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Active YOLO for Lobster Part Detection in Industrial Contexts

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Extended Abstract

The manufacturing industry is experiencing a significant transformation driven by digital technologies and artificial intelligence (AI) -based solutions. As manufacturers aim to boost productivity while maintaining human involvement, integrating robots poses new challenges. Emerging technologies like brain-machine interfaces and advanced AI are essential, leading to a new paradigm known as Industry 5.0 [1].

Industry 4.0 revolutionized manufacturing with AI, the Internet of Things (IoT), cloud computing, cyber-physical systems (CPSs), and cognitive computing, creating "smart" environments where interconnected machines autonomously optimize production. This shift has significantly increased productivity and performance. However, Industry 5.0 further evolves by emphasizing collaboration between humans and robots, leveraging human creativity and advanced machinery. It aims to enhance efficiency and enable mass personalization, where products are tailored to individual needs. The core value of Industry 5.0 is human centricity, with machines handling repetitive tasks and humans focusing on cognitive and critical thinking tasks [2]. On the one hand and according to [3], the key technologies supporting a human-centric AI in manufacturing include *i)* Active Learning (AL): AI systems continuously learn from human feedback, enhancing human-machine synergy; *ii)* Explainable AI (XAI): Ensures AI decisions are transparent and understandable, fostering trust and collaboration; *iii)* Simulated Reality: Uses virtual environments to simulate real-world scenarios for training and decision-making; *iv)* Conversational Interfaces: Enable natural language interactions between humans and machines, improving usability; *v)* Security: Ensures data and system security as digitalization increases the attack surface. On the other hand and within this transformation, object detection (OD) plays a crucial role [4] by applying it in different systems like defect detection for quality control, in collaborative robots (cobots), with robot arms for palletising and pick and place automated system, and in video surveillance systems. Furthermore, it is worth mentioning, that the most recent development of these systems is based on YOLO detectors for their precision and inference speed efficiency trade-off [5].

In eastern Canada, the lobster fishery industry is the most commercially important fishery in Atlantic Canada [6, 7]. Integrating cutting-edge techniques and technologies within New Brunswick lobster manufacturers is crucial to match the industrial development era. To this end, a large lobster parts detection dataset has been collected by the R.E.I.4.0 laboratory at the Faculty of Engineering of the University of Moncton. It includes several thousand color and grayscale images of lobsters collected in a context simulating an industrial environment [8]. All collected images have been annotated into six classes: tail, claw, head, body, force claw, and folded tail, with their corresponding bounding box coordinates. The dataset also contains images without the lobster or its parts appearing (background).

Thus, we propose a new YOLO-based lobster part detection system by exploiting an AL approach. Considering a limited label budget, AL aims to select the most effective images to be annotated to improve the model efficiency by applying a selection-based metric for N cycles until the label budget is reached. While AL is an annotation cost optimization-based machine learning approach, it is still underexploited and applied in OD. Three main selection categories exist in the general literature: those based on the informativeness of samples, representativeness, and hybrid approaches [9].

In this work, we first evaluate the uncertainty selection metric based on entropy with the latest YOLO series update, i.e., YOLOv10 [10]. This detector presents the best holistic inference speed-accuracy performance for real-time detection. The initial active YOLOv10 training cycle used 0.5% randomly selected annotated data; then, 4 active cycles were carried out with an increment of 0.5%. The label quota budget is 2.5%, representing about 500 annotated images from the training dataset. For evaluation, we used a noisy version of the test set, simulating adverse industrial environment conditions, such as the addition of blur, and textures simulating the effect of water on images, reflections, and more severe intensity variations compared to the original images.

The preliminary mAP50 result of active YOLOv10 compared to YOLOv10 trained from scratch and fine-tuned from the COCO trained model, when using a 2.5% random annotated image, are very competitive with 0.778, 0.802, and 0.831, respectively. Indeed, the entropy calculation only considers the prediction score. However, the consistency and reliability of the predicted bounding boxes should also be considered in the strategy applied to object detection systems. This is the primary objective of our ongoing experiments.

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