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RESEARCH ARTICLE

Automated Technology for Strawberry Size Measurement and Weight Prediction Using AI

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ABSTRACT In this study, we propose an automated system for measuring the size of strawberries and predicting their weight using AI technology. The system combines computer vision techniques with LiDAR sensor data to accurately estimate the dimensions of strawberries and infer their weight. By integrating deep learning models, such as HRNet for keypoint detection, and leveraging the capabilities of LiDAR sensors, we minimize human intervention and achieve precise size measurement. The relative errors for the width and height of the strawberries are 3.71% and 5.42%, respectively, with the width exhibiting a lower error rate. The standard deviation for the width and height of the strawberries are 0.19% and 0.24%, this indicates that the individual strawberries had very low error rates in terms of their measurements for the width and height. Weight prediction was performed through regression analysis with width and height estimation. Experimental results demonstrate that our approach enables accurate weight prediction with a relative error of 10.3%. This automated technology holds great potential for strawberry harvesting and classification tasks, facilitating the automation of these processes.

INDEX TERMS Deep learning, strawberry size, LiDAR, point cloud.

I. INTRODUCTION

The increasing global climate change, coupled with a decrease in agricultural population and aging issues, has heightened the necessity for the adoption of AI technology in the agricultural field [1]. As a solution to address the challenges in global agricultural activities, the development of smart farming technologies incorporating big data, information and communication technology (ICT), and robotic automation has gained prominence [2], [3]. One of the necessary steps for agricultural automation technology is the development of techniques to evaluate the external quality of fruits and vegetables, enabling accurate harvesting and sorting based on precise quality standards. Typically, the external quality of fruits and vegetables is assessed considering factors such as size, color, texture, shape, and visual defects [4].

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Strawberries are among the most popular and valuable fruits in terms of taste and nutritional value, cultivated and extensively traded not only in the United States and certain European countries but also in East Asian nations like South Korea, Japan, and China, despite their cold climate. Strawberries are generally delicate in texture and require swift harvesting and sorting processes to prevent quality degradation caused by rapid overripening. For domestic production, sales, and exportation of strawberries, growers need to grade the harvested strawberries before packaging. The quality of strawberries varies based on criteria such as ripeness, shape, size, and flavor, traditionally assessed manually by farm workers. However, manual grading through visual inspection is labor-intensive, time-consuming, and may not guarantee consistent grading. Moreover, the multi-stage process involved in manual grading can lead to physical damage to strawberries and result in economic losses during exportation. Therefore, computer vision provides a means to perform these tasks swiftly and automatically [5].

A computer vision-based automated strawberry grading system can offer a solution to overcome such labor-intensive and time-consuming processes [6]. However, generating more convenient and reliable results with higher accuracy poses a significant challenge for automated grading systems. Previous studies on strawberry recognition based on computer vision have developed strawberry sorting systems using machine vision techniques.

Traditional methods for estimating the shape and size of strawberries have often relied on algorithms based on morphology, color, thresholding, and geometric approaches. However, research depending on these geometric or color-based functions often leads to inaccurate results and is constrained to approximate measurements from strictly controlled heights [7]. To address these limitations, our study leveraged advanced fruit detection algorithms using deep learning, notably the YOLO (You Only Look Once) algorithm. YOLO has evolved up to version 8 and has proven effective not only for fruit detection but also for accurate identification [8]. Additionally, Tang et al. enhanced the YOLOv4 small model, detecting fruits under varying lighting conditions, and displaying substantial robustness and stability even under significant lighting changes [9]. YOLO v7 has shown superior performance in detecting Camellia tree fruits in complex field scenes compared to previous versions [10]. Recent research efforts have merged state-of-the-art deep learning techniques with conventional image processing algorithms for real-time fruit detection and accurate fruit counting in practical field scenarios. Notably, a study achieved a high accuracy of 93.2% in counting the total bunches of bananas [11]. Despite the advancements in fruit detection and recognition technologies, research into precise size measurements and weight predictions for the purpose of standardization in harvesting and classification remains an ongoing challenge. This challenge is especially apparent for small fruits like strawberries, where accurate size and weight predictions are essential for classification [12].

This paper proposes a novel method for automating strawberry size measurement using a mobile device equipped with both a camera and LiDAR sensor, aiming to enhance harvesting value. The LiDAR sensor captures point cloud data representing spatial information of the real world in three dimensions [13]. Point cloud data consists of points with distance (referred to as depth) information from the LIDAR sensor, allowing calculation of distances between specific points in the scanned space. Moreover, the recent prevalence of mobile devices with integrated LiDAR sensors and cameras enables simultaneous scanning of the real world in both two-dimensional (2D) and three-dimensional (3D) data.

As shown in Table 1, Research involving the implementation of geometric and radiometric features in 3D spatial analysis has been conducted to detect apples, comprehend the seasonal growth process of apples, and recognize apple shapes and sizes [14]. Additionally, there have been ongoing efforts to monitor the growth of strawberries. This research focuses on obtaining multi-temporal 3D point cloud data for individual strawberry canopies. This data allows for the extraction of point counts per entity, height, ground projection area, and canopy volume profiles [15]. However, the utilization of LIDAR sensors for automated size measurement is still in its early stages, and its practical applicability is currently limited.

Recent advancements have led to the ubiquity of mobile devices equipped with LiDAR sensors and cameras, allowing the simultaneous scanning of the real world in both 2D and 3D data. Our research successfully utilized this technology to detect measurement points on strawberries using the obtained 3D point cloud data and depth data. Additionally, we calculated the distances between these points. Our approach successfully combines the strengths of deep learning models and point cloud data to accurately measure strawberry size to the extent of manual measurements. Furthermore, we have confirmed that weight prediction, which serves as the classification criterion based on the measured size, is feasible within an acceptable margin of error.

This research proposes the following methods to accurately recognize individual strawberries and automate size and weight predictions. The approach is as follows:

(1) Easily obtain 2D RGB, 3D depth, and point cloud data of strawberries through the mobile's built-in LiDAR sensor and camera, even under non-stringent conditions.

(2) Utilize deep learning algorithms to rapidly recognize the four key points of strawberries using the acquired image information.

(3) Calculate the distances between the four key points, enabling accurate measurement of strawberry size without rigid constraints on measurement distances, leveraging 3D depth and point cloud data.

(4) Predict the weight of strawberries without causing special damage or manipulation based on precise strawberry size measurements. Contribute to the automation of strawberry classification by aligning results within the error range of classification criteria.

In the next section, we introduce how our team minimizes human intervention by leveraging the deep learning algorithm and advantages of the LiDAR sensor. Additionally, in Section III, we provide details about the proposed method, and in Section IV, we describe the experiments conducted to verify the accuracy, acceptable error range, and clarity of the proposed approach.

TABLE 1. Size measurement techniques and methods in fruits: A comparative analysis of research cases in apples, strawberries.

Fruit	Techniques	Size parameters	Performance	References
Apple	RGB camera	Fruit Width	RMSE=2.0 mm	Wang et al., 2018
Apple	MVS, SfM	Fruit Width	RMSE=5.1 mm, MAE=3.7 mm	Gene-Mola et al., 2021
Apple	LiDAR-based sensor	Fruit Width	RMSE : 4.1–15.8%, MAE=3.5–12.4 mm	Tsoulias et al., 2020
Strawberry	RGB camera	Fruit Width, Height	RMSE : 6.3%, 6.7%	Oo and Aung., 2018
Strawberry	MVS based 3D data	Fruit Width, Height	RMSE : 1.49 mm, 1.53 mm	Joe Q. He et al., 2017

II. RELATED WORK

In this field, we examine the proposed method and limitations of previous research and introduce the utilization of computer vision deep learning techniques and LiDAR sensors as a solution to overcome these limitations.

A. AUTOMATIC STRAWBERRY SIZE MEASUREMENT AND WEIGHT ESTIMATION

Traditionally, strawberry size measurement for harvesting and classification has been conducted visually or by directly weighing the strawberries using scales. With the advancement of AI technologies, automatic fruit detection and assessment from 2D RGB images have been developed, enabling the determination of harvesting readiness [16]. However, studies relying solely on 2D images have limitations as they cannot preserve physical distance information (e.g., cm, in) in the real world. Depending only on 2D images necessitates strict workbench environments due to the conversion of distances from pixel level to actual measurements, making it highly impractical. Conventional computer vision (CV) approaches utilizing morphological, color-based, thresholding, and geometric methods have demonstrated excellent performance.

The research group (Bato et al. and Nagata et al.) developed a strawberry classification system using machine vision technology and defined the shape and size of strawberries for automatic classification based on the t-test method by calculating strawberry image area and centroid [17], [18]. A volume intersection method for reconstructing the three-dimensional shape of strawberries was proposed for automatic grading and packaging [19]. It provided a square root mean square error between 0.5 mm and 2 mm when compared to actual data measured with a laser scanner. Liming and Yanchao suggested an image processing algorithm for estimating strawberry shape and size using the split-line method, which requires centroid information. Strawberries were classified into four categories based on their shape for an automated strawberry grading system. The maturity grading accuracy was 88.8%, and the shape classification accuracy was estimated to be over 90% [20]. They also used elementary geometry to capture four key points for estimating the diameter and length of individual strawberries. As a result, the accuracy of strawberry classification was around 94-97%, the diameter was around 94%, and the length was predicted with an accuracy of 89-93% [21]. However, the inability to generalize and susceptibility to noise are weaknesses of classical computer vision approaches. CV engineers need to manually design features, which can become cumbersome and infeasible as the variability of the data increases [7].

To overcome these limitations, recent research employing state-of-the-art deep learning (DL) techniques is actively progressing. State-of-the-art methods employing deep learning (DL), such as the SOTA Convolutional Neural Networks (CNN), have demonstrated superiority in tasks such as segmentation [22] and keypoint detection [23]. The spectral features of CNNs have also been utilized for strawberry quality or ripeness detection, and CNN models have proven to perform well in image-related tasks like classification [24]. Furthermore, Mask R-CNN has been effective for pixel-level understanding (semantic segmentation) of images and has been applied to determine strawberry shape [25]. The Strawberry R-CNN model achieved a mean average precision (mAP) of 0.9019 for ripe strawberries and 0.8447 for unripe strawberries, with an overall mAP of 0.8733 [26]. Additionally, the superiority of the YOLO algorithm as a tool for automated fruit detection and harvesting continues to be explored. Even in the context of strawberries, the use of YOLO algorithms has proven effective, with the proposal of the DSE-YOLO algorithm [27] to detect various growth stages, achieving a mean average precision (mAP) of 86.58. Despite this ongoing progress in automating strawberry recognition and harvesting through deep learning (DL) in complex field conditions, research on precise size measurement and weight prediction for the standardization of the harvesting and classification processes remains relatively scarce. Notably, automatic size estimation has been a focus of various research efforts in recent years, predominantly applied to larger fruits like apples, mangoes, oranges, and grapes, with limited application to smaller-sized strawberries [28]. He et al. developed a low-cost Multi-View Stereo (MVS) imaging system for strawberry size measurement, capturing 360° data around the target strawberries. This method derived 3D point clouds from the samples, which were then analyzed using custom software, demonstrating a high level of agreement compared to manual measurements. However, this approach still requires stringent environmental conditions for strawberry fixation and necessitates fitting Oriented Bounding Boxes (OBB) to measure relative size [29]. Estimating strawberry weight is proportional to size, shape, and density. Utilizing point clouds and RGB+depth-based state-of-the-art neural networks,

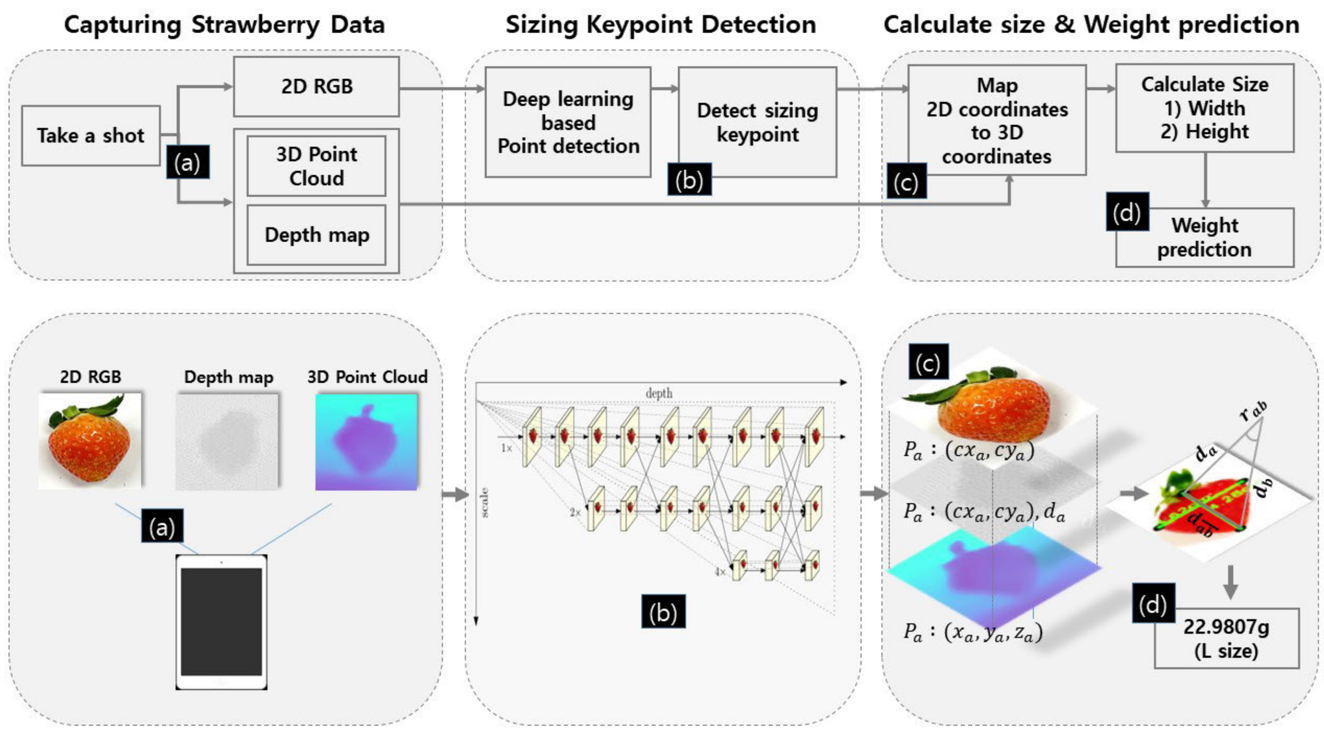


FIGURE 1. Illustrates the three-step process for strawberry size and weight prediction: (a) Strawberry images and point clouds were collected simultaneously using a mobile device equipped with a camera and LiDAR sensor. (b) The deep learning-based point detector detected the 2D coordinates from the photos of the measurement points. (c) Using a single captured image, depth map, and point cloud data, the size was calculated. The points p_a in the depth map are in 2D coordinates (cx_a, cy_a) that correspond to the RGB image, and each point has a distance d_a from the sensor. Finally, the program calculates the size $d_{\bar{ab}}$ with d_a and d_b, and the angle r_{ab} between two points. (d) Weight prediction was performed based on the calculated size.

we have demonstrated weight estimation with approximately 80% accuracy [30].

In our research, we employed YOLOv6 for strawberry detection and HRNet (High-Resolution Network) to estimate keypoints on strawberries. Leveraging the LiDAR sensor integrated into mobile devices, our approach achieved precise automatic size measurements without spatial constraints. Furthermore, based on precise size measurements, we confirmed the possibility of highly accurate weight estimation.

B. DEEP LEARNING-BASED KEYPOINT ESTIMATION MODEL

To train a deep learning model for detecting measurement points, numerous strawberry images annotated with pixel-level coordinates of the measurement points are required. To achieve this, we captured individual images of 1010 strawberries. In these strawberry images, we added coordinates for four keypoints: the endpoints of the longest equatorial axis, the height direction, and the strawberry's own vertices, regardless of whether the calyx was open or closed. We used these 4 keypoints to train our deep learning model. Regarding the keypoint estimation problem, HRNet (High-Resolution Network) is a state-of-the-art deep neural network architecture that has proven its effectiveness in human pose estimation tasks [31]. HRNet offers advantages over previous architectures [32], [33], [34]. Unlike previous approaches that used low-level resolution to restore high-level representation, HRNet connects high-resolution sub-networks in parallel instead of sequentially, efficiently preserving high-level representations. Furthermore, this architecture employs iterative multi-scale fusion, which maintains both low-level and high-level representations at similar scales, unlike previous fusion schemes that simply aggregated the two representations. The high-resolution representations learned in HRNet are spatially accurate. Inspired by this approach, our team adopted an HRNet-based keypoint detection model as the size adjustment point detector.

C. LIDAR APPLICATION

With the advancement and widespread adoption of LiDAR devices, various applications and research utilizing LiDAR technology have emerged in our daily lives [35], [36], [37]. LiDAR technology has also been employed in the recognition and size measurement of plant growth and fruit development [14], [15]. In these studies, LiDAR technology enables the conversion of distance into spatial information of the real world. It now allows stable and accurate measurement of distances close to the actual world and provides reliable data without significant constraints on height differences. However, there are still some challenges.

(1) Human intervention is required to select points for distance measurement.

(2) In mobile devices, slight movements during spatial scanning can lead to measurement errors.

Considering these issues, we designed an approach to minimize human errors by automating the following two procedures. First, the sizing point detector identifies sizing points without human intervention. Second, to eliminate calculation errors caused by hand movements during strawberry scanning, we simultaneously captured images and point cloud data.

III. PROPOSED METHOD

The objective of this study is to demonstrate the accurate measurement of strawberry width and height using a device equipped with a camera and LiDAR sensor, based on a single image and point cloud data. Furthermore, we enable the prediction of individual strawberry weights based on these length measurements.

The length measurement can be divided into two steps. Firstly, individual strawberries are automatically recognized using a deep learning model and four key points are identified. Then, the distance between the equatorial and vertical axis points is calculated based on these four key points. As step-by-step solutions, our team utilizes the YOLOv6 [38] deep learning model for strawberry detection and applies an HRNet-based keypoint estimation model to find the pixel coordinates of each sizing point in the 2D image. By aligning the coordinates of the image, depth map, and point cloud, we accurately measure the length.

First, a mobile device equipped with a camera and LiDAR sensor is used to capture strawberries with a white background, categorized by size. As shown in Figure 1a, a dataset is generated consisting of images, depth maps, and point cloud data through a single capture. Next, a deep learning-based point detector, as illustrated in Figure 1b, detects the positions of measurement points representing the contour of strawberries in the 2D image. A computer vision deep learning model is employed as a measurement point detector to determine the pixel coordinates of multiple measurement points. Finally, the size is calculated based on the depth information from the point cloud. The depth map represents the depth information of each point in the 2D coordinates, similar to the 2D image. As shown in Figure 1c, each detected point from the previous step is mapped to a point in the point cloud, and a distance from the LiDAR sensor is assigned. Using the actual distance information between the device and scanned space, the real size can be determined using depth and inclusion angles. Based on this size, automatically calculated weight is predicted, aiming to achieve automation in strawberry harvesting and sorting tasks.

A. HRNET-BASED SIZING POINT DETECTOR

We applied the HRNet [31] based keypoint estimation model as our sizing point detector. HRNet demonstrates excellent overall performance by simultaneously connecting multi-resolution subnetworks while maintaining high-resolution representations around the key points in the image [39]. This feature has been utilized in human pose estimation models and is also suitable for accurately detecting keypoints in simpler objects like strawberries.

The structure of our Point Detector is based on HRNet-W48. W48 represents the width of the subnetworks in the third stage, relatively larger than another variant of HRNet, HRNet-W32. The network architecture consists of four parallel stages of subnetworks, and as a result, the parallel multi-resolution subnetworks process maintains the same resolution representations across different stages of the network. All parallel subnetworks iteratively exchange information with each other, allowing bidirectional information exchange and ensuring rich representations [31].

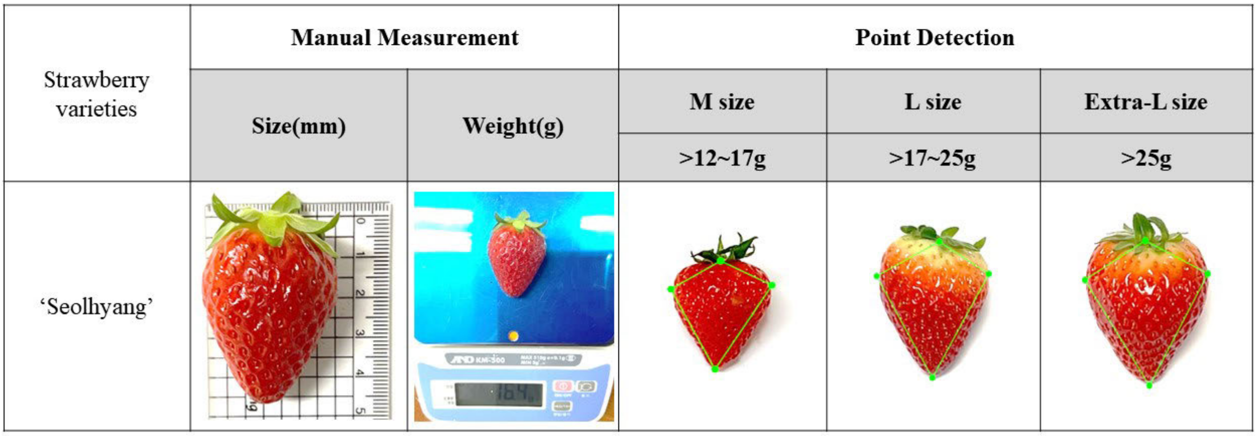
In the final stage, the high-resolution output of the last stage estimates the heatmaps of each keypoint. The loss is calculated as the Euclidean distance (d_i^2) between the ground truth coordinates (cx_i, cy_i) and the estimated coordinates ($\tilde{cx_i}, \tilde{cy_i}$) of the keypoints [40].

$$\begin{aligned}\text{Mean Squared Error} &= \frac{1}{n}\sum_{i=1}^{n} d_i^2 \\ &= \frac{1}{n}\sum_{i=1}^{n} \sqrt{(cx_i - \tilde{cx_i})^2 + (cy_i - \tilde{cy_i})^2}\end{aligned} \tag{1}$$

The loss function utilizes the mean squared error as follows Equation 1, which aims to find the shortest distance between the measured coordinates of the 4 keypoints on the strawberry and the equatorial (width) and vertical axes (height). The keypoint detection results for the strawberries were as follows: As trained, our model successfully recognized 2 keypoints along the longest equatorial axis of the strawberry in the images. Additionally, irrespective of the presence of the calyx, the model accurately detected the coordinates of the strawberry's vertices along the height direction. In total, the model detected 4 keypoints.

B. PHYSICAL DISTANCE CALCULATION

To calculate the actual size, spatial information corresponding to the detected four keypoints needs to be provided. For this process, we mapped the depth map captured from the same viewpoint and angle as the 2D image, as shown in Figure 1. The depth map contains distance information recorded by a LiDAR sensor (ToF sensor with 10 µm pitch px, Sony Group Corp) that records the distance between the real world and the device at each point. In particular, the LiDAR sensor embedded in the iPad Pro allows for rapid acquisition of 3D point clouds and, due to its cost-effectiveness compared to standard surveying equipment, portability, and convenience in data collection and processing, it can be easily employed for strawberry data collection [41], [42]. We captured the strawberry image, depth map, and point cloud simultaneously using an iPad Pro device (11-inch 3rd generation, Apple Inc.) equipped with a camera and



*Size is determined by the maximum diameter of the equatorial section(USDA)

*Size classification of strawberries based on weight(KAMIS 2019)

FIGURE 2. **The individual strawberry sizes and weights are manually measured using different methods. The length is measured manually using a ruler (mm), while the weight is measured individually using a weighing scale (g). The strawberries are classified into three categories based on their weights. M-size strawberries are classified as those weighing between >12 g to 17 g, L-size strawberries weigh between >17 g to 25 g, and Extra-L-size strawberries weigh above >25 g. All three categories of strawberries have a minimum length of 25 mm along the equatorial axis, meeting the criteria for the "Extra" class according to USDA standards.**

TABLE 2. **The dataset consists of a total of 1010 individual strawberries captured based on three weight criteria. The dataset includes 2D RGB images, depth maps, and point clouds for each strawberry. The equatorial width and height of the strawberries were measured manually using a ruler (mm), while the weight of each strawberry was individually measured using a weighing scale (g).**

Strawberry classification criteria	2D RGB Image (#)	Depth map (#)	3D Point cloud (#)	Width (mm)			Height (mm)			Weight (g)		
				#	AVE.	STDEV.	#	AVE.	STDEV.	#	AVE.	STDEV.
M size	390	390	390	390	30.366	2.1709	390	35.449	2.6277	390	14.24	1.4041
L size	380	380	380	380	34.641	1.7663	380	40.876	3.1162	380	20.855	2.2111
Extra-L size	240	240	240	240	39.829	3.6841	240	48.133	5.5725	240	32.036	6.8039
Total	1010	1010	1010	1010	34.114	4.4453	1010	40.404	6.1478	1010	20.833	7.8019

LiDAR sensor. The camera and LiDAR sensor capture simultaneously from the same region and viewpoint, enabling accurate mapping of the image and depth map without any errors. In the final step, the target size is calculated using the distance between the two detected points and the angle between the two points, as shown in Figure 1(d) [43], [44]. Each point from the LiDAR sensor is projected at equal angular intervals. Therefore, the angle between two points is equal to the unit angle multiplied by the point spacing between the two points [40]. In this case, $d_{\bar{ab}}$ in Equation 2 is the straight-line distance between the two points, similar to the manual length measurement method using a ruler.

$$d_{\bar{ab}} = \sqrt{(d_b \sin\theta_{ab})^2 + (d_a - d_b \cos\theta_{ab})^2} \qquad (2)$$

The $d_{\bar{ab}}$ means distance between point **a** and point **b**, d_a means distance of point **a** from a LiDAR sensor, and θ_{ab} means angle between point **a** and point **b**.

C. WEIGHT ESTIMATION

The weight of the strawberry is proportional to its size, density, and shape. Since the momentary density of the strawberry varies depending on its sweetness and moisture content, it cannot be inferred solely from the image. By utilizing vision technology, accurate weight estimation without causing damage to individual strawberries can minimize the reclassification process and reduce the harvesting and packaging steps. For weight estimation, the calculated equatorial and vertical lengths obtained from the RGB data, depth map, and point cloud were used in regression analysis to estimate the weights through weight coefficient estimation. The target for weight estimation was around 90% accuracy, aiming to enable appropriate automatic sorting without additional manual processing during harvesting [30], [45], [46]. Actual weight information (g) was obtained for each of the 1010 individual strawberries, and experiments were conducted to evaluate how accurately the weight could be estimated based on the predicted width and height measurements along the equatorial axis.

IV. NUMERICAL EXPERIMENTS

A. DATASET

For the strawberry size measurement experiment, a total of 1010 individual strawberry data were directly collected. Among them, 70% of the data was used to train the deep learning and point detection models for strawberry recognition. Afterward, a random 30% (303 samples) of the entire dataset comprising 1010 individual strawberry data was used to train the strawberry's keypoint detection model. The model was trained to recognize four keypoints of the strawberry, enabling the prediction of the width and height. The computer used for training had the following specifications: CPU: Intel (R) Core (TM) i7-9800X CPU @ 3.80 GHz, GPU: Four NVIDIA 1080ti GPUs, and 128 GB of RAM. The training process took approximately 6 hours, with 580 epochs set for training. A total of 707 images were used for training and 303 images for validation. Among these, 3 strawberries exhibited unclear keypoint recognition, indicating that approximately 1% of keypoints were not distinctly recognized. Consequently, statistical values were derived from the remaining 300 data points. For the purposes of this experiment, the individual strawberry data was categorized as follows. Post-harvest, strawberries typically undergo a repacking process based on their size. The equatorial length (width) and weight are the primary criteria for classification. According to the 2021 OECD Strawberry International Standard, strawberries are classified into ''Extra'' class, Class I, and Class II, with the size regulation determined by the maximum diameter of the equatorial cross-section. The minimum size is specified as 25 mm for the ''Extra'' class and 18 mm for Class I and Class II. Additionally, to ensure the quality of each class, the number of unsatisfactory strawberries or the weight-based tolerance range should be maintained within 5% for the ''Extra'' class and 10% for Class I and Class II. Therefore, it is important for strawberries to be packed in similar quantities within a weight error range of 5–10%. In our experiment, we utilized the 'Seolhyang' variety of strawberries, and based on the general criteria according to the individual strawberry weight, we classified them into three categories (Korea Agricultural Products Distribution information: Kamis 2019). As shown in Figure 2, the M size ranges from 12 g to less than 17 g, the L size ranges from 17 g to less than 25 g, and the Extra L size is 25 g or more. We manually measured the size of each individual strawberry in the equatorial and vertical directions, and the weight of each individual strawberry was measured using a digital scale. For data collection, each strawberry was placed on white paper, and independent captures were taken using the iPad Pro (A2228, Apple Inc., China). During data collection, the strawberries were measured at a height of 10–20 cm above a white background. the capture angle was adjusted to ensure consistency between the manually measured length and the length visible in the captured image. Table 2 provides information on the collected dataset. The average width of the 1010 strawberries was found to be 34.1 mm, with a standard deviation of 4.44. Similarly, the average height was measured as 40.4 mm, with a standard deviation of 6.14. Furthermore, the average weight of the strawberries was determined to be 20.8 g, with a standard deviation of 7.8.

B. EXPERIMENT RESULTS

The experimental results for strawberry size are presented in Table 3, the average relative errors for width and height size were (a) 3.71% and (b) 5.42% respectively. The average relative error for weight was (c) 10.3%. The relative error quantifies the difference between the measured and the actual

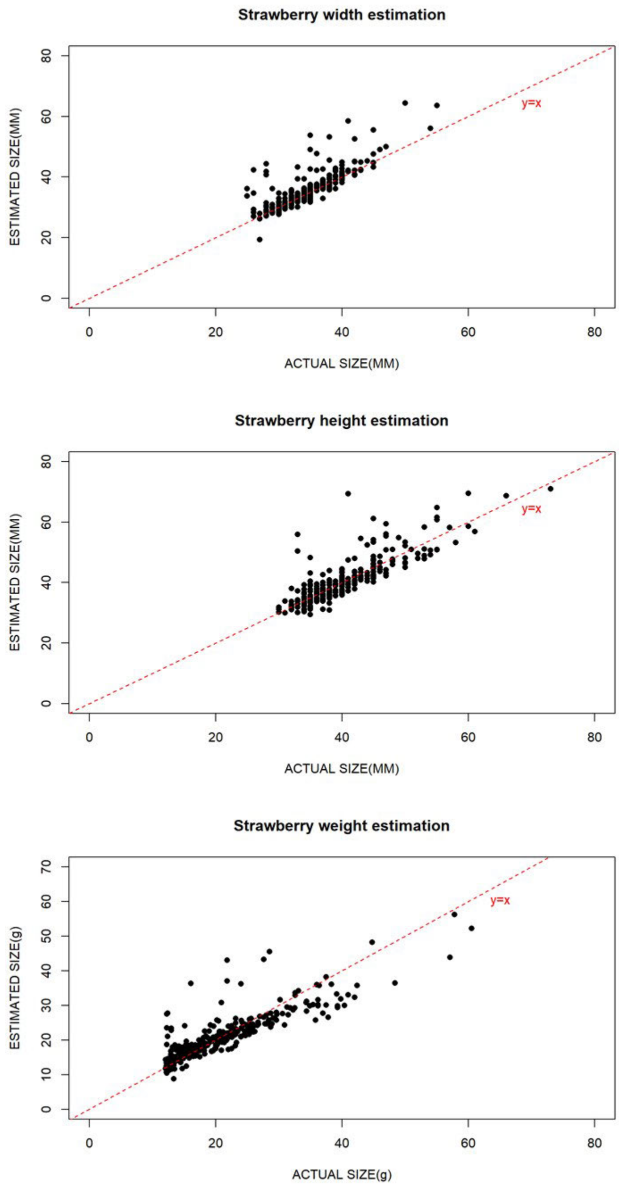


FIGURE 3. **Out of a total of 1010 collected data points, 70% were used for training the deep learning model for keypoint recognition, while approximately 30% (303 samples) of the strawberries were randomly selected for size prediction. Among these, 3 data points with keypoint recognition errors were excluded, leaving a representation of the distribution of 300 measured and predicted values.**

length, as expressed by Equation3.

$$\text{Relative error} = \frac{\text{Absolute error}}{\text{Actual size}} = \frac{\text{Actual size - Absolute error}}{\text{Actual size}} \tag{3}$$

For M-sized strawberries (27 g–17 g), the mean absolute error (MAE) for width was approximately 1.08 mm, with a relative error of about 3.4%. In contrast, L-sized strawberries exhibited a width MAE of approximately 1.31 mm and a relative error of about 3.6%. The largest strawberries, Extra-L-sized (25 g and above), showed a width MAE of 1.8 mm and a relative error of about 4.1%. It was observed that as the size increased, there was a tendency for the error

TABLE 3. Presents the results of the size estimation experiment. 'Abs. Err.', 'Rel. Err.', and 'S.E.' represent the abbreviations for absolute error, relative error, and standard error, respectively. The relative errors for the Width and Height of the strawberries are (a) 3.71% and (b) 5.42%, with the Width exhibiting a lower error rate. The average relative error for weight was (c) 10.3%.

Strawberry classification criteria	Abs.Err. (S.E.)			Rel.Err. (S.E.)		
	Width (mm)	**Height** (mm)	**Weight** (g)	**Width** (mm)	**Height** (mm)	**Weight** (g)
M size	1.085918 (0.0938)	2.019504 (0.1829)	1.581265 (0.1326)	0.0349 (0.0027)	0.056842 (0.0044)	0.103719 (0.0101)
L size	1.319723 (0.1518)	2.012499 (0.1548)	1.677938 (0.1717)	0.036544 (0.0035)	0.049426 (0.0034)	0.079984 (0.0069)
Extra-L size	1.806011 (0.2332)	2.781799 (0.2473)	4.067826 (0.3718)	0.041663 (0.0042)	0.057666 (0.0046)	0.140275 (0.0118)
Total	1.346807 (0.0891)	2.199816 (0.1104)	2.214453 (0.1354)	(a) 0.037142 (0.0019)	(b) 0.054246 (0.0024)	(c) 0.103552 (0.0056)

rate to increase by around 0.7%. Regarding the height of the strawberries, there was a total MAE of 2.1 mm with a relative error of 5.42%. This revealed a slight increase in the error rate of approximately 1–2% compared to the width, which could be attributed to the uncertainty of manual measurements caused by differences in capturing angles due to the three-dimensional shape of the strawberries. Furthermore, the equatorial axis length exhibited a standard deviation of 0.0019 (0.19%), while the height showed a standard deviation of 0.0024 (0.24%), indicating consistent and reliable results. The Root Mean Square Error (RMSE) for width estimation was 5.0%, and for height estimation, it was 6.8%, corresponding to an accuracy of approximately 95% and 93.2%, respectively. These results demonstrate slightly improved accuracy compared to previous studies utilizing 2D images for width and height estimation [21].

In terms of classification criteria for strawberries, the equatorial axis length plays a more crucial role, and in weight prediction as well, more emphasis is placed on the equatorial axis length. This results in an average absolute discrepancy of approximately 1.3 mm, which can be considered highly accurate. However, there is a tendency for the average relative error to be inflated by certain sizes with relatively larger relative errors. This is attributed to the discrepancy in recognizing the major axis during keypoint detection and length prediction, introducing errors during the actual measurement of strawberries. Nevertheless, despite the presence of an average absolute discrepancy of only approximately 1–2 mm, it is evident that precise keypoint recognition and length prediction can be achieved.

Figure3 in the graph represents data collected from 1010 images, with 70% used for deep learning-based keypoint recognition and 30% (303 images) randomly sampled for size prediction based on their respective sizes. Among these, 3 images with keypoint recognition errors were excluded, leaving 300 data points. It can be observed that the measured values and predicted values are distributed without significant errors. Some instances with larger errors were present, occurring at a probability of less than 1–2%.

The estimation of strawberry weight was conducted based on the average error of approximately 1.3 mm in width (along the equator axis) and 2.1 mm in height (vertical axis), using individual strawberry's 2D RGB data, depth map, and point cloud. Regression analysis was performed using the predicted equatorial width and height values obtained from a total of 1010 data points. The regression equation derived from the

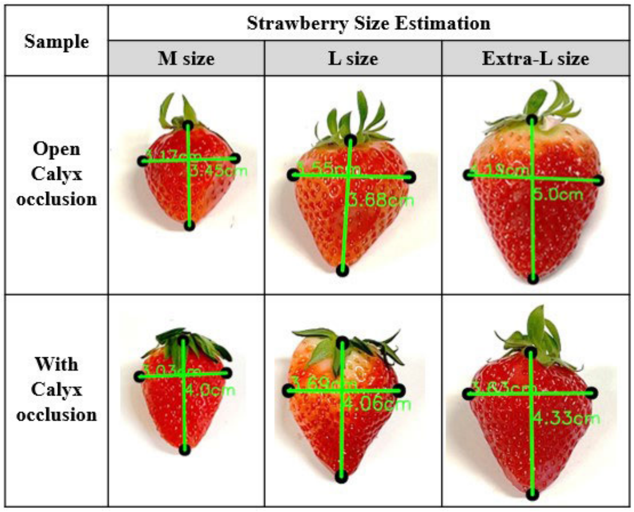


FIGURE 4. Some examples of size measurement results. Irrespective of the status of the calyx, successful keypoint recognition was achieved, facilitating precise size measurement.

calculated weights is as follows Equation 4.

$$\text{Weight Estimation} = 0.8323 \times \text{width} + 0.3719 \times \text{height} + (-23.3061) \quad (4)$$

Using this regression equation, the weight was predicted and calculated for 30% (303 samples) of the data. Among these, 3 data points with keypoint recognition errors were excluded, resulting in a dataset of 300 for analysis. According to Table 3, for M-sized strawberries, an error of approximately 1.5 g MAE occurred, resulting in a relative error rate of about 10.3%. For L-sized strawberries, an error of approximately 1.6 g MAE occurred, with a relative error rate of 7.9%. For Extra-L-sized strawberries, an error of about 4.0 g MAE was observed, leading to a 14% relative error rate. The error rate exceeding 10% in the Extra-L size is attributed to the lower proportion of Extra-L size strawberries, which accounted for 23.7% of the dataset in this experiment as shown in Table 2. On average, a relative error rate of 10.3% was observed, which does not significantly deviate from the acceptable error range of about 5–10% based on weight standards (OECD International Strawberry Standards, 2021). Figure 4 displays some examples of size measurement results. It is evident that regardless of the status of the calyx, accurate keypoint recognition was achieved for four points.

TABLE 4. Comparison table with previous strawberry sizing methods. Because the conventional method derives the actual size from the image, all environmental elements between the camera and the strawberry had to be tightly controlled. On the other hand, our method (using a LiDAR sensor) does not require such a setup.

Strawberry Size Measurement	2D Image Recognition (Oo and Aung., 2018) [21]	3D Image Recognition (He et al., 2017) [29]	Using Deep Learning-Based Point Detector & LiDAR sensor
Data	2D image	MVS based 3D data	2D RGB image, Depth map, Point cloud
Point detection	Point detection from extracted strawberry (etc. geometric calculation)	Direct point detection (SIFT algorithm)	Direct point detection (HRNet based model)
Size measurement	Distance conversion using calibrated pixel distance	Distance calculation based on Point cloud analysis & Orienting bounding box (OBB) fitting	Distance calculation based on depth and Point cloud information of each point
Device installation	Necessary	Necessary	Not Necessary
Background plate	Necessary	Necessary	Not Necessary
Camera calibration	Necessary	Necessary	None (Mobile Applicable)
Shape classification	94% to 97%	-	Approximately 99%
Rel. Err./MAE/RMSE	Rel. Err. Width : 4.8%, Height 5.2%	RMSE Width : 1.49 mm, Height : 1.53 mm	Rel. Err. : Width 3.7%, Height 5.4% MAE : Width 1.3 mm, Height 2.1 mm
Standard errors	Not provided	Not provided	Width : 0.19%, Height 0.24%
Weight	Not provided	Not provided	MAE : 2.21 g, Rel. Err. : 10.3%

C. DISCUSSION

Our proposed method exhibited excellent precision and tolerance performance with very low errors, as shown in Tables 3. As demonstrated in Table 4, research utilizing 3D Depth and Point cloud data through LiDAR sensors offers practical and substantial advantages compared to methods that rely solely on 2D images [21], [29]. Regardless of whether the sepals were open or closed, the keypoint was accurately detected, and the size measurement was successfully conducted. This demonstrates the robustness of the proposed method in accurately measuring the size of strawberries, irrespective of the state of the sepals. Thus, the proposed method offers consistent performance regardless of environmental variations or the condition of the strawberries, providing reliable and stable measurements for strawberry sizing. One of the key advantages of using LiDAR sensors for strawberry size measurement and weight estimation is that it does not require environmental control. In the past, methods relying only on 2D images required meticulous environmental control and camera calibration to map the spatial information of each pixel [21]. The method that exclusively utilizes 3D images also had limitations, as it required fixing strawberries in strict environmental conditions and measuring relative sizes by fitting Orienting bounding boxes (OBB) [29]. To achieve this, careful consideration of all components (such as the distance between strawberries and the camera, camera lens angles and curvatures, lighting setups, etc.) and designing the external environment were necessary for strawberry classification. However, such precise environmental control is not suitable for small-scale businesses or easy applications. In contrast, the proposed method does not technologically require such constraints. The operator measuring the size does not need to know information such as camera specifications or the distance to the target. LiDAR sensors [36] can record the distance from the viewpoint to the target space with an accuracy of up to 0.0001 mm, similar to a 2D image. In summary, anyone can instantly measure the size using a single mobile device, regardless of location. In terms of vision-based deep learning-based keypoint detection, the proposed method enables immediate estimation of the size and further extends to weight estimation without the need for contour extraction. By recognizing more keypoints and estimating the weight based on variables such as strawberry perimeter, equatorial length, height, and depth, more accurate weight estimation can be achieved. The technical novelty of this paper lies in proposing a dimension measurement framework through the registration by aligning RGB and 3D LiDAR data. Additionally, from an EdgeAI perspective, it develops software that implements ONNX-converted deep learning models to run on mobile platforms in iOS and Android environments. This software operates independently, separate from cloud platforms, showcasing the capability for autonomous use. However, addressing significant adversarial samples and achieving precise keypoint recognition for a more diverse range of strawberry shapes pose challenges for future work. Furthermore, predicting weight through the recognition of a greater number of keypoints for more accurate measurement of area, and subsequently estimating weight based on this, is predicted to further reduce error values.

V. CONCLUSION

This paper presents a dataset utilizing the built-in LiDAR sensor in a mobile camera for automatic size measurement and weight prediction in strawberry classification. The dataset includes 2D RGB, depth, 3D point cloud, keypoint detection, and size and weight information. Through deep learning-based keypoint recognition and automatic length measurement of width and height, as well as weight prediction, experiments were conducted. The results demonstrated precise length measurements with a Mean Absolute Error (MAE) of 1.3 mm for the width and 2.1 mm for the height of strawberries. Furthermore, the MAE for strawberry weight was 2.2 g. This resulted in a 10.3% relative error in weight measurement, falling within the acceptable range for strawberry classification criteria. This signifies that strawberries can be classified and packaged easily using vision technology through mobile devices, without the need for manual size or weight measurements. This advancement allows for the unification of harvesting and classification tasks using AI, leading to increased efficiency. As research in the field of strawberry recognition and harvesting continues to progress, applying the methodologies discussed in this paper in practical settings holds the promise of significant labor and time savings. This can lead to highly accurate size-based classification and efficient packaging of strawberries, which is expected to yield substantial benefits. Despite the remarkable advancements in artificial intelligence technology, previous research heavily relies on specialized algorithms that are highly dependent on specific data formats. Despite the development and widespread use of devices, their capabilities are not fully utilized in many applications. Our research demonstrates that even a simple connection between deep learning models and point cloud data can surpass the performance of previous size estimation methods that require meticulous control of environments and algorithms. Moreover, this method can be easily used and applied through mobile devices, enabling cost-effective utilization in various small-scale farms.

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REFERENCES

[1] N. C. Eli-Chukwu, "Applications of artificial intelligence in agriculture: A review," *Eng., Technol. Appl. Sci. Res.*, vol. 9, no. 4, pp. 4377–4383, 2019.

[2] F. Balducci, D. Impedovo, and G. Pirlo, "Machine learning applications on agricultural datasets for smart farm enhancement," *Machines*, vol. 6, no. 3, p. 38, Sep. 2018.

[3] P. Jayaraman, A. Yavari, D. Georgakopoulos, A. Morshed, and A. Zaslavsky, "Internet of Things platform for smart farming: Experiences and lessons learnt," *Sensors*, vol. 16, no. 11, p. 1884, Nov. 2016.

[4] C. Costa, F. Antonucci, F. Pallottino, J. Aguzzi, D.-W. Sun, and P. Menesatti, "Shape analysis of agricultural products: A review of recent research advances and potential application to computer vision," *Food Bioprocess Technol.*, vol. 4, no. 5, pp. 673–692, Jul. 2011.

[5] N. Aleixos, J. Blasco, F. Navarró, and E. Moltó, "Multispectral inspection of citrus in real-time using machine vision and digital signal processors," *Comput. Electron. Agricult.*, vol. 33, no. 2, pp. 121–137, 2002.

[6] B. Zhang, W. Huang, J. Li, C. Zhao, S. Fan, J. Wu, and C. Liu, "Principles, developments and applications of computer vision for external quality inspection of fruits and vegetables: A review," *Food Res. Int.*, vol. 62, pp. 326–343, Aug. 2014.

[7] N. O'Mahony, S. Campbell, A. Carvalho, S. Harapanahalli, G. V. Hernandez, L. Krpalkova, D. Riordan, and J. Walsh, "Deep learning vs. traditional computer vision," in *Proc. Sci. Inf. Conf.*, 2019, pp. 128–144.

[8] F. Xiao, H. Wang, Y. Xu, and R. Zhang, "Fruit detection and recognition based on deep learning for automatic harvesting: An overview and review," *Agronomy*, vol. 13, no. 6, p. 1625, Jun. 2023.

[9] Y. Tang, H. Zhou, H. Wang, and Y. Zhang, "Fruit detection and positioning technology for a *Camellia oleifera* C. Abel orchard based on improved YOLOv4-tiny model and binocular stereo vision," *Exp. Syst. Appl.*, vol. 211, Jan. 2023, Art. no. 118573.

[10] D. Wu, S. Jiang, E. Zhao, Y. Liu, H. Zhu, W. Wang, and R. Wang, "Detection of camellia oleifera fruit in complex scenes by using YOLOv7 and data augmentation," *Appl. Sci.*, vol. 12, no. 22, p. 11318, Nov. 2022.

[11] F. Wu, Z. Yang, X. Mo, Z. Wu, W. Tang, J. Duan, and X. Zou, "Detection and counting of banana bunches by integrating deep learning and classic image-processing algorithms," *Comput. Electron. Agricult.*, vol. 209, Jun. 2023, Art. no. 107827.

[12] J. C. Miranda, J. Gené-Mola, M. Zude-Sasse, N. Tsoulias, A. Escolà, J. Arnó, J. R. Rosell-Polo, R. Sanz-Cortiella, J. A. Martínez-Casasnovas, and E. Gregorio, "Fruit sizing using AI: A review of methods and challenges," *Postharvest Biol. Technol.*, vol. 206, Dec. 2023, Art. no. 112587.

[13] U. Weiss and P. Biber, "Plant detection and mapping for agricultural robots using a 3D LiDAR sensor," *Robot. Auto. Syst.*, vol. 59, no. 5, pp. 265–273, May 2011.

[14] N. Tsoulias, D. S. Paraforos, G. Xanthopoulos, and M. Zude-Sasse, "Apple shape detection based on geometric and radiometric features using a LiDAR laser scanner," *Remote Sens.*, vol. 12, no. 15, p. 2481, Aug. 2020.

[15] K. K. Saha, N. Tsoulias, C. Weltzien, and M. Zude-Sasse, "Estimation of vegetative growth in strawberry plants using mobile LiDAR laser scanner," *Horticulturae*, vol. 8, no. 2, p. 90, Jan. 2022.

[16] M. B. Lopez and O. Yliopisto, "European association for signal processing," in *Proc. 6th Int. Conf. Image Process. Theory, Tools Appl.* Oulu, Finland: IPTA, Dec. 2016.

[17] P. M. Bato, M. Nagata, Q. Cao, K. Hiyoshi, and T. Kitahara, "Study on sorting system for strawberry using machine vision (Part 2)—Development of sorting system with direction and judgement functions for strawberry (Akihime variety)," *J. JSAM*, vol. 62, no. 2, pp. 101–110, 2000.

[18] M. Nagata, P. M. Bato, M. Mitarai, Q. Cao, and T. Kitahara, "Study on sorting system for strawberry using machine vision (Part 1)—Development of software for determining the direction of strawberry (Akihime variety)," *J. JSAM*, vol. 62, no. 1, pp. 100–110, 2000.

[19] K. Imou, Y. Kaizu, M. Morita, and S. Yokoyama, "Three-dimensional shape measurement of strawberries by volume intersection method," *Trans. ASABE*, vol. 49, no. 2, pp. 449–456, 2006.

[20] X. Liming and Z. Yanchao, "Automated strawberry grading system based on image processing," *Comput. Electron. Agricult.*, vol. 71, pp. 32–39, Apr. 2010.

[21] L. M. Oo and N. Z. Aung, "A simple and efficient method for automatic strawberry shape and size estimation and classification," *Biosystems Eng.*, vol. 170, pp. 96–107, Jun. 2018.

[22] K. He, G. Gkioxari, P. Dollár, and R. Girshick, "Mask R-CNN," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 42, no. 2, pp. 386–397, Feb. 2020.

[23] Z. Cao, G. Hidalgo, T. Simon, S.-E. Wei, and Y. Sheikh, "OpenPose: Realtime multi-person 2D pose estimation using part affinity fields," *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 43, no. 1, pp. 172–186, Jan. 2021.

[24] Z. Gao, Y. Shao, G. Xuan, Y. Wang, Y. Liu, and X. Han, "Real-time hyperspectral imaging for the in-field estimation of strawberry ripeness with deep learning," *Artif. Intell. Agricult.*, vol. 4, pp. 31–38, Jan. 2020.

[25] Y. Yu, K. Zhang, L. Yang, and D. Zhang, "Fruit detection for strawberry harvesting robot in non-structural environment based on mask-RCNN," *Comput. Electron. Agricult.*, vol. 163, Aug. 2019, Art. no. 104846.

[26] J. Li, Z. Zhu, H. Liu, Y. Su, and L. Deng, "Strawberry R-CNN: Recognition and counting model of strawberry based on improved faster R-CNN," *Ecological Informat.*, vol. 77, Nov. 2023, Art. no. 102210.

[27] Y. Wang, G. Yan, Q. Meng, T. Yao, J. Han, and B. Zhang, "DSE-YOLO: Detail semantics enhancement YOLO for multi-stage strawberry detection," *Comput. Electron. Agricult.*, 198, Jul. 2022, Art. no. 107057.

[28] S. Naik and B. Patel, "Machine vision based fruit classification and grading—A review," *Int. J. Comput. Appl.*, vol. 170, no. 9, pp. 22–34, Jul. 2017.

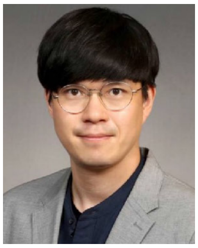
[29] J. Q. He, R. J. Harrison, and B. Li, "A novel 3D imaging system for strawberry phenotyping," *Plant Methods*, vol. 13, no. 1, pp. 1–8, Dec. 2017.

[30] A. Tafuro, A. Adewumi, S. Parsa, G. E. Amir, and B. Debnath, "Strawberry picking point localization ripeness and weight estimation," in *Proc. Int. Conf. Robot. Automat.* Piscataway, NJ, USA: Institute of Electrical and Electronics Engineers, 2022, pp. 2295–2302.

[31] K. Sun, B. Xiao, D. Liu, and J. Wang, "Deep high-resolution representation learning for human pose estimation," in *Proc. IEEE/CVF Conf. Comput. Vis. Pattern Recognit.*, 2019, pp. 5693–5703.

[32] Y. Chen, Z. Wang, Y. Peng, Z. Zhang, and G. Y. J. Sun, "Cascaded pyramid network for multi-person pose estimation," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit.*, Jun. 2018, pp. 7103–7112.

[33] B. Xiao, H. Wu, and Y. Wei, "Simple baselines for human pose estimation and tracking," in *Proc. Eur. Conf. Comput. Vis.*, 2018, pp. 466–481.
[34] H.-S. Fang, S. Xie, Y.-W. Tai, and C. Lu, "RMPE: Regional multi-person pose estimation," in *Proc. IEEE Int. Conf. Comput. Vis.*, Jun. 2017, pp. 2334–2343.
[35] K. Ko, H. Gwak, N. Thoummala, H. Kwon, and S. Kim, "SqueezeFace: Integrative face recognition methods with LiDAR sensors," *J. Sensors*, vol. 2021, pp. 1–8, Sep. 2021.
[36] N. Mehendale and S. Neoge, "Review on LiDAR technology," *SSRN 3604309*, 2020.
[37] C. Debeunne and D. Vivet, "A review of visual-LiDAR fusion based simultaneous localization and mapping," *Sensors*, vol. 20, no. 7, p. 2068, Apr. 2020.
[38] C. Li, L. Li, H. Jiang, K. Weng, Y. Geng, L. Li, Z. Ke, Q. Li, M. Cheng, W. Nie, Y. Li, B. Zhang, Y. Liang, L. Zhou, X. Xu, X. Chu, X. Wei, and X. Wei, "YOLOv6: A single-stage object detection framework for industrial applications," Sep. 2022, *arXiv:2209.02976*.
[39] L. Alzubaidi, J. Zhang, A. J. Humaidi, A. Al-Dujaili, Y. Duan, O. Al-Shamma, J. Santamaría, M. A. Fadhel, M. Al-Amidie, and L. Farhan, "Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions," *J. Big Data*, vol. 8, no. 1, pp. 1–74, Mar. 2021.
[40] S. Kim, H. Moon, J. Oh, Y. Lee, H. Kwon, and S. Kim, "Automatic measurements of garment sizes using computer vision deep learning models and point cloud data," *Appl. Sci.*, vol. 12, no. 10, p. 5286, May 2022.
[41] A. Spreafico, F. Chiabrando, L. T. Losè, and F. G. Tonolo, "The IPAD pro built-in LiDAR sensor: 3D rapid mapping tests and quality assessment," *Int. Arch. Photogramm., Remote Sens. Spatial Inf. Sci.*, vol. 43, pp. 63–69, Jun. 2021.
[42] M. Vogt, A. Rips, and C. Emmelmann, "Comparison of iPad pro's LiDAR and TrueDepth capabilities with an industrial 3D scanning solution," *Technologies*, vol. 9, p. 25, Jun. 2021.
[43] C. Gollob, T. Ritter, R. Kraßnitzer, A. Tockner, and A. Nothdurft, "Measurement of forest inventory parameters with apple iPad pro and integrated LiDAR technology," *Remote Sens.*, vol. 13, no. 16, p. 3129, Aug. 2021.
[44] S. Tatsumi, K. Yamaguchi, and N. Furuya, "ForestScanner: A mobile application for measuring and mapping trees with LiDAR-equipped iPhone and iPad," *Methods Ecol. Evol.*, vol. 14, no. 7, pp. 1603–1609, Jul. 2023.
[45] B. Zhang, N. Guo, J. Huang, B. Gu, and J. Zhou, "Computer vision estimation of the volume and weight of apples by using 3D reconstruction and noncontact measuring methods," *J. Sensors*, vol. 2020, pp. 1–12, Nov. 2020.
[46] S. Muhammad, H. Mousavi, and V. B. S. Prasath, "On the feasibility of estimating fruits weights using depth sensors," in *Proc. 4th Int. Congr. Developing Agricult., Natural Resour., Environ. Tourism Iran, Tabriz Islamic Art Univ. Cooperation With Shiraz Univ. Yasouj Univ.*, 2019.



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