Estimating the feeding time of individual broilers via convolutional neural network and image processing

A. Nasiri[1], A. Amirivojdan[1], Y. Zhao[2] and H. Gan[1,*]
[1]*Department of Biosystems Engineering and Soil Science, University of Tennessee, Knoxville, TN 37996, USA*
[2]*Department of Animal Science, University of Tennessee, Knoxville, TN 37996, USA*
[*]Corresponding author: Hao Gan, hgan1@utk.edu

Abstract

Broilers need to access feed for their daily nutrient. Therefore, feeding behavior is one of broiler chickens' most critical welfare indicators. Since feeding costs remain the biggest cost in raising broilers, understanding feeding behavior can provide important information regarding the usage of poultry resources and insights into farm management. Monitoring poultry behaviors is typically performed based on visual human observation. In spite of the successful applications of this method, its implementation in large poultry farms is time-consuming, laborious, and expensive. Thus, there is a need for automated approaches which can overcome these challenges. On the other hand, there is no research on the feeding time estimation of individual broilers in commercial farms. Consequently, this study aimed to evaluate the feeding time of individual broilers by a Convolutional Neural Network (CNN)-based algorithm. To achieve the goal of this research, videos from a poultry farm were acquired, and 1500 labeled images were used for training the CNN model. Three 1-minute labeled videos were applied to evaluate the proposed algorithm's performance. The algorithm achieved an overall feeding time estimation of each broiler per visit to the feeding pan accuracy of 87.3%. In addition, the obtained results prove that the proposed algorithm can be used as a real-time tool in poultry farms.

Keywords: broiler, feeding time, CNN, image processing

Introduction

The feeding behavior of broilers plays a critical function in the breeding process. Deviation from the daily food consumption pattern is the early disease symptom. Thus, understanding poultry feeding behavior helps evaluate their use of feed resources, improve their health status, and provide vital economic and welfare implications for poultry production. As a result, new techniques are needed to extract the feeding behavior of broilers that are useful in warning against their health status and improving the breeding process.

Several studies have been conducted to investigate the feeding behavior of poultry under the influence of various environmental stimuli, management practices, and breeding systems. These studies often monitor poultry behaviors by manual observation or remotely (Li et al., 2020a). Manual observation is an accurate and simple method to analyze the behavior of small samples and limited behavioral responses. However, increasing the sample size is time-consuming and laborious to monitor multiple behaviors simultaneously. Therefore, it is necessary to develop automated methods to handle large sample sizes and multiple behaviors.

Broilers' behavior in the experimental or commercial farm can be examined by applying automated techniques (e.g., audio analysis, radio-frequency identification (RFID) devices, and image processing) to analyze the health and welfare of the poultry. For example, audio analysis can be applied as a poultry behavior-based early warning system, detecting growth rates, and predicting health conditions. Collecting and analyzing the individual chickens' sounds can distinguish them from a hen. In this respect, detecting which broiler is making the sound, collecting individual sounds on a farm, and ambient noise are significant challenges (Li et al., 2020b). Wireless wearable sensors such as accelerometers and RFID microchips are primarily used to track people's location and activity remotely. The performance of the RFID system depends on the number of broilers and installed antennas. Due to the large number of broilers on commercial farms and the sensor cost in relation to the value of the individual bird, attaching an RFID device to every broiler is currently unrealistic. In addition, RFID systems can be employed for a limited number of broilers due to the time-consuming installing and recycling tags tasks (Li et al., 2020b).

Image processing is an efficient, non-invasive, and cost-effective method for analyzing animal behavior. This technology includes image-capturing systems and various algorithms to recognize the behavior. Kashiha et al. (2013) investigated real-time broiler distribution indicators using image processing methods. These authors reported unusual feeding and drinking behaviors in broilers with 95% accuracy. Also, Nasiri et al. (2022) proposed a computer vision-based system to recognize lameness in broilers. Despite using image-processing techniques to analyze particular poultry behaviors, there needs to be more research on their application in investigating broiler feeding behaviors.

As a specialized image processing version, video monitoring is a low-cost and straightforward method to detect feeding behavior. In this regard, effectively extracting information from surveillance videos is a fundamental problem. For each frame, the first step is to distinguish the broilers from the background. Segmentation threshold based on histogram analysis, Otsu segmentation, maximum entropy segmentation method, and multi-level threshold segmentation are among the methods applied to detect objects from the background (Kashiha et al., 2013; Gou et al., 2014; Gou et al., 2015). Their performance depends on the differentiation between broilers from various background conditions and varying light conditions. Furthermore, it is difficult to distinguish them individually when broilers are huddled together. Each broiler can be detected in the video sequence by creating specific marks on every broiler and using pattern recognition techniques. Therefore, the automatic recognition of broilers through video footages is a fundamental issue, and selecting the appropriate feature is crucial.

The performance of image processing technology can be improved using machine learning methods. Valletta et al. (2017) utilized PCA to extract pheasant egg characteristics and k-means clustering to identify individual pheasant eggs. In this regard, deep learning algorithms, as a type of machine learning method, have been used to identify and classify objects in many applications, including animal behavior recognition. For example, YOLO, R-CNN, and other modern CNNs have been utilized to identify broilers (Li et al., 2021).

Accordingly, the study's objective was to develop an algorithm based on image processing techniques and a deep learning model to recognize broilers' feeding time. The performance of the developed algorithm was validated by comparing the achieved results with the manual observations in the labeled videos.

Materials and methods

Acquisition of broilers' video

Data were collected at a commercial-scale broiler research farm (Tyson Foods, Inc.) with 20,000 birds and a stocking density of 12.2 birds/m^2. A total of 12 surveillance cameras (Dahua Technology USA Inc., Irvine, CA) were installed on the ceiling of the farm (approximately 3 meters above ground) to collect RGB videos at speeds of 13 and 14 frames per second.

Head detection model and data collection

Broilers' feeding behavior can be chewing, biting, or putting the head in the feeder. Since it is difficult to tell whether broilers are chewing or biting, a feeding visit is commonly decided by checking whether the broiler's head is in the feeder. Accordingly, this study defines broiler feeding behavior as broilers placing their heads in the feeder area. In this process, the feeder occupation time by the broiler's head is calculated as feeding time. Therefore, for each frame, it is obligatory to detect the broiler's head as a factor closely related to the detection of feeding behavior. This study used the regression-based algorithm to address the broilers' head detection issue.

You only look once (YOLO), proposed in 2016, formulates the object detection problem as a regression problem. Compared to two-stage detectors, YOLO is speedy. YOLO calculates the region of interest and image classes in one algorithm implementation. First, a neural network is processed on the whole image. Then, the image is divided into different cells, and the objects in each cell are projected (Fang et al., 2019; Wageeh et al., 2021).

The database used in this study was created by selecting sample frames from surveillance video sequences to train and test the network. A more diverse database can be achieved by selecting frames with different postures of broilers (e.g., standing, lying, sitting, and with different lighting conditions). A total of 1,500 images were selected for manual labeling. Then, the head of each broiler was labeled in the text format expected for training the YOLO model. In this article, the transfer learning method was adopted to solve the problem of the insufficient number of samples during the training process. For training the pre-trained YOLO on the COCO dataset, the dataset images were randomly divided into training and test subsets with a ratio of 9:1.

Broiler's head tracking algorithm

YOLO object detection does not treat objects in every video frame the same. In other words, each broiler detected in the video frames is assigned a unique tag/identifier. Thus, it is necessary to use the tracking algorithm regarding its high efficiency in the later stages. In each frame, the broiler tracking algorithm calculates the central point of the bounding box around the broiler's head marked by the trained YOLO model. Then, the algorithm delivers the central point along with the specific identifier to an array that stores the characteristics of the detected broilers in the last 10 frames. In the next step, the Euclidean distance between the coordinates of the central point of the broiler's head identified in the current frame is measured with the coordinates of the center points of the previous frame. The broiler receives its last stored identification if the calculated distance is less than 20 pixels. If the distance is more than 20 pixels, then it means the algorithm is identifying a new broiler that will receive a new identification. This process is done for all the identified chicks in the current frame. Also, the maximum number of missed detection before a tracking label is removed by the algorithm was set to 10 frames.

Algorithm for estimation of the feeding time

The feeding behavior of broiler chickens is related to a particular area where the broiler's head is placed inside the feeder. In this study, there is a need to define the feeding area in the monitoring scene to investigate broilers' feeding time. This area was manually determined in each video. In Figure 1, the blue circle represents the feeding area. The trained YOLO recognizes and marks the broiler head with a bounding box. Furthermore, the tracking algorithm tracks detected heads as long as they are inside the red area (Figure 1). When the center point of the head-labeled bounding box intersects and enters the feeding area (blue circle), feeding behavior may occur. The following index was used to determine whether a specific object covered a location (Eq. 1).

$$Index_{\text{UVVW}} = \frac{\text{XYVZ [U \textbackslash VZW} \cap \text{6VVW!?\^{} ZYVZ}}{\text{6VVW!?\^{} ZYVZ}} \quad (1)$$

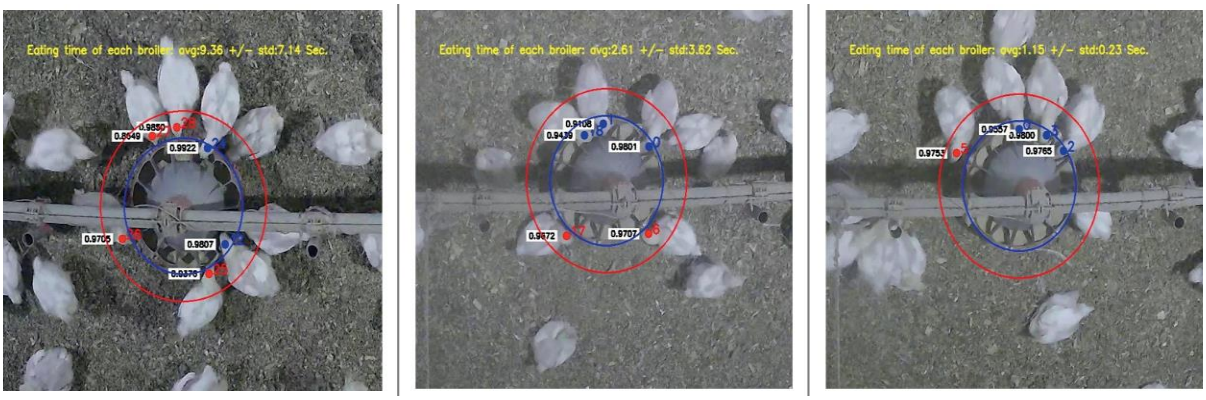

Figure 1: Samples of the developed algorithm result. Broilers' heads with blue dots: feeding behavior; Broilers' heads with red dots: non-feeding behavior.

The $Index_{feed}$ greater than 0 shows that the broiler has the head in the feeder. The feeding time of each broiler can be estimated by counting the number of frames that the broiler's head is inside the feeding area. Accordingly, the feeding behavior can be detected along with the feeding time. Figure 2 shows the workflow of the developed algorithm for feeding time estimation.

The Python language was applied to write the algorithm used in the present research under the Tensorflow deep learning framework. Also, practical training was conducted using a computer with 32-core processors, 64 GB of RAM, and Nvidia Quadro RTX5000 16G graphics card.

Results and discussion

Head detection

In the training step, 192,000 iterations were performed, and after every 100 iterations, the model weights were saved. Figure 3 illustrates the values of mAP (mean Average Precision) and loss function for model training. The error was very high in the first 200 iterations, fluctuated significantly, then decreased. This model did not have any significant performance increase after about 100,000 iterations. The highest performance was attained at iteration 132,996, in which the mAP and loss function values were 0.9320 and 0.0303, respectively. Also, the test data's mAP value was 0.94. The trained model can recognize the broiler's head when the image is captured. The detection result is determined by a bounding box that has a label and a number indicating the likelihood of belonging to this label. Figure 1 presents samples of the detection results.

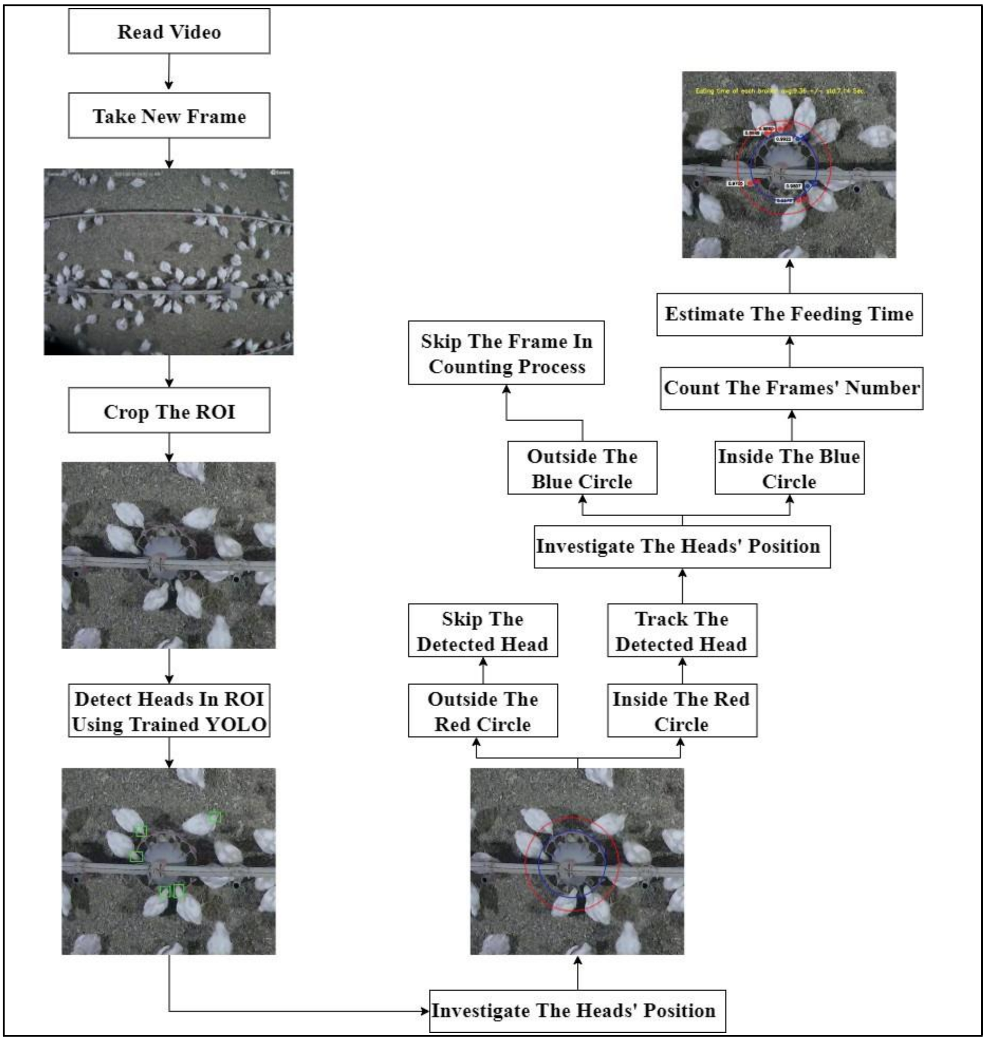

Figure 2: The workflow of the developed algorithm for feeding time estimation.

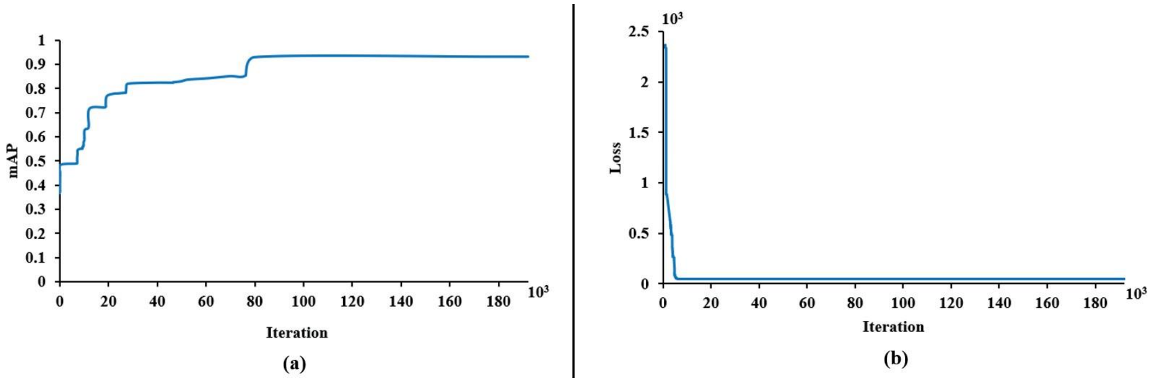

Figure 3: (a) mAP (mean Average Precision) and (b) loss function for each iteration of the training process

Evaluating the developed algorithm

The developed algorithm can continuously judge feeding behavior occurrence in every frame. The algorithm was evaluated by selecting 1-minute videos from 3 different days (consisting of 2280 frames), which were annotated manually and accurately. The number of frames each broiler spends on feeding can be obtained by applying the proposed algorithm to each video frame. Finally, the feeder occupation time is obtained for each broiler, which is equivalent to the feeding time of the same broiler.

Figure 4 presents the results of the diagnosis of feeding behavior for each video. For the first video, the detected heads were two more than the actual number. The same error can be seen in the other videos. This issue occurred due to an error in the detection model or tracking algorithm. It means that either the detection model failed to distinguish a specific head or the tracking algorithm assigned more than one identification to one head. The developed algorithm achieved an overall head detection accuracy of 82.8%. The overall accuracy of the feeding time estimation and feeding time of each broiler per visit to the feeding pan was 97.9% and 87.3%, respectively. The developed algorithm demonstrated that each broiler spends a feeding time of 18.46 seconds per visit to the feeding pan. Some broilers occasionally spend a short feeding time. It is essential to mention that when the head of a specific broiler is inside the feeder, the feeding behavior may not occur, considered during the manual annotation of these videos. Distinguishing the exact feeding time where the broiler's head is inside the feeder is a challenging image processing task. The mentioned point can explain the reason for less than 90% accuracy in estimating feeding time per broiler. The obtained results prove that the developed algorithm can be utilized in commercial poultry farms for effective management as an automatic and non-invasive tool for feeding time estimation.

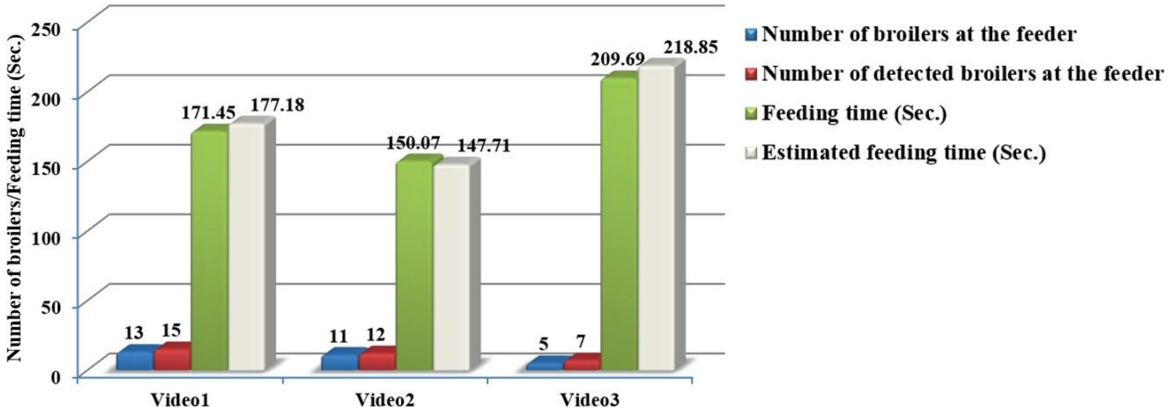

Figure 4: Results of evaluating the developed algorithm for three different 1-minute videos

Several research has been conducted to investigate automated monitoring of animals' feeding behavior, such as pigs (Yang et al., 2018) and broilers (Li et al., 2020a; Li et al., 2021). Nevertheless, most of these studies have been carried out in a research farm and did not include feeding time estimation. Therefore, the highlights of this study include that (1) the proposed algorithm in this study was performed on a commercial farm; (2) the algorithm estimated the feeding time of each broiler per visit to the feeding pan.

Conclusions

The United States is the world's largest producer of broiler chickens, as it produced more than 9 billion broilers in 2021, with a value of $31.5 billion. Broilers should be fed to meet their daily nutritional needs, on the other hand, feeder cost is the most critical expense factor in growing broilers. Therefore, understanding poultry feeding behavior provides vital economic and welfare implications for poultry production. Detection and tracking the broiler's head are essential in judging daily behaviors such as feeding behavior. This study proposed an algorithm based on image processing techniques and a deep learning model to estimate broiler feeding time. The developed algorithm can determine whether feeding behavior occurs for each surveillance video frame. The algorithm achieved an overall feeding time estimation accuracy of 97.9%.

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