**Greenhouse Lettuce Growth Indices Estimation: A Review**

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**Abstract.** Lettuce growth indices like dry weight, fresh weight, leaf area, diameter and height are important in determining the growth of lettuce. Traditionally, lettuce growth assessment is done destructively by manual sampling and measure which will need more labor, resources and time. Currently, many researchers propose non-destructive methods in plant growth indices estimation have obtained good results. However, through a search revealed there do not have existing reviews specifically focused on single or multiple lettuce crops growth indices estimation, underscoring the originality and relevance of the present study. This paper aims to contribute to a comprehensive overview on the lettuce growth indices estimation method and result accomplished over the year. It also discusses the potential research gaps for further improvement.

# INTRODUCTION

Climate change has become a significant threat to agriculture sectors especially in developing countries due to the limited adaptive capability [1],[2]. Increasingly frequent disasters like drought could pose a severe threat to the vulnerable communities that depend on farming for their source of likelihood especially with the absence of technology and financial resources to cope with the impacts of droughts [3],[4]. With the effect of disaster in agriculture, yield reductions may occur, and it may result in food insecurity. Recently, food insecurity has become one of the worldwide concerns due to the threat of climate change and increased food demand for growing population [5]. According to United Nation, the current world’s population of 7.7 billion is expected to reach 9.7 billion in 2050 [6]. Thus, ensuring food security under these conditions is a critical global issue. To reduce environment impact on agriculture and the food insecurity in rising population, precision agriculture that applies technology in observing, measuring, analysing and managing the crops and fields have the potential to be the solution [7]. Precision agriculture in controlled environment not only integrates technologies to optimize agricultural production processes for farm management, but also in indoor settings may reduce the impact of disaster caused by climate change [8]. Not only that, controlled environment in agriculture has gained popularity due to its ability to grow various leafy crops using soilless cultivation, which only requires less water and space for cultivation [9]. One of the most consumed and cultivated leafy vegetables, lettuce have been found resulting 40% larger sized in hydroponic system cultivation compared to soil-based system [10],[11]. As lettuce not only serves rich nutrients like vitamin C, vitamin E, calcium, protein, copper and potassium, it also has a rapid growth rate and short growth period, which make it suitable in investigating the product quality in planting [11],[12]. To optimize the cultivation practices and increase the production, the lettuce growth monitoring by accurately estimate the growth indices is crucial [13]. Lettuce growth indices including lettuce height, lettuce leaf area, lettuce diameter, fresh weight and dry weight are the important features in growing lettuce and ensuring the quality [14].

Traditionally, plant growth indices are sampled manually and destructively, the inaccurate measurement in plant brunch weight may happen if the plants are sampled before they reached harvest [15]. As the consideration of sustainable agriculture and the effectiveness of measuring plant growth indices, non-destructive techniques like computer vision technology have been used by several researchers [16],[17]. With the ability to extract features from the images and correlate with the manually measured growth indices, non-destructive growth monitoring can achieve since the image-derived features can estimate the growth indices [13]. Although the related studies on lettuce growth indices estimation exist, there is a lack of review on this specific topic. In this paper, the related research on lettuce growth indices estimation has been discussed in section two followed by the research gap in lettuce growth indices estimation. Lastly, the summary of the findings and suggestions for future work is included in the last section.

# RELATED WORKS

To estimate the plant growth indices of lettuce, dataset from online challenge of 3rd Autonomous Greenhouse Challenge organized by Wageningen University and Research and Tencent was widely used among researchers. This dataset was collected in the Greenhouse Horticulture Business Unit in Bleiswijk, The Netherlands in 2021. 4 varieties of lettuce, Lugano, Salanova, Satine and Aphylion were chosen as the crops in this challenge. The RealSense D415 cameras were hung above the crop to collect the RGB images and aligned depth images. The depth images can convert to 3D point clouds as all ground truth information is provided in JSON file. There have 388 RGB images (24-bit PNG) and 388 depth images (16-bit PNG) in the dataset. To collect the crop traits like fresh weight, dry weight, height, diameter and leaf area, the organizer conducted the destructive measurements of the selected crops once a week [18]. Table 1 included some research using this dataset for lettuce growth indices estimation.

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| **TABLE 1.** Existing method with dataset [18] | | | | |
| **Paper** | **Train Test Split** | **Input** | **Model** | **Result** |
| [19] | Train (87%): 338  Test (13%): 50 | RGB images,  Depth images | CNN,  ResNet50v2 as pretrained model architecture | from 0.88 to 0.95  NRMSE from 5.62% to 7.92% |
| [20] | Train (80%): 270  Validation (20%): 68  Test: 50 | RGB images,  Depth images | CNN, DCNN,  2 pretrained ResNet18 encoders in mid-fusion | NMSE = 0.068 |
| [21] | Train (80%): 272  Validation: 50  Test (20%): 68 | RGB images,  Depth images | 5 models (CNN, FCN) | from 0.84 to 0.9696  NRMSE from 10% to 15.63% |
| [22] | Train: 310  Validation: 38  Test: 40 | RGB images,  Depth images | Dual transformer,  CNN | from 0.86 to 0.9701  NRMSE from 11% to 22.57% |
| [23] | Train: 341  Test: 50 | RGB images,  Depth images | U-Net | from 0.9 to 0.963  MAPE from 6% to 87.4% |
| [24] | Train (70%)  Test (30%) | RGB images,  Depth images,  Geometric features | U-Net,  Multi-branch regression | = 0.938  MAPE = 17.7% |
| [28] | Train (4-fold)  Verification (10% from train set)  Test (1-fold) | RGB images | Mask R-CNN with RepVGG | from 0.91 to 0.96  MAPE from 0.05 to 0.1073 |
| [29] | Train (4-fold)  Verification (10% from train set)  Test (1-fold) | RGB images,  Depth images | Mask R-CNN with 2 RepVGG | from 0.93 to 0.9739  MAPE from 0.05 to 0.1622 |

With the availability of RGB images and aligned depth images in this 3rd autonomous greenhouse challenge dataset, Gang et al. [19] estimated lettuce growth traits. In the first stage, RGB images predicted fresh weight, dry weight, and diameter, while depth images predicted height. For the RGB image input model, 3x3 and 1x1 convolutional layers were applied due to the input size of the images are larger than the pre-trained model’s original input size. Then, transfer learning was employed using pre-trained model, ResNet50V2 with ImageNet dataset to the Convolutional Neural Network (CNN). To perform suitable training and prevent overfitting, additional fully connected layer and dropout layers were set. The depth model used a similar architecture but without ResNet50V2. Outputs from both models were combined and fed into two fully connected and dropout layers. In the second stage, these results were passed through an Artificial Neural Network (ANN) with two fully connected and dropout layers to refine dry weight predictions and leaf area. This proposed model had achieved 0.88 to 0.95 of Coefficients of Determination (R2) and it had potential in real-time sensing since it achieved 0.83 seconds of average time in each lettuce image processing [19].

Rather than using RGB images and depth images separately in different training model, Raja et al. [20] proposed multi-input, multi-output Convolutional Neural Network (MIMO-CNN) which used early and mid-fusion approaches to combine RGB images and depth images in a single model as input and result multiple continuous traits as output. Based on fresh weight magnitude, all the images are grouped to bin and sampled inversely proportional to the number of images in the particular bin. Another sampling method called stratified sampling that is based on plant variety was tried. Early-fusion and mid-fusion approaches were tried to combine RGB and depth inputs to a single model. The initial convolution layer is changed to 4 channel inputs instead of 3 for early-fusion approach but causes worse results, so it is not further examined. Whereas, for the mid-fusion approach, 2 pre-trained ResNet18 encoders for RGB images and depth images are used. In depth encoder, an extra convolutional layer from 1 to 3 channels was added to act as colour mapping layer. Additionally, deformable convolutional layers replaced all the standard convolution layers and the original convolution layers’ pre-trained weights were used in new deformable convolution layer in the second architecture. At last, Normalized Mean Squared Error (NMSE) and Mean Squared Error (MSE) were used to evaluate the model for all the lettuce traits. MIMO-DCNN have resulted 0.068 of NMSE [20].

Furthermore, Q. Zhang et al. [21] proposed TMSCNet, a 3 stages multi-branch self-correcting trait estimation network consists of 2 master models with CNN model architecture for preliminarily estimating lettuce’s growth indices and 3 auxiliary models with a CNN and two Fully Connected Network (FCN) model architecture to correct the preliminary results from master models automatically. For the TMSCNet, the 2 master models had similar network architectures and network parameters but different input. A master model inputting RGB images whereas the other master model involved depth images. To prevent the elimination of gradient, batch normalization layer was applied. For the RGB input model, there are 4 branches in the fully connected layers each output fresh weight, dry weight, diameter and leaf area respectively. While, in the full connection layer of depth images input model, there have only consist of one branch which is used to estimate the height of the lettuce. Next, one of the models in auxiliary models was the CNN based architecture as well which used to predict the lettuce varieties. Additionally, the rest of auxiliary models were self-correcting models using Deep Neural Networks (DNN). Unlike the CNNs, the DNNs used the preliminary predictions as inputs. TMSCNet achieved the R2 of 0.9514 (fresh weight), 0.9696 (dry weight), 0.9129 (height), 0.8481 (diameter), and 0.9495 (leaf area) [21].

Besides, Z. Wu et al. [22] introduced a hybrid model of dual-transformer and CNN (HDTC) for detecting the lettuce growth traits automatically to reduce lettuce appearance divergence in different growth stages. The dataset from 3rd Autonomous Greenhouse Online Challenge was also used to conduct this experiment. The dual transformer was used to extract the multi-scale representations of the lettuce images from coarse-grained and fine-grained patches. The primary transformer used wider embedding dimensions in utilizing coarse-grained patch size and the complementary transformer used smaller embedding dimensions in extracting fine representation. To solve the missing depth representations problem, the residual module was addressed. While the feature coupling bridge was obtained to project multi-scale and depth representations on a unifies space. HDTC model get R2 of 92.97% on average performance in estimating fresh weight, dry weight, lead area, diameter and height [22].

Unlike previously mentioned research who used CNN based models for direct prediction, Y. Zhang et al. [23] included RGB and depth images but employ semantic segmentation techniques to extract the features then mapped the segmented result to the corresponding point cloud for lettuce growth indices prediction. In Y. Zhang et al. [23], one of the image segmentations models called U-Net was involved. RGB images were employed in U-Net model for segmentation. The segmentation result from RGB images were mapped with depth images. Then, the segmented RGB images and depth images were converted to the corresponding point cloud. U-Net architecture was used only for image segmentation and point cloud segmentation while the others geometric traits were estimated from the segmentation results. Image segmentation result was used with OpenCV library’s function to find all the lettuce edge pixels and identify the pair of points that are farthest pixel distance from edge pixels. For the point cloud segmentation results in diameter prediction, the 3D point cloud was first projected along the z-axis into 2D image. Graham scan was used to find points in the 2D convex hull. Then, the pairs of points that are farthest Euclidean distance from the 2D convex hull was the lettuce diameter. The others geometric traits like fresh weight, dry weight and leaf area were also estimated based on image segmentation results and point cloud segmentation results. The predicted results for the lettuce height, diameter, leaf area, fresh weight and dry weight had achieved R2 of 0.935, 0.905, 0.963, 0.963, 0.963 respectively [23].

Moreover, this research proposed 2 different networks which are leaf segmentation network using U-Net and multi-branch regression network with RGB images, depth images and geometric features. U-Net architecture was employed to segment out lettuce leaves and backgrounds from RGB images. From the segmented images, some functions like edge and contour detection from OpenCV library were used to extract geometric traits like size-related traits and morphology-related traits. Once the geometric traits of lettuce were extracted, there were passed to the multi-branch regression network with RGB and depth images. To speed up the training process, min-max normalization was obtained for all the inputs. For extracting and fusing RGB images, depth images and geometric traits effectively, late fusion architecture was employed. For RGB and depth branches, ResNet-34 was used to extract the features, but the final fully connected layer was replaced by the features extracted from RGB images and depth images from the last flatten layer. Whereas, for the geometric traits branch, multilayer perception (MLP) was applied for extracting the features. After the feature extraction, all results from those 3 branches were flattened and combined. Lastly, the combined results were passed to the regression block for estimating the lettuce fresh weight. As results, multi-branch regression network achieved 0.938 of R2 for all varieties of lettuce [24].

Instance segmentation was designed to solve semantic segmentation and object detection concurrently by not only detecting the object but also drawing the contour and edges [25],[26]. As some semantic segmentations are good in differentiate background and objects but there are not good in differentiate same objects of the same category in images [27]. So, rather than using RGB and depth images in estimating lettuce growth indices, Hou et al. [28] used only RGB images with instance segmentation method to estimate the lettuce phenotypic traits. They proposed a Mask R-CNN model with RepVGG backbone instead of ResNet to improve the performance and to estimate lettuce phenotypic traits 2 fully connected layers have constructed to extract the features and estimate the traits. This proposed model has achieved R2 0.96 (fresh weight), 0.9596 (dry weight), 0.9392 (height), 0.9136 (diameter) and 0.9592 (leaf area) [28]. Furthermore, Hou et al. [29] further improves the model performance in having two RepVGG backbone to process both RGB and depth images. Depth images were refined using Ku et al.’s [30] deep completion algorithm, and the original eight convolutional layers in the phenotypic branch were replaced with a residual structure for better RGB–depth fusion. This improved model achieved higher R2 values: 0.9732 (fresh weight), 0.9739 (dry weight), 0.9424 (height), 0.9268 (diameter), and 0.9689 (leaf area).[28],[30]

Besides the dataset widely used by some researchers as mentioned above, some researchers self-collected the data as shown in Table 2 and estimating lettuce growth indices using enhanced CNN, segmentation methods and some pre-trained models. For example, L. Zhang et al. [13] collected 3 different lettuce cultivars; Tiberius, Flandria and Locarno grew from April 22, 2019, to June 1, 2019, in an experimental greenhouse located at Beijing, China, yielding 286 digital and 286 depth images. The images were collected 7 times a week after transplanting. The destructive measurements like leaf area, leaf fresh weight and leaf dry weight were conducted at the same time as image collection. After data preprocessing and data augmentation, the dataset was passed to a CNN model for estimating the lettuce growth traits. Support Vector Regression (SVR) and Random Forest (RF) were also used to estimate lettuce growth traits since there are widely used and achieve good results in crop growth monitoring. Before conducting model training in SVR and RF classifier, some features like texture, shape and colour were extracted from the segmented image. Pearson correlation was used to select features highly related to destructive measurements. Model performance was evaluated using R² and normalized root mean square error (NRMSE). The CNN outperformed SVR and RF, achieving the best results in estimating leaf fresh weight, leaf dry weight and leaf area with the highest (R2) of 0.8983 and NRMSE of 26% in leaf fresh weight [13].

In addition, Xu et al. [31] enhanced the dataset in L. Zhang et al. [13] by planting “Tiberius” lettuce in the same greenhouse, adding 200 RGB images for a total of 486. Depth images without valid values in the lettuce area were removed, leaving 366, which were split 8:1:1 for training, validation, and testing. Whereas the ratio of train, validation and test set for RGB remain the [13] original which was 6.4:1.6:2 for better comparison. The dataset was enlarged 26 times by using the data augmentation method from L. Zhang et al. [13]. Once the dataset was ready, the data was passed to 7 different models for model comparison. The hyperparameter and parameter were set as 300 epochs, 128 min-batch size and Adam optimizer except for VGG16 because of the computation, VGG16 was set as 96 mini-batch size. Among these 7 models, CNN\_284 have the best estimation results with RGB images by having the highest R2 in 0.9240 and the lowest NRMSE in 0.2224. While the models like ResNet18, EfficientNet, VGG16 and MobileNet were facing overfitting problems. So, the CNN models were further evaluated in estimating the lettuce growth traits with RGB images and RGB-D images. As a result, CNN\_284 had achieved the best performance compared to other CNN models with the R2 of 0.9764 and 0.1086 of NRMSE.

DCNN with pretrained model was also being introduced by Buxbaum et al. [32] in estimating lettuce biomass. One of the lettuce cultivars called Lactuca saltiva were grown indoors. In a data collection event consists of 54 RGB images with 848x480 pixels, 54 aligned depth images and 54 destructive measurements of plant biomass. Total of 3888 lettuces were collected with the biomass measurements in the data collection stages. This study improves the model learning ability in encoding single channel depth data to three-channel RGB format by using “jet” colour scheme which maps depth values to RGB colours. Then, the images were normalized, cropped and augmented. Buxbaum et al. [32] proposed model inputting RGB images and depth images followed by feature extraction with ResNet50 and fully connected layer in regression head. This proposed deep neural network on plant biomass estimation had achieved 1.13g of RMSE and 7.3% of MAPE [32].

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| **TABLE 2.** Existing method with different dataset | | | | | |
| **Dataset** | **Paper** | **Train Test Split** | **Input** | **Model** | **Result** |
| Self-collected | [13] | Train (80%): 229  Test (20%): 57 | RGB images,  Depth images | CNN | from 0.89 to 0.9156  NRMSE from 19% to 26% |
| Original dataset from [13]  Similar experiment setup | [31] | Train (80%): 294  Validation (10%): 36  Test (10%): 36 | RGB images,  Depth images | CNN,  Pretrained model | (CNN\_284): 0.9764  NRMSE (CNN\_284): 0.1086  MAPE: 9.74% |
| Self-collected | [32] | Train: 2484  Test: 864 | RGB images,  Depth images | DCNN with ResNet50 | RMSE: 1.13g  MAPE: 7.3% |
| Self-collected | [33] | Train: 232  Test: 70 | RGB images,  Depth images | DeepLabV3+ with MobileNetV2,  Multi-modal input | from 0.9 to 0.968  MAPE from 9.2% to 21.3% |
| Self-collected | [34] | Train: 850  Test: 200  Set monitoring: 168 | Images | Mask R-CNN,  Exponential growth equation | Growth rate: 23.25% per day  Mean accuracy: 97.63% |
| Self-collected  Image collection – | [35] | Train (70%)  Validation (30%) | Images | Mask R-CNN,  Linear regression equation | Training loss = 0.21  Validation loss = 0.31 |

Other than that, some researchers also involved semantic segmentation like DeepLabV3+ and instance segmentation such as Mask R-CNN in the lettuce plant growth indices estimation. Ojo et al. [33] cultivate Rex cultivar of lettuce hydroponically in 2 growth cycles (March 27, and May 8, 2023). Each growth cycle consists of 151 plants, with images taken on 6 different days from transplant to harvest, and ground truth data collected destructively at the cycle’s end. As a result, 302 pairs of RGB images and depth images in PNG format were collected. Ojo et al. [33] introduced a multi-modal fusion based deep learning model in estimating lettuce growth indices. They proposed a multimodal fusion deep learning model, replacing the DeepLabV3+ backbone with MobileNetV2 for automatic leaf–background segmentation from RGB images. Performance comparisons with Pyramid Scene Parsing Network (PSPNet), Feature Pyramid Network (FPN), and U-Net showed DeepLabV3+ with MobileNetV2 achieved the highest mIoU (0.9979), accuracy (0.9985), IoU-leaf (0.9978), and IoU-background (0.9980). Segmented images were used to extract geometric traits, together with RGB and depth data were fed into a multimodal regression network using ResNet50 for feature extraction. Features from all branches were flattened and concatenated before passed to the regression block. In conclusion, R2 of 0.968 (fresh weight), 0.943 (dry weight), 0.906 (diameter), 0.953 (leaf area) and 0.965 (height) has achieved using the multimodal regression network [33].

Moreover, Lu et al. [34] and Reyes-Yanes et al. [35] involved instance segmentation in their research. For instance, Lu et al. [34] used Mask Region-based Convolutional Neural Network (Mask R-CNN) to detect the lettuce and segment the lettuce areas in the images which collected from 5 lettuce in a greenhouse. The data collection was conducted in a full lettuce growth period which is 20 days and lettuce images were collected every 30 minutes from 6:00 to 18:00. Mask R-CNN was first used to detect lettuce and segment the lettuce area. By getting the lettuce area, growth rate can be determined since the lettuce area versus time. Then the exponential growth equation was used to further estimate growth rate. The mean accuracy of 97.63% have achieved in estimating lettuce area using Mask R-CNN and 23.25% per day have achieved for the growth rate of lettuce [34].

Reyes-Yanes et al. [35] collected images from various sources, including top and side views of plants taken every half hour from 6:00 to 18:00, along with manual measurements taken twice daily. Google search engine was used to enhance the image dataset with different lettuce growth stages and scenarios images. These two methods result in 1350 images collected and LabelMe software was used to obtain 3150 instances. Then Mask R-CNN was employed to perform crop segmentation, and the manual measurements were used to compare to the estimated lettuce depth, height and width from the proposed model. This research has achieved 0.21 training loss and 0.31 validation loss in Mask R-CNN. OpenCV and Green’s theorem were used to extract 7 features from segmented regions, including height, width, depth, and centroid positions. Lastly, the growth rate estimation was conducted using variations in area for each plant in time, whereas for the fresh weight estimation, linear regression techniques with the features extracted and manual measurements were obtained. To validate their proposed method, a new batch of Little Gem Romaine Lettuce are grown, and 750 top and side view images are collected, each showing 3 plants. The images after pre-processing will pass through the proposed method starting from model training using Mask R-CNN, feature extraction and lastly growth rate and fresh weight estimation. In conclusion, 0.42g of RMSE with all parameters except ‘Volume’ selection have achieved which is the lowest compared to other criterions [35].

# DISCUSSION

From the reviewed literature, most studies on lettuce growth indices estimation focus on single-crop images. For example, the commonly used dataset [18], contains only one lettuce per image. While single-crop images simplify image processing and model training, multi-crop images are more relevant for real-time applications [36] and can reduce time and resources in data collection. So, one of the research gaps are lack of research on multiple lettuce crops in an image for one shot lettuce growth indices estimation. Although several researchers have achieved better results on using Convolutional Neural Networks (CNN) models in this area, it does not extend towards the model in transitioning from estimating a single lettuce growth index to estimate lettuce growth indices for multiple crops.

Furthermore, some researchers [28],[34],[35] involved Mask R-CNN instance segmentation in lettuce growth indices estimation. As Mask R-CNN is a classification-based instance segmentation, which needs labelled dataset with each object annotation for training. It may be time consuming and costly since it needs manual annotation by the experts. So, the lack efficiency of applying instance segmentation to locate the crop and estimate growth indices can also be one of the research gaps.

EBesides, another potential research gap is the limited studies on the effectiveness of pretrained models in transfer learning from transitioning from single-lettuce to multi-lettuce crops in an image. As discussed, some researchers [31–33] have achieved good performance in single lettuce growth indices estimation by using pretrained models through transfer learning. As transfer learning allows reusing knowledge captured from training on large dataset for a specific task with limited data,[37] reducing time and resources of the proposed model needed at the same time help the model converge faster [38].

# CONCLUSION

In conclusion, non-destructive techniques in lettuce plant growth indices estimation have the potential to help in plant assessment processes. Accurate estimation of traits such as fresh weight, dry weight, height, leaf area, and diameter can optimize cultivation practices and boost yield. However, there are some limitations in lettuce plant growth indices like it does not extend to more real time scenario that involved multiple crops estimation at once. So, further research can be considered to do the model transitioning of single lettuce growth indices estimation to multiple lettuce growth indices estimation.

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