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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 have been detected in the images obtained using the YOLOv4 (You Only Look Once Version 4) object detection algorithm, the leaf area index for each detected lettuce plant using the HSV (Hue, Saturation, Value) colour space has been calculated. The leaf area index serves as a fundamental metric in the analysis, aiding in accurately measuring the size of the lettuce plants. For the size estimation approach, a dataset containing HSV-calculated max area pixel index values of lettuce plants grown from 1 to 7 weeks has been used. By clustering pixel values using the Gaussian Mixture Models (GMM) algorithm, the cluster representing 1-week-old lettuce plants with the lowest pixel values has been identified, 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, it was possible to infer the growth period and readiness for harvesting for each plant. This method offers valuable insights into monitoring lettuce growth and optimising 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 and area estimation using the HSV colour space and leaf area index, accurate and cost-effective size calculations have been achieved. The integration of Gaussian Mixture Model clustering with the dataset further enhanced the precision of the 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, revolutionising 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 Petropoulou (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, standardised, and data-driven decision-making. However, spectral indexes describing lettuce growth and larger than the currently accessible datasets are crucial to addressing 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 optimising resource allocation and minimising the environmental impact through data-driven decision-making (Braun, 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, labour-intensive, and susceptible to errors. This paper focuses on applying image processing techniques, coupled with advanced machine learning algorithms, to address the challenges associated with lettuce size estimation and growth stage prediction. The objective of the 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) colour space can provide a comprehensive framework for non-intrusive, automated lettuce growth analysis. Through this approach, it is pursued 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 estimate lettuce size using image processing techniques. Detailed insights into the dataset used, the YOLOv4 model, and the HSV-based max area index calculation method have been provided. Furthermore, the Gaussian Mixture Model (GMM) clustering technique, employed to enhance the accuracy of lettuce growth stage prediction, has been discussed. 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.

Materials and Method

Dataset for Image Recognition

The dataset used in this study was generated by Petropoulou (2022). 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 utilisation of depth algorithms for lettuce area measurements (Rahimikhoob, 2023). However, in this study, the datasets were collected using a monocular camera, enabling the calculation of the lettuce area index using the HSV model at a lower cost.

The acquired dataset includes four different varieties of lettuce. In this project, the lettuce varieties “Lugano” and “Aphylion” were utilised to establish a relationship between pixel size and harvest time for green leaf lettuce plants. The analysed 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.

Description and Working Principle

The dataset was prepared to work with the YOLOv4 model for lettuce detection. The focus was 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 (see Fig. 1) (Bochkovskiy, 2020).

The output contains the location of the lettuce and bounding box information. Fig. 2, with YOLOv4’s three scale prediction heads, illustrates how it is possible to 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.

In this study, images of lettuce were taken from the same angle at a height of 0.9 metres over a period of 1-7 weeks. Therefore, the bounding box areas of the images change proportionally to the growth stages of lettuce. The HSV method has been applied to the lettuce images to obtain the actual pixel values. By doing so, the max area index for the lettuce plants is calculated. A specific HSV colour range is determined to match the characteristic green colour of the lettuce. The image is transformed into the HSV colour space, and pixels within the specified colour range are identified. Then, the contours of the lettuce are detected based on the pixel values, and area calculations are performed using these contours (Zhong, 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, their pixel values have been clustered 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, GMM has been used to determine and separate pixel values according to the growth weeks (Huang, 2023).

In conclusion, this study utilised 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 inferences about the harvesting time of lettuce.

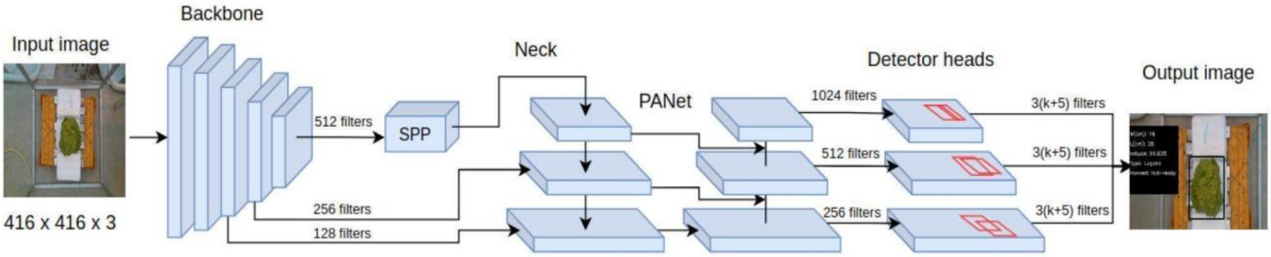

Fig. 1. Object detector: lettuce detection

The 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 utilisation 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 optimise object detection. Furthermore, the neck structure includes the Spatial Pyramid Pooling (SPP) technique, which expands the detector's receptive field, thereby enhancing detection accuracy.

The detector section of the YOLOv4 model 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 utilising 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.

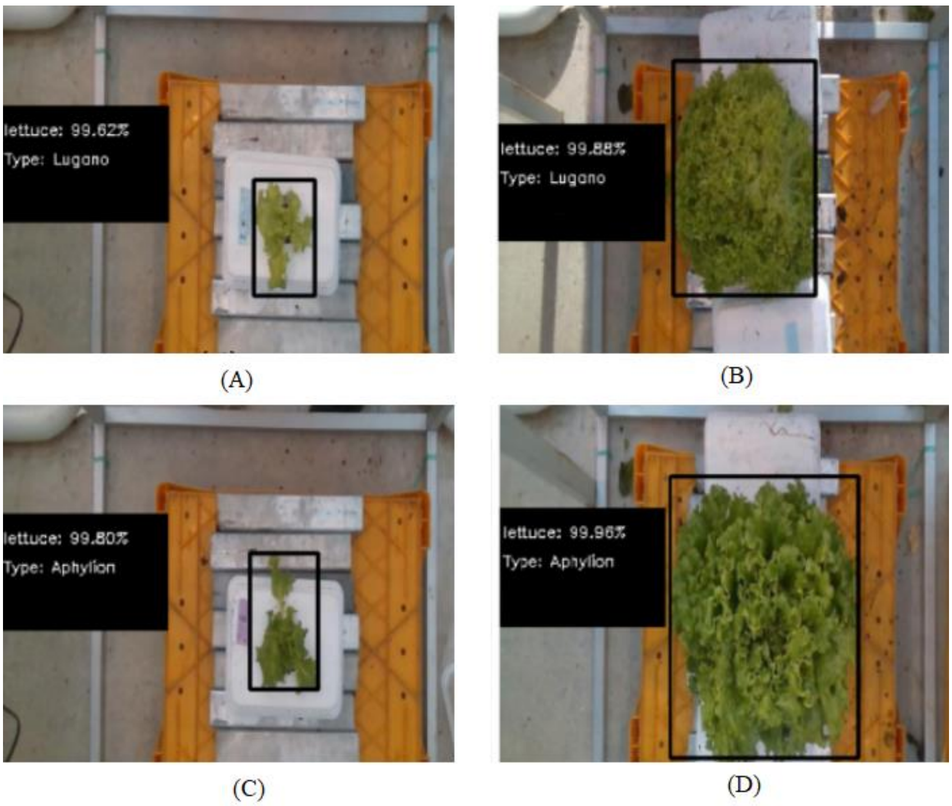

Fig. 2. Object detection: images of the lettuce marked with bounding boxes

Fig. 2 presents the outputs of lettuce detection using YOLOv4 on "Lugano" and "Aphylion" lettuce images. 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. With 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 (Ji, 2023).

The 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.

The detection outputs offer critical data for monitoring and comprehending the lettuce growth dynamics 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 stages of lettuce growth. 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 revolutionise agricultural processes and contribute to sustainable crop management (Hu, 2022).

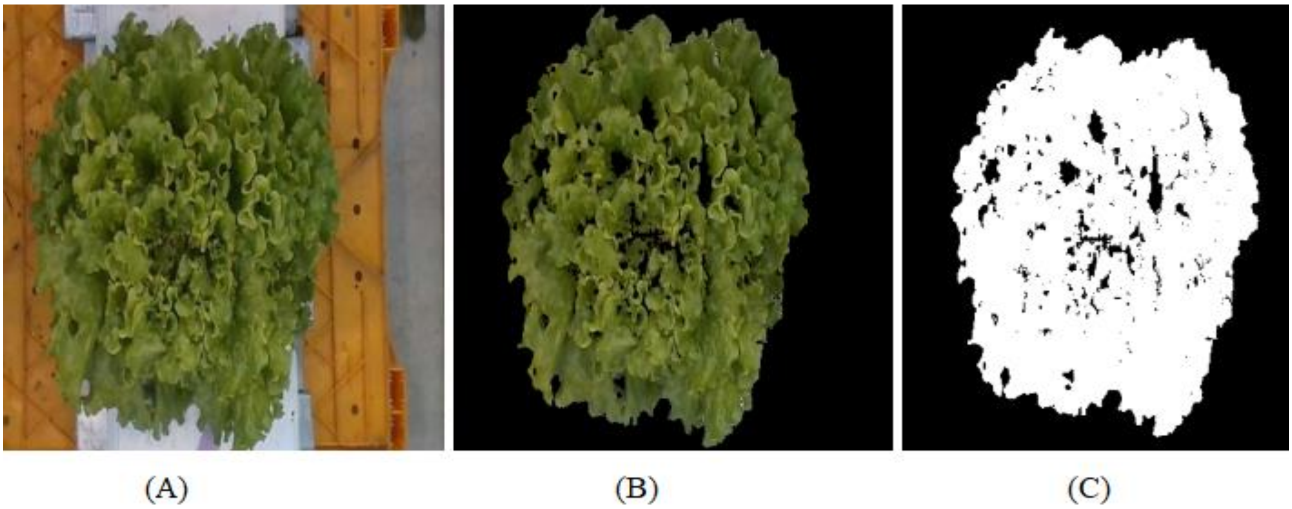

Fig. 3. HSV-based colour localisation and object detection process.

The input image (A), transformed to the HSV colour space(B), and a mask created for the specified colour range (C) display the image, where connected component analysis has been applied to the colour 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 colour space is a mathematical model used to represent colours. It includes fundamental properties for defining colours:

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

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

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

1. HSV colour space-based automatic HSV colour segmentation: the image is first converted to the HSV colour space, and lower and upper thresholds (lower and upper) are determined for colour filtering. Subsequently, using this filter, regions of interest (ROIs) are highlighted in the HSV colour space.
2. ROI random sampling: the random sampling process is not present in the code.
3. HSV similarity comparison: by using the HSV colour filter (lower and upper thresholds), a similarity comparison is performed in the HSV colour space. This enables the detection of regions of interest (lettuce).

Fig. 3 presents the lettuce detection using HSV with the application of the mentioned methods. Initially, the image is transformed into the HSV colour space to increase sensitivity to the green colour. Subsequently, a green colour 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 developing automatic object detection techniques using computer vision and image processing.

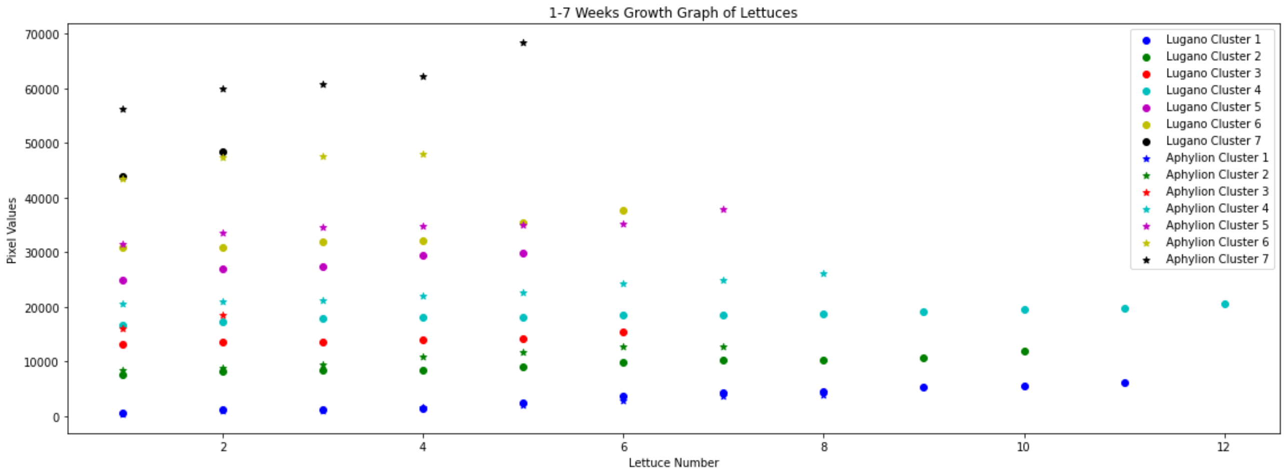

Fig. 4. Cluster with GMM of the growing period of 7 weeks

Fig. 4 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 grouping the pixel values of plants for these 7-week periods and making interpretations for suitable lettuce data for harvesting.

The Gaussian Mixture Model (GMM) is a statistical model utilised to identify distinct groups within a dataset and segregate data points belonging to these groups (Chander, 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, determining the cluster values of lettuce images in the test data indicates which cluster the plant is in during the 1–7-week growth period. This process will enable making inferences about the harvesting status of the plant.

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 the effective separation of data points belonging to these groups. As a result, GMM allows a better understanding and analysis of the dataset in various applications.

The default formula for GMM:
$p(x) = \Sigma_{i=1}^{7} \omega_i * N(x|\mu_i, \Sigma_i)$ (eq4)
Here
p(x) represents the total likelihood probability for data point x;
i is the weight of the i-th component, and the total weights must sum up to 1, (i.e., $\Sigma_{i=1}^{7} \omega_i = 1$);
$N(x|\mu_i, \Sigma_i)$ is the normal distribution of the i-th component:
x is the data point;
μ_i is the mean value of the i-th component (and represents the probability of the data point belonging to this component);

Statistical analysis

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

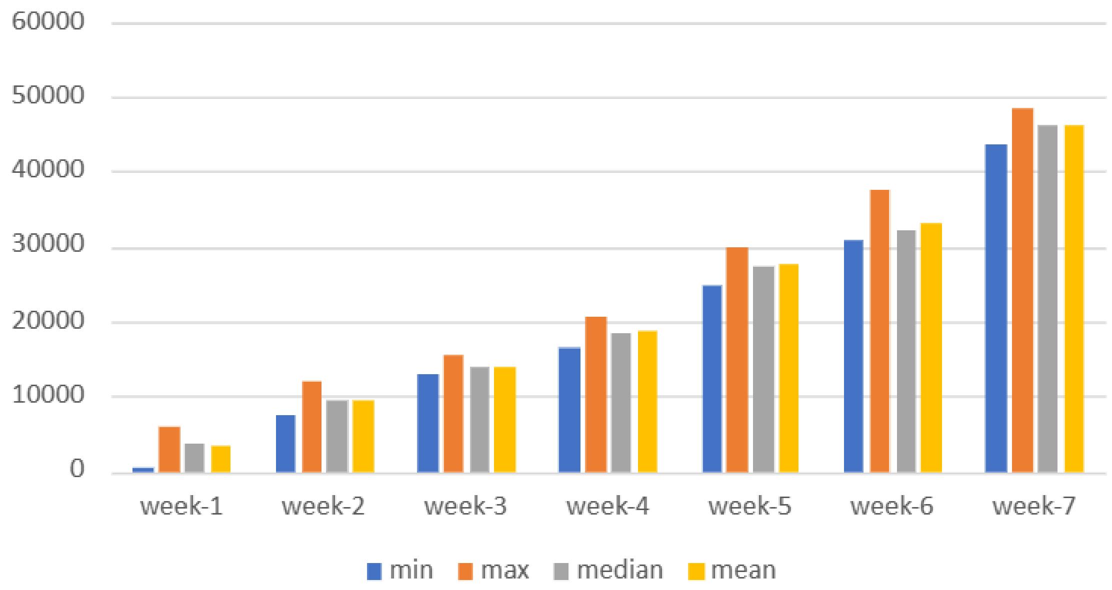

Fig. 5. Max, Min, Mean, and Median graphs of "Lugano" lettuce

When examining the growth periods of the "Aphylion" plant, maximum, minimum, mean, and median pixel values for each cluster were visualised 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.

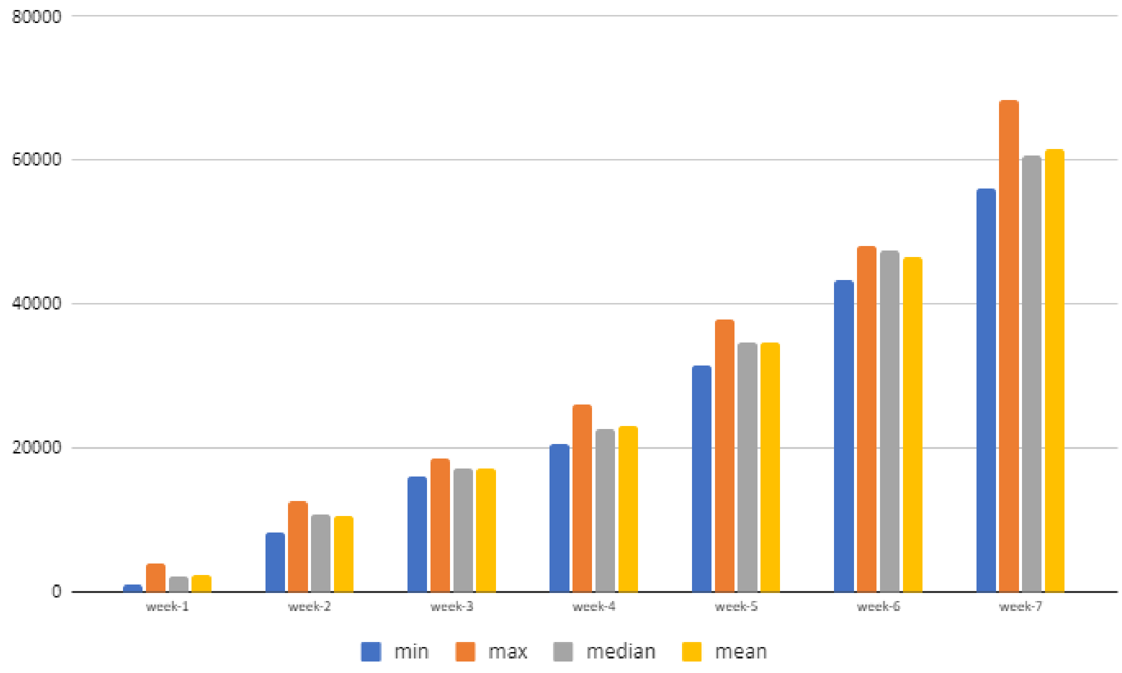

Fig. 6. Max, Min, Mean, and Median graphs of "Aphylion" lettuce

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 similarly. These visualisations 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.

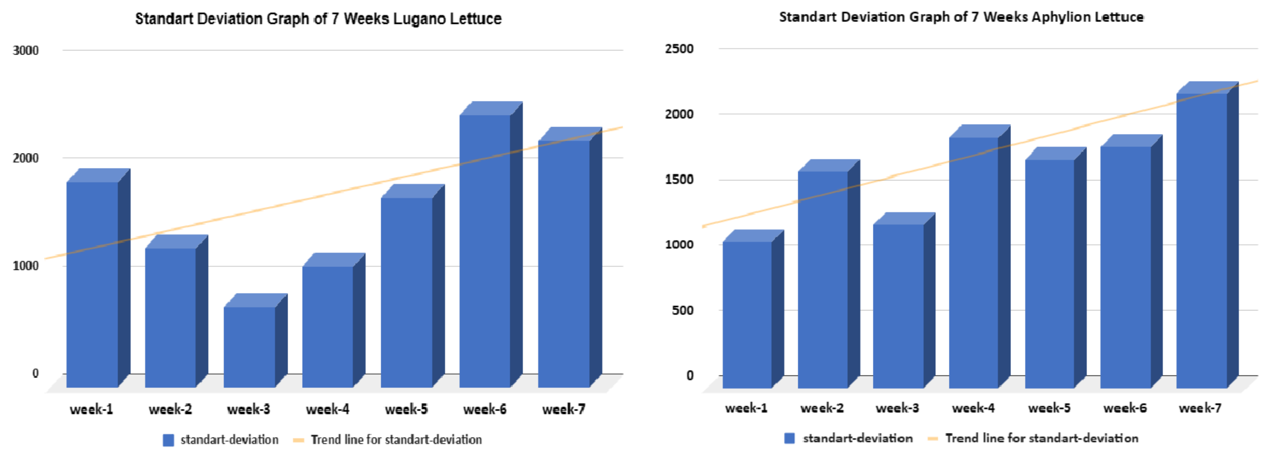

Fig. 7. Standard deviation graph of "Aphylion" and "Lugano" lettuce growing period of 7 weeks

The growth periods of 7 distinct clusters of the "Aphylion" plant in the standard deviation graph (see Fig. 7) clearly illustrate 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 the "Aphylion" plant undergoes different growth phases, encompassing both consistent and fluctuating periods.

Similarly, the growth periods of 7 distinct clusters of the "Lugano" plant are also depicted through the standard deviation graph presented in Fig. 7. Upon analysing 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 instance, the [43463, 47320, 47622, 48104] cluster), indicating increased variations in growth rates between periods. The standard deviations of both plant clusters are quite different. The standard deviations of the LUGANO plant clusters are generally lower, which may indicate that the dataset is more homogeneous. The standard deviations of the APHYLION plant clusters are generally higher, which may indicate greater variability in the data set and more diversity among plants.

Experiments and Results

The objective was to develop lettuce size estimation algorithms using a monocular camera as a cost-effective alternative to traditional stereo camera setups (Zhao, 2023). The primary goal of the research was to determine the readiness of lettuce plants for harvesting by applying computer vision techniques (Raza, 2018).

The initial step of the approach used involved using the YOLOv4 object detection algorithm to detect lettuce plants in images captured by the monocular camera. Once the plants were identified, the HSV colour space to compute the maximum area index for each detected lettuce plant has been employed.

Maximum area index played a crucial role in the analysis, enabling precise measurement of the sizes of lettuce plants. For the size estimation method, a dataset containing HSV-calculated maximum area pixel index values of lettuce plants during 1 to 7 weeks of growth has been employed. Employing Gaussian Mixture Model (GMM) clustering on the pixel values helped identify 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.

Associating the detected lettuce plants with their respective clusters, made it possible to 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.

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

Overall, the study results demonstrate the successful applicability of a monocular camera-based smart agriculture system for lettuce harvest detection. Integrating object detection with the YOLOv4 algorithm and area estimation using the HSV colour space and maximum area index helps achieve accurate and cost-effective size calculations. The incorporation of Gaussian Mixture Model clustering with the dataset further enhanced the accuracy of the lettuce growth and harvest prediction (Birrell, 2019).

Conclusions

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 colour space demonstrates the potential to provide an effective method for monitoring and predicting automatic lettuce growth. The combination of image capture, colour space-based area calculation, and Gaussian Mixture Model (GMM) clustering enables a better understanding of the lettuce growth process in a more precise and efficient manner while also contributing to the optimisation 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 method developed shows 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 optimisation 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 visualisation 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 optimisation of modern agricultural practices and the promotion of sustainable farming.

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References

1. Petropoulou, A. S., van Marrewijk, B., de Zwart, F., Elings, A., Bijlaard, M., van Daalen, T., Hemming, S. (2023). Lettuce Production in Intelligent Greenhouses—3D Imaging and Computer Vision for Plant Spacing Decisions. *Sensors*, 23(6). doi:10.3390/s23062929
2. Braun, A.-T., Colangelo, E., & Steckel, T. (2018). Farming in the Era of Industrie 4.0. *Procedia CIRP*, 72, 979–984. doi:10.1016/j.procir.2018.03.176
3. Rahimikhoob, H., Delshad, M., & Habibi, R. (2023). Leaf area estimation in lettuce: Comparison of artificial intelligence-based methods with image analysis technique. *Measurement*, 222, 113636. doi:10.1016/j.measurement.2023.113636
4. Bochkovskiy, A., Wang, C.-Y., & Liao, H.-Y. M. (2020). YOLOv4: Optimal Speed and Accuracy of Object Detection. CoRR, abs/2004.10934. https://arxiv.org/abs/2004.10934
5. Zhong, H., & Wang, R. (2022). A visual-degradation-inspired model with HSV colour-encoding for contour detection. *Journal of Neuroscience Methods*, 369, 109423. doi:10.1016/j.jneumeth.2021.109423.
6. Huang, H., Liao, Z., Wei, X., & Zhou, Y. (2023). Combined Gaussian Mixture Model and Pathfinder Algorithm for Data Clustering. *Entropy*, 25(6). doi:10.3390/e25060946
7. Ji, S.-J., Ling, Q.-H., & Han, F. (2023). An improved algorithm for small object detection based on YOLO v4 and multi-scale contextual information. *Computers and Electrical Engineering*, 105, 108490. doi:10.1016/j.compeleceng.2022.108490
8. 8. Hu, N., Wang, S., Wang, X., Cai, Y., Su, D., Nyamsuren, P., Wei, H. (2022). LettuceMOT: A dataset of lettuce detection and tracking with re-identification of re-occurred plants for agricultural robots. *Frontiers in Plant Science*, 13. doi:10.3389/fpls.2022.1047356
9. Chander, S., & Vijaya, P. (2021). 3 - Unsupervised learning methods for data clustering. In D. Binu & B. R. Rajakumar (Eds.), *Artificial Intelligence in Data Mining*, 41–64. doi:10.1016/B978-0-12-820601-0.00002-1
10. Zhao, D., Ji, C., & Liu, G. (2023). Monocular 3D Object Detection Based on Pseudo Multimodal Information Extraction and Keypoint Estimation. *Applied Sciences*, 13(3). doi:10.3390/app13031731
11. Raza, M., Chen, Z., Ur Rehman, S., Wang, P., & Wang, J.-K. (2018). Framework for estimating distance and dimension attributes of pedestrians in real-time environments using a monocular camera. *Neurocomputing*, 275, 533–545. doi:10.1016/j.neucom.2017.08.052.
12. Birrell, S., Hughes, J., Cai, J. Y., & Iida, F. (2020). A field-tested robotic harvesting system for iceberg lettuce. *Journal of Field Robotics*, 37(2), 225–245. https://doi.org/10.1002/rob.21888

SALOTŲ LAPŲ PLOTO INDEKSO NUSTATYMAS NAUDOJANT MONO KAMERĄ

Santrauka

Tyrimu buvo siekiama sukurti pikselių vertės analizės naudojant vaizdo kamerą metodą siekiant nustatyti skirtingus salotų augalų augimo etapus. Nuotraukose kamera užfiksuoti salotų augalų vaizdai buvo apdorojami naudojant YOLOv4 (You Only Look Once Version 4) objektų aptikimo algoritmą ir apskaičiuojamas kiekvieno aptikto salotų augalo lapų ploto indeksas HSV (Hue, Saturation, Value) spalvinėje erdvėje. Lapų ploto indeksas yra pagrindinis šios analizės rodiklis, padedantis tiksliai išmatuoti salotų augalų dydį. Lapų ploto įvertinimas buvo patikrintas naudojant vaizdų rinkinį, kuriame buvo fiksuoti salotų vaizdai joms augant nuo 1 iki 7 savaičių. Duomenų analizei buvo panaudotas Gauso mišinio modelis (GMM), kuris padėjo klasterizuoti lapų ploto pikselių reikšmes, o 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 augimo 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 vaizdų gavimo priemones. Šis tyrimas parodo, kaip, panaudojant dirbtinio intelekto gilųjį mokymąsi, mašininė rega 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 paremtą technologinį procesą. Atlikti eksperimentai demonstruoja sėkmingą mono kameros integravimą į išmaniąją žemės ūkio sistemą, skirtą salotų derliaus laiko nustatymui. Objektų aptikimui naudotas 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.

Reikšminiai žodžiai: dirbtinis intelektas, vaizdo apdorojimas, hidroponika, žemės ūkis, automatika

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