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# Monitoring Harmful Behavior in Cage-Free Laying Hen Houses Using Artificial Intelligence

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***Abstract.***

*Harmful behaviors such as feather pecking, aggression, and cannibalism represent major welfare and economic challenges in cage-free laying hen production systems. Early detection of such behaviors is essential for improving animal welfare and reducing losses, yet continuous monitoring in commercial environments remains difficult. This study investigated the feasibility of using artificial intelligence (AI) and computer vision techniques to monitor harmful behavior in a commercial cage-free laying hen house.*

*Approximately 2,000 hours of video were collected from a commercial facility housing about 10,000 hens. Bird detection was performed using a fine-tuned YOLOv8s neural network, while individual movement tracking was achieved using the ByteTrack algorithm. Because direct detection of pecking behavior proved unreliable under commercial conditions due to crowding, occlusions, and limited visibility, an alternative approach based on group movement patterns was developed. Bird positions, speeds, and movement directions were analyzed to identify unusual collective activity.*

*Analysis of approximately 50 hours of manually reviewed footage identified 228 behavioral events, including fast attacks, slow attacks, fights, curiosity-driven following, aggregation around points of interest, and collective migration events. Fast attacks and fights generated distinctive rapid movement patterns, whereas slow attacks, which may ultimately lead to mortality, were difficult to identify both automatically and through human observation.*

*The results demonstrate that AI-based movement analysis can detect unusual collective activity in commercial hen houses. However, harmful and non-harmful behaviors often produce similar movement patterns, limiting the accuracy of motion-based detection alone. Future systems should combine movement analysis with individual identification, behavioral sequence analysis, and contextual information to enable reliable real-time monitoring of laying hen welfare.*

***Keywords.***
*Laying hens, Artificial intelligence, Computer vision, Behavior recognition, Precision livestock farming.*

## Background and Objectives

Harmful behaviors such as severe feather pecking, aggression, and cannibalism remain among the most important welfare challenges in commercial laying hen production systems (Cronin & Glatz, 2021). While cage-free housing systems allow birds to express a wider range of natural behaviors than conventional cages, they also increase opportunities for social interactions that may escalate into harmful behavior. Environmental enrichment, perches, nest boxes, and other management interventions can reduce aggression and improve welfare, but they do not completely eliminate the problem (Taylor et al., 2023).

Effective prevention of harmful behavior requires continuous monitoring of bird activity. Traditional approaches, including direct observation and RFID-based tracking systems, are labor-intensive, invasive, and difficult to implement in large commercial flocks (Bari et al., 2020). Recent advances in computer vision and artificial intelligence (AI) have enabled automated monitoring of poultry welfare, including behavior classification, activity assessment, feather condition evaluation, and health monitoring (Subedi et al., 2025). However, reliable detection of aggressive behavior under commercial cage-free conditions remains challenging because of high stocking density, bird occlusions, variable lighting, and the complexity of social interactions.

## Materials and Methods

The study was conducted in a commercial cage-free laying hen house in northern Israel containing approximately 10,000 birds. Four high-resolution cameras were installed in the facility, and approximately 2,000 hours of video footage were collected during a 24-day recording period.

Bird detection was performed using a fine-tuned YOLOv8s neural network trained to identify hens, hen heads, and humans. Individual movement tracking was achieved using the ByteTrack tracking-by-detection algorithm (Zhang et al., 2022). The detection model achieved strong performance for whole-bird identification and provided accurate movement information for behavioral analysis.

Instead of direct identification peck detection, the study adopted an alternative approach based on group movement patterns. Bird locations, speeds, directions, and spatial relationships were analyzed to identify unusual activity potentially associated with harmful behavior. This approach is consistent with recent research that uses movement dynamics and behavioral monitoring as indicators of welfare status (Li et al., 2023; Siriani et al., 2023).

## Results

The AI system successfully detected and tracked birds throughout the commercial environment. The YOLOv8s model achieved strong performance for whole-bird detection and human identification, providing reliable movement data for behavioral analysis. Analysis of approximately 50 hours of manually reviewed footage identified 228 behavioral events. Several distinct movement patterns were documented, including:

**Fast attacks** involving rapid pursuit and pecking.

**Slow attacks**, characterized by prolonged harassment of a victim that may eventually result in death.

**Fights** between healthy birds involving rapid movement without substantial displacement.

**Curiosity-driven chasing**, in which birds followed another bird carrying a visible object such as a feather or eggshell.

**Aggregation around points of interest**, such as newly laid eggs.

**Collective movement events**, involving synchronized movement of large groups of birds.

Fast attacks and fights typically lasted only a few seconds and could be detected through rapid coordinated movement. In contrast, slow attacks sometimes continued for several hours and were difficult to identify both automatically and through direct human observation. Two such events leading to mortality were documented.

## Discussion and Conclusions

The results demonstrate the potential of AI-based computer vision systems for monitoring collective activity in commercial cage-free laying hen houses. However, the study also highlights a fundamental challenge: harmful and non-harmful behaviors often generate remarkably similar movement patterns.

For example, curiosity-driven following and aggressive pursuit may both involve multiple birds moving rapidly in the same direction (Fig. 1). Likewise, aggregation around a newly laid egg can resemble the movement signatures associated with fights or attacks. As a result, algorithms based solely on movement information are prone to false-positive detections (Siriani et al., 2023).

**Fig. 1. Example of confusing behavior: curiosity-driven following after a hen with an object in the beak which can be false detected as fast attach.**

Particularly challenging was the detection of slow attacks. Although these events may have the most serious welfare consequences, they involve subtle and prolonged interactions rather than obvious rapid movements. This is consistent with the literature emphasizing the difficulty of identifying the early stages of harmful behavior (Cronin & Glatz, 2021).

The results highlight both the potential and the current limitations of AI-based welfare monitoring systems and provide a foundation for future development of practical real-time monitoring tools for commercial poultry production.

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