Fish Species Recognition and Tracking in a Fish Pass Context

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Hizkia Informatique - Ibaï Begi - SICAAV

Vidéo Counting Systems

- Ibaï Begi: Fish pass counting with uni/multi camera system
- SICAAV: Eel and Elver counting on a ramp

Currently running on 25 sites

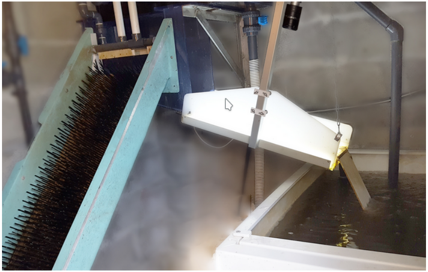

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Figure 2: Modular Panels

Figure 3: Cassing

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Figure 4: Underground Chamber

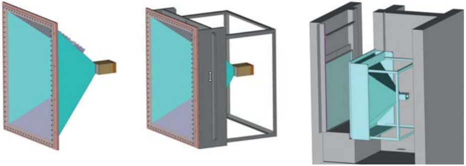

Figure 5: Removable Chamber

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Figure 6: Lamprey from

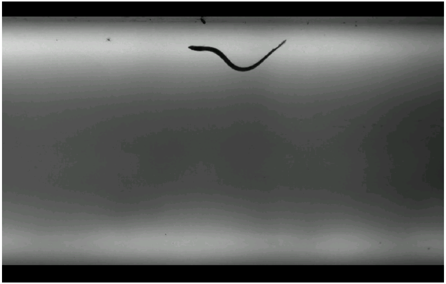

Figure 7: Eel from Soustons

Goal

Build a fish recognition tool to improve fish tracking and sequence refinement to facilitate migratory studies.

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- Detect and recognize fish species in a fish pass without missing any big migratory species,
- Work with lighter model as the solution could be embedded to do on-site detection,
- Improve the counting tool and his UI to synergize operators checking and data improvement.

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- Complexity of imagery (water quality, multiple output systems, fish similarities...) that defers from one site to another,
- Utilize/adapt state of the art object detection/recognition systems,
- Work in cooperation with migratory study associations to understand their need and facilitate their work,
- Deploy the new tool on each video counting system Hizkia has.

1. Presentation
2. Motivations
3. Approach to Object Detection
   - One-Stage VS Two-Stage Approach
   - State of the Art
4. Data & Tools
5. Results and Discussions
6. What's Next

One-Stage VS Two-Stage Approach

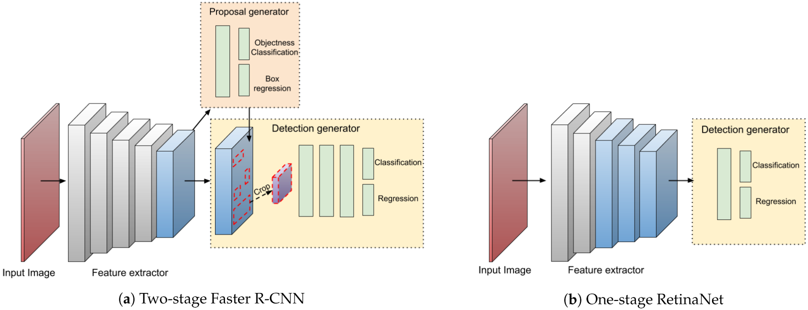

Figure 8: Example of One and Two Stage Architecture

Performance Comparison

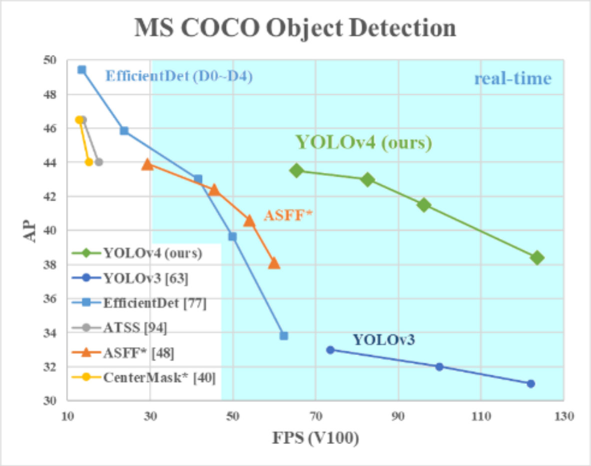

Figure 9: Object detection Benchmark

YOLO

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- Small Weight(14MB before pruning for Yolov5small)
- At equivalent speed Yolov5 has better accuracy (+5% mAP than EfficienDet at same FPS)

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   - Data
   - Preliminary Dataset
   - YOLO Ultralitics
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Raw(-ish) Data

3 years of video counting from different sites, with fish count and taxon information.

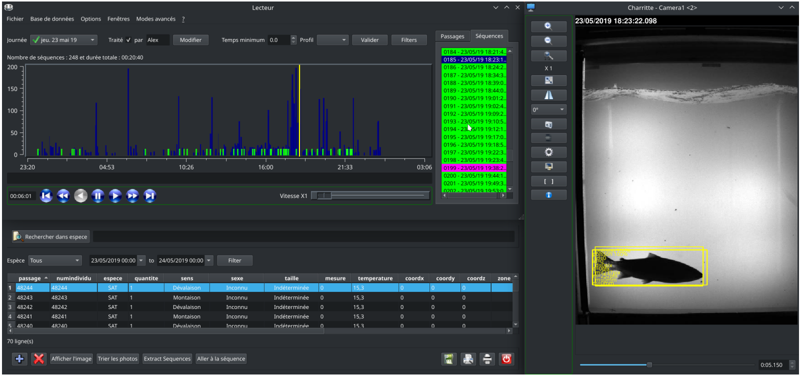


Figure 10: Video counting software

Labeling the data

Problem : The lack labeled data

We can extract the image + labels as *.txt* from the bounding boxes drawing tool embedded in App

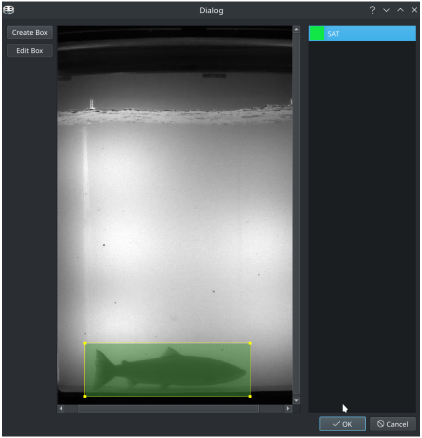
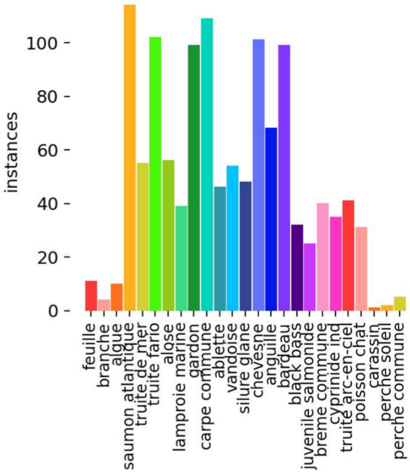


Figure 11: Detouring tool

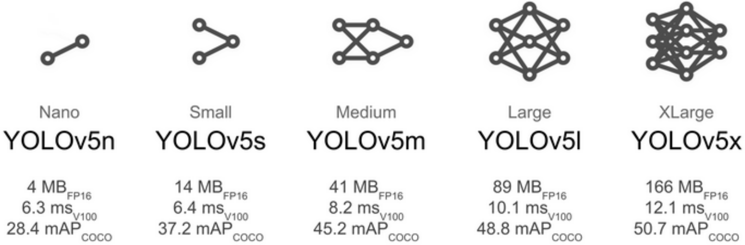
Preliminary Dataset

- 1467 instances + 147 for testing
- 25 classes (19 in test)



Ultralitics Yolov5

- ML enterprise-grade no-code provider
- Authors of the new open source YOLOv5 architecture
- Multiple size of architecture $\pm$ efficient



Images

IMAGES

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   - Results
   - Discussed Client Needs
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Results

Best Results on YOLOv5s

- Trained on 100 epochs
- 30 unchanged hyperparameters from Ultralitics
- With first dataset we can obtain a 83% accuracy
- Achieved inference time: 8.8ms

Results

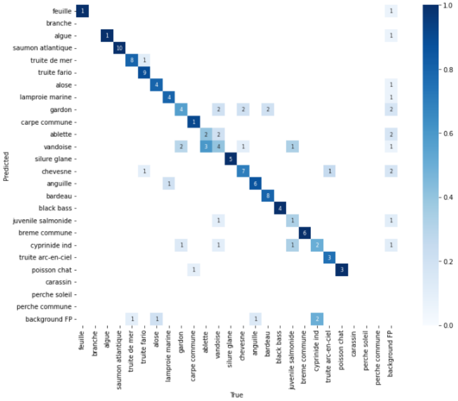

Figure 13: Confusion Matrix of test results

Needs

Feedback

- *"We have no need for automatic recognition"* $\sim$ *Migradour*
- *"Automatic recognition could able us to focus on more interesting things"* $\sim$ *Migado*

Actual Needs

- Filter out video with uninteresting information
- Rely totally on the tool, or only verify unique set of labeled fishes
- do not miss any migratory species

Data to take into consideration

What do professionals look for while stripping data

Help for classification

- Seasonality
- Fish coat (can vary from regions and seasons)
- Multiple taxon instances
- Swim technique

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- Add more labeled data do the dataset(research has shown that we need at least 500 instances of each class to have the best improvement in accuracy)
- Pruning the model and test if model can be ran on real time with machine on site
- Binaries eels images from SICAAV, this could improve detection precision
- Implement a dashboard to have direct results of detection. The idea is to produce a mosaic of images with fish and their class. The operator will only have to validate each image and their classification.

Merci!

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