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Investigating Deep Learning for Identification of Crabs and Lobsters on Fishing Boats

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Abstract

This paper describes a collaboration between marine and computer scientists to improve fisheries data collection. We evaluate deep learning (DL)-based solutions for identifying crabs and lobsters onboard fishing boats. A custom made electronic camera systems onboard the fishing boats captures the video clips. An automated process of frame extraction is adopted to collect images of crabs and lobsters for training and evaluating DL networks. We train Faster R-CNN, Single Shot Detector (SSD), and You Only Look Once (YOLO) with multiple backbones and input sizes. We also evaluate the efficiency of lightweight models for low-power devices equipped on fishing boats and compare the results of MobileNet-based SSD and YOLO-tiny versions. The models trained with higher input sizes result in lower frames per second (FPS) and vice versa. Base models are more accurate but compromise computational and run time cost. Lighter versions are flexible to install with lower mAP than full models. The pre-trained weights for training models on new datasets have a negligible impact on the results. YOLOv4-tiny is a balanced trade-off between accuracy and speed for object detection for low power devices that is the main step of our proposed pipeline for automated recognition and measurement of crabs and lobsters on fishing boats.

CCS Concepts

• ***Computing methodologies*** $\rightarrow$ ***Artificial intelligence; Object detection; Machine learning; Neural networks;***

1. Introduction

The fisheries industry is contributing enormously to the economy around the globe. Crabs and lobsters are among the valuable fisheries products that share the seafood demands of the growing human population [(GS]. The collection of fisheries data is a challenging task, however, collaborative research by marine and computer scientists can provide low-cost solutions. The fisheries data tends to be collected by multiple traditional and technological means [HMP*15, Por10, UK.22, MGB*19]. Each method aims to collect data to maintain proper record of catch, discards, by-catch, etc. Hold *et al.* [HMP*15] evaluated the potential of using onboard camera systems to collect data of brown crabs, and lobsters in Wales. Automation is essential in improving the standards of data collection and monitoring at low cost. The onboard camera systems on fishing boats have improved the amount and quality of data collection as a cheaper alternative to onboard observers to get the same coverage, and computer-automated image extraction and measurement can increase the application of video systems for data collection in a time and cost efficient manner. Our proposed computer automated system works on the videos captured by the camera systems.

2. Literature

The main types of object detection include few-shot, transformer-based, single-stage, and two-stage detectors. We focus on one-stage and two-stage detectors. YOLO [RDGF16] and Faster R-CNN [RHGS15] are examples of these two types of detectors, respectively. The literature presents extensive work on fish detection, and some research on ML-based object detection techniques for identifying crabs and lobsters. For example, Cao *et al.* [CZLS20] proposed a detector for underwater crab detection named Faster MSS-DLite. They performed experiments with 5125 images for training and testing MSSDLite. The merged SSD and MobileNetV2 backbone achieved a precision of 98.84% with a frame rate of 74 per second. Chen *et al.* [CZLD] designed a lightweight crab detection and gender identification method called GMNet-YOLOv4 based on YOLOv4 with GhostNet backbone. This modified detection model achieved mAP of 97.23%, which was 2.82% higher than the base model. Recently, Ji *et al.* [JPXZ23] used Mobile-CenterNet and MobileNetV2 for underwater river crab detection that achieved an AP of 97.86% and run time speed of 48.18 FPS. Wu *et al.* [WXC*23] used abdomen parts for identifying swimming and mud crabs with two data sets using DL-based network named PDN (Part-based Deep Learning Network) with three over-

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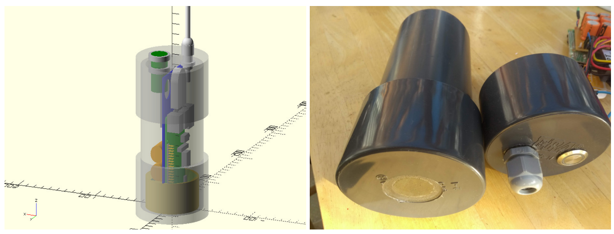
S.No.	Network	Input Size	mAP_{50}	Recall	F1 Score	FPS	Training Loss	Training Steps
1	Faster R-CNN Inception v2	640 x 640	**89.3%**	68.6%	77.6%	10.0	1.4	50k
2	Faster R-CNN ResNet-50	640 x 640	82.1%	64.8%	72.5%	4.3	2.1	50k
3	Faster R-CNN ResNet-101	640 x 640	76.7%	58.7%	66.5%	3.6	2.3	50k
4	SSD Inception v2	640 x 640	54.0%	55.6%	54.8%	22.0	9.2	50k
5	SSD ResNet-50	640 x 640	75.3%	**71.0%**	73.1%	10.0	**0.6**	50k
6	SSD ResNet-101	640 x 640	49.5%	63.8%	55.7%	5.5	3.4	50k
7	SSD MobileNetV1	640 x 640	31.7%	54.1%	40.0%	25.4	17.5	50k
8	SSD MobileNetV2	640 x 640	47.5%	54.8%	50.9%	25.4	8.3	50k
9	SSDLite MobileNetV1	640 x 640	54.2%	55.3%	54.8%	25.4	7.0	50k
10	SSDLite MobileNetV2	640 x 640	50.0%	52.2%	51.1%	16.5	9.2	50k
11	SSD MobileNetV3-Large	640 x 640	88.8%	69.6%	**78.0%**	30.0	1.1	50k
12	SSD MobileNetV3-Small	640 x 640	39.5%	59.3%	47.4%	**41.3**	1.4	50k
13	YOLOv3	320 x 320	59.3%	64%	66%	32.0	0.06	6k
14	YOLOv3	416 x 416	67.7%	68%	67%	21.3	0.07	6k
15	YOLOv3	608 x 608	87.0%	89%	79%	12.8	**0.03**	6k
16	YOLOv4	320 x 320	97.2%	95%	**97%**	32.0	0.89	6k
17	YOLOv4	416 x 416	**97.4%**	**96%**	**97%**	21.3	0.67	6k
18	YOLOv4	608 x 608	96.9%	92%	95%	11.2	0.70	6k
19	YOLOv3-tiny	320 x 320	62.7%	57%	67%	**64.0**	0.13	6k
20	YOLOv3-tiny	416 x 416	79.1%	72%	78%	**64.0**	0.17	6k
21	YOLOv3-tiny	608 x 608	78.9%	60%	72%	**64.0**	0.31	6k
22	YOLOv4-tiny	320 x 320	61.2%	64%	63%	**64.0**	0.08	6k
23	YOLOv4-tiny	416 x 416	86.4%	84%	79%	**64.0**	0.05	6k
24	YOLOv4-tiny	608 x 608	89.5%	89%	85%	**64.0**	0.23	6k

Table 1: *Evaluation of Faster R-CNN, SSD, SSDLite and YOLO v3, v4 and tiny versions.*

lapping and non-overlapping strategies. The overlapping strategy partitions combined with edge textures achieved maximum mAP of 94.5%. Li *et al.* [LYT22] used YOLOv4 with a modified channel attention mechanism to extract weighted multi-scale features. They improved the AP by 5.03% at the rate of 15 FPS. Mahmood *et al.* [MBA*20] published his work on Western rock lobster detection and created a synthetic dataset of lobster body parts. They trained YOLOv3 on the datasets. The results show that the synthetic data improved mAP by 25.9% in underwater images.

3. Experiments

We mount the camera unit directly above the catch table to record video clips. The camera unit is a sealed, tough, and waterproof plastic unit as shown in Figure 1. The high-resolution videos are recorded and downloaded to a WiFi-enabled device. We used 44 videos of different lengths between 5 to 35 minutes to create our datasets for training and evaluation purposes. The main challenges in data collection include dissimilar setups (such as the appearance of the catch tables), highly varied poses of animals, presence of unwanted objects in the scene like bycatch, ropes, pots, mud, gloves. Another problem is the variation in lighting due to moving vessels, outdoor weather conditions and different times of day during the fishing trips. We trained Faster R-CNN, SSD and YOLO on our datasets and evaluated the performance of the models on test data. Figure 2 shows detection bounding boxes on images. The results of our trainings are given Table 1 below.



(a) CAD view showing internal components (b) Internal hardware removed

Figure 1: *a) The internal components of the camera. b) The outer cover for protection.*

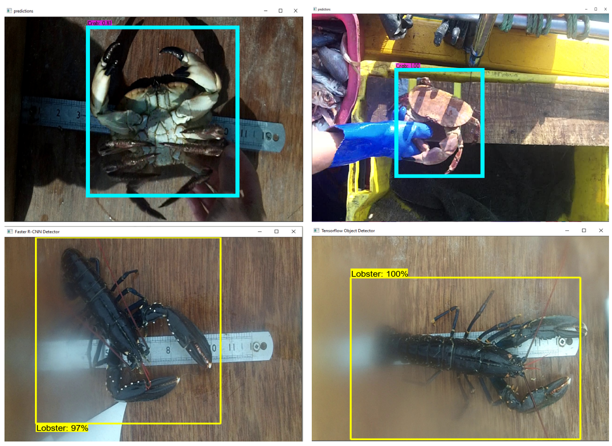


Figure 2: *Detection of crabs and lobsters in images.*

4. Results/Conclusion

This research investigates state-of-the-art DL models for detecting crabs and lobsters on fishing boats. The trials include Faster R-CNN and SSD with inception v2, ResNet-50, and ResNet-101 backbones. Faster R-CNN achieved high mAP, while SSD performed at high FPS rate. The trials with SSD light-structured MobileNet backbones resulted in lower mAP values and significantly faster than Faster R-CNN and SSD models. The results show a trade-off between speed and accuracy among the base and lightweight models. The selection of input size is significant. The computational cost of low input size is less but higher input size improves the precision in most cases. The performance of SSD with MobileNets is less affected by the input size variations. The research shows a negligible impact of pre-trained weights for training models on new datasets. The results of YOLOv4 are better than YOLOv3. The YOLO-tiny versions are an alternative for deployment on low-power devices. The YOLOv4-tiny achieved a maximum mAP of 89.5% with 64 FPS and is an efficient solution to detect crabs and lobsters on fishing boats and similar problems.

References

[CZLD] CHEN X., ZHANG Y., LI D., DUAN Q.: Chinese mitten crab detection and gender classification method based on gmnet-yolov4. *Available at SSRN 4314563*. 1

[CZLS20] CAO S., ZHAO D., LIU X., SUN Y.: Real-time robust detector for underwater live crabs based on deep learning. *Computers and Electronics in Agriculture 172* (2020), 105339. 1

[(GS] (GSA) G. S. A.: Role of aquaculture in feeding the growing human population for their protein needs. 2023. URL: https://www.globalseafood.org/blog/what-is-aquaculture-why-do-we-need-it/. 1

[HMP*15] HOLD N., MURRAY L. G., PANTIN J. R., HAIG J. A., HINZ H., KAISER M. J.: Video capture of crustacean fisheries data as an alternative to on-board observers. *ICES Journal of Marine Science 72*, 6 (2015), 1811–1821. 1

[JPXZ23] JI W., PENG J., XU B., ZHANG T.: Real-time detection of underwater river crab based on multi-scale pyramid fusion image enhancement and mobilecenternet model. *Computers and Electronics in Agriculture 204* (2023), 107522. 1

[LYT22] LI A., YU L., TIAN S.: Underwater biological detection based on yolov4 combined with channel attention. *Journal of Marine Science and Engineering 10*, 4 (2022), 469. 2

[MBA*20] MAHMOOD A., BENNAMOUN M., AN S., SOHEL F., BOUSSAID F., HOVEY R., KENDRICK G.: Automatic detection of western rock lobster using synthetic data. *ICES Journal of Marine Science 77*, 4 (2020), 1308–1317. 2

[MGB*19] MERRIFIELD M., GLEASON M., BELLQUIST L., KAUER K., OBERHOFF D., BURT C., REINECKE S., BELL M.: ecatch: Enabling collaborative fisheries management with technology. *Ecological Informatics 52* (2019), 82–93. 1

[Por10] PORTER R. D.: Fisheries observers as enforcement assets: Lessons from the north pacific. *Marine Policy 34*, 3 (2010), 583–589. 1

[RDGF16] REDMON J., DIVVALA S., GIRSHICK R., FARHADI A.: You only look once: Unified, real-time object detection. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (2016), pp. 779–788. 1

[RHGS15] REN S., HE K., GIRSHICK R., SUN J.: Faster r-cnn: Towards real-time object detection with region proposal networks. *Advances in neural information processing systems 28* (2015). 1

[UK.22] UK. M. M. O. M.: Inshore vessel monitoring [i-vms] for under-12m fishing vessels registered in england. *Guidance-MMO* (2022). 1

[WXC*23] WU C., XIE Z., CHEN K., SHI C., YE Y., XIN Y., ZAREI R., HUANG G.: A part-based deep learning network for identifying individual crabs using abdomen images. *Frontiers in Marine Science 10* (2023), 1093542. 1