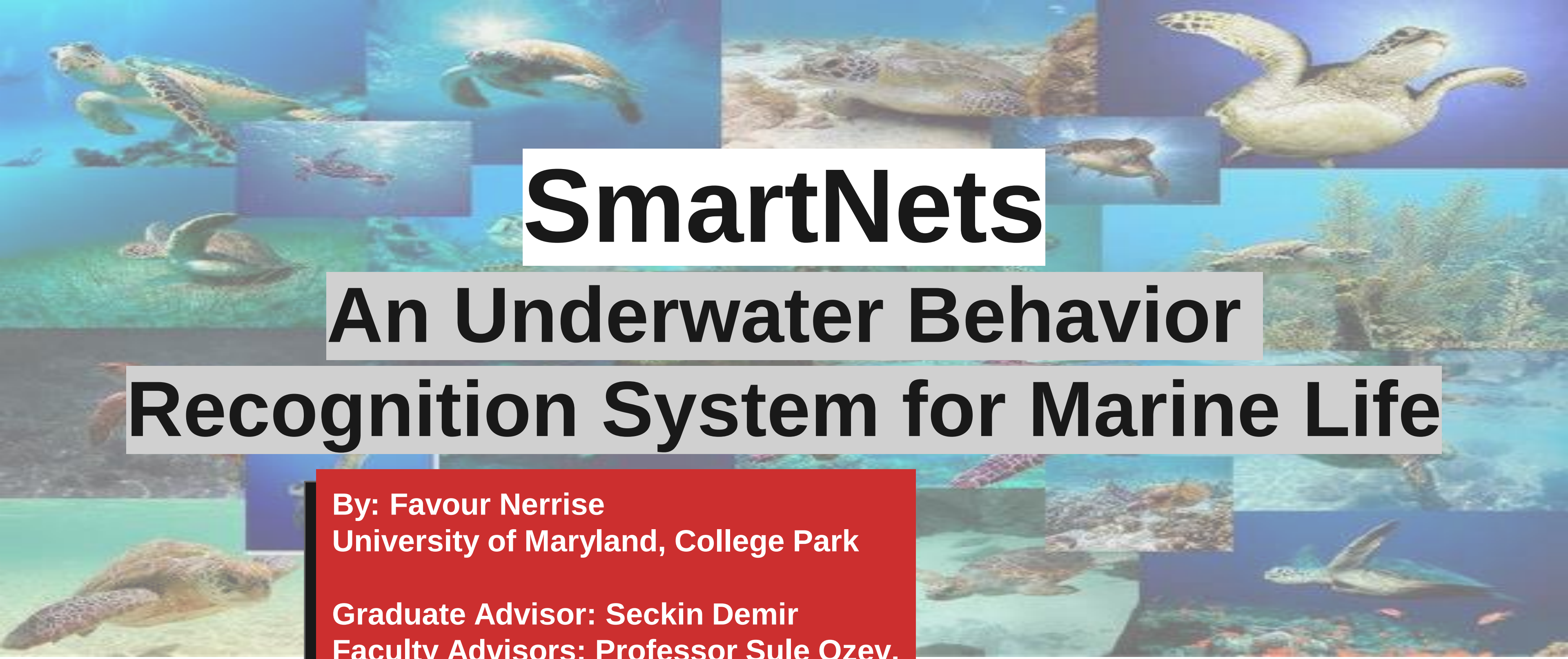

SmartNets

An Underwater Behavior Recognition System for Marine Life

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Background

- ➔ Bycatch, unintended capture of marine species, is a prominent issue that affects sea animals like sea turtles and damages the habitat.
- ➔ Smart Nets is an object recognition system that detects sea turtles and uses LED illumination levels as stimuli to warn turtles of potential danger.
- ➔ Experiments showed that the proposed approach provides up to 92.7% energy savings

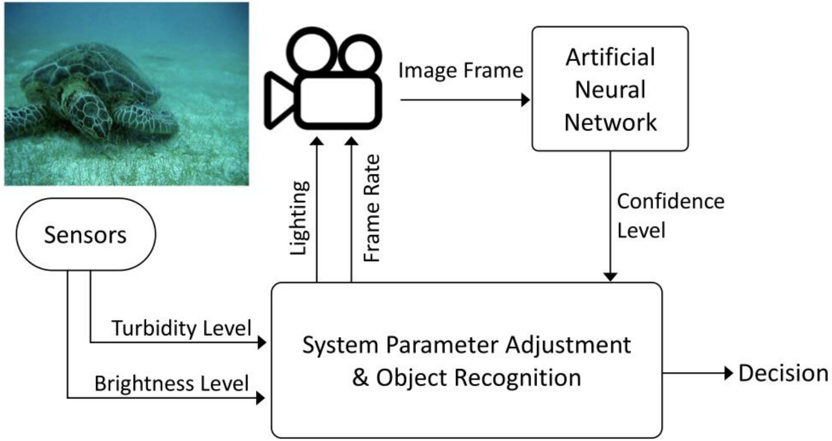

Fig. 1: Block diagram of the recognition system

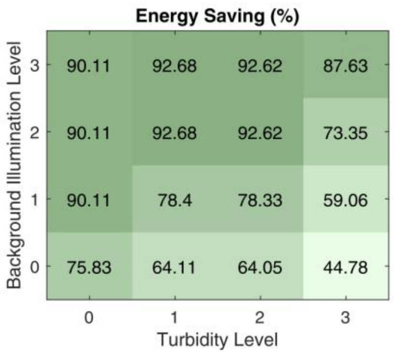

Fig. 2: Energy saving percentage compared to base frame rate and LED lighting under different environments

Source: DEMIR et al., 2020

Problem & Objective

- ➔ How can we automate marine life behavior analysis to better optimize warning stimuli/sensory cues?
- ➔ How do sea turtle orientations (angle and depth) affect response behavior to stimuli?

Methodology

- ➔ Generated 270 clips of manually identified sea turtle behaviors
  - ◆ u-turn behavior (n=141)
  - ◆ reversal behavior (n=129)
- ➔ Convert clipped videos to single image sequences (270 x 60fps)
- ➔ Created ground truth labels for observed sea turtle depth
- ➔ Trained, validated, and tested pretrained CNN (YOLO v4) on Open Images v6 sea turtle dataset
- ➔ Retrieved 2D bounding boxes coordinates from predictions
- ➔ Converted 2D bbox coords into 3D bbox coords (bird's eye view)

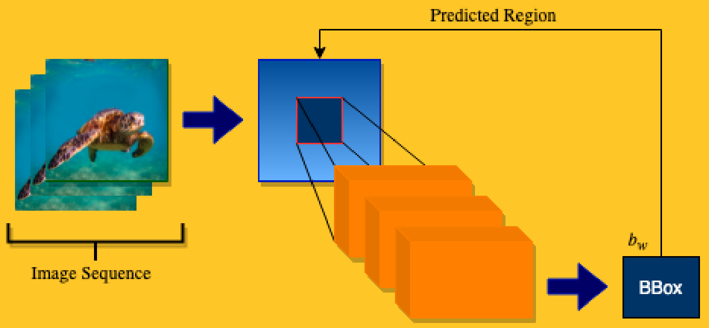

Fig. 3: Model of object detection + bbox retrieval

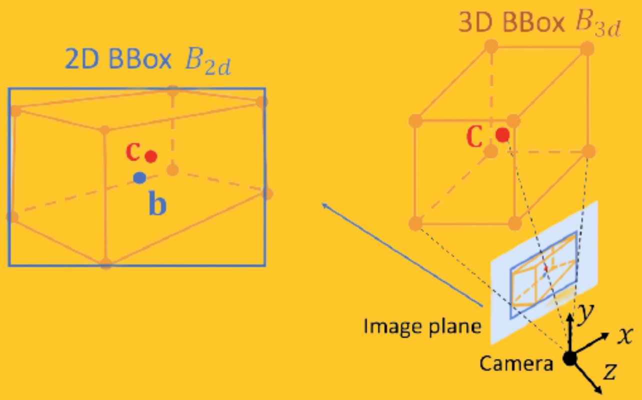

Fig. 4: The geometric similarity in 2D/3D projection (Liu, 2019)

Results

Objection Detection Progress

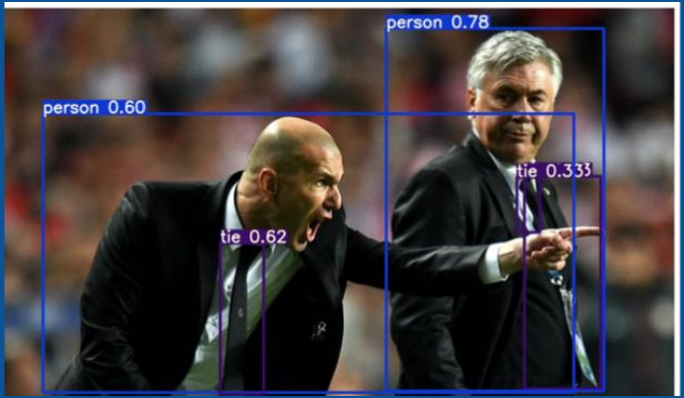

Fig. 5: 2D bounding boxes for pre-trained model

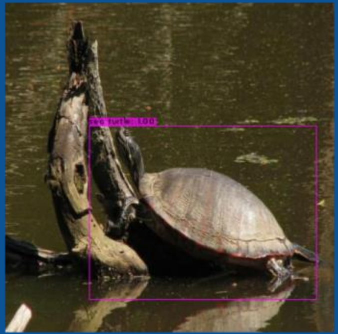

Fig. 6: 2D bounding boxes for sea turtle detection

➔ **Sea Turtle Detection Accuracy**: mAP@IoU50 = 85.67%

➔ Additional results:

Metric	mAP@0.5	mAP[0.5,0.95]
Baseline YOLO v4	62.8	44.3
SeaTurtle-YOLO v4	**85.67**	43.11

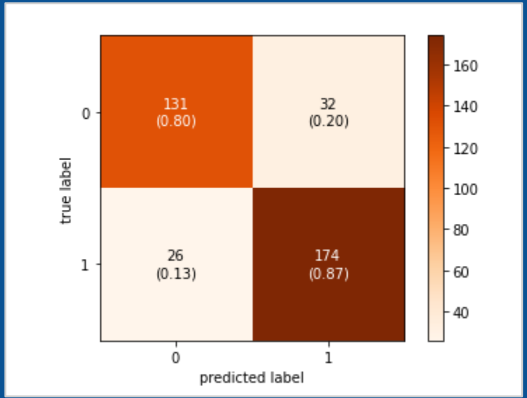

Fig. 7 & 8: Evaluation metrics for sea turtle prediction

Challenges

- Open-source data limitations
  - Acquisition & pre-processing
- Computing Difficulties
  - Transfer learning needed
  - Long training computing times and cost
- 3D Bounding Box Estimation
  - Lacking camera calibrations
  - Time-consuming manual ground truth sensor locations
- Benchmarking
  - No similar model available for marine life behavior analysis

Conclusions/ Remarks

- ➔ Developed automated sea turtle depth estimation behavior model
- ➔ Sea turtle object detection accuracy surpasses YOLO v4 standard benchmark @mAP50 = 85.64%
- ➔ Performed mathematical 2D Bounding Box => 3D Bounding Box coordinate conversion
- ➔ Training requires high computing speed and memory
- ➔ Limited accessible and current open-source data for sea turtles

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Thank You!

Questions?