Research on tuna purse seine fishing target detection and recognition method for Unmanned Aerial Vehicle aerial images based on knowledge distillation

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Introduction

- *1. Transition from Traditional to UAV-Based Detection*
- *2. Key Challenges in UAV-Based Detection*
- *3. Proposed Lightweight Deep Learning Framework*
- *4. Validation through Real-World Deployment*

Materials

- ***Custom Datasets Due to Lack of Benchmarks***

Existing public datasets (e.g., COCO, ImageNet) lack sufficient representation of pelagic tuna schools and FADs. This study instead employs two purpose-built datasets to ensure domain relevance.

- **Close-Range Imagery Collection**

Collected by researchers using handheld wide-angle cameras (12 MP) aboard purse seiners in a defined equatorial Pacific region. The dataset contains 74 high-resolution videos (40 GB total), professionally annotated to support model training and validation.

- **Aerial Imagery via UAV Missions**

Acquired using a multirotor UAV deployed from a tuna seiner in the same Pacific region. The aerial image set focuses on FADs, with 900 high-quality images selected based on strict clarity and visibility criteria for field-based model evaluation.

Methods

- **Dual-Phase Evaluation Protocol**

Combined lab tests (precision, recall, mAP) on close-range images with field validation using 900 UAV shots to assess real-world performance.

- **Laboratory and Field Metrics**

Lab: Precision, Recall, AP via IoU.

Field: Accuracy, miss/false rates, tracking, and environmental robustness at 5 fps.

- **Transfer Learning Strategy**

Froze pre-trained YOLOv6 (COCO) backbone, only retrained the classifier to adapt to marine targets with limited data.

- **Hyperparameter Optimization**

Used genetic algorithm to optimize learning rate and augmentation, improving model accuracy and robustness.

- **Knowledge Distillation**

Compressed teacher model into student model via logit and feature distillation, enhancing efficiency without sacrificing performance.

- **YOLOv6 as Benchmark Model**

YOLOv6 offered the best speed-accuracy trade-off with anchor-free design and hardware-aware architecture for real-time marine use.

Results

- **Novel Deep Learning Framework Proposed:** *An optimized model based on YOLOv6 was developed for real-time marine object detection, utilizing model compression and knowledge distillation techniques.*
- **Optimal Model Identified for Balance of Speed and Accuracy:** *Among the variants tested, the YOLOv6t-student model (Model 13) achieved the best balance, attaining a 0.722 mAP0.5 at a computational cost of just 24.89 GFLOPs.*
- **Exceptional Real-World Detection Accuracy Confirmed:** *Field testing in the Pacific Ocean demonstrated the model's high effectiveness, with a 94.81% accuracy in detecting FADs, including perfect (19/19) detection in defocused conditions.*
- **Isomorphic Teacher Model Most Effective in Distillation:** *Knowledge distillation analysis showed that an isomorphic teacher model (YOLOv6t) yielded the best student performance, while a complex teacher increased recall but reduced overall accuracy.*
- **Framework Presents a Viable Cost-Effective Alternative:** *The solution provides a cost-effective UAV-based monitoring system, offering a practical alternative to helicopters with potential for future sensor integration.*

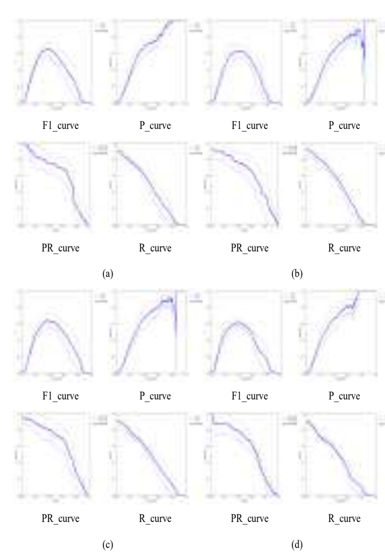

Fig.1 Comparative performance evaluation of YOLOv6 variants (a)yolov6 s (b)yolov6 m (c)yolov6l (d)yolov6t. Metrics: P (Precision), F1 (F1-Score), PR (Precision-Recall curve), R(Recall)..

Fig.2 Experimental Results on the Detection of FAD from Offshore UAV Testing

Conclusions

- **AI-Driven Modernization for Fisheries:** *This research demonstrates how AI vision systems modernize tuna fishing by significantly enhancing detection efficiency and providing a pathway to integrate with other sensors for comprehensive monitoring.*
- **A Practical and Cost-Effective UAV Solution:** *The framework offers a viable alternative to helicopter surveillance, reducing operational costs and safety risks while maintaining high detection capabilities, thus supporting the industry's transition to UAVs.*
- **Acknowledgement of Current Limitations:** *The study notes limitations, as field testing was primarily conducted on FADs due to operational constraints, with detection of free-swimming schools remaining for future work.*
- **Potential for Future Enhancement with More Data:** *It is anticipated that future collection of high-quality UAV footage will provide richer datasets, further improve model accuracy and enable robust recognition of free-swimming fish schools.*
- **Foundational Step Towards Data-Driven Fisheries:** *The computationally efficient techniques developed are a significant advancement, enabling intelligent autonomous reconnaissance and representing a pivotal breakthrough in transforming fisheries into data-driven industries.*

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