Tarres, J., Robledillo, D., Piles, M. (2026) Automated tracking of broiler chicken activity with deep learning and object tracking algorithm, *Proceedings 13th World Congress on Genetics Applied to Livestock Production* 23597: https://doi.org/10.31274/wcgalp.23597
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Automated tracking of broiler chicken activity with deep learning and object tracking algorithm

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Introduction

A substantial proportion of the resources consumed by growing animals is devoted to physical activity, which constitutes a key indicator of welfare, health, and production efficiency. Sánchez *et al*. (2022) developed a computer vision system based on artificial intelligence techniques that enables continuous monitoring of animal movement and quantification of their physical activity. The system integrates a deep convolutional neural network for individual identification with the Hungarian algorithm and the Kalman filter to track animals across consecutive frames. Despite the system achieving satisfactory results in short tracking sequences, its overall performance remains limited, indicating that additional training is needed to reliably extract robust physical activity metrics. Once fully optimised, this computer vision system could also be applied to other areas of animal production, such as behavioural analysis, assessment of social interactions within groups, and early detection of outbreaks of disease.
The aim of this research is to adapt this computer vision system to automatically quantify chicken activity through instance segmentation and tracking, and to perform basic behavioural analyses.

Materials & Methods

Algorithms for artificial vision and individualized tracking of chickens. The first requirement for individualized object tracking in video data is an accurate localization method for each target object - in this case, chickens. In computer vision, the task of identifying one or more objects of a specific class in an image is known as instance segmentation. This process assigns every pixel in the image to a predefined class and then groups neighbouring pixels of the same class to form distinct object instances. Instance segmentation thus enables not only the identification and counting of chickens within a frame but also provides the necessary spatial information for tracking individuals across consecutive frames.
One of the most advanced and widely used frameworks for instance segmentation is the MaskR-CNN library (He *et al*., 2018), which builds on deep convolutional neural networks, typically using a ResNet101 backbone coupled with a Feature Pyramid Network to improve multiscale detection. The output of Mask R-CNN is a structured prediction for each detected object, including the segmentation mask, classification label, and the bounding box coordinates enclosing the object.
Effective detection requires training the Mask R-CNN model to recognise chickens under the specific conditions of our videos. Training involves estimating the parameters of the ResNet101 backbone and the region-based detection layers using manually annotated images. During this process, a set of labelled images (training set) is provided to the model, and its parameters are iteratively optimised via backpropagation to minimise detection and segmentation errors. Cross-validation is used to assess generalisation performance and avoid overfitting, ensuring that the model can accurately detect chickens in unseen frames.
Once detected in each frame, chickens were tracked across photograms using the Simple Online and Real-Time Tracking (SORT) library (Bewley *et al*., 2016). SORT combines the Hungarian algorithm for optimal assignment of detections to existing trajectories with a

Kalman filter to predict object motion between frames. This combination provides a computationally efficient, real-time-capable tracking pipeline, enabling continuous identification of individual chickens throughout each video sequence.

Collection of images: training and identification of chickens. Training of the ResNet101-based Mask R-CNN model was performed using images captured with a 2D RGB camera of high 3K resolution (2,880 × 1,620 pixels), mounted on the ceiling of the barn approximately 2 m above the chickens. The camera was positioned to cover an area comprising 12 pens, each measuring 180 × 150 cm and housing 20 Ross broiler chickens. For model training, images were cropped to 1,440 × 1,440 pixels, ensuring each training image contained a single pen.
Images were collected over two production batches between December 2024 and March 2025. Within each batch, image acquisition was performed at 7, 14, 21, and 28 days of age during the fattening period (0–35 days of life). Early-stage images were selected to ensure clear visual separation among birds, whereas later images captured more challenging scenarios where chickens were clustered or partially overlapping, increasing the complexity and realism of the training dataset.
To enrich the dataset and improve model robustness, standard data augmentation techniques were applied, including random rotations, flips, and geometric distortions. These operations artificially increase dataset variability and reduce the need for additional manual annotations. For each training iteration, a subset of annotated images was withheld for validation to evaluate detection and segmentation performance.

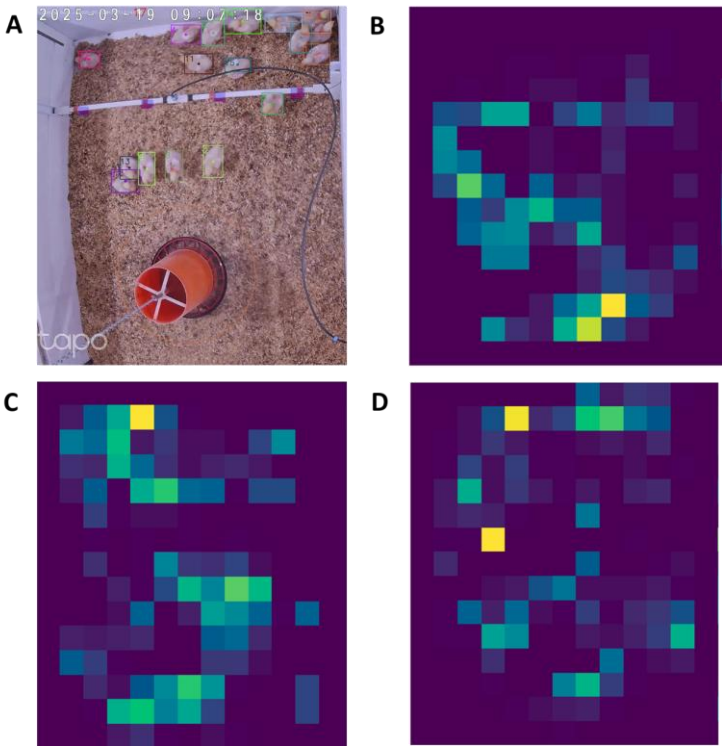

Figure 1. (A) Computer vision images of animals monitored during the growing period and inferred heatmaps 15x13 at different daily time hours: 3am (B), 12pm (C) and 6pm (D).

Upon completion of training with a set of 146 annotated and 138 augmented images, the instance segmentation model achieved a mean Average Precision (mAP) of 0.95 for pixel-level assignment to the chicken class in the validation set of 34 images, indicating high segmentation accuracy and reliable identification of chickens across diverse visual conditions.

Pen average tracking measurements. Once the ResNet101 network was trained, the Mask R-CNN system was applied to a dataset of 288 videos of one-hour in length. To visualise spatial patterns of chicken distribution, heatmaps were generated by aggregating the detected centre positions within predefined spatial grid squares across each one-hour video (Fig. 1). Based on the outputs of the tracking algorithm, several behavioural and activity metrics were derived.
To reduce noise caused by small positional shifts in stationary animals, two correction procedures were applied: (1) displacements shorter than half the average body length (i.e., below a 10-pixel threshold) were filtered out, and (2) positional data were smoothed using Nadaraya–Watson (NW) kernel regression with a bandwidth of 10 (Bierens, 1994).
Animal activity was quantified as the cumulative Euclidean distance between consecutive center positions for each individual. Instantaneous speed and acceleration were computed using positions separated by 25 frames (corresponding to 1 second at the frame rate used). Short, rapid reversals in movement (switchbacks) were identified by comparing the smoothed NW regression trajectory with the raw positional data and calculating the resulting Euclidean deviations, which were subsequently averaged for each animal.
Visits to the feeder and drinker were also quantified. Specific regions of interest (ROIs) corresponding to the feeder and drinker were defined, and a visit was detected when the Intersection over Union (IoU) between the chicken's bounding box and the ROI exceeded 95%. To avoid inflated visit counts, two filters were applied: only visits lasting more than 5 seconds were considered true drinking or feeding events, and consecutive visits separated by less than 10 seconds were merged into a single event.

Results & Discussion

Daily activity patterns exhibited a clear diurnal rhythm, with pronounced morning peaks associated with increased visits to feeders and drinkers, followed by a midday resting period and a secondary rise in activity in the afternoon (Fig. 2).

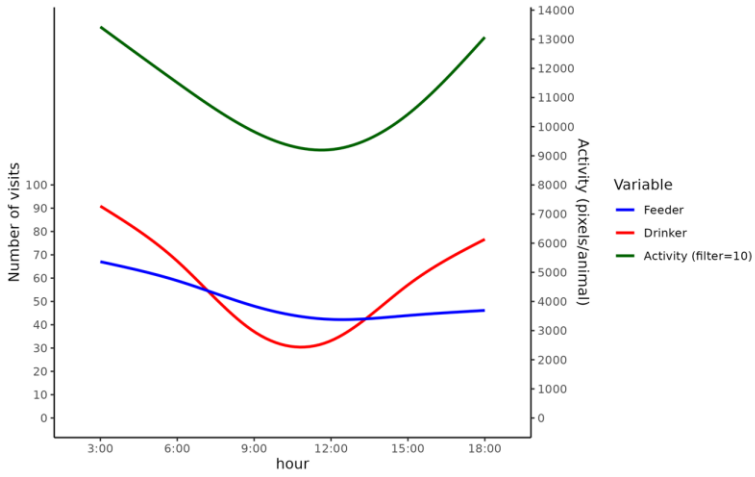

Figure 2. Daily evolution of cumulated activity and feeder and drinker visits per pen

Broilers moved an average of 55.31 metres per hour at day 7 of life. As the birds aged, overall physical activity progressively declined, reaching 37.67 metres per hour at 28 days (Table 1). This total activity reflects numerous short movements which, in early life stages, were generally longer, faster, and more linear. In contrast, older birds displayed a higher length of switchbacks (0.31 cm at 7 days vs. 0.51 cm at 28 days), a pattern that may reflect reduced locomotor efficiency or emerging mobility challenges. The Nadaraya–Watson smoothing method substantially reduced noise in the raw tracking data and produced clearer trajectories for behavioural interpretation (Fig. 3).

Table 1. Differences in distance, speed, acceleration and switchback of the movements with the ageing process using Nadaraya–Watson (NW) regression (bandwidth=10).

Age (days)	Feeder visits	Drinker visits	Distance (m/h*animal)	Switchback (cm)	Speed (cm/s)	Acceleration max. (cm/s2)
7	61.17	35.12	55.31	0.31	1.65	81.14
14	52.83	32.50	52.79	0.34	1.46	73.26
21	36.67	28.83	42.71	0.39	1.02	63.48
28	31.38	25.19	37.67	0.51	0.91	56.25

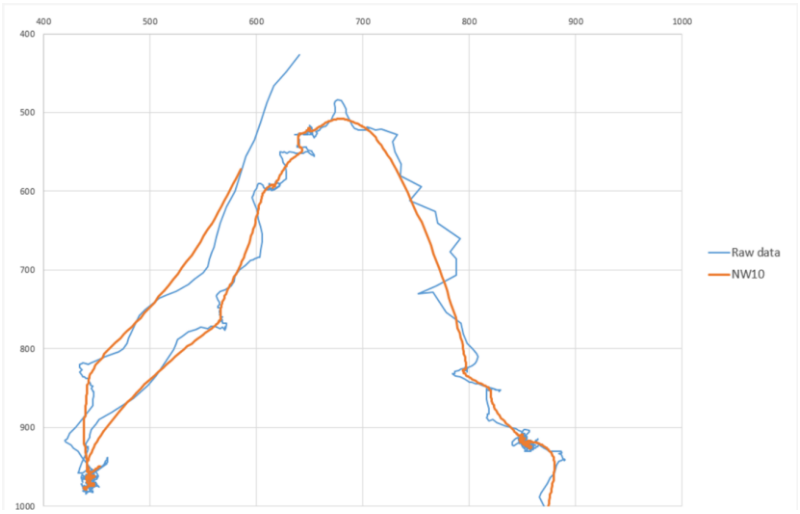

Figure 3. Tracking comparison between raw data and corrections with Nadaraya-Watson regression (bandwidth=10) for one animal.

Conclusions

This automated computer vision approach provides a reliable method for monitoring broiler activity, a critical factor affecting animal welfare, health, and productivity in poultry production. In addition, it facilitates behavioural studies by enabling automatic quantification of activity budgets, including feeding, drinking, and resting patterns, offering a scalable tool for both research and farm management applications.

Acknowledgements

This research has been funded by *track4life* project (PID2024-158124OB-I00).

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