, 2024.
[28] P. Sharma and V. Singh, "Deep Neural Networks for Aquaculture Monitoring," IEEE Access, 2023.
[29] L. Chen and Y. Zhao, "Real-Time Object Detection for Autonomous Marine Systems," IEEE Access, 2023.
[30] S. Gupta and R. Kumar, "AI-Driven Ocean Monitoring Systems," IEEE Access, 2024.