Broiler Mobility Assessment Via a Semi-Supervised Deep Learning Model and Neo-Deep Sort Algorithm

M. Jaihuni[1], H. Gan[2], T. Tabler[1], H. Qi[3], M. Prado[1] and Y. Zhao[1,*]
[1]*Department of Animal Science, University of Tennessee, Knoxville, TN 37996, USA*
[2]*Department of Biosystems Engineering, University of Tennessee, Knoxville, TN 37996, USA*
[3]*Department of Electrical Engineering and Computer Science, University of Tennessee, Knoxville, TN 37996, USA*
*Corresponding author: Yang Zhao, yzhao@utk.edu

Abstract

Broiler mobility is a vital welfare indicator which may influence their ability to access feed and water. Classical broiler mobility assessment methods are laborious and cannot provide continuous insights into individual bird's conditions. In this paper, we proposed a semi-supervised Deep Learning (DL) model, YOLOv5, combined with our newly developed variant of the conventional Deep Sort tracking algorithm, Neo-Deep Sort, for individual broiler detection and trajectory tracking, respectively. Initially, 1,650 labeled images from five different days were employed to train the YOLOv5 model. Through the semi-supervised learning (SSL) which significantly reduced the lengthy data labelling process, this narrowly trained model was then used for pseudo-labeling 2,160 images, of which 2,153 (99%) were successfully labeled. Thereafter, the YOLOv5 model was fine-tuned on the newly labeled images. Lastly, the meticulously trained YOLOv5 and the Neo- Deep Sort algorithm were applied to detect and track 28 broilers in two pens and consequently categorized them in terms of hourly and daily moving distances and speeds. As a result of the SSL, the YOLOv5 model's mean Average Precision (mAP) in identifying birds with a 50%-100% confidence increased from 81% to 98%. As compared with the manually measured covered distances of broilers, the combined model provided individual broiler's hourly moved distances with a validation accuracy of about 80%. Eventually, individual and flock level mobilities were quantified while overcoming the occlusion, false and miss detection issues. The vision-based algorithm developed in this study may serve effectively to track indicators critical for broiler production performance and welfare.

Keywords: broiler welfare, mobility, YOLOv5, semi-supervised learning, Neo-DeepSort

Introduction

Welfare plays a commendable role in rendering qualitatively healthy and quantitatively superior poultry productions. Fundamentally, it is a multifaceted phenomenon which demonstrates chickens' physical conditions, living habitat feasibility, and mental situations. In this context, mobility tremendously affects individual bird's welfare level (Gocsik et al., 2017). Impaired or zero locomotion in birds may indicate issues such as insufficient nutrient consumption needed for growth, possible existing pain or stress, lameness, housing constraints, or even mortality. Impaired locomotion has been highly identified in about 15-28% of birds in poultry farms (Knowles et al., 2008).

The traditional Gait Scoring (GS) and Kinematics (GK) methods have been widely applied to assess locomotion and mobility status in individual chickens (Okinda et al., 2020). While the former method needs to be carried out by an expert tasked to observe and determine gait level one chicken at a time, the latter methods utilize statistical and algorithmic approaches to extract locomotion features, like walking ability, sitting, and standing postures, and correlate with the predefined GS levels. As in the works of Periera et al., (2021) and Doorweerd et al., (2021), such features of individual birds are studied and correlated with their predetermined GS levels. Their results are influential in determining major lameness and locomotion problems in individual broilers, though generally due to the welfare management urgencies, it is more effective to provide timely and subjective insights into the overall activities of individual and flock day in and day out. On the other hand, several alternative Artificial Intelligence (AI) and Deep Learning (DL) methods have been proposed to tackle the locomotion problem and provide further information on other activities of chickens. Nasiri et al., (2022) and Naas et al., (2021) have developed very effective pose estimation and speed-based lameness and behavior detection methodologies using DL models. They have achieved high accuracies in correlating lameness GS levels and behavior classifications with broilers skeletal positions and visual analysis. Lin et al., (2018) and Fang et al., (2020) have applied a Convolutional Neural Network (CNN) based DL model to detect individual chickens in a shallow setup; consequently, their movements were calculated manually matching consecutive frames.

The objectives of this study were the utilization of the semi-supervised learning (SSL) for bringing more data into DL model development, the addition of a new algorithm on top of the Deep Sort algorithm and solving the trajectory estimation and activity levels of individual broilers and estimate flock level mobility.

Materials and methods

Experimental design

The experiment was carried out in the Animal Science Department labs located in the Johnson Animal Research and Teaching Unit (JRTU), University of Tennessee Knoxville, USA. It consisted of 28 chickens (Cobb 700), male and female ones mixed with 1:1 ratio, which were reared for a period of 54 days between October 18- December 10, 2021. Day-old chicks were divided into two pens with 12 and 16 birds, respectively. Each pen had a 100 cm x 150 cm pen with a standard camera (Amcrest UltraHD 5MP) mounted at a 3m height overlooking the pen. The cameras recorded broiler movements continuously for 15 minutes per hour for 24 hours.

Semi-supervised learning

With time and human resource constraints in labelling huge datasets, the (SSL) is an influential method in tackling big datasets for DL model development. (Ouali et al., 2020). In this study, firstly, to develop the initial YOLOv5 model, we employed a dataset with 1,650 labelled images extracted from the recordings of 5 random days when the broilers were 7, 17, 26, 36, and 41 days of age. Later, the partially trained model was applied on the next batch of 2,160 unlabeled images extracted from the recordings corresponding to broilers being 4, 18, 30, 44, and 47 days of age. Eventually, the new successfully predicted images were fetched to the partially developed YOLOv5 model for further training.

YOLOv5 DL model

The You-Only-Look-Once version 5 (YOLOv5) is a vastly applied object detection DL model based on computer vision technique, the CNN. The YOLO models are primarily designed to perform object localization and classification in a single-stage regression process. Therefore, it is deemed one of the most effective models for real time applications (Redmon et al., 2016, Wang et al., 2022). We used the mean Average Precision (mAP) YOLOv5 model performance metric (Nepal et al., 2022, Liu et al., 2021).

$$mAP = \sum_{)@\&} {}^{AP(q)}\S_{Q} \qquad (1)$$

Deep sort algorithm

Deep Simple Online and Realtime (Sort) algorithm is a robust algorithm that is convenient for real-time applications thanks to its fast run time speed (Parico et al., 2021). The integration of deep features extracted via CNN model from the detected frames increases the likelihood of tracking objects effectively even when they are located very near or are occluded (Y. Ge et al., 2022, N. Wojke et al., 2017). As a result of consecutive frame association, motion prediction and deep features, the tracking algorithm can attach identification (ID) numbers to each detected object and track them. On the other hand, one problem arises during dense occlusion instances where this algorithm would not be able to associate objects in newer frames.

Neo-deep Sort algorithm

The problem of occlusion instances poses a major hinderance for calculating overall individual broiler mobilities. Hence, here we tried the following algorithm to correlate new and old IDs assigned on detected objects by the Deep Sort algorithm. Essentially, the algorithm would detect when a previously detected ID is lost and consequently it tries to identify when one/more new IDs appear in the Deep Sort algorithm results. It then processes several steps to correlate the new ID with the lost ID or delete those instances which are falsely detected, as shown in Figure 1. If they are located at a distance smaller than threshold distance, set by one step-size of a broiler as calculated in Duggan et al., 2016, then the two IDs are deemed to be the same.

The final model consists of the YOLOv5 model for object detection, Deep Sort tracking algorithm, and the new proposed algorithm. As we got the results after these 3 steps, then the flock level and individual broiler's displacements and their respective speeds were extracted and hence categorized accordingly.

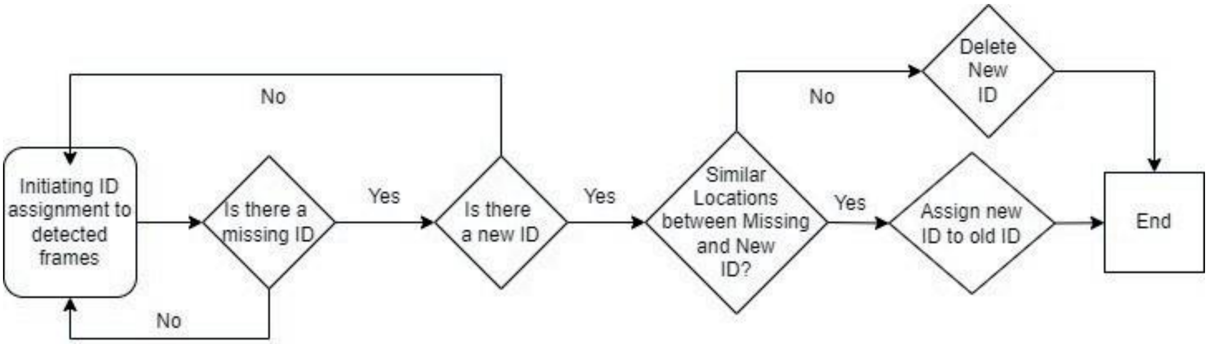

Figure 1: Neo-deep sort algorithm flowchart for tracking individual broilers

Calculating individual broiler and flock level mobilities

The coordinates of all the detected chickens were provided by the model in terms of maximum (x,y) values with the corresponding bounding box width and heights. These values were used to assign a centroid coordinate (x_c,y_c) for each detected frame by the equation (2). The centroid values for consecutive frames were used to get individual displacement values by the respective broiler and hence the total flock displacements. We tried to validate the model's results with respect to baseline manual measurements as well. This might lead us to some degree of calibration of the model that would eradicate the misleading results.

$$(x_c, y_c) = \left(x + \frac{x_{width}}{2}, y + \frac{y_{height}}{2}\right) \quad (2)$$

Results and discussion

The broilers mobility was recorded for 15 minutes per hour daily for 54 days, rendering a total of 1268 recordings. This data was utilized for training and development of the YOLOv5 model through the SSL approach. Eventually, broiler mobility analysis was carried out with the proposed YOLOv5 - Neo-DeepSort model.

Semi-supervised YOLOv5 training

The initial training of the model with the manually labelled images resulted in the validation mAP levels of 81%; it may require more training data to achieve a success rate above 90% with higher confidence levels. Overall, the primary trained YOLOv5 model could be considered effective enough to be employed on the unlabeled dataset to achieve one of our objectives. The primary trained YOLOv5 model was used to predict labels for these images, which successfully predicted broilers in 2153 of them. It can be deduced that, while the SSL does provide highly reliable results by pseudo labeling images, it may also introduce low level of error to the model. This error is deemed negligible as it would not adversely affect final accuracy levels. Afterwards, the newly labelled 2153 images were split into 80:20 sets for training and testing purposes, respectively. As a result of the second training, the YOLOv5 model's predictive capabilities were enhanced. Especially, the mPA level has increased to 98% from the previous value of 81%.

YOLOv5-Neo-DeepSort application

The final model was applied on the video recordings of the broilers from two separate cameras overlooking respective Pen#1 (12 broilers) and Pen#2 (16 broilers). As discussed earlier, the data under study consisted of recordings of when broilers were 11, 18, 24, 30, 36, 41, 47 days old. Therefore, we were able to see the broiler mobility levels at different ages throughout the rearing process. It is worth mentioning that the model was trained by the data from Pen#2 and the resultant trained model was applied on one familiar environment, Pen#2, and a completely new environment, Pen#1.

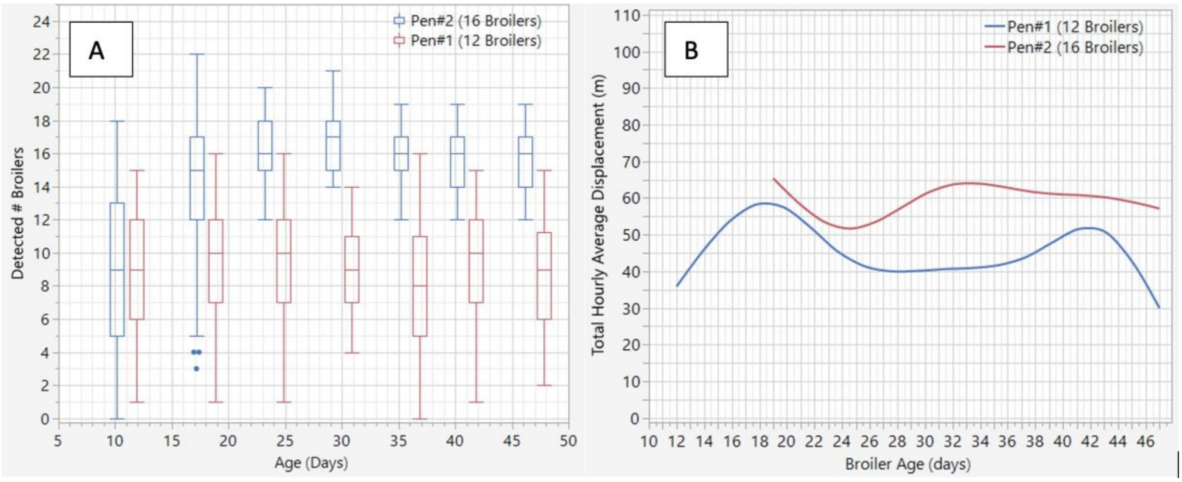

Figure 2: a) Broiler detection results by the final model b) Daily average displacement levels

Broiler detection levels

The general performance of the final model is depicted in the distribution and box-plot graphs in Figure 2a. On average, the model was proportionately, 9/12 and 14/16, almost equally successful in detecting the number of broilers in both pens. But in general, it performed better in Pen#2 over the course of 7 weeks. As seen in Figure 2 boxplots, the model was consistently performing better in detecting broilers in Pen#2 as compared to Pen#1. Although, the model falters in the first of batch of data from Pen#2, but it rendered better results in the consequent datapoints. On the other hand, in the Pen#1the performance is comparatively lesser successful but still reasonably high.

Total displacement of broilers at flock level

The average daily covered distance by all the broilers and the corresponding broiler ages in each pen are demonstrated in Figure 2b. As the broilers grew their weights increased constantly until the saturation point at the end of the second month. But the total displacement level has had a different trend in both pens. As seen in this figure, the average daily displacements are highest when broilers are of age 18 days. Comparatively, Pen#2 has had a higher displacement level as compared to Pen#1. It can be safely pointed out that higher stocking densities, such as in Pen#2, do cause higher levels of mobility.

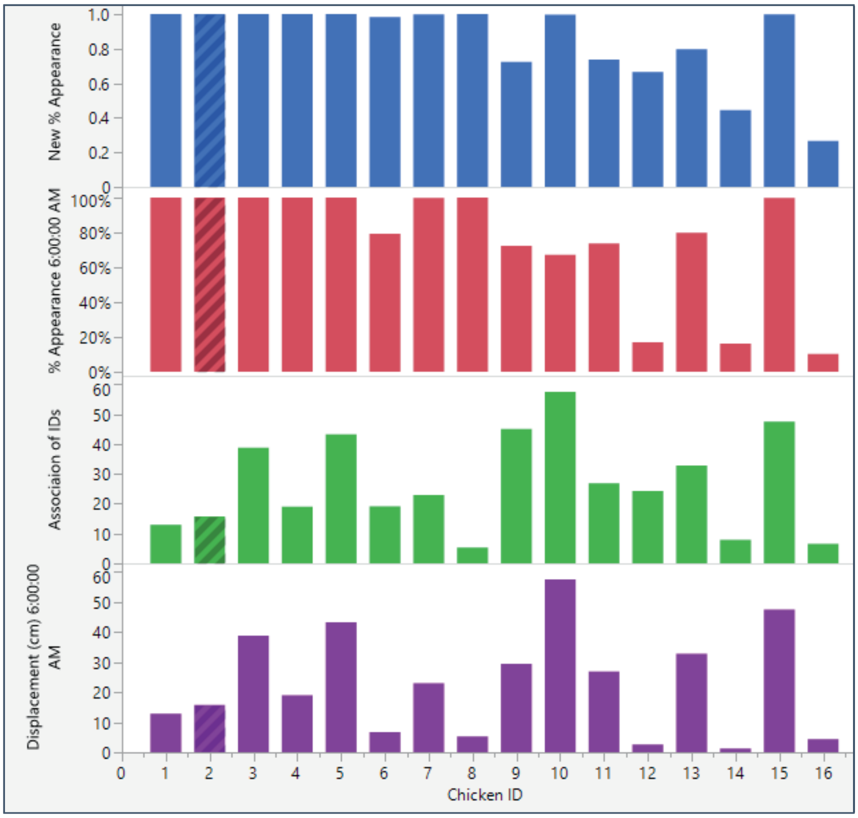

Figure 3: Different IDs' association process

New algorithm application

Figure 3 shows a sample hourly displacement tracking of the birds in a specific day. For example, at 6:00AM, as per preliminary results, most of the broilers have moved moderately but bird #12, 14, and 16 have shown no or very low mobility. But after the algorithm was applied, it was able to associate different broiler instances to give a final picture of the mobility of birds. In this hour in Figure 4b, the ID#6, 9, 10, 12, 14, and 16 were associated with ID#126, 118, 108, 87, 115, and 146, respectively. Henceforth, the final mobility level of the broilers is calculated by adding the individual displacements of the associated IDs. As seen in Figure 4b, the above-mentioned birds' final displacement levels have changed after this process. For example, bird # 6 had displacement of about 10cm, which increased to about 20cm after ID association. As in the case of bird # 14, even after the ID association the resultant mobility level and tracking appearance percentage still falls below 100%. Hence, we can conclude that even after the ID association process, we might not get a very high % of some broiler's appearances. But even a 50% appearance level can give us a statistically sound on how much a broiler is mobile.

Individual broiler mobility categorization

Figure 4 shows hourly displacement levels of different broilers in Pen#2. For instance, at 7:00AM most of the broilers are moving at a moderate to high level, but birds #7, 9, and 13 have shown no or very little mobility. This information is very vital as further investigation on these birds can be carried away accordingly. Consequently, we can see that in the next hour, i.e., 8:00AM, all the birds showed moderate to high mobility levels. Hence, we can conclude the immobility of some birds at 7:00AM, might have not been due to sickness or injury as the birds were normally moving in the subsequent hours. Another explanation could be that chickens establish a peck order, and it may have been that these 3 birds were the more timid birds at the bottom of the peck order and were waiting for the other birds to feed and get a drink before they took their turn. The missing IDs can be due to the inability of the final model as it was not able to detect them successfully. Hence, we can conclude that in some hours, the final models' overall performance might be low. But in general, it can sufficiently provide vital mobility information.

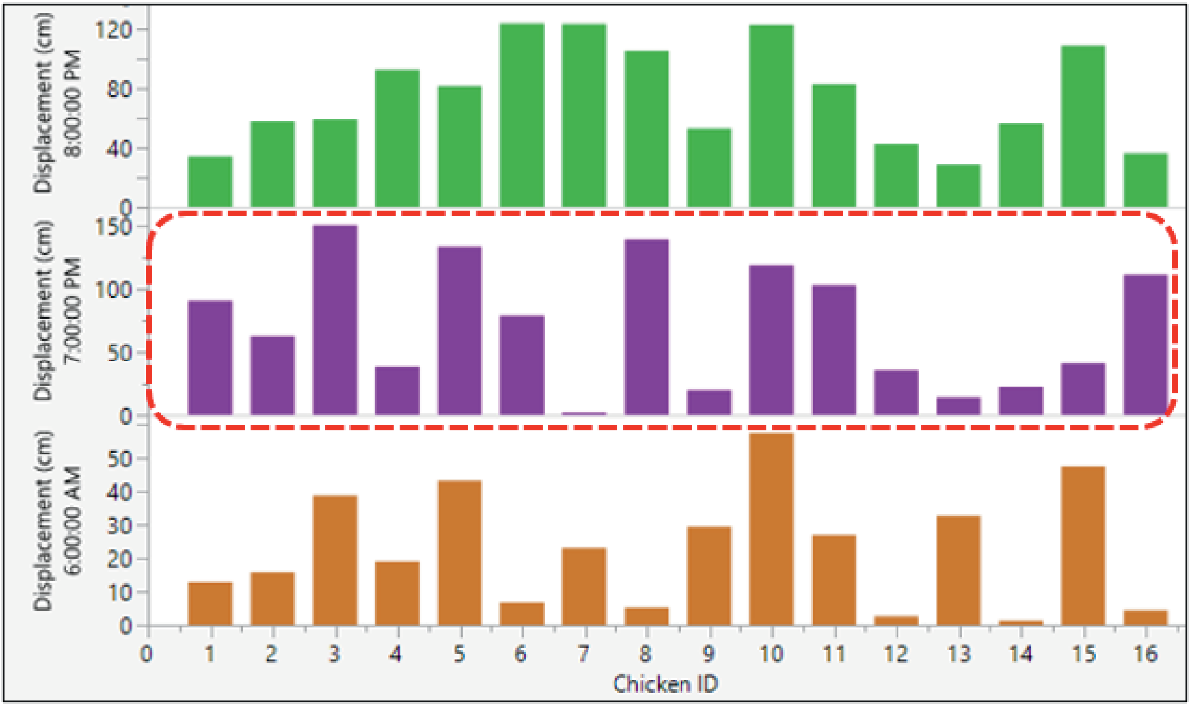

Figure 4: Individual broiler hourly mobility levels

Conclusions

Broilers daily moving and displacement levels significantly impact their health conditions. Hence, lower broiler welfare is detrimental in rendering higher quality meat to the market. In this study, we have proposed a semi-supervised deep learning YOLOv5 model alongside a DeepSort tracking algorithm. Additionally, we have developed a new algorithm that would tackle tracking issues related to bird's occlusion instances that result in tracking information loss. The dataset included hourly videos of 28 broilers in two pens recorded by standard RGB cameras. A total of 7 days' hourly videos corresponding to 7 consecutive weeks were studied. The SSL method paved the way to train a primary YOLOv5 model with 1650 images, which was then utilized for labelling 2160 new images. The final YOLOv5 model was further trained on the new dataset and used to detect broilers in videos recorded by standard RGB cameras. The SSL method helped in increasing the YOLOv5 detection accuracy from 81% to 98%. The DeepSort algorithm was influential in tracking birds, but it had limitation in solving the occlusion problem. Our proposed algorithm lessened this problem to some extent. The final model provided individual broilers hourly displacement levels with an 80% validation accuracy. Henceforth, broilers' individual and flock level displacements and speeds were successfully computed throughout their growth period from day 4 to day 50.

Acknowledgments

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