71st ICoMST
GIRONA - CATALONIA - SPAIN
3rd-8th August - 2025

ASSESSING THE PERFORMANCE OF DETECTRON2 AND YOLOv8 IN DETECTING MULTI-SCALE CARCASS COMPONENTS

Jyoti P. Mishra[1,2], Alessandro Ferragina[1,3], Stephen Hegarty[2], Carlos Esquerre[1] and Ruth M. Hamill[1*]

[1]Food Quality and Sensory Science Department, Teagasc, Ashtown, Dublin 15, Ireland

[2]Centre for Advanced Photonics and Process Analysis, Munster Technological University, Bishopstown Campus, Cork, Ireland

[3]Department of Veterinary Science, University of Parma, Italy

*Corresponding author email: ruth.hamill@teagasc.ie

I. INTRODUCTION

The meat industry seeks to increase automation, targeting integration of robotics in processing lines considering the growing demand for non-contact hygienic production, reduction in waste and providing resilience to labour availability challenge [2,4]. Advances in computer vision and artificial intelligence (AI) can play pivotal roles in this transition, enabling a fresh perspective on the automation of traditionally manual tasks [3]. In many sectors, machine learning and deep learning techniques have revolutionized automatic object detection and segmentation, forming a new foundation for exploration of robotic applications in meat processing. Ongoing research continues to refine deep learning algorithms, driving significant innovation in the field. This study aims to compare two deep learning frameworks (i.e You Only Look Once (YOLO) and Detectron2), in detecting and segmenting carcass components of varying sizes, with potential downstream application in robotic processing and automatic cut-planning.

II. MATERIALS AND METHODS

At 24 hours post-mortem, RGB images were acquired from 118 beef carcass sides representing a range of categories (young bulls, cows, heifers, and steers), fat scores (2, 3, 4), conformation classes (E, U, R, O, P), and weights ranging from 122 to 297 kg. The images were captured in a single abattoir chill, under ambient lighting conditions on three dates. Each image was manually annotated to identify six key carcass components: carcass side, aitch bone, spine, rib cage, rib 5, and rib 10. Annotation was performed using Label Studio, an open-source tool that stores annotations in JSON format within a SQLite or PostgreSQL database [1]. The annotated images were then exported in formats compatible with Detectron2 (COCO format) and YOLOv8 (YOLO format). To account for dataset variability, 25 images were set aside as test data, while the remaining 93 images underwent augmentation techniques, including horizontal and vertical flipping, rotation, and adjustments in brightness and contrast, resulting in a final dataset of 465 images. This dataset was further divided into 410 images for training and 55 images for validation. Model training was conducted on Google Colaboratory using both the Detectron2 framework and YOLOv8. The trained models were subsequently used to predict the test images, and their performance was evaluated by calculating Average Precision (AP) for both bounding box detection and segmentation (masking). The evaluation was performed by comparing model predictions with ground truth annotations, using an Intersection over Union (IoU) threshold, which was incrementally increased in steps from 0.50 to 0.95.

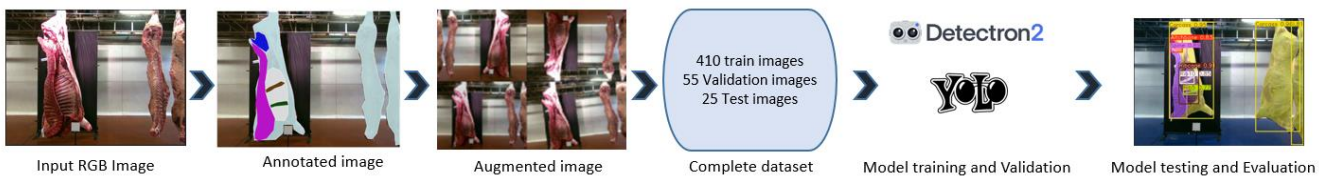
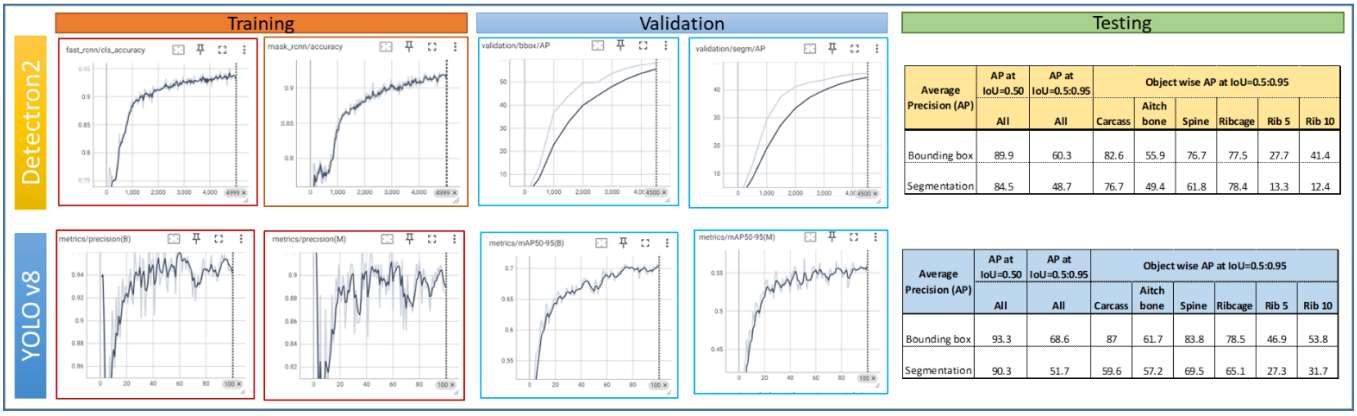


Figure 1. Work flow for model training, validation and testing

III. RESULTS AND DISCUSSION

The overall training accuracy for both models ranged between 80% and 95%, while the validation accuracy dropped to a range of 42% to 70% (Figure 2). In terms of test evaluation, the two models targeted different output parameters. Detectron2 provided detailed evaluation metrics, including Average Precision (AP) at multiple IoU thresholds and Average Recall (AR). In contrast, YOLOv8 offered a more comprehensive Precision-Recall analysis, incorporating confusion matrices and F1 confidence curves. As shown in Figure 2, AP values decreased as the IoU threshold

increased. Additionally, bounding box detection consistently outperformed segmentation, with AP values for bounding boxes being 3–5% higher at IoU = 0.5 and 12–17% higher at IoU = 0.50:0.95.



Average Precision (AP)	AP at IoU=0.50	AP at IoU=0.5:0.95	Object wise AP at IoU=0.5:0.95					
	All	All	Carcass	Aitch bone	Spine	Ribcage	Rib 5	Rib 10
Bounding box	89.9	60.3	82.6	55.9	76.7	77.5	27.7	41.4
Segmentation	84.5	48.7	76.7	49.4	61.8	78.4	13.3	12.4

Average Precision (AP)	AP at IoU=0.50	AP at IoU=0.5:0.95	Object wise AP at IoU=0.5:0.95					
	All	All	Carcass	Aitch bone	Spine	Ribcage	Rib 5	Rib 10
Bounding box	93.3	68.6	87	61.7	83.8	78.5	46.9	53.8
Segmentation	90.3	51.7	59.6	57.2	69.5	65.1	27.3	31.7

Figure 2. Comparision of performances of Detectron2 and YOLO v8 in carcass componnet detection and segmentation

Overall, YOLOv8 achieved 3–8% higher AP compared to Detectron2. At IoU = 0.50:0.95, YOLOv8 outperformed Detectron2 by 8.3% in bounding box detection and 3% in segmentation. The AP values varied depending on object type. YOLOv8 performed better for smaller or more precise carcass components, such as rib 5 and rib 10, showing an AP increase of 12–19%. Conversely, Detectron2 was more precise in segmenting larger structures, such as the carcass and rib cage, with an AP increase of 13–17%.

Regarding computational efficiency, Detectron2 exhibited faster training times compared to YOLOv8. Detectron2 completed 5,000 epochs in approximately 41 minutes, whereas YOLOv8 required 54 minutes for just 100 epochs, indicating a significantly higher computational demand for YOLOv8.

IV. CONCLUSION

Both Detectron2 and YOLOv8 demonstrated their effectiveness in detection and segmentation of larger carcass components like carcass sides, aitch-bone, spine and rib cage. Though YOLOv8 exhibited slightly better performance in detecting and segmenting the smaller components like rib5 and rib10, higher precision is desired for vision driven robotic application. However, the performance of both models could potentially be further improved by optimizing illumination conditions, which may enhance detection accuracy and consistency.

ACKNOWLEDGEMENTS

This work was supported by Meat Technology Ireland (MTI) a co-funded Industry/Enterprise Project (TC 2021 0031) and a Teagasc Walsh Scholarship Award (WS 2021039) to Jyoti P. Mishra. We acknowledge the facilitation of Georgios Anagnostou, Teagasc and staff at Liffey Meats, Ballyjamesduff, Co. Cavan

REFERENCES

1. de Almeida, G. P. S., dos Santos, L. N. S., da Silva Souza, L. R., da Costa Gontijo, P., de Oliveira, R., Teixeira, M. C., De Oliveira, M., Teixeira, M. B., & do Carmo França, H. F. (2024). Performance Analysis of YOLO and Detectron2 Models for Detecting Corn and Soybean Pests Employing Customized Dataset. Agronomy, 14(10).

2. Echegaray, N., Hassoun, A., Jagtap, S., Tetteh-caesar, M., & Kumar, M. (2022). Meat 4 . 0 : Principles and Applications of Industry 4 . 0 Technologies in the Meat Industry. 1–20.

3. Hamill, R. M., Ferragina, A., Mishra, J. P., Kavanagh, A., Hibbett, M., Gagaoua, M., Colreavy, J., & Rady, A. (2024). Chapter 13 - Toward Meat Industry 4.0: opportunities and challenges for digitalized red meat processing. In Food Industry 4.0: Emerging Trends and Technologies in Sustainable Food Production and Consumption (pp. 259–281). Academic Press

4. Xu, W., He, Y., Li, J., Zhou, J., Xu, E., Wang, W., & Liu, D. (2023). Robotization and intelligent digital systems in the meat cutting industry: From the perspectives of robotic cutting, perception, and digital development. Trends in Food Science and Technology, 135, 234–251.