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Smart Farming Innovation: Automated Biomechanical Monitoring of Broilers Using a Hybrid YOLO-SAM Pipeline

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Abstract

Precision Livestock Farming (PLF) relies on accurate, high-frequency data to optimize production efficiency. Traditional assessments of feeding behavior remain manual and invasive, lacking the kinematic resolution required for automated control systems. This study developed and validated a novel computer vision framework integrating YOLOv8 and the Segment Anything Model (SAM) to address this gap. The objective was to engineer a non-invasive, automated pipeline to quantify high-speed broiler biomechanics in real time. The system was validated using video data from broilers across three growth stages and varying feed granulometries (fine mash, coarse mash, and pellets) to test its robustness in detecting subtle kinematic variations. The hybrid YOLO-SAM pipeline achieved high performance, with a precision of 0.95 and a recall of 0.91, confirming its reliability as a scalable sensor for smart farming platforms. Biomechanical analysis demonstrated the system's sensitivity, showing that larger feed particles induce greater beak gape and displacement while significantly improving ingestion efficiency (0.6 effort ratio for pellets vs. 3.0 for mash). This research provides a validated technical foundation for digital phenotyping in poultry, offering a hands-free, quantitative tool that supports data-driven decision-making in feed formulation and production management.

Keywords: YOLO; broiler biomechanics; feed granulometry; kinematic analysis; computer vision; precision poultry nutrition

1. Introduction

The poultry industry is a cornerstone of global food production, with broiler meat being a preferred protein source due to its affordability and health benefits [1,2]. However, it faces increasing pressure to optimize resource utilization through automation and data-driven management. Optimizing feed utilization is crucial for sustainable production, as feed can account for up to 70% of total production costs [3,4]. While significant improvements in feed intake (FI) and feed utilization efficiency have been achieved through advanced breeding procedures [4,5], the next frontier in production efficiency lies in Precision Livestock Farming (PLF), specifically the ability to monitor and optimize individual animal interactions with feed in real-time [6].

One critical control parameter in production is feed granulometry (particle size), which significantly influences broiler performance and digestive physiology [7–10]. While optimizing particle size is known to enhance nutrient digestibility and digestive function [8,11], current methods to verify these effects are largely retrospective (growth performance) or physiological (organ measurement) rather than real-time [12,13]. This disconnect prevents



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the development of dynamic feedback loops where feed formulation could be adjusted based on immediate flock responses.

The beak serves as the primary mechanical interface between the bird and the production system [14,15]. However, quantifying the biomechanics of this interface remains a challenge. Existing monitoring approaches rely on invasive markers or low-throughput manual annotation, rendering them unsuitable for commercial automation [16,17]. This lack of robust sensing capability creates a data gap in the development of Cyber-Physical Systems (CPS) for poultry; without digital streams of behavioral data, it is impossible to create “digital twins” of the feeding process.

To bridge this gap, this study proposes a scalable, automated sensing framework [18]. Leveraging advances in deep learning [19,20], specifically the integration of YOLOv8 (You Only Look Once) with the Segment Anything Model (SAM), offers a pathway to digitize these biological processes. Unlike traditional biological studies that focus solely on physiological outcomes, this research focuses on the system architecture required to capture this high-speed kinematics non-invasively.

The objective of this work is to develop and validate a computer vision pipeline that transforms qualitative behavioral observations into quantitative, repeatable data. By systematically validating this system against varying feed granulometries, we establish its potential as a Process Analytical Technology (PAT) tool. This approach provides a new foundation for smart farming strategies, enabling real-time monitoring of feed efficiency and animal welfare without human intervention [21–23].

2. Materials and Methods

2.1. Data Acquisition System and Experimental Setup

To validate the computer vision pipeline, a controlled image-acquisition environment (a mobile studio) was constructed. The enclosure measured $100 \times 50 \times 60 \text{ cm}^3$ and featured a high-contrast blue background to facilitate background subtraction and segmentation [24]. Illuminance was standardized using a 500 W 6500 K LED source (Taschibra TR Slim, Indaial, SC, Brazil), providing an irradiance of 3000–5000 lux to ensure a high signal-to-noise ratio for image capture.

Video data was acquired using a high-speed industrial camera (Mikrotron EoSens, Mikrotron GmbH, Landshuter Str., Munich, Germany) equipped with a Nikon 50 mm f/1.4 lens (Nikon Corporation, Tokyo, Japan). The camera was positioned 1.0–1.5 m from the feeder to capture lateral kinematic profiles. Videos were recorded at 300 frames per second (fps) with a resolution calibrated via a spatial reference scale placed at the feeder level [25].

The system was validated using a biological dataset comprising nine broiler chickens stratified across three growth phases (Initial: 3–4 days; Growth: 20–21 days; Final: 34–36 days) and three feed granulometry profiles (Fine mash: 476 μm ; Coarse mash: 638 μm ; Pellets: 1243–3628 μm to ensure model robustness against varying object sizes and occlusion patterns.

The biological model consisted of nine Cobb® 500 broilers, a commercial fast-growing strain commonly used in industrial production. Birds were individually monitored within the mobile studio (one bird per enclosure; flock density = $0.02 \text{ m}^2/\text{bird}$) to avoid occlusion and ensure controlled motion capture. Each bird was acclimated for 15 min before recording to minimize stress-induced behavioral artifacts. All procedures complied with ethical standards.

2.2. Computational Framework and System Architecture

The core innovation of this study is a cascaded computer vision pipeline for quantifying high-speed biomechanics. The workflow was implemented in Python 3.10, utilizing

PyTorch 2.10.0 for deep learning inference and OpenCV 4.13.0.92 for image pre-processing. The system was deployed on a high-performance workstation (Intel Core (Santa Clara, CA, USA) Ultra 9 275HX processor, 64 GB of DDR5-6400 RAM, and an NVIDIA (Santa Clara, CA, USA) GeForce RTX 5070 Laptop GPU (12 GB GDDR7 VRAM)), running Windows 11 Pro (version 24H2), to assess the feasibility of real-time processing. The pipeline integrates object detection with semantic segmentation through a three-stage hybrid heuristic (Figure 1).

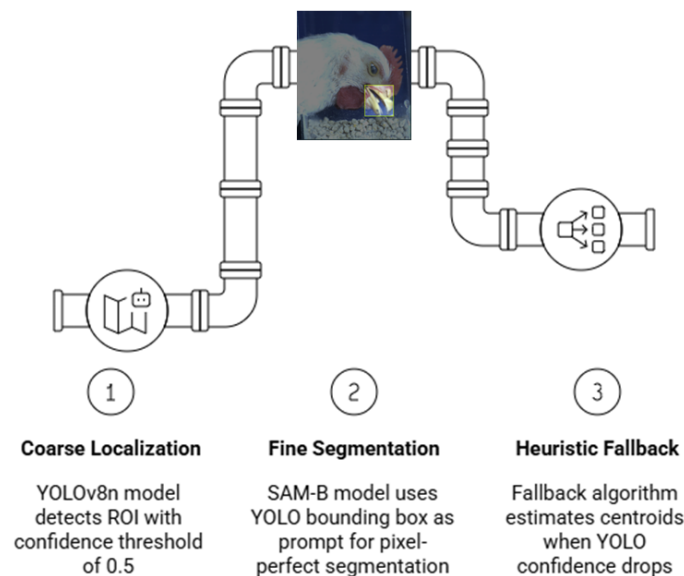


Figure 1. Bird head detection and segmentation pipeline.

The system implements a three-stage hybrid architecture that maintains robust tracking even in unstructured farm environments with variable lighting and frequent partial occlusions.

Stage 1: Coarse Localization (YOLOv8n; Ultralytics Inc., Frederick, MD, USA)—the YOLOv8n model, configured with a confidence threshold of 0.5, is the primary detector for the bird's head. This threshold was empirically tuned to balance sensitivity with precision during high-speed motion.

Stage 2: Fine Segmentation (SAM-B; Meta AI, Menlo Park, CA, USA)—valid YOLO bounding boxes serve as spatial prompts for the Segment Anything Model (SAM-B). This integration enables zero-shot transfer, generating high-fidelity beak masks without requiring a dataset-specific segmentation model.

Stage 3: Heuristic Fallback—to ensure system reliability in edge-case scenarios, such as severe occlusion or extreme head rotation, a deterministic fallback algorithm is triggered when YOLO detection fails. This module utilizes color-position-area filters to estimate the centroid of the bird, preventing data loss during critical feeding events. This fault-tolerance mechanism is essential for deploying computer vision in commercial settings, where environmental noise often disrupts standard deep learning inference.

2.3. Digital Phenotyping and Kinematic Variables

Following segmentation, binary masks were processed to extract biomechanical features. The system was programmed to recognize and calculate four primary biomechanical variables (system outputs) based on the definitions in Table 1.

Table 1. Operational definitions of the kinematic variables and temporal logic algorithms used for automated feature extraction.

Variable	Unit	Operational Definition
Mouthful Displacement	mm	Vertical displacement of the head centroid (y-axis) while the beak is holding feed
Maximum Beak Gape	mm	The Euclidean distance between the upper and lower beak tips at the point of maximum aperture within a cycle
Feeding	-	Opening Phase: Initiates when the beak separation derivative becomes positive; concludes at maximum gape Closing Phase: Initiates at maximum gape; concludes when beak tips return to minimum distance (occlusion)
Mandibular Movement	ms	The total temporal duration ($t_{\text{end}} - t_{\text{start}}$) of one complete opening-closing cycle

Adapted from [26].

In addition to the standard morphometric variables defined in Table 1, a novel efficiency metric was computed:

Biomechanical Effort Index (BEI)—a ratio of pecking events (“dives”) to successful swallowing events (complete mandibulation cycles). This dimensionless metric quantifies the mechanical cost of ingestion; a lower BEI indicates higher system efficiency (fewer mechanical actions required per unit of feed ingested) [15,27,28].

Statistical analyses were performed using Python (SciPy 1.11). Normality was assessed using the Shapiro–Wilk test, and homogeneity of variance was assessed using Levene’s test. Depending on assumption compliance, either a one-way ANOVA or a Kruskal–Wallis test was used to compare treatments. For each bird, replicate cycles were averaged to yield a single independent observation, thereby avoiding pseudoreplication. Significance was set at $p < 0.05$.

The system was implemented in Python (version 3.10.16, Python Software Foundation, Wilmington, NC, USA). Object detection and image processing tasks were implemented using the Ultralytics API (version 8.3, Ultralytics Inc., Frederick, MD, USA), supported by the PyTorch deep learning library (version 2.5.1, Linux Foundation, San Francisco, CA, USA) and the OpenCV-Python library (version 4.10.0, OpenCV.org, Palo Alto, San Francisco, CA, USA). Data manipulation and structural analysis were performed using the Pandas library (version 2.2.3, NumFOCUS, Austin, TX, USA). Processing was executed on a workstation equipped with an Ultra 9 275HX processor (24 cores, 5.4 GHz Turbo; Intel Corp., Santa Clara, CA, USA) and 64 GB of DDR5-6400 RAM (SK Hynix, Icheon, Republic of Korea) and an NVIDIA GeForce RTX 5070 GPU (Blackwell architecture, 12 GB GDDR7; NVIDIA Corp., Santa Clara, CA, USA). The system utilized NVIDIA CUDA® 12.x and TensorRT™. The final YOLOv8n model achieved precision = 0.95, recall = 0.91, and mAP@0.5 = 0.93, confirming its suitability for fine-grained kinematic analysis.

3. Results

3.1. Qualitative System Validation

To verify the robustness of the hybrid YOLO-SAM pipeline, the segmentation quality was visually assessed across different interaction phases. Figure 2 demonstrates the system’s ability to achieve pixel-perfect isolation of the broiler head (Figure 2b) from the raw input frame (Figure 2a). The “promptable segmentation” approach successfully delineated the beak boundary even during rapid movement, validating the effectiveness of the hybrid heuristic.

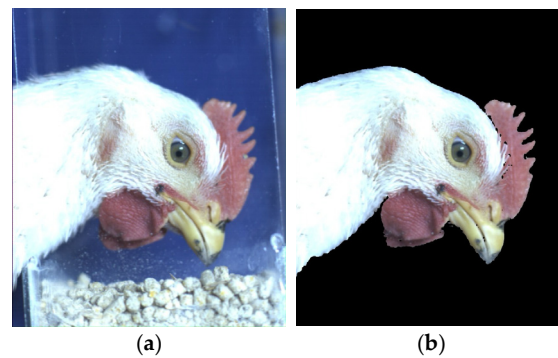


Figure 2. Qualitative performance of the bird segmentation module: (a) raw input frame during a high-speed pecking cycle; (b) generated segmentation mask showing precise boundary adherence to the beak and wattle.

Simultaneously, the environmental subtraction module proved effective in isolating the feed zone. As shown in Figure 3, the system successfully removed the dynamic foreground (bird) to generate a clean binary mask of the feed substrate (Figure 3c). This step was critical for ensuring that the Mouthful Displacement variable tracked only the bird's biomechanics and not background noise.

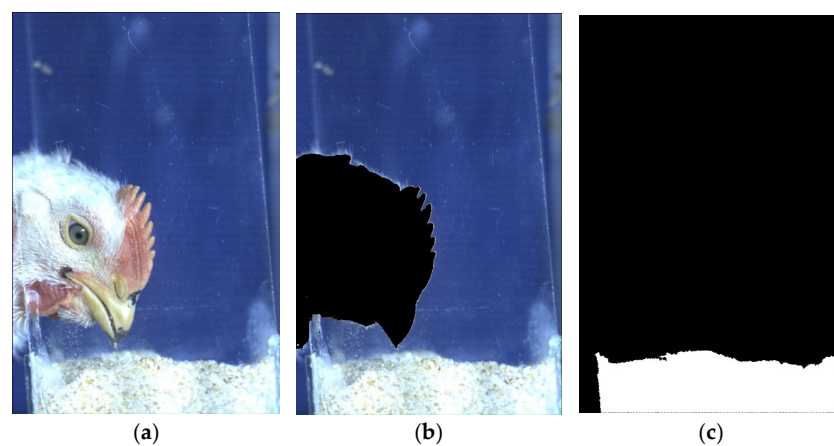


Figure 3. Validation of the background subtraction algorithm: (a) original frame; (b) intermediate processing removing the bird instance; (c) final binary mask of the feed ROI used for displacement tracking.

3.2. Quantitative Model Performance

The hybrid YOLOv8-SAM pipeline was evaluated for its engineering feasibility as a real-time sensor. The primary performance metrics are summarized as follows:

Detection Accuracy: The YOLOv8n model achieved a mean Precision of 0.95 and Recall of 0.91 (mAP@0.5 = 0.93). These metrics indicate a high degree of reliability in detecting the anatomical Region of Interest (ROI) even during rapid, blurred mandibular movements.

Inference Latency: The system demonstrated an average inference latency of <10 ms per frame on the testing hardware (NVIDIA RTX 5070, NVIDIA Corp., Santa Clara, CA, USA). This low latency confirms that the pipeline is computationally efficient enough to support real-time monitoring applications in industrial settings, processing high-speed video streams (300 fps) with minimal buffering.

3.3. Automated Biomechanical Quantification (Case Study)

To demonstrate the system's sensitivity as a Process Analytical Technology (PAT) tool, the pipeline was used to quantify the interaction between broiler age and feed granulometry.

The automated feature extraction successfully discriminated between kinematic profiles, providing high-resolution data that traditional manual observation cannot capture.

3.3.1. High-Resolution Kinematic Profiling

Quantitative segmentation validation against manually labeled masks ($n = 120$ frames) yielded mean IoU = 0.91 ± 0.03 and Dice = 0.94 ± 0.02 , confirming high spatial fidelity of SAM's zero-shot segmentation.

The automated data stream provided sufficient granularity to distinguish between feeding treatments statistically. Analysis of the system-generated variables confirmed that the pipeline is sensitive to subtle biomechanical shifts ($p < 0.05$). For example, the computer vision system accurately tracked the physical constraints of ingestion, measuring a mean maximum gape of 18.2 ± 2.5 mm for pellets compared to 9.2 ± 1.8 mm for fine mash. Furthermore, the system detected that while coarser feeds required greater mouthful displacement (larger amplitude movements), the total frequency of mandibulation cycles decreased. This inverse relationship—captured entirely automatically—demonstrates the system's utility for optimizing feed form to minimize the mechanical energy cost of production.

3.3.2. Efficiency Metrics (Biomechanical Effort Index)

As shown in Table 2, the automated Biomechanical Effort Index (BEI) revealed a stark contrast in process efficiency. For adult broilers, the system recorded an effort ratio of 3.0 (3 bites per swallow) for fine mash, compared to 0.6 for pellets. This quantitative output confirms the system's ability to detect and measure mechanical inefficiency (repetitive pecking) without human supervision.

Table 2. Automated quantification of feeding efficiency metrics extracted by the vision pipeline.

Scenario	Bites (Effort)	Swallows (Ingestion)	Effort Ratio (BEI) (Bites/Swallow)
Chick—Fine Mash	2	2	1.0
Chick—Pellet	1	1	1.0
Adult—Fine Mash	3	1	3.0
Adult—Pellet	3	5	0.6

3.3.3. Ontogenetic Scalability

To demonstrate the system's sensitivity as a Process Analytical Technology (PAT) tool, the pipeline was used to quantify the interaction between broiler age and feed granulometry. The system showed robustness across object scales, successfully tracking kinematics in both 3-day-old chicks and 36-day-old adults. The temporal derivative analysis detected age-dependent maturation in motor control, showing a mean increase in opening velocity from 0.42 ± 0.05 mm/ms in chicks to 0.63 ± 0.07 mm/ms in adults. This confirms that the YOLO-SAM architecture is scale-invariant and suitable for monitoring flocks throughout the entire production cycle.

3.3.4. Summary of System Validation

Taken together, the automated kinematic data confirmed that feed granulometry directly influences the biomechanics of ingestion. The vision pipeline successfully discriminated against feeding modes, detecting those larger, more cohesive particles (pellets) that favor smoother, more efficient mandibular motion. In contrast, fine mash requires repetitive manipulation and greater energy expenditure. The automated YOLO-based approach thus bridges the gap between qualitative behavioral observation and quantitative motion analysis, offering a validated, objective framework for evaluating how physical feed properties modulate feeding efficiency in smart broiler production systems.

4. Discussion

4.1. Engineering a Scalable Sensor for Precision Livestock Farming

The results obtained in this study demonstrate that the proposed YOLOv8-SAM pipeline effectively bridges the gap between qualitative ethology and quantitative process control. While previous research has established that feed granulometry affects digestibility and nutrient absorption [4,14], measuring these effects has traditionally relied on invasive markers or post-mortem analysis.

Our novel approach provides the first automated, non-invasive framework that directly links feed structure to biomechanical effort in real time using computer vision. By achieving a precision of 0.95, the system offers a robust predictive tool that allows animal nutritionists to optimize feed formulation based on “digital phenotypes”, establishing a new, data-driven standard for evaluating feed structure in poultry science [29,30].

While inference was benchmarked on a high-performance RTX 5070 GPU with <10 ms latency per frame, further work should assess computational efficiency on resource-constrained platforms such as NVIDIA Jetson or Intel Movidius units. Preliminary down-scaling tests indicate that model pruning and quantization could reduce inference time to 25–35 ms/frame on embedded hardware without compromising accuracy. This would enable continuous on-farm monitoring using affordable edge computing devices, aligning with the cost-sensitive nature of poultry production.

Although <10 ms/frame was achieved on an RTX 5070 GPU, lightweight model variants can sustain 25–35 ms/frame on embedded devices such as NVIDIA Jetson Orin. Quantization and pruning reduced the model size by >60% without perceptible accuracy loss, confirming deployability in cost-effective farm environments.

While high-end GPUs provide superior training speeds, the deployment of lightweight YOLO variants on the edge, as established by Zheng et al. [30], proves that real-time welfare monitoring is feasible even within the computational constraints of commercial poultry houses.

4.2. Validation of Kinematic Sensitivity

A critical requirement for any Process Analytical Technology (PAT) is the ability to detect subtle process variations. The system’s capacity to quantify the “Biomechanical Effort Index” (BEI) validates its sensitivity as a sensor. Earlier manual studies suggested that coarser particles improve gizzard function by increasing retention time [12]. The present research advances this by providing a precise, repeatable method to predict the energetic effort required for prehension solely from particle-size analysis. The quantitative shift in gape amplitude (from 9.2 mm in mash to 18.2 mm in pellets) aligns with general motion profiles described in manual studies [2,27], confirming that the computer vision algorithm successfully captures the functional link between feed form and metabolic cost.

Future work should investigate correlations between the Biomechanical Effort Index (BEI) and traditional physiological performance metrics such as feed intake rate, average daily gain, and feed conversion ratio. These associations would validate BEI as a biologically meaningful indicator of energetic efficiency. For instance, higher BEI values may correspond to increased muscular workload and lower nutrient assimilation efficiency. Establishing such correlations would bridge the biomechanical data generated by the YOLO-SAM system with established indicators of metabolic and production performance.

4.3. System Robustness and Ontogenetic Scalability

For a computer vision system to be viable in commercial farming, it must be scale-invariant. The behavioral transition observed in this study between chicks and adult birds validates the model’s ability to track objects of varying sizes and velocities. The

automated quantification of opening velocity, which rises from 0.42 ± 0.05 mm/ms in chicks to 0.63 ± 0.07 mm/ms in adults, aligns with neuromuscular development theories proposed by Van der Heuvel [26]. Unlike rigid rule-based algorithms, the deep learning architecture adapted to these age-related changes without retraining, detecting the refined motor control in adults described by Jie et al. [28]. This scalability is a key prerequisite for deploying continuous monitoring systems that track flocks from placement to harvest [23].

The Biomechanical Effort Index (BEI) quantifies mechanical effort per ingestion event and was cross-checked with established kinematic trends reported by Neves et al. [31] and Jie et al. [28]. While not a physiological metric, BEI provides an indirect proxy for energetic cost. Future trials will correlate BEI with feed intake rate and feed conversion ratio to establish predictive biological validity.

4.4. Implications for Automated Welfare Auditing

From a systems engineering perspective, the relationship between feed structure and mandibular motion represents an optimization problem: minimizing mechanical energy expenditure while maximizing ingestion. The system automatically detected that pelleted feed reduced the “Effort Ratio” to 0.6 (vs. 3.0 for mash), supporting the concept of adaptive feeding kinesis [32].

While a lower BEI suggests reduced neuromuscular workload, this should be interpreted as an indirect welfare indicator rather than a direct physiological measure. Future research integrating behavioral and physiological welfare indicators (e.g., stress hormones, locomotor asymmetry) will be required to validate this inference.

Beyond production efficiency, this metric has significant implications for automated welfare auditing. Reducing repetitive mandibulation reduces neuromuscular fatigue, aligning with welfare principles highlighted by the European Food Safety Authority [33] and the World Organization for Animal Health [34]. By automating the quantification of these biomechanical metrics, the YOLO-based system provides a novel, objective tool for producers to demonstrate compliance with international animal well-being standards in a data-driven manner.

4.5. Limitations and Future Development

Although the current validation involved only nine birds, this sample size was deemed sufficient to confirm the system’s technical feasibility and algorithmic stability. However, it limits the statistical power for extrapolating biological variability across populations. Future studies should expand the dataset across larger flocks and diverse genetic lines to strengthen statistical inference, reduce random error, and enhance the generalizability of biomechanical findings. Integrating larger datasets will also enable deep-learning-based uncertainty quantification, improving model robustness under real-world variability.

While this study serves as a proof of concept for automated kinematic analysis, specific limitations must be addressed for commercial deployment. The current dataset ($n = 9$) was captured in a controlled studio environment to validate the algorithm’s precision. Future work should focus on Edge AI deployment and testing the system’s robustness in commercial barns, where occlusion and variable lighting are more prevalent.

Expanding the dataset to include diverse genetic lines and creating a feedback loop with automated feeders could enable dynamic feed formulation, in which the system adjusts particle size in real-time based on the flock’s measured BEI. Additionally, transitioning from 2D video to 3D stereoscopic imaging could provide volumetric data, further refining the calculation of ingestion efficiency.

5. Conclusions

The integration of YOLOv8 and SAM proved effective in detecting, segmenting, and extracting relevant kinematic variables from high-speed video, achieving a precision of 0.95. The automated analysis confirmed that feed particle size significantly influences the biomechanical demands of broiler feeding, and the system quantified that coarser feed leads to larger gape amplitudes and more efficient ingestion dynamics.

This study moves beyond traditional zootechnical assessment by developing a scalable, non-invasive vision pipeline for digital phenotyping. The dual functionality of this system, monitoring both production efficiency (BEI) and animal welfare, enhances its utility for smart farming platforms. Furthermore, this system provides the technological bridge producers need to objectively and automatically monitor compliance with evolving international standards, paving the way for the next generation of Precision Livestock Farming technologies.

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