EQual: Egg Quality Grading Using YOLOv5

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Abstract: Egg quality inspection is crucial for ensuring both consumer safety and profitability in the poultry industry. In most industries, egg inspection for grading relies solely on manual methods, using time-consuming and subjective evaluations to determine egg quality. This paper presents EQual, a non-destructive candling method approach to classifying egg grading quality following USDA standards: Class AA, A, and B-based on the internal and external characteristics of eggs such as stains, cracks, and air cells using the YOLOv5 model and Raspberry Pi 5 microcomputer. An enclosed staging platform with uniform illumination was utilized to acquire images, resulting in a dataset of 7,440 samples for testing and training. Experimental results demonstrate the device's ability to accurately classify egg grades, garnering a total accuracy of 90.1%. These results underscore the prototype's efficiency in determining egg quality, highlighting its potential to improve profitability and service quality for farmers and resellers.

Key Words: YOLOv5; Tensorflow; table eggs; Raspberry pi 5; machine learning

1. INTRODUCTION

Eggs are a crucial component of the human diet, valued for their rich nutritional content and versatility. As a source of high-quality protein, eggs supply all nine essential amino acids, making them a complete protein source that plays a key role in muscle repair, growth, and overall health (Morales Brown, 2024). However, eggs degrade over time due to biological and environmental factors that affect their overall quality. The air cell inside the egg expands as moisture and carbon dioxide escape through the porous shell. Fresh eggs contain a small air cell, and as the egg ages, larger air pockets form. Thus, air cell size serves as an excellent indicator of freshness (Seidler, 2004).

Several studies have employed the candling method to examine and analyze the internal structure of eggs. Egg candling is a process used to assess both interior and exterior egg quality (National Poultry Judging Manual, 2021). In evaluating egg quality, specific standards established by the United States Department of Agriculture (USDA) must be followed. Poultry eggs are categorized into three grades: AA, A, and B. Grade AA eggs must have a clean, unblemished shell with no stains or cracks and an air cell measuring 1/8 inch or less. Grade A eggs share the same shell quality as Grade AA but may have an air cell ranging between 1/8 to 3/16 inch. In contrast, Grade B eggs have rough or stained shells and contain an air cell larger than 3/16 inch (*Market eggs - interior egg grading by candling*, 2021). Air cell size is traditionally measured manually using a specialized ruler. Previous research has demonstrated the effectiveness of candling in detecting egg abnormalities. The candling method has been used to identify visible defects such as cracks, spots, and signs of fertilization (Ragni, 2010). More recently, machine learning has been integrated into the process. One study implemented the YOLOv5 algorithm to detect leaky or cracked eggs by developing an automated device equipped with a camera and light source to enhance detection accuracy (Luo, 2023).

One of the primary factors influencing egg quality degradation is time. A study was conducted to examine the effects of storage duration and conditions on egg freshness. The research found that eggs stored at room temperature experienced significant air cell expansion, reaching 6.4 mm by the 28th day—approximately 6 mm larger than the acceptable limit for Grade A eggs (Kopacz and Drążbo, 2018). In contrast, refrigerated eggs exhibited only minimal changes during the same period. While refrigeration slows down deterioration, prolonged storage still causes the air cell to expand, resulting in thinning of the yolk and albumen (Jones, 2023). Eventually, these changes lead to spoilage.

This study aims to develop a system for grading poultry eggs using image processing. The primary objective is to create a prototype that accurately classifies eggs based on quality indicators beyond size and weight. Specifically, the study will: (a) analyze grading and classification standards based on national and USDA guidelines, (b) build a database of poultry egg grading parameters, (c) train a YOLOv5 model using Tensorflow for quality detection through image processing, (d) integrate the system with a Raspberry Pi and candling method for real-time classification, and (e) evaluate the system's efficiency in improving grading accuracy and industry profitability.

YOLO series has been effectively used in detecting cracks and measuring air cell size through candling, aligning with the device's objectives. Its ability to perform fast and accurate detection makes it an ideal choice for grading eggs based on visual defects. YOLOv5 was selected for the Egg Quality Analyzer due to its efficiency, ease of use, and proven reliability in similar studies. It runs well on Raspberry Pi devices, making it suitable for projects with limited resources. While newer YOLO versions offer improvements, they require more complex setups and powerful hardware.

The significance of this study lies in enhancing poultry quality control through a smart Egg Grade Quality Grader utilizing image processing and Raspberry Pi. Farmers benefit from accurate grading based on internal and external egg attributes, reducing waste and boosting profitability. Distributors gain consistent quality control, better inventory management, and reduced return rates. Consumers receive safer, fresher eggs with greater transparency, while agribusinesses can improve production efficiency. Finally, the study provides a foundation for future researchers to advance food quality assessment and agricultural technology, promoting a more sustainable and modernized industry.

2. METHODOLOGY

Fig. 1 illustrates the egg quality analysis system, which classifies eggs based on exterior and interior characteristics using machine learning. Tensorflow handles deep learning, while YOLOv5 performs object detection. The process begins with image collection—eggs are placed in a clear tray, and dual cameras capture detailed images. These images undergo preprocessing, including cleaning, resizing, and formatting, ensuring compatibility with YOLOv5. The model, trained on labeled egg images, detects key features such as shell integrity, air cell size, and internal defects. Some parts remain unchanged to retain prior knowledge, while others are fine-tuned for egg classification.

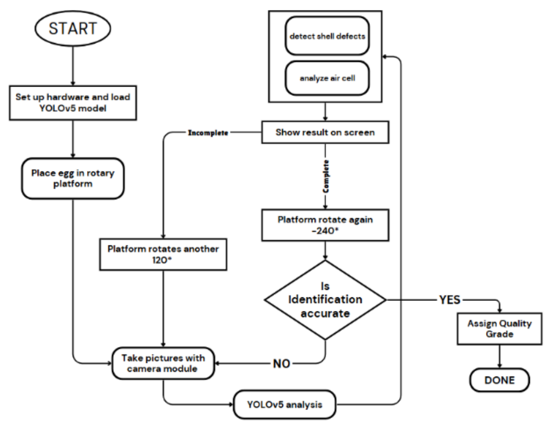

Fig. 1. System Flow Chart

The system then predicts egg quality, sorting eggs into Class AA (highest quality), Class A (good with minor flaws), or Loss (unfit for sale). Each class is assigned a numerical value: AA = 0.5, A = 1.0, and B = 2.0. During candling, the machine captures an image before rotating the egg twice by 120 degrees, then back -240 degrees to its original position. A post-processing step ensures classification accuracy by verifying confidence levels and consistency. If misclassified, the system reevaluates the image. The final classification is displayed on an LCD, providing an automated, accurate, and efficient grading solution.

2.1 Experimental Setup

Figure 2 presents the circuit diagram of the proposed prototype. The system is centered around a Raspberry Pi 5, which functions as the main processing unit. It is interfaced with a High-Quality Raspberry Pi

Camera Module 3, featuring a 12.3-megapixel Sony IMX500 image sensor to facilitate accurate visual inspection of egg quality. A touchscreen display is integrated to support intuitive user interaction and provide real-time system feedback. For effective candling, a concentrated light source is employed and controlled via a 220V/12V relay module, allowing the Raspberry Pi to safely switch higher voltages using its low-current GPIO outputs. The directional control of the light source is achieved through a stepper motor driven by a ULN2003A driver module, a high-voltage, high-current Darlington transistor array. This configuration enables precise angular positioning as dictated by the system's programmed instructions. To maintain thermal stability and ensure reliable performance during continuous operation, a 12V cooling fan is incorporated. This component mitigates heat buildup within the enclosure, thereby preserving the integrity and longevity of the electronic components.

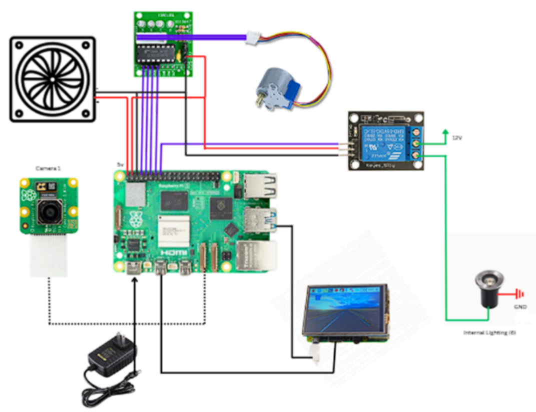

Fig. 2. Circuit Representation

Figure 3 shows that the prototype is a box-shaped structure with a closed front. Inside, it contains an egg-shaped object mounted on a small stand, placed on a flat platform. On the right side of the box, there is a slanted panel with a display screen, which shows the result of the grading process.

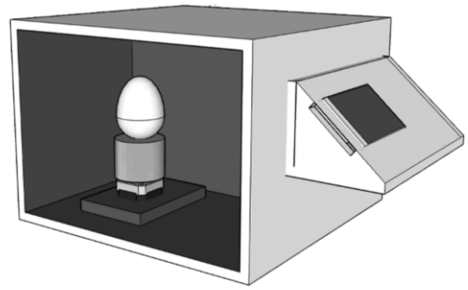

Fig. 3. Prototype (Isometric Front)

Figure 4 shows the setup of an egg grading system. The upper image highlights key components inside the device, including the sample egg placed on a rotary platform and a camera module positioned above it to capture images for analysis. The lower image shows the complete device with a casing and an LCD screen on a slanted panel. The screen displays the grading results, making the system easy to monitor and operate. This setup is designed to automatically assess the quality of eggs using image processing.

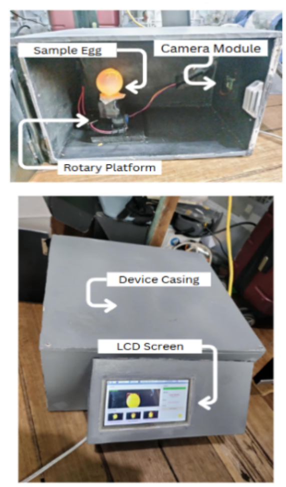

Fig. 4. Egg Grading System Setup

2.2 Data Acquisition

Table 1 presents the dataset composition, which was gathered manually by using a concentrated light beam for candling and camera, for the development and validation of the egg quality inspection system. A total of 5,952 labeled images (approximately 80% of the dataset) were allocated for training purposes. Each image was meticulously annotated to reflect specific egg characteristics based on USDA grading standards. The remaining 1,488 images (representing 20% of the dataset) were reserved for testing the model's performance on previously unseen data. Within the testing set, the model generated 1,693 individual egg detections, indicating the presence of multiple eggs in some images. This resulted in an average of approximately 1.14 eggs per image. This diverse dataset composition played a vital role in enhancing the model's ability to generalize effectively across a variety of real-world conditions, thereby contributing to its overall accuracy and robustness.

Table 1. Dataset

System Training	System Testing	System Validation from Testing	Total
5952	1488	1693	7440

Table 2 shows the USDA criteria for grading eggs into AA, A, or B categories. The classification is based on several quality factors such as shell appearance, candling results, air cell depth, and albumen firmness. Each grade reflects a specific standard of freshness and overall quality.

Table 2. USDA Standard for Poultry Chicken Eggs

Factors	Grade AA	Grade A	Grade B
Shell (Outer)	Free from Crack and Smooth Surface	Free from Crack and Smooth Surface	Ridge or Rough, Free from Crack, Scattered Stains
Shell (Inner)	Clean and free from Cracks	Clean and free from Cracks	Shell not broken, slightly stained
Air cell	1/8 inch or less in Depth	3/16 inch or less in Depth	More than 3/16 inch or less in Depth
Albumen	Clean Firm	Reasonabl e Firm	Clear, weak or watery

2.3 YOLOv5 Architecture

The YOLOv5 model is widely recognized for its exceptional efficiency in object detection tasks, offering an optimal balance between processing speed and detection accuracy. As illustrated in Figure 5, the architecture of YOLOv5 comprises three fundamental components: the backbone, neck, and head. The backbone operates as the primary feature extractor, processing input images to identify critical visual elements such as edges, textures, and structural patterns. The neck functions as an intermediary layer, refining and aggregating multi-scale feature representations from the backbone. This step enhances the model's ability to detect objects of varying sizes and scales with improved precision. The head component is responsible for the final detection tasks, utilizing anchor boxes and regression techniques to accurately localize and classify objects within the image. For the purposes of this study, the YOLOv5m variant was selected, as it provides a robust trade-off between model complexity and performance. Model training was conducted on an NVIDIA Tesla T4 GPU (15102 MiB) using the Tensorflow framework within a Python 3.8.10 environment. The specific hyperparameters employed during training are detailed in Table 3.

Table 3. Training Hyperparameters

Hyperparameters	Value
Input Resolution	320x320
Batch Size	16
Epochs	1000
Training Duration	29.26 Hrs
Momentum	0.937
Initial Learning Rate	0.01
Memory Usage	15,102 MiB

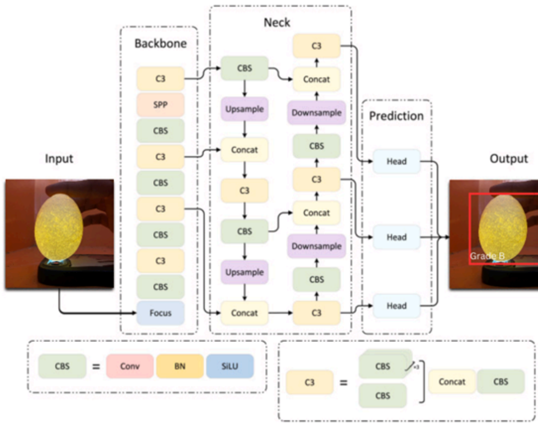

Fig. 5. YOLOv5 Architecture

2.4 Evaluation Metrics

Table 4 shows the confusion matrix used in evaluating the performance of the machine learning model. The confusion matrix serves as the foundation for calculating key performance metrics—Accuracy (Acc), Precision (Pr), Recall, and F1-score—which are essential in assessing the efficiency and effectiveness of the system. These metrics are derived from the matrix values: True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN). Specifically, Precision reflects the proportion of correctly identified positives, Recall indicates the model's ability to detect all relevant instances, and the F1-score represents the harmonic mean of Precision and Recall, offering a balanced measure of predictive performance.

Table 4. Confusion Matrix

	Actual Value	
Predicted Value	TP	FP
	FN	TN

$$Acc = \frac{TP+TN}{TP+TN+FP+FN} \qquad \text{(Eq. 1)}$$

$$Pr = \frac{TP}{TP+FP} \qquad \text{(Eq. 2)}$$

$$Recall = \frac{TP}{TP+FN} \qquad \text{(Eq. 3)}$$

$$F1score = \frac{(2 \times Pr \times Recall)}{(Pr+Recall)} \qquad \text{(Eq. 4)}$$

3. RESULTS AND DISCUSSION

3.1 System Testing

The developed system was tested by acquiring data from a total of 5 eggs, each representing one of the following quality parameters: Grade AA, Grade A, Grade B, Cracked, and Stained.

Figure 6 is an example of the results generated by the system. Before this, the system prompts the user to capture an image, displaying the live camera feed. Once the user clicks the 'Start AI Analysis' button, the system analyzes the captured egg using image processing and machine learning techniques. The system then provides the egg's grade and identifies any defects. In this output, the system detects cracks on the egg and assigns it a "Rejected" grade, with a confidence level of 0.0%. The detected defects, listed as "Crack, Crack," are displayed in red text to highlight the issue. The user interface also includes a progress bar indicating the analysis stage and a button to initiate another evaluation, ensuring continuous egg classification.

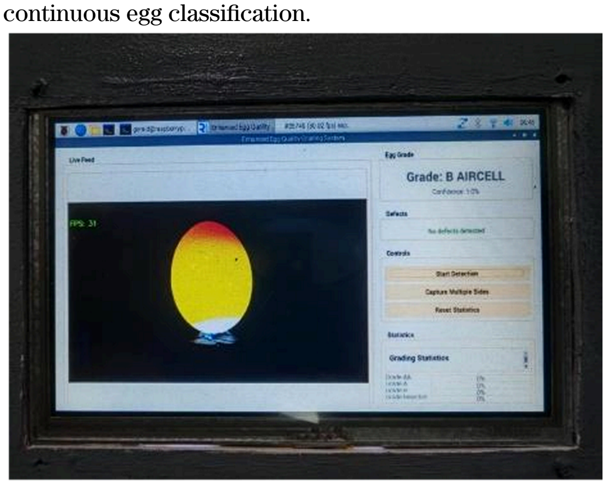

Fig. 6. System Interface

The samples gathered are of various eggs at different stages and freshness, from the highest quality to the lowest quality eggs. In the testing phase, the researchers utilized five eggs. These eggs underwent 10 tests for each parameter.

Table 5. System Testing

GRADE	IMAGE	RESULT
AA		Testing: 10/10 Accuracy: 100%
A		Testing: 10/10 Accuracy: 100%
B		Testing: 10/10 Accuracy: 100%
Stain		Testing: 7/10 Accuracy: 70%
Crack		Testing: 9/10 Accuracy: 90%

3.2 Statistical Treatment

Table 6 presents the confusion matrix evaluating the performance of the proposed egg grading system across four classification categories: Grade AA, Grade A, Grade B, and Rejected (R). The diagonal entries indicate correct classifications, while off-diagonal entries represent misclassifications. The system successfully classified all ten Grade AA samples with 100% accuracy. For Grade A, eight samples were correctly identified, while one was misclassified as Grade AA and another as Rejected. Grade B had nine correct classifications, and one sample misclassified as Rejected. The Rejected category yielded eight correct predictions, with one sample each misclassified as Grade A and Grade B.

From this matrix, the system achieved an overall accuracy of 87.5%, determined by the proportion of correct predictions (35 out of 40 total instances). Furthermore, evaluation metrics such as precision, recall, and mean Average Precision (mAP) were calculated to provide a more nuanced understanding of model performance. The model recorded a mAP of 77.15%, reflecting strong detection and classification capabilities across all categories. Despite its high performance, the confusion matrix highlights minor classification ambiguities among the Grade A, Grade B, and Rejected categories—suggesting opportunities for further optimization in the training process or feature extraction layers.

Table 6. Confusion Matrix of the System

		PREDICTED				
ACTUAL		AA	A	B	R	total
	AA	10	0	0	0	10
	A	0	8	1	1	10
	B	0	0	9	1	10
	R	0	1	1	8	10
	total	10	9	11	10	40

The overall accuracy of the device shown in Table 7, evaluated through precision and recall values, demonstrates its effectiveness in egg classification. The highest accuracy scores were recorded for Grade AA eggs, with 91.7% precision and 98.2% recall. Grade B eggs achieved 93.7% precision and 93.6% recall, while Grade A eggs attained 84% precision and 78.1% recall. In contrast, lower recall values were observed for cracked eggs (58.9%) and stained eggs (67.2%). These results highlight the efficiency of the prototype in determining egg quality, emphasizing its potential to improve profitability and service quality for farmers and resellers.

Table 7 Performance Metrics

Category	Accuracy	Precision	Recall	Map	F1
Grade AA	96.95%	91.7%	98.2%	87.1%	84.8%
Grade A	91.67%	84.0%	78.1%	84.9%	80.9%
Grade B	88.65%	93.7%	93.6%	96.6%	93.6%
Cracks	52.44%	76.4%	58.9%	58.9%	66.5%
Stain	96.29%	83.8%	67.2%	75.1%	74.6%
Total	90.14%	85.9%	79.2%	80.5%	82.1%

Figure 7 shows a graph that illustrates the training performance of the YOLOv5 model used for egg grading over multiple epochs. The x-axis represents the number of training epochs, while the y-axis indicates the performance scores ranging from 0 to 1. Three key evaluation metrics are shown: mAP@0.5 (mean Average Precision at 0.5 threshold), Precision, and Recall. At the beginning of the training, all three metrics start relatively low, indicating that the model initially struggled to detect and classify eggs accurately. However, around epoch 55, there is a significant improvement, where all metrics rise sharply and then remain consistently high with only minor fluctuations. This suggests that the YOLOv5 model quickly learned to effectively detect and grade eggs, maintaining strong accuracy, high precision, and reliable recall throughout the training process.

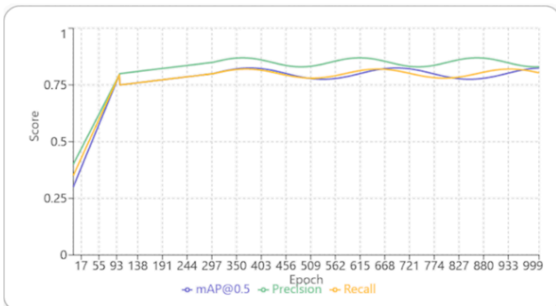

Fig. 7. Training and Validation over Epochs

4. CONCLUSIONS

In this study, a device that integrates YOLOv5, a machine learning algorithm, to analyze images and determine the grade and freshness of eggs is proposed and developed. The system utilizes a Raspberry Pi 5 microcontroller and is trained on an image dataset collected from local farms and resellers, focusing on internal and external egg characteristics such as stains, cracks, and air cells. The device successfully enhances productivity by enabling resellers to meet consumer demands for specific egg grades, ultimately boosting their profits.

To improve future research in food safety and engineering, several key recommendations are proposed. Expanding grading parameters to include external qualities like cage marks and internal factors such as yolk and albumen quality will enhance classification accuracy. Developing a machine capable of grading multiple eggs simultaneously by integrating advanced sensors can significantly improve efficiency. Securing financial support from investors will aid in the commercial production and refinement of the device. Upgrading to more advanced software, such as YOLOv8, can further enhance performance and accuracy.

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