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DEEP LEARNING BASED IMAGE RECOGNITION FOR THE DETECTION OF NATURAL BEHAVIORS IN LAYING HENS

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Abstract

Eggs are an important source of protein, widely favored and needed by the public. The production and quality of eggs are closely related to the rearing environment of laying hens. Common rearing methods include conventional cages, enriched cages, floor systems, and free-range systems. Different housing environments may influence the production efficiency of hens. In recent years, increasing attention has been given to balancing animal welfare with production efficiency. Animal welfare is closely related to animal behavior; however, such behavior is still difficult to quantify.

This study employed two algorithms to detect whether chickens were engaged in feeding behavior. The first algorithm involved bounding box annotations of chickens that were feeding and used the YOLOv11 model to directly detect feeding individuals. The second algorithm used both bounding boxes and eight keypoints on the chicken's body for annotation and applied the YOLOv11-pose model to detect posture. It then determined feeding behavior based on whether the beak overlapped with the feeder.

Both algorithms were tested in caged and multi-tier aviary environments. The results of the first algorithm showed a precision of 31.7% and recall of 86.7%, while the second algorithm yielded a precision of 81.3% and recall of 86.7%. Preliminary findings suggest that the second algorithm provides more reliable detection results.

Keywords: laying hens, feedimg behavior, machine vision technology, chicken postures, deep learning

INTRODUCTION

Eggs are an essential source of protein, widely consumed and regarded as an indispensable commodity in daily life. Enhancing the welfare of laying hens can reduce stress, promote natural behaviors, and strengthen health and immunity, thereby improving both egg production and egg quality. Housing systems for laying hens are generally categorized as conventional cages, enriched cages, floor systems, and free-range systems, each of which may influence hens' ability to express natural behaviors. To better assess welfare outcomes across these environments, computer vision techniques can be applied to detect and analyze chicken behaviors. By examining the relationship between housing systems and natural behavior expression, this approach provides an objective basis for evaluating differences in animal welfare under diverse rearing conditions.

MATERIALS AND METHODS

In this study, a PTZ camera (GK5341C-X30-PE, Global King, Taiwan) was installed in the conventional cage system at Yong Shun Xing Farm in Tainan and in the multi-tier floor system at Quan You Farm in Changhua. The camera captured one image every 120 seconds from 5 to 6 different viewpoints in a recurring cycle, allowing the recording of various natural behaviors of laying hens. The captured images were transmitted to a cloud server, with an original resolution of 2592 × 1944 pixels. Images representing different behaviors were selected from the server folders for annotation using the Computer Vision Annotation Tool (CVAT), as shown in Figures 1 and 2. Two annotation methods were applied—bounding-box annotation and keypoint annotation—to investigate model performance in behavior recognition.For training, two models were employed: YOLOv11l for bounding-box detection and YOLOv11l-pose for keypoint-based recognition. The training images were resized to 640 × 480 pixels. A total of eight chicken keypoints were selected: beak, comb, body center, right knee, right toe center, left knee, left toe center, and tail. This study focused on two behaviors—feeding and drinking. For each behavior and each annotation method, 100 images were prepared for training, validation, and testing, with a split of 78 images for training, 11 for validation, and 11 for testing. The detailed distribution of feeding and drinking images is shown in Table 1.In the first approach, behaviors were detected directly using bounding-box annotation. In the second approach, chicken keypoints were first detected and then analyzed through image-processing methods: when the beak entered a region of interest (e.g., a feeder or waterline), the action was classified as feeding or drinking. Finally, the precision, recall, and F1 score of both recognition approaches were compared and analyzed.

Fig.1 boundingbox annotation

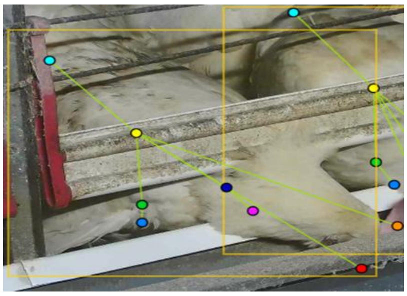

Fig.2 keypoint annotation

Table 1 Dataset Distribution of Feeding and Drinking Behaviors

	Train	Validation	Test
Eating	74	9	9
Drinking	60	7	7

RESULTS & DISCUSSION

The behavior recognition results are shown in Figure 3. In the first method, feeding behavior was detected directly using bounding boxes, whereas in the second method, the beak position was first identified and then evaluated to determine whether it was located within the feeder area before being classified as a feeding event. For the first behavior recognition algorithm, the precision of feeding and drinking detection was 0.875 and 0.800, respectively, with recall values of 0.778 and 0.571, and F1 scores of

0.824 and 0.667. For the second behavior recognition algorithm, the precision of feeding and drinking detection was 0.800 and 0.889, respectively, with recall values of 1.000 and 0.714, and F1 scores of 0.842 and 0.833.The results indicate that the model combining keypoints with regions of interest achieved higher F1 scores for both feeding and drinking behavior recognition compared to the direct bounding-box detection model, suggesting that the second method provides better performance for detecting feeding and drinking behaviors in hens.

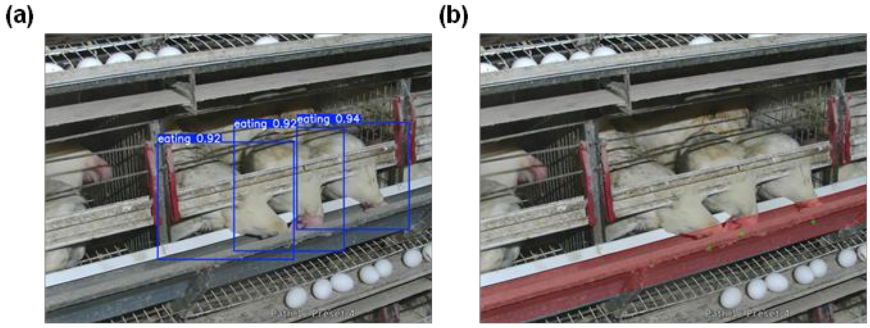

Fig.3 Example results of behavior recognition:
(a) direct bounding-box detection.
(b) pose estimation combined with region-of-interest recognition.

CONCLUSIONS

In this study, two algorithms were developed to recognize feeding and drinking behaviors in laying hens. The findings demonstrated that the keypoint-based method combined with image-processing techniques outperformed the conventional bounding-box approach, achieving higher accuracy in behavior recognition. This highlights the potential of integrating keypoint detection with spatial analysis as an effective strategy for monitoring poultry welfare.Looking forward, future research can leverage the eight defined keypoints in conjunction with advanced image-processing techniques to detect a broader range of natural chicken behaviors. Such applications would provide deeper insights into the relationship between housing systems and behavioral expression, thereby contributing to the evaluation and improvement of laying-hen welfare under different rearing environments.

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