Comparing Global Shutter and Rolling Shutter Cameras for Pattern Detection in Motion on a Ground Robot

James Kemeshi[1], Young Chang[1,*], Pappu Kumar Yadav[1], Mohammad Ashik Alahe[1]

[1]Department of Agricultural and Biosystems Engineering, South Dakota State University, Brookings, SD 57007, USA

[*]Corresponding Author

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Abstract.

To promote the adoption of precision farming technology (PF), we developed a cost-effective Unmanned Ground Vehicle (UGV) called the Reduction-To-Below-Two grand (R2B2). In this paper, we present an initial study of the R2B2 system in which two types of imaging sensors are compared. The first one is Arducam's AR0234 which uses a global shutter camera (GSC) technology, while the other one is Arducam's IMX462 which uses a rolling shutter camera (RSC) technology. Since the cost of the AR0234 is approximately three times the price of the IMX462, we made a comparison based on the detection accuracy achieved by a YOLOv8 model to determine the possibility of using the latter for pattern detection in place of the former, hence reducing the total cost of the R2B2-UGV. To compare the effect of varying speeds of the R2B2-UGV (0.75 m/s, 1.00 m/s, 1.25 m/s, and 1.50 m/s), illumination incident on the surface of the target (100 Lux, 650 Lux, and 1250 Lux), and terrain conditions (smooth and undulating) on the accuracy of detecting four classes of patterns (ArUco markers) by a trained YOLOv8 model, we designed an indoor 4 × 3 × 2 factorial experiment with three replications. In this experiment, we deployed a custom YOLOv8 model on two Raspberry Pi 4 units (one for each camera) mounted on the R2B2-UGV to detect four classes of patterns. Results showed that the average detection accuracies of the model while using the GSC-AR0234 and the RSC-IMX462 were 84.7 % and 70.1 %, respectively. Further investigations revealed that illumination and camera shutter type had a statistically significant effect ($p < 0.05$) on the accuracy of the model. This result was expected due to the wide-angle lens and shutter mechanism of the RSC-IMX462 that introduced distortions to the target. However, we can improve the accuracy of the RSC-IMX462 using image processing techniques like edge detection algorithms. If the expected outcome proves true, we can further justify the R2B2 project by reducing the cost of developing an autonomous UGV capable of machine vision (MV) applications using RSCs. Findings from this experiment could influence the design considerations of current and future producers of

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commercial UGVs capable of PF operations and result in a reduced price of purchasing and maintaining UGVs, hence driving the adoption of PF technology by small-scale farmers. Future work will include MV applications such as in-row navigation based on semantic segmentation and plant disease detection using the RSC and an edge-computing device.

Keywords.
Rolling Shutter, Global Shutter, Machine Vision, YOLOv8, Pattern Recognition, Mobile Robots

Introduction

Precision farming (PF) has been highlighted as the way forward to meet the increasing demand for food production (Devkota et al., 2020), projected to rise by 50% in 2050 due to an estimated global population of 9 billion (FAO & ITU, 2018; USDA, 2023). However, there has been resistance to the adoption of PF technology, especially among small-scale farmers (SSFs). This resistance is partly attributed to the costs associated with obtaining and maintaining PF equipment, such as unmanned ground vehicles (UGVs), and some concerns related to return on investment (ROI) (USDA, 2023). A significant factor influencing the cost of commercially available UGVs capable of performing PF tasks are the components of these UGVs, including perception and data collection components like cameras and LiDAR sensors. Optimally selecting these components such that they are both cost-effective and efficient is a way to reduce the cost of developing UGVs, which will reflect their shelf price.

Rolling shutter cameras (RSC), which are relatively less expensive than their global shutter counterparts, capture images by sequentially scanning targets row-by-row from top to bottom (Fan et al., 2021). When capturing images in motion, this mechanism of scanning row-by-row results in skew-like distortions known as the rolling shutter effect and it becomes more profound with increased motion speed (Ait-Aider et al., 2006; Lao et al., 2018). However, the rolling shutter effect may not be substantial in agricultural machine vision applications which generally requires ground robots to move at lower speeds.

A review was conducted to determine the methods researchers used in the past to perform comparisons between different cameras, the targets used, and some application areas of global shutter cameras (GSCs) and RSCs. In a study by Holešovský et al. (2021), an experimental comparison was performed between an event camera and a GSC to determine the application domain in which the former performs better than the latter. Similar to our approach, their first method involved testing the cameras on simple pattern recognition tasks. The task required detecting printed 3 x 3 mm fiducial markers (Figure 1) attached to a rotating disk with varying speeds in a controlled illumination environment, using an intensity reconstruction method called E2VID.

Figure 1: Fiducial markers (Garrido-Jurado et al., 2014)

Barrios-Avilés et al. (2018) compared an event-based camera (EBC) and a frame-based camera (FBC) in a task to track a moving object under varying lighting conditions. The experiment was conducted to determine the response time and robustness of both the EBC and the FBC to varying lighting conditions while tracking the moving object, and the results showed that the EBC was more stable under changing lighting conditions compared to the FBC. We adopted a part of this experiment to assess the robustness of the GSC and the RSC to varying lighting conditions.

In this study, we sought to address a gap in existing research, which primarily focused on comparing event-based and frame-based cameras for object tracking and movement detection. A literature review revealed that minimal experimental work has been conducted to evaluate the performance of GSCs and RSCs in machine vision applications. Drawing upon methodologies from previous studies, we designed an experiment to observe the effect of the GSC-AR0234 and the RSC-IMX462 shutter types (ArduCam; Shanghai, China) under varying conditions on the accuracy of a custom YOLOv8 model in a pattern detection task (Jocher et al., 2023). The primary objective was to assess the feasibility of utilizing the more cost-effective RSC-IMX462, priced at one-third of the GSC-AR0234 at the time of purchase, for machine vision applications in agriculture. This investigation represents a significant stride toward the goal of the Reduction-To-Below-Two grand (R2B2) project by Kemeshi et al. (2024), which aims to facilitate the adoption of UGVs by SSFs in the US through cost reduction.

Materials and Methods

Experiment Site

The experiment was conducted within a semi-controlled environment situated at the Raven Precision Agriculture Center, South Dakota State University, Brookings, South Dakota, USA.

Object Detection Model

At the time of preparing this document, You Only Look Once version 8 (YOLO v8) was the latest version of the YOLO series of algorithms. This version is popular for its fast object detection capabilities, including detection speed and accuracy.

For this experiment, a comprehensive dataset consisting of 1354 images was preprocessed to size 640 × 640 in concordance with the requirement for training a YOLOv8 model. The dataset, which included four types of ArUco markers, underwent annotation utilizing Roboflow's web-based annotation tool as detailed in Table 1 (Dwyer et al., 2024). Following annotation, the labeled dataset was utilized to train a custom YOLOv8 model on Google Colab using the T4 GPU. Upon successful completion of the training process, the model achieved a mean average precision at 50% recall (mAP50) of 0.945 and mAP50-95 of 0.887 for all classes. Table 2 shows more details of the validation result. Subsequently, the customized YOLOv8 model was deployed onto two Raspberry Pi 4 units (Model B, Raspberry Pi Foundation, Cambridge, United Kingdom) for further experiments.

Table 1: Details of annotation using Roboflow

Annotation Classes	Train Set	Validation Set	Test Set
Images	974	272	135
Class 1	370	105	49
Class 2	350	107	50
Class 3	362	105	46
Class 4	381	91	53

Table 2: Validation results of the custom YOLOv8 model

Class	mAP50	mAP50-90
All	0.945	0.877
Class 1	0.928	0.842
Class 2	0.941	0.882
Class 3	0.972	0.908
Class 4	0.939	0.877

Target/ Ground Truth Data

The ground truth data comprises a target consisting of 6 ArUco markers, each measuring 77 × 77 mm. These makers were randomly selected from a pool of eight ArUco markers of four classes, as shown in Figure 2. The target itself is presented as an A4 print, incorporating two class 1 markers, one class 2 marker, two class 3 markers, and one class 4 marker.

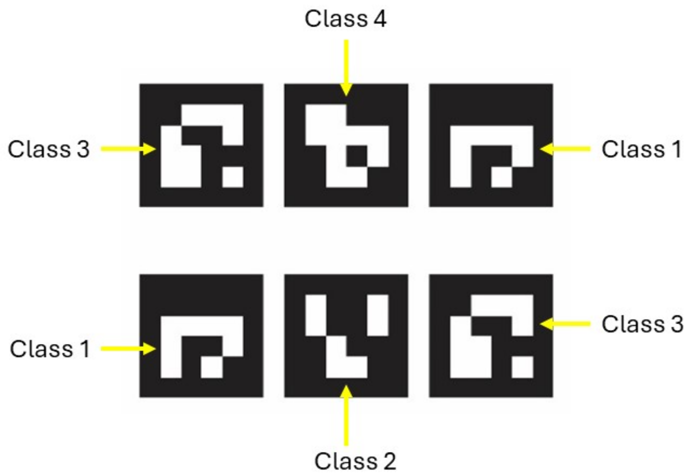


Figure 2: 77 × 77 mm ArUco markers (Target)

UGV Platform and Experimental Design

In this experiment, we mounted two Raspberry Pi 4 units on the R2B2-UGV, enabling simultaneous control of the GSC-AR0234 and the RSC-IMX462 via a secure shell. The experiment followed an indoor 4 × 3 × 2 factorial design with three replications, as detailed in Table 3. We examined the effect of varying speeds of the R2B2-UGV (0.75 m/s, 1 m/s, 1.25 m/s, and 1.50 m/s), illumination incident on the surface of the target (100 Lux, 650 Lux, and 1250 Lux), and terrain conditions (smooth and undulating) on the model's accuracy to detect four classes of patterns, namely ArUco markers. An external lighting source with three levels was used to control the light incident on the target's surface (Xbuyee 300W LED light, Shanghai, China), and illuminance levels were measured using a digital lux meter (AP-881D, AOPUTTRIVER, China). The terrain conditions were simulated by placing four wood blocks (19.05 × 38.1 × 1219.2 mm; H×W×L) at 482.6 mm intervals to create an undulating ground. The UGV's speed was pre-set in the navigation code to achieve the required speed levels. Figure 3 provides a visual representation of the experimental setup and materials.

Table 3: Combination of factors for each treatment

Treatment	Combination of Factors
1	0.75 m/s, smooth, 100 Lux
2	0.75 m/s, smooth, 650 Lux
3	0.75 m/s, smooth, 1250 Lux
4	0.75 m/s, undulating, 100 Lux
5	0.75 m/s, undulating, 650 Lux
6	0.75 m/s, undulating, 1250 Lux
7	1.00 m/s, smooth, 100 Lux
8	1.00 m/s, smooth, 650 Lux
9	1.00 m/s, smooth, 1250 Lux
10	1.00 m/s, undulating, 100 Lux
11	1.00 m/s, undulating, 650 Lux
12	1.00 m/s, undulating, 1250 Lux
13	1.25 m/s, smooth, 100 Lux
14	1.25 m/s, smooth, 650 Lux
15	1.25 m/s, smooth, 1250 Lux
16	1.25 m/s, undulating, 100 Lux
17	1.25 m/s, undulating, 650 Lux
18	1.25 m/s, undulating, 1250 Lux
19	1.50 m/s, smooth, 100 Lux
20	1.50 m/s, smooth, 650 Lux
21	1.50 m/s, smooth, 1250 Lux
22	1.50 m/s, undulating, 100 Lux
23	1.50 m/s, undulating, 650 Lux
24	1.50 m/s, undulating, 1250 Lux

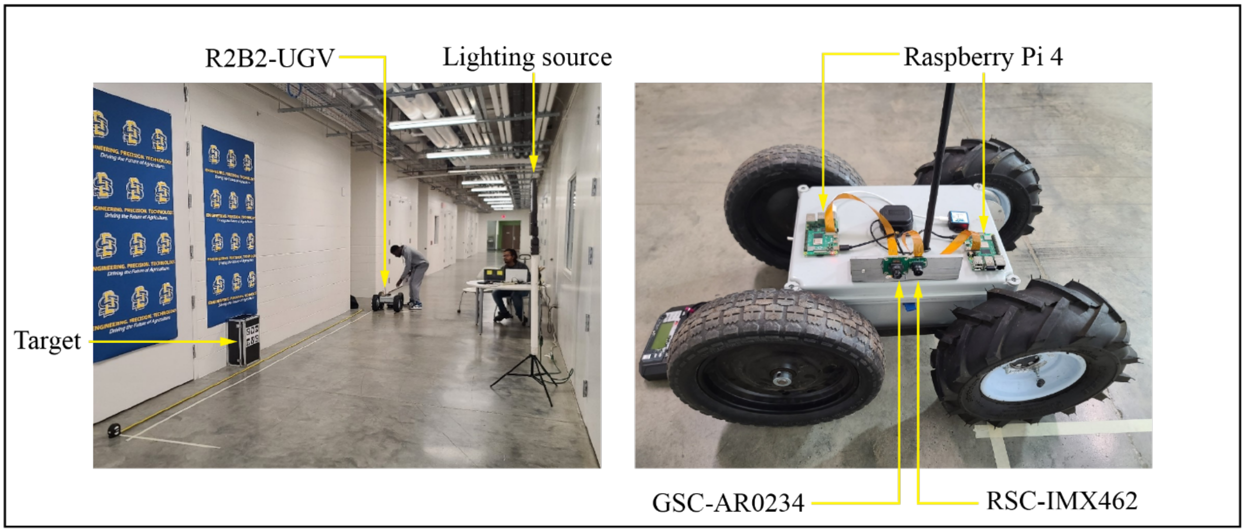


Figure 3: Experiment setup

Data Extraction

To calculate the average detection accuracy for each treatment, only frames containing complete target information were taken into consideration. The detection accuracy for these frames was computed using Equation 1 and subsequently added to an excel file for further analysis.

$$Accuracy = \frac{Correct\ detections}{Expected\ Detections}\ x\ 100 \tag{1}$$

Results and Discussion

A custom YOLOv8 model was deployed onto two Raspberry Pi 4 units and used in a pattern detection task. Employing two cameras simultaneously, we assessed the impact of each camera's shutter type on the model's accuracy with varying environmental conditions. Figure 4 shows two frames captured by each camera from the same treatment. Notably, the fisheye effect stemming from the wide-angle lens of the RSC-IMX462 was evident.

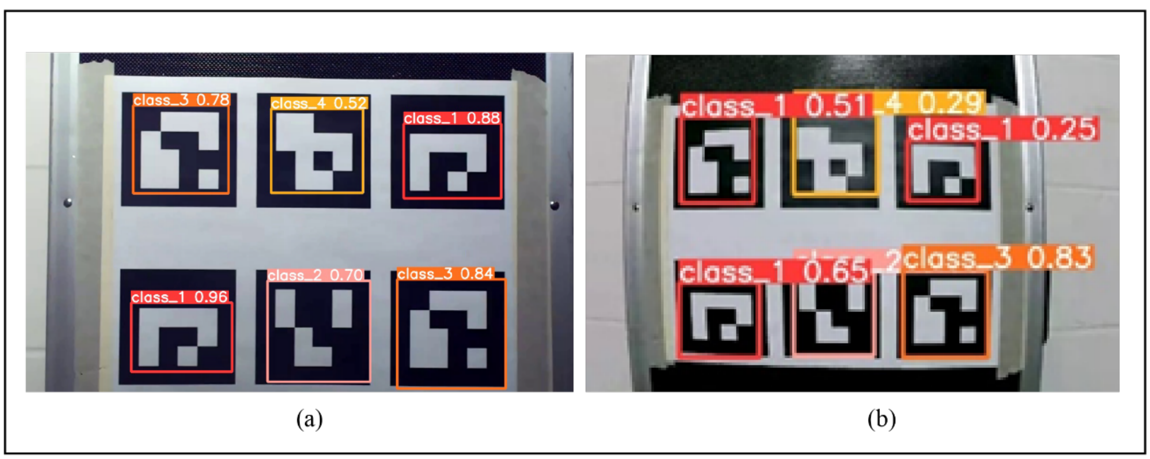


Figure 4: Frame from GSC-AR0234 (a) and RSC-IMX462 (b)

Figure 5 presents a scatter plot diagram illustrating the average accuracies of the model across all 72 runs (3 replicates of 24 treatments) for both cameras. The plot indicates that the GSC-AR0234 performed better than RSC-IMX462, and this was affirmed by a Mann-Whitney U-test

(MacFarland & Yates, 2016) conducted to ascertain the statistically significant difference in the accuracies of the cameras, subsequent to confirming the non-normal distribution of the data through a Shapiro-Wilk test. This outcome aligns logically with the notion that the fisheye effect of the RSC-IMX462 could be a major factor contributing to the diminished accuracy of the model. Overall, the model demonstrated average detection accuracy of 84.7% and 70.1% with the GSC-AR0234 and RSC-IMX462, respectively.

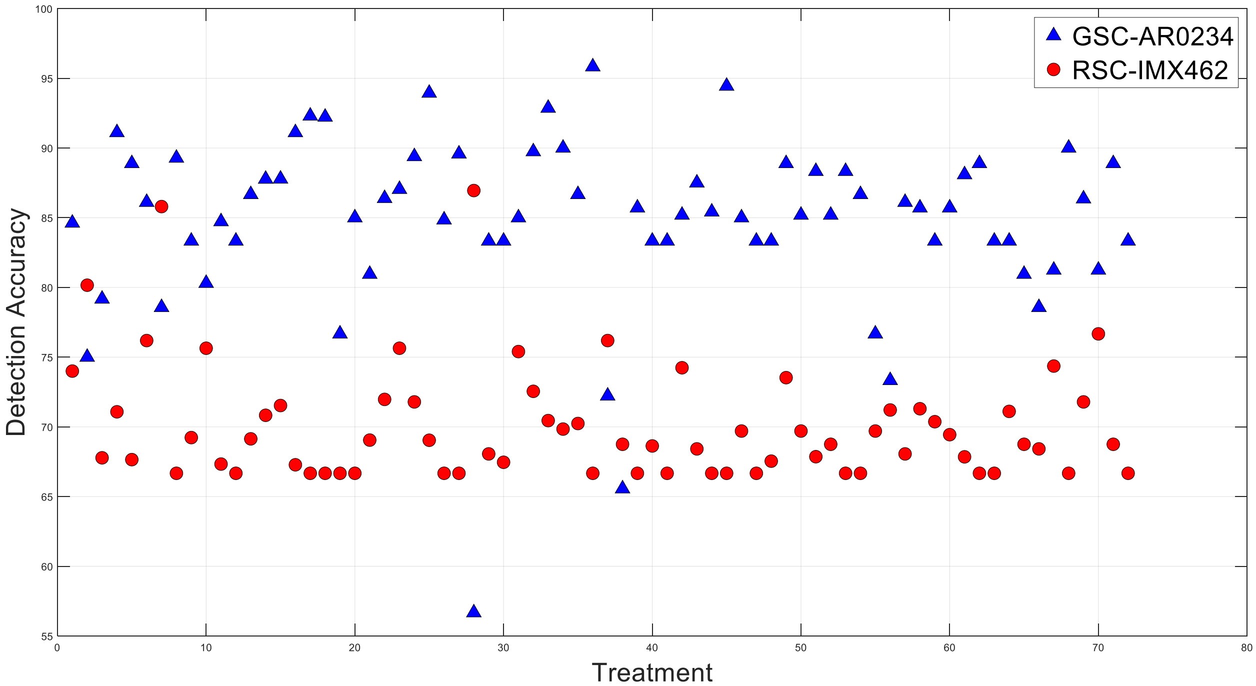
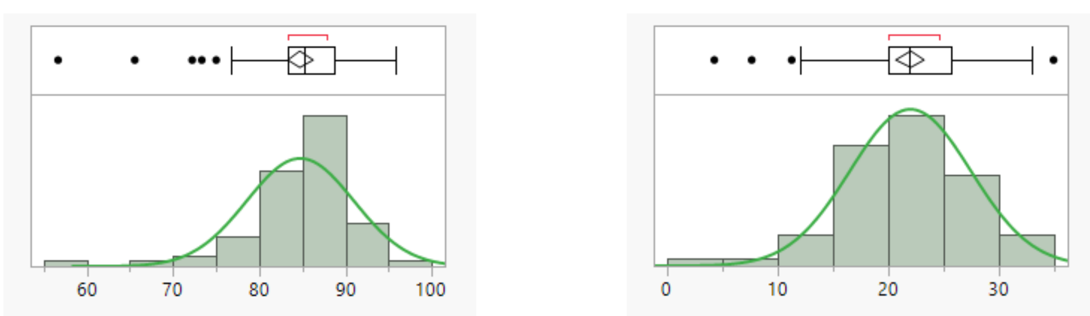


Figure 5: Scatterplot for accuracy distribution for both GSC-AR0234 and RSC-IMX462

Furthermore, the dataset of the GSC-AR0234 underwent a Box-Cox transformation to achieve a normal distribution as shown in Figure 6. The box plot in Figure 7 shows the average accuracy across all replicates for each treatment. A trend can be observed showing that with higher illuminance, there is a significant improvement in the model's performance. This observation was backed up by a 3-factor ANOVA (speed, illumination, and terrain), which was conducted to compare these factors and identify the primary contributors to the models' accuracy (Table 4). The results revealed that the illumination condition had a significant effect ($p < 0.05$) on the accuracy, which is logical, considering that the motion of the UGV was not fast enough to cause any blurring effect on the target, and the vibration caused by the rough terrain was not frequent enough to create distortions in each frame.



(a) Left-skewed distribution (b) Normalized distribution

Figure 6: Visualization of the distribution of GSC-AR0234 dataset

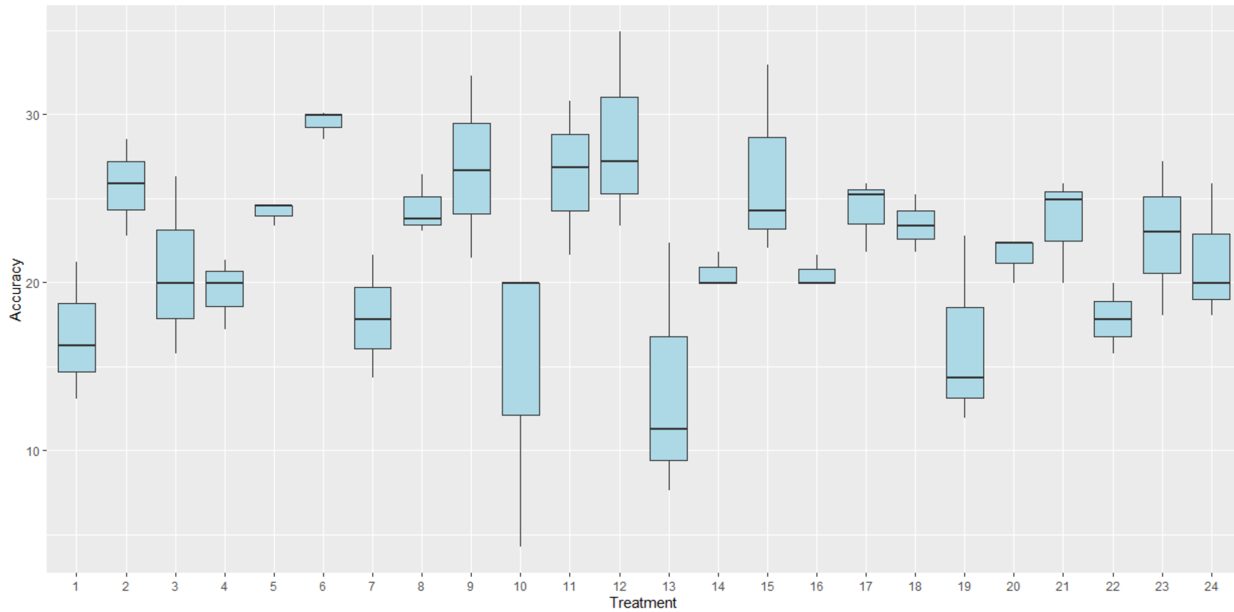


Figure 7: Boxplot of accuracy distribution over three replications for GSC-AR0234

Table 4: 3-factor ANOVA

	Df	Sum Sq	Mean Sq	F value	Pr (>F)	
Speed	3	74.6	24.9	1.386	0.162	
Illumination	2	850.7	425.4	23.713	$6.88\text{x}10^{-8}$	***
Terrain	1	42.2	42.2	2.350	0.132	
Speed* Illumination	6	68.6	11.4	0.637	0.700	
Speed* Terrain	3	35.6	11.9	0.662	0.580	
Illumination* Terrain	2	1.5	0.7	0.041	0.960	
Speed* Illumination* Terrain	6	193.2	32.2	1.795	0.120	
Residuals	48	861.0	17.9			

Lastly, we performed Tukey's multiple comparison test to compare the treatments (Table 5). The results show that treatments with lower speeds, rough terrain, and high illuminance showed better performance (Treatments 6 and 12). A possible cause for this is that the simulated rough terrain reduced the speed of the R2B2-UGV, and this aided the model's performance. Additionally, the results indicated that the treatments of low illuminance showed low performance (Treatments 10 and 13).

Table 5: Treatment Grouping Based on Tukey's Test for GSC-AR0234

Treatment(s)	Group
6	a
12	b
2-5, 7-9, 11, 13-18, 20-24	abc
1 and 19	bc
10 and 13	c

Notably, for the RSC-IMX462, the accuracy could be substantially improved by image processing techniques, such as fisheye distortion correction algorithms (Wei et al., 2012; Zhang et al., 2016).

Conclusion

In this study, we assessed the impact of camera shutter mechanisms on the accuracy of a customized YOLOv8 model for pattern recognition in diverse environmental conditions. Simultaneously utilizing global shutter and rolling shutter cameras, we investigated whether a statistically significant difference existed in their effects on the model's accuracy. Results indicated an average detection accuracy of 84.7% and 70.1% for the GSC-AR0234 and the RSC-IMX462, respectively. Our future efforts will focus on enhancing the accuracy of the model with the rolling shutter camera by implementing fisheye distortion correction algorithms. Successful implementation of these correction algorithms could pave the way for the cost-effective integration of rolling shutter cameras, which are generally more budget-friendly than global shutter cameras, in pattern recognition and tracking applications. This project is promising for the cost-effectiveness of autonomous navigation in mobile robots. Ultimately, reducing the overall development costs of autonomous UGVs supports the justification of the R2B2 project. Such cost reductions could lead to increased adoption of UGVs among the SSFs.

Acknowledgements

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