LiDAR for measuring growth of plant in smart farm

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Abstract

Despite being of great importance to the economy and society of Thailand, the agricultural sector is unable to generate as much income as it should. The low average growth rate of agricultural production per labor is the main problem. Due to traditional farming practices, the resulting yields are only as effective as they should be, as it cannot compete with countries that are able to effectively apply digital technology and innovation. This study aims to address this issue by utilizing LiDAR (Light Detection and Ranging) technology and machine learning which used for predicting the accuracy of plant stage prediction to monitor the height and color of plants at three stages, consisting of stage 1 for plants aged 0-7 days, stage 2 for plants aged 7-14 days, and stage 3 for plants aged 15-45 days to accurately determine their harvesting stage. This concept was demonstrated using LiDAR measurements of lettuces that is Green Cos. Point clouds were generated from 3D RGB images and depth information from LiDAR camera (Intel RealSense L515) at three stages of the plant. For machine learning, feature extraction and model training and evaluation were used. Results showed height feature prediction is 80% accuracy, RGB image feature prediction was 100% and height with RGB image feature prediction was 90%. This can be further applied to real-world use in smart farming in the future.

Keywords: light detection and ranging (LiDAR), machine learning, RGB images, feature extraction, model training

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Introduction

The agricultural sector is considered extremely important to the economy and society of Thailand. It is the largest employer in the country and a significant source of income for many households. However, when considering the returns on income in the agricultural sector, it is found that despite employing over 40% of the country's workforce, it does not generate as much income as it should. Farmers have a lower average income compared to other professions, and lack income stability. Analyzing the causes and significant factors affecting the income of farmers with relatively low income reveals that production costs and productivity are the primary factors that affect farmers' income. In-depth analysis of data shows that the average growth rate of agricultural production value per labor per year is only 2.80%, and the agricultural production value per hectare per year is only 2.30 %, which is considerably low (Duangnirat, 2019). According to data from the World Bank, Thailand's agricultural productivity growth rate is also lower than that of other countries in the region. Upon analyzing this main problem, it is discovered that the average growth rate of agricultural production per labor is very low. This is because it is not able to compete with countries that are able to effectively apply a mix of digital technology and innovation.

The technology that will be used to address the problems in this research is LiDAR (Intel Realsense L515) is a remote sensing method that uses light in the form of a pulsed laser to measure ranges to the target. The output of LiDAR is the point clouds data that are used for many purposes. The LiDAR used in this research is the L515 model, which comes with an RGB camera that provided the outputs as 3D point clouds. The output consists of red color, blur color, green color and depth information. The plants used in this experiment is Green Cos Lettuces which has short life cycle about 45 days.

Recent researches have demonstrated the capabilities of using 3D LiDAR sensors for plant species classification, utilizing 3D point clouds with range and reflectance values for feature extraction and recognition of plant species without individual plant detection or RGB colorization (Weiss, Biber, Laible, Bohlmann, & Zell, 2010). In addition, LiDAR has been applied for discrimination between plants, weeds, and soil through measuring distance and reflectance values (Andújar et al., 2013). Statistical methods such as Canonical Discrimination Analysis and regression analysis have been used for actual height prediction of plants, with LiDAR as the primary tool for data collection (Andújar, Escolà, Rosell-Polo, Fernández-Quintanilla, & Dorado, 2013). Other studies have employed LiDAR for measuring geometrical variables such as points per plant, height, ground projected area, and canopy volume profile to remove gaps and empty spaces in the canopy point cloud (Saha, Tsoulias, Weltzien, & Zude-sasse, 2022). Ultrasonic sensors have also been utilized for automatic discrimination of grasses and weeds based on their heights (And´ujar, Escol`a, Dorado, & Fern´andez-Quintanilla, 2011) although they operate on sound waves as opposed to light waves used by LiDAR. LiDAR technology, along with ultrasonic sensors, provides a cost-effective and easy-to-operate solution. It is capable of scanning any type of object and has a wider field of view and lower divergence of the light beam compared to ultrasonic sensors. LiDAR sensors gather more data per reading, measuring the distance between themselves and surrounding objects with high spatial density (resolution) at a very high sampling frequency of thousands of points per second. This allows for the reconstruction of 2D (x, y) and 3D (x, y, z) structures (Polo et al., 2009; Tsoulias, Paraforos, Fountas, & Zude-Sasse, 2019). LiDAR systems can also use ultraviolet (UV), or visible (VIS) light pulses to estimate distances to objects. The reflected light pulse intensity and type of light can provide additional information on the detected target. By analyzing the reflection value when using NIR light pulses, it is possible to detect chlorophyll, which is found in living plants and strongly reflects near-IR light, a well-known effect in satellite image analysis (Soudarissanane, Lindenbergh, Menenti, & Teunissen, 2011). Additionally, the color of an object can indicate the reflection value of a point, with bright colors showing strong reflectivity (Herrero-Huerta, Bucksch, Puttonen, & Rainey, 2020). Therefore, vegetation with green colors can produce high reflection values in the returning laser beams of the LiDAR sensor. To use LiDAR for plant stage classification, a machine learning model must be built. Previous research has focused on separating reflectance and geometrical features, with a focus on coordinate systems. The system is trained on previously collected plant data and tested on new plant data. This approach has proven to be highly accurate (Weiss, Biber, Laible, Bohlmann, & Zell, 2010).

Several studies have explored the use of LiDAR sensors for various applications in plant-related research. Weiss, Biber, Laible, Bohlmann, & Zell (2010) focused on plant species classification using 3D LiDAR sensors, achieving success in separating individual plants. Andújar et al. (2013) investigated weed detection and discrimination using LiDAR and other methods, showcasing high accuracy and potential for herbicide spraying efficiency. Andújar, Escolà, Rosell-Polo, Fernández-Quintanilla, & Dorado (2013) developed prototypes for weed detection in maize fields using ultrasonic and LiDAR sensors and used LiDAR to estimate plant growth, leaf area, and volume in different crops characterized tree-row crops using a LiDAR system and employed 2D LiDAR scanners for obtaining structural characteristics of plants. These studies collectively highlight the effectiveness and potential of LiDAR in plant-related research.

From the research mentioned, it appears that only selecting LiDAR reflection properties to determine distance, or solely using RGB color properties, did not yield accurate predictions of the growth stage. However, in this study, both depth and RGB color features were used in classification of growth stage. In the context of predicting growth stage of plants, both RGB images and LiDAR data can be used as features in machine learning models. RGB images can provide information about the color and texture of the plants, while LiDAR data can provide information about the height and shape of the plants. By using both types of data, it may be possible to improve the accuracy of the growth stage predictions. The hypothesis was that by combining both depth and RGB color features, the prediction of the growth stage of plants would be more accurate.

Methodology

1. Preparation of plants

In this study, the sample is Green Cos Lettuce as shown in (Figure 1).

Figure 1 Green cos lettuce.

A total of 12 plant seedlings were used in this study, divided into three stages. Stage 1 consisted of 4 seedlings aged 0-7 days, stage 2 consisted of 4 seedlings aged 8-14 days, and stage 3 consisted of 4 seedlings aged 15-45 days. All of the seedlings were green cos, were grown using soil that required fertilizer application once the plants were 7 days old. Organic fertilizer was used, and the plants were watered twice daily in the morning and evening. The seedlings were grown on a farm located in Khon Kaen province based on the data collection of 50 days.

2. Experimental setup

The experimental setup consisted of a LiDAR system, specifically the Intel RealSense L515, including a 3D camera that provides point cloud and RGB images as shown in (Figure 2).

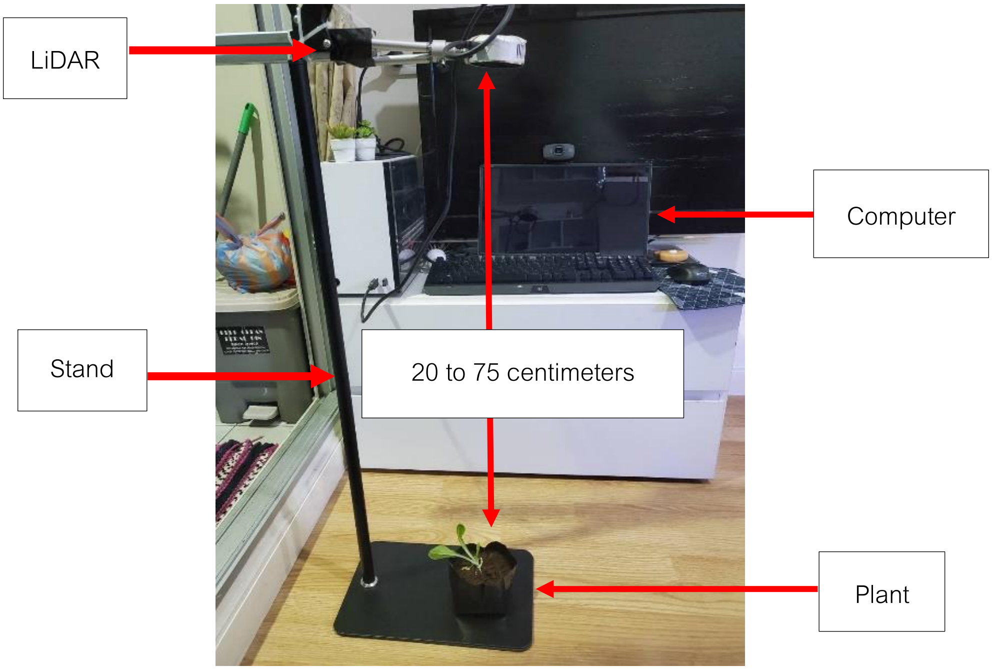

Figure 2 The Experimental Setup consists of LiDAR (Intel Realsense L515), Computer, Stand, Plant.

LiDAR (Intel Realsense L515) is used to measure the plants and gives output as point cloud and RGB images. A computer is used to analyze the point clouds and RGB images by using python language via Pycharm program. A stand is used to hold the LiDAR that measures only the top part of the plants. The plants consisted of three stages of plants. The distance between the LiDAR and the plants was 20 to 75 centimeters.

3. Data collection

For this experiment, 12 Cos lettuce plants in three stages of growth were used which taking five measurements per plant at randomly selected angles by rotating the plant. In each stage, there were four trees, and in total, there were 12 trees across the three stages. Therefore, there was 60 measurements of these plants as shown in (Table 1).

4. Data pre-processing

The LiDAR output, which includes point cloud data and RGB images. For the cropping process, it involves removing unnecessary parts such as cutting away the plant container and the surrounding environment beyond the tree itself to facilitate the use of the point cloud data. The principle is to measure the height from the LiDAR sensor to the ground level of the plants, and use it to create a range of plant heights. After that, the x and y coordinates were adjusted to cover the desired area of the as shown in (Figure 3).

Table 1 The output of 12 green cos lettuces from the top view with 5 measurements per plant.

stage	data/outcome (top view, 5 measurements per plant)			
stage 1 (4 pots) (0 to 7 days)	plant number 1 	plant number 2 	plant number 3 	plant number 4 
stage 2 (4 pots) (0 to 7 days)	plant number 5 	plant number 6 	plant number 7 	plant number 8 
stage 3 (4 pots) (0 to 7 days)	plant number 9 	plant number 10 	plant number 11 	plant number 12 

Figure 3 The cropped output of green cos lettuce by using Python program.

5. Machine learning

Machine learning is a field of artificial intelligence that focuses on developing algorithms and models that enable computers to learn and make predictions or decisions without being explicitly programmed. It involves training a machine learning model on a dataset to identify patterns and relationships, and then using that model to make predictions or take actions on new, unseen data. Machine learning techniques are widely used in various domains, including image recognition, natural language processing, recommendation systems, and autonomous vehicles, among others. The goal of machine learning is to enable computers to learn from data and improve their performance over time without human intervention.

For machine learning, which consists of logistic regression, feature extraction, confusion matrix and model training and evaluation were used. Feature extraction was used to handle the non-equal number of points in the point clouds by using histograms, which provide an approximate representation of the distribution of numerical data. The histogram includes RGB color data with a range of values between 0 and 1, with 50 features each for red, green, and blue colors, as well as 50 features for depth information with a range between 20 and 75 centimeters. The decision to use 50 features from the histogram is based on the need to condense the numerical data distribution into a manageable format. With the help of histograms, the challenge posed by varying point densities in point clouds can be overcome by providing an estimate of the data distribution. Specifically, the histogram is composed of 50 features for each of the red, green, and blue colors, as well as 50 features for depth information. In this research, a model was created using 9 plants, which represented 75% of all plants, and contained 45 measurements each, resulting in a total of 45×200 features. The model was trained using logistic regression which is a statistical method for analyzing a dataset in which there are one or more independent variables that determine an outcome. It is used to model the probability of a certain class to predict the three growth stages of the plants. The model was then evaluated using three plants from each growth stage, which represented 25% of all plants. The evaluation used 15×200 features of RGB color and depth. The purpose of this machine learning is to create a training model for predicting the growth stage of plants that we want to test. Python is used to help with the process, and the module called sklearn is utilized to improve the accuracy of the stage prediction.

Results and discussion

1. Feature extraction

This results in 200 features per plant, which are used in the model training and evaluation stages as shown in (Figure 4).

It can be seen that the intensity of red color as shown in (Figure 4a) and blue color as shown in (Figure 4c) ranges from 0 to 0.2 (0 to 20 centimeter), due to the fact that the light used to collect data is affected by external environmental factors, resulting in a slight difference in the intensity values of red and blue colors. Meanwhile, the intensity of green color as shown in (Figure 4b) ranges from 0 to 0.4 (0 to 40 centimeter), which is greater than that of red and blue colors, due to the presence of green leaves on plants. This is consistent with the previous experiment, in which the reflection value of green light was relatively high (Herrero-Huerta, Bucksch, Puttonen, & Rainey, 2020). Additionally, the height value is shown to range from 0.6 to 0.7 (60 to 70 centimeter) as shown in (Figure 4d), indicating that the system can classify the height of plants, with stage 1 plants having a height value from LiDAR ranging from 70 to 75 centimeters, stage 2 plants ranging from 65 to 70 centimeters, and stage 3 plants ranging from 60 to 65 centimeters. It can be seen that the experiment successfully differentiated the stages of plants using their height, with a high degree of accuracy, consistent with the previous experiment in which different types of plants were successfully separated using different statistical methods (Andújar et al., 2013; Andújar, Escolà, Rosell-Polo, Fernández-Quintanilla, & Dorado, 2013) but with similar levels of accuracy.

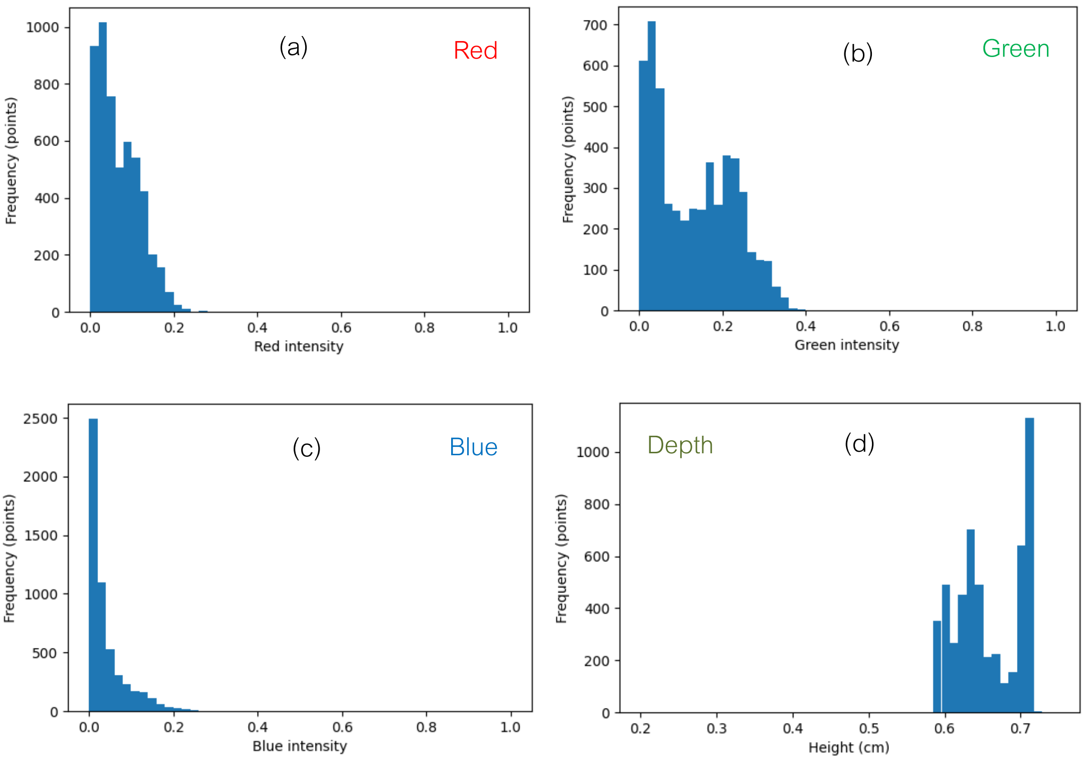

Figure 4 The output of the point clouds. (a) is the output of red color intensity, (b) is the output of green color intensity, (c) is the output of blue color intensity and (d) is the output of depth.

In the event that this monitoring system is used, it is recommended that calibration be performed for plant height measurement every time. This is because different plant species have different heights, which results in different measurement distances. Additionally, external environmental light may cause interference due to varying light intensity in different areas. Therefore, calibration should be done before each measurement.

2. Classification accuracy

In this step, the confusion matrix is involved. The confusion matrix is a performance measurement tool in machine learning that summarizes the results of a classification model. It presents the number of true positive (TP), true negative (TN), false positive (FP), and false negative (FN) predictions made by the model. It allows for a comprehensive evaluation of the model's performance by providing insights into its accuracy, precision, recall, and other evaluation metrics.

The dataset was divided into 4 cases, with each case using a different set of plants for training and testing. This was done to evaluate the accuracy of the system in different scenarios. The training and testing plants were chosen randomly, and each case had a different combination of training and testing plants. The aim of this approach was to ensure that the model was robust and could generalize well to new data. By using different sets of plants for training and testing, we could measure the accuracy of the system in a variety of scenarios and evaluate its overall performance.

The process of dividing plants to create a training model involves using a fold technique, specifically a 9-fold cross-validation. This entails splitting the plants into 12 samples, with 9 samples used for training the model, and the remaining 3 samples used for testing. This is done to evaluate whether the system can accurately predict the stages of the plants.

A training model and tested plants are developed to compare the accuracy of predicting plant stages. The model was created first, and then the tested plants were used to evaluate its ability to accurately determine the growth stage of the plants. The results will show to what extent the model can predict the stage of the plants as shown in (Table 2).

Table 2 The accuracy of each case of the tested plant.

case	tested plant number	accuracy		
		height	color	height + color
1	1, 5, 9	100%	100%	100%
2	2, 6, 10	67%	100%	100%
3	3, 7, 11	80%	100%	100%
4	4, 8, 12	100%	100%	100%

- In case 1, plants with the identification numbers 1, 5, and 9 will be used as test plants, while the remaining plants will be used to create a training model.
- In case 2, plants with the identification numbers 2, 6, and 10 will be used as test plants, while the remaining plants will be used to create a training model.
- In case 3, plants with the identification numbers 3, 7, and 11 will be used as test plants, while the remaining plants will be used to create a training model.
- In case 4, plants with the identification numbers 4, 8, and 12 will be used as test plants, while the remaining plants will be used to create a training model.

The accuracy of height prediction was found that indicating the model was able to predict the height of the plants with moderate accuracy. On the other hand, the accuracy of color prediction was found to be 100%, indicating that the model was able to predict the color of the plants with high accuracy.

Furthermore, when the model was trained to predict both height and color together, the overall accuracy increased to 100%. This suggests that combining the two features improved the accuracy of the model. Overall, the use of linear regression was beneficial in this experiment, as it allowed for the accurate prediction of important plant features that can be used to assess the growth and health of the plants. Based on the experimental results, it can be observed that if only the height variable is measured, the predicted growth stage is not as accurate as it should be. Therefore, RGB images are introduced to improve the accuracy of the growth stage prediction. It is possible that this is due to the variation in the greenness level of cos lettuce, which affects the height measurement. Furthermore, this research also encountered errors in height measurement, similar to previous studies (Andújar, Escolà, Rosell-Polo, Fernández-Quintanilla, & Dorado, 2013) which found that relying solely on height measurement cannot accurately differentiate the height of plants. Alternatively, a potential approach to predict the stage of plants could involve a shift from using machine learning to utilizing deep learning, specifically convolutional neural networks (CNNs). This approach has been successfully applied in the classification of Benjapakee Buddha amulet images (Butploy, & Boonying, 2020), achieving an accuracy of up to 80%. In comparison, the current research's accuracy using height data alone ranged from only 67% to 80%. Therefore, other geometrical variables such as volume are used to improve the accuracy of the growth stage prediction (Saha, Tsoulias, Weltzien, & Zude-sasse, 2022).

Conclusion

The experiment employed LiDAR technology in conjunction with actual plants. The experimental setup included an Intel RealSense L515 camera, which generated both point cloud and RGB images. These datasets were subsequently analyzed using a computer. The study utilized three stages of Cos lettuce, comprising a total of 12 plants. Data collection involved capturing five measurements per plant from various random angles. Python was used to filter out irrelevant background information from the LiDAR data. Machine learning techniques were applied for feature extraction, model training, and evaluation. To handle the varying number of points in the point clouds, histogram-based feature extraction was utilized. Each plant was characterized by 200 features representing RGB color and depth information. The logistic regression algorithm was employed to train the model, utilizing nine plants with a total of 45 measurements. The trained model was then tested using three plants from each stage. The results demonstrated moderate accuracy in predicting plant height and high accuracy in predicting plant color. From the experimental results, it can be observed that using only RGB color data for predicting the plant stage yields an accuracy of 100%. However, when using only plant height data to predict the stage, the accuracy dropped to 80% only. On the other hand, combining both RGB color and height data for stage prediction resulted in an accuracy of 90%. It is worth noting that the accuracy of stage prediction using only RGB color data was higher. This finding presents an interesting point that can be explored in future work. Logistic regression and feature extraction techniques proved to be valuable in accurately predicting essential plant characteristics, thereby facilitating the assessment of plant growth and health. One limitation of this research was the absence of a comprehensive smart farming implementation, which would have allowed the experimental outcomes to align more closely with the objectives of smart farming application. Future work could involve measuring plant growth using plant volume and utilizing color data to determine the growth stage of plants, rather than relying solely on height and RGB color information, in order to achieve more accurate predictions of plant stages.

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