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INDIVIDUAL RIB IDENTIFICATION VIA KEYPOINT DETECTION IN DEEP LEARNING

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I. INTRODUCTION

Meat processing is a labour-intensive industry, dealing with high biological variability, carbon-intensive production, and challenging work conditions. The adoption of automation in meat processing is crucial for reducing waste, enhancing efficiency, and to enhance worker welfare. Despite technological advancements, automation in beef processing remains costly, inflexible, and lacks scalability. Several authors have highlighted the potential of Artificial Intelligence (AI)-driven automation and robotic processing to improve efficiency in meat processing [3]. Computer vision has emerged as a powerful tool for AI-based applications, with deep learning significantly expanding its applicability [2]. Recent studies have demonstrated the use of machine learning and deep learning to identify key carcass components, which has substantial implications for robotic operations [4]. However, limited research has focused on precisely identifying individual anatomical structures in biologically variable samples with computer vision. This study investigates the potential of Key point based object detection using detectron2, for the precise detection of individual ribs in a variable sample of bovine carcasses.

II. MATERIALS AND METHODS

At 24 hours post-mortem, RGB images were taken from 40 beef carcass sides, covering different 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 using a line scan camera under controlled lighting conditions. Each image had a resolution of 855 × 320 pixels. To prepare the dataset, each image was manually annotated to mark a key point on the left-hand side (LHS) and right-hand side (RHS) of individual ribs (from rib 1 to rib 11). Annotation was done 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 COCO format, which is compatible with Detectron2. The dataset was split into training (80%), validation (10%), and testing (10%), with 32 images for training and 4 images each for validation and testing. Model training was conducted on Google Colaboratory using Detectron2. Four types of image augmentation were applied: horizontal flip, vertical flip, rotation, and brightness adjustment. The model was trained for 2,500 iterations and fine-tuned using the validation dataset. Predictions were made for test images, and model performance was evaluated using Average Precision (AP) and Average Recall (AR). AP was calculated based on Object keypoint similarity (OKS), which considers the Euclidean distance between predicted and ground truth keypoints. The per-keypoint standard deviation (sigma) value was set to 0.1 during OKS computation and the AP value was estimated by varying the OKS from 0.50 to 0.95.

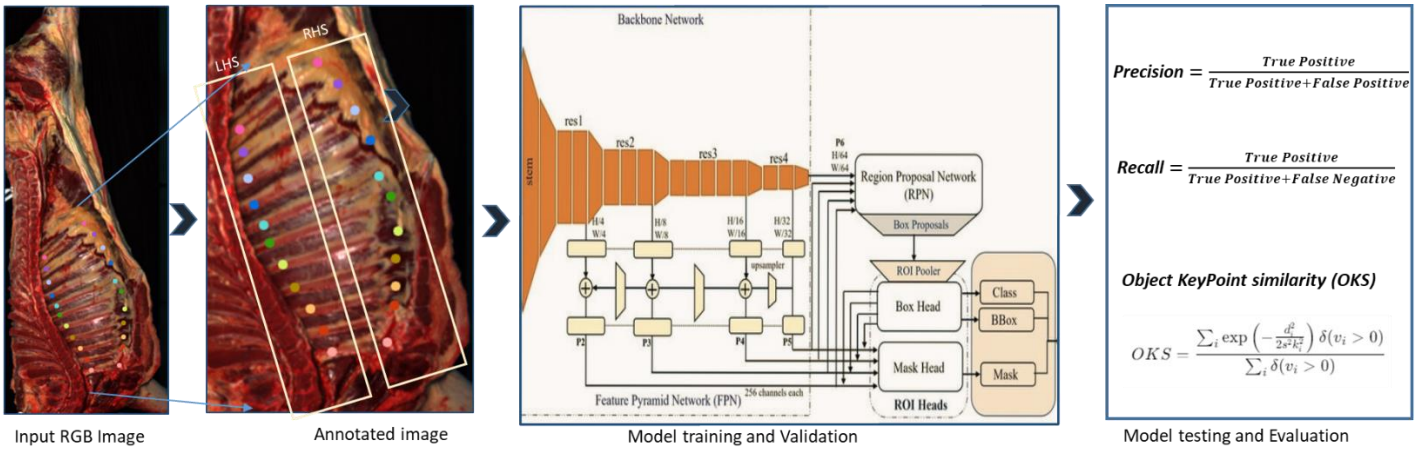


Figure 1. Work flow for model training, validation and testing

III. RESULTS AND DISCUSSION

The keypoint loss curve and Average Precision (AP) curve (Figure 2) show that the error stabilizes after 2,000 epochs, meaning the model does not improve further. The validation results give an average precision (AP) of 0.93 and an average recall (AR) above 0.95, even as the Object Keypoint Similarity (OKS) threshold increases from 0.50 to 0.95. The high AP and AR values are likely due to the relatively low stringency of the whole carcass being the object, which is large relative to the target key-point. Future studies will evaluate the model under higher stringency for example by considering only the ribcage as target. Visual inspection, however, shows that the predicted keypoints are closely located relative to the ground truth (Figure 2), suggesting the approach is promising for this target research question.

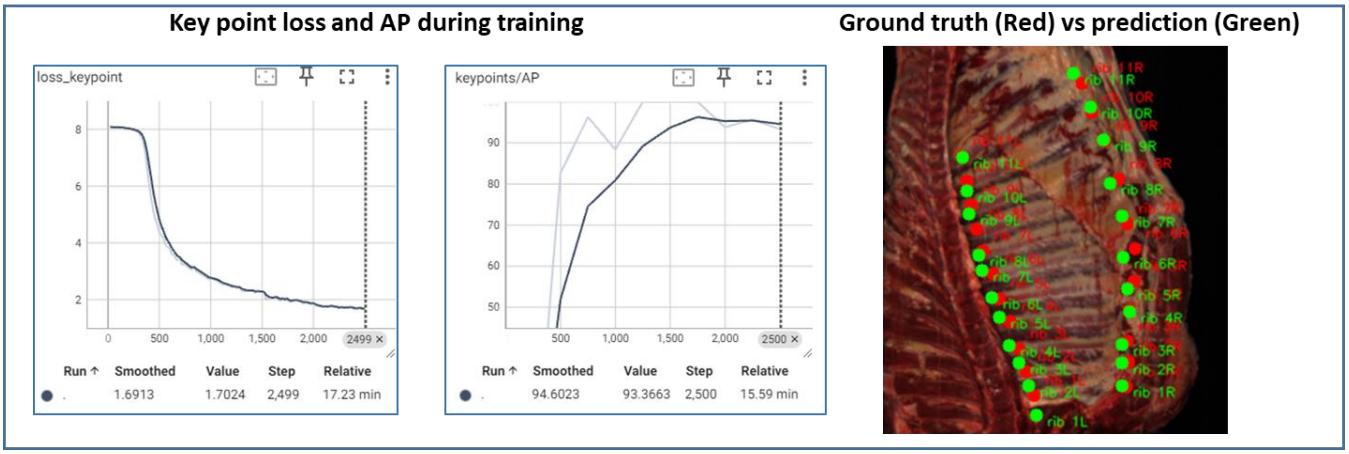


Figure 2. Performance of detectron2 model during training, validation and testing

IV. CONCLUSION

Detectron2 detects the endpoints of individual ribs with low deviations from the ground truth as can be visually observed in the test images. Further improvements in evaluation parameters, including average precision and average recall, may accrue after redefining the object boundary, incorporating additional keypoints and training on a larger, more diverse dataset.

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