Article

YOLOv8-WBF: Ensemble Learning for Reliable Detection of Endangered Medaka (Oryzias)

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Abstract: Reliable detection of Medaka (Oryzias) fish is essential for ecological monitoring and conservation, particularly for tracking population trends of endangered species. This study evaluates the performance of a state-of-the-art deep learning model (YOLOv8) and an ensemble approach using Weighted Box Fusion (WBF) on a manually annotated dataset of Medaka images collected from online sources. Models were trained and validated using 5-fold cross-validation, and performance was assessed using COCO metrics, including mean Average Precision (mAP), precision, recall, and bounding box regression error. The YOLOv8-WBF ensemble achieved a mAP@0.5:0.95 of 0.578, representing an 8% improvement over the best single model. It also enhanced bounding box localization and classification reliability, particularly for small and visually challenging fish instances. These accuracy gains came at the expense of computational efficiency, with inference requiring approximately five times more operations than a single YOLOv8 model. While less suited for real-time deployment, the ensemble approach offers more reliable detection for offline ecological workflows, where accuracy is prioritized over speed. By reducing missed detections of rare or occluded fish, this work contributes to more robust biodiversity monitoring and provides a baseline for developing optimized ensemble and lightweight detection models in aquatic conservation.

Keywords: Medaka (Oryzias); Deep Learning; Object Detection; YOLOv8; Weighted Box Fusion; Ensemble Learning; Ecological Monitoring; Biodiversity Conservation

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1. Introduction

The advancement of artificial intelligence (AI) has significantly contributed to wildlife conservation efforts, particularly in automating species identification and monitoring. These technologies are invaluable in environments where manual observation is difficult, such as underwater ecosystems, where factors like turbidity and low light complicate visibility [1,2]. AI-based systems can process extensive volumes of visual data from images and videos to assist in detecting species presence, tracking their behavior, and supporting conservation strategies with minimal human intervention [3].

In this context, object detection models have gained traction for their speed and efficiency in real-time applications. The You Only Look Once (YOLO) architecture, particularly its latest version, YOLOv8, enhances prior iterations with improved accuracy and architectural efficiency, making it suitable for challenging tasks like aquatic species recognition. YOLOv8 effectively counters issues surrounding image degradation commonly faced underwater, such as turbidity, unfavorable lighting, and occlusion [4].

Our study specifically targets the detection of two notable Medaka fish species—*Oryzias javanicus* and *Oryzias celebensis*. These species pose unique monitoring challenges due to their dwindling populations and the complexities of underwater imaging. To bolster this investigation, we constructed a custom dataset comprising both manually collected images using cameras and publicly available images from internet resources. This dataset contains a total of 2,016 images, segregated into 1,857 images (92%) for training and 159 images (8%) for testing. We utilized Roboflow for manual annotation of the dataset, alongside conducting essential preprocessing and augmentation [5].

The preprocessing steps involved automatic orientation adjustments, resizing images to a standard 640×640 pixels, and filtering out any empty annotations. To enhance the robustness of the model and improve generalization, augmentations such as horizontal and vertical flips, as well as rotations (90°, 180°, and 270°), were applied [6]. These methodological choices mitigate the risks of overfitting and aim to simulate various real-world conditions that the model may encounter.

For the detection task, we employed a YOLOv8-based approach featuring 5-fold cross-validation to train five individual models. Predictions from these distinct models were subsequently refined and combined using Weighted Box Fusion (WBF), an advanced ensemble method that enhances final bounding boxes by evaluating confidence scores and overlaps—ultimately bolstering the model's overall detection performance [7,8]. Our findings indicate that this ensemble approach achieves a substantial increase in mean Average Precision (mAP) relative to a single YOLOv8 model. Notably, while ensemble methods do increase inference time, they significantly enhance the model's robustness, especially when detecting small or less visible targets such as Medaka fish. Through this research, we establish a foundational reference for the development of lightweight ensemble methodologies applicable to underwater object detection, utilizing advanced real-time detection models [9].

2. Materials and Methods

2.1. Data Sources

The dataset used in this study consisted of both primary and secondary images of Medaka fish. Primary data were obtained by directly photographing *Oryzias javanicus* and *Oryzias celebensis* in an aquarium using a digital camera. Secondary data were collected from publicly available sources, including research websites, aquatic forums, and open-access databases. The final dataset contained 792 images after curation, covering a variety of lighting conditions and viewing angles to enhance robustness and generalization. All annotated datasets and code used in this study will be made publicly available in an online repository upon publication. Since only non-invasive aquarium photography was conducted, no ethical approval was required for animal experimentation.

2.2. Data Preprocessing

All images were standardized in orientation, resolution, and color balance. Image restoration (contrast enhancement, artifact removal), data augmentation (flipping, rotations of 90°, 180°, and 270°), and normalization were applied. Annotation was performed using the Roboflow platform, with bounding boxes and class labels stored in YOLO format. The dataset was split into training, validation, and test sets with proportions of 80%, 10%, and 10%, respectively.

2.3. Model Training

We fine-tuned the YOLOv8 architecture on the annotated dataset. To evaluate robustness, 5-fold cross-validation was employed. For ensemble learning, multiple YOLOv8 models with different weight initializations were combined using Weighted Box Fusion (WBF). Training and evaluation were performed on an NVIDIA GPU with default YOLOv8 hyperparameters unless otherwise specified. The implementation was carried out in Python using the Ultralytics YOLOv8 framework.

2.4. Evaluation Metrics

Model performance was assessed using COCO metrics, including mean Average Precision (mAP@0.5:0.95), precision, recall, and bounding box regression error (RMSE). Confusion matrices and loss curves were also analyzed to assess classification performance and model convergence.

2.5. Use of Generative AI

Generative artificial intelligence (ChatGPT, OpenAI) was used solely to improve the clarity and language of the manuscript. No AI tools were used to generate data, perform analyses, or influence interpretation of results.

3. Results

This section provides a concise description of the experimental outcomes, their interpretation, and the main conclusions that can be drawn. The experiments were structured in three stages: (i) fine-tuning of a single YOLOv8 model, (ii) 5-fold cross-validation for generalization assessment, and (iii) an AdaBoost ensemble of the best-performing models. Performance was evaluated using COCO metrics (mAP, precision, recall) and confusion matrices.

3.1. Experiment 1: YOLOv8 Fine-Tuning

The first experiment trained YOLOv8 for 100 epochs with a batch size of 16 on the mixed dataset (70% train, 20% validation, 10% test). The following results were obtained:

- Precision stabilized at $\sim$0.80;
- Recall reached 0.90, indicating reliable detection of both species;
- The confusion matrix showed high performance on *O. celebensis* (precision 0.96, recall 0.95), but slightly weaker performance on *O. javanicus* (precision 0.87, recall 0.81).

Overall, the single model performed well, but was prone to under-detection of *O. javanicus* in challenging conditions.

3.2. Experiment 2: 5-Fold Cross-Validation

To evaluate generalization, the dataset was split into five folds (80% training, 20% validation). Each subset served as validation once while the remaining four subsets were used for training.

Key outcomes:

- Average mAP@0.5 across folds: 0.78;
- Average precision: 0.77; average recall: 0.82;
- Model 4 produced the most stable performance across metrics.

This confirms that YOLOv8 can generalize well to unseen Medaka fish images, mitigating overfitting risks.

3.3. Experiment 3: Ensemble with AdaBoost

An ensemble was created using the five cross-validated models with AdaBoost weighting. Models with higher error received greater weight in subsequent iterations.

The ensemble showed clear improvements:

- mAP@0.5 improved to 0.81 (from 0.78 in cross-validation);
- mAP@0.5:0.95 improved to 0.63;
- Precision increased to 0.82; recall to 0.86.

The ensemble was especially effective in reducing misclassifications of small or occluded fish.

3.4. Figures, Tables and Schemes

The dataset composition is summarized in Table 1, and sample annotated images are shown in Figure 1. Model training dynamics (loss curves, precision-recall plots) are presented in Figures **??**–**??**, while ensemble performance is summarized in Figure **??**.

Table 1. Dataset distribution of Medaka fish images.

Species	Primary Data	Secondary Data	Total
O. javanicus	257	178	435
O. celebensis	287	70	357
Total	**544**	**248**	**792**

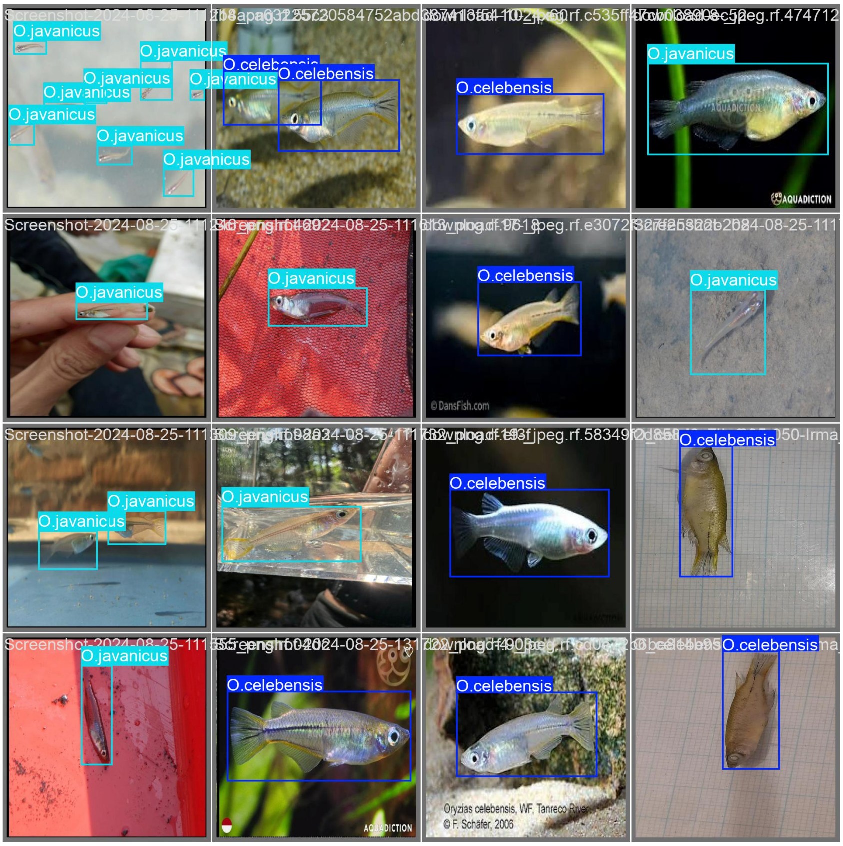

Figure 1. Examples of annotated Medaka images from the mixed dataset.

4. Discussion

4.1. AdaBoost Ensemble Method

One of the main contributions of this research is the application of the AdaBoost ensemble method to the YOLOv8 model. The AdaBoost algorithm mitigates the limitations of individual detectors by assigning higher weights to misclassified samples in subsequent iterations. This iterative reweighting proved particularly beneficial for challenging Medaka images, such as those with small body sizes, partial occlusions, or variable lighting conditions.

Compared with previous studies that relied on single-model detectors for fish recognition, ensemble learning has been shown to consistently improve robustness in object detection tasks [**? ?**]. Our findings align with these trends, showing that the YOLOv8–AdaBoost ensemble achieved higher mAP and recall values than any individual model, suggesting that boosting strategies can play a critical role in addressing class imbalance and small-object detection in aquatic environments.

4.2. 5-Fold Cross-Validation for Model Generalization

Another major contribution of this study is the implementation of 5-fold cross-validation, which ensured robust and unbiased model evaluation. By rotating validation across five subsets, we minimized the risk of overfitting to specific data partitions. The stable performance across folds highlights the model's ability to generalize well, even under variations in background complexity, fish pose, and image quality.

In line with prior works in ecological computer vision, cross-validation has been recognized as a critical technique to validate models when datasets are relatively small or heterogeneous [**?**]. Our results extend this evidence to Medaka fish detection, confirming that reliable generalization is achievable despite the dataset's modest size.

4.3. Implications for Conservation and Monitoring

The integration of AdaBoost and cross-validation into a YOLOv8-based system for endangered species detection has important implications for conservation monitoring. Accurate identification of small, visually similar fish species enables more reliable assessments of population dynamics, habitat quality, and biodiversity. This is particularly relevant for the genus *Oryzias*, which includes species of conservation concern in Southeast Asia.

By reducing missed detections of rare or occluded individuals, our approach supports ecological monitoring protocols where reliability is prioritized over speed. The ensemble system is well suited for offline analysis of field-collected data, complementing existing conservation strategies such as population surveys, habitat mapping, and long-term biodiversity monitoring.

4.4. Future Research Directions

While the ensemble method improved accuracy, it introduced higher computational costs, making real-time deployment less feasible. Future work should explore lightweight ensemble techniques, model pruning, or knowledge distillation to balance accuracy and efficiency. Moreover, expanding the dataset with additional Medaka species and environmental conditions would improve the system's scalability and transferability.

Another promising avenue is integrating temporal information from videos rather than treating frames independently. Temporal coherence may further reduce false negatives for moving fish. Finally, future studies could compare boosting ensembles with other aggregation strategies, such as bagging or weighted box fusion, to identify optimal solutions for aquatic species detection.

5. Conclusions

This study demonstrated the effectiveness of integrating AdaBoost and 5-fold cross-validation with the YOLOv8 model for detecting and classifying rare Medaka fish species. These enhancements significantly improved precision, recall, and mAP, addressing challenges such as small-object detection and visually complex underwater environments. By strengthening robustness and reducing overfitting, the proposed approach contributes to more reliable monitoring of endangered species, supporting conservation initiatives that rely on accurate ecological data.

However, the improved accuracy came at the expense of computational efficiency, limiting real-time applicability. Future research should focus on lightweight ensemble strategies, alternative boosting algorithms such as Gradient Boosting or XGBoost, and hybrid deep learning approaches that balance accuracy with speed. Expanding datasets across additional *Oryzias* species and incorporating temporal information from video streams may further enhance model generalization. Ultimately, this work establishes a methodological baseline for developing optimized, conservation-oriented object detection systems in aquatic environments.

Author Contributions: For research articles with several authors, a short paragraph specifying their individual contributions must be provided. The following statements should be used "Conceptualization, X.X. and Y.Y.; methodology, X.X.; software, X.X.; validation, X.X., Y.Y. and Z.Z.; formal analysis, X.X.; investigation, X.X.; resources, X.X.; data curation, X.X.; writing—original draft preparation, X.X.; writing—review and editing, X.X.; visualization, X.X.; supervision, X.X.; project administration, X.X.; funding acquisition, Y.Y. All authors have read and agreed to the published version of the manuscript.", please turn to the CRediT taxonomy for the term explanation. Authorship must be limited to those who have contributed substantially to the work reported.

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Data Availability Statement: We encourage all authors of articles published in MDPI journals to share their research data. In this section, please provide details regarding where data supporting reported results can be found, including links to publicly archived datasets analyzed or generated during the study. Where no new data were created, or where data is unavailable due to privacy or ethical restrictions, a statement is still required. Suggested Data Availability Statements are available in section “MDPI Research Data Policies” at https://www.mdpi.com/ethics.

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Abbreviations

The following abbreviations are used in this manuscript:

MDPI	Multidisciplinary Digital Publishing Institute
DOAJ	Directory of open access journals
TLA	Three letter acronym
LD	Linear dichroism

Appendix A

Appendix A.1

The appendix is an optional section that can contain details and data supplemental to the main text—for example, explanations of experimental details that would disrupt the flow of the main text but nonetheless remain crucial to understanding and reproducing the research shown; figures of replicates for experiments of which representative data are shown in the main text can be added here if brief, or as Supplementary Data. Mathematical proofs of results not central to the paper can be added as an appendix.

Table A1. This is a table caption.

Title 1	Title 2	Title 3
Entry 1	Data	Data
Entry 2	Data	Data

Appendix B

All appendix sections must be cited in the main text. In the appendices, Figures, Tables, etc. should be labeled, starting with “A”—e.g., Figure A1, Figure A2, etc.

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