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AI-Based Monitoring for Enhanced Poultry Flock Management

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Abstract: The exponential growth of global poultry production highlights the critical need for efficient flock management, particularly in accurately counting chickens to optimize operations and minimize economic losses. This study advances the application of artificial intelligence (AI) in agriculture by developing and validating an AI-driven automated poultry flock management system using the YOLOv8 object detection model. The scientific objective was to address challenges such as occlusions, lighting variability, and high-density flock conditions, thereby contributing to the broader understanding of computer vision applications in agricultural environments. The practical objective was to create a scalable and reliable system for automated monitoring and decision-making, optimizing resource utilization and improving poultry management efficiency. The prototype achieved high precision (93.1%) and recall (93.0%), demonstrating its reliability across diverse conditions. Comparative analysis with prior models, including YOLOv5, highlights YOLOv8's superior accuracy and robustness, underscoring its potential for real-world applications. This research successfully achieves its objectives by delivering a system that enhances poultry management practices and lays a strong foundation for future innovations in agricultural automation.

Keywords: poultry monitoring; computer vision; artificial intelligence; flock management; agriculture automation

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1. Introduction

Chicken meat, one of the world's most consumed proteins, contributes billions of euros annually to the global economy [1,2]. In 2024, global poultry production is projected to reach approximately 138.75 million metric tons, marking a significant increase from 115 million metric tons in 2016. This growth aligns with a broader trend in agriculture, where poultry has surpassed other meat types in production volume [3], as illustrated in Figure 1.

As demand increases, poultry farms face mounting pressure to optimize operations, particularly in flock management, to prevent economic losses caused by miscounts and resource mismanagement. Accurate chicken counts are crucial, as errors in these data can have significant economic and operational repercussions.

First, inaccurate counts can lead to financial losses. Misrecording the number of chickens may result in incorrect inventory decisions, such as over-purchasing or under-purchasing essential supplies like feed or medication. These errors not only increase operational costs but also disrupt financial planning and undermine long-term profitability.

Second, data inaccuracies directly affect productivity. Precise counts are essential for adjusting feed quantities to match the actual flock size, thereby preventing both overfeeding and underfeeding. Such discrepancies can negatively impact flock growth and operational efficiency, hindering the optimization of production processes.

Lastly, imprecise data compromises decision-making quality. Poor data can lead to suboptimal choices in genetic selection or management practices, reducing competitiveness and productivity. This cascading effect diminishes operational efficiency and the quality of the final product.

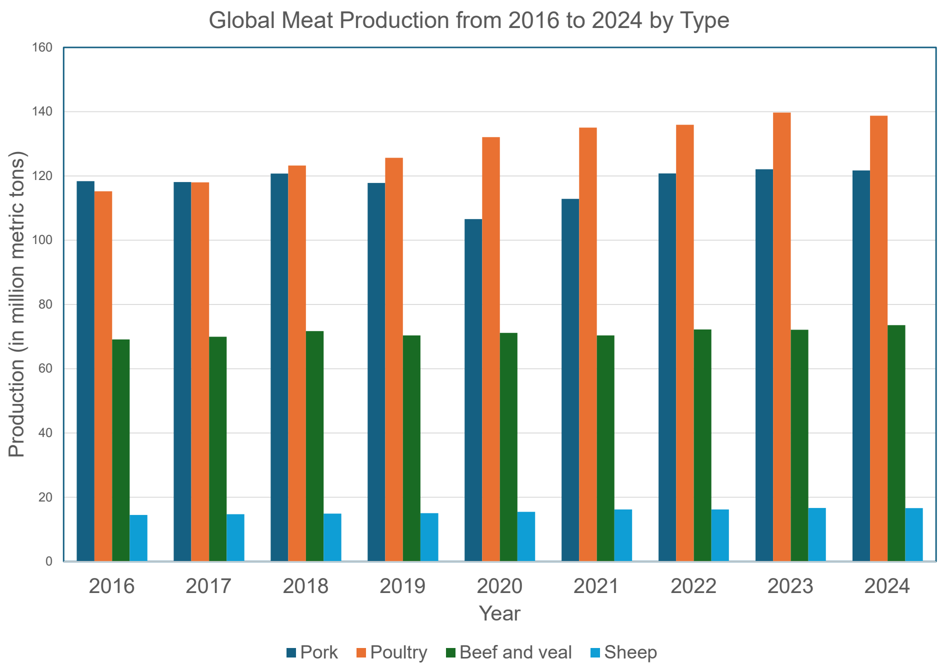


Figure 1. Production of meat worldwide from 2016 to 2024 by type (in million metric tons). The data for 2024 are estimated as of the writing of this article. Source: FAO; OECD; 2016 to 2023.

Such inaccuracies can lead to suboptimal decisions in flock management, affecting various aspects of poultry farming, from the health and welfare of chickens to the overall productivity of the farm [4]. Inaccurate counts may result in overstocking or understocking resources, mismanagement of feed and water, and inefficiencies in disease control, all of which directly impact the profitability and sustainability of poultry operations.

To address these challenges, the poultry industry is increasingly embracing technological innovations to enhance operational efficiency. Among these, artificial intelligence (AI) has emerged as a transformative tool with the potential to revolutionize poultry farming. Specifically, advanced object detection algorithms within AI offer a promising solution for automating the chicken counting process. These algorithms can process real-time data from cameras installed in poultry houses, accurately identifying and counting individual chickens with remarkable precision [5,6].

As AI technology continues to evolve, its role in poultry farming is expected to expand, aligning with broader agricultural trends toward automation and data-driven decision-making [7]. This shift not only boosts productivity and improves chicken welfare but also enables the industry to meet the growing global demand for chicken meat while maintaining high standards of efficiency and sustainability.

Considering the above, the research problem is identified as the lack of an effective method for accurately counting poultry, which hinders efficient management during their stay in breeding sheds. This issue stems from the limitations of existing manual and semi-automatic methods, which are incapable of effectively processing the large volumes of data generated in such environments or adapting to the specific conditions of chicken coops.

To address this gap, this research aims to develop a computer vision-based counting system capable of providing reliable and automated estimations of the poultry population. This approach not only addresses the challenges of accurate counting but also facilitates the management and processing of large data volumes within the unique environmental conditions of breeding sheds.

Accordingly, the research question guiding this study is the following: How can computer vision be leveraged to enable reliable and efficient chicken counting while managing the data volume and environmental challenges of breeding sheds?

This study contributes to advancements in poultry management by developing an AI-driven system for precise chicken counting using the YOLOv8 model. The model is trained on custom datasets of poultry images captured in real-world environments. It effectively addresses challenges like occlusions (instances where chickens overlap or obstruct one another) and dense flock conditions (highly crowded environments).

The primary aim of this research is to develop and validate an AI-driven automated poultry flock management system utilizing the YOLOv8 model. The scientific objective is to advance the application of artificial intelligence in poultry management by overcoming critical challenges like occlusions, lighting variability, and dense flock conditions, thereby enriching the broader understanding of computer vision techniques in complex agricultural settings. Concurrently, the practical objective is to design a reliable and scalable system that enhances flock management by enabling automated monitoring and data-driven decision-making in real-world farming environments. This system aims to reduce economic losses, improve resource efficiency, and promote sustainable agricultural practices. By achieving these objectives, it offers a scalable and impactful solution to enhance the accuracy and efficiency of poultry management while addressing broader challenges in agriculture.

The remainder of this article is organized as follows: Section 2 provides a review of relevant background information. Section 3 outlines the methodology employed in this study. Section 4 presents and analyzes the experimental results. Section 5 discusses the practical implications and limitations of the research. Finally, Section 6 concludes with a summary of the key findings.

2. Background

Object detection in poultry farming, particularly in chicken detection, has seen significant advancements with the emergence of deep learning models. These models have demonstrated exceptional capabilities in identifying and classifying objects within images and video streams, paving the way for more accurate and scalable systems for real-time monitoring in commercial poultry farms.

2.1. AI's Impact on Agriculture

The application of artificial intelligence (AI) in agriculture has revolutionized traditional farming practices by increasing efficiency, promoting sustainability through optimized resource use, and enhancing responsiveness to global food demands. AI technologies—including machine learning, computer vision, and robotics—have introduced precision agriculture, a data-driven approach that improves resource allocation and decision-making. This transformation aligns with the broader trend of "Agriculture 4.0" [8,9], which integrates digital tools, data analytics, and automation to advance agricultural productivity and sustainability.

Recent advancements in spatial–spectral image classification, which combines spatial and spectral data for improved image analysis, further illustrate AI's potential in agricultural monitoring. For example, reference [10] employed a spatial–spectral classification technique with edge-preserving chromaticity mapping, significantly enhancing the accuracy of remotely sensed imagery. This method integrates colorimetric edge preservation with principal component analysis to incorporate spatial context, demonstrating that maintaining spatial details improves classification reliability. In agriculture, such techniques enable precision monitoring by enhancing image clarity and data accuracy, directly aligning with the objectives of AI-based poultry monitoring models. By optimizing image quality and data precision, these methods support AI-driven agricultural solutions, particularly in high-density settings where accurate detection is critical.

AI-driven systems have also transformed crop management through the integration of data from IoT sensors (for soil and climate monitoring), drones (for aerial crop health assessments), and satellite imagery (for large-scale field analysis). These technologies provide real-time, actionable insights into crop health, soil conditions, and climate variables, enabling precision interventions in irrigation, pest control, and fertilization. Such interventions significantly reduce chemical use and minimize environmental impacts [11,12]. Furthermore, automating tasks like crop health monitoring and disease detection with advanced machine learning models has improved both efficiency and accuracy compared to traditional methods, such as manual inspections and visual assessments [13,14].

In livestock management, AI applications—particularly deep learning models for behavior and health monitoring—have significantly enhanced the ability to track animal welfare. Convolutional neural networks (CNNs), known for their accuracy in image-based analysis, facilitate the early detection of health issues by monitoring animal behavior, enabling proactive management practices [12,13]. Additionally, AI's predictive capabilities in yield forecasting and climate adaptability optimize resource use, reduce waste, and improve yield predictions, helping agriculture adapt more effectively to climate variability and resource constraints [9,14].

Beyond productivity gains, advancements in AI address broader social and ethical considerations, including data privacy, labor impacts, and the promotion of fair and unbiased AI applications. By fostering resource-efficient and environmentally friendly farming practices, AI technologies help farmers transition to sustainable methods, a critical step toward meeting the growing global food demand driven by population growth [9,14]. However, challenges remain in areas such as data quality—ensuring datasets are diverse and representative—model interpretability for transparent decision-making, and ethical considerations. Addressing these challenges is essential for the continued development and responsible deployment of AI in agriculture [11,12].

2.2. Classical Machine Learning Approaches

Early efforts in chicken detection primarily relied on traditional computer vision techniques, which utilized handcrafted features and classical machine learning classifiers. Techniques such as HOG (Histogram of Oriented Gradients) [15] were widely employed to detect objects by identifying edges and shapes, while SIFT (Scale-Invariant Feature Transform) and SURF (Speeded-Up Robust Features) [16,17] were used for feature extraction to identify distinct characteristics of chickens in images.

To classify objects within images, these feature descriptors were often combined with machine learning algorithms such as Random Forests and SVM (Support Vector Machines) [18]. While these approaches achieved some success in controlled environments, they proved less effective in real-world poultry farming conditions. Factors such as environmental variability, inconsistent lighting, and occlusions significantly hindered the accuracy and robustness of these methods, limiting their applicability for real-time or large-scale monitoring in dynamic settings like poultry farms.

2.3. Deep Learning Algorithms for Chicken Detection

Deep learning has revolutionized object detection, offering more accurate and scalable solutions for applications like chicken detection. Convolutional Neural Networks (CNNs) [19] form the backbone of many object detection tasks by efficiently processing image data. In the context of chicken detection, CNN-based architectures such as VGGNet [20] and ResNet [21] have been employed to extract hierarchical features from images, enabling the effective distinction of chickens from their surroundings. The deep feature extraction layers in these models allow for greater detail and precision in detection.

Building on the capabilities of CNNs, Region-Based Convolutional Neural Networks (R-CNNs) [22] introduced a significant advancement by dividing images into regions and applying CNNs to each region for object identification. Faster R-CNN [23], a widely adopted variant, strikes a balance between speed and accuracy, making it particularly effective for detecting chickens. Its architecture incorporates a Region Proposal Network (RPN) that generates candidate regions for object detection, enabling the identification of multiple chickens within a single image. The integration of region-based methods with deep learning has demonstrated high efficacy in poultry monitoring, addressing the complexities of dense and dynamic farm environments.

2.4. YOLO (You Only Look Once) Models

The YOLO (You Only Look Once) family of object detectors is among the most widely adopted models for chicken detection, valued for its real-time performance and high accuracy. Since the introduction of YOLO [24], successive versions, from YOLOv3 to the latest YOLOv8, have been successfully applied in poultry monitoring. These models offer significant speed advantages, making them particularly well-suited for real-time detection in dynamic environments such as commercial chicken farms.

YOLOv8, the latest iteration, introduces architectural refinements that enhance both detection accuracy and processing efficiency. One of YOLO's key strengths lies in its ability to detect multiple chickens within a single image by processing the entire image in one pass. This capability is critical for monitoring large flocks efficiently, enabling the identification of abnormal behaviors, health issues, or other anomalies in real time. By combining speed, accuracy, and scalability, YOLO models provide an effective solution for poultry monitoring in modern agricultural settings.

2.5. Single Shot Detectors (SSDs) and Transformer-Based Models

Single Shot Detectors (SSDs) [25] represent another deep learning framework employed in chicken detection. Known for their speed and lightweight architecture, SSD models are particularly advantageous in environments with limited computational resources. The combination of SSD with MobileNet is especially well-suited for deployment on mobile and embedded devices, providing a cost-effective solution for implementing detection systems in resource-constrained farm settings.

Recent advancements in transformer-based models have also begun to influence object detection tasks, including chicken detection. Detection Transformers (DETR) [26], for instance, eliminate the need for traditional region proposals and anchors. Instead, they leverage transformers to model relationships across different parts of an image, offering a more efficient and robust approach to object detection. DETR has demonstrated promise in addressing the challenges of chicken detection, particularly in complex farm environments characterized by occlusions and visual clutter. These capabilities make transformer-based models a valuable addition to the toolkit for poultry monitoring in modern agricultural systems.

2.6. Recent Advances in AI-Driven Poultry Monitoring

The application of artificial intelligence in poultry management has progressed rapidly, with innovative approaches enhancing precision, efficiency, and sustainability. Recent studies highlight AI's transformative potential across various aspects of poultry farming, including flock monitoring, environmental control, and disease detection.

Reference [13] investigated the integration of YOLOv8 with DeepSORT for tracking behaviors in cage-free hens, achieving a high multi-object tracking accuracy (MOTA) of 94%. This system effectively detects critical behavioral patterns, such as smothering and piling, which are vital indicators of poultry welfare in high-density environments. Such real-time behavioral monitoring enables early intervention, ultimately improving animal welfare and operational efficiency in commercial poultry farms.

Another notable advancement is the Poultry-Edge-AI-IoT system developed in [27], which combines edge computing and IoT technologies to monitor environmental factors within poultry houses. This system uses a gated recurrent unit (E-GRU) deep learning model to predict hazardous levels of gases like ammonia (NH_3) and carbon dioxide (CO_2), as well as temperature fluctuations. By providing real-time predictions of harmful conditions, the system safeguards poultry health and enhances productivity through precise environmental control.

AI has also proven valuable in disease detection. Reference [28] developed a diagnostic system leveraging the EfficientNetB7 model to identify poultry diseases via fecal image analysis. Their system achieves a classification accuracy of 97.07% in distinguishing healthy and diseased conditions. This non-invasive diagnostic tool facilitates early detection of diseases, mitigating the risk of outbreaks, reducing economic losses, and ensuring better flock health management.

These advancements underscore AI's critical role in automating poultry monitoring processes. By providing accurate, real-time data on flock behavior, environmental conditions, and health indicators, AI-driven systems enhance decision-making, support early interventions, and promote sustainable poultry farming practices.

2.7. Challenges in Chicken Detection

Chicken detection presents several challenges, with one of the most significant being occlusion, where chickens overlap or cluster together, making it difficult to detect each individual accurately. Variations in chicken size, pose, and orientation further complicate detection tasks, as these factors affect the accuracy and reliability of detection systems.

Understanding chicken poses is particularly critical for behavioral analysis. The Multi-Chicken Pose (MCP) estimation system introduced in [29] provides a novel solution by leveraging transfer learning to estimate multiple chicken poses simultaneously. This approach addresses occlusion-related challenges while offering valuable insights into poultry welfare monitoring, thus enhancing the effectiveness of behavior analysis in dynamic farm environments.

To further mitigate detection challenges, techniques such as Non-Maximum Suppression (NMS) [30] have been employed to reduce multiple detections of the same object, ensuring more accurate identification. Additionally, Focal Loss [31] has been introduced to address class imbalance by focusing on harder-to-detect chickens, improving the overall robustness of detection systems.

Multi-scale feature detection, implemented in networks like Faster R-CNN and YOLOv5, enhances the ability to handle objects of varying sizes, a common issue in dynamic farm environments. These advancements collectively contribute to overcoming the inherent challenges of chicken detection, enabling more precise monitoring and analysis in poultry management systems.

2.8. Datasets for Chicken Detection

Publicly available datasets specifically tailored for chicken detection remain scarce. However, general-purpose datasets such as COCO [32] and ImageNet [33] are frequently used to pre-train models, which can then be fine-tuned on chicken-specific data to improve performance.

In most cases, researchers and commercial entities working in poultry detection rely on custom datasets, often generated from real-world farm environments. These datasets typically consist of images or real-time video captured from cameras installed in poultry houses. Farm-generated data provide a valuable resource for training detection models as they reflect the variability and challenges of actual farm conditions. To prepare these datasets, chickens are annotated with bounding boxes or other labels, creating the ground truth data required for supervised learning. Such custom datasets are critical for addressing the unique challenges of chicken detection, including occlusion, variations in size and pose, and diverse environmental conditions.

2.9. Practical Applications and Systems

Real-time poultry monitoring systems are increasingly leveraging YOLO-based models for practical applications in commercial farming. These systems are utilized to count chickens, track their movement, and monitor behavior, enabling the detection of abnormal patterns that may indicate health issues or welfare concerns.

The integration of Internet of Things (IoT) devices [34] has further enhanced the deployment of these detection models on edge devices, such as Raspberry Pi or NVIDIA Jetson. This advancement facilitates real-time detection and analysis directly at the farm level, reducing latency and dependence on centralized processing. By combining AI-based detection with IoT-enabled edge computing, these systems offer scalable, cost-effective solutions that improve operational efficiency and promote proactive poultry management.

2.10. Background Conclusions

Advancements in machine learning, particularly through deep learning models such as YOLO and Faster R-CNN, have revolutionized real-time monitoring in poultry farming. These models have proven effective in managing large flocks, tracking movement, and identifying health issues, thereby addressing key challenges in modern poultry management.

The next frontier in chicken detection involves the integration of object detection with behavioral analysis and IoT technologies. By combining these innovations, future systems can enable more intelligent, automated monitoring solutions that not only improve operational efficiency but also enhance animal welfare and sustainability in commercial poultry farming.

3. Materials and Methods

3.1. Dataset Creation

The dataset creation process was critical to ensuring the accuracy and robustness of the chicken counting model. This process involved several key stages designed to capture the entire chicken production cycle, from the chick stage to slaughter age.

The chickens used in this study were commercial broiler chickens, selected for their rapid growth and high feed conversion efficiency, characteristics that make them ideal for research focused on optimizing poultry management systems. Observations spanned the complete production cycle, from 1-week-old (beginning of the experiment) to 6-week-old (end of the experiment), providing comprehensive coverage of growth stages. At the start of the study, the birds' average weight was approximately 150 g, increasing to 2.54 kg by the final week.

The stage of growth significantly influenced detection accuracy. During the early stages (1–3 weeks), smaller bird size and higher activity levels posed challenges, such as increased movement and overlapping of birds. However, these issues were effectively managed by the YOLOv8 model, demonstrating its robustness in complex environments. In contrast, during later stages (4–6 weeks), larger bird size and reduced activity improved detection accuracy. These variations were incorporated into the model training process to ensure consistent performance across all growth stages. By accounting for these developmental differences, the model was able to achieve reliable results throughout the production cycle.

3.1.1. Chicken Coop Setup

A chicken coop was constructed with dimensions of 6 m in length and 4 m in width, providing a controlled environment suitable for housing up to 100 chickens. This setup replicated real poultry production conditions, enabling continuous observation of the chickens' growth and development. Figure 2 shows the exterior view of the chicken coop used during the experiment.

The pen provided a total usable area of 24 m^2. By the final week of the study, the average weight of the 100 chickens housed in the coop was 2.54 kg per bird, resulting in a stocking density of 10.58 kg/m^2. This density is significantly below the regulatory maximum of 33 kg/m^2, as outlined in animal welfare standards [35], ensuring compliance and optimal conditions for poultry welfare throughout the experiment.

Figure 2. Exterior view of the chicken coop.

The coop featured rice husk bedding, selected for its excellent absorbent properties. To maintain cleanliness and prevent moisture buildup, the bedding was replaced weekly. Environmental conditions inside the coop were carefully controlled, with temperatures maintained between 22 and 32 °C and adequate ventilation to ensure a comfortable atmosphere. Lighting was provided for 12 h through natural daylight, supplemented with 8 h of artificial lighting daily, in accordance with poultry welfare standards.

3.1.2. Data Collection and Processing

Surveillance cameras were installed on the ceiling of the chicken coop to capture images and continuously record the production process. The cameras used were IP ColorVu Lite models, selected for their ability to capture high-resolution images (1920 × 1080 pixels) even in low-light conditions. Figure 3 illustrates the camera arrangement, with four cameras positioned to provide full coverage of the coop. Each camera was oriented to point directly at the ground, as marked within the red box in Figure 3.

During real-time video processing, occasional errors were observed, where frames appeared incomplete or corrupted, displaying as black or gray. These issues were traced to data transfer errors or packet loss during transmission. To address packet loss and data errors, the system included functionality to automatically detect faulty frames. When a faulty frame was identified, the system executed a frame reading restart to resume sequence processing without significantly disrupting analysis continuity. This mechanism minimized the loss of critical data and ensured high-quality input for the deep learning algorithm during the detection and counting of chickens.

Data collection was conducted weekly over six weeks, capturing images at different growth stages to comprehensively observe the chickens' development. A total of 1300 images were extracted from the recorded videos and manually annotated. Boundaries around each chicken in the images were marked to create ground truth labels for training the detection model. Figure 4 shows an example of an annotated image from the dataset.

Figure 3. Layout of the four cameras used for data collection during the experiment. Cameras used for capturing the data are marked with a red box. The white device in the center of the ceiling was not used for this project.

Figure 4. Image from the dataset captured using the surveillance camera.

The maximum number of animals the algorithm can process in a single image depends on factors such as image resolution and bird density. High-resolution images provide greater pixel detail for more accurate individual identification but require increased computational power. Conversely, when bird density is high, contour overlap becomes a challenge, complicating accurate detection. As shown in Figure 4, overlapping contours can make individual segmentation more difficult, particularly when chickens are in close proximity.

To balance detection accuracy and computational efficiency, images were processed at a resolution of 640 × 480 pixels, as recommended by the Ultralytics YOLOv8 documentation. At this resolution, the algorithm can detect up to 300 birds in a single image, defined by the `max_det` parameter in the YOLOv8 framework. For this study, `max_det=300` was selected to ensure efficient processing under experimental conditions, as the coop housed only 100 birds. This setup provided sufficient accuracy while optimizing computational requirements.

3.1.3. Dataset Division and Validation

To train the YOLOv8 model, the labeled dataset was divided into 70% for training and 30% for validation. This split was chosen to ensure that the model could be thoroughly evaluated during training while maintaining a sufficient amount of data for training the model. The validation set played a critical role in fine-tuning the model's hyperparameters and providing an objective measure of its performance, helping to prevent overfitting.

A separate test set was not employed during this phase, as the format recommended by Ultralytics emphasizes the use of training and validation datasets for iterative evaluation. The validation set consisted of data not seen by the model during training, ensuring unbiased evaluation and enabling necessary adjustments throughout the training process.

The dataset organization adhered to the directory structure recommended in the Ultralytics YOLO guidelines. A main directory was created with subdirectories `train` and `val`, each containing two folders: `images` and `labels`. For example, training images were stored in `train/images/`, while their corresponding label files, containing bounding box coordinates and class annotations, were stored in `train/labels/`.

A YAML configuration file was used to define the dataset structure, including paths to the `train` and `val` directories and the number of classes in the dataset. This configuration file was essential to ensuring that YOLOv8 could correctly interpret and process the training and validation data, allowing for efficient and accurate training of the model.

3.2. Model Training

The training of the YOLOv8 model was an iterative process designed to optimize its parameters for accurate chicken detection in the dataset. The following steps outline the key components of the training process.

3.2.1. Dataset Annotation

To prepare the dataset for model training, a manual annotation process was conducted using the labelImg annotation tool [36] widely used in the computer vision community. Each chicken in the images was marked with a bounding box. Special attention was given to ensure accuracy and consistency in annotations, especially in cases with occlusions or lighting variations. To maintain label quality, the following were implemented:

- Cross-validation: Annotations were reviewed by at least two annotators to minimize errors.
- Clear guidelines: Specific criteria were established for annotation, including marking only visible chickens and accurately outlining their body boundaries.

3.2.2. YOLOv8 Model Architecture

The YOLOv8 architecture was selected for its superior speed and accuracy. This state-of-the-art model was trained on the annotated dataset to optimize its parameters for precise chicken detection and localization. Its design integrates anchor-free detection and enhanced feature extraction, making it particularly suitable for complex environments like poultry houses.

3.2.3. Why YOLOv8? A Comparison with SSD and Faster R-CNN

The choice of YOLOv8 over SSD and Faster R-CNN was based on several factors.

- Real-time detection and speed: YOLOv8 operates as a one-stage detector, where classification and bounding box regression are performed simultaneously. This results in faster inference compared to two-stage models like Faster R-CNN [37,38], making it ideal for real-time applications in poultry management.
- High accuracy in complex environments: YOLOv8 achieves superior precision and recall (often exceeding 90%) in crowded settings, such as poultry houses [37,38]. In contrast, SSD sacrifices some accuracy for speed [39], and Faster R-CNN, while accurate, is slower and less suited for real-time tasks [39].

- Anchor-free detection: YOLOv8's anchor-free approach simplifies detection and improves accuracy in environments with overlapping objects such as clustered chickens [37]. This feature is particularly advantageous over SSD, which can struggle in such scenarios [39].
- Efficiency in training and data processing: YOLOv8 reduces the complexity of object detection pipelines by eliminating the need for region proposal networks seen in Faster R-CNN. This makes it more efficient in handling large datasets [40].

3.2.4. Hyperparameter Selection

The training process involved careful selection of hyperparameters to balance computational efficiency and model accuracy. Table 1 provides a summary of the key hyperparameters used during training.

- Model and Data Configuration: The model `yolov8m.pt` was used, alongside a custom dataset configuration file (`dataset.yaml`) specifying paths to data and the number of classes.
- Epochs and Early Stopping: Training ran for 150 epochs, with an early stopping patience of 100 to prevent overfitting.
- Batch Size and Image Size: A batch size of 8 was selected to accommodate GPU memory limitations, while images were resized to 640 × 480, balancing detail and computational load.
- Learning Rate and Momentum: An initial learning rate (`lr0`) of 0.01 and a momentum of 0.937 were chosen to ensure smooth and efficient convergence.

These hyperparameters were refined based on guidance from Ultralytics [41] and experimental results to achieve optimal performance.

Table 1. Key hyperparameters for YOLOv8 training.

Hyperparameter	Value	Description
`mode`	train	Training mode selected.
`model`	yolov8m.pt	Pretrained model file specifying structure and weights.
`data`	dataset.yaml	Path to the dataset configuration file.
`epochs`	150	Total number of training epochs.
`patience`	100	Early stopping patience for validation metrics.
`batch`	8	Batch size per training iteration.
`imgsz`	640	Target image resolution for training.
`device`	0	Computational device (e.g., GPU or CPU).
`lr0`	0.01	Initial learning rate.
`lrf`	0.01	Final learning rate fraction for adjustment.
`momentum`	0.937	Momentum factor for optimization.
`weight_decay`	0.0005	L2 regularization to prevent overfitting.

3.2.5. Training Process

During the training process, several optimization techniques were employed to enhance the model's accuracy in detecting and counting chickens. The YOLOv8 model was trained iteratively, with performance metrics such as precision, recall, and overall accuracy used to evaluate its performance at each stage. These metrics guided adjustments to the model's parameters, ensuring continuous improvement and robustness.

As illustrated in Figure 5, the training scheme involves feeding the YOLOv8 model a large dataset of annotated images containing chickens and their precise locations. This process teaches the model to detect and localize chickens in new, unseen images effectively.

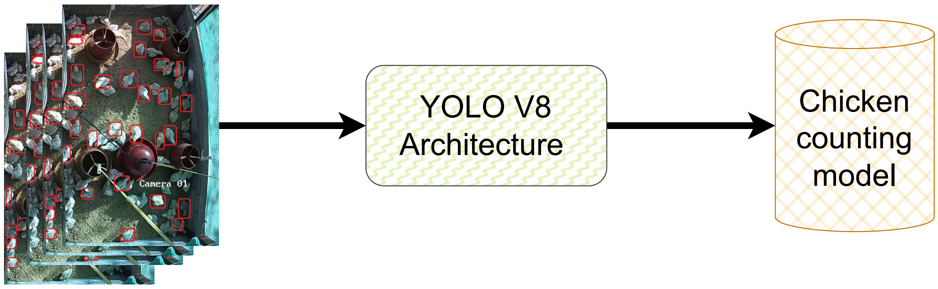


Figure 5. Training scheme using YOLOv8. The model is trained on a large dataset of images containing chickens, annotated with their exact positions, to enable accurate detection in new images.

4. Results

4.1. Experiment Setup

The experiment was conducted with a flock of broiler chickens ranging in age from 1 week to 6 weeks, with an average flock size of 100 chickens. Environmental conditions were carefully controlled, maintaining temperatures between 22 °C and 32 °C. Chickens were exposed to natural daylight during the day and artificial lighting for 8 h at night.

For the annotation process, images were manually labeled using the labelImg tool (version 1.8.6) [36], a widely adopted tool in computer vision applications. Each chicken was enclosed within a bounding box, with particular attention to challenging scenarios such as occlusions and varying lighting conditions. The annotations were saved in YOLO format, adhering to consistent and accurate guidelines. To ensure label quality, a cross-validation approach was implemented, with annotations reviewed by at least two independent annotators. Clear guidelines emphasized marking only visible chickens and accurately delineating their body boundaries.

Training was performed on a workstation equipped with an NVIDIA RTX 3080 Ti GPU (12 GB VRAM), Intel i7-12700K CPU, and 32 GB RAM, using PyTorch 1.13 and the Ultralytics YOLOv8 framework. The training process took approximately 5 h to complete 100 epochs.

Throughout training, key metrics such as box loss, confidence loss, and classification loss were monitored to evaluate the model's progress. The model's performance was assessed using precision, recall, mAP@0.5, and mAP@0.5:0.95. The YOLOv8m (medium) version was selected for its balance of accuracy and speed. The model utilized the default YOLOv8 loss function, which combines localization, confidence, and classification losses. Training employed the Adam optimizer, with an initial learning rate of 0.001 that decreased progressively over the course of training.

A batch size of 16 images per iteration was used, with input images resized to 640×640 pixels. Images were extracted from videos recorded at 25 frames per second (fps). Data augmentation techniques, including random rotation, scaling, cropping, and adjustments to brightness and contrast, were applied to improve model generalization.

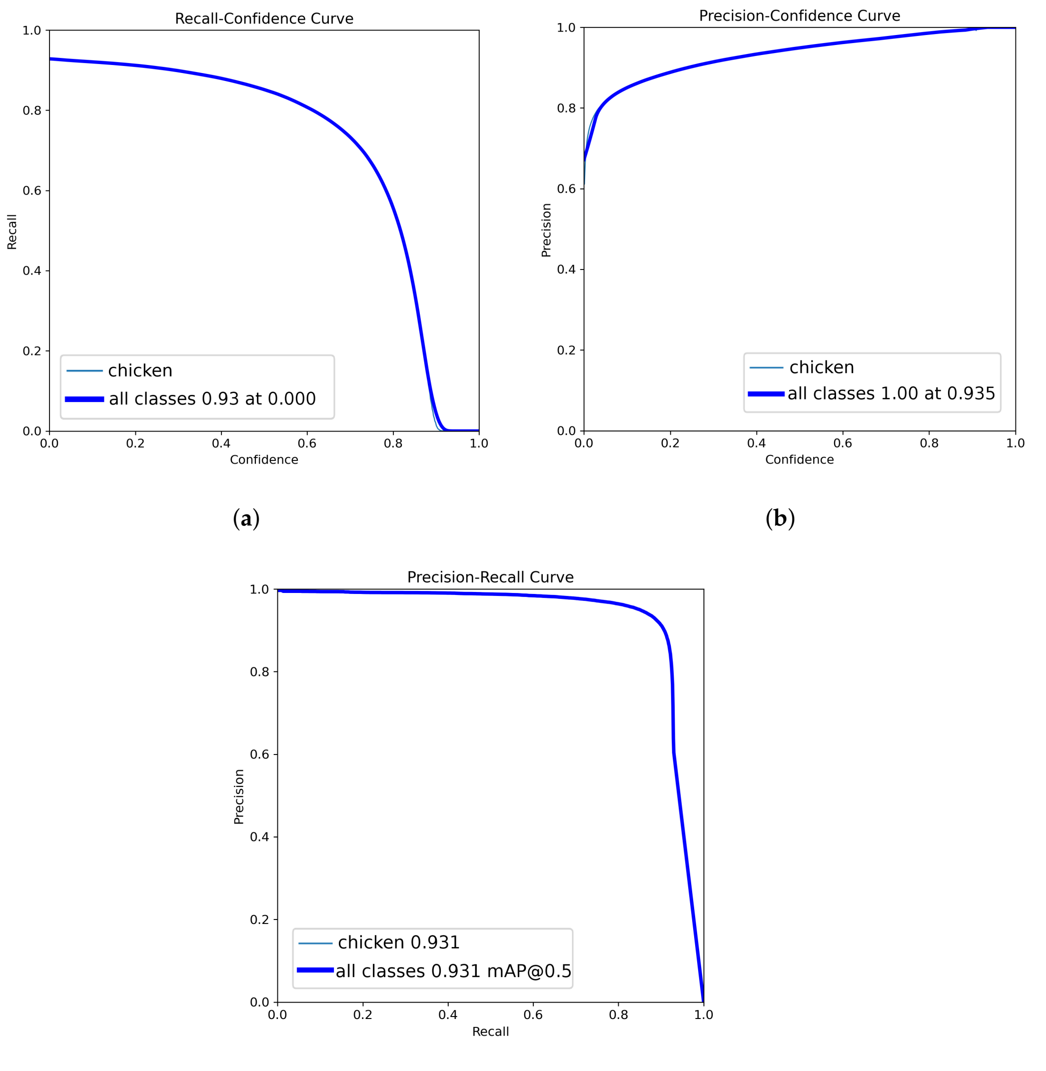
The breeding and care of the poultry were overseen by experienced poultry farming professionals hired specifically for this project. These experts ensured compliance with animal welfare standards, including daily health monitoring and behavioral observations. No significant health issues or mortalities were reported during the study, ensuring consistent and reliable conditions for data collection.

4.2. Training Results

The training of the YOLOv8 model demonstrated significant performance improvements in chicken detection accuracy. Key metrics, including precision, recall, mAP@0.5, and mAP@0.5:0.95, highlight the model's effectiveness in detecting chickens across varied farm environments.

To provide a comprehensive understanding of the model's behavior during training, three performance curves are presented, illustrating key aspects of its detection capabilities.

- Recall–Confidence Curve (Figure 6a): The Recall–Confidence curve illustrates the trade-off between recall and confidence thresholds. As confidence thresholds increase, recall gradually decreases, reflecting the model's precision-focused behavior at higher confidence levels.
- Precision–Confidence Curve (Figure 6b): Precision improves with increasing confidence thresholds, stabilizing at 1.0 around a threshold of 0.935. This trend demonstrates the model's strong predictive power when high-confidence predictions are prioritized.
- Precision–Recall Curve (Figure 6c): The Precision–Recall curve, with a mean Average Precision (mAP) of 0.931 at an IoU threshold of 0.5, illustrates the balance between precision and recall, achieving high precision while maintaining adequate recall.



(**a**) (**b**) (**c**)

Figure 6. Performance curves of the trained YOLOv8 model. (**a**) Recall–Confidence Curve. (**b**) Precision–Confidence Curve. (**c**) Precision–Recall Curve.

These curves complement the quantitative metrics and emphasize the model's robustness, particularly in high-confidence scenarios where accurate detection is crucial.

Additionally, if available, loss curves and epoch-wise performance improvements are presented to highlight the model's convergence and training stability. These visualizations illustrate the reduction in training and validation losses over epochs, providing insight into the model's optimization process and confirming its steady performance gains throughout training.

The combination of these metrics and visualizations underscores the YOLOv8 model's suitability for real-time poultry monitoring, even under diverse and challenging conditions. Its high precision and recall demonstrate its potential for accurate and efficient chicken detection in commercial farming applications.

Performance Metrics

Table 2 presents the performance metrics of the YOLOv8 model after additional training. The model achieved high precision (93.1%) and recall (93.0%), demonstrating a strong balance between detection accuracy and thoroughness. Furthermore, the model's mAP@0.5 improved to 93.1%, and its mAP@0.5:0.95 increased to 62.5%, significantly outperforming earlier versions and highlighting its capability in handling varying Intersection over Union (IoU) thresholds.

Table 2. Performance metrics of the YOLOv8 model on the training and test sets.

Metric	Training (%)	Test (%)
Precision	93.5	93.1
Recall	85.0	93.0
F1-score	88.9	91.0
mAP@0.5	90.0	93.1
mAP@0.5:0.95	58.2	62.5

The high F1-score on the test set (91.0%) reflects the model's ability to maintain a balance between precision and recall, ensuring reliable detection even in challenging conditions. The increase in mAP@0.5:0.95 to 62.5% further underscores the model's improved performance across a range of IoU thresholds, indicating enhanced generalization capability for detecting objects of varying sizes and overlaps.

These results affirm the YOLOv8 model's suitability for real-time poultry monitoring, providing a robust and scalable solution for detecting and counting chickens under diverse environmental conditions.

4.3. Performance Analysis

The YOLOv8 model's performance was evaluated under various conditions to ensure its robustness and applicability in realistic farm environments.

4.3.1. Inference Process

Test images captured by surveillance cameras were processed through the trained YOLOv8 model to predict bounding boxes around each chicken. This inference process facilitated the accurate counting of chickens within each image. The evaluation utilized the inference scheme illustrated in Figure 7.

The inference process demonstrated the model's ability to reliably detect and count chickens across various scenarios, including images with occlusions and variable lighting conditions. These results affirm the model's potential for practical deployment in real-time poultry monitoring systems.

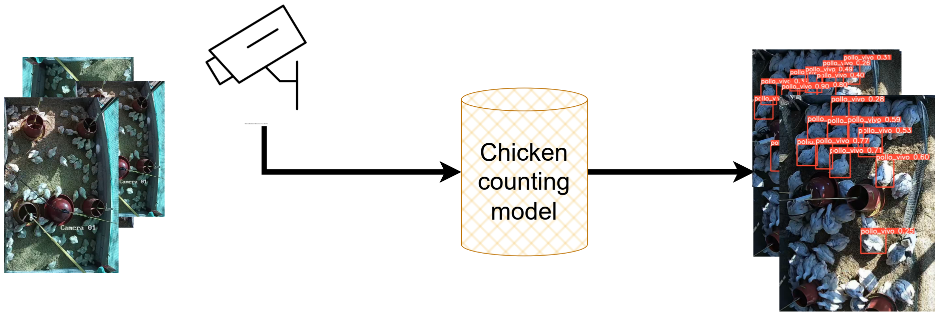


Figure 7. Inference process using the YOLOv8 trained model. The model processes input images captured from surveillance cameras and outputs detected chickens with bounding boxes.

4.3.2. Performance Under Different Conditions

The YOLOv8 model was evaluated under varying lighting and occlusion conditions to assess its robustness. Results demonstrated that YOLOv8 maintained consistent performance even in challenging scenarios, such as when chickens were partially occluded or in low-light environments. This level of reliability is crucial for practical deployment in poultry farms, where environmental conditions can vary significantly.

Despite its strong performance, some instances of missed detections were observed, which can be attributed to several factors.

- Occlusion: Occlusion remains one of the primary challenges, as chickens often cluster together, partially or fully covering one another. This issue is particularly prevalent in crowded areas of the coop where movement is unpredictable, increasing the likelihood of missed detections. Multi-view camera setups or depth-sensing technologies could help address this limitation.
- Lighting Variations: Shadows, reflections, and poor lighting within the coop can affect the model's ability to detect chickens. While YOLOv8 performs well under controlled lighting conditions, the dynamic lighting often found in real-world environments such as poultry farms can pose challenges. Bright reflections can confuse the model, while poorly lit areas may obscure chickens from view. Incorporating adaptive lighting techniques or infrared imaging could enhance performance in such scenarios.
- Image Resolution: The resolution of input images significantly impacts detection accuracy. Although YOLOv8 is optimized for 640×640 pixels, higher resolutions (e.g., 1920×1080) provide more detail, improving accuracy, particularly in complex scenes. Conversely, lower-resolution images (e.g., 320×320) may lack the detail needed to correctly identify chickens, especially in crowded or cluttered environments. Employing higher-resolution images in critical areas could mitigate this limitation.

YOLOv8 demonstrated robust detection capabilities across different conditions, highlighting its suitability for real-world poultry monitoring. However, addressing these limitations through strategies such as higher-resolution imaging, depth-sensing technologies, or multi-camera setups could further enhance detection accuracy and reliability, particularly in complex environments.

4.3.3. Visual Evaluation

In addition to quantitative metrics, a visual evaluation of the model's detections was conducted. Output images were analyzed to verify the accuracy of chicken detection and counting. The results showed that the model accurately identified most chickens present in the images. Figure 8 presents examples of the system's detection results during its operation.

Figure 8. Labeling results achieved by the trained model. Red bounding boxes indicate detected chickens along with the confidence values generated by the model.

4.4. Comparison with Existing Methods

To contextualize the performance of the YOLOv8 model, its results were compared with previous methods employed in chicken counting tasks.

4.4.1. Comparison with YOLOv5 Model

The performance of the YOLOv8 model was benchmarked against the YOLOv5 model, which has been previously utilized for chicken counting tasks. YOLOv8 outperformed YOLOv5 in both precision and inference speed, demonstrating significant advancements in handling occlusions and lighting variations. These enhancements mark a notable improvement in the robustness and accuracy of detection models within the poultry farming context. As outlined in Table 3, YOLOv8 exhibited higher accuracy and better adaptability to variable illumination conditions compared to YOLOv5.

Table 3. Comparison of YOLOv5 and YOLOv8 on chicken counting tasks.

Criteria	**YOLOv5**	**YOLOv8**
Accuracy	High	Higher
Inference Speed	Moderate	Fast
Real-time Detection	Yes	Yes
Handling Occlusions	Moderate	High
Handling Illumination Variations	Moderate	High

Table 4 provides a detailed comparison of key performance metrics between YOLOv5 and YOLOv8 on the test set. YOLOv8 demonstrated significant improvements across all evaluated metrics, particularly in recall and mean Average Precision (mAP). These metrics underscore YOLOv8's superior ability to accurately detect chickens under challenging conditions, such as occlusion and variable lighting.

Table 4. Comparison of performance metrics between YOLOv5 and YOLOv8 on the test set.

Metric	**YOLOv5 (%)**	**YOLOv8 (%)**	**Improvement (%)**
Precision	90.2	93.1	+2.9
Recall	55.0	93.0	+38.0
F1-score	68.7	91.0	+22.3
mAP@0.5	60.0	93.1	+33.1
mAP@0.5:0.95	35.0	62.5	+27.5

The results demonstrate that YOLOv8 significantly surpasses YOLOv5 in precision, recall, and overall detection accuracy. Its improvements in recall (+38.0%) and mAP@0.5 (+33.1%) are particularly noteworthy, indicating that YOLOv8 is highly effective in detecting chickens even in complex scenarios. These enhancements solidify YOLOv8 as a reliable and efficient model for real-time poultry monitoring applications.

4.4.2. Innovations Introduced

The application of YOLOv8 introduced several key innovations in the task of chicken counting, significantly enhancing its practicality for real-world use. These include:

- Real-time Detection: YOLOv8's architecture enables efficient real-time detection of chickens, a critical feature for monitoring dynamic environments in poultry farms.
- Robustness to Occlusions: The model demonstrates improved handling of occlusions, effectively detecting chickens even in crowded conditions where individuals may be partially obscured.
- Adaptability to Lighting Variations: YOLOv8 exhibits strong performance under variable lighting conditions, including low-light scenarios and environments with shadows or reflections, surpassing YOLOv5 in these aspects.

4.5. Practical Implications

The experimental results validate the YOLOv8 model's effectiveness for practical applications in poultry management, demonstrating its potential to enhance operational efficiency and animal welfare.

4.5.1. Applications in Poultry Management

The model's capability to accurately count chickens in real time enables farmers to make informed decisions about flock management. This improves resource allocation and overall operational efficiency while promoting better animal welfare. Agricultural producers can adopt the proposed method by deploying a complete system that integrates both hardware and software components. The hardware setup involves installing surveillance cameras, such as IP ColorVu Lite models, in poultry houses to continuously capture images of the animals. These cameras are connected to a computing system running the YOLOv8-based object detection algorithm, which processes the video feeds in real time to count the number of animals present. The software is designed to be user-friendly, featuring automated error detection, data logging, and a streamlined interface for consistent and accurate flock monitoring. By integrating this system into their operations, producers can optimize critical resources, such as feed and medication, while improving flock management efficiency. This approach not only reduces waste and operational costs but also supports sustainable farming practices by ensuring precise and timely interventions based on real-time data.

4.5.2. Resource Optimization

Automating the chicken counting process reduces labor intensity and minimizes human errors, leading to more efficient resource utilization in poultry farms. By accurately tracking flock size in real time, farmers can better allocate critical resources such as feed, water, and medication, ensuring that supplies are neither underused nor wasted. This precision not only lowers operational costs but also supports sustainable farming practices by optimizing resource distribution and reducing environmental impact.

5. Discussion

5.1. Model Accuracy and Robustness

The results validate the high accuracy and robustness of the YOLOv8 model, highlighting its potential for applications in the poultry industry. The model achieved a precision of 93%, demonstrating its ability to accurately count chickens even under challenging conditions such as occlusions and lighting variations. These findings are particularly notable compared to traditional manual methods, which are prone to errors and require considerable labor. Moreover, the model's consistent performance across varying environmental conditions reinforces its suitability for deployment in real farm settings, where conditions frequently fluctuate.

5.2. Advantages over Traditional Methods

In flock management, traditional manual counting methods, which rely on initial and final verifications during the production cycle, have significant limitations in terms of both accuracy and efficiency. By contrast, the AI-based approach developed in this study provides substantial improvements. Leveraging computer vision algorithms, the system enables continuous and precise counting throughout the flock's life cycle. This overcomes the challenges faced by manual methods, such as high chicken density, overlaps, variable lighting conditions, and human fatigue.

Flock handlers typically only have exact chicken counts at two points: the start of the flock (as chicks) and at the end (before slaughter), limiting monitoring capabilities during intermediate stages. While quantitative data directly comparing the accuracy of manual and AI-based methods are currently unavailable, prior research indicates that AI systems can outperform manual methods by 10–20% in accuracy, particularly in high-density environments. For instance, Lempitsky and Zisserman (2010) demonstrated the effectiveness of computer vision systems in counting tasks under complex conditions [42]. Similarly, Kumar et al. (2023) validated the high precision of computer vision systems in industrial settings, emphasizing their adaptability to challenging environments [43]. Additionally, Zhang et al. (2016) addressed density variability using a multi-column convolutional neural network, further supporting the adaptability of AI-based systems in dense and overlapping scenarios [44].

Future research will focus on detailed quantitative comparisons between manual and AI-based methods in real operational environments. Developing a robust dataset for such comparisons will further validate the advantages of AI systems over traditional approaches and provide a clearer understanding of their impact on flock management efficiency.

5.3. Practical Applications and Benefits

The development of an AI-based poultry monitoring system was complemented by the creation of a user-friendly prototype web application. This application serves as the primary interface for managing and monitoring multiple chicken coops, enabling farm managers to make data-driven decisions efficiently. Built using Flask [45], the application integrates directly with the YOLOv8 model and processes video feeds from surveillance cameras installed within the chicken coops.

5.3.1. System Overview

Figure 9 illustrates the camera view interface, where detected chickens are annotated with bounding boxes and IDs, enabling immediate visual confirmation of counting results. This real-time monitoring capability forms the core functionality of the system.

Access to the application is secured through a login interface (Figure 10), ensuring only authorized users can manage the system. Once logged in, users are greeted with a dashboard (Figure 11), where they can navigate through various sections, including coop management, system configuration, and report generation.

Figure 9. Camera view interface integrated into the system. Detected chickens are displayed with bounding boxes and confidence values.

Figure 10. Login window for the application. Secure access ensures data integrity during poultry management.

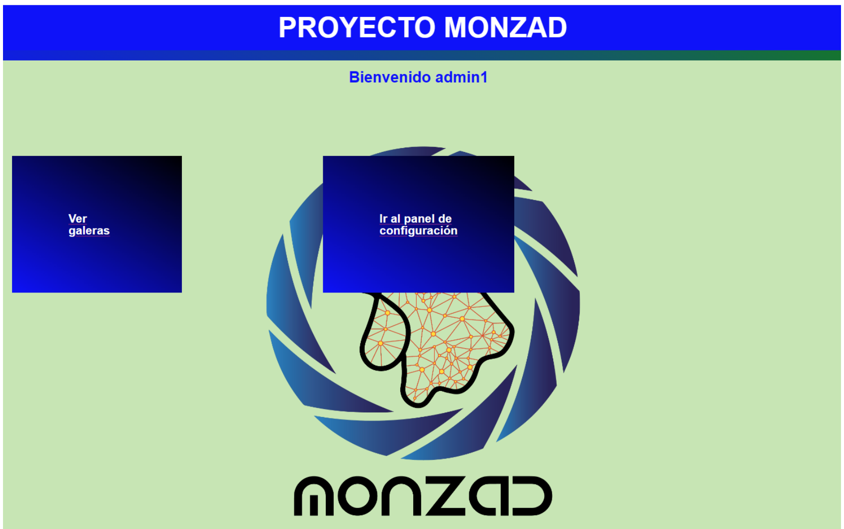


Figure 11. Dashboard interface. Users can access main features, including coop management and system configuration.

5.3.2. Multi-Coop Management and Reporting

A critical feature of the application is its ability to manage multiple coops simultaneously. Figure 12 displays the coop management interface, allowing users to select and monitor different coops. This functionality is essential for large-scale operations requiring continuous observation of multiple flocks.

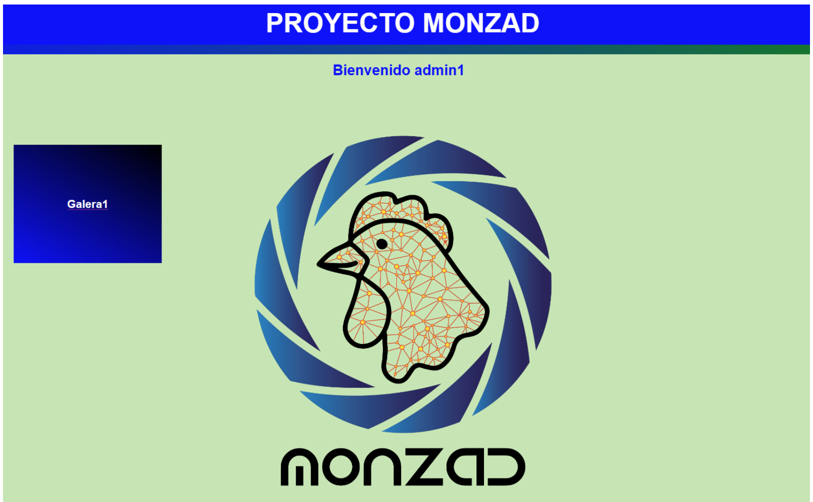


Figure 12. Coop management interface. Users can view and manage connected coops.

Detailed reporting tools are also included, as shown in Figure 13. Users can generate comprehensive reports summarizing data, such as the number of live and possibly dead chickens over specific periods. These reports are instrumental in monitoring trends, optimizing resource allocation, and improving flock management.

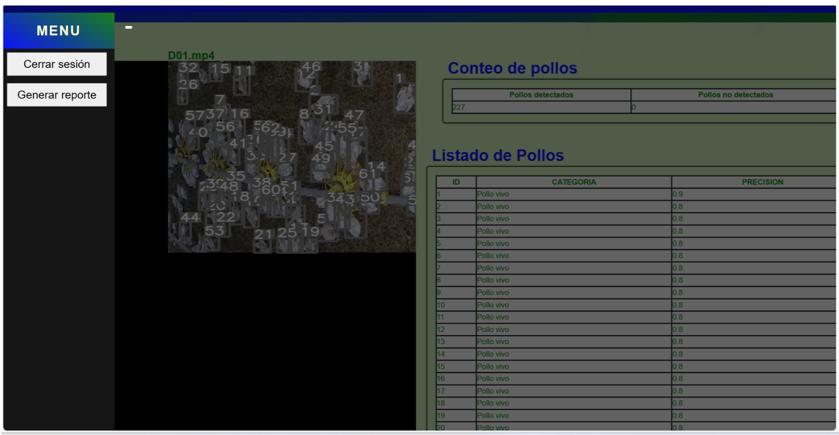


Figure 13. Report generation interface. Provides detailed summaries of poultry data, including live and possibly dead chickens.

5.3.3. User Management and System Configuration

The application includes a robust user management system, enhancing data security by ensuring only authorized personnel can access sensitive information. Figures 14–16 showcase the menu interface, user registration panel, and account management panel, respectively.

The system configuration panel, illustrated in Figure 17, allows users to link the trained YOLOv8 model and configure the database connection. This flexibility ensures the system can be updated with new models or datasets as AI technology advances.

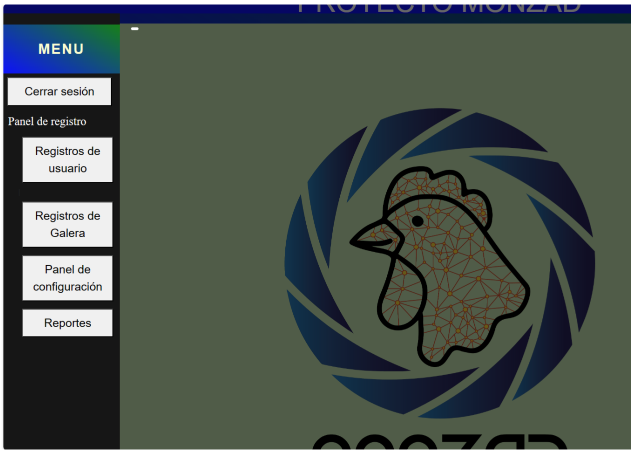


Figure 14. Menu interface. Allows access to various sections, including report generation.

Figure 15. User registration panel. Ensures secure access by limiting usage to authorized personnel.

Figure 16. Account management panel. Enables administrators to manage registered users.

Figure 17. System configuration panel. Allows linking of trained YOLOv8 models and database setup.

5.3.4. Historical Data and Records

The poultry study records interface, shown in Figure 18, provides a comprehensive overview of each flock's historical data. Users can navigate through records and generate reports for specific dates, supporting long-term analysis and decision-making.

Figure 18. Poultry study records interface. Enables navigation through historical data and report generation.

5.3.5. Practical Benefits

The prototype application enhances the practicality and usability of the AI-based poultry monitoring system. By offering real-time monitoring, multi-coop management, and comprehensive reporting capabilities, the system empowers farm managers to optimize operations, reduce human error, and improve animal welfare. The inclusion of secure user management and customizable settings further underscores the application's value in modern poultry farming.

5.4. Limitations and Challenges

Despite the promising results, several limitations must be acknowledged to provide a balanced understanding of the potential and constraints associated with deploying this model in real-world poultry farm environments.

One primary limitation is scalability. Expanding this AI-based system to monitor larger flocks or multiple locations introduces significant computational and resource demands. For example, higher-resolution input data or larger datasets would necessitate more powerful GPU resources, potentially impacting accessibility and increasing costs. Memory and storage requirements would also rise due to the need for processing and managing greater volumes of data.

Furthermore, achieving real-time detection across large-scale farms could result in latency issues, which might compromise the practical usability of the system. To address these challenges, techniques such as model pruning, quantization, or deploying lightweight variants (e.g., YOLO-Tiny) could be explored. These strategies aim to maintain performance efficiency while reducing computational overhead. By addressing these scalability considerations, future implementations could achieve a balance between accuracy, resource efficiency, and real-time applicability, enhancing the system's adaptability for broader applications in poultry farm management.

5.5. Future Opportunities and Expansion

Beyond species-specific applications, the system presents opportunities for adaptation across diverse environmental contexts. For instance, deploying the model in outdoor open-range farms would allow testing under more complex conditions, including variable lighting, terrain, and weather patterns. Conversely, controlled indoor environments, such as high-density automated farms with artificial lighting, could provide additional insights into optimizing system accuracy in specialized settings.

Integrating advanced sensors and multi-view cameras could further enhance detection capabilities in these environments, offering a comprehensive tool for agricultural monitoring. The system also has potential for applications beyond poultry farming. For example, similar methodologies could be applied to other livestock or species, enabling cross-species adaptability.

In addition, scaling the system to a commercial poultry setting with the same chicken species represents a significant opportunity. Testing the algorithm in commercial environments with higher-density flocks and larger enclosures would enable evaluation of its robustness and accuracy under more demanding conditions. Addressing challenges such as variability in lighting, flock density, and movement patterns in these real-world scenarios would provide valuable insights into the system's scalability and adaptability. These advancements would be instrumental in driving the broader adoption of AI-driven solutions in commercial poultry management.

5.6. Integration with Poultry Management Systems

Integrating this system with existing poultry management platforms offers the potential to create a comprehensive solution for flock management. Such integration would enable farmers to fully leverage the benefits of automation, facilitating a data-driven approach to resource allocation, health monitoring, and operational efficiency.

Moreover, incorporating this technology into broader farm management systems could drive innovation in the poultry industry. The development of interconnected tools and solutions could further enhance productivity and animal welfare while encouraging sustainable farming practices. By enabling seamless integration with current platforms, the system can serve as a foundation for future advancements in agricultural automation, solidifying its role as a transformative technology in modern poultry farming.

5.7. Adaptability of the Proposed System

The proposed system comprises two main components: the administration module, which serves as the primary user interface, and the AI-driven model, responsible for detecting and counting broiler chickens within the coop. While this study focuses on broiler chickens, the underlying concept and infrastructure presented are adaptable to other poultry breeds and even livestock species in environments with similar conditions. Adapting the system to new settings requires modifications to the AI model, specifically retraining it with a dataset tailored to the target breed or species.

AI models, particularly those utilizing computer vision, rely heavily on training data that accurately reflect the characteristics and environmental conditions they encounter. For instance, transitioning from broiler chickens to layer hens or other poultry breeds necessitates capturing and annotating new data from the target group. This process follows the steps outlined in this study for data collection, model training, and validation.

Although the current model is optimized for broiler chicken farming, the flexible design of the administration module allows seamless integration with new AI models. This adaptability significantly broadens the system's potential applications, making it suitable for deployment in various environments or for managing other farm animals.

The modular design ensures compatibility with diverse datasets and models, facilitating its use in open-range poultry farming, automated livestock management, or monitoring other species. By leveraging this adaptability, the system can contribute to more sustainable and efficient farming practices across different agricultural domains. Future research should focus on extending the system's applicability to various species and environmental contexts, thereby enhancing the versatility and impact of AI-driven solutions in agriculture.

6. Conclusions

This study successfully developed and validated an AI-based automated chicken counting system using the YOLOv8 model. The system demonstrates high accuracy, achieving a 93% precision rate under real farm conditions, significantly addressing the limitations of traditional manual methods. By automating the counting process, the system reduces human error, enhances operational efficiency, and enables more effective management of poultry flocks.

The results underscore the transformative potential of adopting advanced AI technologies in agriculture, particularly in poultry management. The system's ability to perform real-time counts and adapt to varying environmental conditions ensures its applicability across a broad range of productive scenarios. Moreover, the innovations introduced in this study pave the way for applying similar technologies in other areas of agriculture and livestock management.

However, scalability remains a key challenge, particularly for implementation in larger farms or operations with significantly higher flock sizes. To address this, future work could explore strategies such as integrating distributed processing techniques, where multiple processing units (e.g., edge servers or cloud nodes) collaborate to manage large data volumes in real time. Additionally, deploying lighter AI models optimized for low-power devices could reduce computational demands and increase infrastructure flexibility. Data compression algorithms and federated learning techniques could also facilitate large-scale data management while maintaining model accuracy across diverse locations and conditions.

Despite these challenges, the system represents a significant advancement in automated poultry management. It provides a practical and efficient tool for improving productivity and animal welfare. With continued development and broader application, this approach has the potential to significantly transform the poultry industry and drive innovation across agricultural sectors.

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