

FishDet-M: A Unified Large-Scale Benchmark for Robust Fish Detection and CLIP-Guided Model Selection in Diverse Aquatic Visual Domains

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Abstract—Accurate fish detection in underwater imagery is essential for ecological monitoring, aquaculture automation, and robotic perception. However, practical deployment remains limited by fragmented datasets, heterogeneous imaging conditions, and inconsistent evaluation protocols. To address these gaps, we present *FishDet-M*, the largest unified benchmark for fish detection, comprising 13 publicly available datasets spanning diverse aquatic environments including marine, brackish, occluded, and aquarium scenes. All data are harmonized using COCO-style annotations with both bounding boxes and segmentation masks, enabling consistent and scalable cross-domain evaluation. We systematically benchmark 28 contemporary object detection models, covering the YOLOv8 to YOLOv12 series, R-CNN based detectors, and DETR based models. Evaluations are conducted using standard metrics including mAP, mAP@50, and mAP@75, along with scale-specific analyses (AP_S , AP_M , AP_L) and inference profiling in terms of latency and parameter count. The results highlight the varying detection performance across models trained on *FishDet-M*, as well as the trade-off between accuracy and efficiency across models of different architectures. To support adaptive deployment, we introduce a CLIP-based model selection framework that leverages vision-language alignment to dynamically identify the most semantically appropriate detector for each input image. This zero-shot selection strategy achieves high performance without requiring ensemble computation, offering a scalable solution for real-time applications. *FishDet-M* establishes a standardized and reproducible platform for evaluating object detection in complex aquatic scenes. All datasets, pretrained models, and evaluation tools are publicly available to facilitate future research in underwater computer vision and intelligent marine systems.

Index Terms—fish detection, underwater vision, object detection, benchmark dataset, CLIP-based model selection, YOLO, deep learning, marine robotics, ecological monitoring

I. INTRODUCTION

Accurate fish detection in underwater environments remains a major challenge due to the visual degradation caused by turbidity, occlusion, light scattering, and dynamic backgrounds [1], [2], [3]. These conditions reduce contrast, distort color, and introduce clutter, impairing the reliability of vision-based detection models. Occlusions from vegetation, rocks, or dense schools of fish further obscure targets [4], [5]. Although deep learning has advanced underwater perception, its effectiveness is constrained by fragmented datasets that often lack diversity, consistent annotation formats, and representation of complex real-world conditions [6], [7], [8], [9].

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To address these limitations, several domain-specific datasets have emerged. The SmallFish dataset focuses on detecting small targets in poor visibility [1], DUFish captures densely packed schooling behavior [10], and DePondFi introduces pond-based fish imagery from naturally challenging conditions [8]. In parallel, detection models have evolved to address underwater visual distortions. FishDet-YOLO incorporates enhancement modules for low-contrast targets [11], YOLOv8 TF introduces transformer-enhanced refinement and class-sensitive learning [12], and the IDLAFD UWSN framework leverages hybrid architectures to improve detection under blur and occlusion [13].

Despite these advances, the field still lacks a unified benchmark capable of supporting large scale and cross-domain evaluation in realistic aquatic environments. To bridge this gap, we introduce *FishDet-M*, a consolidated benchmark constructed by harmonizing 13 publicly available datasets into a single annotation format aligned with the COCO protocol. *FishDet-M* spans diverse underwater environments including coral reefs, aquaculture tanks, and brackish waters, and provides 296,885 annotated fish instances across 105,556 images. This benchmark supports the evaluation of 28 leading detection models, including YOLO variants, DETR-based architectures, and region proposal networks.

The contributions of this work are summarized as follows:

- **FishDet-M Benchmark:** We introduce a unified benchmark dataset for fish detection that integrates 13 publicly available underwater datasets into a harmonized annotation format compatible with the COCO standard. The dataset includes diverse environments, species, and visual conditions.
- **Comprehensive Evaluation of Detection Models:** We evaluate 28 advanced object detection architectures including YOLOv8 through YOLOv12, DETR-based models, and R-CNN models. The evaluation uses standardized metrics such as mean average precision (mAP), scale-aware scores (AP_S , AP_M , AP_L), inference time, and parameter count.
- **CLIP-Based Adaptive Model Selection:** We propose a context-aware mechanism that utilizes vision-language alignment with CLIP to automatically select the most appropriate detection model based on input image content, enabling dynamic and robust inference.
- **Performance Insights and Deployment Guidelines:** We analyze model robustness under conditions such as occlusion and poor visibility, providing actionable

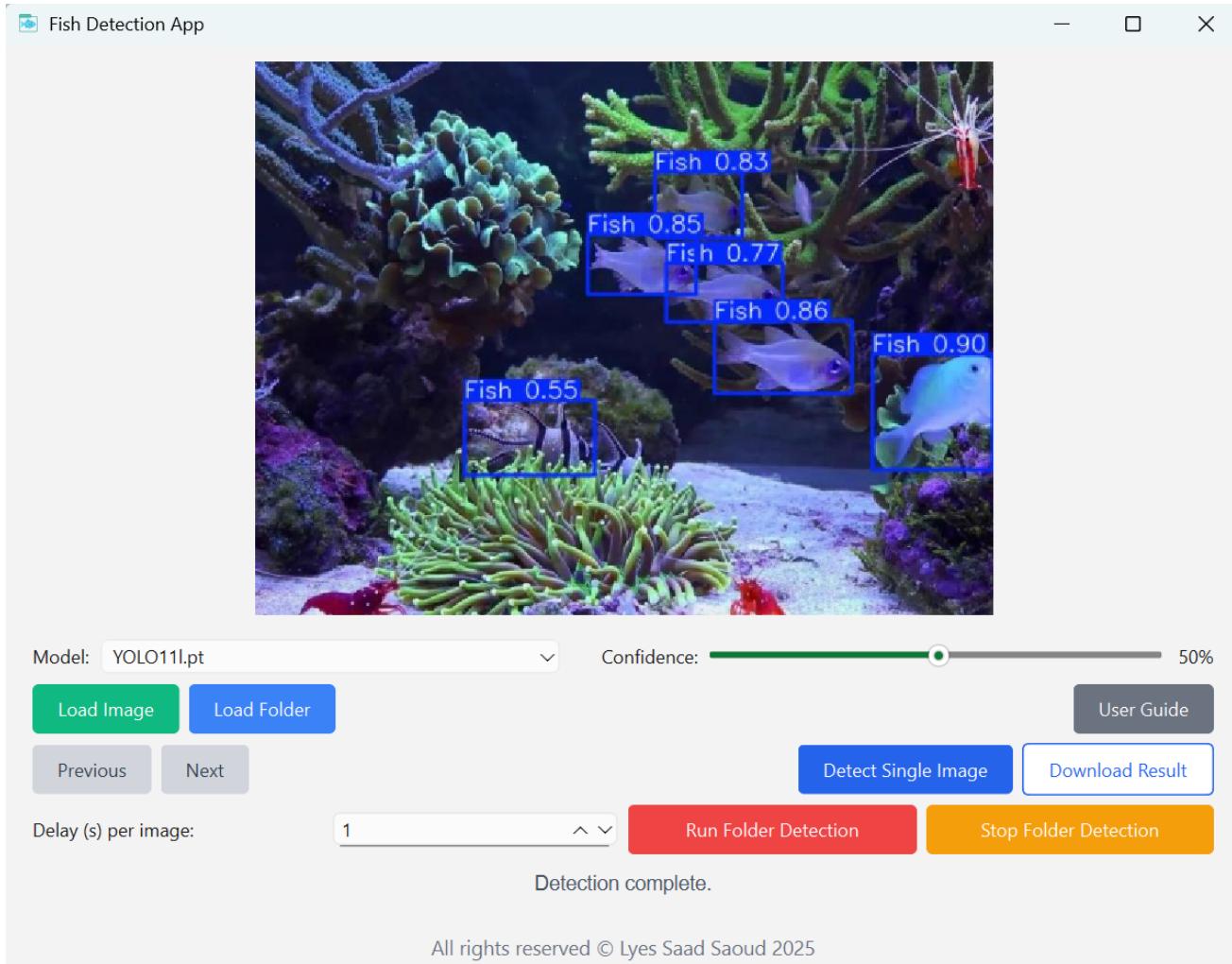


Fig. 1: Interactive application interface for comparing detection outputs on FishDet-M. Supports multiple models, bounding box overlays, and threshold control.

recommendations for selecting models suitable for real-time ecological monitoring, aquaculture management, and robotic deployment.

- **Public Release to Support Reproducibility:** The full dataset, source code, checkpoints, and evaluation tools are released publicly through our GitHub repository to promote reproducible research and facilitate further development.

II. RELATED WORKS

A. Underwater Fish Detection Challenges and Solutions

Underwater fish detection remains a challenging task due to the complex optical properties of marine environments. Turbidity, light scattering, and occlusion degrade visibility and introduce background clutter [3], [6], making accurate detection difficult, particularly for deformable and low contrast targets.

To mitigate these effects, recent methods combine underwater specific image enhancement, such as illumination correction and color restoration, with adapted deep learning detectors [14],

TABLE I: Representative fish detection datasets used in underwater computer vision research

Dataset	Environment	Size	Annotations	Species Diversity
SmallFish [1]	Murky tanks	5,000	BBoxes	Low
DePondFi [8]	Pond	8,000	BBoxes	Medium
DUFish [10]	Open water	6,300	BBoxes and Masks	High
FishTrack23 [17]	Varied habitats	20K	Tracks and BBoxes	High
OcclusionSet [4]	Reef zones	3,500	BBoxes	Medium

[11]. However, performance still drops in scenes with severe occlusion or high visual complexity [15].

Dataset limitations further compound these issues. Many existing datasets focus on controlled settings with limited species diversity or environmental variation [1], [16]. Newer datasets like DUFish [10] and FishTrack23 [17] improve diversity and realism, but the broader dataset landscape remains fragmented. Table I summarizes representative datasets.

Deep learning has improved detection performance with models such as YOLO, Cascade R-CNN, and DETR [18], [19], [20], enhanced by attention modules, deformable layers, and domain adaptation [11], [21], [12]. Hybrid convolutional and transformer based architectures further improve robustness [12], while fine tuning on augmented datasets aids generalization to unseen conditions.

Challenges persist due to occlusion, camouflage, and inter-species variability [4], [22]. Addressing these requires context aware training and robust augmentation strategies. Evaluation protocols are expanding beyond mean average precision and intersection over union to include scale aware metrics, latency, and model size [1], [10], supporting real time deployment.

Despite advances, cross domain variation and inconsistent benchmarks limit generalizability [23]. Overcoming these issues remains essential for enabling reliable fish detection in diverse marine environments.

B. Fish Detection Datasets and Benchmarks

The effectiveness of detection models relies heavily on diverse and well-annotated datasets. Many earlier datasets are restricted to clear or shallow environments, limiting their generalizability. Real-world aquatic scenes vary significantly in turbidity, lighting, and species composition, necessitating diverse benchmarks for robust evaluation [9], [1].

Recent efforts have addressed these limitations by expanding ecological and visual variability. DePondFi [9] offers annotated pond imagery where YOLO models achieve high mAP@50 scores. Fish4Knowledge supports both detection and classification in marine environments, with FishNet detector achieving over 92 percent detection precision [24]. SmallFish is tailored to small object detection in murky conditions [1].

FishTrack23 [17] emphasizes dense tracking across habitats, while LifeCLEF 2014 [25] serves as a benchmark for fish recognition. Other datasets like UOMT [26] and FS48 [27] address salient object detection and re-identification. OzFish [28], [29] include species-level annotations for fish in Australian shores.

Table II provides a comparative overview of these datasets, highlighting environments, tasks, and public availability. Despite their contributions, the field still lacks unified annotation standards, benchmark protocols, and cross-study comparability. Upcoming datasets such as FishDet-M aim to address these challenges through structured metadata and realistic test conditions.

C. Deep Learning Models for Underwater Object Detection

Deep learning has substantially advanced underwater detection performance, particularly in environments where image quality is degraded by turbidity, occlusion, and variable lighting [11], [21], [28]. Foundational models like YOLO [12], Faster R-CNN [30], and DETR have been widely adapted for marine detection pipelines.

To address visual limitations, researchers have introduced attention mechanisms, deformable layers, and fusion modules that enhance feature representation for partially visible targets. Transformers have also been incorporated into convolutional

backbones, enabling long-range feature modeling in low-contrast conditions [12], [13].

Specialized variants such as FishDet-YOLO and YOLOv8-TF focus on underwater data distributions and address class imbalance [11], [12]. Domain adaptation techniques, including adversarial learning and style transfer, further help bridge performance gaps between synthetic and real-world datasets [31].

Hybrid models that fuse convolution and transformer components leverage the spatial localization strengths of CNNs and the semantic context modeling of transformers. This combination enhances detection accuracy in cluttered, occluded, and dynamic marine scenes [12].

These architectures are increasingly designed with deployment in mind. Their applications range from ecological monitoring and fishery management to robotic exploration and real-time fish tracking [32], [33], [34].

D. Occlusion Handling and Species Variability

Occlusion is a persistent challenge in underwater scenes, particularly in crowded habitats or reef zones. Solutions include 3D geometric modeling, plan mirror-based occlusion mitigation, and rotated bounding box regression [35], [36]. Transformer-enhanced YOLO models and approaches using repulsion loss have also shown improved performance on overlapping targets [4].

Generative augmentation using models such as DCGAN and UIEGAN contributes occlusion-rich samples, enhancing training diversity [37], [38]. Temporal tracking methods further improve robustness by associating occluded objects across frames [39].

Species variability adds further complexity due to morphological and chromatic diversity. Fine-grained models use attention mechanisms, patch localization, and multi-branch architectures to detect subtle inter-species differences [40], [41]. Camouflaged species, which exploit background matching or polarized light, remain especially challenging [42].

Advanced strategies such as active detection and few-shot learning are being used to adapt models efficiently with minimal data [43]. Lightweight models like MobileNetV2, when fine-tuned with semantic modules, offer promising trade-offs between performance and computational load [44].

Table III outlines the key approaches for addressing occlusion and species-level variation in detection systems.

E. Evaluation Metrics and Benchmarking Protocols

Reliable benchmarking in underwater detection depends on consistent and comprehensive evaluation criteria. Standard metrics such as mAP, IoU, precision, and recall are commonly reported [46], [47], but variations in implementation and dataset usage often hinder reproducibility [48].

To address detection at different object scales, researchers employ APS, APM, and APL metrics that reflect performance on small, medium, and large objects. These are critical for understanding behavior in turbid conditions, where smaller fish are more likely to be missed [49], [50].

Practical deployments also require runtime metrics such as inference time, memory usage, and model size. These determine

TABLE II: Representative fish detection datasets and benchmarks.

Dataset	Environment	Main Task	Performance Highlights	Availability	Link
DePondFi [9]	Pond, South India	Real-time object detection	YOLOv8: mAP@50 = 0.92; Ensemble = 0.94	✓	Link
Fish4Knowledge-2010 [24]	Marine scenes	Detection and classification	mAP = 92.3%, Accuracy = 89.7%	✓	Link
SmallFish [1]	Murky, cluttered	Detection of small targets	Enhanced mAP via Fish-Finder algorithm	✗	–
FishTrack23 [17]	Multi-habitat	Multi-object tracking	20,000 expert tracks	✓	Link
LifeCLEF 2014 [25]	Video footage	Detection and recognition	Evaluated in open competition	✓	Link
UOMT [26]	Mixed marine	Salient object detection	Supports multitask learning	✓	Link
FS48 [27]	Controlled lighting	Re-identification	Multi-view detection using FSNet	✗	–
DeepFish [28]	Tropical Australia	Classification and sizing	Evaluated with SOTA models	✓	Link
OzFish [21]	Coastal marine	YOLO-based detection	Robust YOLOv8/NAS results	✓	Link

TABLE III: Summary of methods addressing occlusion, species variability, and camouflage.

Technique	Description
3D tracking models [15], [36]	Geometric modeling for occlusion tracking using mirror imaging and spatial cues
Rotating box detection [35]	Uses oriented boxes to resolve overlaps in dense scenes
Enhanced YOLO models [4]	Incorporates modules and repulsion loss for occlusion robustness
Synthetic data generation [37], [38]	Adversarial networks used to balance datasets with rare and occluded samples
Underwater image enhancement [37]	Improves contrast and clarity prior to detection
Multi-object tracking [39]	Maintains temporal consistency in sequential data
Vision transformers with FGVC [40]	Discriminative attention modules for fine-grained classification
Dual-branch fusion networks [41]	Integrates inter-species similarity and semantic fusion
Attention mechanisms [45]	Enhances localized feature extraction in camouflage detection
Polarocrypsis [42]	Biological camouflage using polarization cues
Active detection models [43]	Epistemic uncertainty used for sample selection
Transfer learning [44]	Fine-tunes pretrained models using edge and texture-aware modules

whether models can be implemented on embedded devices or underwater robots with limited computational resources [51].

Image quality assessment metrics, including UWEQM [52] and QDE [48], are also important. These help quantify the impact of enhancement and restoration steps on overall detection reliability. Recent multi-exposure and fusion-based schemes offer richer evaluations that integrate contrast, chroma, and structural consistency [53].

Standardizing benchmarking protocols and dataset splits will improve comparability across studies. New efforts should aim to combine performance metrics with deployment considerations and perceptual quality assessments to guide model selection for real-world marine applications.

F. Applications in Aquaculture, Robotics, and Marine Monitoring

Fish detection models play a vital role across aquaculture, robotics, and environmental monitoring. In aquaculture, deep learning enables automated fish counting, size estimation, and health assessment under turbid and low-light conditions [54], [55], [56]. Lightweight models such as AquaYOLO and CUIB-YOLO [57], [58] are optimized for embedded deployment and integrate with smart feeding and water monitoring systems [59].

TABLE IV: Overview of the FishDet-M dataset splits and annotations.

Feature	Training Set	Validation Set	Test Set
Number of Images	83,093	10,654	11,809
Number of Fish Instances	228,558	32,961	35,366
Annotated Species	>50	>50	>50
Bounding Boxes	Yes	Yes	Yes
Environmental Diversity	Broad	Broad	Broad

In underwater robotics, fish detection supports navigation, obstacle avoidance, and targeted sampling, which are essential for autonomous missions such as coral reef surveys, pollution tracking, and marine mapping [60], [61], [62], [63]. Recent works have also emphasized aquaculture infrastructure inspection and defect segmentation using semantic segmentation and detection pipelines [64].

In conservation, detection models assist biodiversity tracking, mariculture zone mapping, and ecosystem health monitoring. Integration with drones and satellite imaging enables detection of trends driven by environmental changes and human activity [65], [66], [67].

Despite progress, variability in species, morphology, and water conditions continues to challenge robustness. Efforts in model compression, domain adaptation, and multi-sensor fusion are ongoing. Efficient models such as AASNet and quantized YOLO variants are promising for edge deployment in marine settings [68], [69]. These applications demonstrate the growing importance of fish detection in sustainable aquaculture, autonomous exploration, and ecological assessment [23], [54], [67], [70].

III. DATA RECORDS

The FishDet-M benchmark comprises 105,556 images and 296,885 annotated fish instances, partitioned into training, validation, and test sets using stratified sampling to ensure balanced representation across habitat types, visibility conditions, and fish densities. Key statistics for each split are summarized in Table IV.

FishDet-M exhibits extensive visual heterogeneity, with image resolutions ranging from 78×53 to 4608×3456 pixels (mean: 715×468) and instance densities spanning from single fish to dense aggregations with up to 256 individuals per frame (mean: 2.81 instances per image).

Object-level statistics are visualized in Fig. 2. The distribution of bounding box areas in Fig. 2a shows a right-skewed

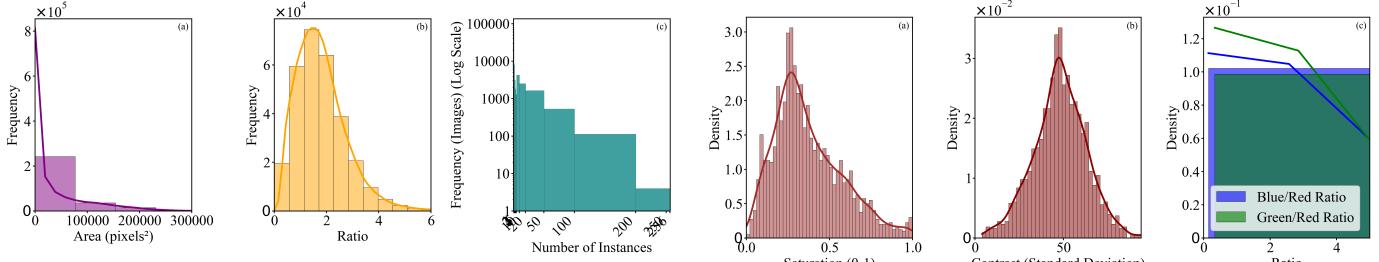


Fig. 2: Distribution of object-level statistics across FishDet-M. (a) Bounding box area. (b) Aspect ratio. (c) Number of instances per image (log scale).

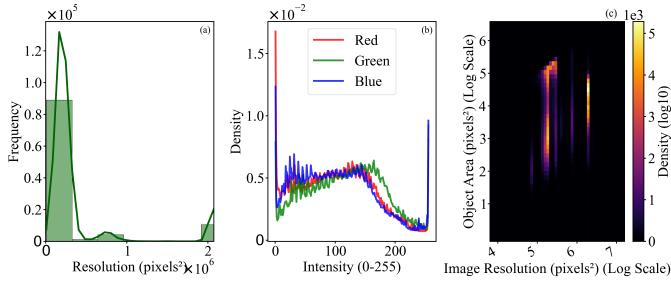


Fig. 3: Visual property distributions. (a) Image resolution. (b) RGB intensity histograms. (c) Object area vs. image resolution (log-log scale).

curve dominated by small and medium-sized objects. Aspect ratios in Fig. 2b peak between 1 and 2. The histogram of instances per image in Fig. 2c, plotted on a log scale, reveals a long-tail pattern where most images contain few fish while a smaller subset includes densely packed schools.

Visual properties at the image level are summarized in Fig. 3. The image resolution histogram in Fig. 3a illustrates the diversity in spatial coverage. RGB intensity histograms in Fig. 3b reveal that most scenes are low-light and dominated by green-blue hues, typical of underwater capture [71]. The object-to-image resolution heatmap in Fig. 3c, shown on a log-log scale, emphasizes the prevalence of small objects across both low- and high-resolution imagery.

Additional underwater-specific imaging characteristics are highlighted in Fig. 4. The saturation histogram in Fig. 4a shows a dominance of muted tones, consistent with light absorption and scattering. Contrast distribution in Fig. 4b, computed via grayscale standard deviation, confirms low overall contrast. The channel ratio plots in Fig. 4c illustrate strong blue and green biases relative to red, confirming the spectral distortion typical of aquatic environments [71].

Additional spatial insights are provided in Fig. 5. The histogram of mean image intensities in Fig. 5a serves as a proxy for visibility degradation due to haze and backscatter. The bounding box center heatmap in Fig. 5b reveals a central bias in object placement, reflecting typical framing tendencies in human-operated data acquisition.

To facilitate exploratory analysis and model transparency, we developed an interactive desktop GUI as shown in Fig. 1.

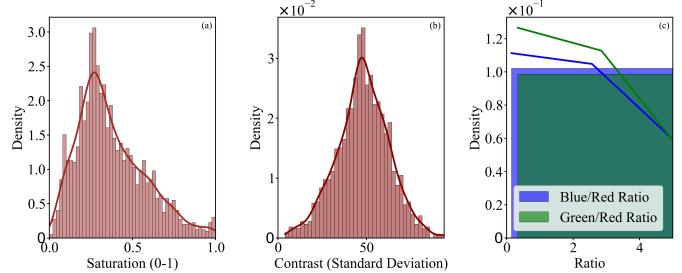


Fig. 4: Underwater visual characteristics. (a) Saturation. (b) Contrast (std. dev.). (c) Color channel ratios (Blue/Red, Green/Red).

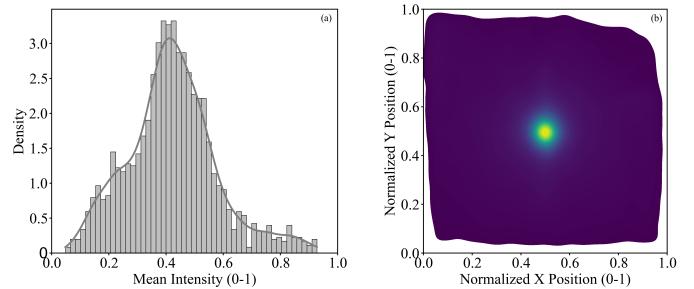


Fig. 5: Scene-level statistics. (a) Image mean intensity (haze proxy). (b) Spatial distribution of bounding box centers.

The tool enables comparative evaluation of detection outputs from YOLO-based and transformer-based models, with support for adjusting confidence thresholds and overlaying predicted bounding boxes. Additional metadata such as mAP scores and inference times are presented in real time, assisting researchers in identifying model suitability for varied aquatic conditions.

IV. METHODS

Dataset Aggregation and Annotation. FishDet-M consolidates 13 underwater fish detection datasets, combining publicly available repositories and datasets. Data originate from coral reefs, aquariums, coastal zones, and estuaries, comprising both still images and video frames. All annotations were standardized to the COCO format[72], with bounding boxes harmonized into a unified, species-agnostic *fish* category. This ensured annotation integrity across varying formats and naming conventions. Invalid or ambiguous annotations were removed during quality control.

Environmental and Visual Diversity. FishDet-M covers a broad range of real-world conditions including clear and turbid waters, shallow and deep scenes, artificial and natural lighting, motion blur, and object occlusion. These variations simulate practical deployment scenarios and improve model robustness. The dataset also includes terrestrial and laboratory views for extended diversity and evaluation of domain transfer.

Harmonization and Quality Assurance. Dataset integration involved coordinate format unification, validation of box dimensions, and manual correction of missing or erroneous annotations. All bounding boxes follow the COCO format

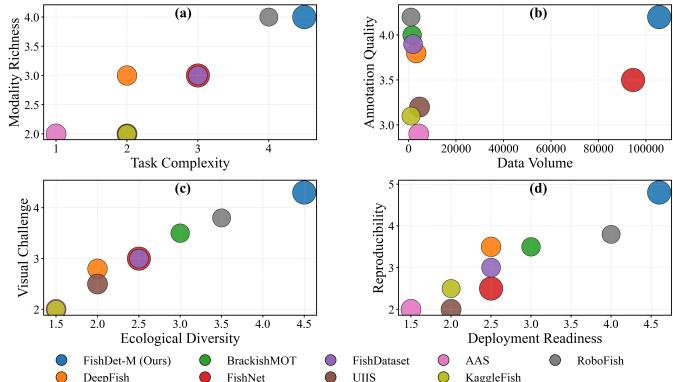


Fig. 6: Comparative positioning of major fish detection datasets across four key axes: (a) task complexity vs. modality richness, (b) data volume vs. annotation quality, (c) ecological diversity vs. visual challenge, and (d) deployment readiness vs. reproducibility. Bubble size indicates dataset scale (number of annotated fish instances).

x_{\min} , y_{\min} , width, height [72]. Rigorous validation steps ensured dataset consistency and excluded corrupted samples.

Partitioning Strategy. A source-aware stratified split maintained proportional representation of each dataset within training (80%), validation (10%), and test (10%) sets. This preserved the ecological and visual diversity of smaller datasets and prevented bias from large contributors like FishNet[73].

Dataset Selection Criteria. Selection was guided by eight criteria: task complexity, modality richness, volume, annotation quality, ecological diversity, visual challenge and deployment readiness. Representative datasets included DeepFish [28], FishNet [73], Brackish-MOT [32], and TrashCan 1.0 [33]. The complete list of source datasets is listed in table V. Non-representative or duplicate frames were removed to focus on annotated fish instances and prevent data leaks. To visualize representativeness, Fig. 6 presents a four-panel bubble chart contrasting key dimensions (e.g., task complexity vs. modality richness), with FishDet-M consistently positioned in the upper-right quadrant, highlighting its diversity, annotation volume, and readiness for real-world deployment.

CLIP-Based Model Selection. We integrated a CLIP-based module to automatically select the most appropriate detection model from 28 candidates using semantic similarity between image embeddings and prompt texts as shown in Fig. 7. This mechanism enables context-aware inference without manual selection or heuristics.

Technical Validation. We benchmarked 28 models across YOLOv8-v12 [18], [74], [75], [76], YOLO-NAS[77], Cascade R-CNN[19], Sparse R-CNN[78], DETR variants[20], [79], [80], RetinaNet[81], and MobileNetv2-SSD[82]. Models were trained on FishDet-M using default hyperparameters. Evaluation used mAP, mAP₅₀, mAP₇₅, AP_S, AP_M, and AP_L, precision-recall curves, and F1 scores. Efficiency was assessed via FPS, model size, and latency.

Hardware and Software. All experiments were run on an RTX 4090 GPU with an Intel i9-14900K CPU and 64GB RAM under Windows 11. Codebases included PyTorch [83],

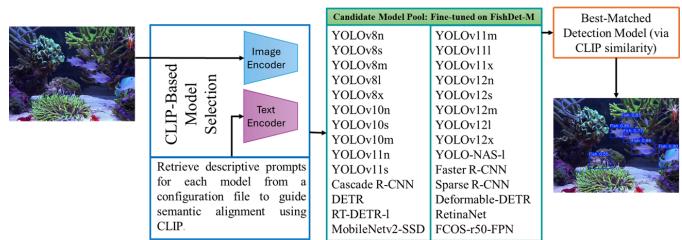


Fig. 7: CLIP-based model selection pipeline. The input image is embedded via the CLIP image encoder, and its similarity is computed with a set of model-specific textual prompts embedded using the CLIP text encoder. The model with the highest alignment score is automatically selected for downstream detection.

Ultralytics [84] and MMDetection[85]. All detection metrics were computed using pycocotools[86] with mixed-precision evaluation.

V. RESULTS AND DISCUSSION

This section provides a comprehensive evaluation of object detection models for underwater fish detection, presenting both quantitative performance metrics and qualitative analyses of model behavior. We assess model performance on the aggregate FishDet-M benchmark, examine their efficiency characteristics, and investigate their generalization capabilities across various sub-test splits, reflecting diverse underwater conditions.

A. Quantitative Evaluation

We evaluated 28 object detection models on the FishDet-M benchmark to analyze performance and computational efficiency across a range of architectures. Table VI presents accuracy, scale-specific detection, and inference metrics.

The YOLO family consistently achieved the highest detection accuracy. YOLO12x reached 0.491 mAP, followed by YOLO12l (0.487) and YOLO11l (0.484). These models performed strongly across small, medium, and large object scales (AP_S, AP_M, AP_L), confirming their adaptability to varying fish sizes. YOLO-NAS-l also provided strong results (0.470 mAP) with efficient inference.

Lighter models such as YOLOv8n and YOLOv10n offered excellent speed-accuracy balance. YOLOv8n achieved 251 FPS using only 3.2 million parameters, making it ideal for real-time and resource-constrained scenarios.

In contrast, transformer-based models including DETR, RT-DETR-l, and Deformable-DETR showed lower mAP (0.317–0.390), struggled with small object detection, and exhibited higher latency (15 to 45 milliseconds), making them less suitable for real-time deployment in aquatic environments.

Region proposal models such as Cascade R-CNN (0.449 mAP) offered solid accuracy but lower speed. Single-stage alternatives like RetinaNet (0.448 mAP) and FCOS (0.475 mAP) provided better efficiency at 30–38 FPS.

1) *Precision-Recall Analysis:* The Precision-Recall curves in Fig. 8a show most models begin with high precision and drop as recall increases. MobileNetV2-SSD declines steeply at recall

TABLE V: Summary of existing datasets used as image sources for constructing our comprehensive FishDet-M dataset, detailing their types, sizes, and descriptions

Dataset	Type	Size	Description
Brackish-MOT [32]	MOT	89 videos	Hazy underwater videos with multi-object fish tracking bounding boxes
UIIS [34]	Instance Seg.	4628 images	General-purpose underwater instance segmentation across categories
TrashCan 1.0 [33]	Object Detection	7212 images	Debris detection dataset including fish annotations
Fish4Knowledge-2023 [87]	Fish Detection	1897 images	Bounding-box labeled images of fish from underwater videos
Fish Dataset [16]	Detection, Seg.	1850 images	Aquarium images of Crucian carp with detection and segmentation masks
FishNet [73]	Cl., Det	94,532 images	Large-scale dataset for multi-species classification with bounding boxes
Fish Video [88]	Fish Detection	322 images	Video-derived frames with annotated fish instances
FISH-video [89]	Fish Detection	506 images	Fish tank video frames with annotated fish instances
Med. Fish [90]	Fish Detection	1247 images	Labeled fish images from Mediterranean Sea species
DeepFish [28]	Fish Det., Seg.	3200 / 620	Images with labeled fish instances in tropical Australia
Aquarium [91]	Fish Detection	638 images	Aquarium animal dataset with fish-focused bounding boxes
AAS [92]	Fish Detection	4239 images	Multi-class marine dataset with 72% fish representation
FishExtend [93]	Fish Detection	3122 images	Diverse fish images under various environmental conditions
FishDet-M (Ours)	Fish Detection	105,556 images	Unified benchmark combining 13 datasets for large-scale, diverse fish detection

TABLE VI: Detection performance summary of 28 deep learning object detection models, including YOLO, R-CNN, and Transformer-based architectures, evaluated on the FishDet-M test set. Metrics reported include mAP@50, mAP@50:95, and inference speed (ms). Training is done using Ultralytics [84], mmdetection [85] and Supergradients [77]

Model	mAP	mAP ₅₀	mAP ₇₅	AP _S	AP _M	AP _L	Params (M)	Inf. Speed (ms)	FPS
YOLOv8n [18]	0.433	0.776	0.445	0.251	0.409	0.602	3.2	3.97	251.78
YOLOv8s [18]	0.455	0.808	0.469	0.274	0.434	0.618	11.2	4.02	248.85
YOLOv8m [18]	0.471	0.828	0.490	0.286	0.456	0.632	25.9	5.10	196.01
YOLOv8l [18]	0.478	0.834	0.505	0.294	0.466	0.638	43.7	6.12	163.50
YOLOv8x [18]	0.481	0.837	0.505	0.297	0.472	0.638	68.2	7.07	141.52
YOLOv10n [74]	0.442	0.784	0.460	0.261	0.413	0.610	2.3	4.98	200.77
YOLOv10s [74]	0.461	0.812	0.483	0.277	0.439	0.626	7.2	5.03	198.91
YOLOv10m [74]	0.476	0.833	0.501	0.295	0.461	0.633	15.4	6.65	150.41
YOLO11n [75]	0.450	0.796	0.465	0.262	0.426	0.620	2.6	5.24	190.68
YOLO11s [75]	0.471	0.824	0.491	0.283	0.460	0.629	9.4	5.27	189.71
YOLO11m [75]	0.480	0.838	0.502	0.297	0.468	0.635	20.1	6.52	153.45
YOLO11l [75]	0.484	0.842	0.506	0.302	0.470	0.639	25.3	9.72	102.90
YOLO11x [75]	0.483	0.840	0.509	0.300	0.472	0.639	56.9	9.76	102.40
YOLO12n [76]	0.443	0.789	0.456	0.255	0.415	0.616	2.6	7.56	132.20
YOLO12s [76]	0.470	0.823	0.490	0.281	0.451	0.634	9.3	7.76	128.89
YOLO12m [76]	0.483	0.841	0.507	0.299	0.470	0.642	20.2	8.12	123.17
YOLO12l [76]	0.487	0.847	0.516	0.306	0.483	0.639	26.4	13.66	73.20
YOLO12x [76]	0.491	0.848	0.521	0.315	0.485	0.641	59.1	13.41	74.59
YOLO-NAS-1 [77]	0.470	0.805	0.488	0.285	0.453	0.620	66.9	16.01	62.5
Faster R-CNN [30]	0.379	0.690	0.374	0.192	0.348	0.538	41.0	34.8	28.7
Cascade R-CNN [19]	0.449	0.758	0.470	0.260	0.422	0.607	69.1	40.5	24.7
Sparse R-CNN [78]	0.357	0.615	0.375	0.127	0.305	0.565	62	50.4	19.9
DETR [20]	0.390	0.708	0.390	0.154	0.335	0.600	41.0	36.0	27.8
Deformable-DETR [80]	0.317	0.648	0.269	0.12	0.24	0.507	34.0	45	22.1
RT-DETR-I [79]	0.381	0.696	0.383	0.156	0.354	0.588	32	15.1	66
RetinaNet [81]	0.448	0.764	0.465	0.238	0.416	0.627	34.0	26.6	37.6
MobileNetv2-SSD [82]	0.288	0.519	0.294	0.032	0.185	0.554	3	40	25
FCOS-r50-FPN [94]	0.475	0.838	0.472	0.203	0.383	0.599	32.1	29.7	33.7
FishDet-M-CLIP	0.444	0.742	0.472	0.235	0.415	0.620	—	12.46	80.28

0.4, and other models such as Sparse R-CNN and Deformable-DETR also exhibit earlier degradation. At IoU=0.75 Fig. 8b, the precision starts lower and declines earlier, particularly for transformer models.

2) *F1 Score*: F1 score trends for IoU thresholds of 0.50 and 0.75 are shown in Fig. 8c and 8d. YOLO variants peaked early and declined smoothly, while Sparse R-CNN and DETR peaked later. Deformable-DETR displayed a flatter curve with early decline. At stricter IoU thresholds, models showed more uniform patterns, with FCOS and MobileNetV2-SSD dropping sharply beyond 0.6 confidence.

3) *Evaluation on Sub-Test Splits*: To better understand the contribution of each constituent dataset, we conducted a detailed evaluation of model performance on the individual test partitions of the thirteen source datasets. Results indicate notable variability depending on dataset complexity. For example, YOLO12x achieved an mAP of 0.846 on DeepFish [28], which features underwater scenes with large prominent fish instances. In contrast, the same model scored 0.371 on FishDataset [16], where overlapping and occluded, similar-looking fish in a tank present significant visual challenges. Across the full benchmark, FishDet-M produced consistent

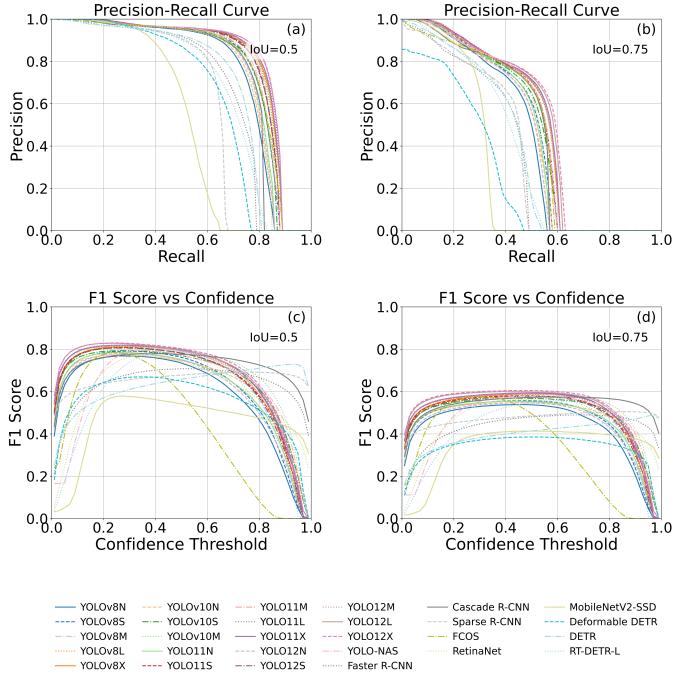


Fig. 8: F1 score and Precision-Recall curves for 28 object detection models at IoU thresholds of 0.50 and 0.75. Subfigures (a) and (b) show F1 score trends, and (c) and (d) depict precision-recall curves.

performance in the range of 0.481 to 0.491 for the highest-performing models (see Table VI), demonstrating generalization across diverse visual domains.

The individual datasets can be broadly grouped into three performance tiers based on their environmental characteristics. Datasets in the high-performance tier, such as DeepFish [28] and FishVideo [89], typically include large fish with minimal background interference and stable lighting conditions. The moderate tier includes datasets like FishNet [73] and Fish4Knowledge [87], which involve variable fish sizes, mixed lighting conditions, and moderate occlusion. The most challenging tier comprises datasets such as TrashCan 1.0 [33] and Brackish-MOT [32], where visual noise, low image quality, high turbidity, and frequent occlusion significantly hinder detection accuracy. Detailed metrics for all evaluated models on each dataset are provided in the supplementary material (Table SI through SXIII). These results confirm that while FishDet-M does not achieve the highest accuracy on any single dataset, it consistently promotes generalizable feature learning across domains. This is further evidenced by the narrow variance in model performance across subsets. An average precision value of -1 indicates that no qualifying objects were present in the corresponding sub-test split based on size thresholds.

B. Qualitative and Generalization Analysis

In addition to quantitative metrics, visual inspection and cross domain testing provide further insight into model robustness under diverse underwater conditions. Fig. 9 presents outputs

TABLE VII: Models Performance Comparison on unseen test data from a different source with sample size of 1500 [95]

Model	mAP	mAP ₅₀	mAP ₇₅	AP _S	AP _M	AP _L
YOLOv8n [18]	0.542	0.826	0.607	0.252	0.460	0.630
YOLOv8s [18]	0.575	0.853	0.646	0.295	0.492	0.661
YOLOv8m [18]	0.596	0.867	0.673	0.286	0.511	0.684
YOLOv8l [18]	0.615	0.879	0.699	0.322	0.523	0.705
YOLOv8x [18]	0.611	0.879	0.689	0.303	0.516	0.704
YOLOv10n [74]	0.579	0.842	0.660	0.242	0.486	0.675
YOLOv10s [74]	0.592	0.859	0.671	0.252	0.496	0.688
YOLOv10m [74]	0.622	0.877	0.704	0.286	0.519	0.718
YOLO11n [75]	0.584	0.842	0.662	0.228	0.489	0.686
YOLO11s [75]	0.607	0.863	0.685	0.266	0.515	0.704
YOLO11m [75]	0.609	0.866	0.688	0.272	0.511	0.705
YOLO11l [75]	0.622	0.875	0.706	0.287	0.521	0.717
YOLO11x [75]	0.629	0.882	0.715	0.302	0.534	0.720
YOLO12n [76]	0.586	0.865	0.660	0.255	0.497	0.680
YOLO12s [76]	0.626	0.887	0.713	0.290	0.535	0.719
YOLO12m [76]	0.625	0.886	0.713	0.285	0.532	0.721
YOLO12l [76]	0.629	0.876	0.715	0.298	0.534	0.723
YOLO12x [76]	0.625	0.874	0.706	0.303	0.525	0.721
YOLO-NAS-1 [77]	0.602	0.840	0.683	0.283	0.511	0.695
Faster R-CNN [30]	0.452	0.729	0.498	0.156	0.337	0.552
Cascade R-CNN [19]	0.566	0.817	0.644	0.219	0.457	0.669
Sparse R-CNN R50 FPN [78]	0.486	0.736	0.554	0.116	0.336	0.620
DETR [20]	0.540	0.827	0.607	0.143	0.388	0.677
Deformable-DETR [80]	0.297	0.709	0.074	0.048	0.221	0.372
RT-DETR-I [79]	0.501	0.759	0.556	0.136	0.366	0.644
RetinaNet [81]	0.578	0.842	0.654	0.236	0.475	0.676
MobileNetV2-SSD [82]	0.414	0.656	0.453	0.006	0.188	0.601
FCOS [94]	0.583	0.852	0.651	0.271	0.484	0.678

from 28 models across four representative images, selected to highlight common failure scenarios.

In camouflage conditions, where fish resemble the background, most models produce inaccurate or oversized bounding boxes due to low contrast. Occlusion by coral or overlapping structures leads to missed or fragmented detections, especially when background textures are similar to fish bodies. Small object detection remains particularly challenging, with limited pixel footprint resulting in frequent false negatives. In dense scenes with multiple fish and reduced visibility, models often merge instances or fail to localize targets precisely, revealing limitations in crowded environments.

To evaluate generalization, we tested all models on a separate dataset of 1500 unseen images from a different source [95]. As shown in Table VII, top models from the YOLO family, including YOLO12l and YOLO11x, maintained high accuracy (mAP approximately 0.63) across object scales. Lightweight variants such as YOLOv8n and YOLOv10n also performed reliably. In contrast, transformer-based detectors such as Deformable DETR showed a noticeable drop in accuracy, particularly for small objects, while region proposal models like Faster R-CNN showed moderate transferability. Single-stage detectors such as RetinaNet and FCOS proved more stable under domain shift.

Together, these visual and cross-dataset evaluations confirm the adaptability of the models trained on FishDet-M and highlight persistent limitations including camouflage, occlusion, small object detection, and dense scene separation. These remain open challenges for reliable fish detection in natural underwater environments.

C. CLIP-Based Model Selection Analysis

We analyzed the behavior of the CLIP-guided model selector to understand its preferences across the FishDet-M dataset. As shown in Fig. 10, YOLOv8x was the most frequently selected model, followed by YOLOv8l, YOLOv12m, and YOLOv11n. These models likely dominated due to stronger feature representation and better alignment with CLIP's semantic cues. In



Fig. 9: Object detection results from 28 models across four challenging underwater images. Each row shows the original image followed by predictions from the models in the following order: GT (Ground Truth), Y8, Y10, Y11, Y12 (YOLOv8-v12 variants), YNAS (YOLO-NAS-L), DETR, DefD (Deformable DETR), RTD (RT-DETR), R-CNN (Faster, Cascade, and Sparse R-CNN), RNet (RetinaNet), FCOS, and MobSSD (MobileNetV2-SSD). The images represent varying detection difficulty: Image 1 shows a camouflaged fish with background-matching color and texture; Image 2 contains a partially occluded fish among visually similar corals; Image 3 includes two small fish with limited pixel footprint; and Image 4 depicts a dense school of fish with significant inter-object occlusion and low contrast against the background

contrast, older or lighter models (e.g., YOLOv10m, YOLOv8m) were selected less often.

To further examine this trend, we visualized the distribution of CLIP similarity scores for each model in Fig. 11. YOLOv8x, YOLOv8l, and YOLOv12m consistently achieved higher median scores with compact interquartile ranges, indicating reliable semantic alignment. Models with broader or lower scoring distributions were less favored, reflecting CLIP’s tendency to prioritize stable semantic proximity.

These findings confirm that the CLIP selector does not act randomly but favors models with consistent visual-language correspondence. This supports the feasibility of language-driven model routing for adapting detection pipelines to diverse underwater conditions, as demonstrated in recent work on bias-aware underwater AI using CLIP similarity [96]. The specific prompt used for CLIP-guided selection is provided in the supplementary material for full reproducibility.

D. Discussion and Insights

The evaluation on FishDet-M highlights consistent performance advantages of the YOLO family, particularly YOLO12x, which offered strong accuracy across object scales and efficient inference suitable for real-time marine applications [76],

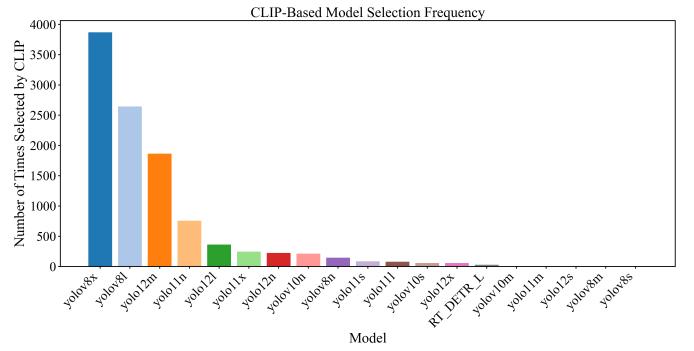


Fig. 10: Frequency of model selections based on CLIP similarity across the full FishDet-M dataset.

[75], [51]. Lightweight YOLO variants also performed well, balancing speed and accuracy effectively.

Transformer based detectors such as DETR, Deformable DETR, and RT DETR-I showed limited performance, especially on small objects, and incurred higher latency [20], [80], [79]. Region based models like Cascade R-CNN and single stage detectors such as RetinaNet and FCOS [19], [81], [94] achieved moderate accuracy with better efficiency but did not match

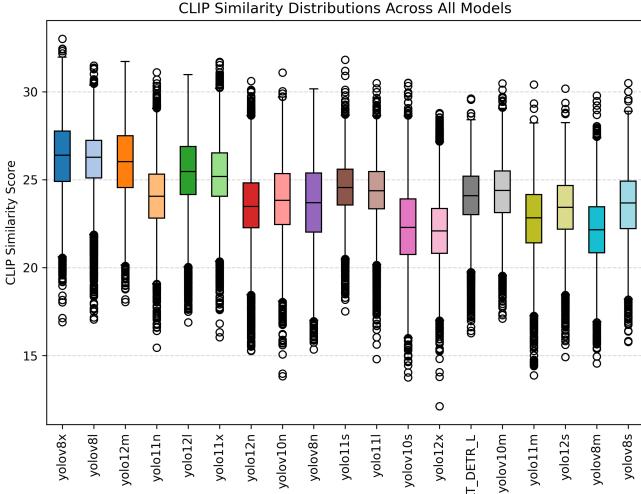


Fig. 11: Distribution of CLIP similarity scores across all candidate models. Each box summarizes the semantic alignment over the entire dataset.

YOLO’s top results .

F1 score and precision recall analyses revealed that models behaved similarly at lower IoU thresholds but diverged under stricter matching (IoU 0.75), where lightweight and transformer models were more sensitive to localization demands. This underscores the need to evaluate models across varying thresholds to assess reliability.

Evaluation across individual datasets showed wide performance variation from 0.359 mAP on FishDataset [16] to 0.846 on DeepFish [28]. This reflects the diversity of underwater conditions. The merged FishDet-M benchmark provided a balanced training distribution, enabling generalizable models that avoid overfitting to specific domains.

Generalization tests on an unseen dataset confirmed this robustness. Many YOLO variants performed comparably or better on new data, reinforcing the value of diverse, consolidated training sets for deployment in real-world underwater applications [95].

We also evaluated an adaptive model selection system, FishDet-M-CLIP, which used CLIP similarity to select contextually appropriate models. Although its accuracy (mAP 0.444) and speed (80 FPS) did not surpass the top YOLO models, it outperformed many traditional and transformer based models, validating the feasibility of language guided model routing for variable conditions.

Qualitative results revealed some failure cases including inaccurate localization in camouflage scenes, missed detections under occlusion, and poor handling of small or blurred objects. False positives around coral and complex structures also persisted, emphasizing ongoing challenges in fine grained discrimination and context-aware detection under underwater conditions.

E. Dataset and Ethics

FishDet-M is a large-scale benchmark for fish detection across diverse underwater settings [18]. It merges 13 publicly

available and licensed datasets covering marine, brackish, and aquarium environments into a fish detection dataset. This integration addresses prior inconsistencies in dataset structure and evaluation [9].

The dataset includes 105,556 images and 296,885 fish annotations, with stratified splits for training, validation, and testing that maintain variation in habitat, clarity, and density. Image sizes range from 78×53 to 4608×3456 pixels, averaging 711×465 , with fish counts from 1 to 256 per image. Annotations are labeled under a species-agnostic *Fish* category to prioritize general detection while allowing downstream classification. A thorough quality assurance process ensured format consistency, label standardization, and removal of corrupted or ambiguous data.

All data originate from ethically sourced repositories [28], [92], [73], [93], [88]. The release aims to advance reproducible research in marine science, aquaculture, and conservation [10], [97].

VI. LIMITATIONS AND FUTURE DIRECTIONS

Despite its comprehensiveness, FishDet-M retains several limitations. Real-world underwater environments remain highly variable, with extreme turbidity, dynamic lighting, and cluttered backgrounds posing significant challenges for current detection models [1], [32]. Future datasets may incorporate synthetic augmentation or multisensor data to improve robustness under such conditions.

At present, FishDet-M focuses exclusively on object detection and localization. However, downstream applications such as behavioral analysis and species-specific tracking require richer annotations, including pose, individual identity, and activity labels [98]. Expanding the annotation scope would enable deeper biological insights.

While YOLO-based models outperform others in handling small or occluded fish, limitations remain in complex scenes [4]. Multi-scale feature fusion and context-aware detection architectures could help mitigate these issues and enhance robustness under occlusion and scale variation.

Generalization analysis further underscores the need to diversify training data. Although models trained on FishDet-M perform well on external benchmarks, broader inclusion of geographic regions, water types, and depths would enhance global applicability.

In terms of adaptive inference, our CLIP-guided model selector shows promise by dynamically routing inputs to suitable detectors. However, this strategy introduces computational overhead and marginally reduces accuracy compared to the top fixed models. Exploring optimized prompts, confidence-weighted voting, or ensemble strategies may offer better speed-accuracy tradeoffs for real-time systems.

Explainability remains an open frontier. Integrating XAI techniques could elucidate model decisions and failure modes in complex underwater environments. This is critical for high-stakes applications in marine conservation and aquaculture, where trust and interpretability are essential.

As reported in Table VII, top-performing detectors such asvYOLOv12x achieve mAP values exceeding 0.62 on unseen

data, outperforming their scores on the FishDet-M test set. This suggests a strong generalization capacity resulting from training on an aggregated dataset such as FishDet-M. This trend extends beyond YOLO, as other detectors such as Faster R-CNN (0.452 mAP), RetinaNet (0.578 mAP), and DETR (0.540 mAP) also exhibit higher scores.

FishDet-M provides a strong foundation for advancing fish detection research. Continued progress will depend on extending annotation depth, improving cross-domain generalization, and refining adaptive and interpretable inference strategies for dynamic underwater settings.

VII. CONCLUSION

FishDet-M is a unified benchmark dataset developed to address persistent challenges in underwater fish detection. By merging 13 heterogeneous sources into a standardized repository, it resolves issues related to fragmentation and inconsistent evaluation protocols. We benchmarked 28 object detection models, including YOLOv8 through YOLOv12, Transformer based architectures, and R-CNN variants. The results indicate the consistent superiority of YOLO models, particularly YOLO12x and YOLO11m, in balancing detection accuracy, robustness across object scales, and inference efficiency. Transformer models exhibited reduced performance when detecting small or occluded fish and imposed greater computational demands. Evaluation across diverse aquatic conditions revealed substantial variation in detection difficulty. Generalization tests demonstrated that models trained on FishDet-M maintain reliable performance on previously unseen data, underscoring the dataset's utility in supporting adaptable and field deployable detection systems. By releasing FishDet-M alongside its annotation scripts and trained models, we aim to foster reproducible research and accelerate innovation in marine science, ecological monitoring, and intelligent aquatic systems.

CODE AVAILABILITY

All FishDet-M resources, including the dataset, benchmarking scripts, pretrained models, and documentation, are publicly available through the official project page: <https://lyessaadsaoud.github.io/FishDet-M/>.

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DECLARATION

During the preparation of this work, we used Grammarly and AI tools to improve the English grammar and flow of the paper.

REFERENCES

- [1] L. Liu, J. Wu, H. Zhao, H. Kong, T. Zheng, B. Qu, and H. Yu, "Fishfinder: A robust small target detection method for aquaculture fish in low-quality underwater images," *Journal of Fish Biology*, vol. 106, no. 3, pp. 908–920, 2025.
- [2] A. Salman, S. Maqbool, A. H. Khan, A. Jalal, and F. Shafait, "Real-time fish detection in complex backgrounds using probabilistic background modelling," *Ecological Informatics*, vol. 51, pp. 44–51, 2019.
- [3] S. Fayaz, S. A. Parah, and G. J. Qureshi, "Underwater object detection: architectures and algorithms – a comprehensive review," *Multimedia Tools and Applications*, vol. 81, no. 15, pp. 20 871–20 916, June 2022.
- [4] E. Li, Q. Wang, J. Zhang, W. Zhang, H. Mo, and Y. Wu, "Fish detection under occlusion using modified you only look once v8 integrating real-time detection transformer features," *Applied Sciences*, vol. 13, no. 23, 2023.
- [5] P. Anantha Prabha, S. Sachin, U. Srinithish, M. Deva Priya, and S. Karthick, "Automated underwater fish species recognition using deep learning-based techniques," in *Proceedings of International Conference on Recent Trends in Computing*, R. P. Mahapatra, S. K. Peddoju, S. Roy, and P. Parwekar, Eds. Singapore: Springer Nature Singapore, 2024, pp. 807–815.
- [6] V. Pagire and A. Phadke, "Underwater fish detection and classification using deep learning," in *2022 International Conference on Intelligent Controller and Computing for Smart Power (ICICCSP)*, 2022, pp. 1–4.
- [7] D. Marable, K. Barker, S. Tippaya, M. Wyatt, S. Bainbridge, M. Stowar, and J. Larke, "Accelerating species recognition and labelling of fish from underwater video with machine-assisted deep learning," *Frontiers in Marine Science*, vol. Volume 9 - 2022, 2022.
- [8] A. Sasithradevi, R. Suganya, P. Prakash, S. Mohamed Mansoor Roomi, M. Vijayalakshmi, S. Nathan, P. Kasthuri, J. Persiya, L. Brighty Ebenezer, S. Jain, S. Verma, S. Balasubramanian, M. Sai Subramaniam, T. Sai Sri Ram, M. Pranav Phanindra Sai, C. Raj, A. Yadav, R. Payak, S. Paul Choudhury, and R. Singh, "Depondfi'23 challenge on real-time pond environment: Methods and results," *IEEE Access*, vol. 12, pp. 157 975–157 987, 2024.
- [9] V. Mohankumar and S. Anbalagan, "A benchmark dataset and ensemble yolo method for enhanced underwater fish detection," *ETRI Journal*. [Online]. Available: <https://doi.org/10.4218/etrij.2024-0383>
- [10] Y. Jiang, Y. Wang, Y. Zhang, Q. Guo, M. Zhao, and H. Qin, "A feature-enhanced and adaptive routing framework for fish school detection on auvs for degraded underwater imaging environments," *IEEE Internet of Things Journal*, vol. 11, no. 10, pp. 18 335–18 350, May 2024.
- [11] C. Yang, J. Xiang, X. Li, and Y. Xie, "Fishdet-yolo: Enhanced underwater fish detection with richer gradient flow and long-range dependency capture through mamba-c2f," *Electronics*, vol. 13, no. 18, 2024.
- [12] C. Shah, M. M. Nabi, S. Y. Alaba, I. A. Ebu, J. Prior, M. D. Campbell, R. Caillouet, M. D. Grossi, T. Rowell, F. Wallace, J. E. Ball, and R. Moorhead, "Yolov8-tf: Transformer-enhanced yolov8 for underwater fish species recognition with class imbalance handling," *Sensors*, vol. 25, no. 6, 2025.
- [13] M. A. Duhayyim, H. M. Alshahrani, F. N. Al-Wesabi, M. Alamgeer, A. M. Hilal, and M. A. Hamza, "Intelligent deep learning based automated fish detection model for uwsn," *Computers, Materials & Continua*, vol. 70, no. 3, pp. 5871–5887, 2022.
- [14] P. J. Reddy, M. Malathi, and A. N. Julaiha, "Deep fish: An approach to fish species identification through deep learning techniques," in *Emerging Trends in Expert Applications and Security*, V. S. Rathore, V. Piuri, R. Babo, and V. Tiwari, Eds. Singapore: Springer Nature Singapore, 2024, pp. 261–272.
- [15] M. Jia-Fa, X. Gang, S. Wei-Guo, and X. Liu, "A 3d occlusion tracking model of the underwater fish targets," in *2015 IEEE International Conference on Electro/Information Technology (EIT)*, May 2015, pp. 082–086.
- [16] Q. Liu, X. Gong, J. Li, H. Wang, R. Liu, D. Liu, R. Zhou, T. Xie, R. Fu, and X. Duan, "A multitask model for realtime fish detection and segmentation based on YOLOv5," *PeerJ Computer Science*, vol. 9, p. e1262, 2023.
- [17] M. Dawkins, J. Prior, B. Lewis, R. Failletaz, T. Banez, M. Salvi, A. Rollo, J. Simon, M. Campbell, M. Lucero, A. Chaudhary, B. Richards, and A. Hoogs, "Fishtrack23: An ensemble underwater dataset for multi-object tracking," in *2024 IEEE/CVF Winter Conference on Applications of Computer Vision (WACV)*, Jan 2024, pp. 7152–7161.
- [18] G. Jocher, A. Chaurasia, and J. Qiu, "Ultralytics yolov8," 2023. [Online]. Available: <https://github.com/ultralytics/ultralytics>

- [19] Z. Cai and N. Vasconcelos, "Cascade r-cnn: High quality object detection and instance segmentation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, p. 1–1, 2019.
- [20] N. Carion, F. Massa, G. Synnaeve, N. Usunier, A. Kirillov, and S. Zagoruyko, "End-to-end object detection with transformers," in *Computer Vision – ECCV 2020: 16th European Conference, Glasgow, UK, August 23–28, 2020, Proceedings, Part I*. Berlin, Heidelberg: Springer-Verlag, 2020, p. 213–229.
- [21] K. Chieza, D. Brown, J. Connan, and D. Salie, "Automated fish detection in underwater environments: Performance analysis of yolov8 and yolo-nas," in *Artificial Intelligence Research*, A. Gerber, J. Maritz, and A. W. Pillay, Eds. Cham: Springer Nature Switzerland, 2025, pp. 334–351.
- [22] J. Fabic, I. Turla, J. Capacillo, L. David, and P. C. Naval, "Fish population estimation and species classification from underwater video sequences using blob counting and shape analysis," in *2013 IEEE International Underwater Technology Symposium (UT)*, March 2013, pp. 1–6.
- [23] L. Saad Saoud, Z. Niu, L. Seneviratne, and I. Hussain, "Real-time and resource-efficient multi-scale adaptive robotics vision for underwater object detection and domain generalization," in *Proceedings of the IEEE International Conference on Image Processing (ICIP)*, 2024, pp. 3917–3923.
- [24] M. Iqtaif, M. H. Alqaryouti, A. E. Sadeq, A. Aburomman, M. Baniata, Z. Mustafa, and H. Y. Chan, "Enhanced fish species detection and classification using a novel deep learning approach," *International Journal of Advanced Computer Science and Applications*, vol. 15, no. 10, 2024.
- [25] C. Spampinato, S. Palazzo, B. Boom, and R. B. Fisher, "Overview of the lifeclef 2014 fish task," in *Working Notes for CLEF 2014 Conference, Sheffield, UK, September 15–18, 2014*, ser. CEUR Workshop Proceedings, L. Cappellato, N. Ferro, M. Halvey, and W. Kraaij, Eds., vol. 1180. CEUR-WS.org, 2014, pp. 616–624. [Online]. Available: <https://ceur-ws.org/Vol-1180/CLEF2014wn-Life-SpampinatoEt2014.pdf>
- [26] Y. Wei, Y. Wang, B. Zhu, C. Lin, D. Wu, X. Xue, and R. Wang, "Underwater detection: A brief survey and a new multitask dataset," *International Journal of Network Dynamics and Intelligence*, vol. 3, no. 4, p. 100025, 2024, published: 25 December 2024.
- [27] S. Fan, C. Song, H. Feng, and Z. Yu, "Take good care of your fish: fish re-identification with synchronized multi-view camera system," *Frontiers in Marine Science*, vol. Volume 11 - 2024, 2024.
- [28] A. Saleh, I. H. Laradji, D. A. Konovalov, M. Bradley, D. Vazquez, and M. Sheaves, "A realistic fish-habitat dataset to evaluate algorithms for underwater visual analysis," *Scientific Reports*, vol. 10, no. 1, p. 14671, 9 2020.
- [29] Australian Institute of Marine Science (AIMS), University of Western Australia (UWA), and Curtin University, "Ozfish dataset - machine learning dataset for baited remote underwater video stations," 2019, accessed 22-Jul-2025.
- [30] S. Ren, K. He, R. Girshick, and J. Sun, "Faster r-cnn: towards real-time object detection with region proposal networks." p. 91–99, 2015.
- [31] L. Saad Saoud, M. Elmezain, A. Sultan, M. Heshmat, L. Seneviratne, and I. Hussain, "Seeing through the haze: A comprehensive review of underwater image enhancement techniques," *IEEE Access*, vol. 12, pp. 145 206–145 233, 2024.
- [32] M. Pedersen, D. Lehotský, I. Nikolov, and T. B. Moeslund, "Brackishmot: The brackish multi-object tracking dataset," in *Image Analysis*, R. Gade, M. Felsberg, and J.-K. Kämäriäinen, Eds. Cham: Springer Nature Switzerland, 2023, pp. 17–33.
- [33] J. Hong, M. Fulton, and J. Sattar, "Trashcan: A semantically-segmented dataset towards visual detection of marine debris," *arXiv preprint arXiv:2007.08097*, 2020. [Online]. Available: <https://arxiv.org/abs/2007.08097>
- [34] S. Lian, H. Li, R. Cong, S. Li, W. Zhang, and S. Kwong, "Watermask: Instance segmentation for underwater imagery," in *2023 IEEE/CVF International Conference on Computer Vision (ICCV)*, Oct 2023, pp. 1305–1315.
- [35] P. Zhang, L. Wang, G. Wang, and D. Li, "Eornet: An improved rotating box detection model for counting juvenile fish under occlusion and overlap," *Engineering Applications of Artificial Intelligence*, vol. 124, p. 106528, 2023.
- [36] J. Mao, G. Xiao, W. Sheng, Z. Qu, and Y. Liu, "Research on realizing the 3d occlusion tracking location method of fish's school target," *Neurocomputing*, vol. 214, pp. 61–79, 2016.
- [37] M. Sudhakara, M. J. Meena, K. R. Madhavi, P. Anjaiah, and L. P. K., "Fish classification using deep learning on small scale and low-quality images," *International Journal of Intelligent Systems and Applications in Engineering*, vol. 10, no. 1s, pp. 279–288, October 2022, research Article. [Online]. Available: <https://www.ijisae.org/index.php/IJISAE/article/view/2292>
- [38] C. Qiu, S. Zhang, C. Wang, Z. Yu, H. Zheng, and B. Zheng, "Improving transfer learning and squeeze- and-excitation networks for small-scale fine-grained fish image classification," *IEEE Access*, vol. 6, pp. 78 503–78 512, 2018.
- [39] R. van Essen, A. Mencarelli, A. van Helmond, L. Nguyen, J. Batsleer, J.-J. Poos, and G. Kootstra, "Automatic discard registration in cluttered environments using deep learning and object tracking: class imbalance, occlusion, and a comparison to human review," *ICES Journal of Marine Science*, vol. 78, no. 10, pp. 3834–3846, 11 2021.
- [40] R. J. M. Veiga and J. M. F. Rodrigues, "Fine-grained fish classification from small to large datasets with vision transformers," *IEEE Access*, vol. 12, pp. 113 642–113 660, 2024.
- [41] X. Geng, J. Gao, Y. Zhang, and R. Wang, "A dual-branch feature fusion neural network for fish image fine-grained recognition," *The Visual Computer*, vol. 40, no. 10, pp. 6883–6896, October 2024.
- [42] P. C. Brady, A. A. Gilerson, G. W. Kattawar, J. M. Sullivan, M. S. Twadowski, H. M. Dierssen, M. Gao, K. Travis, R. I. Etheredge, A. Tonizzo, A. Ibrahim, C. Carrizo, Y. Gu, B. J. Russell, K. Mislinski, S. Zhao, and M. E. Cummings, "Open-ocean fish reveal an omnidirectional solution to camouflage in polarized environments," *Science*, vol. 350, no. 6263, pp. 965–969, 2015.
- [43] C. Shah, M. M. Nabi, S. Y. Alaba, R. Caillouet, J. Prior, M. Campbell, M. D. Grossi, F. Wallace, J. E. Ball, and R. Moorhead, "Active detection for fish species recognition in underwater environments," in *Ocean Sensing and Monitoring XVI*, W. Hou and L. J. Mullen, Eds., vol. 13061, International Society for Optics and Photonics. SPIE, 2024, p. 130610D.
- [44] S. Berlia, V. K. Singh, M. Kumar, R. Mahato, and M. Mishra, "Enhanced fish species identification using transfer learning on balanced datasets," in *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, June 2024, pp. 1–5.
- [45] J. Zhai, L. Han, Y. Xiao, M. Yan, Y. Wang, and X. Wang, "Few-shot fine-grained fish species classification via sandwich attention covnet," *Frontiers in Marine Science*, vol. Volume 10 - 2023, 2023.
- [46] S. T. K R, K. S. Ananda Kumar, S. P. R, and V. L, "Comparative analysis of neural architectures for underwater object detection," in *2024 Second International Conference on Advances in Information Technology (ICAIT)*, vol. 1, July 2024, pp. 1–7.
- [47] M. Abdalhafez, I. M. H. AbdelDaim, M. E. H. Eltaib, and M. Abdalrahim, "Enhanced detection and classification of underwater objects using rov and computer vision," *JES. Journal of Engineering Sciences*, vol. 52, no. 2, pp. 73–86, 2024.
- [48] M. Shen, M. Yang, J. Zhong, H. Liu, and C. Pan, "Underwater image quality evaluation: A comprehensive review," *IET Image Processing*, vol. 19, no. 1, p. e70068, 2025.
- [49] H. Ma, Y. Zhang, S. Sun, W. Zhang, M. Fei, and H. Zhou, "Weighted multi-error information entropy based you only look once network for underwater object detection," *Engineering Applications of Artificial Intelligence*, vol. 130, p. 107766, 2024.
- [50] S. Bhalla, A. Kumar, and R. Kushwaha, "A novel underwater marine dataset with diverse scenarios for robust object detection," in *Proceedings of the 2024 Sixteenth International Conference on Contemporary Computing*, ser. IC3-2024. New York, NY, USA: Association for Computing Machinery, 2024, p. 1–11.
- [51] W. Liu, Q. Ma, P. Liu, and H. Zhao, "A performance evaluation method for distant early warning sonar mobile area search," in *2023 3rd International Conference on Electronic Information Engineering and Computer Science (EIECS)*, Sep. 2023, pp. 360–364.
- [52] P. Guo, H. Liu, D. Zeng, T. Xiang, L. Li, and K. Gu, "An underwater image quality assessment metric," *IEEE Transactions on Multimedia*, vol. 25, pp. 5093–5106, 2023.
- [53] Q. Jiang, X. Yi, L. Ouyang, J. Zhou, and Z. Wang, "Toward dimension-enriched underwater image quality assessment," *IEEE Transactions on Circuits and Systems for Video Technology*, vol. 35, no. 2, pp. 1385–1398, Feb 2025.
- [54] M. Elmezain, L. Saad Saoud, A. Sultan, M. Heshmat, L. Seneviratne, and I. Hussain, "Advancing underwater vision: A survey of deep learning models for underwater object recognition and tracking," *IEEE Access*, vol. 12, 2025, early Access.
- [55] W. Akram, A. Casavola, N. Kapetanović, and N. Miškovic, "A visual servoing scheme for autonomous aquaculture net pens inspection using rov," *Sensors*, vol. 22, no. 9, p. 3525, 2022.
- [56] W. Akram, T. Hassan, H. Toubar, M. Ahmed, N. Miškovic, L. Seneviratne, and I. Hussain, "Aquaculture defects recognition via multi-scale semantic segmentation," *Expert systems with applications*, vol. 237, p. 121197, 2024.
- [57] M. Vijayalakshmi and A. Sasithradevi, "Aquayolo: Advanced yolo-based

- fish detection for optimized aquaculture pond monitoring,” *Scientific Reports*, vol. 15, no. 1, p. 6151, February 2025.
- [58] Q. Zhang and S. Chen, “Research on improved lightweight fish detection algorithm based on yolov8n,” *Journal of Marine Science and Engineering*, vol. 12, no. 10, 2024.
- [59] B. Teixeira, A. P. Lima, C. Pinho, D. Viegas, N. Dias, H. Silva, and J. Almeida, “Feedfirst: Intelligent monitoring system for indoor aquaculture tanks,” in *OCEANS 2022, Hampton Roads*, Oct 2022, pp. 1–7.
- [60] Y.-S. Ryuh, G.-H. Yang, J. Liu, and H. Hu, “A school of robotic fish for mariculture monitoring in the sea coast,” *Journal of Bionic Engineering*, vol. 12, no. 1, pp. 37–46, 2015.
- [61] H. Wang, Z. Gao, B. Li, and N. Gao, “Research on robotic fish swarm network technology based on underwater acoustic communication,” in *2023 IEEE International Conference on Image Processing and Computer Applications (ICIPCA)*, Aug 2023, pp. 475–479.
- [62] M. Ahmed, A. B. Bakht, T. Hassan, W. Akram, A. Humais, L. Seneviratne, S. He, D. Lin, and I. Hussain, “Vision-based autonomous navigation for unmanned surface vessel in extreme marine conditions,” in *2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 2023, pp. 7097–7103.
- [63] M. U. Din, A. Humais, W. Akram, M. Alblooshi, L. Saad Saoud, A. Alblooshi, L. Seneviratne, and I. Hussain, “Marine X: Design and implementation of unmanned surface vessel for vision guided navigation,” in *2023 21st International Conference on Advanced Robotics (ICAR)*. IEEE, 2023, pp. 226–231.
- [64] W. Akram, A. B. Bakht, M. U. Din, L. Seneviratne, and I. Hussain, “Enhancing aquaculture net pen inspection: A benchmark study on detection and semantic segmentation,” *IEEE Access*, 2024.
- [65] W. Zhang, L. Zhang, Y. Zhong, P. Lin, and F. Zhang, “Recognition and calculation of fish rafts in mariculture on the basis of artificial intelligence,” in *Proceedings of the 2023 International Conference on Wireless Communications, Networking and Applications*, P. Siarry, M. A. Jabbar, S. K. S. Cheung, and X. Li, Eds. Singapore: Springer Nature Singapore, 2025, pp. 203–210.
- [66] L. Falconer, S. Halstensen, S. F. Rinø, C. Noble, T. Dale, R. Alvestad, and E. Ytteborg, “Marine aquaculture sites have huge potential as data providers for climate change assessments,” *Aquaculture*, vol. 595, p. 741519, 2025.
- [67] L. Saad Saoud, A. Sultan, M. Elmezain, M. Heshmat, L. Seneviratne, and I. Hussain, “Beyond observation: Deep learning for animal behavior and ecological conservation,” *Ecological Informatics*, vol. 85, p. 102893, 2024.
- [68] J. Kong, S. Tang, J. Feng, L. Mo, and X. Jin, “Aasnet: A novel image instance segmentation framework for fine-grained fish recognition via linear correlation attention and dynamic adaptive focal loss,” *Applied Sciences*, vol. 15, no. 7, 2025.
- [69] W. Wang, B. He, and L. Zhang, “High-accuracy real-time fish detection based on self-build dataset and rird-yolov3,” *Complexity*, vol. 2021, no. 1, p. 4761670, 2021.
- [70] M. U. Din, A. B. Bakht, W. Akram, Y. Dong, L. Seneviratne, and I. Hussain, “Benchmarking vision-based object tracking for usvs in complex maritime environments,” *IEEE Access*, 2025.
- [71] L. Hong, X. Wang, G. Zhang, and M. Zhao, “Usod10k: A new benchmark dataset for underwater salient object detection,” *IEEE Transactions on Image Processing*, vol. 34, pp. 1602–1615, 2025.
- [72] COCO Consortium, “Coco - common objects in context,” 2014, accessed: 2025-07-15. [Online]. Available: <https://cocodataset.org>
- [73] F. F. Khan, X. Li, A. J. Temple, and M. Elhoseiny, “Fishnet: A large-scale dataset and benchmark for fish recognition, detection, and functional trait prediction,” in *2023 IEEE/CVF International Conference on Computer Vision (ICCV)*, 2023, pp. 20439–20449.
- [74] A. Wang, H. Chen, L. Liu, Y. Wang, Y. Zhong, C. Shan, Z. Guo, C. Xu, and S. Chen, “Yolov10: Real-time end-to-end object detection,” *arXiv preprint arXiv:2405.14458*, 2024, <https://arxiv.org/abs/2405.14458>.
- [75] G. Jocher and J. Qiu, “Ultralytics yolo11,” 2024. [Online]. Available: <https://github.com/ultralytics/ultralytics>
- [76] Y. Tian, Q. Ye, and D. Doermann, “Yolov12: Attention-centric real-time object detectors,” 2025. [Online]. Available: <https://github.com/sunsmarterjie/yolov12>
- [77] S. Aharon, Louis-Dupont, Ofri Masad, K. Yurkova, Lotem Fridman, Lkdci, E. Khvedchenya, R. Rubin, N. Bagrov, B. Tymchenko, T. Keren, A. Zhilko, and Eran-Deci, “Super-gradients,” 2021.
- [78] P. Sun, R. Zhang, Y. Jiang, T. Kong, C. Xu, W. Zhan, M. Tomizuka, Z. Yuan, and P. Luo, “Sparse r-cnn: An end-to-end framework for object detection,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 45, no. 12, pp. 15 650–15 664, Dec 2023.
- [79] Y. Zhao, W. Lv, S. Xu, J. Wei, G. Wang, Q. Dang, Y. Liu, and J. Chen, “Detrs beat yolos on real-time object detection,” pp. 16 965–16 974, June 2024.
- [80] X. Zhu, W. Su, L. Lu, B. Li, X. Wang, and J. Dai, “Deformable detr: Deformable transformers for end-to-end object detection,” 2021. [Online]. Available: <https://arxiv.org/abs/2010.04159>
- [81] T.-Y. Lin, P. Goyal, R. Girshick, K. He, and P. Dollár, “Focal loss for dense object detection,” vol. 42, no. 2, Feb 2020, pp. 318–327.
- [82] W. Liu, D. Anguelov, D. Erhan, C. Szegedy, S. Reed, C.-Y. Fu, and A. C. Berg, “Ssd: Single shot multibox detector,” pp. 21–37, 2016.
- [83] A. Paszke, S. Gross, F. Massa, A. Lerer, J. Bradbury, G. Chanan, T. Killeen, Z. Lin, N. Gimelshein, L. Antiga, A. Desmaison, A. Kopf, E. Yang, Z. DeVito, M. Raison, A. Tejani, S. Chilamkurthy, B. Steiner, L. Fang, J. Bai, and S. Chintala, *PyTorch: an imperative style, high-performance deep learning library*. Red Hook, NY, USA: Curran Associates Inc., 2019.
- [84] G. Jocher, J. Qiu, and A. Chaurasia, “Ultralytics YOLO,” Jan. 2023. [Online]. Available: <https://github.com/ultralytics/ultralytics>
- [85] K. Chen, J. Wang, J. Pang, Y. Cao, Y. Xiong, X. Li, S. Sun, W. Feng, Z. Liu, J. Xu, Z. Zhang, D. Cheng, C. Zhu, T. Cheng, Q. Zhao, B. Li, X. Lu, R. Zhu, Y. Wu, J. Dai, J. Wang, J. Shi, W. Ouyang, C. C. Loy, and D. Lin, “Mmdetection: Open mmlab detection toolbox and benchmark,” 2019. [Online]. Available: <https://arxiv.org/abs/1906.07155>
- [86] T.-Y. Lin and M. C. Consortium, “Pycocotools: Coco api for python,” <https://github.com/cocodataset/cocoapi>, 2015, accessed: 2025-07-15.
- [87] g18L5754, “Fish4knowledge dataset dataset,” <https://universe.roboflow.com/g18l5754/fish4knowledge-dataset>
- [88] A. MURME, “Fish video dataset,” <https://universe.roboflow.com/aarjoo-murme/fish-video-ls42k>, nov 2023, visited on 2025-05-21. [Online]. Available: <https://universe.roboflow.com/aarjoo-murme/fish-video-ls42k>
- [89] seoultech, “Fish-video dataset,” <https://universe.roboflow.com/seoultech/fish-video>, may 2022, visited on 2025-05-21. [Online]. Available: <https://universe.roboflow.com/seoultech/fish-video>
- [90] I. A. Catalán, A. Álvarez Ellacuría, J.-L. Lisani, J. Sánchez, G. Vizoso, A. E. Heinrichs-Maquilón, H. Hinz, J. Alós, M. Signorioli, J. Aguzzi, M. Francescangeli, and M. Palmer, “Automatic detection and classification of coastal mediterranean fish from underwater images: Good practices for robust training,” *Frontiers in Marine Science*, vol. Volume 10 - 2023, 2023.
- [91] aquarium, “detect aquarium dataset,” <https://universe.roboflow.com/aquarium-lru12/detect-aquarium>, sep 2023, visited on 2025-06-30. [Online]. Available: <https://universe.roboflow.com/aquarium-lru12/detect-aquarium>
- [92] M.-Q. Le, T.-N. Le, T. V. Nguyen, I. Echizen, and M.-T. Tran, “Aquatic animal species (aas),” 2023, data set.
- [93] PAFD, “Fish clean dataset,” <https://universe.roboflow.com/pafdf/fish-clean>, feb 2023, visited on 2025-06-30. [Online]. Available: <https://universe.roboflow.com/pafdf/fish-clean>
- [94] Z. Tian, C. Shen, H. Chen, and T. He, “Fcos: Fully convolutional one-stage object detection,” pp. 9626–9635, Oct 2019.
- [95] test, “fish_dataset_florence_1 dataset,” https://universe.roboflow.com/test-fflhx/fish_dataset_florence_1, Aug. 2024, accessed on 2025-07-20.
- [96] L. Saad Saoud and I. Hussain, “Eba-ai: Ethics-guided bias-aware ai for efficient underwater image enhancement and coral reef monitoring,” 2025. [Online]. Available: <https://arxiv.org/abs/2507.15036>
- [97] A. Salman, S. A. Siddiqui, F. Shafait, A. Mian, M. R. Shortis, K. Khurshid, A. Ulges, and U. Schwanecke, “Automatic fish detection in underwater videos by a deep neural network-based hybrid motion learning system,” *ICES Journal of Marine Science*, vol. 77, no. 4, pp. 1295–1307, 02 2019.
- [98] A. Jalal, A. Salman, A. Mian, S. Ghafoor, and F. Shafait, “Deepfins: Capturing dynamics in underwater videos for fish detection,” *Ecological Informatics*, vol. 86, p. 103013, 2025.