



**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 J. 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)

Xia Li^{1,2}, Min Shen^{1,2}, Hengmei Qiu^{1,2}, Liangsheng Chen^{1,2}

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

Minsung Sung and Son-Cheol Yu, Yogesh Girdhar

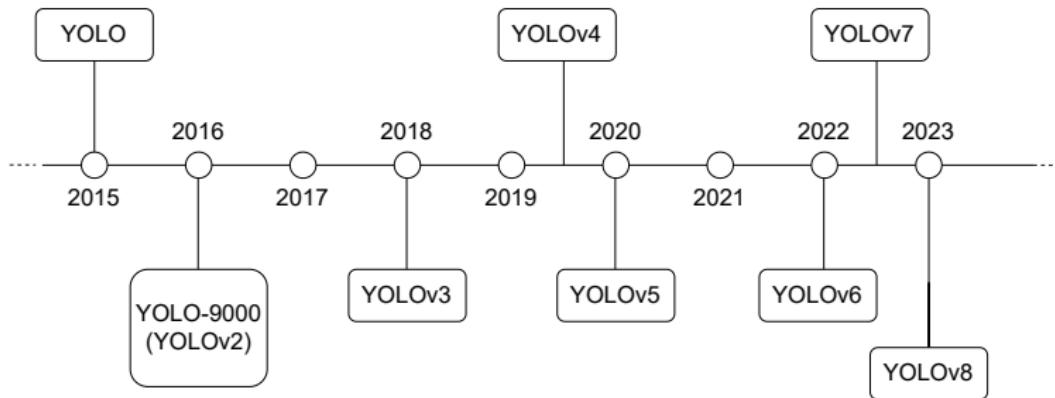
YOLO-Fish: A robust fish detection model to detect fish in realistic underwater environment (2022)

Abdullah Al Muksit^a, Fakhrul Hasan^a, Md. Fahad Hasan Bhuiyan Emon^a, Md Rakibul Haque^b, Arif Reza Anwary^c, Swakkhar Shatabda^{a,*}

Enhancing aquatic ecosystem monitoring through fish jumping behavior analysis and YOLOv5: Applications in freshwater fish identification (2025)

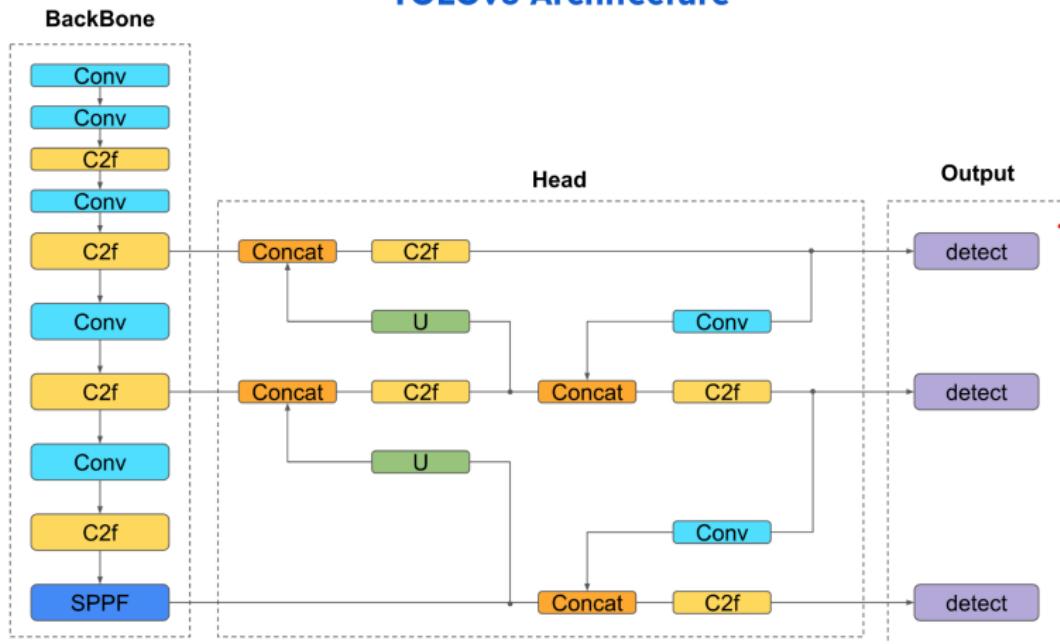
Ronghui Li ^{a,b}, Kaibang Xiao ^{a,b,*}, Senhai Lin ^{a,b}, Zedong Wu ^{a,b}

10 years of YOLO

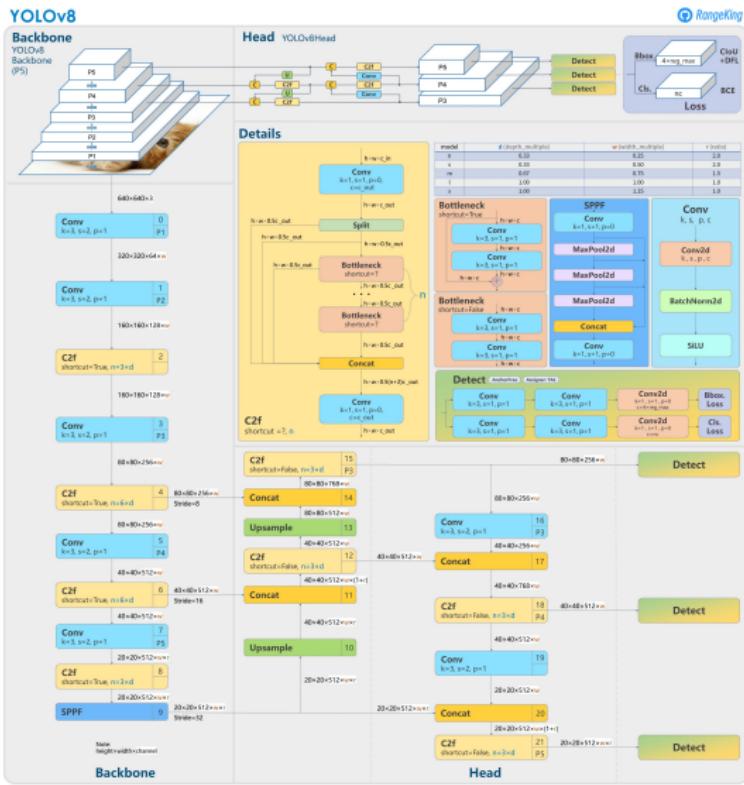


YOLOv8

YOLOv8 Architecture

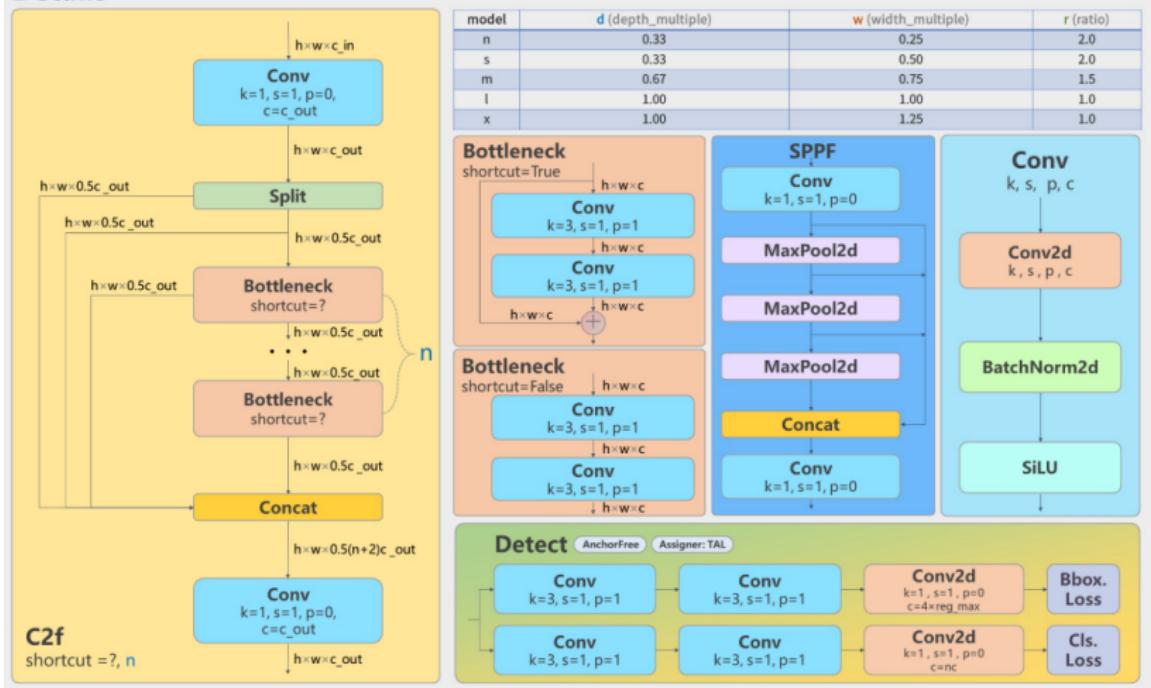


Complete Architecture



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>Anampses clarkii</i> 4049(1021)	65. <i>Chromis lunulata</i> 2534(536)	66. <i>Chromis trifasciata</i> 190(79)	67. <i>Mugil cephalus</i> 450(71)	68. <i>Acanthurus nigrofasciatus</i> 218(71)
69. <i>Siganus jordani</i> 241(58)	70. <i>Hemigymnus meleagris</i> 299(53)	71. <i>Acanthurus leucosternon</i> 98(42)	72. <i>Ctenochaetus striatus</i> 147(28)	73. <i>Paracirrhites arcuatus</i> 181(27)	74. <i>Dascyllus reticulatus</i> 90(23)	75. <i>Hemitaurichthys mitchilli</i> 42(16)	76. <i>Halichoeres zuluensis</i> 206(15)
77. <i>Apogonichthys</i> 49(8)	78. <i>Acanthurus</i> 56(5)	79. <i>Pomacentrus semicirculatus</i> 29(6)	80. <i>Zanclorhynchus cornutus</i> 21(6)	81. <i>Anampses nigrofasciatus</i> 16(8)	82. <i>Diplodus vulgaris</i> 41(6)	83. <i>Siganus laqueus</i> 25(6)	

<- Fish4Knowledge

Configuration files

```
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 ^{val} 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

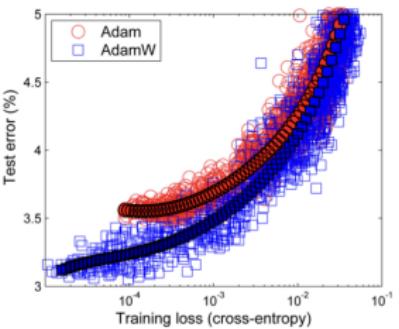
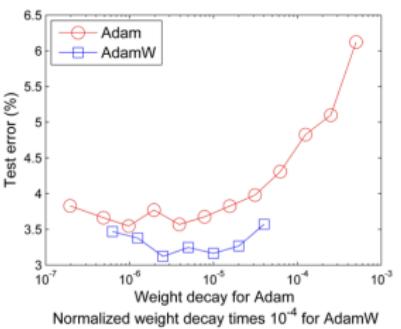
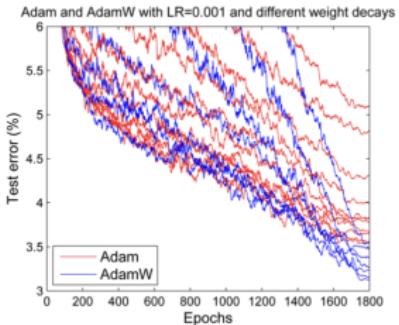
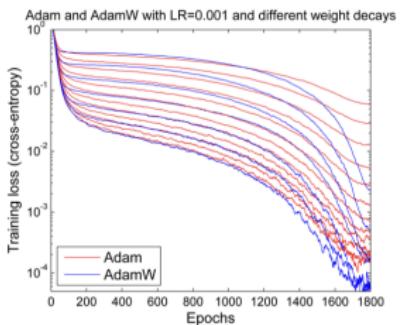
AdamW

Algorithm 2 Adam with L₂ 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:    $g_t \leftarrow \nabla f_t(\theta_{t-1}) + \lambda \theta_{t-1}$ 
7:    $m_t \leftarrow \beta_1 m_{t-1} + (1 - \beta_1) g_t$                                       $\triangleright$  here and below all operations are element-wise
8:    $v_t \leftarrow \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$ 
9:    $\hat{m}_t \leftarrow m_t / (1 - \beta_1^t)$                                           $\triangleright \beta_1$  is taken to the power of  $t$ 
10:   $\hat{v}_t \leftarrow v_t / (1 - \beta_2^t)$                                           $\triangleright \beta_2$  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:   $\theta_t \leftarrow \theta_{t-1} - \eta_t \left( \alpha \hat{m}_t / (\sqrt{\hat{v}_t} + \epsilon) + \lambda \theta_{t-1} \right)$ 
13: until stopping criterion is met
14: return optimized parameters  $\theta_t$ 

```



2

Loss Function

$$\text{loss} = L_{cls} + L_{box} + L_{DFL}$$

- **Classification loss:** crucial for predicting the correct class of objects.
- **Box loss:** ensures that the bounding boxes around objects are accurate.
- **DFL:** Distributed Focal Loss, boosts performance by distributing the loss function across different object scales and classes.

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	0.0	0.3	Copies and pastes objects across images to increase object instances

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/validation/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  
1/50 7.46G nan nan nan 94 640: 100% [██████████] 209/209 [07:41]  
<00:00,  
          Class Images Instances Box(P) R mAP50 mAP50-95: 100% [██████████] 33/  
33 [01:01]  
          all 1042 3657 0 0 0 0  
  
Epoch GPU_mem box_loss cls_loss dfl_loss Instances Size  
2/50 7.42G nan nan nan 182 640: 100% [██████████] 209/209 [10:14]  
<00:00,  
          Class Images Instances Box(P) R mAP50 mAP50-95: 100% [██████████] 33/  
33 [00:32]  
          all 1042 3657 0 0 0 0
```

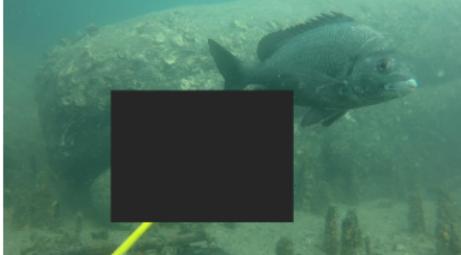
Mixup feature



Mosaic feature



Cutout feature



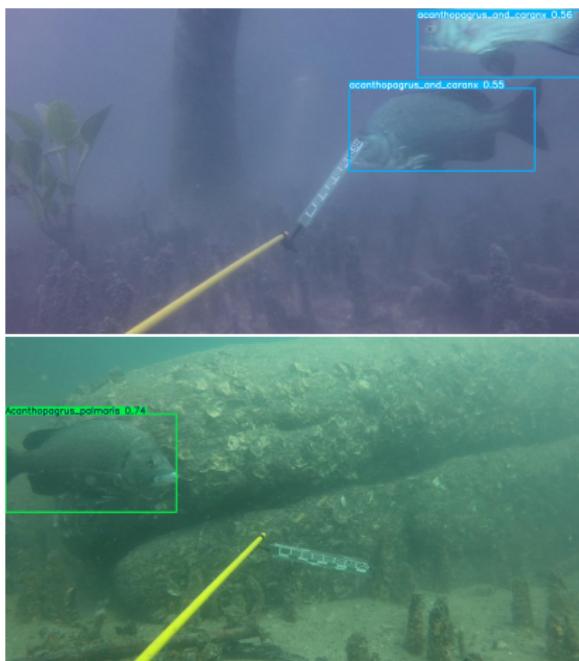
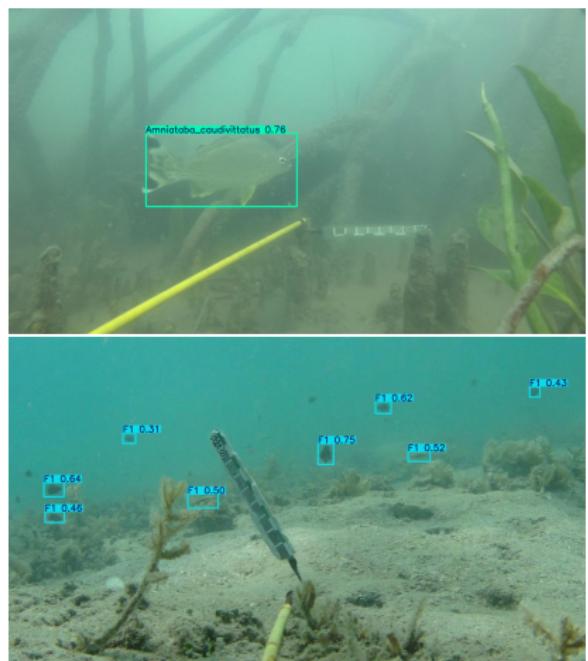
NMS

The **Non-Maximum Suppression** is a technique that cleans up the output of a detection model by filtering out redundant and overlapping bounding boxes to ensure that each object is identified only once. It operates by iterating through the predicted bounding boxes and making decisions based on two key metrics: **confidence scores** and the **IoU** threshold:

- ① Sort by confidence
- ② Select the best box
- 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

③ Tracking

④ Results

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.

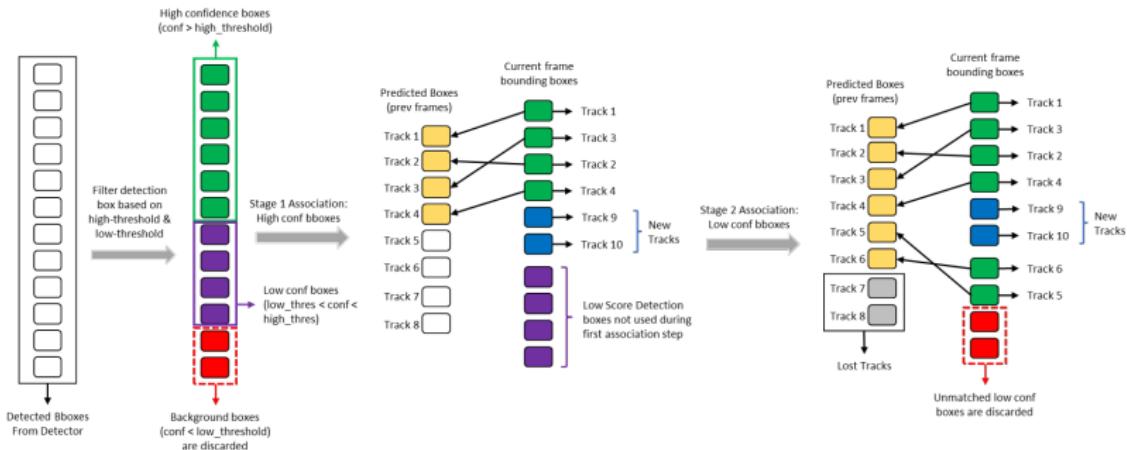


3. After Occlusion (ID

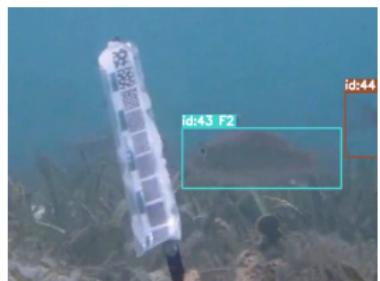
Switch)

The fish reappears identified as a new object ID 7.

The ByteTrack Algorithm



Correct Object Re-identification



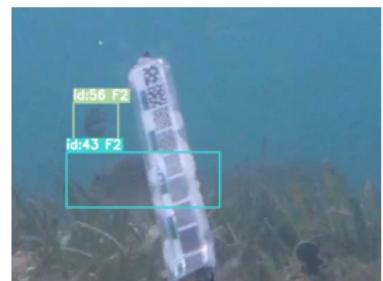
1. Before Occlusion

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

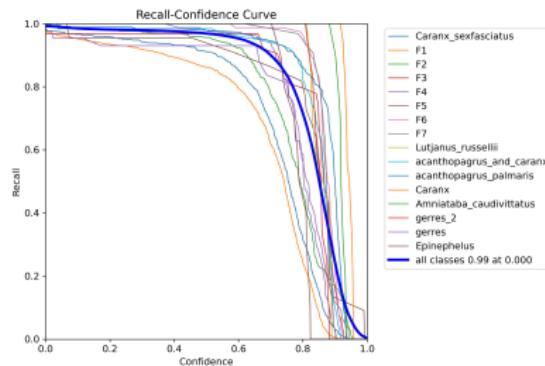
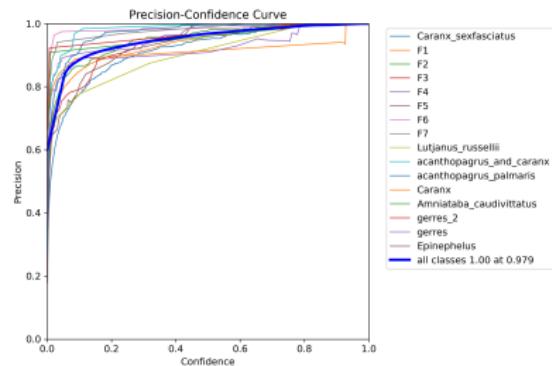
② Detection

③ Tracking

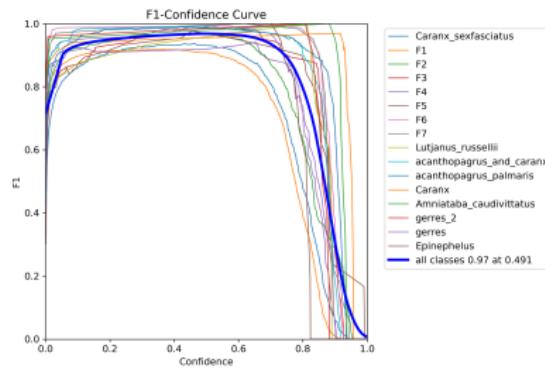
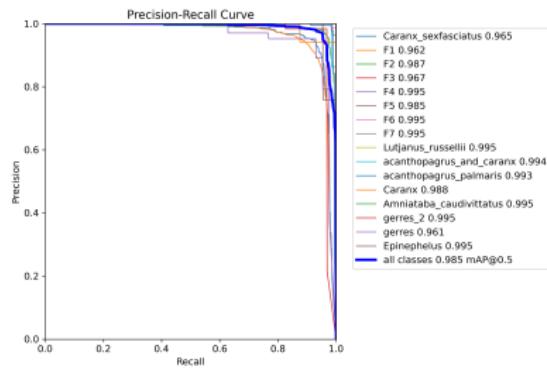
④ Results

⑤ Conclusions

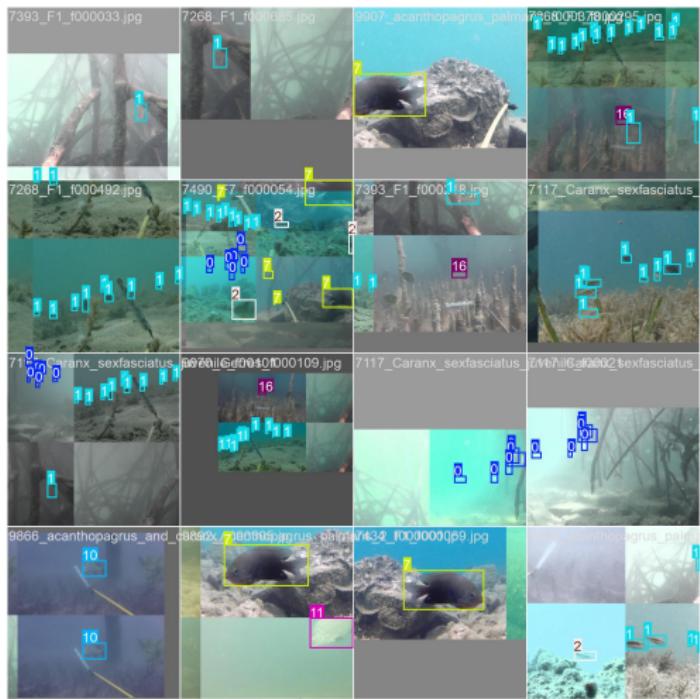
Fish Detection (DeepFish): Metrics



Fish Detection (DeepFish): Metrics



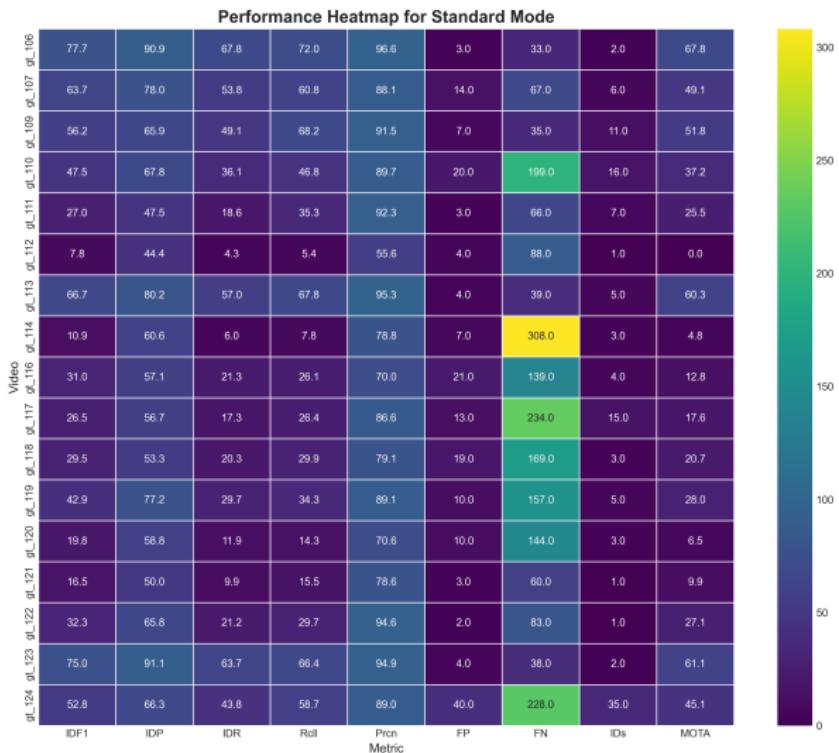
Fish Detection (DeepFish): Training Batch



Fish Detection (DeepFish): Validation Batch



Fish Tracking (F4K): Metrics



① Theory

② Detection

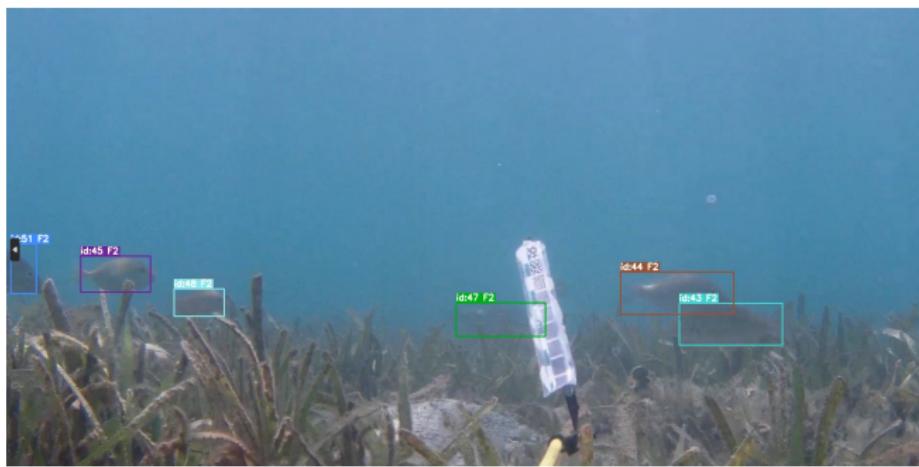
③ Tracking

④ Results

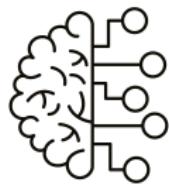
⑤ Conclusions

Conclusions

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



Future Work



Improve Detector
Robustness



Deploy on Video
Devices



Enable
Behavioral
Analysis

- [1] Ilya Loshchilov and Frank Hutter.
Decoupled weight decay regularization, 2019.