

Attempt Towards Automated Guided System for Cage-free Raising Egg Harvesting

Rubel Ahmed ^{1,*}, Takahashi Kei ¹, Wumenjiang Abudoula ¹, Tasuku Miyoshi ¹, Nobuya Tanimoto ², and Kazuaki Oozeki ²

¹ Department of Mechanical Engineering, Iwate University, Morioka, Japan; Email: takakei617@gmail.com (T.K.), umarjan_abla@hotmail.com (W.A.), tmiyoshi@iwate-u.ac.jp (T.M.)

² P&A Technologies Inc., Morioka, Iwate, Japan; Email: {n_tanimoto, k_oozeki}@pa-tec.com (N.T., K.O.)

*Correspondence: jxrubelahmed@gmail.com (R.A.)

Abstract—Nowadays, Automated Guided Vehicle (AGV) fetched a remarkable reformation in the agriculture research area. Automatically egg harvesting from poultry farms is still challenging in the present era. Poultry production is switching to cage-free raising. However, the cage-free raising method requires manual harvesting of eggs, which burdens the farmers. The entitled research work demonstrates an Automated guided vehicle capable of harvesting eggs and distinguishing by depending on the color of the eggs and the conditions of the eggs. This study developed an AGV to automatically localize the robot at the harvesting counter and collect eggs using a robotic arm. The robot can move omnidirectionally. A robotics arm has been equipped on the robot body, and its end-effector is designed by three fingers structured. The designed system ensured the safety of the eggs and distinguished the fractured eggs or good eggs. In addition, the robot can distinguish white and brown eggs using machine learning and check whether these eggs have cracked or not. The proposed system is trained by taking several situation images. Bird-view camera information using to localize the robot at the harvesting point. Finally, analyze the mentioned system's performance, and the system's egg harvesting rate is 93% on different types of eggs. The introduced mobile robot is easy to operate, and it showed a praiseworthy performance indoor environment. Operating this robot makes it possible to increase the harvesting of the eggs with less labor cost.

Keywords—egg harvesting robot, AGV, mecanum vehicle, three finger end-effector

I. INTRODUCTION

Over the past few years, attention to animal welfare laws has risen globally [1]. In the field of poultry farming, there is a growing interest in switching from raising in cage, in which hens spend their entire lives in a small cage and lay eggs efficiently. To raising outside the cage, in which hens can satisfy their native behavior (e.g., dustbathing to remove lipids [2]) [3, 4]. In Switzerland and Austria, cage keeping has been banned. It is also suggested that the quality of eggs from cage-free hens is improved [5, 6]. This trend is expected to lead to a worldwide shift to cage-free systems.

Farmers have to harvest eggs every day. Automated robots for cage-free egg retrieval have been studied by Bastiaan *et al.* [7] and Chang *et al.* [8] research article only focus on harvesting eggs laid on the floor. However, eggs laid outside the nest have a higher potential for microbial contamination than eggs laid inside the nest boxes [9, 10]. One way to prevent hens from laying eggs outside the nest is to use egg-laying boxes. Laying hens can lay eggs in nest boxes by training them. Sorensen *et al.* [11] trained six generations of 400 hens to lay eggs in the nest, and reported that about 95% of the eggs were laid in the egg-laying box. Icken *et al.* [12] trained 7784 hens to lay eggs in the nest, and reported that an average of 96% of the eggs were laid in the egg-laying box. This study also shows that the tendency to lay eggs outside the nest is related to genetics, and can be further improved. Also, the Spoutnic (2019), By circling and teaching chickens to lay eggs in nest boxes, an autonomous poultry-farming robot developed by TIBOT Technologies (Cesson-Sévigné France) was created to address the issue of floor eggs [13]. Therefore, it is possible to reduce the number of eggs outside the nest by using nest boxes.

Guoian *et al.* [14] stated that the future of the poultry industry will require a system that improves egg safety and does not harm livestock. The use of nest boxes is expected to increase to reduce outside the nest eggs to improve safety. However, if the eggs are left in the nest boxes, the contact time between the hen and the eggs will be longer and the risk of microbial contamination will increase. Therefore, it is necessary to move the eggs from the nest box to another place immediately. Therefore, the nest boxes need to be inclined so that the eggs can roll out and be transferred to other containers. Using a nest box and harvesting the eggs that roll out of them can increase safety. It is possible to increase safety by harvesting rolled eggs. By allowing the eggs to roll out, it will be possible to separate the moving space of robot from the hens and harvest eggs without harming the hens. In egg harvest, it is important to be able to work in a variety of possible environments, regardless of the size or layout of the poultry farm, or whether it is indoors or outdoors.

This study proposed an automated mobile robot working indoors to harvest the eggs. At present, all of the

experiment has been done in an indoor environment. In previous studies, some research concerns eggs picking and color identification. Nevertheless, this research is mainly concerned with identifying eggs' color and the condition of the eggs. Therefore, the presented robot user can easily separate different eggs in different places. Four cameras are attached to this research for several purposes. Two cameras are the robot's localization, and others are addressed for object recognition. Image processing techniques solve the object recognition task. The robot can safely collect eggs from the harvesting box and distinguish the break and good eggs. Furthermore, the authors designed an eggs collector box on the robot body to place the distinguishing eggs in different parts. Therefore, the researcher believed that the system performed safely in an indoor environment without damaging eggs.

II. OVERVIEW OF THE SYSTEM

This platform discusses the structural design of the proposed AGV (Automated Guided Vehicle). The AGV is constructed by a mecanum vehicle produced by TOSADENSHI. The size of the robot is 85 cm × 64 cm × 105 cm (length × width × height). Four mecanum wheels are attached to the vehicles, and the merits of the mecanum vehicle are that it can move in any direction without changing the front face of the vehicle. The robot wheels are designed by roller wheels attached at 45-degree angles. The designed robot is shown in Fig. 1, in addition, a 6-axis robot arm (Universal Robots, UR5e) is mounted on it. At the top of the arm, an end-effector is constructed with the camera. The details about the end-effectors and its fingers' functionality are discussed below.

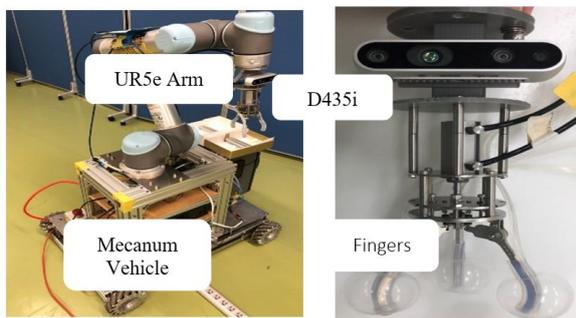


Figure 1. Egg harvesting robot with three fingers end-effector.

A. End-effector

A three-finger end-effector developed in our laboratory is attached with a robotic arm for picking and delivering the eggs displayed in Fig. 1 on right side. This robot hand was developed based on the concept of soft robotics. The fingertips of the arm are developed by a balloon catheter to gripe the object. As a result, the fingertip can increase the pressure at the gripping time on the object's surface, and it realizes the pressure at the delivery time. The fingers of the end-effectors can raise maximum 0.7 Mpa pressure. However, this mentioned research used 0.3 Mpa gripping pressure. Therefore, the pressure is fixed, and it

is safe to grip any eggs without damaging the eggs. The functionality of the finger's movement is controlled by spring which prevents excessive force from being applied to the egg and allows it to be grasped without being damaged. In addition, the wrist part attached an Intel RealSense camera(D435i). The purpose of the camera is to recognize the eggs' center points and identify the eggs' condition.

B. System Configuration

The system configuration of the robot is shown in Fig. 2, the Raspberry Pi (Raspberry Pi Foundation, Raspberry Pi 4 Model B / 4GB) is used to control the AGV and the USB camera (logicool, c270) attached to the side of the AGV fuselage, and the visual servo is used to position the AGV. The AGV is positioned by visual servo. In addition, Jetson Nano (NVIDIA, Jetson Nano) is used to control the robot arm, end-effector, and RGB-D camera (intel, RealSense Depth Camera D435i), and image processing. The ceiling-mounted USB wide-angle camera (buffalo, BSW505MBK) is controlled by a laptop PC.

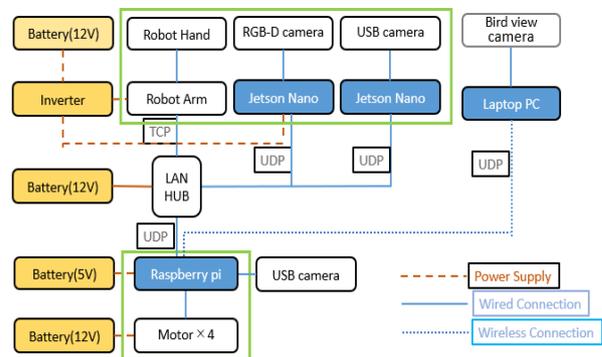


Figure 2. System configuration.

III. WORK FLOW

This section illustrates the introduced system working methodology. The AGV is involved in some specific tasks depending on the camera data. Initially, the robot has to know the target point to harvest the eggs. The user will define the target counter location by selecting the ceiling camera visualization image. Then the robot will calculate the target point coordinates and current point coordinates. At first, the robot will adjust the y-axis coordinate point and then move forward in the x-axis to find out the target point position. When the robot arrives at the target point, it will adjust the center position of the robot and place the target point by detecting the center point of the AR marker. After that, the robotic arm will execute the operation to detect the egg's center points, and egg sorting works. In this research, we are considering two different colors of eggs. The overall harvesting eggs counter three, and the robot can move one counter to another counter automatically until completing all tasks. The research focused on two parts: transporting the robot to the target point and sorting out the eggs in a defined place. By using the mentioned system, can quickly sort out the eggs within a short time without any damage.

IV. ROBOT LOCALIZATION

A. Transport to Harvest Box

To localize the guided robot at the harvesting point, the user has to set the target point's location by watching the view of the bird-view camera. A bird-view camera has been placed top on the floor. The captured view area by the camera is $5m \times 3m$ (Length \times width) which is shown in Fig. 3. Within this viewed area, the robot can easily visit all of the select target points. The user can select the target point by clicking on the viewed map from the host pc. We designed three harvesting counters to collect eggs by the robot. The controller first selects the three target points by clicking all three spots area, and the priorities of the counter will decide depending on the clicking sequence. When all target points are set up, the robot starts moving from its current localization point to target points. The robot's current and target point's position will be measured by a bird-view camera depending on the coordinates point of the areas. An AR marker is pasted on the robot. The bird-view camera can recognize the robot's current position by capturing the AR Marker position and then comparing the clicked target point's distance from the target point. Fig. 4 describes the complete maneuvering process of the robot from one counter to another by attaching a flowchart.

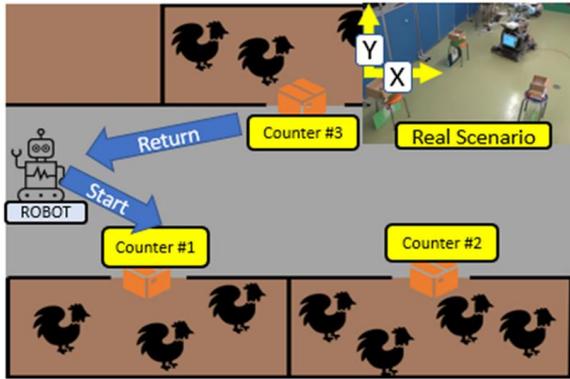


Figure 3. The coordinate of bird view camera.

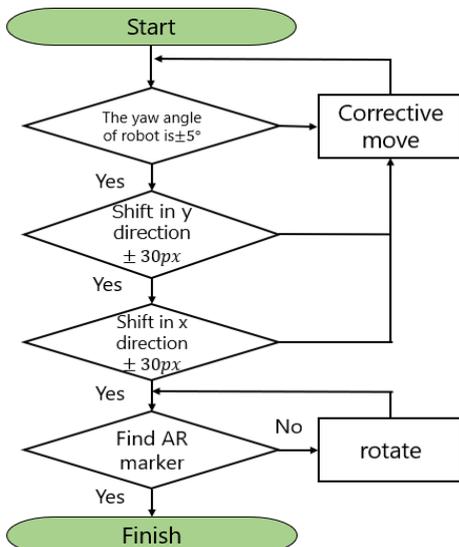


Figure 4. Flowchart of moving to the harvest box camera.

B. Arm Positioning

An AR marker is placed at the bottom side of the target point, and A USB camera is attached on the right down part of the robot to capture the AR marker center point. When the robot arrived at the clicked target point, the robot set up its position by following the center point coordinate of the AR marker. The coordinate system of the AR marker is shown in Fig. 5, While the robot runs on the floor, consider no tilt in the roll and yaw angles. First, control the target value to be $0 [^\circ]$ until the pitch angle of the AR marker is between -5° and $+5^\circ$ so that the robot is horizontal to the harvest box. Then, calculating both the center points of the camera and the AR marker, the system will try to fix the exact location point for the robot from the AR marker. The AGV positioning section's program flow is shown in Fig. 6. The mentioned system localizes the AGV robot keeping a 5cm distance from the target point AR marker.

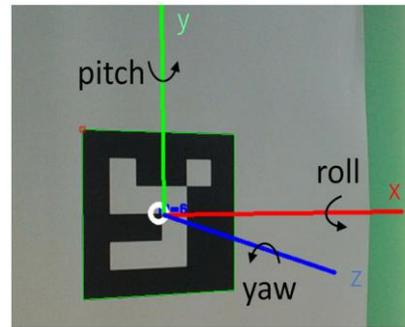


Figure 5. The coordinate of AR marker.

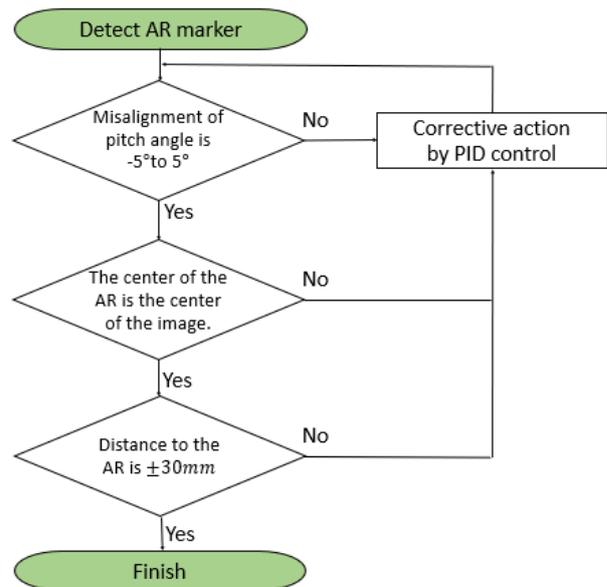


Figure 6. Flowchart of position adjustment.

The principle of measuring the distance to the AR marker is $D[cm]$, where l is the width of the marker as recognized by the camera $[px]$, and L is the actual width of the AR marker $[cm]$. Furthermore, the 640×480 camera resolution is used in the proposed system. Finally, the camera's resolution is converted from $[px]$ to $[cm]$ and expressed by the following equation.

$$W = (640 / 1) \times L \quad (1)$$

$$D = (W / \tan\theta) = \{W / (2\tan*(44.2))\} \cong (W / 0.812) \quad (2)$$

C. PID Control

PID control is employed in this study for positioning after AR marker detection before the harvest box. PID control is expressed by the following formula.

$$err(t) = target - current_value \quad (3)$$

$$P(t) = Kp \cdot err(t) \quad (4)$$

$$I(t) = Ki \cdot (I(t-1) + err(t) \cdot dt) \quad (5)$$

$$D(t) = [Kd \cdot (err(t) - err(t-1)) / dt] \quad (6)$$

$$PID(t) = P(t) + I(t) + D(t) \quad (7)$$

where t is the time level, err (error) is the deviation. P , I , and D are the outputs for proportional, integral, and derivative control, respectively, and Kp , Ki , and Kd are the gains of P , I , and D , respectively. PID is the sum of each output value. The speed of the Mecanum vehicle differs depending on the direction of movement. Therefore, the PID gains for forward/backward, left/right, and rotation movement were adjusted respectively. The control frequency is set to 1k[Hz].

V. RECOGNIZING & GRIPPING EGGS

A. Trained System

A machine learning approach is used to train up the system. In general, hens have two kinds of eggs depending on color, one is white, and another one is brown. This research is concerned about the color distinguishing of the eggs and identifying the fractured eggs and good eggs. We made a basket separated with four parts to place different types of eggs. For that reason, the system needs to train up to identify the eggs' conditions quickly. We consider four types of character: white eggs, brown eggs, white fractured eggs, and brown fractured eggs shown in Fig. 7. These eggs were photographed, and a total of 890 images were prepared, and the training dataset was created on the website [roboflow], which allows online annotation. In addition, we padded the image data by adding noise and rotation and prepared a total of 2136 training data. We used 70% training data, 20% test data, and 10% validation data. The dataset was trained for 150 episodes using the YOLOv5s model.

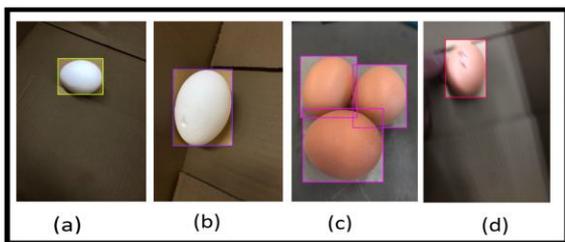


Figure 7. (a) White eggs, (b) White fractured eggs, (c) Brown eggs & (d) Brown fractured eggs.

B. Object Identification

First, the robot localizes the target point to collect eggs for the harvesting box. An Intel RealSense camera is attached on the robot arm's wrist for egg identification. The camera is executed in two tasks in this stage. First, it detects the eggs' position in the harvesting box and distinguishes the fractured or good eggs. Initially, the wrist of the robot arm is placed in the center of the box, and it finds out the location of the eggs by displacing the detected image pixels. Next, the robot arm is moved above the harvest box to observe the inside of the box. Then identify the eggs from the RGB-D camera images, enclose each one in a rectangle, and calculate the px value of its center point coordinate (x_{first} , y_{first}) are stored. Then move the egg 0.1 cm in the x -direction and 0.1 cm in the y -direction, and find the px value of the egg's center point at that point (x_{second} , and y_{second}). The following calculations can be made from the coordinate values of these two points to find the variation x in the x -direction and y in the y -direction that moves the robot arm with the RGB-D camera directly above the egg center point. Fig. 8 displays the overall working flow of the center point placement of the robotics arm. The box center point coordinates to the egg's center point movement of the arm are expressed by the equation below.

$$x = [(320 - x_{second}) \times 0.1] / (x_{second} - x_{first}) \quad (8)$$

$$y = [(320 - y_{second}) \times 0.1] / (y_{second} - y_{first}) \quad (9)$$

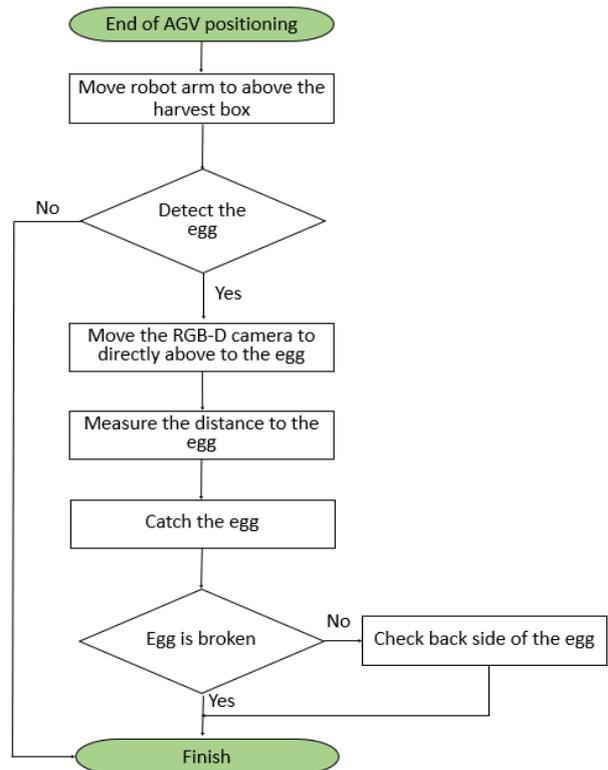


Figure 8. Flowchart of egg recognition and gripping process.

When the arm is placed on the eggs, the camera identifies the color of the eggs using the image processing

technique. Identified image rating and the end-effector functionality are shown in Fig. 9. When the system recognizes the eggs, it starts the picking operation automatically. Depending on the egg's color and condition, the system placed the eggs in the defined part in the basket.

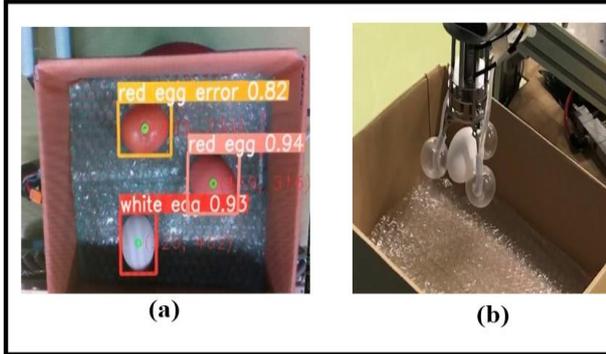


Figure 9. Executing Robot Arm: (a) Recognizing the color and condition of the eggs and (b) Collecting egg by end-effector.

VI. RESULTS

A. Success Rate Verification of Egg Recognition

While evaluating the performance of the system, the orientation and position of the 10 eggs in each harvesting box were changed regularly and tested each egg 25 times by changing the position and posture of the eggs incessantly. A total of 100 tests has been examined, and the recorded data are shown in Table I.

TABLE I. EGGS IDENTIFICATION PERFORMANCE

Types of eggs	Iteration	Number of Successes	Success rate
White egg	25	24	96%
Red egg	25	24	96%
Broken white egg	25	22	88%
Broken red egg	25	23	92%
all	100	93	93%

The results of the experiment are shown in Table I. The success rate of discrimination of perfectly white eggs was 96%, brown eggs were 96%. Moreover, the distinguishing rating of the white fractured eggs was 88%, and brown fractured eggs were 92%.

The mentioned system project added a new USB camera to check the eggs' bottom parts condition. The robot's arm wrist camera is responsible for checking the egg's top part. If the top part of the egg is broken, it will take the decision quickly; the egg is cracked and placed in the fractured egg collecting box. Otherwise, the arm picks up the egg and places it above the second camera to check the bottom part situation. At last, the system will finalize the condition of the eggs. The experimental image of using an extra USB camera and the bottom part checking process is shown in Fig. 10.

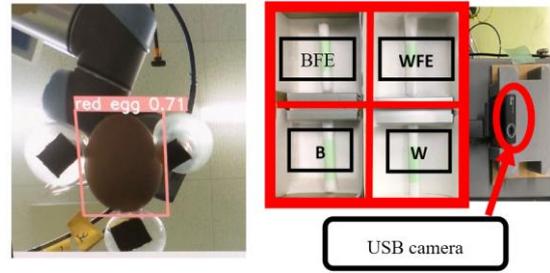


Figure 10. Right side USB camera used for eggs bottom part checking, in the middle, the harvesting basket is designed in four parts, and all parts are individually for different eggs. Left side image checking the bottom view of the eggs down part checking system.

B. Success Rate of Egg Harvesting

The data was collected by operating the robot in a real environment. The system localization performance is worked perfectly. The authors set up the three counters to visit the robot and collect eggs automatically. All of the counters have various kind of eggs. The tested data has been recorded in Table II. where a number code defined White Eggs (W), White Fractured Eggs (WFE), Brown Eggs (B), and Brown Fractured Eggs (BFE). Table II recorded five tests data. For example, the first test total number of eggs is two eggs; one is a good conditioned white egg (W), and another is a good brown egg (B). Some eggs are mentioned in red in the table, which is the lack of performance of the system. The recognition and harvesting process of the system is worked perfectly; that is why the success rate of the test is 100%. All of the other enlisted test results are put in Table II, and by following the same concept, the data has been recorded.

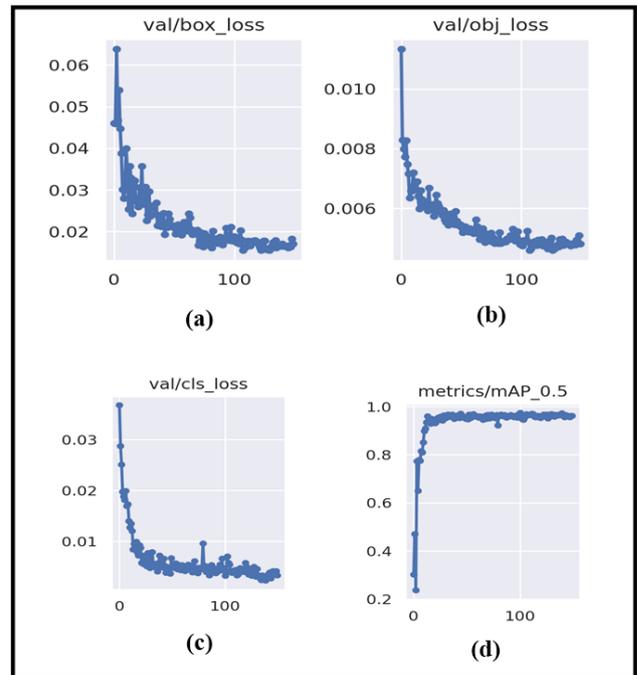


Figure 11. System performance data were analyzed by using machine learning techniques. Here a few amounts of data are lost during the experimental period. (a) Displaying the losses data for finding out the harvesting box (b) losses data for eggs detection time (c) Data losses at the eggs distinguishing time (d) Overall performance of the system around 98.6%.

On the other hand, using the tested data and yolov5 captured features is analyzed some graphical data is shown in Fig. 11. The four graphs data represent the value of the lost data at eggs recognizing, collecting, and distinguishing performance. The presented tested data clearly shows that the system performance is excellent and slightly lost in every section. All of the graphical data mentioning the system's loss depends on the iteration of the task actions.

Furthermore, the experiment analyzed the average performance of the system in all parts of execution. The total performance of the system was 98.6%. Sometimes the system missed recognizing the fractured eggs in both color cases. However, the eggs were picking and releasing implement of the scheme pursuit effectively in all time.

TABLE II. THE RESULT OF DISCRIMINATE EGGS

Total eggs	Box 1	Box 2	Box 3	Success Rate	Success rate
2		W	B	2	100%
	WFE	B		2	100%
3	BFE	B, WFE		3	100%
	W	B	WFE	3	100%
4	B, BFW	W	B	4	100%
	W, B	W, WFE		3	75%
5	W, BFE	B, WFE	W	5	100%
	W, WFE	B, BFE	W	4	80%
6	W, BFE	W, B, WFE	B	6	100%
	B	W, WFE, BFE	B, BFE	5	83%

A number code defined White egg (W), White Fractured Eggs (WFE), Brown eggs (B), and Brown Fractured Eggs (BFE).

VII. CONCLUSION & FUTURE WORK

The automated egg harvesting system collects eggs from the selected target points—the mecanum vehicle working correctly in the indoor environment. The merit of the vehicle is that it can move in any direction. For eggs harvesting time, researchers culled different data angles by using the alluded scheme. The robot localization and eggs gripping performance is worked accurately. The system's effectiveness is reasonable compared to the overall situation—a few moments. The scheme makes an issue identifying the fractured eggs. That has happened at the white eggs in gathering time. The moveable performance of the system from the start point to the various target point is smooth and balanced. The proposed system only can perform at the plane surface. The robot takes one minute to complete a single egg collection. So, authors are attempting to reduce the collecting time and make the system more productive and user-friendly. Now the system can complete all tasks for a single egg for around one minute.

The scribe will improve the mentioned system by adding more extra features to the developed robot.

Furthermore, the presented system will be trained up more testing data to enhance the egg identification performance. The final aim is to add obstacle avoidance techniques to make a fully automated system. Furthermore, the system can be developed using the SLAM method instead of a bird camera view for environment mapping purposes.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Rubel Ahmed: Methodology, Software, Writing-original draft. Takahashi Kei: Data curation, Writing-review & editing. Wumenjiang Abudoula: Visualization, Investigation. Tasuku Miyoshi: Supervision. Nobuya Tanimoto: Writing-review & editing. Kazuaki Oozeki: Validation, Writing-review. The authors would like to thank the valuable comments and suggestions of the anonymous reviewers. All authors have given their approval to the final version.

ACKNOWLEDGMENT

The authors would like to thank the Iwate Strategic Research and Development Promotion Project association and the project was supported financially by the P&A Technologies Inc., Iwate, Japan.

REFERENCES

- [1] C. J. Hewson, "What is animal welfare? Common definitions and their practical consequences," *Can. Vet. J.* vol. 44, pp. 496–499, 2003.
- [2] B. Scholz, J. B. Kjaer, S. Petow, and L. Schrader, "Dustbathing in food particles does not remove feather lipids," *Poult. Sci.*, vol. 93, pp. 1877–1882, 2014.
- [3] Y. Heng, H. Peterson, Hikaru, and X. H. Li, "Consumer attitudes toward farm-animal welfare: The case of laying hens," *Journal of Agricultural and Resource Economics, Western Agricultural Economics Association*, vol. 38, pp. 1-17, 2013.
- [4] S. C. Ricke and M. J. Rothrock Jr. "Gastrointestinal microbiomes of broilers and layer hens in alternative production systems," *Poultry Science*, vol. 99, pp. 660–669, 2020.
- [5] G. Kulshreshtha, C. Benavides-Reyes, A. B. Rodriguez-Navarro, T. Diep, and M. T. Hincke, "Impact of different layer housing systems on eggshell cuticle quality and salmonella adherence in table eggs," *Foods*, vol. 10, no. 11, 2021.
- [6] Z. Islam, A. Sultan, S. Khan, et al. "Impact of varying housing systems on egg quality characteristics, fatty acid profile, and cholesterol content of Rhode Island Red xFyoumi laying hens," *Trop Anim Health Prod*, vol. 53, no. 456, 2021.
- [7] B. A. Vroegindeweij, S. K. Blaauw, J. M. M. Ijsselmuiden, E. J. van Henten, "Evaluation of the performance of poultry bot, an autonomous mobile robotic platform for poultry houses," *Biosystems Engineering*, vol. 174, pp. 295-315, 2018.
- [8] C. L. Chang, B. X. Xie, and C. H. Wang, "Visual guidance and egg collection scheme for a smart poultry robot for free-range farms," *Sensors*, vol. 20, no. 22, 2020.
- [9] D. R. Jones, N. A. Cox, J. Guard, P. J. Fedorka-Cray, R. J. Buhr, R. K. Gast, Z. Abdo, L. L. Rigsby, J. R. Plumblee, D. M. Karcher, C. I. Robison, R. A. Blatchford, M. M. Makagon, "Microbiological impact of three commercial laying hen housing systems," *Poultry Science*, vol. 94, no. 3, pp. 544-551, 2015.
- [10] K. De Reu, K. Grijspeerd, M. Heyndrickx, M. Uyttendaele, J. Debevere, and L. Herman, "Bacterial shell contamination in the egg collection chains of different housing systems for laying hens," *British Poultry Science*, vol. 47, no. 2, pp. 163-172, 2006.

- [11] P. Sorensen, T. Ambrosen, and A. Petersen, "Scandinavian selection and crossbreeding experiment with laying hens. IV. Results from the Danish part of the experiment," *Acta Agric. Scand.*, vol. 30, no. 3, pp. 288-308, 1980.
- [12] W Icken, S Thurner, A Heinrich, A Kaiser, D Cavero, G Wendl, R Fries, M Schmutz, and R Preisinger, "Higher precision level at individual laying performance tests in noncage housing systems," *Poultry Science*, vol. 92, pp. 2276-82, 2013.
- [13] TIBOT Technologies, Spoutnic-© TIBOT TECHNOLOGIES 2022, <https://www.tibot.fr/>. (accessed 22 February 2022).
- [14] G. Q. Ren, T. Lin, Y. B. Ying, G. Chowdhary, and K. C. Ting, "Agricultural robotics research applicable to poultry production: A review," *Computers and Electronics in Agriculture*, vol. 169, 2020.

Copyright © 2023 by the authors. This is an open access article distributed under the Creative Commons Attribution License ([CC BY-NC-ND 4.0](https://creativecommons.org/licenses/by-nc-nd/4.0/)), which permits use, distribution and reproduction in any medium, provided that the article is properly cited, the use is non-commercial and no modifications or adaptations are made.