

# Eggs Detection and Classification Using YOLOV5

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**Abstract:** As poultry product quality increases, so does the need for effective poultry egg sorting due to the limitations of manual processes. Modern farms now utilize automated systems to enhance productivity and accuracy, as well as improve animal welfare. An intelligent egg detection and classification system based on deep learning is proposed in this study. A dataset consisting of white and brown chicken eggs was collected and annotated alongside multiple variants of YOLOv5 to train and evaluate them. Various metrics including precision, recall, F1 score, mAP, and computational time were measured to determine how effective each model was. Results showed that the YOLOv5n model outperformed the rest with an F1 score of 0.98, along with achieving excellent detection accuracy and low computational requirements, thus showing suitability for real time applications. The work done in this paper demonstrated the possibilities given by computer vision in automating egg sorting and laid the groundwork for applying such systems into fully autonomous poultry farms.

## 1 INTRODUCTION

This study aims to enable the automated systems to be involved in poultry industry, by finding the best solution to get the highest accuracy with shortest detection time. In Europe, policies are already in place to phase out cage-based systems to enhance animal health, and China is also exploring similar reforms [1], [2]. Still, considering the large population of China, an immediate transition to free-range systems might fall short of meeting production needs. Cage farming, by contrast, offers better scalability and consistency. Consequently, China is focusing on using advanced technologies to boost the efficiency of egg production within caged systems, aiming to balance scalability with animal welfare and consumer expectations [3]-[5].

Given the growing limitations of conventional poultry management, the adoption of digital technologies and automation has become a key approach to enhancing productivity and competitiveness [6]-[9]. These precision farming technologies improve operational efficiency, reduce costs, and uphold high nutrition safety standards [10]-[13]. However, they also introduce

new challenges, particularly in maximizing flock output, ensuring environmental sustainability, and supporting long-term farming practices [14]-[17].

As the demand for smart egg detection systems increases, researchers have developed various devices and algorithms to address this need. For instance, Ab Nasir [18] designed a computer vision system that extracts eight egg shape features, sorting them into six quality levels with 94.16% accuracy. Alikhanov [19] adapted a similar method to classify eggs on conveyor belts into weight categories (S, M, L, XL) with 94.6% accuracy at two eggs per second. Yang [7] deployed an automated egg grading and defect detection system using computer vision, achieving 94.8% accuracy [5], [32].

Other notable efforts include Okinda [20], who used depth imaging and regression to predict egg volume across varied shapes, and Han [28], who employed visible-near infrared spectroscopy with neural networks and PCA to classify eggs by shell integrity, color, and diet-based origin. Dibakoane [21] used elemental analysis and chemometrics to identify between cage and free-range eggs with high accuracy. Turkoglu [22] used deep learning and BiLSTM to identify surface defects like cracks and dirt with

99.17% accuracy. Wang [23] implemented a YOLOv4-based dirty egg detection model on a Jetson Nano, achieving 75.88% accuracy and processing 2.3 frames per second.

Advancements in object detection, particularly through attention mechanisms and alternate neural backbones, are further enhancing livestock applications (Jiang [24], [25]; Yang [7]). Jiang [26] improved YOLOv7 for duck counting by adding three Convolutional Block Attention Modules, achieving 95.8% accuracy. Yu [27] made YOLOv3 more efficient for detecting estrus in sheep by replacing its backbone with EfficientNet-B0, enhancing deployment and reducing detection time [28]-[30].

While such innovations suggest promising improvements in model performance, their real-world effectiveness for egg detection still requires thorough testing. In this study, we propose a machine vision-based system using YOLOv5 to identify egg positions and differentiate between white and brown eggs. This system is intended to support automated egg detection, collection, and sorting, or to be integrated into a robotic platform for container-based sorting [33], [34].

## 2 MATERIALS AND METHODOLOGY

This section involves five stages to approach the objective of the study.

### 2.1 Egg detection Model Implementation

Figure 1 shows essential checkpoints per step along with a path summary describing the egg detection model deployment process. This involves a three-phase approach:

- A) Data preparation:
  - 1) Collect egg images.
  - 2) Preprocess and filter the collected images.
  - 3) Annotate the images to create a labeled dataset for training, validation, and testing the YOLO model.
- B) Model implementation:
  - 1) Select an appropriate deep learning model.
  - 2) Train the model using training, validation, and test datasets.
  - 3) Evaluate and assess the model's performance using the test dataset.
- C) Model inference:
  - 1) Apply the trained detection model to new egg images.
  - 2) Verify the effectiveness and accuracy of the developed model on unseen data.

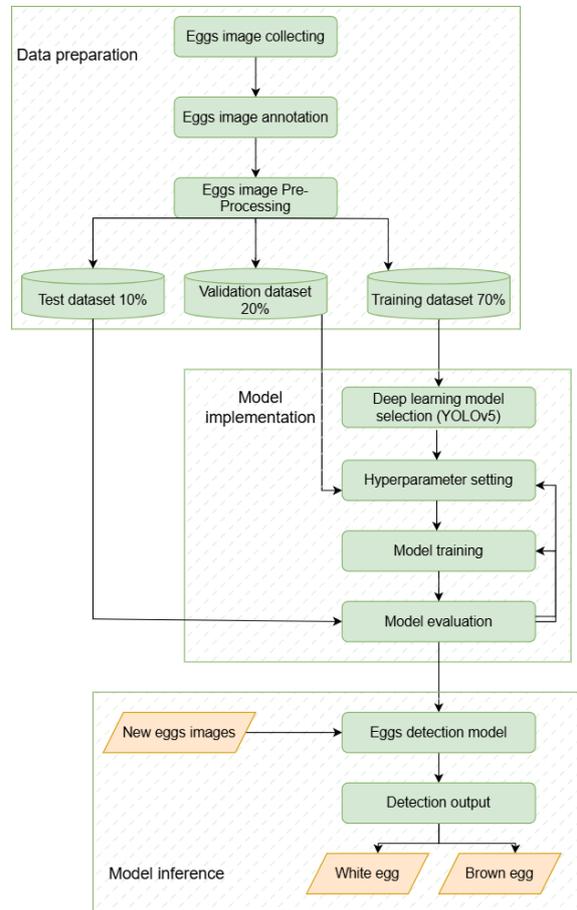


Figure 1: Methodological framework for the Egg detection.

### 2.2 Data Collection

The dataset was obtained by photographing a group of chicken eggs in a studio box, on various grass or dirt surfaces, at different distances from the lens, and in different positions and orientations to simulate all the possibilities that the images to be used for object detection might present in real-time applications. The dataset consists of 972 JPG images with a resolution of 4096 x 1844 pixels, divided into 474 images of brown eggs, 488 images of white eggs, and 10 images containing both types. Figure 2 shows examples of the images used.



Figure 2: Eggs dataset samples.

### 2.3 Data Pre-Processing

The dataset was filtered, annotated, and classified. The process of filtering and labeling the data includes the following steps:

- 1) Exclude blurry images and images that do not clearly contain potential objects.
- 2) Our work is divided into two classes, white and brown chicken eggs. Images containing eggs of other birds have been excluded.
- 3) It has been manually labeled, rectangle annotation is applied on the object, the rectangle covers all the exterior borders of the object.
- 4) Label studio software is used for annotation, the annotated data is exported in YOLO format.
- 5) The final dataset is divided into train, validation and test folders according to the ratio with is mentioned in Figure 1.

### 2.4 Model Training

Python 3.11 was used in the model’s development. Google Colab was used to train and validate the algorithms. The deep learning approach used the deep convolutional neural network (CNN) model to train, detect, and classify the eggs as shown in Figure 3.

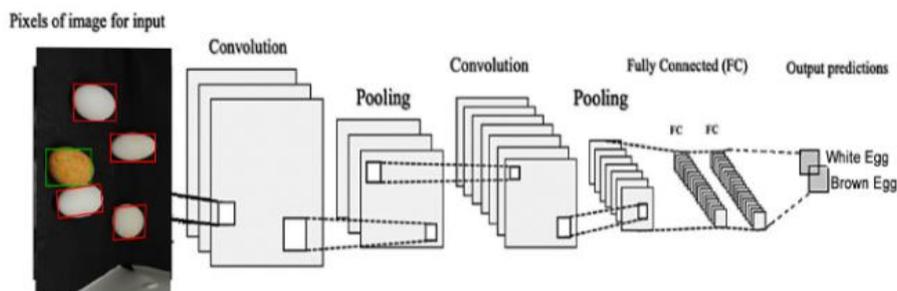


Figure 3: The architecture of the deep learning model employed a CNN.

In this study, the YOLOv5 architecture was employed for efficient object detection. This architecture partitions an image into a grid system, with each grid module responsible for detecting objects within its boundaries. A total of 100 epochs and a batch size of 8 have been performed to test each version. The architecture of YOLO-v5 is utilized for egg detection. The eggs dataset is divided into three groups and was randomly split into an internal training set (70%), a validation set (20%), and a test set (10%).

### 2.5 Model Performance Evaluation Metrics

The detection capability of the proposed model was evaluated using a set of widely adopted performance metrics, including accuracy, precision, recall, F1-score, Intersection over Union (IoU), and mean Average Precision (mAP). These metrics are commonly used in classification and object detection tasks to provide a comprehensive assessment of model effectiveness [31].

Precision reflects the model’s ability to correctly identify relevant targets among all predicted positives, while recall evaluates its capability to detect all relevant instances in the dataset. The F1-score combines precision and recall into a single balanced metric, making it particularly useful when both false positives and false negatives are critical factors in model evaluation.

Intersection over Union (IoU) measures the overlap between predicted and ground-truth regions and is widely used to assess localization accuracy in object detection tasks. A higher IoU value indicates better spatial agreement between predicted outputs and reference annotations. Mean Average Precision (mAP) further extends this evaluation by aggregating precision scores across multiple detection thresholds and classes, providing an overall measure of detection performance.

All evaluation metrics were computed based on the standard definitions involving true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN), as commonly established in the literature [31]. These definitions are extensively used in deep learning-based detection and classification studies and therefore are not restated explicitly in this work.

### 3 RESULTS

This section describes the result of egg detection model using YOLOv5 models. Basically, there are several models for YOLOv5, including: (a) YOLO-V5n, (b) YOLO-v5s, (c) YOLO-v5m, (d) YOLO-v5l, (e) and YOLO-v5x. The result of these models is shown in Figure 4. More details are described in the following subsections: The YOLO-v5 model incorporates box losses in its object detection algorithm to enhance the accuracy of object detection and classification within an image. The goal during training is to minimize the losses to the lowest possible value in the meantime maintain the detection time as less as possible. The precision and recall values approached unity, indicating excellent performance. The mean average precision, the most commonly used statistic, also met expectations. Figure 5 shows the training box loss of the dataset.



Figure 4: Results of Egg detection YOLOv5n model.

A confusion matrix for each YOLOv5 model is used to analyze the accuracy of the collected data in detection and classification of eggs.

The top left cell represents the number of sample of the true predicted brown eggs (True positives), while the middle cell represents the true predicted white eggs (True positives). The cells in the first row except the first cell represent the brown egg labels those incorrectly classified as other labels (white eggs or background), these cells are recognized as (False negative). The first column cells except the first cell are represent the non-brown egg labels those are predicted as brown eggs, this is called (False positive). The rest of the cells represent the non-brown labels those are predicted as non-brown eggs (True negatives).

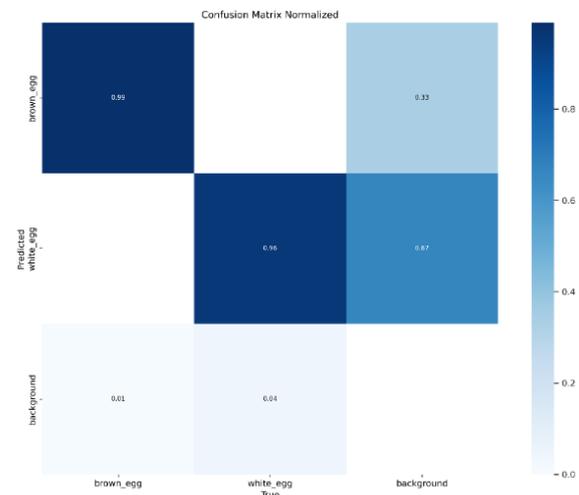


Figure 5: The confusion matrix of the YOLOv5n model.

The confusion matrix of the white eggs are described as the following: The middle cell the percentage of the true predicted white eggs (True positives). The cells in the second row except the middle cell represent the white egg labels those incorrectly classified as other labels (brown eggs or background), these cells are recognized as (False negative). The second column cells except the middle cell are represent the non-white egg labels those are predicted as white eggs, this is called (False positive). The rest of the cells represent the non-white labels those are predicted as non-white eggs (True negative). Table 4 shows the accuracy of each model according to the confusion matrix of each YOLOv5 model.

The highest score achieved by the eggs detection model is 0.98, with a confidence level of 0.365 in YOLOv5n model, Table 1 shows the F1-confidence scores of each YOLOv5 model.

Table 1: F1 score-confidence of YOLOv5 models.

Model	F1 score	Confidence
YOLOv5n	0.98	0.365
YOLOv5s	0.97	0.67
YOLOv5m	0.97	0.728
YOLOv5l	0.97	0.961
YOLOv5x	0.97	0.781

A confidence level greater than 0.869 indicates satisfactory precision in the scores which is considered good for the developed eggs detection model using YOLOv6n model. Table 2 shows the Precision-confidence values of each YOLOv5 model.

Table 2: Precision-confidence values of the trained YOLOv5 models.

Model	Confidence
YOLOv5n	0.869
YOLOv5s	0.836
YOLOv5m	0.814
YOLOv5l	0.841
YOLOv5x	0.875

The relationship between the confidence and recall values is analogous to that shown in Figure 4. Table 3 shows the computational time for each YOLO-v5 model with 100 epoch training. Table 4 shows a comparison of the eggs detection results between YOLO5 models.

Table 3: The results of the YOLOv5 models.

Models	mAP 0.5	Precision	Recall	F1-score
YOLOv5n	0.97	0.98	0.97	0.97
YOLOv5s	0.97	0.98	0.95	0.96
YOLOv5m	0.97	0.99	0.95	0.96
YOLOv5l	0.97	0.98	0.95	0.96
YOLOv5x	0.97	0.99	0.94	0.96

Table 4: The accuracy of YOLOv5 models.

Model	Accuracy
YOLOv5n	94.47%
YOLOv5s	92.27%
YOLOv5m	94.91%
YOLOv5l	91.89%
YOLOv5x	89.96%

## 4 CONCLUSIONS

This work proposes a robust approach that utilizes computer vision for detecting and classifying chicken eggs within the YOLOv5 object detection framework.

This study proved the possibility of employing deep learning methods for semi-automated egg sorting using a custom-brown and white egg dataset, extensive annotation and model variant tuning. Out of all assessed models, best results for F1 score (0.98) precision-confidence and lesser computation cost was seen with real-time achievable deployments, agricultural settings, and maintained with low-cost YOLOv5n models.

Results corroborate that YOLOv5 can accurately detect and classify eggs regardless of changes in the position of the light source and the angle at which it is set, which is a significant improvement on conventional methods that rely on manual approaches. This progress aids in increasing productivity alongside better quality assurance in egg production, and contributes to the development of modern intelligent automation systems for use in agriculture.

In future, efforts for classifying and estimating the weight of non-visible features may be automated, along with robotic systems for comprehensive automation. Efforts also need to be focused on newer architectures like incorporating attention mechanisms into YOLOv8 for better performance in complex agricultural environments without the loss of accuracy.

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