Available at www.sciencedirect.com

INFORMATION PROCESSING IN AGRICULTURE 10 (2023) 1–10

journal homepage: www.elsevier.com/locate/inpa

Detection of abnormal hydroponic lettuce leaves based on image processing and machine learning

Ruizhe Yang [a], Zhenchao Wu [a], Wentai Fang [a], Hongliang Zhang [b], Wenqi Wang [a], Longsheng Fu [a,c,d,*], Yaqoob Majeed [e,f], Rui Li [g], Yongjie Cui [a]

[a] College of Mechanical and Electronic Engineering, Northwest A&F University, Yangling, Shaanxi 712100, China
[b] Xi'an Agriculture Machinery Management and Extension Station, Xi'an, Shaanxi 710065, China
[c] Key Laboratory of Agricultural Internet of Things, Ministry of Agriculture and Rural Affairs, Yangling, Shaanxi 712100, China
[d] Shaanxi Key Laboratory of Agricultural Information Perception and Intelligent Service, Yangling, Shaanxi 712100, China
[e] Faculty of Agricultural Engineering and Technology, University of Agriculture, Faisalabad 38000, Pakistan
[f] Center for Precision and Automated Agricultural Systems, Washington State University, Prosser, WA 99350, USA
[g] Suide County Lanhuahua Ecological Food Co., Ltd., Suide, Shaanxi 718000, China

A R T I C L E I N F O

Article history:
Received 30 June 2021
Received in revised form
25 October 2021
Accepted 8 November 2021
Available online 14 November 2021

Keywords:
Hydroponic lettuce
Machine learning
Image processing
Abnormal leaves
Automatic sorting

A B S T R A C T

Accurate and fast detection of abnormal hydroponic lettuce leaves is primary technology for robotic sorting. Yellow and rotten leaves are main types of abnormal leaves in hydroponic lettuce. This study aims to demonstrate a feasibility of detecting yellow and rotten leaves of hydroponic lettuce by machine learning models, i.e. Multiple Linear Regression (MLR), K-Nearest Neighbor (KNN), and Support Vector Machine (SVM). One-way analysis of variance was applied to reduce RGB, HSV, and L*a*b* features number of hydroponic lettuce images. Image binarization, image mask, and image filling methods were employed to segment hydroponic lettuce from an image for models testing. Results showed that G, H, and a* were selected from RGB, HSV, and L*a*b* for training models. It took about 20.25 s to detect an image with 3 024 $\times$ 4 032 pixels by KNN, which was much longer than MLR (0.61 s) and SVM (1.98 s). MLR got detection accuracies of 89.48% and 99.29% for yellow and rotten leaves, respectively, while SVM reached 98.33% and 97.91%, respectively. SVM was more robust than MLR in detecting yellow and rotten leaves of hydroponic. Thus, it was possible for abnormal hydroponic lettuce leaves detection by machine learning methods.

© 2021 China Agricultural University. Production and hosting by Elsevier B.V. on behalf of KeAi. This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

1. Introduction

As an economical and medicinal vegetable species, lettuce is one of the most common vegetables in China. Lettuce is a good source of various health-beneficial bioactive compounds such as, calcium, Vitamin B_9, Vitamin C, Vitamin E, etc. [1,2]. It can be applied as medicine to clear heat, lower cholesterol levels, and treat neurasthenia [3]. In 2018, production of lettuce was 1.6 million t from a cultivated area of 648 738 ha in China (UN Food & Agriculture Organization, 2020). Because of growing in greenhouses, hydroponic lettuce has advantages of short growth cycle, space saving, and high production capacity compared with traditionally grown lettuce [4].

* Corresponding author at: College of Mechanical and Electronic Engineering, Northwest A&F University, Yangling, Shaanxi 712100, China.
E-mail address: fulsh@nwafu.edu.cn (L. Fu).
Peer review under responsibility of China Agricultural University.
https://doi.org/10.1016/j.inpa.2021.11.001
2214-3173 © 2021 China Agricultural University. Production and hosting by Elsevier B.V. on behalf of KeAi.
This is an open access article under the CC BY-NC-ND license (http://creativecommons.org/licenses/by-nc-nd/4.0/).

Yellow and rotten leaves of hydroponic lettuce need to be sorted manually before packing, which is high labor cost and low efficiency. A reason for emergence of these leaves is that hydroponic lettuce is parasitized by several plant pathogens which cause several kinds of phenomena, such as gray rot, black rot on bottom, and leaf yellowing [5,6]. Abnormal lettuces with yellow and rotten leaves are not quality for fresh market and need to be removed before packing [1,7]. Therefore, there is a strong desire to develop automatic sorting systems to reduce high labor cost of manual sorting.

Abnormal leaves detection on lettuces using machine vision was the first step for sorting, while machine learning has been applied in detecting crop diseases on leaves that similar to yellow and rotten leaves on hydroponic lettuce. Sharif et al. [8] applied a hybrid feature selection method including principal components analysis score, entropy, and skewness-based covariance vector and Multiclass-SVM (M-SVM) for detecting anthracnose disease and melanose disease on leaves of citrus, which achieved true positive rate of 96.9% and 97.1%. Pantazi et al. [9] applied nearest support vector strategy to make three One-Class Classifiers for detecting downy mildew, powdery mildew, and black rot on leaves of several kinds of crops, which got a classification accuracy of 95.0%. Khan et al. [10] applied one-vs-all M-SVM as a base classifier to detect black rot on apple leaves and reached 97.2% classification accuracy on parallel fusion features of color, color histogram, and local binary pattern features. Vijver et al. [11] presented partial least squares discriminant analysis to detect early blight on potato leaves and reported positive predictive value of 0.92. These studies showed that abnormal leaves of many kinds of crops could be detected with high accuracy by machine learning. Therefore, it is promising to use machine learning methods to detect yellow and rotten leaves of hydroponic lettuce.

Multiple Linear Regression (MLR), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and other machine learning models have been widely applied as classifiers in abnormal areas detection of crop leaves. Lu et al. [12] applied Fisher discriminant analysis to detect anthracnose crown rot in an early stage of infected strawberry leaves indoors with a classification accuracy of 90.5%. Hassanien et al. [13] improved moth-flame to detect powdery mildew and early blight on leaves, which reached a classification accuracy of 90.5%. Shuaibu et al. [14] applied MLR to build prediction models for early-stage Marssonina blotch samples of apple leaves and achieved a classification accuracy of 92.0%. Xie et al. [15] defined features ranking KNN to classify healthy and gray mold tomato leaves with a classification accuracy of 97.2%. Oh et al. [16] applied artificial neural network to detect yellow leaves on tomato, which got a classification accuracy of 90.0%. Sun et al. [17] combined simple linear iterative cluster with SVM to detect anthracnose and brown blight leaves of tea plant under complex background and achieved a classification accuracy of 98.5%. SVM had been shown to carry out classification accuracy from 94.3% to 99.1% on many detection tasks of leaf diseases [18–20]. Those studies proved that MLR, KNN, and SVM are promising to detect abnormal areas of leaves with higher accuracy. However, there are no reports of applying these models for detecting abnormal hydroponic lettuce leaves.

Researches of hydroponic lettuce were mostly done by machine learning models on different image features. Lauguico et al. [21] selected Variance_H4, Entropy, Energy, and Information Measure Correlation of hydroponic lettuce to train linear discriminant analysis for a classification of life stages and resulted in 87.92% accuracy. Alejandrino et al. [22] proposed K-means to detect phytomorphological features of hydroponic lettuce and reached an unsupervised clustering percentage of 91%. Zhang et al. [23] presented convolutional neural network to learn a relationship from area and growth-related traits of hydroponic lettuce with R^2 of 0.928. Machine learning combined with image features had great potential for detecting crop diseases [24]. However, these reports relied on complicated image features. Therefore, a more robust and less computation method should be explored.

Therefore, MLR, KNN, and SVM were compared on detecting yellow and rotten leaves of hydroponic lettuce in this study. These leaves were segmented from original images by image processing methods. MLR, KNN, and SVM were employed for hydroponic lettuce leaves detection and evaluated by their performance. An optimum model was selected in terms of detection accuracy and speed.

2. Materials and methods

2.1. Image acquisition

Hydroponic lettuce was collected from Yangling Modern Agriculture Demonstration Park. Images of the hydroponic lettuce were collected by a smartphone (Xiaomi 8se, Xiaomi technology Co. Ltd., Beijing, China). As shown in Fig. 1, the hydroponic lettuce was fixed on a shelf while the smartphone was fixed at aside of that to get images of yellow and rotten leaves. RGB images were got within a distance of 30 cm and an angle of 60^0 between center line of the smartphone and horizontal line, which were taken inside laboratory (latitude: 34°17′22″ N, longitude: 108°4′13″ E, and 510 m in altitude) of Northwest A&F University, Shaanxi, China. In total, 300 original images with 3 024 × 4 032 pixels were collected. In particular, 240 images were applied for color features collection, and 60 images with abnormal leaves were used for performance evaluation of KNN, MLR, and SVM, as shown in Fig. 2.

2.2. Data collection

Color features were extracted from the 240 images, which were important for detection of the yellow and rotten leaves because these leaves have different color compared with normal leaves. Pixels information of RGB, HSV, and L*a*b* were used as color features, which were collected randomly in Python by choosing a pixel of an input image. A label of ground truth was got simultaneously with label 1, label 2, and label 3 for normal leaves, yellow leaves, and rotten leaves, respectively. In total, 1 325 sets of pixel data were collected from the 240 images and divided into training set (1 060 sets, 80%) and testing set (265 sets, 20%).

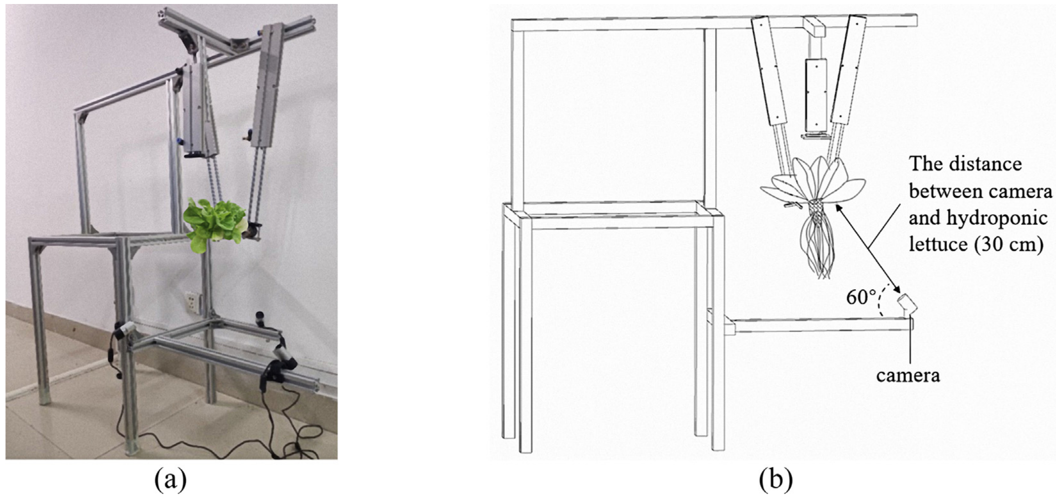


Fig. 1 – (a) Physical diagram and (b) schematic diagram of image acquisition system for hydroponic lettuce.

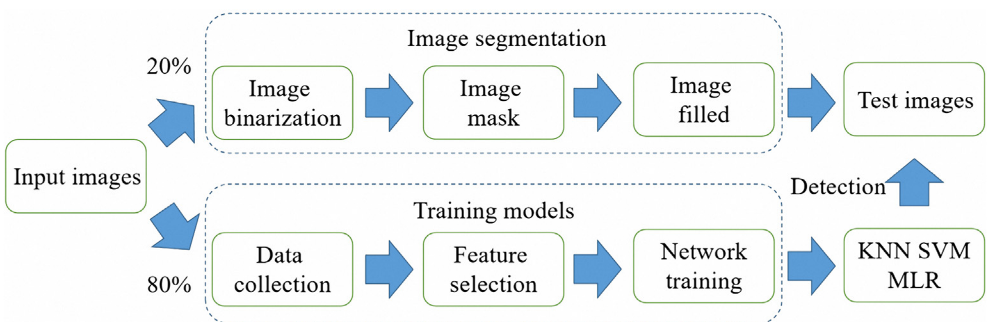


Fig. 2 – Layout structure of hydroponic lettuce detection method.

2.3. *Color features selection*

Significant color features for classifying pixels of healthy, yellow, and rotten leaves were extracted by data analyze. The nine color features needed to be reduced by one-way analysis of variance (one-way ANOVA) in dataset [25], which was performed by PASW Statistics 18 (SPSS Inc., an IBM Company, Chicago, Illinois, USA). A Fisher's least significant differences test was utilized to determine differences between group means in one-way ANOVA ($p \le 0.05$) to reduce the amount of those features. Three kinds of color features would be selected for training models with smaller p and larger F [26].

2.4. *KNN, MLR, and SVM*

KNN was used for predicting an unlabeled example by majority labels of its nearest samples. This example was classified as most examples of a same label in K known closest examples by comparing Euclidean distance, which was defined in Eq. (1) [27]. A pixel was classified as a same kind with most of nearest pixels in this model to detect yellow and rotten leaves.

$$d(x_i, x_j) = (x_i - x_j)^T (x_i - x_j) = \| x_i - x_j \|^2 \tag{1}$$

Where $d(x_i, x_j)$ was the distance of different examples, x_i and x_j were unlabeled examples and near sample position expressed in Euclidean Distance.

SVM was inherently a binary classifier that applied to segment several classes in feature spaces, which was analogous to a definition of a hyperplane for linearly separable variables. It was also applied on a condition of non-linearly separable variables, with an existence of a higher dimensional space where linear segmentation was achieved with a kernel function [28]. Radial basis function (RBF) was a kernel function of SVM, which was chosen as the kernel function of SVM in this paper because of its less hyperparameters than other kernel functions [29].

MLR used several explanatory variables to predict a response variable by modeling linear relationship between explanatory variables and a response variable [30]. A kind of new pixel would be predicted based on this formula in this model, which could be defined as Eq. (2).

$$y_n = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 \tag{2}$$

Where y_n was the response variable, x_1, x_2, and x_3 were selected color features for training models, β_0 was y-intercept, β_1, β_2, and β_3 were slope coefficients of those features.

2.5. Network training

A training hardware included a laptop equipped with a CPU of Intel Core i7-6700HQ (2.6 GHz), 8 GB of RAM, and an NVIDIA GTX 965 M 4 GB GPU, running on a Windows 10 64-bit system. Software tools included Python 3.7, PyCharm 4.0, and Anaconda 3.0.

KNN, SVM, and MLR were trained with those hyperparameters on the selected color features. KNN was trained with K with a default value of 5 that was adjusted by 'neighbors' function. SVM was trained with two hyperparameters, soft margin parameter C and γ in RBF. These best hyperparameters which made models achieve higher accuracy without overfitting problems could be found by controlling variables to draw a line graph.

2.6. Image processing

Image processing was applied to segment hydroponic lettuce from an image. KNN, MLR, and SVM were used to test an effect of detecting yellow and rotten leaves on hydroponic lettuce after training. However, there were complex background information in hydroponic lettuce images, which had potential to lower the accuracy of abnormal leaves detection [31]. Therefore, it was necessary to segment hydroponic lettuce from image by image processing methods.

Image binarization was used to turn colorful images into binary images. And Otsu method was applied for determining a threshold of image binarization segmentation [32]. This method performed automatic image thresholding by returning a single intensity value that segmented image pixels into background and foreground [33]. The precision of binarization were different in different color features [34]. Therefore, it was necessary to test image binarization in HSV and L*a*b*.

There were two methods of image binarization of HSV images and L*a*b* images. One method was employed to decompose HSV images into H, S, and V, and to get a binary image on H, while another was applied to decompose L*a*b* images into L*, a*, and b*, and to get one binary image from 'OR' operation of two binary images on a* and b*. Performance of the two methods was compared by a completeness of segmentation between hydroponic lettuce and the background.

Image mask was applied to restore the closest truth of image with computer technology and to analysis of causes of mask and possible results [35]. White parts in images reached in image binarization were masked to get parts of hydroponic lettuce by combining yellow and green parts. Hydroponic lettuce was then segmented from the background, but some parts that were obscured by fixtures had not been successfully segmented and needed to be filled.

There were two methods to fill image, i.e. flood fill and dilation. Flood fill was applied to determine an area connected to a given node in a multi-dimensional array. Dilation was one of basic operations in mathematical morphology, which usually employed a structuring element for probing and expanding shapes contained in an input image. Performance of the two methods could be compared by completeness of filling images.

2.7. Evaluation indicators

Performance of KNN, MLR, and SVM was evaluated by detection accuracy and speed. Detection accuracy was defined as 1 minus a result of the error calculation which was defined as an absolute value of subtraction between abnormal areas ratio predicted by KNN, MLR, and SVM and abnormal areas ratio got from ground truth. Mark inspection was used to mark abnormal areas predicted by KNN, MLR, and SVM traversal into images, which was obvious to observe detection effect of KNN, MLR, and SVM directly from the mark inspection. ANOVA was used to compare the speed of KNN, MLR, and SVM for different backbones at a significance level of 0.05 based on Tukey's Honest significant difference test.

3. Results and discussions

3.1. Selected color features

One-way ANOVA of nine kinds of color features was shown in Table 1. Because p values of all color features were less than 0.01, it was difficult to decide which color feature has greater impact on a label based on p. However, the F values of a* (1

Table 1 – Results for One-way ANOVA on different kinds of color features in hydroponic lettuce leaves image.

Color feature	Squares sum	Freedom	Mean square	F	p
R	510 111	2	255 055	432	<0.01
G	570 395	2	28 5197	**589**	<0.01
B	305 500	2	152 750	251	<0.01
H	193 902	2	96 951	**577**	<0.01
S	2	2	1	102	<0.01
V	5	2	3	334	<0.01
L*	75 443	2	37 721	502	<0.01
a*	66 467	2	33 233	**1 641**	<0.01
b*	24 363	2	12 181	197	<0.01

Note: F was the ratio of intergroup variation to intragroup variation, which indicated the significance of the item, and the larger the F, the stronger the significance. The p was a test level of a color feature. In this paper, values of p less than 0.05 indicate color features were significant.

641), G (589), and H (577) were higher than that of other features, which showed that a*, G, and H had more sensitivity to training models than other color features with a result of selecting them for training models.

A representation of healthy, yellow, and rotten leaves extracted from a*, G, and H of hydroponic lettuce images was a key to definite models for detecting these leaves. These color features could generalize accurately to one class definition of those leaves, which provided a needed robustness to image transformation resulting from environmental factors like scaling, translation, and rotations or illumination variations. Important information that related to a health condition of hydroponic lettuce was captured because of an ability of the selected color features incorporating color information corresponding to visual manifestation.

3.2. Training results of KNN, MLR, and SVM

KNN, MLR, and SVM were trained and tested with their hyperparameters to apply for detecting yellow and rotten leaves of hydroponic lettuce. KNN, MLR, and SVM were measured on testing set with 203 sets of data which were selected randomly from 1 015 sets of data. KNN got 94.7% testing accuracy based on testing set with K whose default value was 5. Suitable γ and c could be got from the training results which were shown in Fig. 3 with those hyperparameters. SVM got 98.5% testing accuracy based on testing set with γ value of 0.004 and c value of 1 without an overfitting problem. MLR achieved 86.0% testing accuracy based on testing set with $\beta 0 = -3.707$, $\beta 1 = 0.059$, $\beta 2 = -0.003$, $\beta 3 = -0.017$. $\beta 1$, $\beta 2$, and $\beta 3$ were slope coefficient for a*, G, and H.

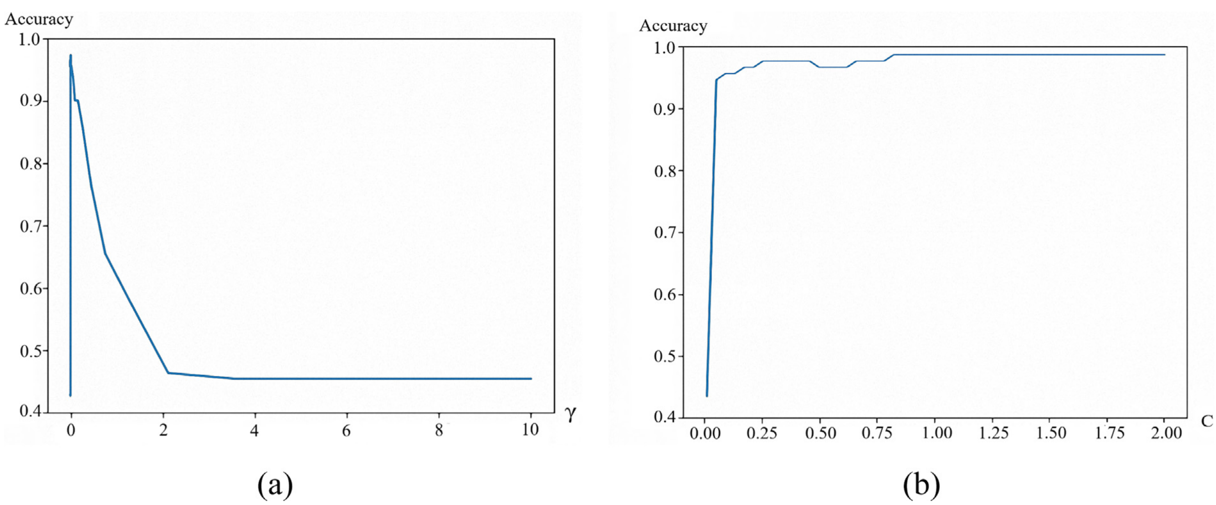


Fig. 3 – Training accuracies with changing SVM hyperparameters to choose suitable (a) γ and (b) C.

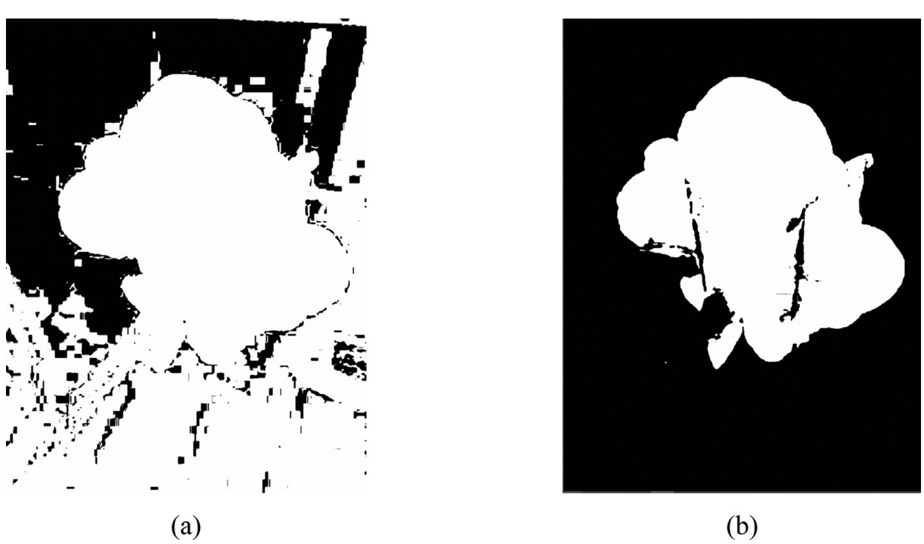


Fig. 4 – Binarization results on (a) H with most background information same as hydroponic lettuce parts and (b) a* and b* with background information almost isolated from hydroponic lettuce.

(a) (b)

Fig. 5 – Comparison of hydroponic lettuce (a) original image with all background information and (b) masked image with hydroponic lettuce segmented from background information.

(a) (b)

Fig. 6 – Filling results of (a) flood fill with some missing part A and (b) dilation with large parts of background B on hydroponic lettuce images.

3.3. *Results of image processing methods*

Hydroponic lettuce parts were segmented from background on different color features, as shown in Fig. 4. These parts were segmented better in binarization results on a*, b* than these parts on H, which may be a result of segmenting green parts on a* and yellow parts on b* by Otsu method. Hydroponic lettuce was made up of green parts and yellow parts while background did not own these parts. Therefore, 'OR' operation on two binary images could achieve better segmentation than one binary image on H between hydroponic lettuce parts and background.

Masked image of hydroponic lettuce was shown in Fig. 5. Most areas of Hydroponic lettuce were segmented from image background, while some parts of hydroponic lettuce that were obscured by fixtures had not been successfully segmented and needed to be filled.

Filling images of flood fill and dilation were shown in Fig. 6. It was obvious that many white parts of background were filled in the image on dilation method. Therefore, dilation method was not suitable for filling images. And a reason of unfilled parts which was shown by red circle in Fig. 6 from flood fill was complex boundary. However, this problem could be solved by putting hydroponic lettuce in center of an image while changing a distance between camera and hydroponic lettuce.

Some limitations of this presented method could possibly arise due to extrinsic factors such as image background which

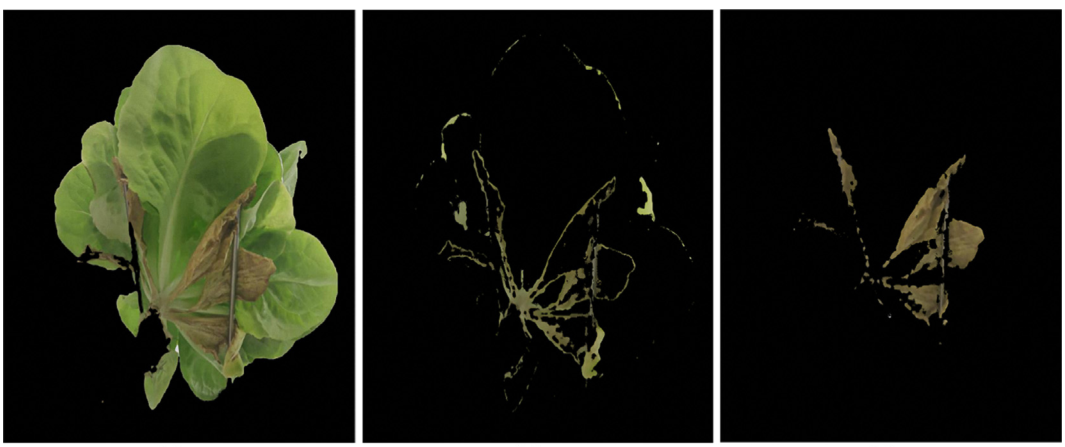
Table 2 – Speed of detecting hydroponic lettuce images by KNN, MLR, and SVM.			
Model	Number of test images	Resolution / pixels × pixels	Detection speed /s
KNN	60	3 024 × 4 032	20.25 ± 3.076[a]
SVM	60	3 024 × 4 032	1.98 ± 0.156[b]
MLR	60	3 024 × 4 032	0.61 ± 0.179[c]

Note: The ‘a’ ‘b’ and ‘c’ in the ‘speed’ column represent a significant difference of different models at the 0.05 level.

contained similar color with yellow and rotten leaves. These limitations were overcome through image processing methods which can overcome extrinsic factors that may corrupt the hydroponic lettuce detection due to image background since they were very robust by isolating and extracting areas of interest (hydroponic lettuce leaves). Additionally, yellow and rotten leaves regarding orientation and lighting were overcome by color features extraction since a*, G, and H are invariant to these variations.

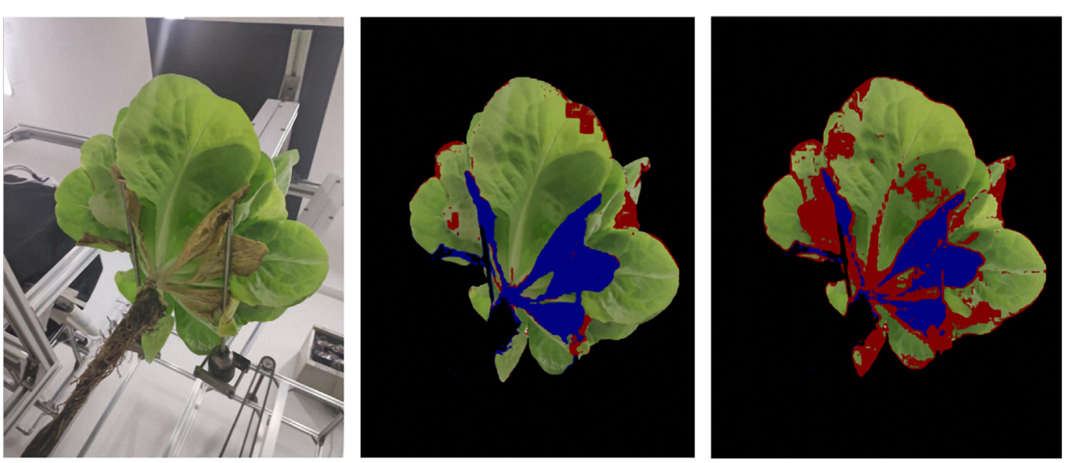
3.4. *Detection time and accuracy of KNN, MLR, and SVM*

There were 60 images with yellow and rotten leaves for performance evaluation of KNN, MLR, and SVM. It took 20.25 s on average to detect an image with 3 024 × 4 032 pixels by KNN, which was much longer than MLR (0.61 s) and SVM (1.98 s), which was shown in Table 2. Therefore, it was not suitable for KNN to detect yellow and rotten leaves of hydroponic lettuce on time wasting. A reason of this phenomenon



(a) (b) (c)

Fig. 7 – (a) Original hydroponic lettuce image and segmentation results of (b) yellow leaves and (c) rotten leaves from a hydroponic lettuce image.



(a) (b) (c)

Fig. 8 – (a) Original hydroponic lettuce image and results of mark inspection by (b) SVM and (c) MLR with blue areas for rotten leaves and red areas for yellow leaves.

Table 3 – Detection results of our and other models for abnormal leaves.

Models	Leaves	Pixels resolution	Accuracy
SVM (Ours)	Hydroponic lettuce rotten leaves	3 024 × 4 032	97.91%
MLR (Ours)	Hydroponic lettuce rotten leaves	3 024 × 4 032	99.29%
SVM (Ours)	Hydroponic lettuce yellow leaves	3 024 × 4 032	98.33%
MLR (Ours)	Hydroponic lettuce yellow leaves	3 024 × 4 032	89.48%
SVM [19]	Strawberry powdery mildew leaves	1 135 × 1 135	94.34%
M-SVM [8]	Citrus anthracnose disease leaves	256 × 256	97.11%
KNN [15]	Tomato gray mold leaves	672 × 512	97.22%

may be that KNN was slow when calculating datasets with samples. It showed that detection speed for an image of MLR was faster than SVM with a significant difference in detection speed between them in Table 2.

The segmentation of yellow and rotten leaves was shown in Fig. 7. Yellow leaves were at the edge of the hydroponic lettuce, while rotten leaves were located in middle areas of it. Results of mark inspection which could identify accuracy of detecting yellow and rotten leaves were shown in Fig. 8. Each kind of hydroponic lettuce pixels was determined by predicted masks with blue areas for rotten leaves and red areas for yellow leaves [36]. There were missed areas in SVM and MLR detection of yellow leaves compared with Fig. 7, which in MLR was more than in SVM.

Detection accuracy of MLR and SVM was shown in Table 3. MLR got it of 89.48% and 99.29% for yellow and rotten leaves, respectively, while SVM reached 98.33% and 97.91% for them, respectively. There was a big deviation in yellow leaves detection of MLR, while MLR was more precise than SVM in rotten leaves detection by 1.38%. SVM got a higher accuracy on yellow leaves than MLR by 8.85% and a lower speed by 1.37 s on average. Detection accuracy was more important than speed. Therefore, SVM could be a suitable model to detect hydroponic lettuce.

The detection accuracies of our models and three other crops detection using SVM, M-SVM, and KNN by Shin et al. [19], Sharif et al. [8], and Xie et al. [15] were concluded. As shown in Table 3, Our SVM achieved 97.91% in rotten leaves and 98.33% in yellow leaves of hydroponic lettuce. Shin et al. [19] got 94.34% in powdery mildew leaves of strawberry with SVM. Sharif et al. [8] reported 97.11% in anthracnose disease leaves of citrus with M-SVM. Xie et al. [15] achieved 97.22% in gray mold leaves of tomato with KNN. Our SVM had a potential for expanding into detection of other crops.

This presented method combined some advantages of SVM with advanced imaging processing methods like image binarization, mask, and filling methods to isolate visual features, i.e. a*, G, and H related to health conditions of hydroponic lettuce leaves. SVM was a flexible intelligent system to discover knowledge in natural environments [37]. This method could further have expanded into detection of other crops condition in order to adapt reasonable crop management practices in the field of precision agriculture.

4. Conclusions

Detection of yellow and rotten leaves in hydroponic lettuce was an important task for lettuce production. One-way ANOVA was applied to select G, H, and a* for training models. To demonstrate the feasibility for detecting yellow and rotten leaves of hydroponic lettuce by KNN, MLR, and SVM, Image binarization, mask, and filling methods were used to segment hydroponic lettuce leaves from the image. It took about 20.25 s to detect an image with 3 024 × 4 032 pixels by KNN, which was much longer than MLR (0.61 s) and SVM (1.98 s). MLR got detection accuracy of 89.48% and 99.29% for yellow and rotten leaves, respectively, while SVM reached 98.33% and 97.91%, respectively. SVM held potential for detecting the abnormal leaves to achieve needs of the lettuce production by setting a single camera with hydroponic lettuce. Further research needed to conduct on developing integrated machine version robots for sorting abnormal hydroponic lettuce.

Funding

This work was supported by the Science and Technology Program in Yulin City of China (CXY-2020-076, CXY-2019-129); Youth Science and Technology Nova Program in Shaanxi Province of China (2021KJXX-94); Key Research and Development Program of Shaanxi (2021NY-135); Recruitment Program of High-End Foreign Experts of the State Administration of Foreign Experts Affairs, Ministry of Science and Technology, China (G20200027075).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

[1] Eshkabilov S, Lee A, Sun X, Lee CW, Simsek H. Hyperspectral imaging techniques for rapid detection of nutrient content of hydroponically grown lettuce cultivars. Comput Electron Agric 2021;181:105968. 10.1016/j.compag.2020.105968.

[2] Kim MJ, Moon Y, Tou JC, Mou B, Waterland NL. Nutritional value, bioactive compounds and health benefits of lettuce (Lactuca sativa L.). J Food Compos Anal 2016;49:19–34. https://doi.org/10.1016/j.jfca.2016.03.004.

[3] Sun J, Zhou X, Mao H, Wu X, Zhang X, Li Q. Discrimination of pesticide residues in lettuce based on chemical molecular structure coupled with wavelet transform and near infrared hyperspectra. J Food Process Eng 2017;40(4):e12509. https://doi.org/10.1111/jfpe.2017.40.issue-410.1111/jfpe.12509.

[4] Sharma N, Acharya S, Kumar K, Singh N, Chaurasia OP. Hydroponics as an advanced technique for vegetable production: An overview. J Soil Water Conserv 2018;17:364–71. https://doi.org/10.5958/2455-7145.2018.00056.5.
[5] Shim CK, Kim MJ, Kim YK, Jee HJ. Evaluation of lettuce germplasm resistance to gray mold disease for organic cultivations. Plant Pathol J 2014;30(1):90–5. https://doi.org/10.5423/PPJ.NT.07.2013.0064.
[6] Esgario JGM, de Castro PBC, Tassis LM, Krohling RA. An app to assist farmers in the identification of diseases and pests of coffee leaves using deep learning. Inf Process Agric 2021. https://doi.org/10.1016/j.inpa.2021.01.004.
[7] Hao X, Jia J, Gao W, Guo X, Zhang W, Zheng L, et al. MFC-CNN: An automatic grading scheme for light stress levels of lettuce (Lactuca sativa L.) leaves. Comput Electron Agric 2020;179:105847. https://doi.org/10.1016/j.compag.2020.105847.
[8] Sharif M, Khan MA, Iqbal Z, Azam MF, Lali MIU, Javed MY. Detection and classification of citrus diseases in agriculture based on optimized weighted segmentation and feature selection. Comput Electron Agric 2018;150:220–34. https://doi.org/10.1016/j.compag.2018.04.023.
[9] Pantazi XE, Moshou D, Tamouridou AA. Automated leaf disease detection in different crop species through image features analysis and One Class Classifiers. Comput Electron Agric 2019;156:96–104. https://doi.org/10.1016/j.compag.2018.11.005.
[10] Khan MA, Lali MIU, Sharif M, Javed K, Aurangzeb K, Haider SI, et al. An Optimized Method for Segmentation and Classification of Apple Diseases Based on Strong Correlation and Genetic Algorithm Based Feature Selection. IEEE Access 2019;7:46261–77. https://doi.org/10.1109/Access.628763910.1109/ACCESS.2019.2908040.
[11] Van De Vijver R, Mertens K, Heungens K, Somers B, Nuyttens D, Borra-Serrano I, et al. In-field detection of Alternaria solani in potato crops using hyperspectral imaging. Comput Electron Agric 2020;168:105106. https://doi.org/10.1016/j.compag.2019.105106.
[12] Lu J, Ehsani R, Shi Y, Abdulridha J, de Castro AI, Xu Y. Field detection of anthracnose crown rot in strawberry using spectroscopy technology. Comput Electron Agric 2017;135:289–99. https://doi.org/10.1016/j.compag.2017.01.017.
[13] Hassanien AE, Gaber T, Mokhtar U, Hefny H. An improved moth flame optimization algorithm based on rough sets for tomato diseases detection. Comput Electron Agric 2017;136:86–96. https://doi.org/10.1016/j.compag.2017.02.026.
[14] Shuaibu M, Lee WS, Hong YK, Kim S. Detection of apple marssonina blotch disease using particle swarm optimization. Trans ASABE 2017;60:303–12. 10.13031/trans.11700.
[15] Xie C, Yang C, He Y. Hyperspectral imaging for classification of healthy and gray mold diseased tomato leaves with different infection severities. Comput Electron Agric 2017;135:154–62. https://doi.org/10.1016/j.compag.2016.12.015.
[16] Oh S, Ashapure A, Marconi TG, Jung J, Landivar J. UAS based Tomato Yellow Leaf Curl Virus (TYLCV) disease detection system. Auton Air Gr Sens Syst Agric Optim Phenotyping IV 2019;11008:110080P. https://doi.org/10.1117/12.2518703.
[17] Sun Y, Jiang Z, Zhang L, Dong W, Rao Y. SLIC_SVM based leaf diseases saliency map extraction of tea plant. Comput Electron Agric 2019;157:102–9. https://doi.org/10.1016/j.compag.2018.12.042.
[18] Freitas EL, Brito AC, de Oliveira SAS, de Oliveira EJ. Early diagnosis of cassava frog skin disease in powdered tissue samples using near-infrared spectroscopy. Eur J Plant Pathol 2020;156(2):547–58. https://doi.org/10.1007/s10658-019-01904-x.
[19] Shin J, Chang YK, Heung B, Nguyen-Quang T, Price GW, Al-Mallahi A. Effect of directional augmentation using supervised machine learning technologies: A case study of strawberry powdery mildew detection. Biosyst Eng 2020;194:49–60. https://doi.org/10.1016/j.biosystemseng.2020.03.016.
[20] Deng X, Huang Z, Zheng Z, Lan Y, Dai F. Field detection and classification of citrus Huanglongbing based on hyperspectral reflectance. Comput Electron Agric 2019;167:105006. https://doi.org/10.1016/j.compag.2019.105006.
[21] Lauguico SC, Concepcion RIIS, Alejandrino JD, Tobias RR, Dadios EP. Lettuce life stage classification from texture attributes using machine learning estimators and feature selection processes. Int J Adv Intell Informatics 2020;6(2):173. https://doi.org/10.26555/ijain.v6i2.466.
[22] Alejandrino J, Concepcion R, Lauguico S, Tobias RR, Almero VJ, Puno JC, et al. Visual classification of lettuce growth stage based on morphological attributes using unsupervised machine learning models. IEEE Reg. 10 Annu. Int. Conf. Proceedings/TENCON, 2020, p. 438–43. 10.1109/TENCON50793.2020.9293854.
[23] Zhang L, Xu Z, Xu D, Ma J, Chen Y, Fu Z. Growth monitoring of greenhouse lettuce based on a convolutional neural network. Hortic Res 2020;7:124. https://doi.org/10.1038/s41438-020-00345-6.
[24] Zou K, Ge L, Zhou H, Zhang C, Li W. Broccoli seedling pest damage degree evaluation based on machine learning combined with color and shape features. Inf Process Agric 2021. https://doi.org/10.1016/j.inpa.2020.12.003.
[25] Fu L, Okamoto H, Kataoka T, Shibata Y. Color based classification for berries of Japanese blue honeysuckle. Int J Food Eng 2011;7:5. https://doi.org/10.2202/1556-3758.2408.
[26] Wang W, Ma Y, Fu L, Cui Y, Majeed Y. Physical and mechanical properties of hydroponic lettuce for automatic harvesting. Inf Process Agric 2020. https://doi.org/10.1016/j.inpa.2020.11.005.
[27] Muslikhin HJR, Yang SY, Wang MS. Object Localization and Depth Estimation for Eye-in-Hand Manipulator Using Mono Camera. IEEE Access 2020;8:121765–79. https://doi.org/10.1109/ACCESS.2020.3006843.
[28] Shen L, Chen H, Yu Z, Kang W, Zhang B, Li H, et al. Evolving support vector machines using fruit fly optimization for medical data classification. Knowledge-Based Syst 2016;96:61–75. https://doi.org/10.1016/j.knosys.2016.01.002.
[29] Anami BS, Malvade NN, Palaiah S. Classification of yield affecting biotic and abiotic paddy crop stresses using field images. Inf Process Agric 2020;7:272–85. https://doi.org/10.1016/j.inpa.2019.08.005.
[30] Zhang F, Upton J, Shalloo L, Shine P, Murphy MD. Effect of introducing weather parameters on the accuracy of milk production forecast models. Inf Process Agric 2020;7:120–38. https://doi.org/10.1016/j.inpa.2019.04.004.
[31] Ngugi LC, Abelwahab M, Abo-Zahhad M. Recent advances in image processing techniques for automated leaf pest and disease recognition – A review. Inf Process Agric 2021:27–51. https://doi.org/10.1016/j.inpa.2020.04.004.
[32] Chowdhury WS, Lu G, Hossain MM. Three-dimensional Reconstruction and Measurement of Avian Eggs through Digital Imaging. I2MTC 2020 - Int Instrum Meas Technol Conf Proc; 2020. p. 9129156. 10.1109/I2MTC43012.2020.9129156.
[33] Ma Y, Zhang W, Qureshi WS, Gao C, Zhang C, Li W. Autonomous navigation for a wolfberry picking robot using visual cues and fuzzy control. Inf Process Agric 2021;8:15–26. https://doi.org/10.1016/j.inpa.2020.04.005.

[34] Shi G, Ranjan R, Khot LR. Robust image processing algorithm for computational resource limited smart apple sunburn sensing system. Inf Process Agric 2020;7:212–22. https://doi.org/10.1016/j.inpa.2019.09.007.

[35] Cao Z, Niu S, Zhang J, Wang X. Fast generative adversarial networks model for masked image restoration. IET Image Process 2019;13:1124–9. https://doi.org/10.1049/iet-ipr.2018.5592.

[36] Reyes-Yanes A, Martinez P, Ahmad R. Real-time growth rate and fresh weight estimation for little gem romaine lettuce in aquaponic grow beds. Comput Electron Agric 2020;179. https://doi.org/10.1016/j.compag.2020.105827 105827.

[37] Li Z, Li Y, Yang Y, Guo R, Yang J, Yue J, et al. A high-precision detection method of hydroponic lettuce seedlings status based on improved Faster RCNN. Comput Electron Agric 2021;182. https://doi.org/10.1016/j.compag.2021.106054 106054.