DETERMINATION OF THE AREA INDEX OF LETTUCE LEAVES WITH A MONOCULAR CAMERA

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Abstract
This study aims to develop a pixel value analysis method using a monocular camera to determine different growth stages of lettuce plants. After the lettuce plants are detected in the images obtained using the YOLOv4 (You Only Look Once Version 4) object detection algorithm, we calculate the leaf area index for each detected lettuce plant using the HSV (Hue, Saturation, Value) color space. The leaf area index serves as a fundamental metric in our analysis, aiding us in accurately measuring the size of the lettuce plants. For the size estimation approach, we used a dataset containing HSV-calculated max area pixel index values of lettuce plants grown from 1 to 7 weeks. By clustering pixel values using the Gaussian Mixture Models (GMM) algorithm, we identified the cluster representing 1-week-old lettuce plants with the lowest pixel values, while the cluster representing 7-week-old lettuce plants had the highest pixel values. This process was repeated for each week, resulting in distinct clusters corresponding to specific weeks of lettuce growth. By associating the detected lettuce plants with their respective clusters, we could infer the growth period and readiness for harvesting for each plant. This method offers valuable insights into monitoring lettuce growth and optimizing harvesting schedules at different stages for lettuce farmers and agricultural researchers through non-intrusive imaging techniques. This study showcases the potential of computer vision and machine learning algorithms in transforming traditional agricultural practices into more efficient and data-driven processes. The conducted experiments demonstrate the successful integration of a monocular camera into a smart agriculture system for lettuce harvest detection. Through the combination of object detection using the YOLOv4 algorithm, area estimation using the HSV color space, and leaf area index, we achieved accurate and cost-effective size calculations. The integration of Gaussian Mixture Model clustering with the dataset further enhanced the precision of our lettuce growth and harvest predictions.
Keywords: artificial intelligence, image processing, hydroponics agriculture, automation

Introduction

Image processing has emerged as a significant field within the domain of computer vision, revolutionizing various industries and applications by extracting meaningful information from visual data. In recent years, the emergence of advanced imaging technologies and machine learning algorithms has propelled image processing to the forefront of agricultural innovation. "According to S. Hemming and others (2022) who prepared the dataset used in the project computer vision algorithms act as a catalyst in remote and non-invasive sensing of crop parameters, decisive for automated, objective, standardized, and data-driven decision making. However, spectral indexes describing lettuces growth and larger datasets than the currently accessible are crucial to address existing shortcomings between academic and industrial production systems that have been encountered." Both researchers and farmers can leverage the power of image processing to gain unparalleled insights into plant growth dynamics, disease detection, and yield estimation. These advancements pave the way for precision agriculture, a paradigm shift aimed at optimizing resource allocation and minimizing environmental impact through data-driven decision-making (Anja-Tatjana et al., 2018). A crucial aspect of image processing in agriculture revolves around the estimation of plant characteristics, such as size, shape, and developmental stage. Accurate measurement of these attributes plays a pivotal role in comprehending crop health, predicting optimal harvest times, and implementing effective cultivation strategies. However, obtaining precise measurements manually can be time-consuming, labor-intensive, and susceptible to errors. This paper focuses on the application of image processing techniques, coupled with advanced machine learning algorithms, to address the challenges associated with lettuce size estimation and growth stage prediction. The objective study is to explore how the integration of the YOLOv4 (You Only Look Once Version 4) object detection model and the HSV (Hue, Saturation, Value) color space can provide a comprehensive framework for non-intrusive, automated lettuce growth analysis. Through this approach, we aspire to contribute to the development of efficient and accurate methods for lettuce monitoring, fostering sustainable agricultural practices, and enabling informed decision-making. Subsequent sections of this paper delve into the methodology employed to achieve lettuce size estimation using image processing techniques. We provide detailed insights into the dataset used, the YOLOv4 model, and the HSV-based max area index calculation method. Furthermore, we discuss the Gaussian Mixture Model (GMM) clustering technique employed to enhance the accuracy of lettuce growthstage prediction. The results and insights garnered through this study offer significant contributions to the field of precision agriculture, laying the groundwork for future advancements in crop management and harvesting practices.

1.Materials and Method

1.1 Dataset for Image Recognition

Dataset used in this study was generated by Hemming and others. The dataset was prepared for the third session of the Autonomous Greenhouse Challenge conducted online and is publicly available on the 4TU.ResearchData website. The dataset comprises 388 pairs of RGB images, depth images, and real-world overhead view data. The RGB images are three-channel 24-bit Portable Network Graphics (PNG) images, while the depth images are single-channel 8-bit PNG images. All images have a consistent resolution of 1080 x 1920 pixels.

In order to train the dataset with the YOLOv4 model, all images were first converted to JPEG format and resized to 800 x 800 pixels. This step was necessary to meet the requirements of YOLOv4 model training, which stipulates equal width and height dimensions. Preparing datasets using stereo cameras for vertical farming systems allows the utilization of depth algorithms for lettuce area measurements (Hadisseh et al., 2023). However, in this study, the datasets were collected using a monocular camera, enabling the calculation of lettuce area index using the HSV model at a lower cost.

Acquired dataset includes four different varieties of lettuce. In this project, the lettuce varieties "Lugano" and "Aphylion" were utilized to establish a relationship between pixel size and harvest time for green leaf lettuce plants. The analyzed dataset consists of 140 RGB images in JPEG format with 3x8-bit channels. The YOLOv4 object detection model was employed to implement the lettuce size detection algorithm, representing a highly effective deep neural network for real-time object detection. The YOLOv4 model was specifically retrained for lettuce growth estimation detection.

1.2 Description and Working Principle

Dataset was prepared to work with the YOLOv4 model for lettuce detection. We focused on two green leaf lettuce varieties, namely "Lugano" and "Aphylion." YOLOv4 introduces three different scale prediction heads compared to previous YOLO versions, which helps detect medium-sized objects and small objects within larger objects. Each prediction head includes three predefined anchor boxes, and when an object is detected, bounding box regression is performed in different prediction heads, resulting in the final prediction box output Fig. 1 (Alexey et al., 2020).

Output contains the location of the lettuce and bounding box information. Fig. 2 with YOLOv4's three scale prediction heads, we can better handle scenarios where lettuce of different sizes and distances may exist. This allows for more accurate lettuce size detection, ranging from medium-sized objects to small lettuces within larger objects.

This study, images of lettuce were taken from the same angle at a height of 0.9 meters over a period of 1-7 weeks. Therefore, the bounding box areas of the images change proportionally to the growth stages of the lettuce. To obtain the actual pixel values of the lettuce, we applied the HSV method to the lettuce images. By doing so, we calculated the max area index for the lettuce plants. A specific HSV color range is determined to match the characteristic green color of the lettuce. The image is transformed into the HSV color space, and pixels within the specified color range are identified. Then, contours of the lettuce are detected based on the pixel values, and area calculations are performed using these contours (Haixin, Rubin 2022).

For this calculation, the area of each contour is computed, and the index representing the maximum area is determined, thereby identifying the largest lettuce. This method allows for the separation of the lettuce from surrounding objects and the background, making it widely used in academic research. Additionally, the max area index provides a valuable criterion for detecting larger lettuces and comparing them with other objects.

After calculating the max area indices for lettuce images taken over a period of 1-7 weeks, we clustered their pixel values using GMM (Gaussian Mixture

Models). GMM models the pixel values of the lettuce as a combination of a certain number of components, thus defining different lettuce formations. Taking into consideration that lettuce may have different pixel values at different growth stages, we used GMM to determine and separate pixel values according to the growth weeks (Huajuan et al., 2023).

In conclusion, this study utilized the GMM-based pixel value clustering method to obtain results about different growth stages in lettuce images taken over a period of 1-7 weeks, enabling us to make inferences about the harvesting time of lettuce.

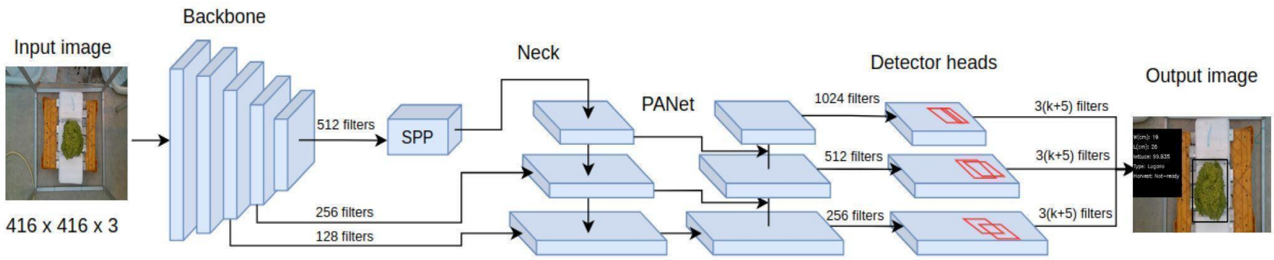


Fig. 1 Object detector: Lettuce detection

YOLOv4 model is employed as an effective deep learning algorithm for lettuce detection. In this approach, the YOLOv4 model is initially trained with a specifically curated dataset to detect lettuce plants.
Throughout the training process, the model enhances its capability to efficiently detect objects of varying sizes, achieved through the utilization of detector layers termed as the "neck." These necks are integrated with a structure called PANet (Path Aggregation Network), which extracts feature maps from different stages of backbone processing to optimize object detection. Furthermore, the neck structure includes the Spatial Pyramid Pooling (SPP) technique, which expands the detector's receptive field, thereby enhancing detection accuracy.

YOLOv4 model's detector section is complemented with heads possessing diverse feature extraction levels. These heads possess the ability to detect objects of different dimensions. Integration of low computational cost modules called Bag of Specials is significant, both in the backbone and the detector of the YOLOv4 architecture. These modules contribute to performance enhancement and incorporate the novel activation function, Mish. As a result, the YOLOv4 model can serve as an advanced and precise object detection algorithm for lettuce detection.

Fig. 1 outlines the stages of utilizing the YOLOv4 model for lettuce detection through a deep learning approach. This method is equipped with feature extraction techniques like PANet and SPP, along with the incorporation of Bag of Specials modules. This integration ensures accurate detection of lettuce plants across various sizes and growth stages, while simultaneously enhancing the model's performance and accuracy.

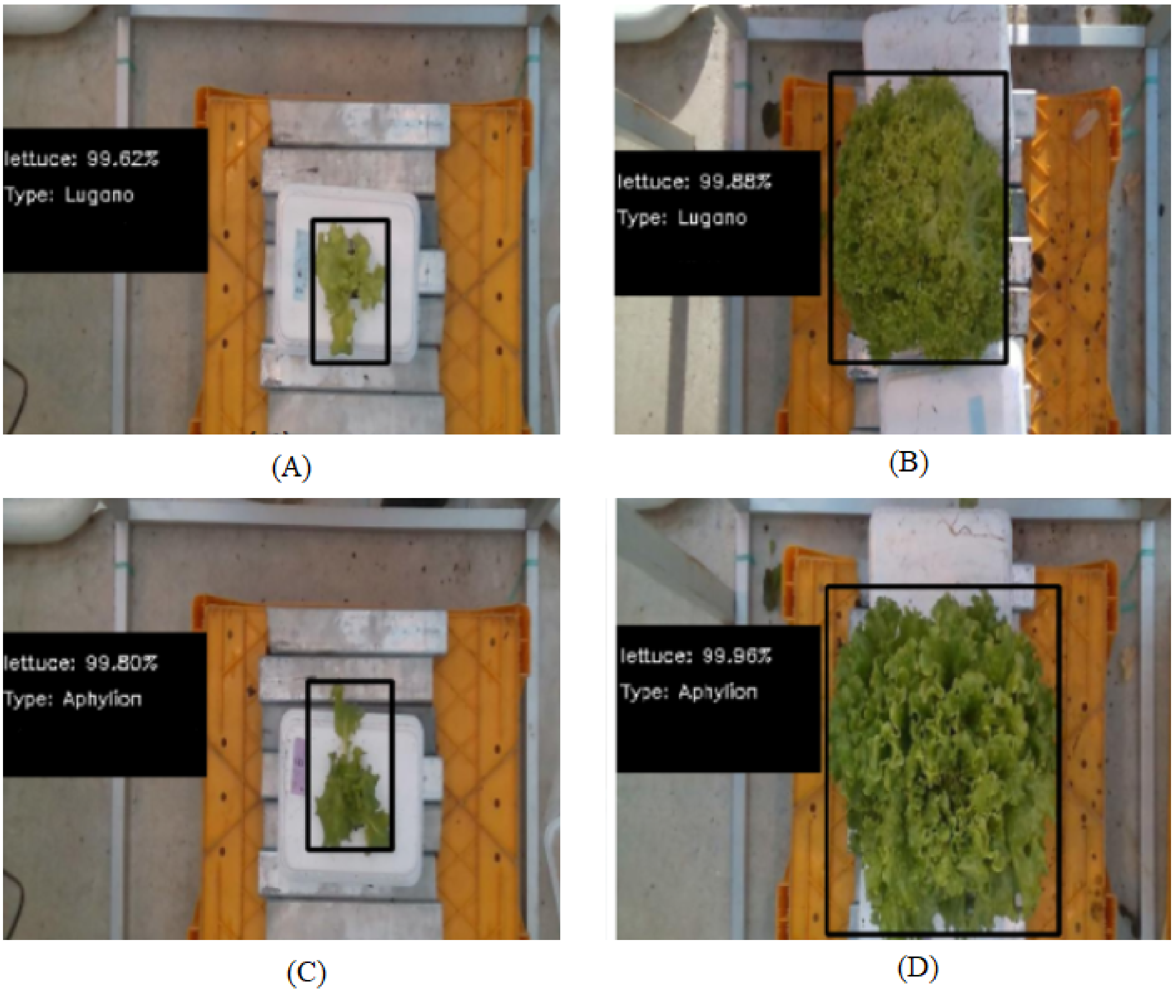


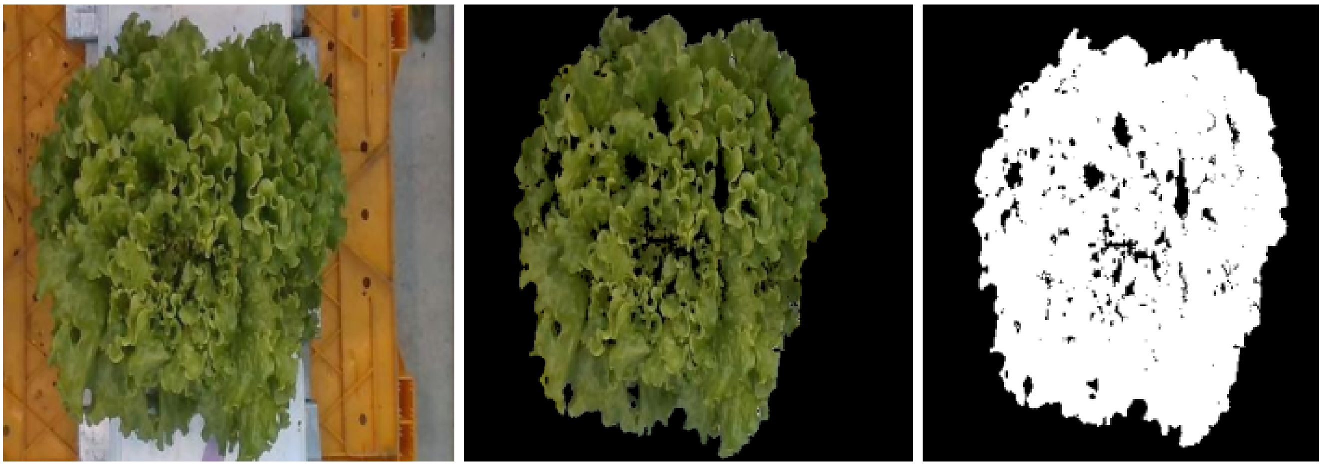
Fig. 2 Object detection: Images of Lettuce Marked with Bounding Boxes.

In Fig. 2, the outputs of lettuce detection using YOLOv4 on "Lugano" and "Aphylion" lettuce images are presented. The lettuce detection process is performed by drawing bounding boxes around the detected lettuce instances. The adjacent legend indicates the lettuce varieties and their corresponding detection accuracy rates. The images "A" and "B" represent the progression of "Lugano" lettuces in different growth periods, while the images "C" and "D" depict visuals of "Aphylion" lettuces at various stages of growth.

The algorithm successfully places bounding boxes around the detected lettuce in both lettuce varieties, precisely delineating their locations. YOLOv4's three-scale prediction heads, the model can effectively address scenarios where lettuce may vary in size and distance, enhancing its robustness and reliability in detecting diverse lettuce formations (Shu-Jun et al., 2023).

Outputs provide valuable insights into the spatial distribution of lettuce plants within the images, enabling researchers and farmers to understand the arrangement and growth patterns of the lettuce varieties. Moreover, the bounding box information allows for detailed spatial occupancy analysis of the lettuce and can be used to estimate its size and area within the image.

Detection outputs offer critical data for monitoring and comprehending the growth dynamics of lettuce throughout the 1-7 week period. As the images are consistently captured from a fixed angle and height over time, the bounding box areas change proportionally with the lettuce's growth stages. Information can be leveraged to comprehend the developmental progress of the lettuce plants and make informed decisions about the optimal harvesting time. Overall, the YOLOv4-based lettuce detection outputs provide significant insights into the spatial distribution and growth patterns of lettuce varieties, paving the way for improved agricultural practices and precision farming techniques. The accurate and efficient detection of lettuce using YOLOv4 showcases the potential of advanced object detection models to revolutionize agricultural processes and contribute to sustainable crop management (Nan et al., 2022).



(A) (B) (C)

Fig. 3 HSV-based color localization and object detection process.

(A) Input image, (B) transformed to the HSV color space and a mask created for the specified color range, (C) displays the image where connected component analysis is applied to the color mask, locating the largest area.

$$H = arccos\frac{\frac{1}{2}(2R-G-B)}{\sqrt{(R-G)^2-(R-B)*(G-B)}} \quad \text{(eq1)}$$

$$S = \frac{max(R,G,B)-min(R,G,B)}{max(R,G,B)} \quad \text{(eq2)}$$

$$V = max(R, G, B) \quad \text{(eq3)}$$

The HSV color space is a mathematical model used to represent colors. It includes fundamental properties for defining colors:

Hue: It is represented as an angle value on the color wheel and represents the naturally perceived color characteristics. For example, it expresses color tones like red, blue, and green.

Saturation: It indicates how pure or pale colors are. A saturation value of 0 means achromatic (gray) colors, while a value of 1 represents fully saturated colors.

Value: It represents the brightness level of colors. A value of 0 corresponds to black, while a value of 1 corresponds to fully bright colors.

1.HSV color space-based automatic HSV color segmentation: The image is first converted to the HSV color space, and lower and upper thresholds (lower and upper) are determined for color filtering. Subsequently, using this filter, regions of interest (ROIs) are highlighted in the HSV color space.

2.ROI random sampling: The random sampling process is not present in the code.

3.HSV similarity comparison: By using the HSV color filter (lower and upper thresholds), a similarity comparison is performed in the HSV color space. This enables the detection of regions of interest (lettuce).

In Fig. 3, you can observe the lettuce detection using HSV with the application of the mentioned methods. Initially, the image is transformed into the HSV color space to increase sensitivity to the green color. Subsequently, a green color filter is employed to highlight only the lettuce regions. Finally, through the implementation of the maximum area index method, the largest green area encompassing the lettuce regions is selected. This approach represents a significant advancement in the development of automatic object detection techniques using computer vision and image processing.

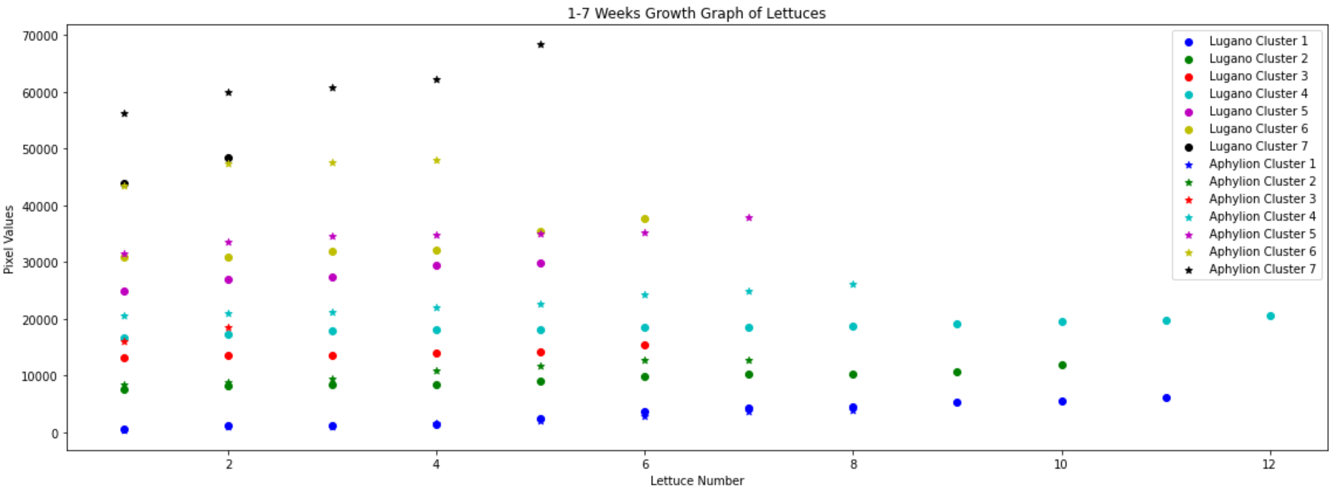


Fig. 4 Cluster with GMM of Growing period of 7 weeks

In [Figure 4] above, it demonstrates the pixel value grouping process using the Gaussian Mixture Model (GMM) with HSV and maximum area index values for "Lugano" and "Aphylion" lettuce plants. The images in the dataset belong to lettuce plants developing between 1 and 7 weeks. GMM enables us to group the pixel values of plants for these 7-week periods and make interpretations for suitable lettuce data for harvesting.

The Gaussian Mixture Model (GMM) is a statistical model utilized to identify distinct groups within a dataset and segregate data points belonging to these groups (Satish et al., 2021). GMM represents data by combining components, each representing a normal distribution for a specific group, hence the term "mixture model."

GMM finds applications in various fields, particularly in data analytics, pattern recognition, image processing, speech processing, and natural language processing. It is employed to detect underlying structures in datasets and cluster data points based on similarities. GMM is trained using the Expectation-Maximization (EM) algorithm. The EM algorithm iteratively updates initially randomly selected component parameters to fit the model to the dataset and trains it. During the training process, it calculates the likelihood of each data point belonging to each component and updates the component parameters based on these probabilities. This process continues until the model reaches the maximum likelihood estimation.

As a result, by determining the cluster values of lettuce images in our test data, it indicates which cluster the plant is in during the 1-7 week growth period. This process will enable us to make inferences about the harvesting status of the plant.

The default formula for GMM:

$$p(x) = \Sigma_{i=1}^{7} \omega_i * N(x|\mu_i, \Sigma_i) \quad \text{(eq4)}$$

Here;

1. p(x) represents the total likelihood probability for data point x.

2. i is the weight of the i-th component, and the total weights must sum up to 1, (i.e. i.e. $\Sigma_{i=1}^{7} \omega_i = 1$).

3. $N(x|\mu_i, \Sigma_i)$ is the normal distribution of the i-th component.

- x is the data point.
- μi is the mean value of the i-th component (and represents the probability of the data point belonging to this component).
- Σi is the covariance matrix of the i-th component, indicating the uncertainty of the data point belonging to this component.

The EM algorithm is used to train the model. It employs an iterative approach to obtain the best fitting values for μ_i and Σ_i as well as the component weights (ω_i). At each iteration, the probabilities of data points belonging to each component (i.e., membership probabilities) are estimated, and these estimations are used to update the component parameters. This process is repeated until the model reaches the maximum likelihood estimation.
The formula and EM algorithm of GMM enable the determination of different groups in the dataset and effective separation of data points belonging to these

groups. As a result, GMM allows us to better understand and analyse the dataset in various applications.

2. Statistical analysis

The growth periods of both Aphylion and Lugano plants, each divided into 7 distinct clusters, were distinctly analyzed based on pixel values obtained through the Gaussian Mixture Model (GMM) method. We observed that both plants exhibited distinct characteristics and different growth trends among these clusters.

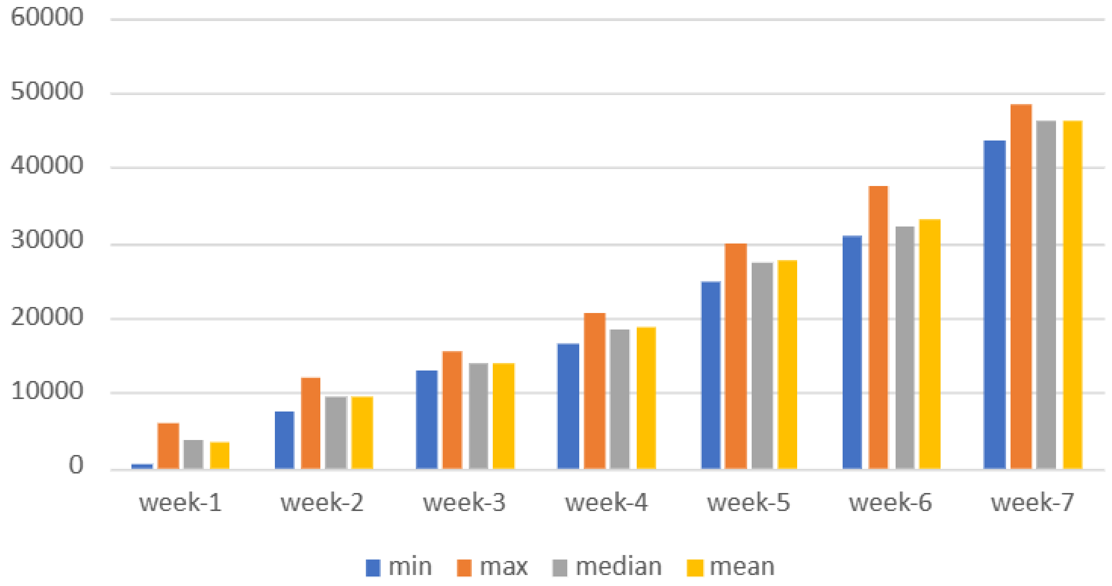


Fig. 5 Max,Min, Mean, Median Graphs of Lugano Lettuce

When examining the growth periods of the Aphylion plant, maximum, minimum, mean, and median pixel values for each cluster were visualized using graphs. This analysis clearly demonstrates varying growth rates and periods among the clusters. For instance, while significant increases in maximum values were observed in certain clusters, others showed a more stable growth trend. This indicates that the plant has different growth rates in different periods.

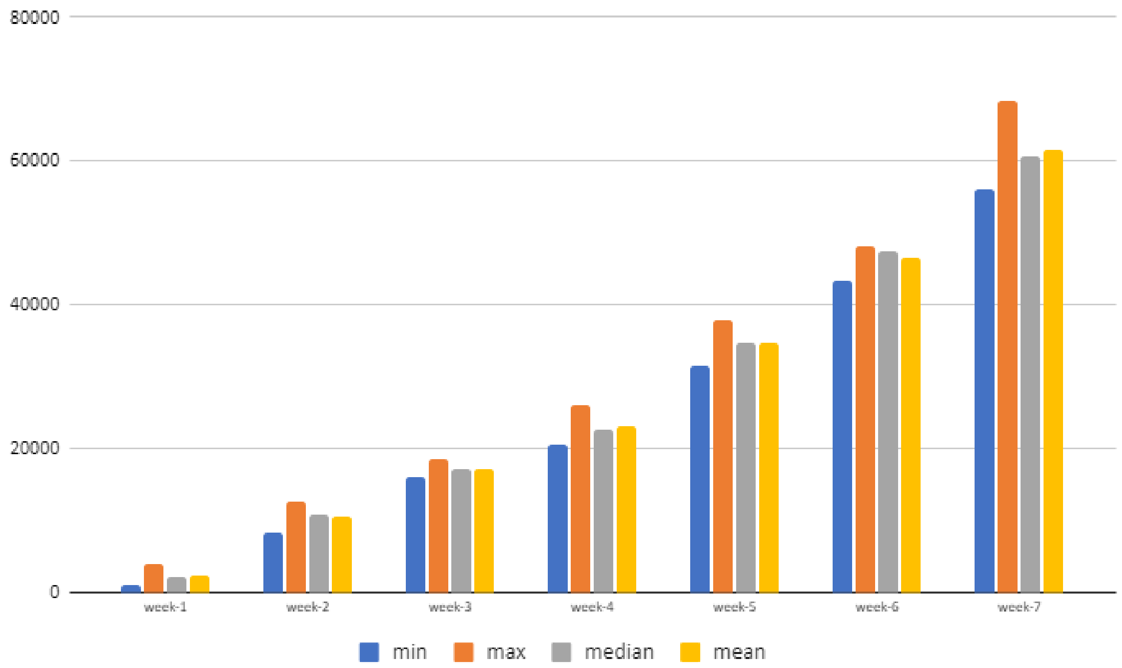


Fig. 6 Max,Min, Mean, Median Graphs of Aphylion Lettuce

Similarly, in the analysis conducted for the Lugano plant, graphs depicting the maximum, minimum, mean, and median pixel values for each cluster's growth periods were shown in a similar manner. These visualizations highlight notable variations in different growth stages of the plant. Particularly, some clusters exhibited jumps in maximum pixel values, while others showed a more balanced growth trend.

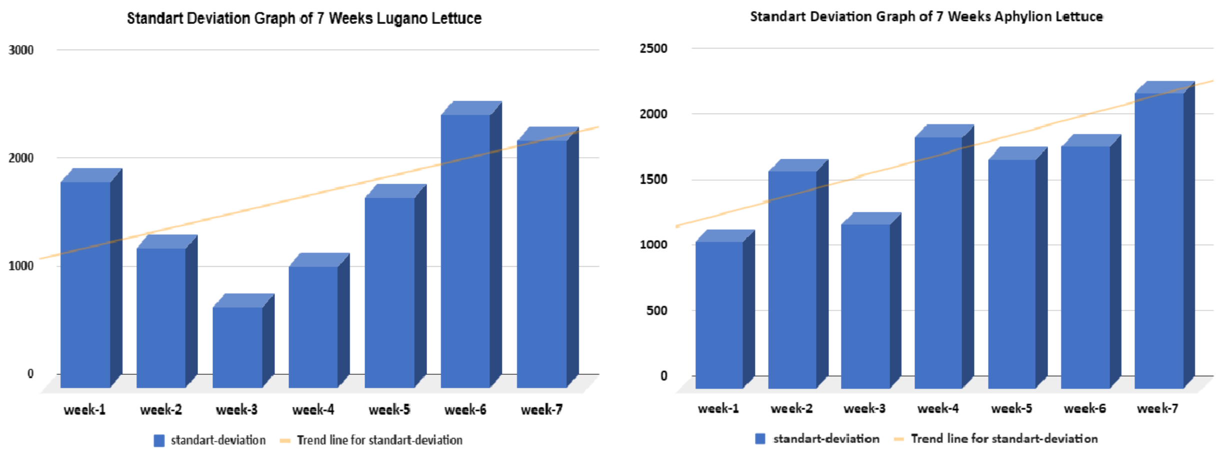


Fig. 6 Standart Deviation Graph of Aphylion and Lugano Lettuce growing period of 7 weeks

When examining the growth periods of Aphylion plant's 7 distinct clusters in Fig. 6, the standard deviation graph clearly illustrates the distribution of growth rates. Upon closer inspection of the graph, it becomes evident how variable the growth rates are for each cluster. While some clusters exhibit low standard deviations (for instance, the [15973, 18460] cluster), indicating more stable and consistent growth during those periods, others show high standard deviations (such as the [56200, 59932, 60748, 62327, 68442] cluster), signifying greater variability in growth rates across periods. This analysis highlights that Aphylion plant undergoes different growth phases, encompassing both consistent and fluctuating periods.

Similarly, the growth periods of Lugano plant's 7 distinct clusters are also depicted through the standard deviation graph Fig. 6. Upon analyzing the graph, it becomes apparent that growth rates generally exhibit lower standard deviations for each cluster. This suggests that the Lugano plant demonstrates a more consistent growth tendency among its growth periods. Nevertheless, certain clusters also display higher standard deviations (for example, the [43463, 47320, 47622, 48104] cluster), indicating increased variations in growth rates between periods.

3. Experiments and Results

Objective was to develop lettuce size estimation algorithms using a monocular camera as a cost-effective alternative to traditional stereo camera setups (Dan et al., 2023). Our primary goal was to determine the readiness of lettuce plants for harvesting by applying computer vision techniques (Mudassar et al., 2018).

Iinitial step of our approach involved using the YOLOv4 object detection algorithm to detect lettuce plants in images captured by the monocular camera. Once the plants were identified, we employed the HSV color space to compute the maximum area index for each detected lettuce plant.

Maximum area index played a crucial role in our analysis, enabling precise measurement of the lettuce plants' sizes. For the size estimation method, we employed a dataset containing HSV-calculated maximum area pixel index values of lettuce plants during 1 to 7 weeks of growth. Employing Gaussian Mixture Model (GMM) clustering on the pixel values, we identified the cluster with the highest pixel values as representing 7-week-old lettuce plants, and the cluster with the lowest pixel values as representing 1-week-old lettuce plants. This process was repeated for each week, resulting in seven distinct clusters, each corresponding to a specific week of lettuce growth.
By associating the detected lettuce plants with their respective clusters, we could infer the growth period and harvesting readiness of each plant. This method facilitated understanding the growth patterns of lettuce plants and determining their suitability for harvesting at different stages.

Our findings underscore a promising approach for lettuce farmers and agricultural researchers to monitor lettuce growth and optimize harvesting schedules using non-intrusive imaging techniques. This study highlights the potential of computer vision and machine learning algorithms in revolutionizing traditional agricultural practices into more efficient and data-driven processes.

Overall, our results from this study demonstrate the successful applicability of a monocular camera-based smart agriculture system for lettuce harvest detection. By integrating object detection with the YOLOv4 algorithm and area estimation using the HSV color space and maximum area index, we achieved accurate and cost-effective size calculations. The incorporation of Gaussian Mixture Model clustering with the dataset further enhanced the accuracy of our lettuce growth and harvest prediction (Simon et al., 2019).

Conclusion

This study examines and evaluates the use of advanced image processing techniques for lettuce size estimation and growth stage prediction. The integration of the YOLOv4 object detection model with the HSV color space demonstrates the potential to provide an effective method for monitoring and predicting automatic lettuce growth. The combination of image capture, color space-based area calculation, and Gaussian Mixture Model (GMM) clustering enables us to better understand the growth process of lettuce in a more precise and efficient manner, while also contributing to the optimization of agricultural practices.

The results of the study provide significant insights into how automatic image processing techniques can be applied in the agricultural sector. The developed methods showcase the effectiveness and speed at which lettuce plant size and growth stage can be predicted. This empowers farmers and researchers with a robust tool to increase efficiency and use resources more effectively by adopting precision agriculture methods.

In the future, building upon the findings of this study, further development and optimization of automated lettuce growth monitoring systems will be possible. The integration of advanced artificial intelligence algorithms can provide more accurate and rapid size predictions, and data analysis and visualization techniques can aid in making more informed agricultural decisions.

In conclusion, this study demonstrates the application of image processing and machine learning techniques in the agricultural sector. The methods for automatic lettuce size and growth prediction could contribute to the optimization of modern agricultural practices and the promotion of sustainable farming.

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Reference list

1. Silke Hemming, Anna Selini Petropoulou, Bart van Marrewijk, Feije de Zwart, Anne Elings, Monique Bijlaard, Tim van Daalen and Guido Jansen (2022), Lettuce Production in Intelligent Greenhouses: 3D Imaging and Computer Vision for Plant Spacing Decisions, *23*(6), 2929.
2Anja-Tatjana Braun, Eduardo Colangelo and Thilo Stecke (2018), Farming in the Era of Industrie 4.0, 979-984.
3. Hadisseh Rahimikhoob, Mojtaba Delshad and Romina Habibi (2023), Leaf area estimation in lettuce: Comparison of artificial intelligence-based methods with image analysis technique, Volume 222, 113636.
4. Alexey Bochkovskiy, Chien-Yao Wang and Hong-yuan Mark Liao, (2020), YOLOv4: Optimal Speed and Accuracy of Object Detection.
5.Haixin Zhong, Rubin Wang, (2022), A visual degradation inspired model with HSV color-encoding for contour detection, Volume 369, 109423.
6.. Huajuan Huang, Zepeng Liao, Xiuxi Wei and Yongquan Zhou, (2023), Combined Gaussian Mixture Model and Pathfinder Algorithm for Data Clustering, *25*(6), 946.
7. Shu-Jun Ji, Qing-Hua Ling and Fei Han (2023), An Improved Algorithm for Small Object Detection Based on YOLOv4 and Multi-Scale, Volume 105, 108490.
8. Nan Hu , Shuo Wang , Xuechang Wang, Yu Cai, Daobilige Su, Purevdorj Nyamsuren, Yongliang Qiao, Yu Jiang, Bo Hai and Hang Wei. (2022), LettuceMOT:A Dataset of Lettuce Detection and Tracking with Re-identification of Re-occurred Plants for Agricultural Robots, Volume 13 - 2022.
9. Satish Chander, P. Vijaya, (2021), Artificial Intelligence in Data MiningTheories and Applications: Unsupervised learning methods for data clustering, 41-64.
10.Dan Zhao,Chaofeng Ji and Guizhong Liu. (2023), Monocular 3D Object Detection Based on Pseudo Multimodal Information Extraction and Keypoint Estimation, 13(3), 1731.
11. Mudassar Raza, Chen Zonghai, Saeed Ur Rehman, Wang Peng and Wang Ji-kai. (2018), Framework for Estimating Distance and Dimension Attributes of Pedestrians in Real-time Environments Using Monocular Camera, Volume 275, 533-545.
12. Simon Birrell, Josie Hughes, Julia Y. Cai and Fumiya Iida, (2019), A field-tested robotic harvesting system for iceberg lettuce, DOI: 10.1002/rob.21888.

SALOTŲ LAPŲ PLOTO INDEKSO NUSTATYMAS PANAUDOJANT MONOKAMERA

Santrauka

Tyrimo metu buvo siekiama sukurti pikselių vertės analizė metodą, naudojant vaizdo kamerą, siekiant nustatyti skirtingas salotų augalų augimo stadijas. Nuotraukose kamera užfiksuoti salotų augalų vaizdai buvo apdorojami naudojant YOLOv4 (You Only Look Once Version 4) objektų aptikimo algoritmą ir apskaičiuojama kiekvieno aptikto salotų augalo lapų ploto indeksas HSV (Hue, Saturation, Value) spalvinėje erdvėje. Lapų ploto indeksas yra pagrindinis mūsų analizės rodiklis, padedantis tiksliai išmatuoti salotų augalų dydį. Lapų ploto įvertinimas buvo patikrintas naudojant vaizdų rinkinį, kuriame buvo fiksuoti salotų vaizdai augimo periode nuo 1 iki 7 savaičių. Duomenų analizei buvo panaudotas Gauso mišinio modelis (GMM) kurio pagalba buvo klasterizuojamos lapų ploto pikselių reikšmes ir sugrupuoti duomenys leido palyginti skirtingus salotų auginimo periodus. Duomenų analizė buvo kartojama kiekvieną salotų augimo savaitę, todėl susidarė atskiros grupės, atitinkančius konkrečias salotų augimo periodus. Susiejant fiksuotus salotų vaizdus su atitinkamomis jų grupėmis, galima nustatyti augalo laikotarpį ir prognozuoti derliaus nuėmimo datą. Darbe panaudoti vaizdų apdorojimo ir analizės metodai suteikia vertingų įžvalgų apie salotų augimo stebėjimą ir įgalina optimizuoti auginimo procesą salotų augintojams naudojant gana nebrangias, mažai kainuojančias vaizdų gavimo priemones. Šis tyrimas parodo kaip mašininė rega, panaudojant dirbtinio intelekto gilųjį mokymąsį, gali būti įdiegta į autonomines žemės ūkio sistemas skirtas salotų auginimui. Vaizdų apdorojimas ir analizė, kompiuterinė rega, mašininio mokymosi algoritmai kuria potencialą transformuojant tradicinį žemės ūkį į efektyvesnį duomenų analize paremta technologinį procesą. Atlikti eksperimentai demonstruoja sėkmingą monokameros integravimą į išmaniąją žemės ūkio sistemą, skirtą salotų derliaus laiko nustatymui. Panaudotas objektų aptikimui YOLOv4 vaizdų atpažinimo algoritmas ir salotų lapų ploto įvertinimas naudojant HSV spalvinėje erdvėje leido tiksliau įvertinti lapų ploto indeksą. Gauso maišymo modelio panaudojimas apdorojant salotų lapų vaizdus įgalina tiksliau prognozuoti galimą derliaus datą.

Raktiniai žodžiai: dirbtinis intelektas, vaizdo apdorojimas, hidroponika, žemės ūkis, automatikaReikšminiai žodžiai: dirbtinis intelektas, vaizdų apdorojimas, hidroponika, žemės ūkis, automatika.

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