Yield monitoring system for radish and cabbage under Korean field conditions

Md Ashrafuzzaman Gulandaz[1], Md Sazzadul Kabir[1], Shafik Kiraga[2], Sun-Ok Chung[1,3*]

[1]Department of Smart Agricultural Systems, Graduate School, Chungnam National University, Daejeon 34134, Republic of Korea
[2]Center for Precision and Automated Agricultural Systems, Irrigated Agriculture Research and Extension Center, Washington State University, Prosser, WA 99350, USA
[3]Department of Agricultural Machinery Engineering, Graduate School, Chungnam National University, Daejeon 34134, Republic of Korea

*sochung@cnu.ac.kr

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Abstract.

Yield monitoring is considered an essential tool to optimize resource utilization and provide an accurate assessment of crops for drylands. The objective of this study was to assess mass-based and volume-based yield monitoring under laboratory simulated and field condition for cabbage and radish. During the experiment, impact plate angles, conveyor speeds, and falling heights were systematically varied to investigate the effects on cabbage and radish yield during harvesting. Digital filtering was applied to reduce the effects of vibrations and inclinations on mass-based yield monitoring systems in both laboratory and field conditions. For volume-based yield monitoring system machine vision approach employed to predict volume from RGB images of cabbages and radishes samples. The camera, along with fluorescent LED light sources, was positioned 1 m above the harvester conveyor, which operated at a speed of 0.50 km/h to meet field requirements, and the RGB camera was employed to capture top-view images at a frequency of 3 Hz. In a conventional manner, Archimedes' law was employed to determine the actual volume of the cabbages and radishes. Image filtering algorithm was applied to reduce the effects of motion, vibration, and slope from RGB image. Three distinct volume estimation methods, namely the box method (BM) and disc method (DM), were applied to predict volume from acquired images. Significant effects of falling height, impact plate angle, and conveyor speed on the impact-based load cell were identified by one-way ANOVA analysis ($p<0.05$) for both cabbage and radish test. The application of linear regression determined the optimal parameters for load cell-based yield measurement, resulting in the highest R^2 value for combination of 0.50 km/h conveyor speed, 10° impact plate angle, and 0.2 m falling height. Furthermore, digital filtering reduced vibration effects, improving yield data accuracy (R^2 = 0.94, R^2 = 0.96), while an equation-based model further enhanced accuracy at a conveyor speed of 0.5 km/h (R^2 = 0.98, R^2 = 0.99) for cabbage and radish respectively. Moreover, the Gaussian filter performed better among other filtering techniques to reduce motion, vibration, and slope effects from RGB image. The box *method (BM) combined with Gaussian filtering outperformed other methods in both laboratory test bench and machine-mounted conditions for cabbage and radish. This research provides valuable insights for improving yield monitoring systems for upland crops.*

Keywords.
Precision agriculture, yield monitoring, load cell, field vibration, RGB image.

Introduction

Chinese cabbage (*Brassica rapa*) is a vegetable indigenous to Southeast Asian nations, notably Korea. Since the fifth century, it has been cultivated in China and eastern Asia. It prepares as a vegetable, eaten raw as a salad, and utilized as a source of medicinal ingredients (Yahia et al., 2011; Omoni et al., 2005). Chinese cabbage is the key component of traditional kimchi in Korea. The yearly per capita consumption of Chinese cabbage exceeds 50 kg, the greatest quantity among Brassicaceae (Xu et al., 2022). Typically, Chinese cabbage is harvested between summer and winter (Xu et al., 2022). Chinese cabbage uses 5.38% of the land in the entire vegetable cultivation area and produces 1.35 million tons of Chinese cabbage per year in Korea (KOSIS 2022). The demand for mechanization in an upland crop such as Chinese cabbage has been increasing due to labor shortages, the age of farmers, and labor-intensive processes (Shin et al., 2015). This has led to the creation of Chinese cabbage collectors and the enhancement of mechanical harvesting techniques (Swe et al., 2021). Knowledge of spatial variability in the field would ensure sustainability, raise gross profitability, and improve site-specific crop management. Although technological advancements in harvesting equipment are necessary for increasing farm production, these benefits would not be realized without this knowledge (Maja and Ehsani, 2010; Kim et al., 2022). As the rate of cultivation and production of Chinese cabbage increases, it would be advantageous to monitor its yield in the field in real time and estimation of its gross profit.

Similarly, radish (*Raphanus sativus* L.) is a globally significant vegetable, commonly eaten raw as a salad vegetable (Zhang et al., 2019), which is also recognized for its potential medicinal properties (Mitsui et al., 2015). As annual or biennial crops, radishes are typically grown in open fields. The global planting area and total annual production reached 3.1 million ha and 95.0 million tons in 2019, respectively (Zhang et al., 2022). However, despite their importance as a crop, their production has been declining worldwide (Kim et al., 2019). For example, Japan experienced a 24% reduction in the yield of Daikon radish from 2006 to 2020. This decline can be attributed to various factors, including labor-intensive and time-consuming radish cultivation operations, limited mechanization, rising labor costs, and a diminishing workforce (Shin et al., 2015). To address these challenges, various countries have begun promoting mechanization as a means to accelerate the harvesting and collection processes of radishes (Hong et al., 2017). With the adoption of mechanization, there is an opportunity to enhance the management of radish fields by mapping the variability in yields and accounting for their spatiotemporal distribution in the field. Therefore, it is crucial to develop a yield-monitoring system for radish mass that is capable of instantly assessing yield and accounting for inter-field and intra-field variability. Real-time yield monitoring and spatiotemporal distribution analysis are critical components of precision agriculture, enabling farmers to verify current-season yields and providing guidance for future seasons (Liu et al., 2022). Many commercial yield monitoring systems, including Green Star (Deere & Company, Moline, IL, USA), Advanced Farming Systems (AFS) (Case IH, CNH Industrial America LLC., Felton, DE, USA), and Grain-Trak (Micro-Trak System, Inc., Mankato, MN, USA) are currently available worldwide.

Several sensing components are employed for monitoring the yield of crops. These include grain flow sensors, moisture content sensors, and cutting width sensors (Chung et al., 2016). The use of vision systems has also been tested recently. Generally, the type of sensing system depends on the harvesting method and the harvesting machine structure (Maja et al., 2010). For instance, contact-type mass flow methods that use impact-type sensors are mounted in the middle of grain transportation routes such as augers and grain tanks for monitoring grain yield (Chung et al., 2016). These types of sensors measure and accumulate the weight of grains in the field. Although a similar sensing principle could apply to radish-harvesting machinery, the sensor design and installation location of these sensors need to be revised in accordance with the machine structure and nature of radish harvesting. Also, in contrast with grain harvesting where the mass flow rate is high, the mass of a single radish tuber is desired during harvesting. Therefore, modification in the design of the sensing components is desirable to suit the radish-harvesting method. Impact-type sensors convert an impact force into a measurable electrical signal and have been extensively developed for grain crops. However, limited examples exist for non-grain crops. Two impact-type weighing systems, one with four load cells and the other with a single load cell, were developed and tested during the 2004 and 2005 tomato harvesting seasons, and both impact plates were located at the end of the harvester conveyor boom (Upadhyaya et al., 2006). These yield-monitoring systems worked well, with prediction errors of less than 2% under field conditions. Various load cell layouts have been used due to the irregular shapes of most crops and the varying structures of conveyor systems (Maja et al., 2010). However, most of the earlier research has focused on validating the performance of commercially available yield-monitoring systems, with little emphasis on factors influencing sensor performance, such as machine structure and harvesting conditions. These factors greatly influence the choice and performance of a yield-monitoring system (Ehsani and Karimi, 2010). Therefore, it is crucial to develop accurate impact-type yield-monitoring systems designed with consideration for the specific harvesting characteristics of radish and cabbage and their growing conditions. The study specifically aims to improve the accuracy and reliability of yield measurements by addressing vibration effects on load cells, particularly for cabbage and radish crops. Additionally, it also introduces a volume-based monitoring system utilizing an RGB camera and image processing algorithm to estimate cabbage and radish volume. These techniques will be assessed in relation to measured volumes, providing insightful information that can optimize radish and cabbage yield assessment in agricultural practices, ultimately improving crop production efficiency.

Materials and Methods

Description of Experimental Field and Sensor Selection

The experiment was conducted on the 20th and 21st of October 2022, and experimental site situated at Iksan, Republic of Korea (36.276° N, 127.220° E). This research was carried out under the supervision of the department of Smart Agricultural Systems, College of Agriculture and Life Sciences, Chungnam National University, Daejeon, and Hyundai Agriculture Company, Iksan, Republic of Korea. The total field area 2016 m^2 shown in fig 1. Chinese cabbage (*Brassica rapa subsp*. Pekinensis) was cultivated in the field, and during the tests, the cabbages were 12 weeks old. The cultivation of cabbage was executed on the ridge of each row, with an average row-to-row distance and row width of 1 m and 0.5 m, respectively.

(a)

(b)

(c)

(d)

Fig 1. Field experimental site: GPS position of experimental field (a), Pictorial view of cabbage collector (b), Plant and row spacing (c) and Size of test area (d)

Similarly, radish field experiment was carried out on October 15th and 16th, 2023, at Hongseong-gun, Chungcheongnam-do, Republic of Korea (36.216° N; 126.186° E) with the meteorological conditions of field temperature 23.5°C to 24.9°C, and relative humidity 46.1–47.8%, under the supervision of the department of Smart Agricultural Systems, College of Agriculture and Life Sciences, Chungnam National University, Daejeon, and Hyundai Agriculture Company, Iksan, Republic of Korea. During the experiment collector was mounted on tractor and tractor was idle state. 30 radishes were used for experiment. For mass and volume measurement Pi camera, ultrasonic sensor and single load cell was installed which connected with DAQ with LabView2020 program. The field used for the experiments had specific dimensions, measuring 50 m in length and 16 m in width. Additionally, radish crop rows were spaced 70 cm apart, with individual plants positioned at intervals of 20 cm. Radish was cultivated in the field, and test was conducted when it was 10-week old shown in fig 2.

(a)

(b)

Fig 2. Experimental site: Collector mounted with machine (a) radish experimental field (b)

For accurate yield monitoring during harvesting, the collector was equipped with a belt-type conveyor, a hydraulic motor system for conveyor operation, and three hydraulic cylinders for folding and unfolding the conveyor. Overall dimensions of collector measured 4.2 m in length, 1.2 m in width, and 2 m in height, with a total weight of 3,642 kilograms, comprising 3,052 kilograms for the tractor, 130 kilograms for the front loader, and 460 kilograms for the collector. In the field, a three-point-hitch-connected collector was used to transfer radishes that were manually harvested onto the conveyor belt, which then transported them into polypropylene sacks for the final collection step. The experiments were conducted with the aim of investigate the factors that influence the performance of load cell systems and conducting a comparative assessment of two different configurations. The variables under investigation included load cell layout, falling height, conveyor speed, and impact plate angle. Table 1 illustrates all the components employed in the experiments along with their specifications.

Table 1. Specifications of components used in yield monitoring system

Items	Components	Model and specification
Mass-based monitoring system	Load cell 	• Model: BCL-10 (Bongshin Loadcell Co., Ltd., Korea) • Rated Capacity: 10 kg • Rated output: 2.0 mV/V ±10%
	Acrylic plate 	• Acrylic plate • Dimension: 300 × 300 (mm) • Thickness: 10 mm
	Vibration sensor 	• Model: MEAS 34 (TE Connectivity, Ltd., USA) • Dimension: 30.5×30.5×24.6 (mm) • Input: DC 4.9 – 16 V • Temperature range: -40 to 105 °C • Accuracy : ±0.5% Non-Linearity
Volume-based monitoring system	Pi camera 	• Model: Camera Module 3 • Size: 25 × 24 × 11.5 (mm) • Regulation: 4608 × 2592 pixels • Optical size: 1/2.43” • Focal length: 4.74 mm
	Ultrasonic sensor 	• Model: HC-SR04 (Shenzhen, China) • Dimension: 45 × 20 × 15 (mm) • Working frequency: 40Hz • Max range: 4m • Measuring Angle: 15 degree
Data acquisition system	NI USB 	• Model: NI 9237 (National Instrument, Taxes, USA) • Channels: 4, 50 kS/s • Range of operation: -40°C to 70°C • 24-bit resolution
	DAQ holder 	• NI cDAQ (Taxes, USA) • 127 samples per slot per slot • 4 counters • 12.5 ns resolution

Field Experimental Setup

Yield monitoring system was developed to monitor and record the required measurements during the field testing of the collector. Based on laboratory test result, a single load cell was used to detect the cabbage and radish yield in the field. Single load cell was connected with laptop which was shown in fig 3. According to laboratory tests, a constant conveyor speed (0.50 km/h), falling height (0.20 m) and impact angle (10^0) were considered, respectively. A LabVIEW program (LabVIEW 2020, National Instruments, Austin, TX, USA) was used to operate the system properly. To ensure accurate weight measurement using a load cell system, a set of known weights (1-5 kg) should be obtained, and the load cell should be connected to the monitoring system as per the manufacturer instructions. Subsequently, the known weights sequentially applied to the load cell, with the corresponding output readings recorded for plotting against the weights to establish the load cell calibration, that process was repeated across multiple points for consistency and accuracy, and subsequently validated with additional known weights. A Finite Impulse Response (FIR) filter was applied by the LabVIEW program to reduce vibration and inclination effects on the monitoring system. Additionally, an equation-based model was employed to obtain a more improved output for cabbage and radish yield monitoring system. Thirty cabbages and radish were picked from the field serially and marked by marker pen. Each was weighed in weighing scale and measured the dimension before putting it in cabbage collector. Collected the weight of individual from the load cell and compare it with the weight of cabbage from the weighing scale.

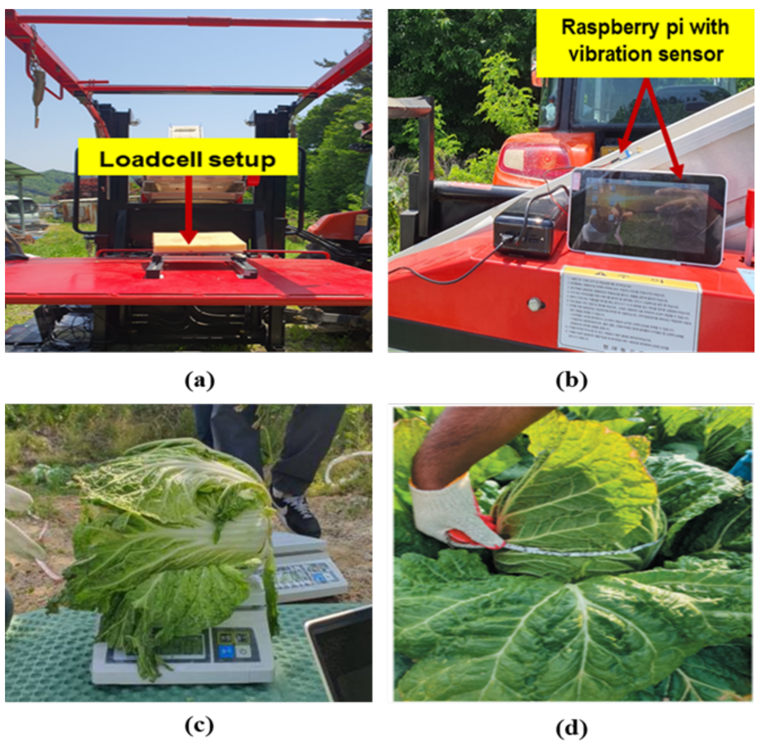


Fig 3. Field experimental setup: load cell setup (a), vibration sensor setup (b), weight measurement (c) and Dimension measurement (d)

The average weight of each cabbage was calculated by taking the mean of three separate measurements made with a digital precision scale that was accurate to within 0.01 g. For the performance evaluation, a total of eight people were employed. The performance tests were carried out on test plot, maintaining a tractor speed of 0.56 km/h, which was considered the standard forward speed for the tractor for cabbage harvesting. The speed of the cabbage conveyor was kept constant at 0.50 km/h throughout all the tests.

Experimental Procedure for Mass Estimation

In the field, radish harvest trials were conducted in randomly selected 5 m x 5 m size plots. Initially, 5 known masses measured for calibration. Then 30 radishes were manually counted from the field serially and marked by marker pen. Each radish and cabbage was weighed in weighing scale and measured the dimension before putting it in collector. Collected weight 3 times of individual radish from the load cell and average the weight and compared with the weight of radish from the weighing scale. The average weight of each radish was calculated by taking the mean of three separate measurements made with a digital precision scale that was accurate to within 0.01 g. The experiment was considered with three different conveyor speeds (0.25, 0.50, 0.75 Km/h) and three impact angle (10^0, 15^0, 20^0). Based on the laboratory test results falling heights 0.20 m was considered for tractor mounted test. Total experimental procedure presented in Table 2. A LabVIEW program was used to operate the system properly. A Finite Impulse Response (FIR) filter was applied by the LabVIEW program to reduce vibration and inclination effects on the monitoring system. The dimensions of the radish in each test plot were measured, and the height-to-diameter ratio was calculated. Additionally, field measurements, such as row spacing, row width, and the number of radish in each row, were recorded prior to commencing the field test, using a measuring tape.

Table 2. Experimental variables, levels parameters for the tests

Experimental variable	Levels		
Mass measurement with tractor mounted condition			
Conveyor speed (Km/h)	0.25	0.50	0.75
Impact plate angle (º)	10	15	20
Falling height (m)		0.20	

Volume-based Radish Yield Measurement

The image acquisition process utilized a Raspberry Pi camera (model: Raspberry Pi camera, Raspberry Pi Foundation, Cambridge, United Kingdom) to capture images at a 3 Hz frequency and saved them in JPEG format on the Raspberry Pi. The three color channels—red, green, and blue—that make up the RGB format of these pictures were merged to produce full-color images. Each picture was taken, saved in JPEG format, and quickly shown on the Raspberry Pi screen. For further examination, the saved photos were put in a special folder on the Raspberry Pi's memory card. Fig 4 illustrate the flow chart of total image acquisition system. Based on literature review generally Korean field vibration and slop 1.10 to 1.38 ms^{-2}. During the tractor-mounted test, the system considered inclination effects up to 10 degrees, motion at 0.5 Km/h, and vibration conditions at 1.38 ms^{-2}. Filtering techniques, including mean and histogram equalization, as well as mean filtering, were employed to reduce various image noises. Perspective transformation methods were also utilized to minimize noise in the 2D images. Volume calculations were conducted using both box and disc methods. The objective was to identify an appropriate filter and method for estimating radish volume from 2D images under conditions involving motion, vibration, and inclination.

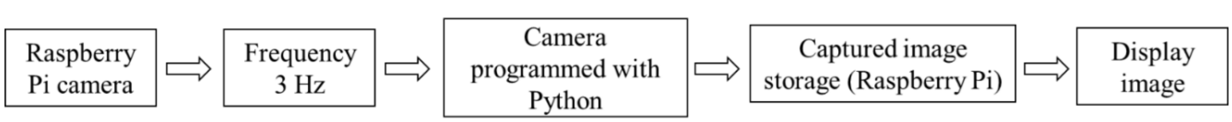


Fig 4. Flow chart of image acquisition system

Image Processing

A sequence of radish and cabbage images was captured in rapid succession using the Pi camera, with a 0.3 second interval between each shot. Fig 5 illustrates the systematic series of processing steps that were applied to these images. Effective noise reduction was achieved in the first phase by image filtering. The image was loaded first, and then it was turned into grayscale. Preprocessing and filtering techniques were then used to improve the quality of the images. Subsequently, a bounding box was employed to separate the radish from its surrounding objects and colors within the image. The resulting cropped image was utilized to determine the RGB values of individual pixels, facilitating the precise identification of the radish edges. To achieve accurate edge detection of the radish and cabbage subsequently measured size and shape, specific edge detection techniques were implemented. These methods were essential in quantifying the image of cabbage and radish by counting the individual pixels that make it up. Once the edges were successfully delineated, path and masking procedures were applied to calculate the pixel area within the captured image. This comprehensive analysis enabled a detailed examination of the radish and cabbage, encompassing their size, shape, and pixel count. All things considered, these methods were invaluable in providing an accurate analysis of the radish images. It included the strategic use of edge detection algorithms to highlight the images edges and boundary extraction for object delineation. The system determined pixel counts, estimated the area of each object in the image, and calculated the objects dimensions. Image processing involves a variety of techniques for analyzing and manipulating images to extract useful information or enhance visual features. Edge detection, thresholding, and bounding-box generation for image analysis. Edge detection is used to identify boundaries within an image. Edges represent significant changes in intensity and are often associated with object boundaries. Sobel operator was applied 3x3 convolution kernels with to highlight vertical and horizontal edges. Thresholding was applied to segment radish and cabbage image into regions based on pixel intensity values. Algorithm steps were histogram computation, probabilities and mean values, threshold iteration and threshold selection. Thresholding was used to simplify image analysis by converting grayscale images into binary images. Otsu's Method was used to automatically determine an optimal threshold by minimizing intra-class variance. Bounding boxes are rectangles that enclose objects or regions of interest in an image. They are useful for object detection, tracking, and localization. Bounding-Box calculation method was used to determine the minimum enclosing rectangle around the identified contours. Figure 5 presents the image processing steps for cabbage and radish volume estimation. After image analysis box method and disc method used for volume estimation of radish and cabbage.

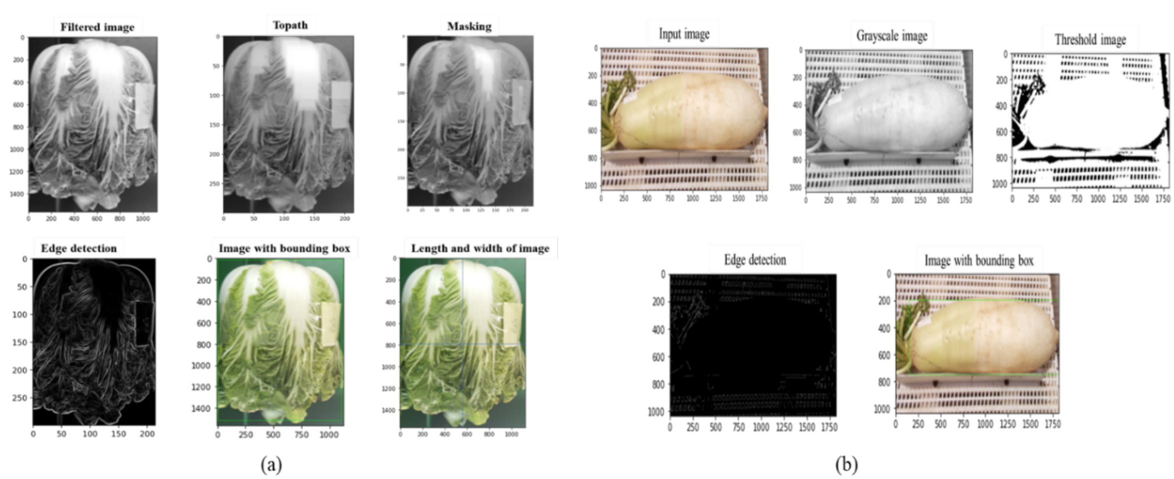


Fig 5. Image processing steps for cabbage and radish volume estimation

Statistical Analysis

Correlation among different conveyer speed, impact angle and falling height, analysis of variance (ANOVA) and coefficient of determination (R^2) with root means square error (RMSE) was used to compare estimated weight with measured weight where level of significance was 0.05. The Data operations and statistical analyses were performed using SAS software (SAS Institute, Inc., Cary, North Carolina, USA).

Results and Discution

Mass-based Yield Monitoring System

Effect of Conveyer Speed and Impact Angle on Mass Estimation

Three conveyor speeds (0.25 Km/h, 0.5 Km/h, and 0.75 Km/h) were considered, along with a constant impact plate angle 10^0,15^0, 20^0 and falling height 0.2 m based on laboratory tests. A FIR filter was employed to reduce the vibration effect on the output of the load cell-based yield monitoring system. Lastly, an equation-based model was used to achieve a more accurate yield prediction. The regression analysis revealed higher R-squared values of 0.94 and 0.94 for conveyor speeds of 0.50 Km/h and 0.25 Km/h, respectively, while a comparatively lower R-square value of 0.91 was obtained for 0.75 Km/h. These results are illustrated in Figure 6 according to conveyer speed (0.25,0.5,0.75 km/h). The R-squared values, which represent the goodness of fit with respect to conveyor speed, were found to be 0.94 for MW and PW (0.25 Km/h), 0.94 for MW and PW (0.5 Km/h), and 0.91 for MW and PW (0.75 Km/h). Strong correlations between weight measurements at different speeds and the measured weight of cabbage were indicated by these values. The Root Mean Square Error (RMSE) was utilized to assess the accuracy of the weight measurements. The RMSE values were 0.10 kg for MW and PW (0.25 Km/h), 0.10 kg for MW and PW (0.5 Km/h), and 0.15 kg for MW and PW (0.75 Km/h) which is depicted in fig 6. Higher measurement accuracy was suggested by the lower RMSE values. During field test, conveyor speed for this yield monitoring system was found to be up to 0.50 Km/h showed best performance.

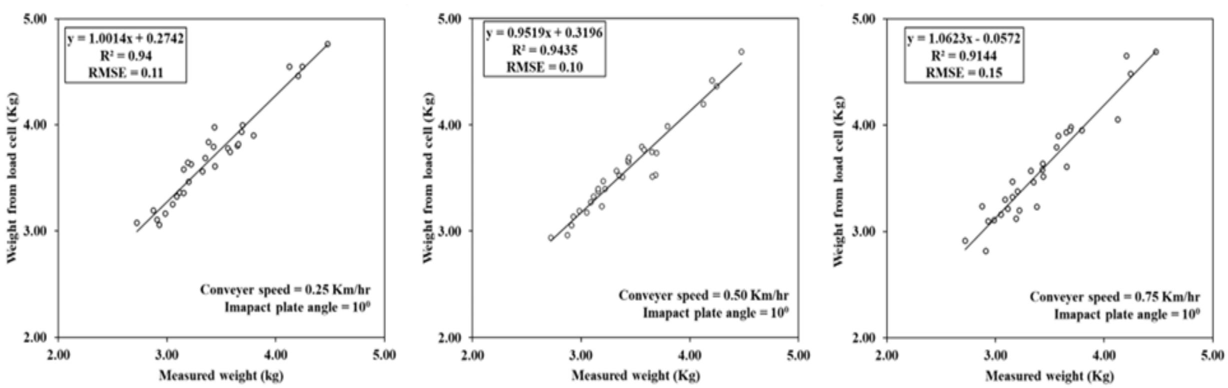


Fig 6. A linear regression model between the measured weight of cabbage and the predicted weight in field for conveyer speed of 0.25 km/h (a), 0.50 km/h (b), and 0.75 km/h (c)

T-test analyses were conducted to compare predicted weight and measured weight obtained at different conveyor speeds. For each method, the t-statistic, which measures the difference between the means of the volume measurements and the actual volume, was calculated. For measured weight and predicted weight (0.25 Km/h), the t-statistic was -1.45, for measured weight and PW (0.5 Km/h), it was -1.40, and for measured weight and predicted weight (0.75 Km/h), it was -1.32. These t-statistic values were compared to the critical t-values for a one-tail test at a significance level of 0.05, which was 1.67. For measured weight and predicted weight (0.25 Km/h) and measured weight and predicted weight (0.5 Km/h), the t-statistics were found not significantly different (p=0.07, 0.08) from the measured weight, indicating no deviation in weight measurements from these methods. However, for measured weight and predicted weight (0.75 Km/h), the t-statistic was found significantly different (p = 0.01) from the measured weight, suggesting that the predicted weight at conveyor speeds 0.25 Km/h and 0.50 Km/h were more accurate compared to the predicted weight at conveyor speed 0.75 Km/h. By applying the equation-based model, a higher R-square value of 0.98 was obtained at a conveyor speed of 0.5 Km/h, where the yield prediction error rate was 7.25%, as compared to R^2 values of 0.95 and 0.92 at conveyor speeds of 0.25 Km/h and 0.75 Km/h, respectively, where the yield prediction error rates were 4.31% and 8.50%, respectively. It has been observed that as the conveyor speed increases, there was a corresponding increase in the yield prediction error rate. This phenomenon is attributed to the proportional impact of vibration with speed. It can be concluded that better accuracy can be achieved for this yield monitoring system under field conditions at a conveyor speed of 0.5 Km/h. These results are depicted in fig 7 based on conveyor speeds (0.25, 0.5, 0.75 km/h). Table 3 Conveyor speed and impact angle are significantly effect on impact plate precision Mass based monitoring system.

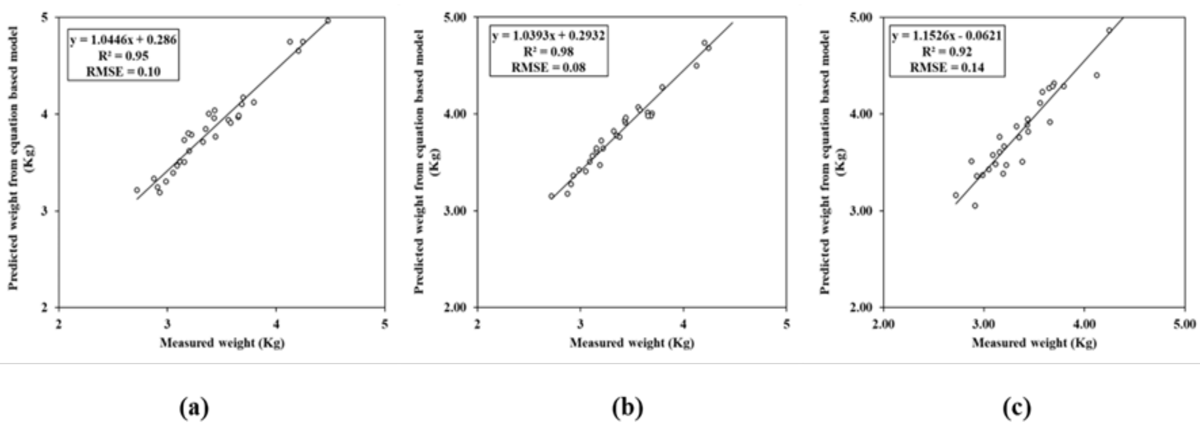


Fig 7. A linear regression model between the measured weight of cabbage (kg) and the predicted weight with equation-based model for conveyer speed of 0.25 km/h (a), 0.50 km/h (b), 0.75 km/h (c)

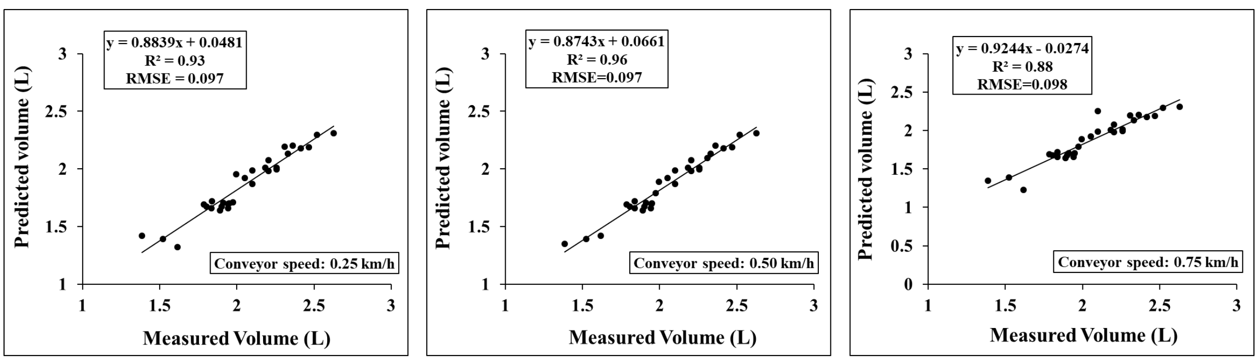
Table 3. Conveyor speed and impact angle are significantly effect on impact plate precision mass based monitoring system

Conveyor speed (km/h)	Falling Height (m)	Impact plate angle	Measured Weight (kg)	Predicted Weight (kg)	R^2	% of error
0.25	0.20	10^0	1.88	1.97	0.94	4.84
		15^0		1.98	0.94	5.52
		20^0		2.01	0.91	6.68
0.50	0.20	10^0	1.88	1.98	0.95	5.31
		15^0		1.96	0.98	4.10
		20^0		2.02	0.92	7.05
0.75	0.20	10^0	1.88	2.07	0.84	10.42
		15^0		2.01	0.89	6.93
		20^0		0.95	0.85	11.05

Volume-based Yield Monitoring

Volume Estimation Using Box Method

The process of volume extraction commenced with the application of the box method, following mean filtering to alleviate motion noise in the 2D image. Subsequently, three distinct linear regression graphs were constructed, aiming to compare the predicted volume against the measured volume. At a conveyor speed of 0.25 km/h, a linear regression graph was generated, resulting an R-square value of 0.93 and RMSE of 0.097 L. This indicated a strong correlation between the predicted and measured volumes, signifying the reliability of the system under this specific speed condition. Upon increasing the conveyor speed to 0.50 km/h, a new linear regression graph was plotted. Notably, the R-square value experienced an increment, reaching 0.96, while the RMSE reduced to 0.09 L. These improved statistical measures suggest enhanced accuracy in volume predictions at the higher conveyor speed, indicating the system's adaptability to varying operational conditions. Similarly, when the conveyor speed was further increased to 0.75 km/h, another linear regression graph was generated. In this scenario, the R-square value was recorded at 0.88, and the RMSE was 0.098 L. While the R-square value decreased relatively and the slight increase in RMSE indicate a marginally reduced predictive accuracy compared to the previous speed setting. Comparing the three speed, 0.50 km/h displayed the highest R-square value (0.96) and at 0.75 km/h showed lowest R-square value (0.88). These findings suggest that at 0.50 km/h conveyer speed is the most suitable for mitigating motion and vibration noise in 2D images. Fig 8 presents the graphical representation of regression coefficients and RMSE.



(a) (b) (c)

Fig 8. Regression co-efficient of measured volume (L) and predicted volume (L) using box method at conveyer speed of 0.25 km/h (a) conveyer speed of 0.50 km/h (b) and conveyer speed of 0.75 km/h (c)

Volume Estimation Using Disc Method

The extraction of volume was executed utilizing the disc method, preceded by the application of mean filtering to alleviate motion noise present in the 2D image. Following this preprocessing step, three distinct linear regression graphs were systematically constructed with the objective of comparing predicted volumes against their measured counterparts. At a conveyor speed of 0.25 km/h, a linear regression graph was generated, resulting in a notable R-square value of 0.90 and a RMSE of 0.096 L. This outcome indicated a robust correlation between the predicted and measured volumes, affirming the reliability of the system at this specific speed setting. Upon elevating the conveyor speed to 0.50 km/h, a subsequent linear regression graph was produced. Remarkably, the R-square value exhibited an increase, reaching 0.94, while the RMSE concurrently decreased to 0.09 L. These improved statistical measures suggest heightened accuracy in volume predictions at the elevated conveyor speed, showcasing the system's adaptability to diverse operational conditions. Similarly, with a further increase in conveyor speed to 0.75 km/h, another linear regression graph was generated. In this instance, the R-square value was recorded at 0.85, and the RMSE was 0.098 L. The modest reduction in R-square value and the slight increase in RMSE may indicate a marginal decrease in predictive accuracy compared to the previous speed setting. Comparing the three speeds, it was observed that at 0.50 km/h, the system exhibited the highest R-square value (0.94), while at 0.75 km/h, the lowest R-square value (0.85) was recorded. These findings suggest that a conveyor speed of 0.50 km/h is most conducive for mitigating motion and vibration noise in 2D images. The graphical representation of regression coefficients and RMSE, presented in fig 9.

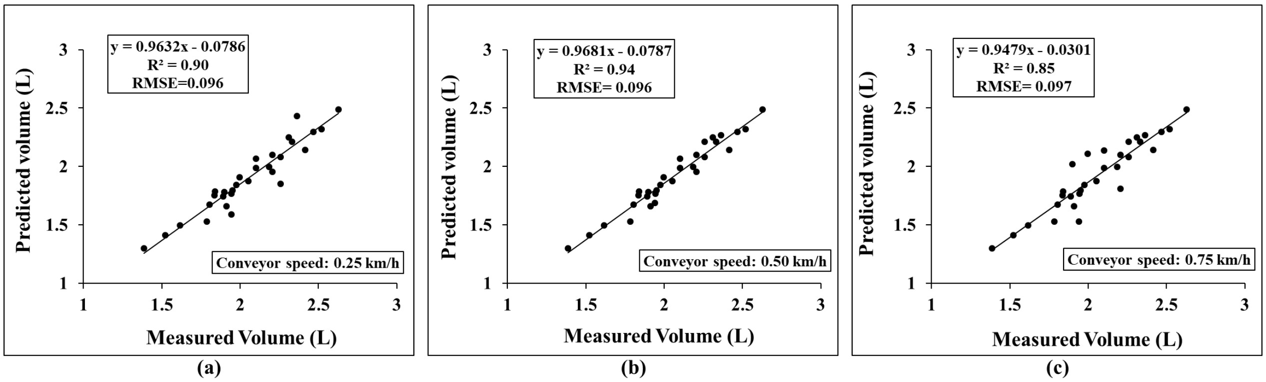


Fig 9. Regression co-efficient of measured volume (L) and predicted volume (L) using disc method at conveyer speed of 0.25 km/h (a) conveyer speed of 0.50 km/h (b) and conveyer speed of 0.75 km/h (c)

Conclusion

Mass-based sensing, the outcomes obtained under tractor-mounted conditions demonstrated the viability of determining radish and cabbage mass using impact plates in specific configurations. The identified differences in impact plate performance suggest the need for exploring alternative load cell layouts to enhance accuracy. A successful yield monitoring system requires meticulous signal processing and data collection. During real field tests, special emphasis should be placed on refining circuit design and signal processing to alleviate the impact of vibrations and slope. It is important to remember that additional external objects like stones, clods, and soil are not included in the individual-based measuring approach used in this study. Comparative results can be achieved through other digital filtering techniques. To avoid harmonic noise from the systems that load cell systems are installed on contaminating the output, anti-aliasing filters and high sample rates must be used. Additionally, small effects at different conveyor speeds were shown by additional trials evaluating the effect of vibration on image quality. The results imply that smaller pixel size camera models may improve cabbage and radish volume estimation while being less vulnerable to vibration effects, which is a desired result for yield monitoring systems based on vision. However, more testing need be carried out in a variety of settings, such as varying exposure durations, conveyor speeds and vibration intensities, in order to establish definitive findings.

Furthermore, the study acknowledges that the volume estimation, relying on RGB color information, is sensitive to varying light conditions. To address this challenge, the potential integration of Artificial Neural Networks (ANN) or other machine learning prediction methods utilizing size and shape features is proposed. Numerous algorithms have been developed and extended, providing a theoretical foundation for volume estimation studies employing these methods. However, the variation in image collection across previous studies is attributed to differences in the crops under examination and the setup of the vision system. This diversity arises because volume estimation methods are essential in various studies encompassing packaging, grading, processing, and conveying. Moreover, the distinct characteristics of different crops for volume estimation further contribute to the lack of universality in existing research results. Consequently, the development of volume-based yield monitoring systems for radish necessitates the consideration of field constraints such as light occlusion and the implementation of specific, accurate image processing methods. In summary, a comprehensive analysis of both mass-based and image-based systems were performed for radish mass and volume estimation. The insights gained from these experiments contribute valuable information for optimizing the performance of the impact plate in mass-based sensing and determining the suitable conveyor speed for accurate radish volume estimation using image-based methods.

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