



**UNIVERSITÀ  
DEGLI STUDI  
DI TRIESTE**

## **Detection, classification and tracking of fishes: an analysis of the YOLOv8 model**

July 25, 2025

## ① Theory

## ② Detection

## ③ Tracking

## ④ Results

## ⑤ Conclusions

## ① Theory

## ② Detection

### ③ Tracking

4 Results

## 5 Conclusions

# History of fish detection

**A potential method for the differentiation between haddock fish stocks by computer vision using canonical discriminant analysis (1995)**

N. J. C. Strachan and L. Kell

**Hierarchical classification with reject option for live fish recognition (2014)**

Phoenix X. Huang · Bastiaan J. Boom ·  
Robert B. Fisher

**Fast Accurate Fish Detection and Recognition of Underwater Images with Fast R-CNN (2015)**

Xiu Li<sup>1,2</sup>, Min Shang<sup>1,2</sup>, Hongwei Qin<sup>1,2</sup>, Liansheng Chen<sup>1,2</sup>

**Vision based Real-time Fish Detection Using Convolutional Neural Network (2017)**

Minsung Sung and Son-Cheol Yu, Yogesh Girdhar

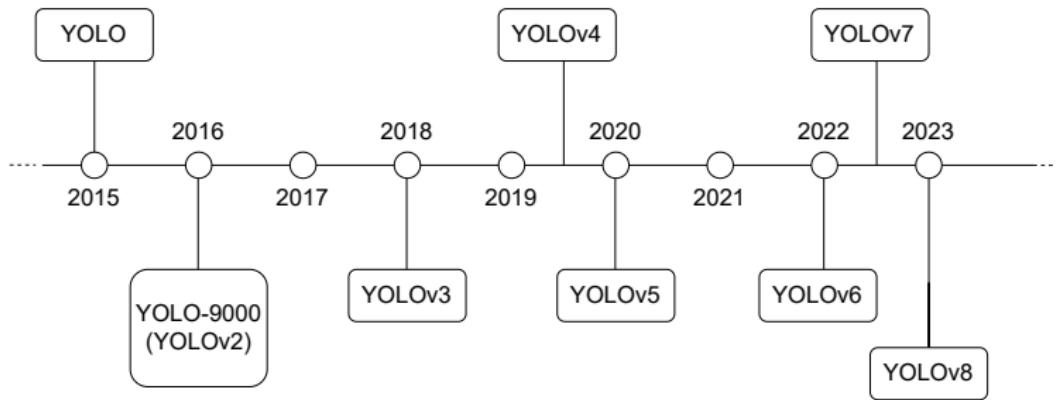
**YOLO-Fish: A robust fish detection model to detect fish in realistic underwater environment (2022)**

Abdullah Al Muksit<sup>a</sup>, Fakhrul Hasan<sup>a</sup>, Md. Fahad Hasan Bhuiyan Emon<sup>a</sup>, Md Rakibul Haque<sup>b</sup>,  
Arif Reza Anwary<sup>c</sup>, Swakkhar Shatabda<sup>a,\*</sup>

Enhancing aquatic ecosystem monitoring through fish jumping behavior analysis and YOLOV5: Applications in freshwater fish identification (2025)

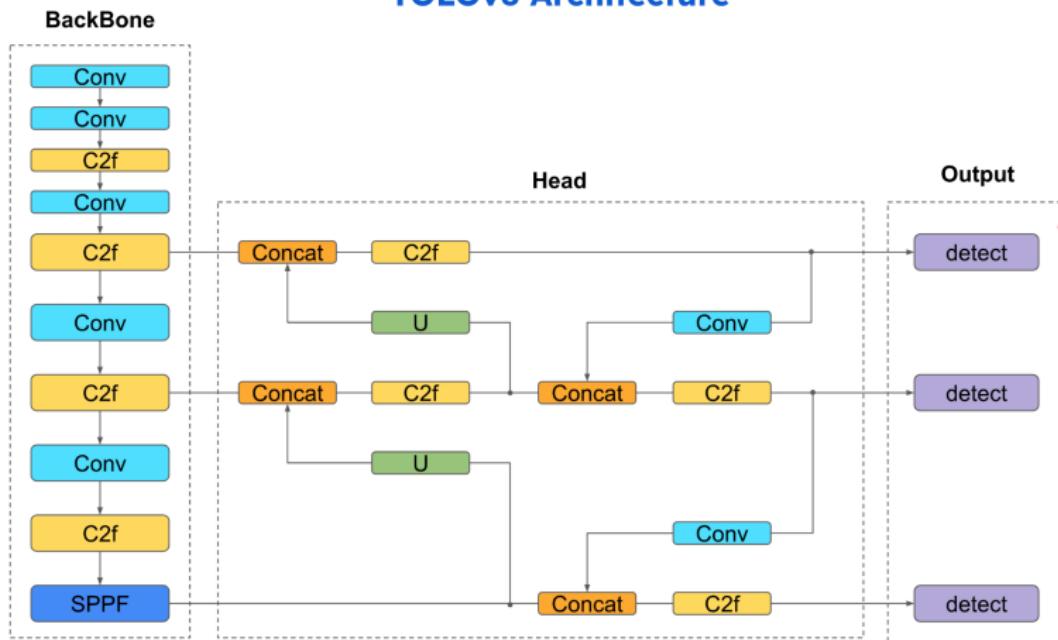
Ronghui Li<sup>a,b</sup>, Kaibang Xiao<sup>a,b,\*</sup>, Senhai Lin<sup>a,b</sup>, Zedong Wu<sup>a,b</sup>

10 years of YOLO



## YOLOv8

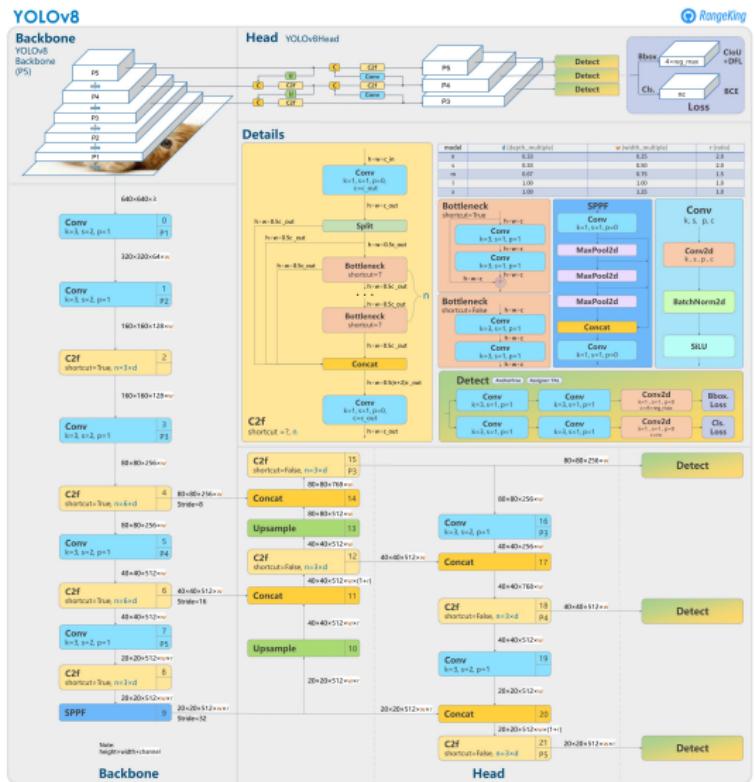
## YOLOv8 Architecture



1

<sup>1</sup>[4]

# Complete Architecture

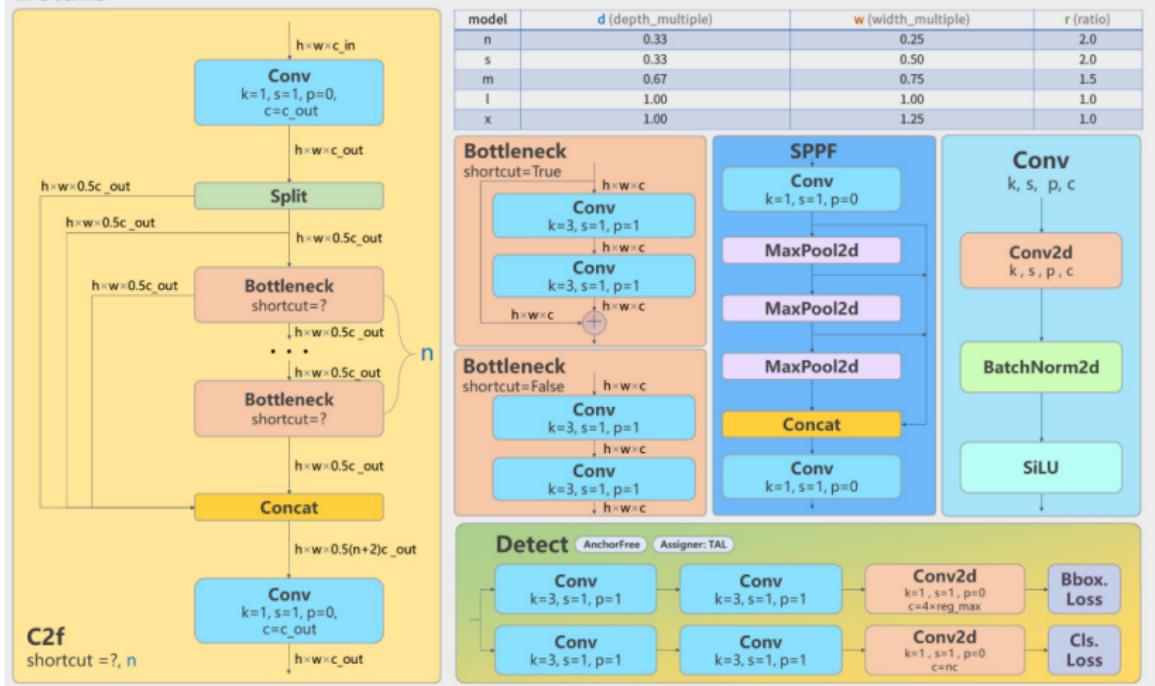


2

 $^2[3]$

# Modules

## Details



## ① Theory

## ② Detection

## ③ Tracking

## ④ Results

## ⑤ Conclusions

# Datasets

**DeepFish →**



	41. <i>Dascyllus reticulatus</i> 12112(4240)		62. <i>Plectroglyphidodon olivaceus</i> 2683(1225)		63. <i>Chromis oxyura</i> 3593(1175)		64. <i>Acanthurus leucosternon</i> 4049(1021)		65. <i>Chromis lunulata</i> 2534(536)		66. <i>Chromis trifasciata</i> 190(79)		67. <i>Mugil asterias</i> 450(71)		68. <i>Anthurus spilosoma</i> 218(71)
	69. <i>Amphiprion percula</i> 241(58)		70. <i>Hemigymnus melapterus</i> 299(53)		71. <i>Acanthurus leucosternon</i> 98(42)		72. <i>Ctenochaetus striatus</i> 147(28)		73. <i>Pomacentrus moluccenis</i> 181(27)		74. <i>Dascyllus reticulatus</i> 90(23)		75. <i>Hemitaurichthys bleekeri</i> 42(16)		76. <i>Hemitaurichthys zoster</i> 206(15)
	77. <i>Apogonichthys ocellatus</i> 49(8)		78. <i>Acanthurus leucosternon</i> 56(5)		79. <i>Pomacentrus semicirculatus</i> 29(6)		80. <i>Zanclorhynchus cornutus</i> 21(6)		81. <i>Acanthurus nigrofasciatus</i> 16(8)		82. <i>Dascyllus reticulatus</i> 41(6)		83. <i>Siganus laqueus</i> 25(6)		

**<– Fish4Knowledge**

# Datasets structure

## DeepFish

```
1   .
2   7117
3     train
4     valid
5   7268
6   7393
7   7398
8   7426
9   7434
10  7463
11  7482
12  7490
13  7585
14  7623
15  9852
16  9862
17  9866
18  9870
19  9892
20  9894
21  9898
22  9907
23  9908
24  classes.txt
25  Nagative_samples
26  test
```

## Fish4Knowledge

```
1   .
2   fish_image
3     fish_01
4       fish_x.png
5       ...
6   gt_bounding_boxes
7     gt_106.xml
8       ...
9   mask_image
10    mask_01
11      mask_x.png
12      ...
13   videos
14     gt_106.mp4
15     ...
```

## YOLO format

```
1   .
2   data.yaml
3   test
4     images
5     labels
6   train
7     images
8     labels
9   val
10    images
11    labels
```

# Configuration files (data.yaml)

```
1 train: path_to_train/images
2 val: path_to_val/images
3 test: path_to_test/images
4
5 nc: 1
6 names: ['Fish']
```

```
1 train: path_to_train/images
2 val: path_to_val/images
3 test: path_to_test/images
4
5 nc: 23
6 names: [
7   'Caranx_sexfasciatus',
8   'F1',
9   'F2',
10  'F3',
11  'F4',
12  'F5',
13  'F6',
14  'F7',
15  'Acanthopagrus_palmaris',
16  'Lutjanus_russellii',
17  'acanthopagrus_and_caranx',
18  'acanthopagrus_palmaris',
19  'Gerres',
20  'Caranx',
21  'Amniataba_caudivittatus',
22  'gerres_2',
23  'gerres',
24  'Epinephelus',
25  'Fish',
26  'juvenile',
27  'palmaris',
28  'EJP',
29  'caudivittatus'
30 ]
```

# YOLOv8 models

Model	size (pixels)	mAP <sup>val</sup> 50-95	Speed CPU ONNX (ms)	Speed A100 TensorRT (ms)	params (M)	FLOPs (B)
YOLOv8n	640	37.3	80.4	0.99	3.2	8.7
YOLOv8s	640	44.9	128.4	1.20	11.2	28.6
YOLOv8m	640	50.2	234.7	1.83	25.9	78.9
YOLOv8l	640	52.9	375.2	2.39	43.7	165.2
YOLOv8x	640	53.9	479.1	3.53	68.2	257.8

# General Parameters

Parameter	Value	Description
Epochs	50-100	Number of training iterations
Batch Size	16	Images processed simultaneously
Image Size	640	Input image resolution (pixels)
Optimizer	AdamW	Adaptive moment estimation with weight decay
Learning Rate	0.001	Initial learning rate with cosine scheduling
Weight Decay	0.0005	L2 regularization strength
patience	10	Epochs to wait before early stopping
Warmup epochs	3	Gradual learning rate increase at start
cos_lr	True	Cosine learning rate scheduler
close_mosaic	10	Disable mosaic augmentation in last N epochs

## Specific Parameters (single-class vs multi-class)

Parameter	Single-class	Multi-class	Description
cls	0.5	1.0	Weight affecting importance of correct class prediction
box	7.5	7.5	Weight influencing emphasis on accurately predicting bounding box coordinates
dfl	1.5	1.5	Weight used for fine-grained classification
mixup	0.0	0.15	Blends two images and their labels, creating composite image
copy_paste	0.1	0.3	Copies and pastes objects across images to increase object instances

## AdamW

$$\phi_{t+1} \leftarrow \phi_t - \alpha \cdot \left( \frac{m_t}{v_t + \epsilon} + \lambda \phi_t \right)$$

Where:

- $m_t \leftarrow \frac{\beta_1 \cdot m_{t-1} + (1 - \beta_1) g_t}{1 - \beta_1^t}$
- $v_t \leftarrow \frac{\beta_2 \cdot v_{t-1} + (1 - \beta_2) g_t^2}{1 - \beta_2^t}$
- $g_t \leftarrow \nabla L_t(\phi_{t-1}) \quad (\text{no } \lambda \phi_{t-1} \text{ here!})$

# Loss Function

$$L_{yolov8} = \theta_{cls} \cdot L_{cls} + \theta_{box} \cdot L_{box} + \theta_{dfl} \cdot L_{dfl}$$

- **Classification loss:** whether the model correctly identifies what type of fish (or object) it is.
- **Box loss:** how well the predicted bounding box overlaps with the ground truth box.
- **DFL:** Distributed Focal Loss, boosts performance by distributing the loss function across different object scales and classes.

# Training

```
(dl-env) x ~/Units/First_Year/Deep_Learning/Deep-Learning/src/object_detector > master * python3 train_yolo.py -  
-data ./Datasets/Deepfish_YOLO/data.yaml --device mps --model s  
↳ CUDA available: False  
↳ MPS available: True  
↳ Detected device: mps  
↳ Loading COCO pretrained YOLOv8s  
Downloading https://github.com/ultralytics/assets/releases/download/v8.3.0/yolov8s.pt to 'models/yolov8s.pt'...  
100% [██████████] 21.5M/21.5M [00:07<00:00, 2.84MB/s]  
X Training Configuration:  
  Mode: multi-class  
  Model: YOLOv8s  
  Classes: 1  
  Epochs: 50  
  Batch size: 16  
  Image size: 640  
  Device: mps  
  Config: ../../Datasets/Deepfish_YOLO/data.yaml  
  
⚡ Starting training...  
New https://pypi.org/project/ultralytics/8.3.169 available ⓘ Update with 'pip install -U ultralytics'  
Ultralytics 8.3.169 🚀 Python-3.13.5 torch-2.7.1 MPS (Apple M3)  
Model summary: 129 layers, 11,135,987 parameters, 11,135,971 gradients, 28.6 GFLOPs  
  
Transferred 349/355 items from pretrained weights  
Freezing layer 'model.22.dfl.conv.weight'  
train: Fast image access ✅ (ping: 0.2±0.1 ms, read: 680.8±166.8 MB/s, size: 155.2 kB)  
train: Scanning /Users/christianfaccio/Units/First_Year/Deep_Learning/Deep-Learning/Datasets/DeepFish_YOLO/training/labels  
val: Fast image access ✅ (ping: 0.1±0.0 ms, read: 786.3±105.5 MB/s, size: 164.2 kB)  
val: Scanning /Users/christianfaccio/Units/First_Year/Deep_Learning/Deep-Learning/Datasets/DeepFish_YOLO/val/labels.cac  
Plotting labels to src/object_detector/runs/train/fish_multi_class_s/labels.jpg...  
optimizer: AdamW(lr=0.001, momentum=0.937) with parameter groups 57 weight(decay=0.0), 64 weight(decay=0.0005)  
, 63 bias(decay=0.0)  
Image sizes 640 train, 640 val  
Using 0 dataloader workers  
Logging results to src/object_detector/runs/train/fish_multi_class_s  
Starting training for 50 epochs...  
  
Epoch GPU_mem box_loss cls_loss dfl_loss Instances Size  
<00:00, 1/50 7.46G nan nan nan 94 640: 100% [██████████] 209/209 [07:41  
33 [01:01 Class Images Instances Box(P R mAP50 mAP50-95): 100% [██████████] 33/  
          all 1042 3657 0 0 0 0  
Epoch GPU_mem box_loss cls_loss dfl_loss Instances Size  
<00:00, 2/50 7.42G nan nan nan 182 640: 100% [██████████] 209/209 [10:14  
33 [00:32 Class Images Instances Box(P R mAP50 mAP50-95): 100% [██████████] 33/  
          all 1042 3657 0 0 0 0
```

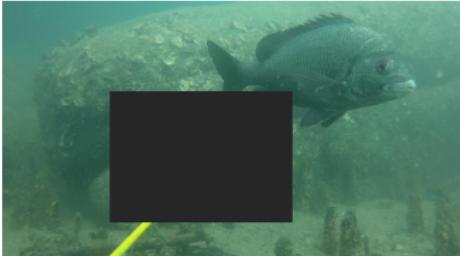
## Mixup feature



## Mosaic feature



## Cutout feature



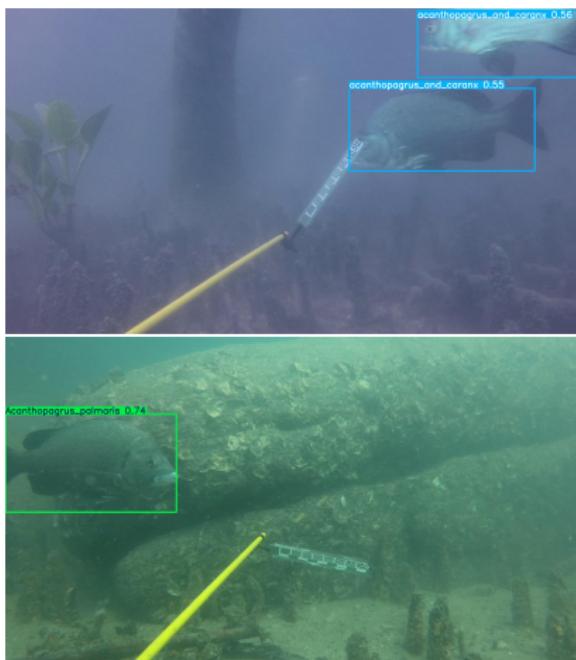
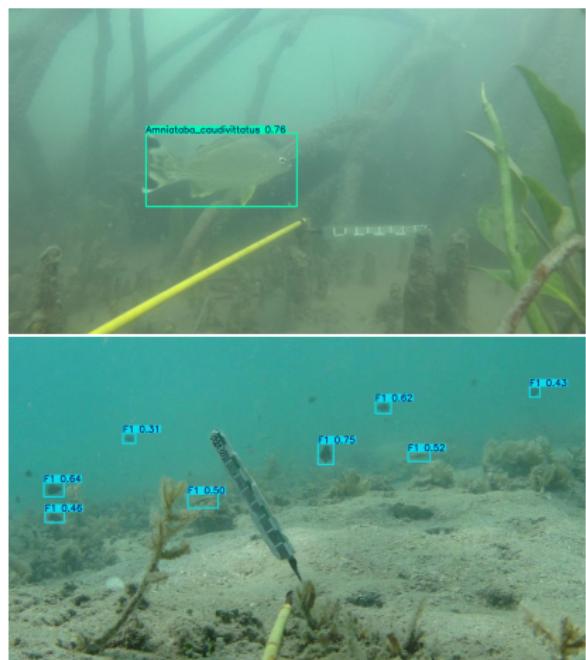
# NMS

The **Non-Maximum Suppression** is a technique that cleans up the output of a detection model by filtering out redundant and overlapping bounding boxes (high IoU) to ensure that each object is identified only once.

- ① Sort by confidence score
- ② Remove high-IoU boxes
- ③ Repeat

(IoU means Intersection over Union and the higher it is for a box, the more it overlaps the others)

## Inference



## ① Theory

## ② Detection

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## ⑤ Conclusions

# The Tracking Challenge: Occlusion & ID Switches



**1. Before Occlusion**

The fish ID 2 is clearly visible and being tracked.



**2. During Occlusion**

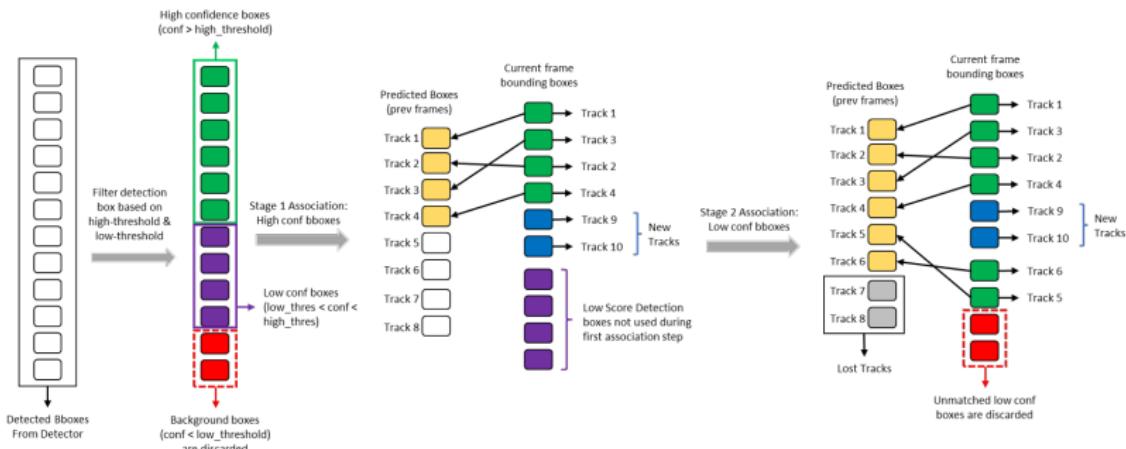
Fish ID 2 is now hidden behind fish ID 3.



**3. After Occlusion (ID Switch)**

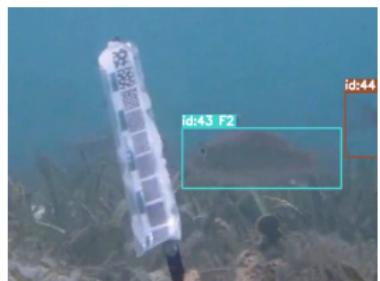
The fish reappears identified as a new object ID 7.

## The ByteTrack Algorithm



3

# Correct Object Re-identification



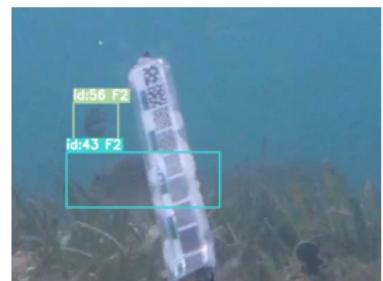
**1. Before Occlusion**

The fish ID 43 is clearly visible and being tracked.



**2. During Occlusion**

Fish ID 43 is now hidden behind an object.



**3. After Occlusion**

The fish reappears. ByteTrack re-identifies it as ID 43.

## ① Theory

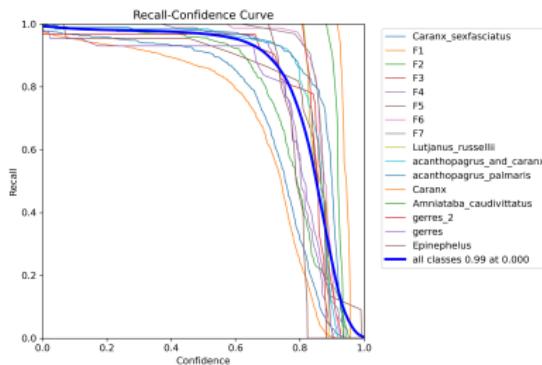
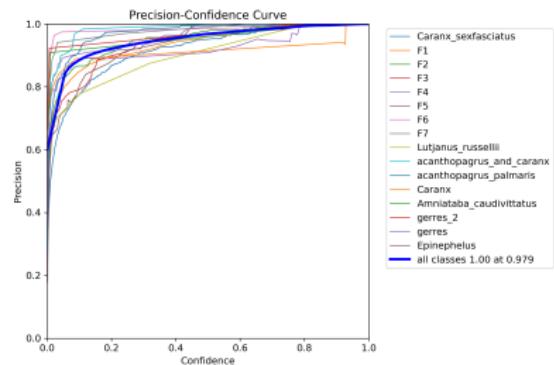
## ② Detection

## ③ Tracking

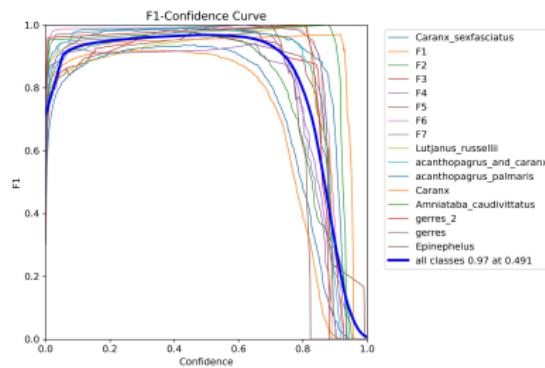
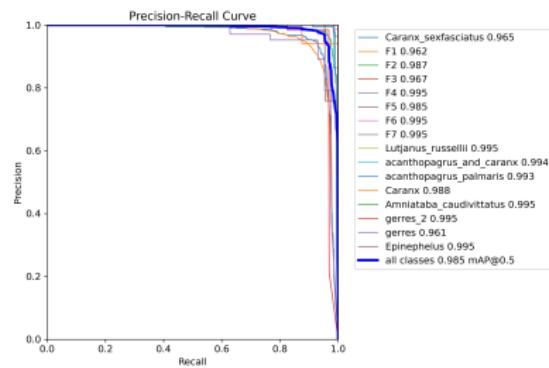
## ④ Results

## ⑤ Conclusions

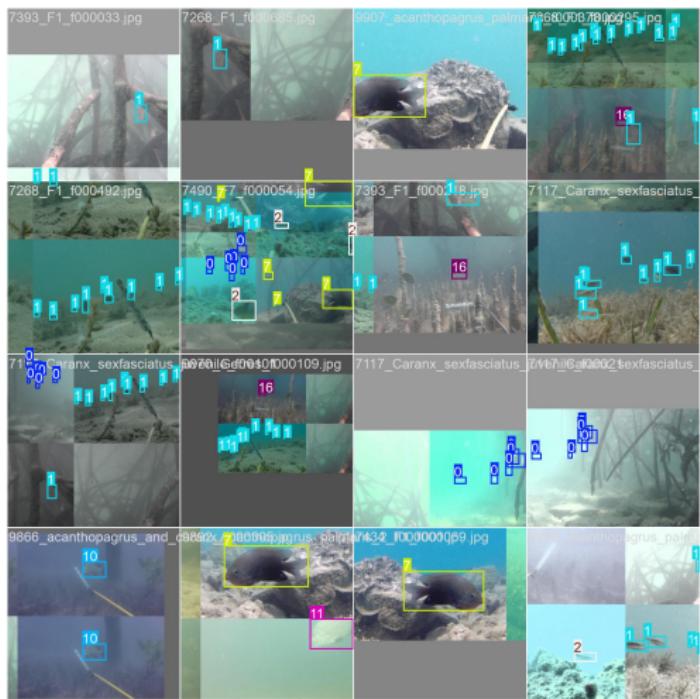
# Fish Detection (DeepFish): Metrics



# Fish Detection (DeepFish): Metrics



# Fish Detection (DeepFish): Training Batch

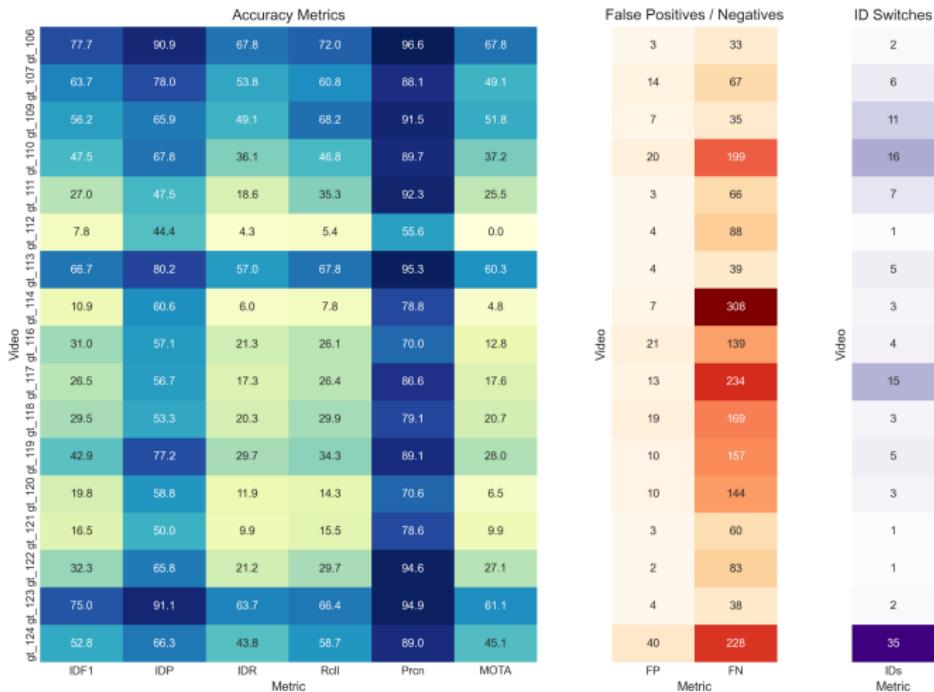


# Fish Detection (DeepFish): Validation Batch



# Fish Tracking (F4K): Metrics

Performance Heatmaps for Standard Mode



## ① Theory

## ② Detection

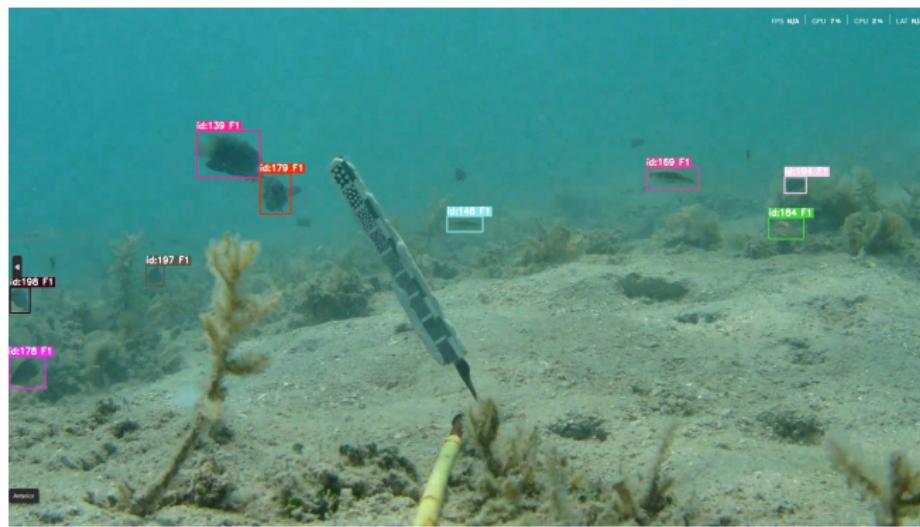
## ③ Tracking

## ④ Results

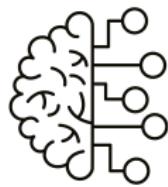
## ⑤ Conclusions

# Conclusions

Successful pipeline for real-time fish detection, tracking, and classification.



## Future Work



**Improve Detector  
Robustness**



**Deploy on Video  
Devices**



**Enable  
Behavioral  
Analysis**

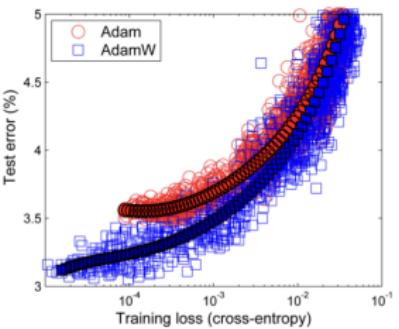
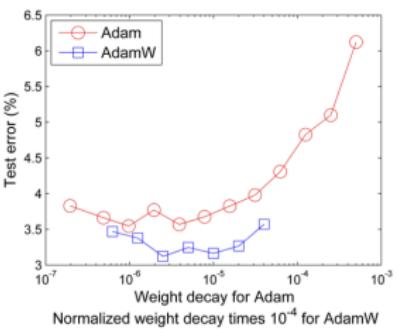
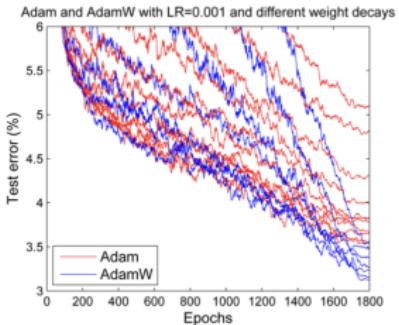
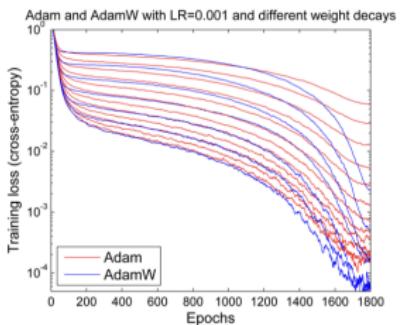
# Thank you!

**Algorithm 2** Adam with L<sub>2</sub> regularization and Adam with decoupled weight decay (AdamW)

---

```
1: given  $\alpha = 0.001$ ,  $\beta_1 = 0.9$ ,  $\beta_2 = 0.999$ ,  $\epsilon = 10^{-8}$ ,  $\lambda \in \mathbb{R}$ 
2: initialize time step  $t \leftarrow 0$ , parameter vector  $\theta_{t=0} \in \mathbb{R}^n$ , first moment vector  $m_{t=0} \leftarrow \theta$ , second moment
   vector  $v_{t=0} \leftarrow \theta$ , schedule multiplier  $\eta_{t=0} \in \mathbb{R}$ 
3: repeat
4:    $t \leftarrow t + 1$ 
5:    $\nabla f_t(\theta_{t-1}) \leftarrow \text{SelectBatch}(\theta_{t-1})$                                  $\triangleright$  select batch and return the corresponding gradient
6:    $\mathbf{g}_t \leftarrow \nabla f_t(\theta_{t-1}) + \lambda \theta_{t-1}$ 
7:    $\mathbf{m}_t \leftarrow \beta_1 \mathbf{m}_{t-1} + (1 - \beta_1) \mathbf{g}_t$                                  $\triangleright$  here and below all operations are element-wise
8:    $\mathbf{v}_t \leftarrow \beta_2 \mathbf{v}_{t-1} + (1 - \beta_2) \mathbf{g}_t^2$ 
9:    $\hat{\mathbf{m}}_t \leftarrow \mathbf{m}_t / (1 - \beta_1^t)$                                           $\triangleright \beta_1$  is taken to the power of  $t$ 
10:   $\hat{\mathbf{v}}_t \leftarrow \mathbf{v}_t / (1 - \beta_2^t)$                                           $\triangleright \beta_2$  is taken to the power of  $t$ 
11:   $\eta_t \leftarrow \text{SetScheduleMultiplier}(t)$                                  $\triangleright$  can be fixed, decay, or also be used for warm restarts
12:   $\theta_t \leftarrow \theta_{t-1} - \eta_t \left( \alpha \hat{\mathbf{m}}_t / (\sqrt{\hat{\mathbf{v}}_t} + \epsilon) + \lambda \theta_{t-1} \right)$ 
13: until stopping criterion is met
14: return optimized parameters  $\theta_t$ 
```

---



5

[1] Datature.

Introduction to bytetrack: Multi-object tracking by associating every detection box, 2024.  
Accessed: [insert access date].

[2] Ilya Loshchilov and Frank Hutter.

Decoupled weight decay regularization, 2019.

[3] RangeKing and Glenn Jocher.

Brief summary of yolov8 model structure.

<https://github.com/ultralytics/ultralytics/issues/189>, 2023.

Accessed July 2025.

[4] Mupparaju Sohan, Thotakura Sai Ram, and Ch Venkata Rami Reddy.

A review on yolov8 and its advancements.

In *International Conference on Data Intelligence and Cognitive Informatics*, pages 529–545.  
Springer, 2024.