

# Application of YOLOv11s Algorithm to Automate Egg Counting in Poultry Farms

Muh. Hakkam Zakka Robbani<sup>1\*</sup>, Akhfa Bagas Alfarizi<sup>2</sup>, Adrian Fardan Andi<sup>3</sup>, Gema Parasti Mindara<sup>4</sup>, Endang Purnama Giri<sup>5</sup>

<sup>1,2,3</sup> Software Engineering Technology, IPB University, Bogor, Indonesia

<sup>4</sup> Computer Engineering Technology, IPB University, Bogor, Indonesia

<sup>5</sup> Computer Science, IPB University, Bogor, Indonesia

Corresponding author: [gemaparasti@apps.ipb.ac.id](mailto:gemaparasti@apps.ipb.ac.id)

## ARTICLE INFORMATION

### Article history:

26 December 2025

Received in revised form

13 October 2026

Accepted 17 October 2026

Available online 17 October 2026

### Keywords:

*smart farming, deep learning, real-time monitoring, poultry farming, computer vision.*

### DOI:

<https://doi.org/10.26740/jieet.v10n01.p39-50>

## ABSTRACT

Chicken eggs are a strategic food commodity and a globally affordable source of animal protein. In the industrial poultry farming sector, accurate daily production data is fundamental for evaluating biological performance, feed efficiency, and supply chain management. However, the conventional manual counting process is highly susceptible to human error caused by physical fatigue and dynamic environmental conditions, resulting in significant data inaccuracies. To address these inefficiencies, this study aims to develop a precise automated egg counting system by implementing the You Only Look Once (YOLO) deep learning algorithm version 11s. This study employed an experimental approach that included data collection, manual annotation, and extensive augmentation techniques to ensure the model's robustness to variations in lighting and spatial orientation. The model was trained using a specific egg dataset and evaluated against standard object detection performance metrics. The experimental results demonstrated superior performance, with the model achieving 97.80% Precision, 98.60% Recall, and 99.10% Mean Average Precision at intersection over union 50%. Furthermore, the F1-Score reached 98.20%, indicating a strong balance between detection accuracy and sensitivity. The system successfully detected and counted eggs in a real-time environment while maintaining stability across various visual scenarios. In conclusion, the proposed architecture proved to be a highly effective solution for automating production recording in poultry farms. These findings offer a practical transition towards digitized precision farming, significantly reducing operational inefficiencies associated with manual monitoring while enabling sound managerial decision-making.



This work is licensed under a Creative Commons Attribution License  
International Non-Commercial-ShareAlike License 4.0.

## INTRODUCTION

Chicken eggs are a strategic national commodity that demands efficient supply chain management. However, on commercial farms, the process of recording daily production results is often still done manually. This conventional method has a fundamental weakness, namely vulnerability to *human error* due to physical fatigue of officers and dynamic environmental conditions of the cage (Linuwih & Handayati, 2025; Sarvari et al., 2024) Inaccurate stock data can

lead to information distortion, hindering livestock performance evaluation and valid managerial decision-making. Therefore, automation is needed to improve recording precision.

Computer vision technology presents a smart solution to address these inefficiencies. One industry-standard algorithm architecture is YOLO. YOLO is a convolutional neural network-based algorithm designed to detect objects in real time by processing the entire image in a single, end-to-end process (Handayani, n.d.; Yang et al., 2023). Recent studies have shown that advanced YOLO variants such as YOLOv11 are highly effective for real-time object detection in poultry environments, particularly for monitoring and counting livestock and egg production (Bumbálek et al., 2025; Pangestu, 2025). Technically, the YOLOv11s architecture introduces significant enhancements, particularly through the integration of the C3k2 and C2PSA modules, which optimize the trade-off between feature extraction depth and computational speed. These characteristics make YOLOv11s particularly superior in speed and low latency, which are crucial for high-volume livestock monitoring.

A number of previous studies have explored the use of YOLO in the poultry farming domain. (Jiang et al., 2025) proposed a YOLOv11-based approach for precise egg feature extraction, demonstrating its applicability for automated egg counting systems. Meanwhile, (Subedi et al., 2023) implemented YOLOv5 and YOLOv7 to monitor eggs on the floor of cage-free poultry environments. Other studies, such as those conducted by (Sandy et al., 2024; Ningsih et al., 2024), focused on the classification of egg physical quality and freshness. However, a significant technical challenge remains in conveyor-based production lines, specifically regarding occlusion and motion blur. When eggs are positioned in high density, they often overlap, making individual detection difficult. Furthermore, the constant movement of the conveyor can degrade image sharpness, requiring a model with robust feature representation to maintain accuracy.

To transition from mere detection to a reliable production record, this study incorporates visual object counting theory using the line crossing method. In a dynamic conveyor environment, counting cannot rely on simple per-frame detection, as this would lead to massive overcounting of the same object as it moves through the camera's field of view. By implementing a virtual counting line and centroid tracking, the system assigns a unique identifier to each detected egg. A count is only triggered when the centroid of a tracked object crosses the predefined line, ensuring that each egg is recorded precisely once. This theoretical approach is vital for maintaining data integrity in real-time streaming scenarios (Wu et al., 2025).

Responding to this gap, this study aims to develop a precise automated egg counting system by implementing the YOLOv11s algorithm integrated with a line-crossing counting logic. The YOLOv11s model was selected based on its architecture, which offers a superior balance between detection accuracy and computational efficiency while requiring fewer parameters than its predecessor (Ultralytics, 2024). This research is expected to provide technical contributions in optimizing detection models in real-world conditions and offer practical solutions for farmers to monitor production trends in real time to support the digitalization of precision farming.

## METHOD

This research follows the workflow for developing a computer vision-based object detection model as shown in the workflow used, Machine Learning Methodology Flow. The method stages consist of seven main parts, namely: (1) Data Collecting, (2) Exploratory Data Analysis, (3) Data Preprocessing, (4) Model Training, (5) Model Evaluation, (6) Deployment, and (7) Monitoring. This methodological structure refers to standard practices in developing modern object detection systems in the field of smart agriculture (Géron, 2019; Yang et al., 2023). Edge-based computer vision systems have also been integrated into poultry production lines to support real-time egg detection and counting. (Hadjisavvas et al., 2024) demonstrated that real-time egg detection using edge computing can significantly reduce latency while maintaining high detection accuracy, making it suitable for real-world farm deployment.

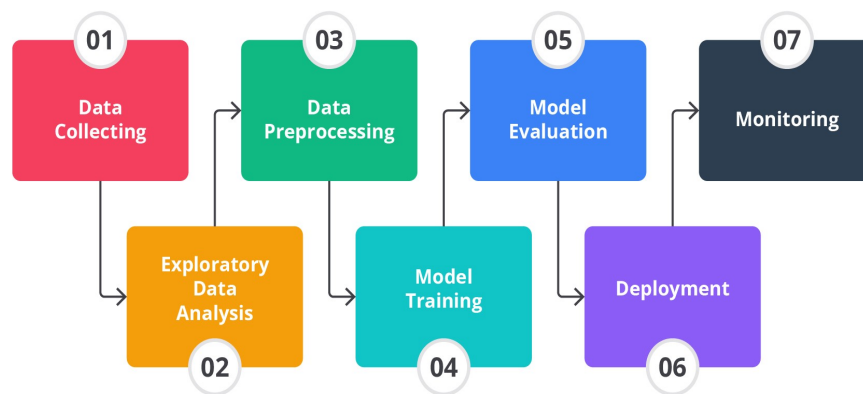


**Figure 1.** Machine Learning Methodology Flow (Géron, 2019)

### 1. Data Collecting

The first stage begins with the process of collecting data in the form of images or videos representing the objects to be detected by the model. This data collection is carried out by ensuring a variety of environmental conditions such as lighting, viewing angle, background, and object complexity, so that the data reflects real-world situations that might be encountered during the implementation stage. This diversity is important so that the model can learn visual patterns more comprehensively and have good generalization in real-world scenarios, as recommended in YOLO-based computer vision research (Yang et al., 2023).

Furthermore, this study adopts a Cross-Dataset Validation strategy to evaluate the model's robustness. This approach ensures that the YOLOv11s architecture, trained on a specific dataset, can maintain high performance when applied to different environmental domains (Zakria et al., 2020). The data acquisition is divided into three primary categories:

### 1) Literature Study

A comprehensive literature review was conducted to establish a theoretical framework regarding digital image processing, real-time object detection, and the architectural evolution of the YOLO (You Only Look Once) family, specifically the YOLOv11s variant. The review includes national and international journals, conference proceedings, and technical documentation related to precision poultry farming and computer vision. These insights provide the scientific basis for configuring the software's hyperparameters and the logic for the automated counting system.

### 2) Dataset Roboflow

To provide a broad range of training samples, this research utilizes secondary datasets obtained from Roboflow, namely the Egg Detection Computer Vision Model (Roboflow 1) and the Egg Computer Vision Model (Roboflow 2). These datasets consist of images containing chicken eggs captured under various orientations, backgrounds, and lighting conditions. Each image is accompanied by bounding box annotations, enabling the model to effectively learn the fundamental visual characteristics of eggs. The secondary datasets are primarily used during the initial training phase to optimize model weights and improve detection accuracy before being evaluated on primary real-time data.

**Table 1.** Egg Detection Dataset Used in the Research

| Number | Data Type                | Quantity | Description                            |
|--------|--------------------------|----------|----------------------------------------|
| 1      | Roboflow Dataset 1       | 52       | Multi-egg images for initial training. |
| 2      | Roboflow Dataset 2       | 44       | Single-egg images for generalization.  |
| 3      | Annotated Egg Samples    | 13       | Manual annotations for fine-tuning.    |
| 4      | Real-time Conveyor Video | 5        | Primary data for real-time testing.    |

Based on Table 1, the dataset utilized in this study comprises 109 source images and 5 real-world videos. Following the acquisition and annotation processes, this yielded 52 multi-egg images for initial training and 44 single-egg images for model generalization, supplemented by 13 manually annotated samples, resulting in a diverse collection of data points utilized for training and real-time testing.

### 3) In-situ Production Video (Primary Data)

Primary data acquisition focuses on obtaining realistic testing scenarios for the application. Since this research focuses on the software's detection capabilities, data was gathered by recording video footage of eggs on an active conveyor belt in a commercial poultry farm. The recordings were captured using a high-definition camera positioned at a top-down angle to minimize object overlap. These videos serve as the ultimate testbed for the application, evaluating how the YOLOv11s algorithm performs against motion blur and continuous movement on a production line. The application implements a "virtual counting line" logic on these videos to track and count the eggs as they pass through the frame, ensuring data integrity without double counting.

## 2. Exploratory Data Analysis

After data collection, exploratory analysis is performed to comprehensively understand the characteristics of the dataset. This stage includes examining data structure, image quality, object distribution, the presence of noise, and variations in visual conditions that may affect training results. EDA is performed to ensure the dataset is in optimal condition and to identify potential issues such as extreme lighting, blur, or irrelevant objects. This analysis is a crucial step before the modeling process, as recommended in modern computer vision pipelines (Alif & Hussain, 2024).

## 3. Data Preprocessing

The dataset was randomly divided into training (80%) and validation (20%) using a Python script. In the preprocessing stage, all images used in this study were automatically prepared by the Ultralytics YOLO pipeline before entering the model training process. Each image was first resized to  $640 \times 640$  pixels according to the parameters *imgsz=640*, so that all data has a uniform dimension and is compatible with the YOLO architecture. Furthermore, pixel values are normalized from the range 0–255 to 0–1 to ensure learning stability and accelerate model convergence. YOLO also automatically converts images to tensor format and batches them as part of its internal mechanisms. This preprocessing stage aims to ensure that all data is in the optimal format for object detection model training.

## 4. Model Training

The next step is to train the object detection model using the YOLO architecture. In this phase, the model learns visual patterns from the dataset through an iterative process involving parameter optimization, loss calculation, and periodic evaluation at each epoch. YOLO's built-in augmentation techniques, such as color shifting, flipping, and mosaic augmentation, are often used to improve the model's generalization capabilities. This training approach has become standard in YOLO-based object detection research due to its efficiency in processing images in real time (Alif & Hussain, 2024).

## 5. Model Evaluation

The model was trained using the YOLO architecture optimized for single-stage object detection, where the training process is performed incrementally through repeated iterations to learn the visual patterns of eggs while monitoring the risk of overfitting. This approach is consistent with previous research showing that modern YOLO variants have strong performance on agricultural detection tasks (Alif & Hussain, 2024; Vinod et al., 2023). After training, performance evaluation was performed using Precision, Recall, mAP50, and mAP50–95 metrics to assess detection accuracy and consistency. The mAP calculation refers to the area under the Precision–Recall curve, which is formulated as:

$$AP = \int_0^1 P(R) dR$$

(Manning et al., 2008)

While the mean Average Precision is calculated as:

$$mAP = \frac{1}{K} \sum_{i=1}^K AP_i$$

(Everingham et al., 2010)

For this study, mAP50 was calculated at an Intersection over Union (IoU) threshold of 0.5, while mAP50–95 is the average of APs over an IoU range of 0.50 to 0.95 with increments of 0.05 as used in modern object detection evaluations (Tharwat, 2021). Testing is performed on validation data and compared with manual calculations, and re-verified at certain intervals to ensure the stability and reliability of the system, as recommended in automated production monitoring research (Wu et al., 2025).

## 6. Monitoring

The final stage is monitoring, which involves monitoring the model's performance after it has been deployed in a real-world environment. Monitoring is performed to identify any decrease in accuracy that may be caused by changing visual conditions, environmental differences, or new data not captured in the training process. If model drift is detected, the model can be updated or retrained. Continuous monitoring is essential to ensure the system remains consistent, reliable, and accurate over time (Wu et al., 2025).

## RESULTS

### 1. Confusion Matrix

A confusion matrix is a commonly used evaluation method in classification and object detection systems to assess the quality of model predictions against actual data. This matrix presents the relationship between the actual labels (true) and the labels predicted by the model (predicted), so that model performance can be clearly seen through the number of correct and incorrect predictions. In the context of object detection, a confusion matrix helps identify a model's ability to distinguish target objects from the background and measures error rates, such as false positives and false negatives. The following figure shows the confusion matrix resulting from the YOLO model evaluation on the validation data used in this study

**Table 2.** Confusion Matrix Results Table

| Matrix              | Matrix |
|---------------------|--------|
| True Positive (TP)  | 136    |
| False Positive (FP) | 3      |
| False Negative (FN) | 1      |
| True Negative (TN)  | 0      |

Based on the confusion matrix, the model detected egg objects with a very high level of accuracy. There were 136 correct predictions for the egg class (true positives), only 3 false positives, and 1 false negative case where the egg was not detected or was incorrectly classified as background. These results indicate that the model is able to consistently recognize egg objects and rarely makes incorrect predictions in the background. This performance aligns with YOLO's characteristics as a single-stage detection algorithm known for maintaining high accuracy across a wide range of visual conditions. Overall, the confusion matrix shows that the model error distribution is very low and most predictions are on the main diagonal of the matrix, indicating stable and reliable detection performance.

## 2. Model Training and Validation Metrix

The training and validation metrics, as visualized in Figure 2, illustrate the learning trajectory of the YOLOv11s model over 60 epochs. This visualization provides a comprehensive overview of the model's capacity for feature extraction, performance stabilization, and accuracy optimization. The resulting patterns align with standard convergence behaviors observed in state-of-the-art object detection research within the agricultural domain.

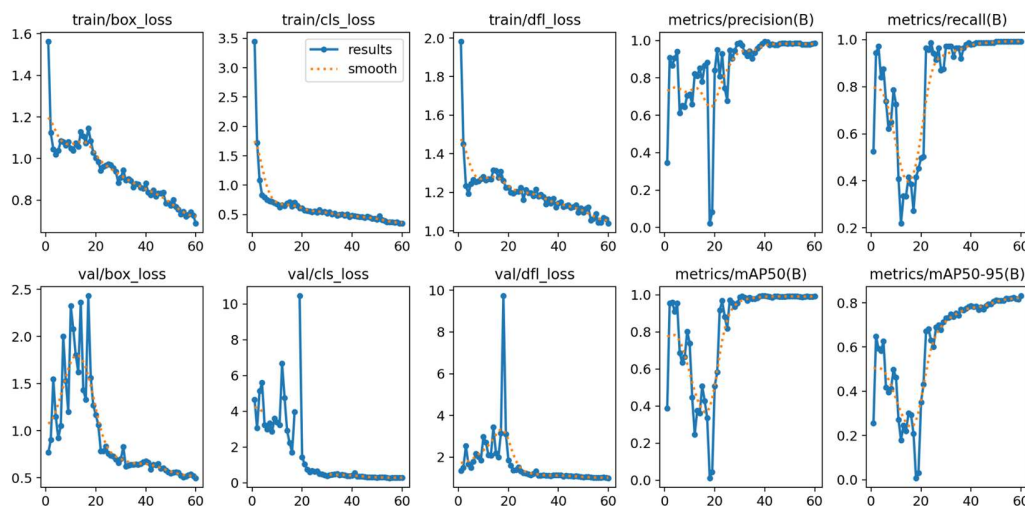


**Figure 2.** Training and Validation Graph Visualization

Based on the quantitative trends observed in the graphs, several key conclusions can be drawn:

### 1) Continuous Optimization of Loss Functions

All training loss components including box\_loss, cls\_loss, and df\_l\_loss exhibit a consistent downward trajectory throughout the 60-epoch duration. This sustained

decrease signifies that the model successfully minimized errors in bounding box localization and object classification, progressively refining its understanding of the visual characteristics of eggs.

## 2) Validation Stability and Generalization

While the validation loss (particularly val/cls\_loss and val/dfl\_loss) showed initial fluctuations during the first 20 epochs, it successfully stabilized in the latter half of the training process. This convergence between training and validation loss indicates that the model is not merely memorizing the training dataset (overfitting) but has developed the ability to generalize effectively to unseen data, which is critical for real-world farm implementation.

## 3) Asymptotic Growth in Detection Metrics

The precision and recall graphs demonstrate rapid initial growth followed by a stable plateau approaching the 1.0 mark. This trend confirms that the model achieved a high degree of reliability, successfully identifying nearly all egg instances (high recall) while maintaining a minimal rate of false-positive detections (high precision).

## 4) Robustness Across Localization Thresholds

The mAP@50 metric consistently reaches near-perfect levels (~0.99), while the mAP@50-95 stabilizes at approximately 0.85. The high value of mAP@50-95 is particularly significant, as it proves the model's precision in producing accurate bounding boxes even under more stringent Intersection over Union (IoU) requirements. This stability ensures that the automated counting system remains accurate despite varying egg positions and lighting conditions on the conveyor belt.

# 3. Evaluation Validation Data

Next, the model was tested on validation data to determine the detection model's performance on the dataset used. The model evaluation results can be seen in Table 3.

**Table 3.** Data Evaluation Test Results

| Evaluation Validation Data | Results |
|----------------------------|---------|
| Precision                  | 97.80%  |
| Recall                     | 98.60%  |
| mAP@50                     | 99.10%  |
| mAP@50-95                  | 85.30%  |
| F1 Score                   | 98.20%  |

The performance of the developed YOLOv11s model was rigorously evaluated using standard object detection metrics, including Precision, Recall, F1-score, and Mean Average Precision (mAP). The evaluation results are detailed as follows:

The model achieved a Precision of 97.80%, signifying a remarkably low false-positive rate. In the context of an automated counting system, this indicates that the model is highly reliable in distinguishing eggs from background noise or conveyor belt artifacts, ensuring that non-egg objects are rarely misidentified. Complementing this, the Recall reached 98.60%, demonstrating the model's robustness in detecting nearly every egg present within the frame. This high sensitivity

is crucial for minimizing false negatives, ensuring that very few eggs pass through the production line undetected.

To assess the balance between these two metrics, the F1-score was calculated at 98.20%. This near-perfect equilibrium suggests that the model is highly optimized and does not exhibit bias toward either precision or recall, making it ideal for the consistent demands of real-time livestock monitoring.

Furthermore, the model's spatial localization accuracy was evaluated using Mean Average Precision. The mAP@50 reached 99.10%, indicating exceptional detection performance at a standard Intersection over Union (IoU) threshold of 0.50. More importantly, the mAP@50–95 recorded a solid 85.30%. This metric, which averages precision across increasingly stringent IoU thresholds (from 0.50 to 0.95), confirms the model's stability and its ability to produce precise bounding boxes even under challenging conditions. These results collectively validate that the YOLOv11s architecture provides the necessary accuracy and reliability for high-volume egg counting in precision poultry farming environments.

#### 4. Testing Results

After conducting the data evaluation test, the model was tested using new data not included in the training or validation datasets. This test aimed to determine the model's ability to detect eggs in real-world conditions and in new images uploaded to the system.

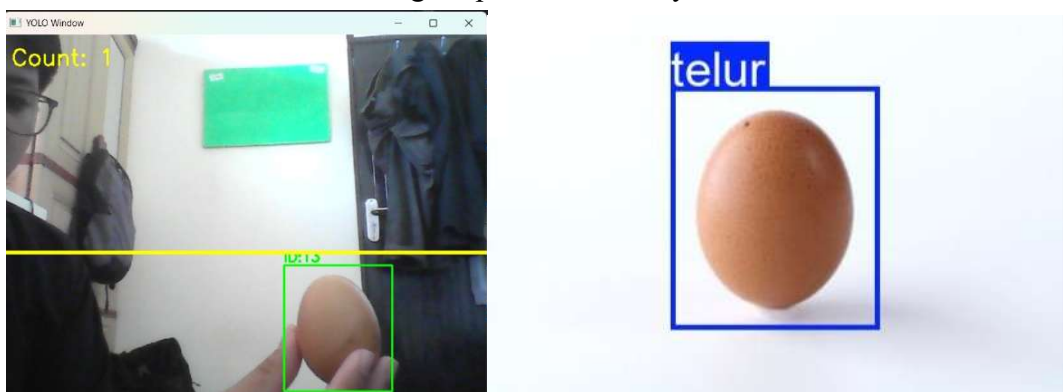


**Figure 3.** Testing Results

Figure 3 shows the results of testing the object detection model using two types of test data. In the first image (left), the model successfully detected the presence of a single egg held by the user, indicated by a green box surrounding the object. Furthermore, the system also displays count information (count: 1), indicating that the model can detect and count objects in real time.

In the second image (right), the model again demonstrates good performance by correctly detecting an egg object in the center of the image. The object is marked with a blue detection box labeled "egg," indicating that the model correctly recognized the object according to the class it was trained on. The detection box appears to precisely follow the shape of the object, indicating that the model is able to produce accurate predictions on test data with a different appearance and background than the training data. These test results indicate that the model can perform optimally

under real world conditions and new images, and is able to detect eggs consistently across various scenarios.

## DISCUSSION

The results show that the YOLOv11s algorithm is capable of detecting and counting eggs with very high accuracy, as indicated by near-perfect precision, recall, and mAP values. These findings are consistent with previous research highlighting the reliability of deep learning-based egg detection systems in real-world poultry environments. Prior studies using YOLO-based architectures have demonstrated that automated egg detection and counting can achieve high accuracy while maintaining real-time performance, supporting the feasibility of deploying such systems in commercial poultry farms (Liu et al., 2023; Zhang et al., 2024).

This performance directly addresses the research problem of automating the egg counting process, which is traditionally conducted manually and is prone to errors. Furthermore, the stable accuracy observed across various IoU thresholds indicates strong model generalization under varying lighting and environmental conditions, reinforcing earlier findings on the robustness of YOLO-based systems in livestock applications. The main contribution of this study lies in the real-world implementation of the YOLOv11s model within an operational poultry farm environment, combined with real-time system integration. These results demonstrate that the proposed approach can serve as a reliable foundation for computer vision-based production monitoring systems and support the advancement of precision farming technologies by enabling more efficient and accurate automated production processes.

## CONCLUSION

This study concludes that the YOLOv11s algorithm is effective for automatically detecting and counting eggs with a very high level of accuracy, thus meeting the need for automated production recording in poultry farms. The developed system is proven to work stably on images and videos, including new test data not included in the training dataset. Based on these results, it is recommended that small and large-scale farmers begin adopting a computer vision-based egg counting system to improve operational efficiency and minimize manual recording errors. Furthermore, further research can explore system integration with an analytical dashboard or the use of industrial cameras for long-term operations to further optimize the system and prepare it for commercial implementation.

## REFERENCE

- Alif, M. A. R., & Hussain, M. (2024). *YOLOv1 to YOLOv10: A comprehensive review of YOLO variants and their application in the agricultural domain* (No. arXiv:2406.10139). arXiv. <https://doi.org/10.48550/arXiv.2406.10139>
- Bumbálek, R., Umurungi, S. N., Ufitikirezi, J. D. D. M., Zoubek, T., Kuneš, R., Stehlík, R., Lin, H.-I., & Bartoš, P. (2025). Deep learning in poultry farming: Comparative analysis of

- Yolov8, Yolov9, Yolov10, and Yolov11 for dead chickens detection. *Poultry Science*, 104(9), 105440. <https://doi.org/10.1016/j.psj.2025.105440>
- Everingham, M., Van Gool, L., Williams, C. K. I., Winn, J., & Zisserman, A. (2010). The Pascal Visual Object Classes (VOC) Challenge. *International Journal of Computer Vision*, 88(2), 303–338. <https://doi.org/10.1007/s11263-009-0275-4>
- Géron, A. (2019). *Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow*. O'Reilly Media.
- Hadjisavvas, N., Nicolaou, N., & Stavrakis, E. (2024). *Real-Time Egg Detection Using Edge Computer Vision*.
- Handayani, T. (n.d.). *IMPLEMENTASI METODE YOU ONLY LOOK ONCE (YOLO) UNTUK DETEKSI KESEGARAN TELUR AYAM BERDASARKAN CITRA CANGKANG*.
- Jiang, Y., Atwa, E. M., He, P., Zhang, J., Di, M., Pan, J., & Lin, H. (2025). Computer Vision-Based Multi-Feature Extraction and Regression for Precise Egg Weight Measurement in Laying Hen Farms. *Agriculture*, 15(19), 2035. <https://doi.org/10.3390/agriculture15192035>
- Linuwih, H., & Handayati, Y. (2025). Quantitative Analysis of Inventory Record Inaccuracy (IRI): A Case Study on Warehouse Stock Discrepancies. *International Journal of Current Science Research and Review*, 08(01). <https://doi.org/10.47191/ijcsrr/V8-i1-26>
- Liu, G., Qiu, K., Chen, Z., Zheng, A., Chang, W., Cai, H., & Zhang, X. (2023). Augmentation of Performance, Carcass Trait, Biochemical Profile and Lipid Metabolism Concerning the Use of Organic Acidifier in Broiler Chickens. *Agriculture*, 13(9), 1765. <https://doi.org/10.3390/agriculture13091765>
- Manning, C., Raghavan, P., & Schütze, H. (2008). *Introduction to information retrieval*. Cambridge University Press.
- Ningsih, S. A., Sutiani, R. A., Ulandari, N. M. S., & Saputra, R. A. (2024). PENERAPAN ALGORITMA YOLO UNTUK MENDETEKSI KUALITAS TELUR AYAM BERDASARKAN WARNA CANGKANG. *METHODIKA: Jurnal Teknik Informatika Dan Sistem Informasi*, 10(2), 35–39. <https://doi.org/10.46880/mtk.v10i2.3062>
- Pangestu, G. (2025). Real-Time Chicken Counting System using YOLO for FCR Optimization in Small and Medium Poultry Farms. *Journal of Development Research*, 9(1), 1–9. <https://doi.org/10.28926/jdr.v9i1.436>
- Sandy, C. L. M., Husna, A., & Rizal, R. A. (2024). Real Time Chicken Egg Size Classification Using Yolov4 Algorithm. *Brilliance: Research of Artificial Intelligence*, 4(2), 577–584. <https://doi.org/10.47709/brilliance.v4i2.4496>
- Sarvari, H., Baghbaderani, A. B., Chan, D. W. M., & Beer, M. (2024). Determining the significant contributing factors to the occurrence of human errors in the urban construction projects: A Delphi-SWARA study approach. *Technological Forecasting and Social Change*, 205, 123512. <https://doi.org/10.1016/j.techfore.2024.123512>
- Subedi, S., Bist, R., Yang, X., & Chai, L. (2023). Tracking floor eggs with machine vision in cage-free hen houses. *Poultry Science*, 102(6), 102637. <https://doi.org/10.1016/j.psj.2023.102637>

- Tharwat, A. (2021). Classification assessment methods. *Applied Computing and Informatics*, 17(1), 168–192. <https://doi.org/10.1016/j.aci.2018.08.003>
- Ultralytics. (2024). *YOLO Training and Validation Documentation—Official Documentation*. <https://docs.ultralytics.com>
- Vinod, A., Mohanty, D. C., John, A., & Depuru, B. K. (2023). *Application of Artificial Intelligence in Poultry Farming—Advancing Efficiency in Poultry Farming By Automating The Egg Counting Using Computer Vision System*. In Review. <https://doi.org/10.21203/rs.3.rs-3266412/v1>
- Wu, Z., Zhang, H., & Fang, C. (2025). Research on machine vision online monitoring system for egg production and quality in cage environment. *Poultry Science*, 104(1), 104552. <https://doi.org/10.1016/j.psj.2024.104552>
- Yang, X., Bist, R. B., Subedi, S., & Chai, L. (2023). A Computer Vision-Based Automatic System for Egg Grading and Defect Detection. *Animals*, 13(14), 2354. <https://doi.org/10.3390/ani13142354>
- Zakria, Deng, J., Cai, J., Aftab, M. U., Khokhar, M. S., & Kumar, R. (2020). Visual Features with Spatio-Temporal-Based Fusion Model for Cross-Dataset Vehicle Re-Identification. *Electronics*, 9(7), 1083. <https://doi.org/10.3390/electronics9071083>
- Zhang, M., Luo, W., Yin, Z., Huang, X., & Yin, J. (2024). Dietary *Lactobacillus delbrueckii* Affects Ileal Bacterial Composition and Circadian Rhythms in Pigs. *Animals*, 14(3), 412. <https://doi.org/10.3390/ani14030412>