DEVELOPMENT AND OPTIMIZATION OF A DEEP-LEARNING-BASED EGG COLLECTING ROBOT

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Highlights

- The egg collecting robot embedded with deep-learning-based computer vision algorithms was constructed.
- The retrained deep learning detector achieved over 93% performance for detecting and locating eggs in images.
- The kernel sizes of 65×65 pixels for erosion and dilation in image processing assisted in extracting geometry features of eggs with the least remaining noises.
- The robot with the soft grouting sponge attached to the gripper had 92-94% success rates in picking white and brown eggs.

ABSTRACT. Manual collection of floor eggs in cage-free (CF) hen housing systems is time-consuming and laborious. The objectives of this research were to 1) develop a robot arm to automatically collect floor eggs and 2) optimize the performance of recognizing and picking eggs via the robot. The robot consisted of a deep-learning-based egg detector, a robot arm, a two-finger gripper, and a hand-mounted camera. The deep learning model, You Only Look Once (YOLO) V3, was embedded into the vision system to detect and locate eggs on a simulated litter floor in real time. Image processing algorithms (e.g., cropping, erosion, etc.) were implemented for the detection and provided the robot with centroid coordinates, orientation, and axis length of detected eggs, so that the gripper can be manipulated with fitted angles and appropriate openings to grasp detected eggs. For optimization, the YOLO V3 was retrained with the dataset of floor eggs and achieved over 93% performance on detecting and locating eggs; the kernel sizes of 65×65 pixels for erosion and dilation in image processing assisted in extracting geometry features of eggs with the least remaining noises; and, among the four testing cases, the soft grouting sponge attached to the gripper had the highest success rates for egg picking. Finally, the robot accomplished 92-94% success rates in picking white and brown eggs. In sum, the developed egg collecting robot can be relied on for picking floor eggs to assist precision management in CF hen housing systems.

Keywords. Laying hen, Floor egg, Robot arm, YOLO V3, Image processing, Soft Gripper.

INTRODUCTION

Floor eggs are of major concern in modern cage-free (CF) hen housing systems, as they can be contaminated by litter or manure and eaten or broken by birds (Li et al., 2020) and longer time an egg resides on the litter floor could result in higher levels of bacterial contamination (Berrang et al., 1997). As a daily task, producers need to collect floor eggs timely to avoid economic loss and reduce food safety issues, which is strenuous and time-consuming. In addition, extended working hours in collecting floor eggs can negatively affect product cost. Matthews and Sumner (2015) estimated that manually collecting floor eggs in a 50,000-hen aviary house (one type of CF hen housing systems) increased product cost by 3 cents/dozen eggs, compared with egg collection in a 199,680-hen cage system. Automatic floor egg collection is, therefore, needed to reduce labor, improve egg-collection efficiency, and increase profitability. One potential solution is to automate the collection of floor eggs using robots.

Robotics have been developed and commercialized in poultry production (Ren et al., 2020). Poultry robots have been designed to disinfect air, aerate litter, increase bird movement, and inspect diseased birds in broiler production (ChickenBoy, 2021; Octopus Robots, 2021; TIBOT, 2021) and to roam throughout houses to reduce floor eggs in egg production (TIBOT, 2021). Egg-collecting robots, despite having not been commercialized, have been researched and achieved great performance for collecting floor eggs in CF hen housing systems. Vroegindeweij et al. (2018) developed a mobile PoultryBot mainly consisted of an image-based egg detector, a bent helical spring, and a controller, which collected floor eggs with a success rate of 46%. Chang et al. (2020) integrated a smart mobile robot with an egg collection channel, a chassis frame, an egg-picking mechanism, a control box, an egg sorting device, an egg storage tank, and a computer vision system. This robot avoided obstacles in a free-range environment, and the success rate of egg collection was 100% and <54% for collecting 1-4 and >5 eggs, respectively. Usher et al. (2017) constructed a mobile robot with a robot arm and an end effector of a suction cup and achieved a 91.6% success rate of collecting eggs in a lab environment.

Although egg-collecting robots have been successfully designed and constructed, there is room for improving robotic performance of recognizing and picking floor eggs. The egg detectors in previous egg-collecting robots were mainly based on image processing algorithms, which may require exhaustive adjustment to achieve acceptable performance and have poor generalization which limits broad applications. Deep learning techniques combined with image processing algorithms have shown great potential in accurately processing poultry-related images in different environments (Li et al., 2021; Li et al., 2020) and are intended to be implemented on-board a robot to detect and locate eggs. Both bent helical

spring (Vroegindeweij et al., 2018) and collection channel (Chang et al., 2020) methods to collect eggs were limited in their ability to reach eggs in corners [the preferred areas for hens to lay eggs (Lundberg & Keeling, 1999)], which may be improved upon by more flexible robot arms. End effectors of suction cups (Usher et al., 2017) may require strict partial vacuum between eggs and cups and accumulate litter and dust inside systems during the suction process, which may be overcome by using finger grippers as end effectors (Zhang et al., 2020). To avoid interference of robot arm manipulation, fixed cameras were typically embedded with complicated robot path planning algorithms or installed beyond the range of robot movement (Zhao et al., 2016), which could limit the ability to locate eggs (Li et al., 2020) due to the distance between the camera and eggs. However, mounting the camera in or on the end effector (hereafter referred to as hand-mounted camera in this instance) can make it move with a robot arm and thus may keep close proximity to eggs of interest for locating eggs precisely, which is intended to be developed and evaluated in this study as well.

The objectives of this research were to 1) develop an egg-collecting robot with a deep-learning-based egg detector, a robot arm, a two-finger gripper, and a hand-mounted camera; and 2) optimize the performance of recognizing and picking eggs with different strategies, which include retraining the deep learning egg detector with the dataset of floor eggs, fine-tuning relevant parameters of image processing algorithms to locate detected eggs, calibrating the robot, and configuring the finger gripper.

MATERIALS AND METHODS

SYSTEM DESCRIPTION

The robot development and system optimization were conducted in the Instrumentation Lab of the Department of Agricultural and Biological Engineering, Mississippi State University, USA (Fig. 1). Litter was obtained from a commercial CF farm to simulate practical conditions of floor eggs. Brown and white eggs for the system development and testing were procured from a local grocery store. The robot arm (Gen 3, KINOVA Inc., Boisbriand, QC, Canada) was mounted on a table and can move freely with 7 degrees of freedom (DoF) and a maximum reach distance of 902 mm. The maximum payload was 2.0 kg that should be sufficient for loading a 40- to 70-g egg. The adaptive two-finger gripper (Robotiq 2F-85, KINOVA Inc., Boisbriand, QC, Canada) was installed at the end of the arm and can be bent once obstructed. The hand-mounted camera (Intel[®] RealSense[™], Intel Corporation, Santa Clara, CA, USA) was used to capture RGB and depth images, but only RGB images were used as they were deemed sufficient for egg recognizing via deep learning. The electronic circuit and connection of the arm, gripper,

and camera were enclosed, and relevant signals between the robot and the laptop (Alienware Area-51 m, Dell Inc., Round Rock, TX, USA) were transmitted via an ethernet cable. The laptop was equipped with 32 GB RAM, 9th Generation Intel(R) Core (TM) i9-9900K processor, and NVIDIA GeForce RTX 2080 8GB GPU card.



Figure 1. Photos of the egg-collecting robot system and experimental laboratory.

OVERALL PROGRAM OF THE ROBOT MANIPULATION

The overall program of the robot manipulation mainly consisted of two parts that were egg recognition and robotic arm controlling for egg collection actions (Fig. 2). The robot was initialized to a position of interest with the maximum height of the front elbow being 39 cm, which is within the height range [30-40 cm (Moneau & Risser, 2021)] of the first floor of aviary systems and suitable to pick floor eggs without obstruction. The camera was then turned on with its lens pointing downward to acquire top-view images and at a height of 21 cm above the floor, and the acquired images were fed into egg recognition algorithms to detect and locate eggs. Geometry features (e.g., centroid coordinates, orientations, etc.) of detected eggs were extracted and converted from the imagery coordinate system to the robot arm coordinate system. The converted features were input into the robotic arm controlling program, so that the gripper can move to the location of the detected egg and rotate to fit the egg orientation. The gripper then closed based on the axis length of the detected egg, grasped it, and dropped it in the storage place. Finally, the arm moved to the home position and prepared for picking the next egg. All the procedures were coded and executed in Python, an open-sourced, high-level, and general-purpose programming language (Python Software Foundation, Wilmington, DE, USA).



Figure 2. Flow chart of the overall program for the robot manipulation.

ALGORITHMS FOR EGG RECOGNITION

The algorithms for egg recognition were composed of a deep learning object detector [You Only Look Once V3, YOLO V3 (Redmon & Farhadi, 2018)] and image processing methods (Fig. 3). The YOLO V3 took the acquired image as an input and divided it into a map with default grids. Predefined anchors were tiled onto each grid cell, and predictions of bounding boxes along with confidences and class names were made accordingly. With the non-maximum suppression rule, the bounding box with the highest confidence was retained for egg detection. The egg detection results used for later analysis included indices, centroid coordinates (x, y), and width and height (w, h) of bounding boxes. The YOLO V3 is lightweight and accurate in most detection tasks and thus may be suitable to serve our purpose of detecting and locating eggs in real time.



Figure 3. Illustration of algorithms for egg recognition. YOLO stands for You Only Look Once, which is the name of the deep learning algorithm.

There could be multiple detected eggs including complete and incomplete ones within one image. To avoid confusion of the robot manipulation, only the detected egg with a minimum index and proper area that was over 70% of the bounding box area ($\sim 10.5 \text{ cm}^2$) of one complete egg was selected for further image processing. Each egg of interest was cropped from the original image based on the selected index, centroid coordinates, width, and height and then converted to grayscale. The cropped image had relatively simple components (an egg and litter), and its histogram had two major peaks, which are the critical features of a bimodal image. As Otsu thresholding is good at dealing with bimodal images (Vala & Baxi, 2013), it was used to segment the egg from background. With the same $n \times n$ kernel (also defined as filters), the binary image was firstly eroded to rule out noises and then dilated to retain the complete size and shape of the region of interest. Different kernel sizes were evaluated to optimize egg segmentation performance. An egg is in an ellipse shape, and the ellipse fitting algorithm (Nasirahmadi et al., 2016) was implemented onto the eroded and dilated image to extract the geometry features (e.g., long- and short-axis lengths and orientation) of the egg.

HAND-EYE CALIBRATION

The robot has seven DoF, corresponding to seven Cartesian coordinate systems, and only the coordinate system at the end of the arm was calibrated to build a connection between the end effector and hand-mounted camera for egg picking, which is so called hand-eye calibration. In the desired position, the gripper was perpendicular to the floor at a height of 8 cm (Fig. 4). The pixel-to-distance conversion factor for the hand-eye calibration was 77.3 pixels/cm based on calibration.



Figure 4. Schematic drawings of a coordinate system $(X_R - O_R - Y_R)$ at the end of the robot arm, an imagery coordinate system $(X_I - O_I - Y_I)$, and some geometry features of a detected egg, which are centroid coordinates (X_e, Y_e) in the imagery coordinate system, long-axis length (L), short-axis length (S), and orientation (\emptyset). "+" indicates a positive direction of an axis in a coordinate system.

Absolute values of coordinates in different coordinate systems were of no interest, and only the speeds of linear and angular movements of the robot arm from the gripper position to egg position were used for the robot control and calibrated using Equations 1-7.

$$LS_x = \left(\frac{W_I}{2} - X_e\right) \div CNV \div T \tag{1}$$

$$LS_{y} = (H_{I} - Y_{e}) \div CNV \div T$$
⁽²⁾

$$LS_z = h_1 \div T \tag{3}$$

$$AS_{\chi} = 0 \tag{4}$$

$$AS_y = 0 \tag{5}$$

For long-axis-based rotation,
$$AS_z = \begin{cases} -\frac{90^\circ - \emptyset}{T}, & \text{if } \emptyset < 90^\circ \\ \frac{90^\circ + \emptyset - 180^\circ}{T}, & \text{if } \emptyset > 90^\circ \end{cases}$$
 (6)

For short-axis-based rotation,
$$AS_z = \begin{cases} \frac{\emptyset}{T}, & \text{if } \emptyset < 90^{\circ} \\ -\frac{180^{\circ} - \emptyset}{T}, & \text{if } \emptyset > 90^{\circ} \end{cases}$$
 (7)

where

 LS_x , LS_y , and LS_z = linear speeds of the robot arm in the *x*, *y*, and *z* axes of the robot Cartesian coordinate system, respectively;

 AS_x , AS_y , and AS_z = angular speeds of the robot arm in the *x*, *y*, and *z* axes of the robot Cartesian coordinate system, respectively;

 (X_e, Y_e) = centroid coordinates in the imagery coordinate system;

 W_I , H_I = width and height of an image, 1,280 and 720 pixels in this case, respectively;

CNV = pixel-to-distance conversion factor, 77.3 pixels/cm in this case;

 h_1 = gripper height, 8 cm in this case;

T is robot manipulation period, 2 sec in this case;

 \emptyset = egg orientation in the imagery coordinate system.

long- or short-axis-based rotation = the gripper rotates to fit the long or short axis of a targeting egg.

ALGORITHMS FOR ROBOTIC ARM CONTROLLING

Robot manipulation was executed based on the calibrated linear and angular speeds (Fig. 5). The robot

was manipulated with sequential commands. The gripper moved linearly in the horizontal plane to the position right above the egg of interest using LS_x and LS_y , rotated to fit egg orientation using AS_x , AS_y , and AS_z , and then moved downward using LS_z . Such a movement strategy can reduce collision between the gripper and egg when the gripper moved downward. The gripper, originally in an open status, then closed based on the axis length of the targeting egg to grasp the egg and moved up using $-LS_z$. The robot movement after the grasping was not required to be as delicate as that during grasping and thus controlled based on Cartesian coordinates and predefined planning path. The gripper and grasped egg moved to the position of the storage place and went down using LS_z . The gripper then opened at the maximum size to release the egg into the storage place, moved up again using $-LS_z$, and returned to the home location based on the Cartesian coordinates. A 2-sec sleep time was executed after each step of robot manipulation so the robot had enough time to execute the computed motions in time (Cowley et al., 2013).



Figure 5. Flow chart of robot manipulation. LS_x , LS_y , and LS_z are linear speeds of the robot arm in the x, y, and z axes of the robot Cartesian coordinate system, respectively; and AS_x , AS_y , and AS_z are angular speeds of the robot arm in the x, y, and z axes of the robot Cartesian coordinate system, respectively.

EXPERIMENTS AND OPTIMIZATIONS

With the system constructed, the performance of the system for egg recognizing and picking should be evaluated and improved with a series of optimization strategies.

Training and Testing the Egg Detector with the Dataset of Floor Eggs

The YOLO V3 was previously trained with millions of images in the Common Objects in Context (COCO) dataset. Per preliminary testing, the pretrained YOLO V3 cannot detect the eggs in current situations, which was way different from general background in the COCO dataset. Therefore, the model needed to be retrained with the dataset in current situations. A total of 200 images containing 1,627 white and brown egg instances were taken, labeled, and fed into the model for the re-training. The training process was conducted in a free cloud server, Google Colab. The retrained YOLO V3 was downloaded from the server and evaluated with another 44 images containing 340 egg instances. The deep learning detector was executed on the PC with an open-source library, Python-OpenCV. Some artificial egg images

(Fig. 6) (nearly 10% of total training images) were also included in the dataset to introduce variations for training and avoid overfitting.



Figure 6. Some sample images in the dataset of floor eggs. The leftmost image contains artificial eggs while the rest two images have real eggs.

Optimizing Parameters of Image Processing

Per observation, using the Otsu thresholding method cannot perfectly segment eggs, because some intensities of litter floor also had high frequency in histograms, which could cause errors for robot manipulation. The erosion and dilation were key steps to exclude noises, and kernel sizes affected the efficiency of these steps. The kernel sizes $(n \times n)$ from 10×10 to 65×65 pixels (with 5×5 -pixel intervals) for erosion and dilation were compared to determine the optimal one. Original images were tested with the YOLO V3 and cropped based on the detection results. A total of 35 cropped brown and white egg images were used to test each kernel size. The processed results were compared with manually segmented results.

Calibrating Sizes of Gripper Openings

As the gripper closed based on actual axis lengths (L or S, Fig. 4) to grasp an egg, real values (in the unit of mm) of opening sizes should be obtained for precise control. The gripper was set with predefined non-unit values of 0-0.95 with 0.05 intervals corresponding to different levels of openings, and each opening was measured three times. The linear relationship between predefined values and actual values was calibrated and fitted as a curve.

Selecting Appropriate Soft Materials Attached to the Gripper

The metal gripper can be rigid to break eggs during egg picking. Four scenarios were compared to determine the optimal one for risk reduction of breaking eggs, which were without any materials attached to the inner sides of the gripper (Scenario a, Fig. 7a), with protective foam attached (Scenario b, Fig. 7b), with flex and seal shipping roll attached (Scenario c, Fig. 7c), and with soft grouting sponge attached (Scenario d, Fig. 7d). The three materials were procured from a local market, and they were cut into 2.0-2.5 cm in width, 3.4-3.8 cm in height, and 1.2-1.5 cm in depth. For each scenario, the long- and short-axis-based algorithms (Equations 6-7) were conducted, and two types of eggs (white and brown) were

tested, each of which was evaluate 25 times. Considering material depth, the gripper with a material attached left 20% more space than the axis length of a detected egg, when it closed to grasp the egg.



Figure 7. Photos of different materials attached to the inner sides of the gripper: (a) without materials attached; (b) with protective foam attached; (c) with flex and seal shipping roll attached; and (d) with soft grouting sponge attached.

To understand the final performance of egg collection, the robot was tested with optimal parameters and materials and improved algorithms after the optimizations. Two types of eggs were tested 25 times, respectively.

EVALUATION METRICS

Metrics for Evaluating the Retrained Deep Learning Model

Three common metrics (i.e., precision, recall, F1 score) were used to evaluate the performance of the retrained YOLO V3 for egg detection (Equations 8-10).

$$Precision = \frac{True \ positive}{True \ positive + False \ positive} \tag{8}$$

$$Recall = \frac{True \ positive}{True \ positive + False \ negative}$$
(9)

$$F1 \ score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$
(10)

Two metrics [i.e., mean intersection over union (MIOU) and root mean square error (RMSE)] were used to evaluate the performance of the retrained YOLO V3 for egg locating (Equations 11-13). *Area of around truth box* \cap *Area of detected box*

$$IOU = \frac{Area of ground truth box + Area of detected box}{Area of ground truth box \cup Area of detected box}$$
(11)

$$MIOU = \sum_{i=1}^{N} IOU_i \tag{12}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \{(\hat{x}_i - x_i)^2 + (\hat{y}_i - y_i)^2\}}{N}}$$
(13)

where

IOU = intersection over union

MIOU = mean IOU

 $IOU_i = IOU$ of the i^{th} measure egg

RMSE = root mean square error

 x_i, y_i = centroid coordinates of the *i*th ground truth egg

 $\hat{x}_i, \ \hat{y}_i$ = centroid coordinates of the *i*th predicted egg

N = total number of measured eggs.

The processing time reported by Python without deployment of GPU (Graphics Processing Unit) was used to evaluate the processing speed of the retrained YOLO V3 for processing 44 images, trained on the cloud server. The processing speed (frame per second, fps) was obtained by dividing the 44 images with the total processing time.

Metrics for Evaluating the Image Processing Algorithms

Normalized difference between the ground truth and prediction was calculated to evaluate the performance of image processing algorithms for extracting the geometry features (i.e., long- and short-axis length and orientation) of eggs (Equation 14), and the results were presented as mean \pm standard deviation. The total number of remaining noises was counted for processing the 35 cropped egg images of each type of eggs, and larger number indicates poorer performance of segmentation.

$$NF_j = \left\{ \frac{\sum_{i=1}^{M} (GT_i - Pred_i)/GT_i}{M} \right\}_j$$
(14)

where

NF = normalized difference

 $j = \text{the } j^{th}$ geometry feature, including long-axis length, short-axis length, and orientation in this case $GT_i = \text{the value of the } i^{th}$ ground truth

 $Pred_i$ = the value of the i^{th} prediction

M =total number of cropped egg images, 35 in this case.

Metrics for Evaluating the Calibration of Gripper Openings

The coefficient of determination (R^2) was determined to evaluate the regression performance between predefined values in the robot and real length of gripper openings (Equations 15-17).

$$RSS = \sum_{i=1}^{N} (L_i - \hat{L}_i)^2$$
(15)

$$TSS = \sum_{i=1}^{N} \left(L_i - \frac{1}{N} \sum_{i=1}^{N} L_i \right)^2$$
(16)

$$R^2 = 1 - \frac{RSS}{TSS} \tag{17}$$

where

RSS = sum of squares of residuals

TSS =total sum of squares

 y_i, \hat{y}_i = ground truth value and predicted value via a fitted curve, respectively

N = total number of measured samples.

Metrics for Evaluating Egg Picking Performance

Success rate, broken rate, dropping rate, and missing rate were used to evaluate the egg picking performance (Vroegindeweij et al., 2014). Broken eggs are the eggs broken by the gripper during the collection attempt; dropping eggs are the eggs grasped by the gripper at first, but falling down during robot movement; and missing eggs are the eggs escaping from the gripper during the collection attempt. The rates were obtained by dividing number of different categories of eggs with total number of testing (25 in this case). The success rate excluded broken, dropping, and missing rates. To exclusively evaluate

the performance of the attached materials for the gripper, only the cases with successful egg detections via deep learning and image processing were accounted for the analysis.

The same four rates were also used to evaluate the final performance of the robot after optimization. Besides the abovementioned definition, the missing eggs may be resulted from failure detections. Total time of egg collection was reported by Python and comprised the time of egg detection and robot manipulation in each round.

RESULTS

PERFORMANCE OF THE RETRAINED DEEP LEARNING MODEL

The performance of the retrained YOLO V3 is presented in Fig. 8. The precision, recall, and F1 score were over 98%, indicating good performance of egg detection. MIOU was 93.2% and RMSE was 0.35 mm, indicating minor errors of egg locating in an image. The processing speed of the retrained YOLO V3 was 5 fps and, considering eggs of interest being static in an image, should be sufficient for real-time processing purposes in this case. Overall, the retrained YOLO V3 was robust and accurate enough to be embedded into the program and assist in the robot control.



Precision = 100.0% Recall = 98.5% F1 score = 99.3% MIOU = 93.2% RMSE = 0.35 mm Processing speed = 5 fps

Figure 8. A sample of detection results and performance of the retained You Only Look Once (YOLO) V3. MIOU is mean intersection over union, RMSE is root mean square error, and fps is frame per second.

PERFORMANCE OF DIFFERENT SIZES OF KERNELS

The normalized difference between the extracted geometry features of ground truth egg and predicted egg with various kernel sizes is displayed in Table 1. Most of the absolute normalized differences were less than 6%. As the kernel sizes increased, total number of remaining noises decreased. And the kernel size of 65×65 pixels was selected to process images later, because it can result in zero noises for both types of eggs and slight increments (0.5-2.5%) of absolute normalized differences for most extracted geometry features (except for orientation of white eggs), compared with the kernel size of 10×10 pixels. The absolute normalized differences of brown eggs were 0.2-6.6% higher than those of white eggs, and the brown eggs had negative normalized differences for the orientation. Standard deviations of the

normalized differences of orientations were 5.4-16.9% larger than those of short- and long-axis lengths

for both types of eggs.

Table 1. Normalized difference between the extracted geometry features of ground truth eggs and predicted eggs processed by various sizes of kernels of image processing and number of remaining noises after image processing.

Vornal siza		Wh	ite egg		Brown egg				
(nivala)	Short-axis	Long-axis	Orientation	Number of	Short-axis	Long-axis	Orientation	Number of	
(pixels)	length (%)	length (%)	(%)	remaining noises	length (%)	length (%)	(%)	remaining noises	
10×10	$1.7{\pm}1.0$	$1.0{\pm}1.1$	2.4±6.9	30	3.9±4.7	1.2±4.9	-6.0±21.6	93	
15×15	$1.7{\pm}1.0$	$1.0{\pm}1.2$	2.5±7.3	11	4.2±4.7	1.7 ± 4.9	-6.6±21.3	47	
20×20	$1.8{\pm}1.0$	1.1 ± 1.1	$2.4{\pm}6.9$	10	5.2±4.3	2.2 ± 4.8	-5.9 ± 19.7	26	
25×25	$1.8{\pm}1.0$	1.1 ± 1.2	2.4±7.3	10	5.2±4.3	2.3 ± 5.0	-6.2 ± 19.6	21	
30×30	1.8 ± 1.0	1.1 ± 1.2	2.1±6.9	10	5.8 ± 3.8	3.2 ± 4.8	-8.2 ± 18.1	15	
35×35	$1.8{\pm}1.0$	1.2 ± 1.2	2.1 ± 7.2	10	5.9 ± 3.8	3.5 ± 5.1	-8.1 ± 18.3	13	
40×40	$1.8{\pm}1.0$	1.2 ± 1.2	$2.0{\pm}6.8$	10	$6.0{\pm}3.6$	3.8 ± 5.0	-8.0 ± 17.9	12	
45×45	$1.9{\pm}1.0$	1.5 ± 1.3	1.7 ± 7.2	6	$6.0{\pm}3.7$	3.9 ± 5.2	-8.0 ± 18.3	7	
50×50	$1.9{\pm}1.0$	1.7 ± 1.3	1.6 ± 6.7	5	6.1±3.6	4.2 ± 5.1	-8.0 ± 18.2	5	
55×55	2.0 ± 1.2	1.9 ± 1.4	1.2 ± 7.2	3	6.2 ± 3.7	4.3 ± 5.2	-7.6 ± 18.3	5	
60×60	2.1 ± 1.2	2.2±1.4	1.2 ± 6.9	0	6.3±3.7	4.8 ± 5.1	-7.7 ± 18.3	1	
65×65	2.2±1.2	2.6±1.5	1.0±7.5	0	6.4±3.8	5.2±5.3	-7.6±18.3	0	

Note: Number of remaining noises is the total number of remaining noises for the algorithms to process 35 cropped egg images. Excluding number of remaining noises, other results are presented as mean \pm standard deviation.

CALIBRATION CURVE OF GRIPPER OPENINGS

In the calibration curve of Fig. 9, the R^2 was over 0.99 for the fitted equation, indicating that the gripper can open/close precisely based on the axis length of detected eggs. The difference among the three times of measurement was less than 0.1 mm, and, if excluding manual measurement errors, this reflected great precision for repeated gripper operations.



Figure 9. The calibration curve of the gripper openings. The predefined values in the robot are non-unit.

PERFORMANCE OF EGG PICKING VIA THE GRIPPER WITH VARIOUS MATERIALS ATTACHED

Table 2 indicates that the gripper with the soft grouting sponge attached had the highest success rate (100%) and smallest broken, dropping, and missing rates (0%) for picking both types of eggs, therefore, the soft grouting sponge was selected as the optimal materials to be attached to the gripper. In Scenarios a and b, the long-axis-based algorithm resulted in a smaller broken rate than the short-axis-based algorithm, and brown eggs were more likely to be broken.

		White egg				Brown egg			
Algorithms	Scenarios	Success	Broken	Dropping	Missing	Success	Broken	Dropping	Missing
		(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
Short-axis- based	а	56	44	0	0	44	52	0	4
	b	64	12	16	8	84	4	0	12
	с	100	0	0	0	96	0	0	4
	d	100	0	0	0	100	0	0	0
	а	60	28	0	12	56	32	0	12
Long-axis- based	b	32	0	28	40	24	4	16	56
	с	96	0	0	4	100	0	0	0
	d	100	0	0	0	100	0	0	0

Table 2. Performance of egg picking via the gripper with different materials attached.

Note: Scenarios a-d indicate the griper without any materials attached, with protective foam attached, with flex and seal shipping roll attached, and with soft grouting sponge attached, respectively as shown in Fig. 7. Short- or long-axis-based algorithm is used to control the gripper rotating to fit the short or long axis of a detected egg, respectively. The rates were only accounted

FINAL PERFORMANCE OF THE ROBOT

Combining the above-mentioned results, the final settings were the retrained YOLO V3, kernel size of 65×65 pixels, calibrated gripper openings, long-axis-based algorithm, and soft grouting sponge attached to the gripper. The robot achieved 92-94% success rate, 0% broken and dropping rates, 4-8% missing rate, and 45-50 sec/round for picking eggs (Fig. 10).



Figure 10. The final performance of the egg collecting robot. Note: The missing rate also included the cases of failure detections.

DISCUSSION

PERFORMANCE OF THE DEEP LEARNING DETECTOR

The high performance (>93%) of egg detection and locating was attributed to the state-of-the-art architecture of YOLO V3 and limited detection environments. This does not mean that the YOLO V3 only works for these environments. Through testing different architectures (e.g., faster region-based convolutional neural network, single shot detector, and region-based fully convolutional network), our previous study demonstrated that the deep learning techniques can detect and locate eggs accurately (with over 91% accuracy at least) under various conditions (e.g., different light intensities, egg cleanliness, etc.)

that were included in the training datasets (Li et al., 2020). Therefore, the YOLO V3 may function well in CF housing environments if relevant images were used for the training. Even if it performed poorly in some extremely complicated conditions, upgraded versions of YOLO models [e.g., YOLO V4 (Bochkovskiy et al., 2020) and YOLO V5 (Ultralytics, 2020)] could also be helpful for improving floor egg detection. Because of limited detection environments and many egg instances per image (>7 eggs in an image), only 200 images that can cover the current situations of the robot development were used to retrain the YOLO V3. The number of training images can be increased if detection environments became expanded to be more practical.

Even though the YOLO V3 in this study cannot be as fast as the original one [45 fps (Redmon & Farhadi, 2018)], the processing speed was suitable for the robot settings. The robot moved the desired position (Fig. 4) at first and then remained stable for egg detection, under which eggs stayed static as well and the 5 fps processing speed was enough for the detection. It should be pointed out that because of the deployment of the lightweight deep learning model and training on cloud server, the GPU in the computer was not used, and the system can also be developed and implemented in some more economical GPU-free devices (e.g., Raspberry Pi).

PERFORMANCE OF IMAGE PROCESSING

The erosion with a larger kernel size can remove more small objects/noises and is more likely to highlight substantive objects (i.e., egg in this case), and the dilation (if with the same kernel size) is to recover the eroded objects of concern to the original size (Gonzalez & Woods, 2002). The smaller sizes of kernels (i.e., 10×10 pixels, Fig. 11), despite resulting from smaller scales of erosion and accordingly smaller absolute normalized differences, were not able to rule out all noises and may lead to errors for robot manipulation, thus not being considered. Eggshell color can affect the processing results. The Otsu thresholding method could treat parts of edges of brown eggs as background due to relatively indistinct contrast between the edges of some brown eggs and background (Fig. 11) (De Wet et al., 2003), which resulted in smaller segmented eggs, shorter predicted short- and long-axis lengths (corresponding to higher normalized difference for orientation). After the dilation, egg sizes that were mainly for extracting short- and long-axis length may return to the original ones but egg shapes that largely affected orientation extraction could not always be recovered (Gonzalez & Woods, 2002), leading to a higher standard deviation of normalized difference for the orientation than for the other two geometry features. These factors should be considered for the development of egg collecting robots.



Figure 11. Sample images processed by the image processing algorithms with kernel sizes of 10×10 pixels for erosion and dilation.

COMPARISON OF DIFFERENT ATTACHED MATERIALS

The softness and adhesion of the gripper are key factors influencing egg picking (Shintake et al., 2018). The metal construction of the original gripper could be too rigid to grasp eggs, causing many broken eggs during egg picking operations. The protective foam was not so rigid as metal but may not be soft enough to avoid breaking eggs. Additionally, the surface of the foam was too smooth and slippery, resulting in eggs escaping from the gripper during or after grasping. The flex and seal shipping roll was soft and its surface was slightly adhesive; therefore, its egg picking performance outperformed the previous two. However, its surface adhesiveness declined as number of egg picking increased, which led to escaping eggs as well. The softness and adhesion of the soft grouting sponge were the best among the four testing cases; therefore, this material had the best egg picking performance. There could be other alternatives of end effectors for picking eggs, such as electromagnet and permanent magnet (Tsugami & Nishida, 2017), elastic membrane (Amend et al., 2018). These end effectors were all proofs-of-concepts for picking eggs in the environments of human living rooms or offices and are recommended to be evaluated for picking up floor eggs in CF hen housing environments.

EFFECTS OF EGG CHARACTERISTICS

Egg characteristics can affect the decisions on the development of egg detection and egg picking algorithms. Because of the longer length for a long axis of an egg, the similar differences became smaller after normalized by long-axis length than by short-axis length (Table 1). The ends along the long axis of an egg have higher vaulted demoes and demo efficiency (higher values indicate better resistance to broken force) than the sides along the short axis, therefore, they can resist greater compressive loads than the sides (Voisey & Hamilton, 1976), resulting in fewer broken eggs for the long-axis-based algorithm. Considering the abovementioned factors, the long-axis-based algorithm was used to extract egg geometry features and control the gripper.

FINAL PERFORMANCE, LIMITATIONS, AND FUTURE RESEARCH

Although the egg collecting robot achieved great egg picking performance (>92% success rate) through a series of optimizations, it still has some limitations and needs improvement before deployed in CF hen housing systems. The operation time of the robot was nearly one minute for detecting and picking one egg in a detection and egg pick cycle. Despite sufficient time for the robot manipulation being available, each detection and egg pick cycle was energy-consuming, and the battery design of the robot should take this into account. The robot was proportionally large relative to floor space of aviary systems, and robot path planning algorithms should be customized to enable the robot arm to reach anywhere on the floor. Touching litter floor can result in potential damage of the gripper, and additional solutions should be created for picking buried eggs in litter. In this study, the robot arm was affixed to a table and unmovable. To allow the robot to collect floor eggs throughout hen houses, it should be integrated with a movable system such as a gantry, track, or wheeled system to allow for x-y mobility within the space.

CONCLUSION

The egg collecting robot was successfully designed and constructed in this study. The retrained YOLO V3 had over 93% performance in detecting and locating eggs. The robot can move to the egg location and the gripper can rotate to fit egg orientations in an image. Different kernel sizes of erosion and dilation in image processing influenced the extraction of egg geometry features differently, and the kernel sizes of 65×65 pixels resulted in no noises after image processing and thus was selected to program the robot. Various types of commercially available materials were attached to the robot gripper and tested to determine the optimal ones for egg picking, and the gripper with the soft grouting sponge achieved the highest success rate for picking white and brown eggs. The final performance of the robot after the optimization was 92-94% for successfully picking both types of eggs.

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