

SORTA: A YOLO-Based Computer Vision System for Automatic Identification and Grading of Chicken Egg Quality Using ESP32-CAM

Mochammad Rifki Ulil Albaab^{1*}, Afis Asryullah Pratama¹, Achmad Sofyan Hakiki¹, Ahmad Faisal Ridhotullah¹, Fulay Fillah¹

¹*Department of Computer Engineering, Information Technology, Politeknik Negeri Jember, Jember, Indonesia*

**Corresponding author: Mochammad Rifki Ulil Albaab; email: mochrifki@polije.ac.id*

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Abstract – This paper presents SORTA (Sorting of Chicken Eggs via Real-Time Vision and Automation), an automated egg quality identification and sorting system that integrates YOLOv8 based object detection, Convolutional Neural Network (CNN) classification, and IoT hardware components. The system employs an ESP32-CAM module to capture real-time egg images, which are transmitted via Wi-Fi to a Python-based inference server running YOLOv8n and a TFLite CNN model. A fusion strategy selects the prediction with a higher confidence score, while a load cell sensor provides weight data to finalize the egg grade according to the SNI 3926:2023 standard. The grading outcome (Grade A, B, C, or Unfit) controls a servo-driven robotic arm that physically sorts the eggs on a mini conveyor. Training on 4,005 augmented images over 15 epochs achieved a validation mAP@50 of 98.8%. In real-world tests at a commercial poultry farm using 100 eggs, the combined CNN+YOLO system achieved 70.0% overall accuracy, outperforming standalone YOLO (44.0%) by 26 percentage points. Weight sensing showed an error margin below 2.2%, and the monitoring website displayed all results in real time. The results demonstrate that the multimodal fusion approach substantially improves sorting reliability compared to single-model baselines, offering a practical and low-cost solution for small-to-medium-scale poultry operations.

Keywords: Computer Vision, Egg Quality Grading, ESP32-CAM, YOLO, CNN, IoT, Automated Sorting

I. Introduction

Eggs are one of the most widely consumed animal protein sources, valued for their nutritional content and affordability. In commercial poultry operations, egg quality directly determines market value and consumer trust. Quality attributes (including shell integrity, cleanliness, surface texture, and weight) are commonly used to classify eggs into commercial grades such as Grade A, B, and C.

In practice, the sorting process at the farm and small to-medium enterprise (SME) level is still predominantly performed manually. Human visual inspection is inherently subjective, time-consuming, prone to fatigue induced errors, and may result in inconsistent grading that causes economic losses for both producers and consumers [1].

Advances in computer vision and deep learning have enabled automated object detection and classification with high accuracy. Among the most prominent approaches is the You Only Look Once (YOLO) family of algorithms, which performs real-time detection in a single forward

pass through a convolutional neural network [2]. Integrated with low-cost embedded platforms such as ESP32-CAM, YOLO offers a viable path toward affordable automation in agricultural settings.

Previous studies have explored egg quality classification using various approaches. Mujiono et al. [3] employed fuzzy logic with an Arduino-based platform, while Ningsih et al. [4] applied to YOLOv8 for color-based shell grading. Putri et al. [5] utilized EfficientNet for digital image classification, and Daulima et al. [6] leveraged CNN for shell-based quality prediction. However, these studies generally focused on software-only classification without integrating hardware-based sorting mechanisms or IoT monitoring capabilities.

To bridge this gap, this paper introduces SORTA (Sorting of Chicken Eggs via Real-Time Vision and Automation), a fully integrated system that combines YOLOv8 detection, CNN classification, weight sensing via HX711, and a robotic arm for physical sorting—all monitored through a Next.js-based web dashboard. The key contributions of this work are: (1) a multi-modal

decision fusion of YOLO and CNN visual classification with load-cell weight measurement; (2) a complete hardware-software integration for real-time automated sorting on a mini conveyor; and (3) empirical validation at an active commercial poultry farm under realistic operational conditions.

The remainder of this paper is organized as follows. Section II describes the related work. Section III presents the system architecture and methodology. Section IV reports experimental results and discussion. Section V concludes the paper.

II. Related Works

Egg quality classification has attracted growing interest from the research community. Mujiono et al. [3] designed an Arduino-based fuzzy logic system using light-dependent resistors (LDR) as input. While effective for basic quality detection, the system lacked image-based analysis and offered no automated physical sorting.

Beyond egg-specific applications, broader IoT-based automation and monitoring systems provide additional design precedents. Widiyatmoko and Suharjo [9] implemented a Raspberry Pi-based environmental monitoring system with real-time Discord notifications, demonstrating a lightweight edge-to-cloud alerting pipeline analogous to SORTA's dashboard logging. Similarly, Alwie et al. [10] developed a Blynk-based IoT control system for automated aquaculture monitoring, illustrating how sensor-driven decision logic can be extended to remote actuator control - a principle directly mirrored in SORTA's servo-driven sorting mechanism.

Ningsih et al. [4] applied YOLOv8 to detect egg quality based on shell color. Although real-time detection was demonstrated, the system did not incorporate weight parameters or IoT connectivity, limiting its deployment in practical farm settings.

Putri et al. [5] employed EfficientNet on digital egg images, achieving high classification accuracy. However, the work was confined to a software environment without integration with physical hardware or automated sorting mechanisms.

Daulima et al. [6] applied CNN for egg shell-based grading with promising accuracy but similarly lacked hardware integration. Yang et al. [7] developed a computer vision system for grading and defect detection, providing a strong benchmark for automated solutions.

The generalizability of YOLO-based detection has also been demonstrated outside the agricultural domain. Maleh et al. [11] applied YOLO to detect orangutan nests in aerial imagery, highlighting the architecture's adaptability to fine-grained, small-object detection tasks under variable environmental conditions similar to those encountered in poultry farm deployment. Azhar et al. [12] combined CNN and YOLO for banknote recognition to assist visually impaired users, employing a fusion strategy conceptually similar to the confidence-based YOLO-CNN fusion adopted in SORTA, further supporting the validity of this hybrid approach.

The common limitation across these prior works is the absence of a unified, end-to-end hardware-software system that performs real-time detection, multi-modal decision fusion, weight-based grading, and physical sorting. SORTA addresses this gap by combining YOLOv8, CNN, load-cell measurement, and a robotic actuator in a single deployable platform.

III. Methodology

A. System Architecture

The SORTA system is built upon a three-layer IoT architecture: (1) the physical layer, comprising ESP32-CAM, IR obstacle sensors, HX711+load cell, a mini conveyor, and a servo-driven robotic arm; (2) the processing layer, consisting of a Python Flask inference server running YOLOv8n and a TFLite CNN model; and (3) the application layer, a Next.js web dashboard for real-time monitoring and data logging. The overall system architecture is shown in Fig. 1.

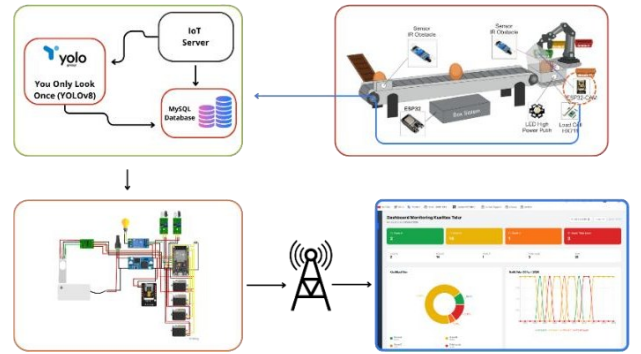


Fig. 1. Overall system architecture of SORTA, integrating IoT hardware, the computer-vision inference server, and the web-based monitoring dashboard.

The system workflow proceeds as follows (Fig. 2). When IR Sensor 1 detects an egg entering the conveyor, the motor is activated. Upon reaching the inspection position (IR Sensor 2), the conveyor halts, the HX711 module records the egg weight using exponential smoothing over three seconds ($\alpha = 0.8$), and the ESP32 DevKit triggers the ESP32-CAM via HTTP GET to capture a JPEG image at VGA resolution (640×480). The image is posted to the server, where YOLOv8n and CNN infer the visual grade independently. A confidence-based fusion selects the output with the higher score. The server then receives the weight, determines the weight-based grade per SNI 3926:2023, and applies a worst-case rule: the lower of the two grades (visual vs. weight) becomes the final grade. The ESP32 receives the final grade and commands the robotic arm to place the egg in the designated slot.

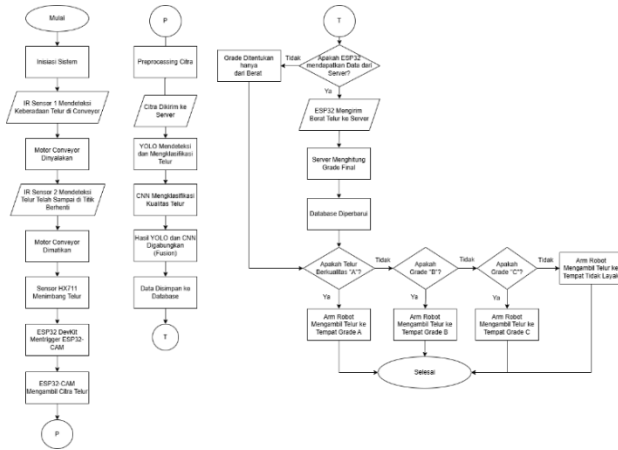


Fig. 2. Flowchart of the SORTA system workflow.

B. Dataset and Preprocessing

A dataset of 2,350 egg images was assembled from public repositories (Roboflow Universe) [8], prior published datasets, and targeted Google image searches. Images were distributed across four classes: Grade A (587), Grade B (535), Grade C (596), and Unfit (632). Manual bounding-box annotation was performed on Roboflow using the YOLO format.

To enhance model generalization, data augmentation was applied: 90° clockwise and counterclockwise rotation, brightness variation (0% to +15%), automatic orientation correction, and stretch resizing to 512×512 pixels. After augmentation, the training set expanded to 4,005 images. The dataset was split into training (70%), validation (15%), and testing (15%) subsets.

C. Model Training

YOLOv8n (nano) was selected for its computational efficiency on resource-constrained hardware. Transfer learning was applied using the official yolov8n.pt pretrained weights. Training was conducted on an Intel Core i5-1155G7 CPU for 15 epochs with a batch size of 16 and an input resolution of 640×640 pixels.

The CNN model (TFLite) was trained independently for visual classification and deployed on the server for inference. The two models operate in parallel, and the confidence-based fusion mechanism selects the prediction with the higher confidence score. When both agree, the consensus grade is used directly.

D. Grade Determination Logic

The final grading logic follows the SNI 3926:2023 national standard. Weight-based thresholds are Grade A (≥ 60 g), Grade B (50-59 g), Grade C (40-49 g), and Unfit (< 40 g). The visual grade from the AI fusion and the weight-based grade are compared, and the worse (lower priority) grade is assigned as the final outcome. For example, if the visual model predicts Grade B but the egg

weighs only 38 g (Unfit), the final grade is Unfit. This conservative approach is intended to minimize the risk of distributing substandard eggs.

The robotic arm servo angles are pre-mapped to each grade slot: Grade A $\rightarrow 80^\circ$, Grade B $\rightarrow 50^\circ$, Grade C $\rightarrow 10^\circ$, and Unfit $\rightarrow 180^\circ$. A smooth step-5 easing algorithm governs servo movement to prevent egg damage from abrupt motion.

IV. Results and Discussion

A. Model Training Results

After 15 epochs, the YOLOv8n model converged with a validation mAP@50 of 98.8% and mAP@50:95 of 86.4%. Precision and recall reached 97.3% and 97.5%, respectively, as summarized in Table I. Training loss components (box loss: 0.706 $\rightarrow$ 0.439; cls loss: 1.675 $\rightarrow$ 0.261; dfl loss: 1.249 $\rightarrow$ 1.113) showed consistent improvement without overfitting, as validation loss decreased in parallel.

TABLE I
YOLOV8N VALIDATION PERFORMANCE PER CLASS

Class	P (%)	R (%)	mAP@50	mAP@50-90
Grade A	93.4	100.0	97.5	81.5
Grade B	96.9	96.2	99.2	82.8
Grade C	98.8	94.3	98.9	88.0
Unfit	100.0	99.3	99.5	92.9
All	97.3	97.5	98.8	86.4

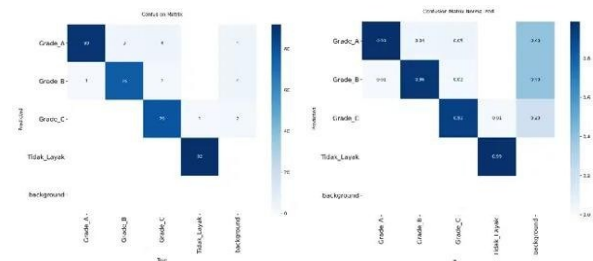


Fig. 3. Confusion and Normalized matrix for YOLOv8n on the validation set.

B. Real-World System Evaluation

End-to-end system testing was conducted at a commercial laying-hen farm in Desa Biting, Arjasa, Jember, East Java, Indonesia, using 100 eggs collected over five weekly sessions (20 eggs each) from April 3 to May 1, 2026. The final grade assigned by SORTA was compared against a manual reference assessment.



Fig. 4. Data collection at the laying-hen farm in Desa Biting, Arjasa, Jember. Left: operator monitoring real-time grading on laptop. Right: SORTA hardware deployed between egg cages during testing

Standalone YOLO achieved only 44.0% accuracy, with a pronounced bias toward the Unfit class (61 of 100 predictions). This behavior stemmed from YOLO's architectural design as an object detector rather than a fine-grained classifier, combined with the low-resolution, non-autofocus camera under variable farm lighting-conditions that differed from the controlled training environment.

The CNN+YOLO fusion system achieved 70.0% overall accuracy, a 26-percentage-point improvement over standalone YOLO. Grade B demonstrated the best per-class F1-score (75.9%), while the Unfit class achieved the highest recall (90.0%), meaning only one truly unfit egg passed through undetected. As summarized in Table II, standalone CNN alone achieved 72.0% accuracy, marginally outperforming the fusion system, but yielding a lower Unfit recall (80.0%).

TABLE II
SPECIFICATIONS ADOPTED FOR THE SIMULATED VSG

Metric	YOLO	CNN	CNN+YOLO
Accuracy (%)	44.0	72.0	70.0
Precision Macro (%)	39.5	72.0	70.0
Recall Macro (%)	43.5	70.3	70.1
F1-Score Macro (%)	30.5	68.1	66.1
Unit Recall (%)	100.0	80.0	90.0

C. Weight Sensor and Timing

Weight sensor validation on five reference eggs yielded a maximum error of 2.19%, confirming adequate calibration for grade-boundary discrimination. The end-to-end processing latency from camera trigger to grade assignment was approximately 4–6 seconds under normal WiFi conditions and up to 14.5 seconds on server fallback.

D. Discussion

The primary source of classification error in both YOLO and the fused system is the domain gap between training (controlled candling-lamp lighting, dark

background) and deployment (variable natural farm lighting). Replacing ESP32-CAM with a higher-resolution autofocus camera and enclosing the inspection zone in a light-controlled box are expected to significantly reduce this gap.

The conservative worst-case grading logic is intentionally strict for food safety reasons: it is preferable to reject a borderline Grade A egg than to allow an unfit egg to reach consumers. Future work may explore adaptive weighting of CNN vs. YOLO confidence scores, or incorporate additional sensors (e.g., UV transmittance for internal defect detection) to improve recall for higher grades.

V. Conclusion

This paper presented SORTA, an IoT-integrated automated egg-grading system combining YOLOv8n object detection, CNN visual classification, and load-cell weight measurement with a robotic sorting actuator. The YOLOv8n model achieved 98.8% mAP@50 on validation data. In real-world farm deployment, the CNN+YOLO fusion attained 70.0% overall accuracy and 90.0% Unfit recall across 100 eggs—substantially outperforming standalone YOLO (44.0%) and ensuring that nearly all unsafe eggs were flagged.

Key lessons learned include: (1) YOLO's strength lies in real-time detection triggering rather than fine-grained classification; (2) CNN provides more balanced per-class discrimination; (3) conservative multi-modal fusion is preferable in food-safety-critical systems; and (4) imaging hardware and lighting consistency are the dominant factors limiting accuracy under real-world conditions.

Future work will focus on upgrading the imaging subsystem, expanding the training dataset with farm-condition images, and exploring adaptive confidence weighting between CNN and YOLO outputs to further improve grading accuracy and system robustness.

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